In [2]:

```
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.model_selection import train_test_split, GridSearchCV
from sklearn.model_selection import cross_val_score, cross_val_predict
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: 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: 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: 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: python-dateutil>=2.7.3 in c:\users\sarah\anaconda3\lib\site-packages (from
pandas>=0.25->seaborn) (2.8.2)
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: 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: 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: 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: 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: 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: 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: six>=1.5 in c:\users\sarah\anaconda3\lib\site-packages (from python-dateut
il>=2.7.3->pandas>=0.25->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-2-520edacd60bc> in <module>
     34 from sklearn.metrics import accuracy_score, recall_score, precision_score, auc, roc_auc_score, roc_curve
     35 from sklearn.metrics import confusion_matrix
---> 36 import scikitplot as skplt
     37 
     38 print('✔ Libraries Imported!')

ModuleNotFoundError: No module named 'scikitplot'
```

In [2]:

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

In [4]:

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

print('✔ Dataset Imported Successfully!\n')
print('It contains {} rows and {} columns.'.format(df.shape[0], df.shape[1]))
```

```
✔ Dataset Imported Successfully!

It contains 10000 rows and 14 columns.
```

In [5]:

```
df.head()
```

Out[5]:

	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 [6]:

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

Out[6]:

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

In [7]:

```
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 [8]:

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

Out[8]:

	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 [9]:

```
#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 11 columns
 Test set: 2000 rows x 11 columns
```

In [10]:

```
def plot_continuous(feature):
    '''Plot a histogram and boxplot for the churned and retained distributions for the specified feature.'''
    df_func = train_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 df, color, label in zip([df_retained, df_churned], colors, ['Retained', 'Churned']):
        sns.histplot(data=df,
                     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();
```

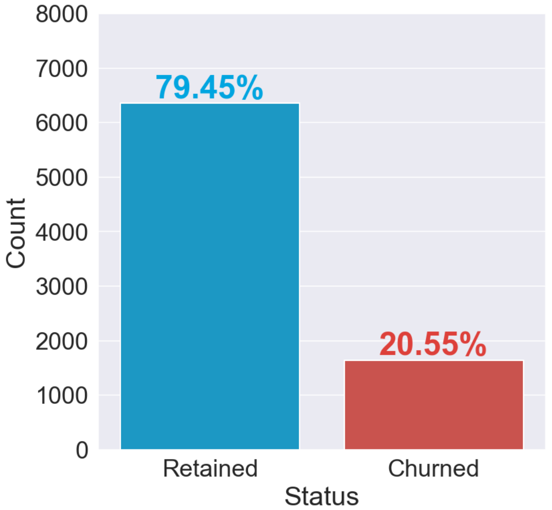
In [11]:

```
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=train_df,
                  palette=colors,
                  ax=ax1)
    ax1.set_ylabel('Count')
    ax1.legend(labels=['Retained', 'Churned'])

    sns.barplot(x=feature,
                y='Exited',
                data=train_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 [14]:

```
#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=train_df, palette=colors, ax=ax)

for index, value in enumerate(train_df['Exited'].value_counts()):
    label = '{}%'.format(round((value / train_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, 8000]);
```



In [ ]:

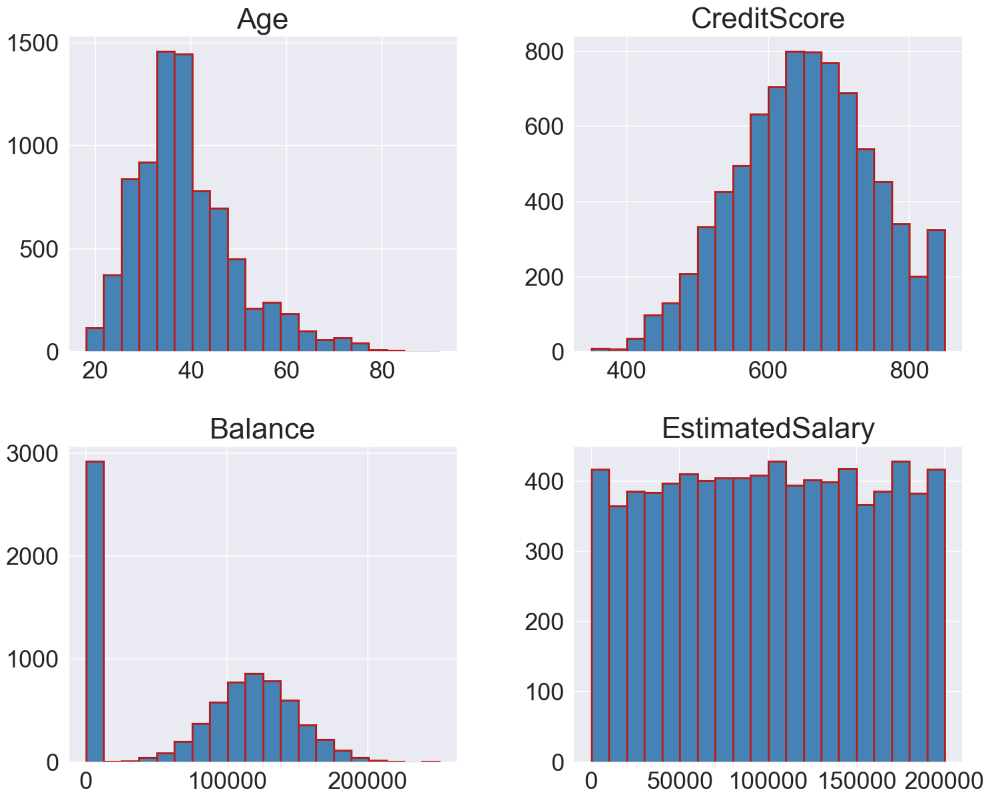
In [15]:

```
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
```

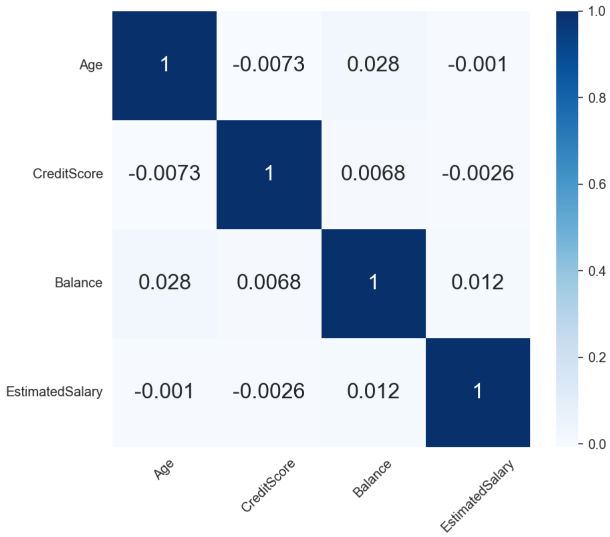
In [16]:

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



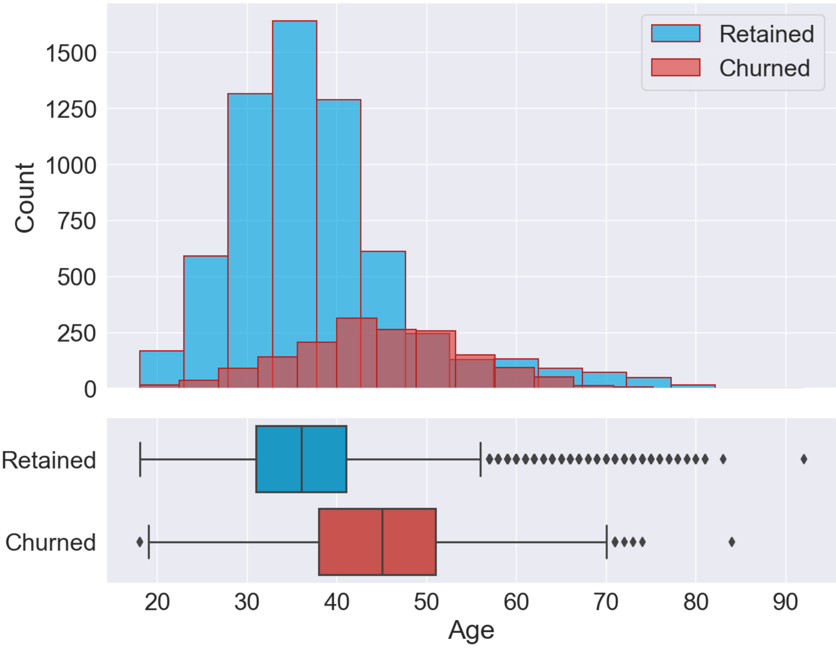
In [9]:

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

sns.heatmap(train_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);
```



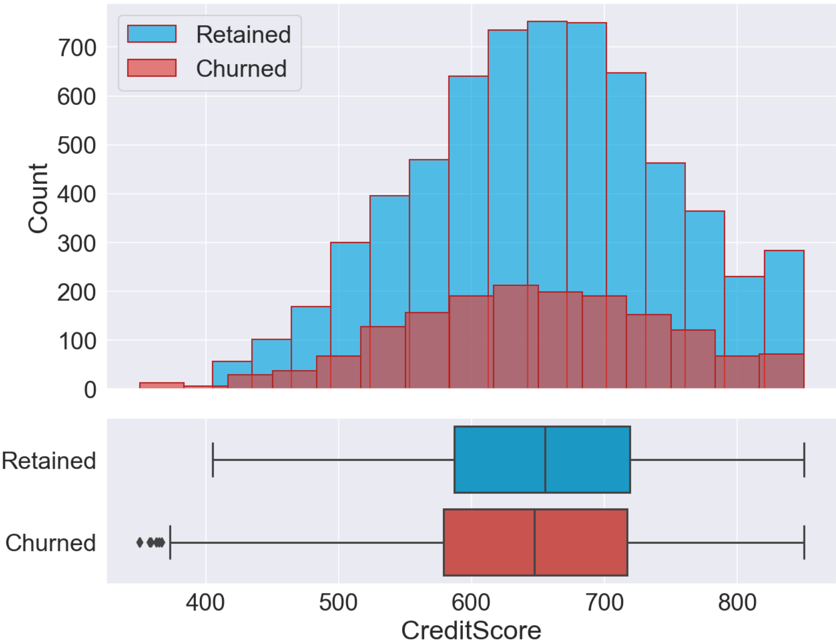
In [17]:

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

plot_continuous('Age')
```



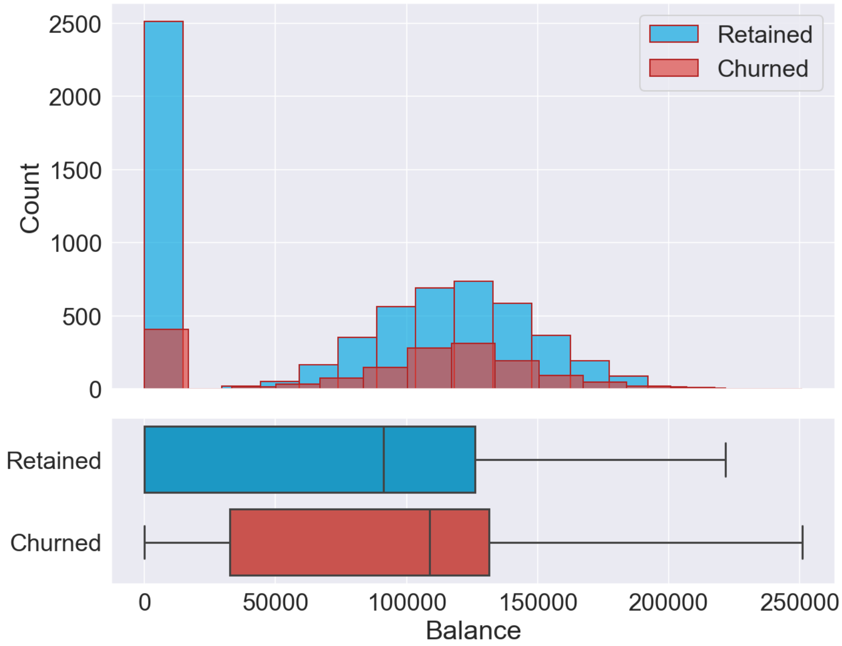
In [18]:

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



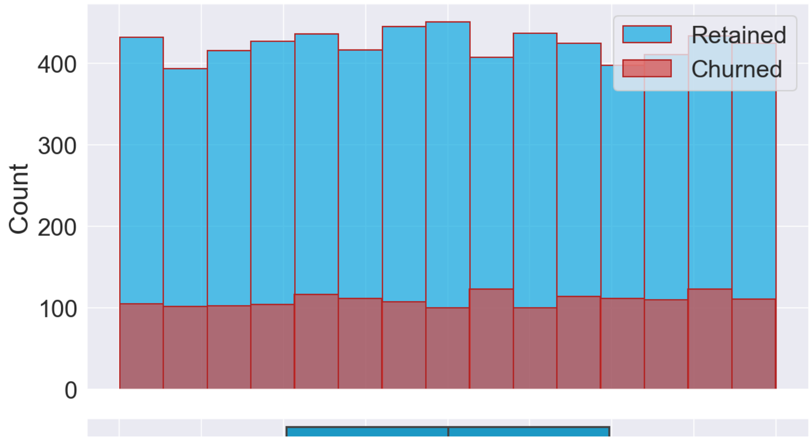
In [19]:

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



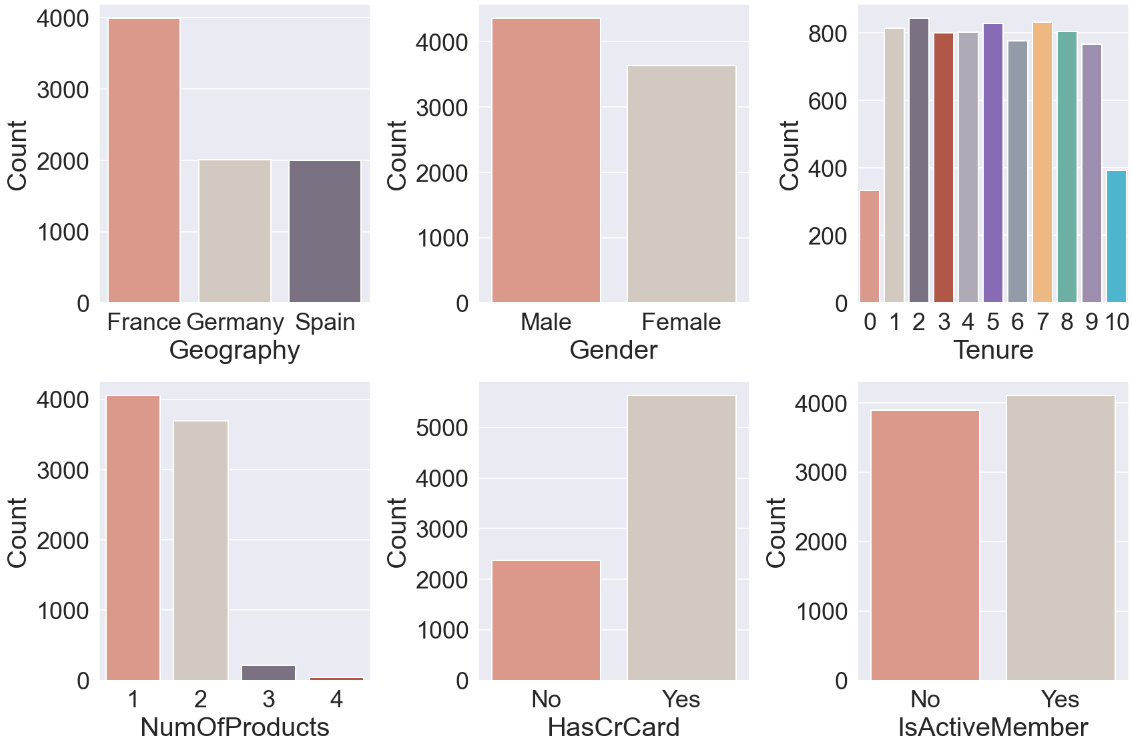
In [20]:

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



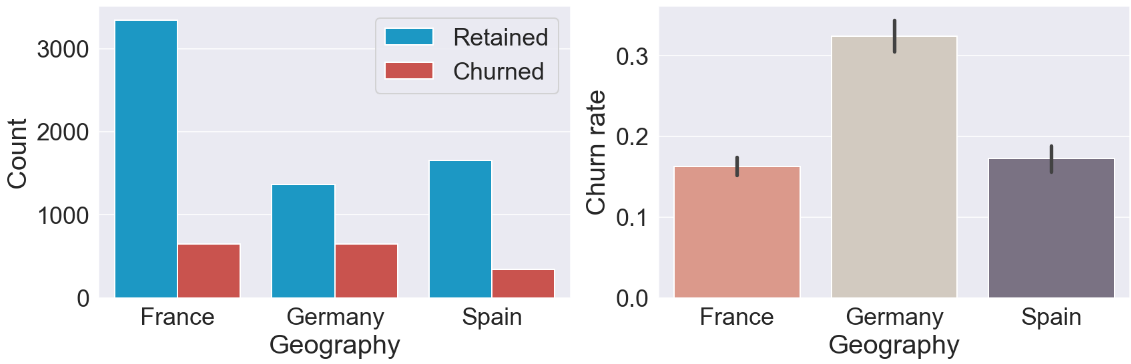
In [21]:

```
df_cat = train_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=train_df, palette=colors_cat)

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

plt.tight_layout();
```



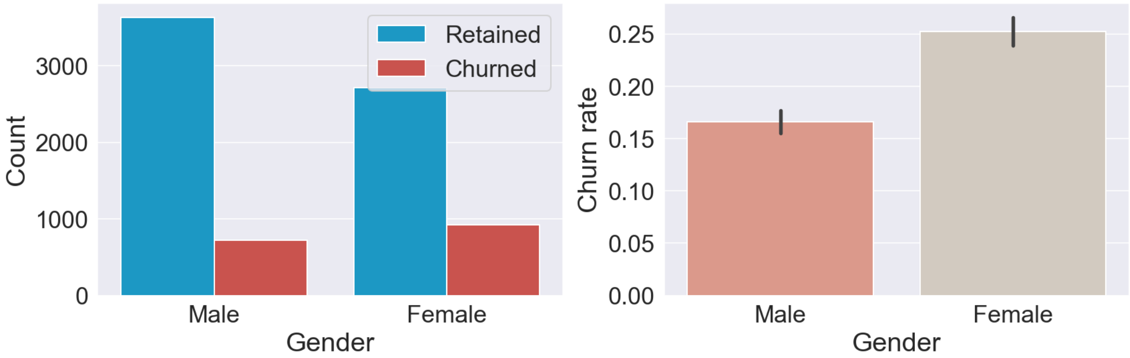
In [22]:

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



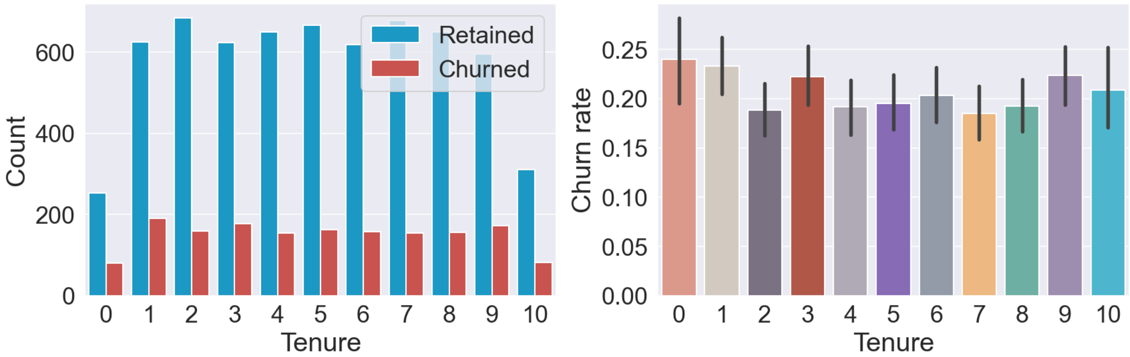
In [23]:

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



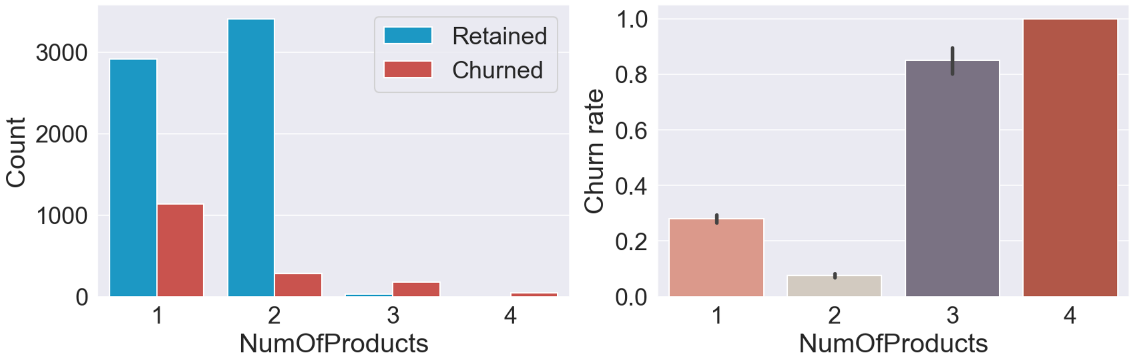
In [24]:

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



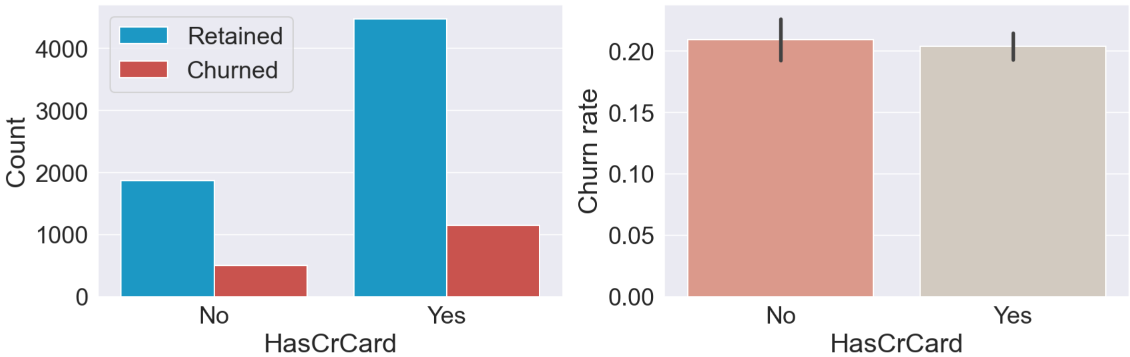
In [25]:

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



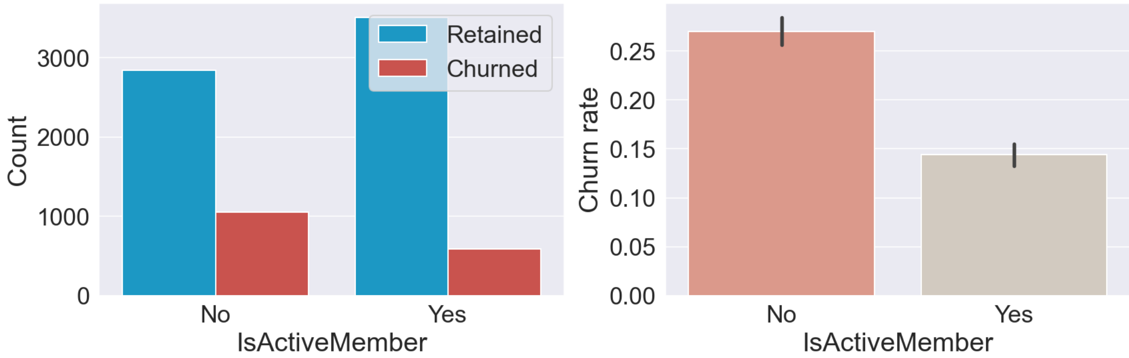
In [26]:

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



In [27]:

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



In [28]:

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

#print('✔ Features Dropped!')
```

In [12]:

```
 #encoding our categorical attributes

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

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

print('✔ Features Encoded!')
```

✔ Features Encoded!

In [13]:

```
train_df.head()
```

Out[13]:

	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	Exited
0	686	3	1	32	6	0.00	2	1	1	179093.26	0
1	632	1	1	42	4	119624.60	2	1	1	195978.86	0
2	559	2	1	24	3	114739.92	1	1	0	85891.02	1
3	561	3	0	27	9	135637.00	1	1	0	153080.40	1
4	517	3	1	56	9	142147.32	1	0	0	39488.04	1

In [14]:

```
scaler = StandardScaler()

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

print('✔ Features Scaled!')
train_df.head()
```

✔ Features Scaled!

Out[14]:

	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	Exited
0	0.356	3	1	-0.656	0.346	-1.218	2	1	1	1.368	0
1	-0.204	1	1	0.295	-0.348	0.697	2	1	1	1.661	0
2	-0.961	2	1	-1.416	-0.695	0.619	1	1	0	-0.253	1
3	-0.941	3	0	-1.131	1.387	0.953	1	1	0	0.915	1
4	-1.397	3	1	1.626	1.387	1.057	1	0	0	-1.060	1

In [15]:

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

print('✔ Sets Created!')
```

✔ Sets Created!

In [16]:

```
y_train.value_counts()
```

Out[16]:

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

In [17]:

```
train_df.describe()
```

Out[17]:

	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	Exited
count	8.000e+03	8000.000	8000.000	8.000e+03	8.000e+03	8.000e+03	8000.000	8000.000	8000.000	8.000e+03	8000.000
mean	5.723e-16	2.248	0.545	-2.100e-16	-4.821e-17	-3.513e-16	1.531	0.704	0.513	-4.496e-18	0.205
std	1.000e+00	0.830	0.498	1.000e+00	1.000e+00	1.000e+00	0.580	0.457	0.500	1.000e+00	0.404
min	-3.130e+00	1.000	0.000	-1.987e+00	-1.736e+00	-1.218e+00	1.000	0.000	0.000	-1.745e+00	0.000
25%	-6.917e-01	1.000	0.000	-6.558e-01	-6.954e-01	-1.218e+00	1.000	0.000	0.000	-8.531e-01	0.000
50%	1.403e-02	2.000	1.000	-1.804e-01	-1.345e-03	3.257e-01	1.000	1.000	1.000	9.811e-04	0.000
75%	6.990e-01	3.000	1.000	4.851e-01	6.927e-01	8.247e-01	2.000	1.000	1.000	8.548e-01	0.000
max	2.058e+00	3.000	1.000	5.049e+00	1.734e+00	2.799e+00	4.000	1.000	1.000	1.731e+00	1.000

In [18]:

```
#Handling imbalanced data-
#over sampling-SMO
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[18]:

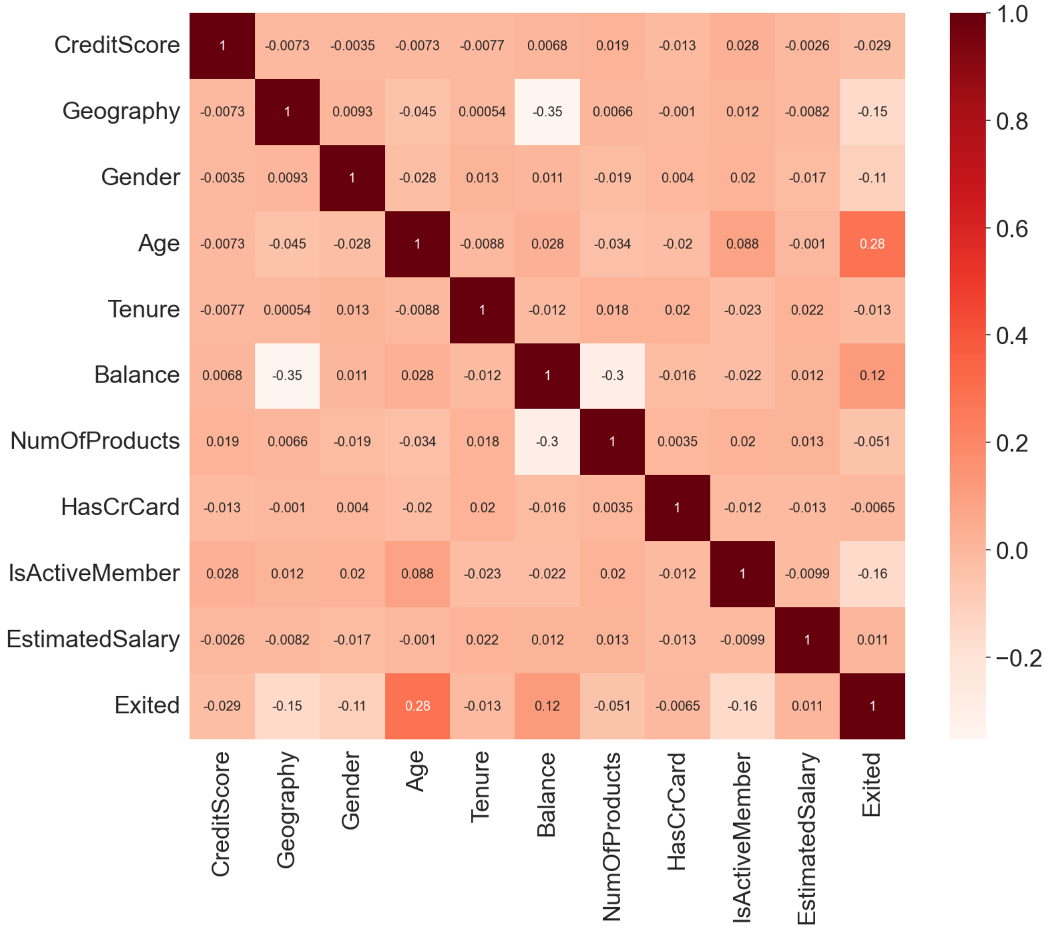
```
0    6356
1    6356
Name: Exited, dtype: int64
```

In [ ]:

```

```

In [37]:

```
#Feature Selection
#filter based

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



In [38]:

```
#Correlation with output variable
#Feature Selection
#filter based
cor_target = abs(cor["Exited"])
#Selecting highly correlated features
relevant_features = cor_target[cor_target>0.1]
relevant_features
```

Out[38]:

```
Geography         0.153
Gender            0.106
Age               0.283
Balance           0.118
IsActiveMember    0.157
Exited            1.000
Name: Exited, dtype: float64
```

In [1]:

```
#pip install mlxtend
```

In [39]:

```
#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= y_train
full_data= X_train.copy()
full_data['Exited']= y



X = X_train
y = y_train

#Define Sequential Forward Selection (sfs)
sfs = SFS(LinearRegression(),
           k_features=6,
           forward=True,
           floating=False,
           scoring = 'r2',
           cv = 0)
#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[39]:

	feature_idx	cv_scores	avg_score	feature_names
1	(3,)	[0.12629363921783998]	0.126	(Age,)
2	(3, 8)	[0.19519095199274095]	0.195	(Age, IsActiveMember)
3	(1, 3, 8)	[0.22822841607598]	0.228	(Geography, Age, IsActiveMember)
4	(1, 2, 3, 8)	[0.2526925270190171]	0.253	(Geography, Gender, Age, IsActiveMember)
5	(1, 2, 3, 6, 8)	[0.2625653880394574]	0.263	(Geography, Gender, Age, NumOfProducts, IsActi...
6	(1, 2, 3, 5, 6, 8)	[0.2639554666828834]	0.264	(Geography, Gender, Age, Balance, NumOfProduct...

In [40]:

```
#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= y_train
full_data= X_train.copy()
full_data['Exited']= y



X = X_train
y = y_train

#Build a logistic regression model
model = LinearRegression()
#Define RFE
#rfe = RFE(model,5)
rfe = RFE(estimator=model, n_features_to_select=6)
#Use RFE to select the top 5 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': full_data.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[40]:

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

In [42]:

```
#embedded

from sklearn.linear_model import LassoCV
from sklearn.model_selection import StratifiedKFold
X = X_train
y = y_train
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 [19]:

```
test_df.head()
```

Out[19]:

	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	Exited
0	596	Germany	Male	32	3	96709.07	2	0	0	41788.37	0
1	623	France	Male	43	1	0.00	2	1	1	146379.30	0
2	601	Spain	Female	44	4	0.00	2	1	0	58561.31	0
3	506	Germany	Male	59	8	119152.10	2	1	1	170679.74	0
4	560	Spain	Female	27	7	124995.98	1	1	1	114669.79	0

In [20]:

```

#encoding our categorical attributes

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

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

print('✔ Features Encoded!')
```

✔ Features Encoded!

In [21]:

```
 #encoding our categorical attributes

test_df.head()
```

Out[21]:

	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	Exited
0	596	1	1	32	3	96709.07	2	0	0	41788.37	0
1	623	3	1	43	1	0.00	2	1	1	146379.30	0
2	601	2	0	44	4	0.00	2	1	0	58561.31	0
3	506	1	1	59	8	119152.10	2	1	1	170679.74	0
4	560	2	0	27	7	124995.98	1	1	1	114669.79	0

In [22]:

```
scaler = StandardScaler()

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

print('✔ Features Scaled!')
test_df.head()
```

✔ Features Scaled!

Out[22]:

	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	Exited
0	-0.513	1	1	-0.677	-0.698	0.301	2	0	0	-0.991	0
1	-0.236	3	1	0.384	-1.380	-1.256	2	1	1	0.829	0
2	-0.461	2	0	0.481	-0.357	-1.256	2	1	0	-0.699	0
3	-1.434	1	1	1.928	1.006	0.662	2	1	1	1.252	0
4	-0.881	2	0	-1.160	0.665	0.756	1	1	1	0.277	0

In [23]:

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

In [24]:

```
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 = 12345)))
models.append(('KNN', KNeighborsClassifier()))
models.append(('DT', DecisionTreeClassifier(random_state = 12345)))
models.append(('RF', RandomForestClassifier(random_state = 12345)))
models.append(('SVM', SVC(gamma='auto', random_state = 12345)))
models.append(('GBC', GradientBoostingClassifier(random_state = 12345)))
models.append(('XGB', XGBClassifier(random_state = 12345)))
models.append(("LightGBM", LGBMClassifier(random_state = 12345)))
models.append(("CatBoost", CatBoostClassifier(random_state = 12345, verbose = False)))

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

In [25]:

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

```
LR: (0.724500)
0.03893327713012695
KNN: (0.757000)
0.222367525100708
DT: (0.719000)
0.07883119583129883
RF: (0.821000)
1.5528407096862793
SVM: (0.791500)
5.462451457977295
GBC: (0.659500)
1.754319667816162
XGB: (0.307500)
1.0516853332519531
LightGBM: (0.445000)
0.22127962112426758
CatBoost: (0.426000)
6.472300052642822
```

In [26]:

```
#but 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)
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(end - start)
```

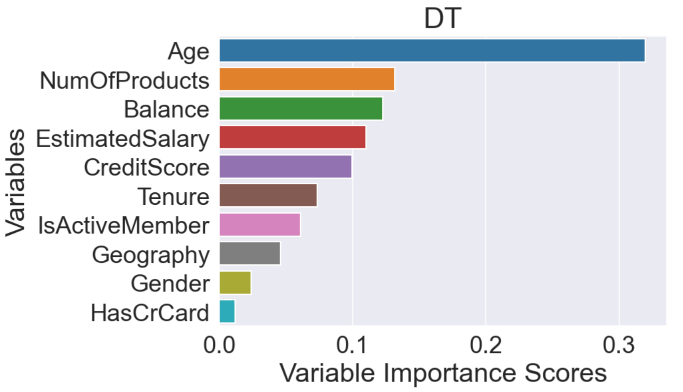
```
LR: (0.659033)
0.03989052772521973
KNN: (0.681934)
0.22739338874816895
DT: (0.643766)
0.06785702705383301
RF: (0.651399)
1.573634386062622
SVM: (0.735369)
5.413566827774048
GBC: (0.872774)
1.7714014053344727
XGB: (0.982188)
1.0392200946807861
LightGBM: (0.949109)
0.19248485565185547
CatBoost: (0.966921)
6.251286268234253
```

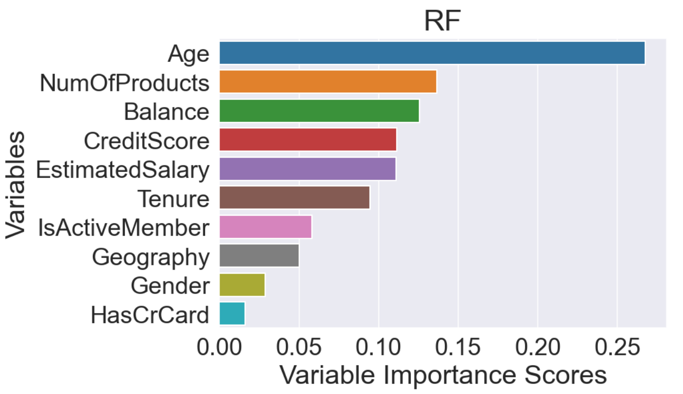
In [27]:

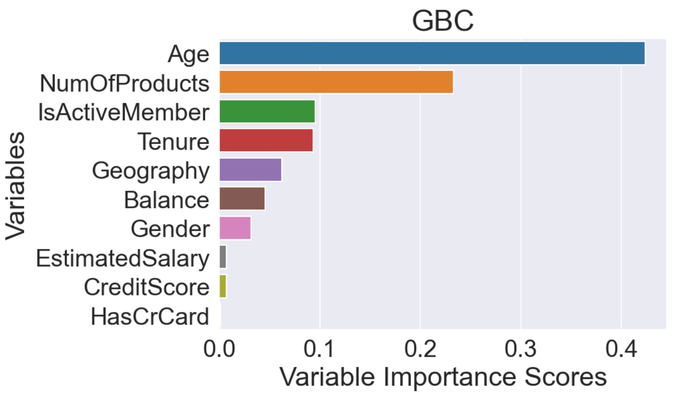
```
models2 = []
models2.append(('DT', DecisionTreeClassifier( random_state = 12345)))
models2.append(('RF', RandomForestClassifier( random_state = 12345)))
models2.append(('GBC', GradientBoostingClassifier( random_state = 12345)))
models2.append(('XGB', XGBClassifier( random_state = 12345)))
models2.append(("LightGBM", LGBMClassifier( random_state = 12345)))
models2.append(("CatBoost", CatBoostClassifier(random_state = 12345, verbose = False)))
```

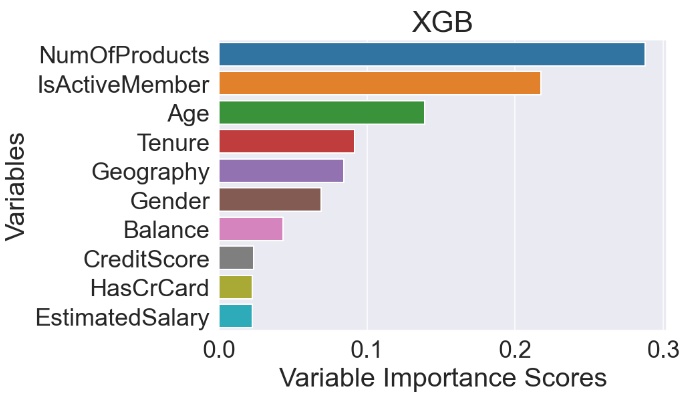
In [61]:

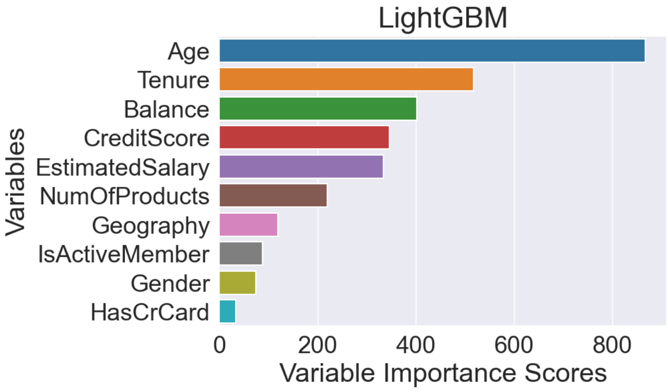
```
for name, model in models2:
        base = model.fit(X_train,y_train)
        y_pred = base.predict(X_test)
        acc_score = accuracy_score(y_test, y_pred)
        feature_imp = pd.Series(base.feature_importances_,
                        index=X.columns).sort_values(ascending=False)

        sns.barplot(x=feature_imp, y=feature_imp.index)
        plt.xlabel('Variable Importance Scores')
        plt.ylabel('Variables')
        plt.title(name)
        plt.show()
```

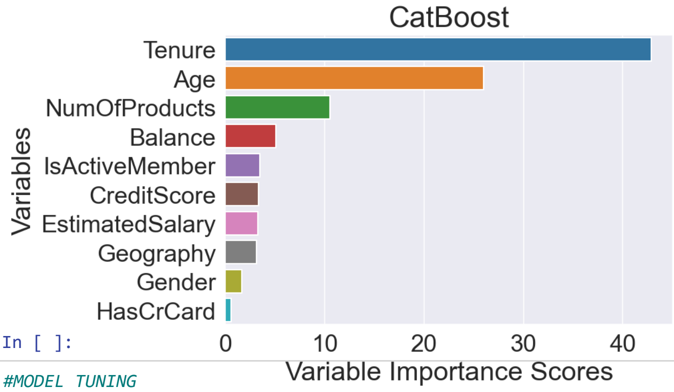












In [ ]:

```
#MODEL TUNING
```

In [ ]:

```
#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': [0.02,0.04,0.05,0.07],
              'subsample'    : [0.9,0.8,0.7,0.6],
              'n_estimators' : [100,500,800,1000],
              'max_depth'    : [4,5,8,9]
             }
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_)
```

In [ ]:

```
#MODEL TUNING for XGB
#Obtaining the Optimal Hyperparameters
from sklearn.model_selection import GridSearchCV
from sklearn.ensemble import XGBClassifier
XGB = XGBClassifier()
parameters = {'learning_rate': [0.02,0.04,0.05,0.07],
              'subsample'    : [0.9,0.8,0.7,0.6],
              'n_estimators' : [100,500,800,1000],
              'max_depth'    : [4,5,8,9]
             }
grid_XGB = GridSearchCV(estimator=XGB, param_grid = parameters, 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_)
```

In [ ]:

```
    #MODEL TUNING for LightGBM
    #Obtaining the Optimal Hyperparameters
    from sklearn.model_selection import GridSearchCV
    from sklearn.ensemble import LGBMClassifier
    LightGBM = LGBMClassifier()
    parameters = {'learning_rate': [0.02,0.04,0.05,0.07],
                  'subsample'    : [0.9,0.8,0.7,0.6],
                  'n_estimators' : [100,500,800,1000],
                  'max_depth'    : [4,5,8,9]
                 }
    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_)
```

In [ ]:

In [43]:

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

models = []
models.append(('GBC', GradientBoostingClassifier(random_state = 12345,learning_rate = 0.05, max_depth = 5, n_estimators = 500, subsample
models.append(('XGB', XGBClassifier(random_state = 12345,learning_rate = 0.05, max_depth = 5, min_samples_split = 2, n_estimators = 500,
models.append(("LightGBM", LGBMClassifier(random_state = 12345,  learning_rate = 0.05, max_depth = 3, n_estimators = 1000)))
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)
```

```
11.833403587341309
GBC: (0.982188)
[00:23:14] 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.


4.491948366165161
XGB: (0.982188)
0.5126285552978516
LightGBM: (0.984733)
26.14893889427185
CatBoost: (0.809160)
```

In [ ]:

In [ ]:

In [ ]:

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