In [1]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

In [4]:

```
Bank_Churn = pd.read_csv('C:/Users/IT/Desktop/Circle K Case Study/ACT India D&A GCC_Data Sc
Bank_Churn.head()
```

Out[4]:

	RowNumber	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure	Balanc
0	1	15634602	Hargrave	619	France	Female	42	2	0.0
1	2	15647311	Hill	608	Spain	Female	41	1	83807.8
2	3	15619304	Onio	502	France	Female	42	8	159660.8
3	4	15701354	Boni	699	France	Female	39	1	0.0
4	5	15737888	Mitchell	850	Spain	Female	43	2	125510.8

In [6]:

```
#missing data quick check
Bank_Churn.isnull().sum()
```

Out[6]:

```
RowNumber          0
CustomerId         0
Surname            0
CreditScore        0
Geography          0
Gender             0
Age                0
Tenure             0
Balance            0
NumOfProducts      0
HasCrCard          0
IsActiveMember     0
EstimatedSalary    0
Exited             0
dtype: int64
```

In [7]:

```
#Column and data type checks
Bank_Churn.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 14 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   RowNumber        10000 non-null  int64
 1   CustomerId       10000 non-null  int64
 2   Surname          10000 non-null  object
 3   CreditScore      10000 non-null  int64
 4   Geography        10000 non-null  object
 5   Gender           10000 non-null  object
 6   Age              10000 non-null  int64
 7   Tenure           10000 non-null  int64
 8   Balance          10000 non-null  float64
 9   NumOfProducts    10000 non-null  int64
 10  HasCrCard        10000 non-null  int64
 11  IsActiveMember   10000 non-null  int64
 12  EstimatedSalary  10000 non-null  float64
 13  Exited           10000 non-null  int64
dtypes: float64(2), int64(9), object(3)
memory usage: 1.1+ MB
```

In [62]:

```
#non-numerical data check
GenAna = Bank_Churn.groupby(['Gender', 'Exited']).size().reset_index(name='counts')
GenAna
```

Out[62]:

	Gender	Exited	counts
0	Female	0	3404
1	Female	1	1139
2	Male	0	4559
3	Male	1	898

In [56]:

```
#non-numerical data check
Bank_Churn[['Geography','Gender']].describe()
```

Out[56]:

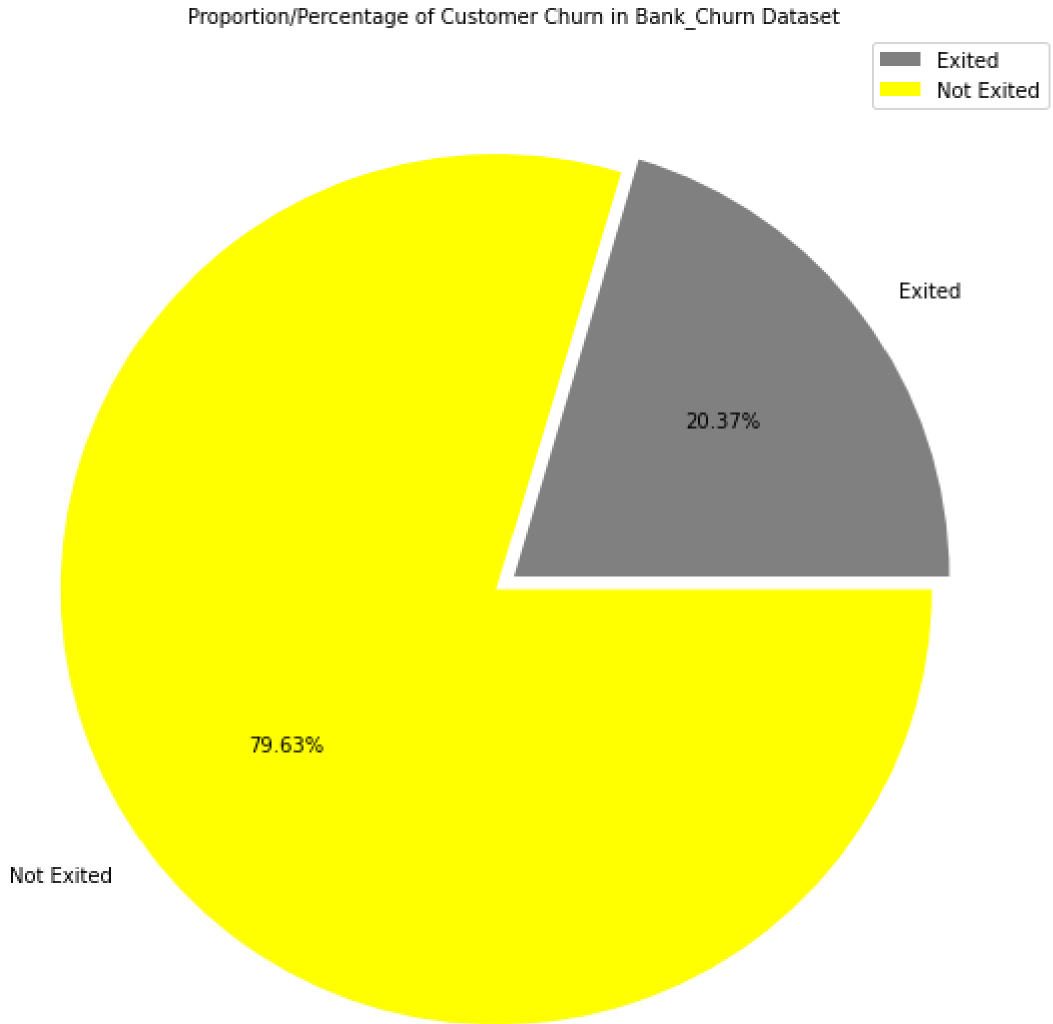
	Geography	Gender
count	10000	10000
unique	3	2
top	France	Male
freq	5014	5457

In [40]:

```
#Create a list that contains the number of exited customer
ExitedList = [Bank_Churn.Exited[Bank_Churn['Exited']==1].count(), Bank_Churn.Exited[Bank_Ch

#set figure size and title
colors = ["grey","yellow"]
plt.subplots(figsize=(10, 10))
plt.title('Proportion/Percentage of Customer Churn in Bank_Churn Dataset', size = 10)

#display the proportion of Customer Churn
plt.pie(ExitedList,labels = ['Exited', 'Not Exited'], autopct='%.2f%%',colors=colors, explo
plt.legend(labels = ['Exited', 'Not Exited'], loc = "upper right")
plt.show()
```



In [14]:

```
#preparing the figure size
fig, axarr = plt.subplots(2, 3, figsize=(15, 15))

#visulazie the count of Exited and NotExited for each feature

sns.countplot('Geography', hue = 'Exited',data = Bank_Churn, ax = axarr[0][0])
sns.countplot('Gender', hue = 'Exited',data = Bank_Churn, ax = axarr[0][1])
sns.countplot('Tenure', hue = 'Exited',data = Bank_Churn, ax = axarr[0][2])
sns.countplot('NumOfProducts', hue = 'Exited',data = Bank_Churn, ax = axarr[1][0])
sns.countplot('HasCrCard', hue = 'Exited',data = Bank_Churn, ax = axarr[1][1])
sns.countplot('IsActiveMember', hue = 'Exited',data = Bank_Churn, ax = axarr[1][2])
```

```
C:\Users\IT\anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWar
ning: Pass the following variable as a keyword arg: x. From version 0.12, th
e only valid positional argument will be `data`, and passing other arguments
without an explicit keyword will result in an error or misinterpretation.
  warnings.warn(
C:\Users\IT\anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWar
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e only valid positional argument will be `data`, and passing other arguments
without an explicit keyword will result in an error or misinterpretation.
  warnings.warn(
C:\Users\IT\anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWar
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without an explicit keyword will result in an error or misinterpretation.
  warnings.warn(
C:\Users\IT\anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWar
ning: Pass the following variable as a keyword arg: x. From version 0.12, th
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without an explicit keyword will result in an error or misinterpretation.
  warnings.warn(
C:\Users\IT\anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWar
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without an explicit keyword will result in an error or misinterpretation.
  warnings.warn(
C:\Users\IT\anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWar
ning: Pass the following variable as a keyword arg: x. From version 0.12, th
e only valid positional argument will be `data`, and passing other arguments
without an explicit keyword will result in an error or misinterpretation.
  warnings.warn(
```
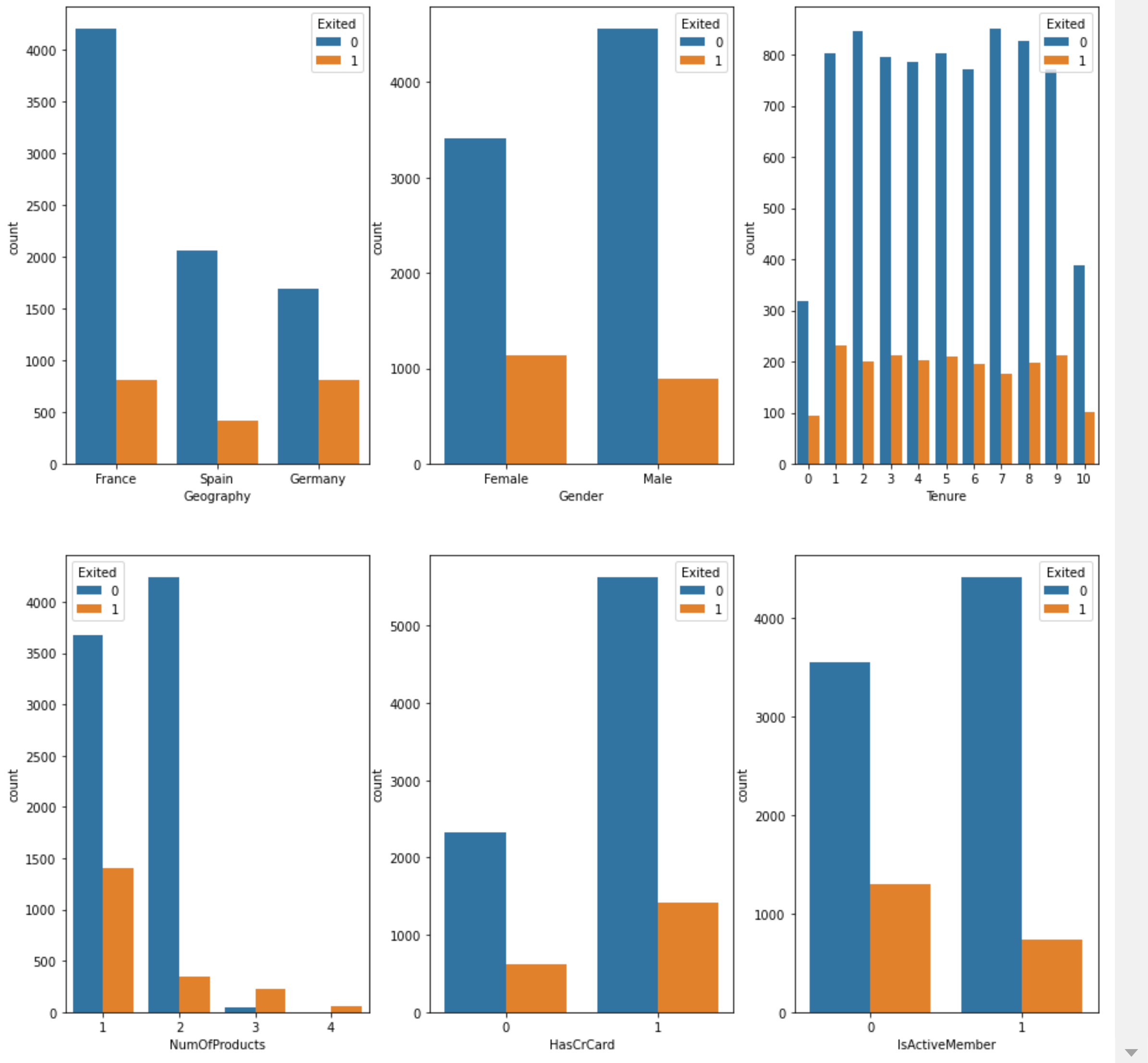

Out[14]:

```
<AxesSubplot:xlabel='IsActiveMember', ylabel='count'>
```



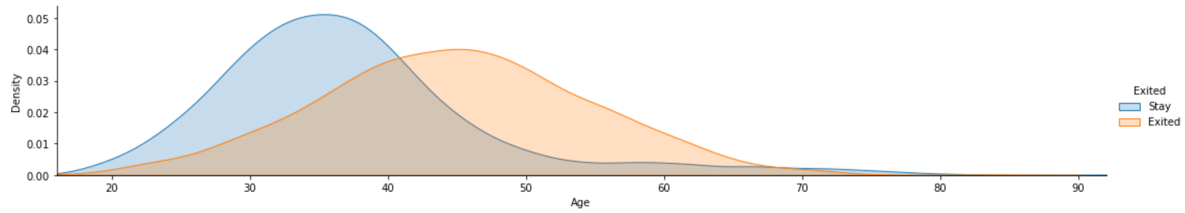
In [19]:

```
#visulaization relation between Age and Exited
FacetGrid = sns.FacetGrid(Bank_Churn, hue='Exited', aspect=5)
FacetGrid.map(sns.kdeplot, 'Age', shade=True )
FacetGrid.set(xlim=(16, Bank_Churn['Age'].max()))
FacetGrid.add_legend(labels = ['Stay', "Exited"])
```

```
C:\Users\IT\anaconda3\lib\site-packages\seaborn\axisgrid.py:156: UserWarnin
g: You have mixed positional and keyword arguments, some input may be discar
ded.
  figlegend = self._figure.legend(handles, labels, **kwargs)
```

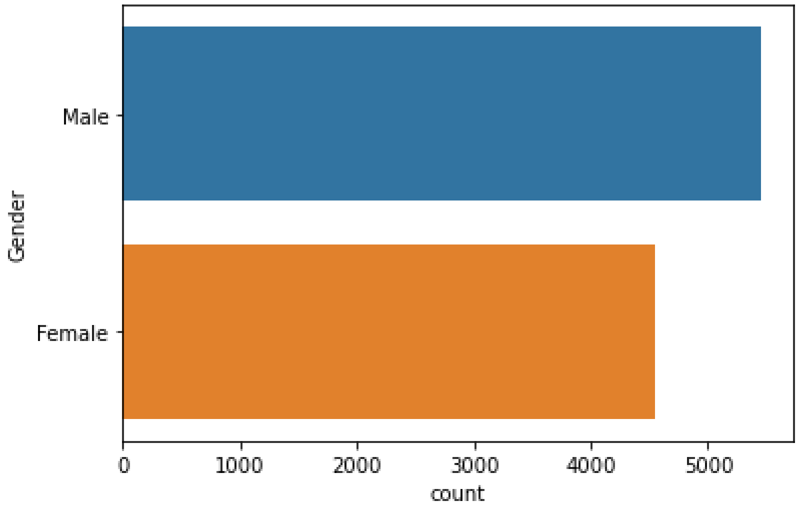
Out[19]:

```
<seaborn.axisgrid.FacetGrid at 0x13605997a30>
```



In [20]:

```
#Vislization of the count of each value in Gender feature

sns.countplot(y=Bank_Churn['Gender'], data=Bank_Churn, order = Bank_Churn['Gender'].value_c
plt.show()
```

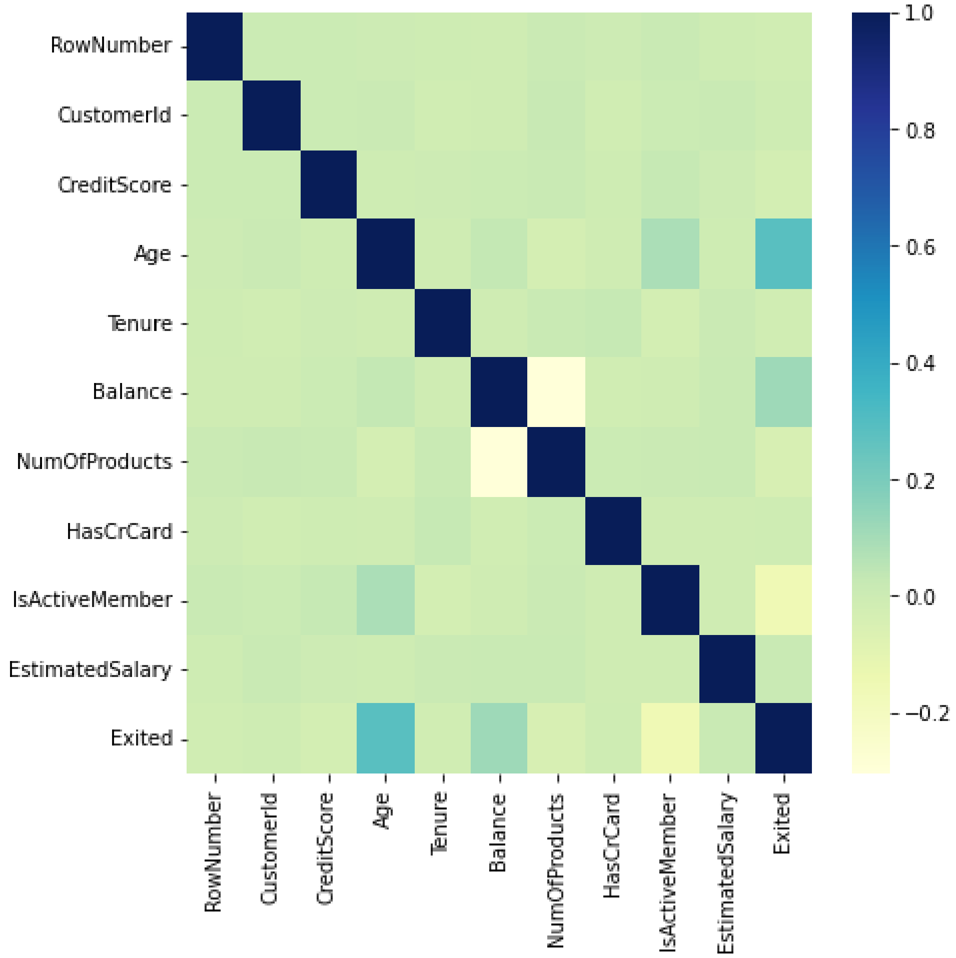


In [22]:

```
plt.figure(figsize=(7,7))
sns.heatmap(Bank_Churn.corr(), cmap="YlGnBu")
```

Out[22]:

```
<AxesSubplot:>
```



In [23]:

```
#Data Cleaning
#Drop the Surname,CustmerId,HasCrCard features from the data set as it will not considert i
Bank_Churn.drop("CustomerId", axis=1, inplace=True)
Bank_Churn.drop("Surname", axis=1, inplace=True)
Bank_Churn.drop("HasCrCard", axis=1, inplace=True)
```

In [27]:

```
#apply one hot encodeing to  Gender and Geography
clean_data = pd.get_dummies(data = Bank_Churn ,columns=['Gender', 'Geography'])
clean_data.head()
```

Out[27]:

	RowNumber	CreditScore	Age	Tenure	Balance	NumOfProducts	IsActiveMember	Estimat
0	1	619	42	2	0.00	1	1	1
1	2	608	41	1	83807.86	1	1	1
2	3	502	42	8	159660.80	3	0	1
3	4	699	39	1	0.00	2	0	
4	5	850	43	2	125510.82	1	1	

In [28]:

```
#rename the coulmuns
data.rename(columns={'Gender_Female':'Female',
                     'Gender_Male':'Male',
                     'Geography_France': 'France',
                     'Geography_Germany' : 'Germany',
                     'Geography_Spain':'Spain'}, inplace = True)
data.head()
```

Out[28]:

	RowNumber	CreditScore	Age	Tenure	Balance	NumOfProducts	IsActiveMember	Estimat
0	1	619	42	2	0.00	1	1	1
1	2	608	41	1	83807.86	1	1	1
2	3	502	42	8	159660.80	3	0	1
3	4	699	39	1	0.00	2	0	
4	5	850	43	2	125510.82	1	1	

In [ ]:

In [30]:

```
#Data prepration for training and testing
Input_features = clean_data.drop(['Exited'], axis = 1)
predict = data['Exited']
```

In [31]:

```
from sklearn.model_selection import train_test_split

#split tha data
X_train, X_test, y_train, y_test = train_test_split(Input_features, predict, test_size = 0.
# Show the results of the split
print("Training set has {} samples.".format(X_train.shape[0]))
print("Testing set has {} samples.".format(X_test.shape[0]))
```

```
Training set has 8000 samples.
Testing set has 2000 samples.
```

In [32]:

```
#improting necassery libraries
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.tree import DecisionTreeClassifier as DecisionTree
from sklearn.metrics import roc_auc_score,confusion_matrix,f1_score,accuracy_score
```

In [33]:

```
# using Logistic Regresion algorithm to build first model
logreg_model = LogisticRegression(solver='liblinear')
fit = logreg_model.fit(X_train, y_train)
fit_prediction_train = fit.predict(X_train)
fit_prediction_test = fit.predict(X_test)

#validation of  Logistic Regresiion
print('Accuracy Score for testing set :' +'{}'.format(accuracy_score(fit_prediction_test, y
print('Accuracy Score for training set :' +'{}'.format(accuracy_score(fit_prediction_train,

print('\nF1 score for testing set :'+'{}'.format(f1_score(fit_prediction_test, y_test)))
print('F1 score for training set:'+'{}'.format(f1_score(fit_prediction_train, y_train)))


print('\nROC AUC Score for testing set: ' +'{}'.format(roc_auc_score(y_test, fit.predict_pr
print('ROC AUC Score for train set: ' +'{}'.format(roc_auc_score(y_train, fit.predict_proba

confusion_matrix(y_test, fit.predict(X_test))
```

```
Accuracy Score for testing set :0.7855
Accuracy Score for training set :0.790125

F1 score for testing set :0.13682092555331993
F1 score for training set:0.09194159004867497

ROC AUC Score for testing set: 0.6708835129103385
ROC AUC Score for train set: 0.6776832006531945
```

Out[33]:

```
array([[1537,   36],
       [ 393,   34]], dtype=int64)
```

In [34]:

```
# using RandomForestClassifier algorithm to build second model
rf = RandomForestClassifier(n_estimators=100)
rf_fit = rf.fit(X_train, y_train)
rf_prediction_train_ = rf_fit.predict(X_train)
rf_prediction_test = rf_fit.predict(X_test)

#validation of RandomForestClassifier
print('Accuracy Score for testing set :' +'{}'.format(accuracy_score(rf_prediction_test, y_
print('Accuracy Score for training set :' +'{}'.format(accuracy_score(rf_prediction_train_,

print('\nF1 score for testing set :'+'{}'.format(f1_score(rf_prediction_test, y_test)))
print('F1 score for training set:'+'{}'.format(f1_score(rf_prediction_train_, y_train)))


print('\nROC AUC Score for testing set: ' +'{}'.format(roc_auc_score(y_test, fit.predict_pr
print('ROC AUC Score for train set: ' +'{}'.format(roc_auc_score(y_train, fit.predict_proba

confusion_matrix(y_test, fit.predict(X_test))
```

```
Accuracy Score for testing set :0.8485
Accuracy Score for training set :1.0

F1 score for testing set :0.547085201793722
F1 score for training set:1.0

ROC AUC Score for testing set: 0.6708835129103385
ROC AUC Score for train set: 0.6776832006531945
```

Out[34]:

```
array([[1537,   36],
       [ 393,   34]], dtype=int64)
```

In [35]:

```
# using GradientBoostingClassifier algorithm to build second model

gb = GradientBoostingClassifier(n_estimators=100)
gb_fit = gb.fit(X_train, y_train)
gb_prediction_train_ = gb_fit.predict(X_train)
gb_prediction_test = gb_fit.predict(X_test)

#validation of GradientBoostingClassifier
print('Accuracy Score for testing set :' +'{}'.format(accuracy_score(gb_prediction_test, y_
print('Accuracy Score for training set :' +'{}'.format(accuracy_score(gb_prediction_train_,

print('\nF1 score for testing set :'+'{}'.format(f1_score(gb_prediction_test, y_test)))
print('F1 score for training set:'+'{}'.format(f1_score(gb_prediction_train_, y_train)))


print('\nROC AUC Score for testing set: ' +'{}'.format(roc_auc_score(y_test, fit.predict_pr
print('ROC AUC Score for train set: ' +'{}'.format(roc_auc_score(y_train, fit.predict_proba

confusion_matrix(y_test, fit.predict(X_test))
```

```
Accuracy Score for testing set :0.851
Accuracy Score for training set :0.879625

F1 score for testing set :0.5565476190476l9
F1 score for training set:0.6345351043643265

ROC AUC Score for testing set: 0.6708835129103385
ROC AUC Score for train set: 0.6776832006531945
```

Out[35]:

```
array([[1537,   36],
       [ 393,   34]], dtype=int64)
```

In [43]:

```
#Resampling data and training the model
# store No. of Exited and indices
Exited_records = data['Exited'].sum()
Exited_indices = np.array(data[data.Exited == 1].index)

# Picking the indices of the normal Exited
normal_indices = data[data.Exited == 0].index

# Out of the indices we picked, randomly select number of normal records = number of Exited
random_normal_indices = np.random.choice(normal_indices, Exited_records, replace = False)
random_normal_indices = np.array(random_normal_indices)

# Merge the 2 indices
under_sample_indices = np.concatenate([Exited_indices,random_normal_indices])

# Copy under sample dataset
under_sample_data = data.iloc[under_sample_indices,:]

# Split data into features and target labels
features_undersample = under_sample_data.drop(['Exited'], axis = 1)
target_undersample = under_sample_data['Exited']

# Show ratio
print("Percentage of NotExited: ", under_sample_data.Exited[under_sample_data['Exited'] ==
print("Percentage of Exited: ", under_sample_data.Exited[under_sample_data['Exited'] == 1].
print("Total number of  resampled data: ", under_sample_data['Exited'].count())
```

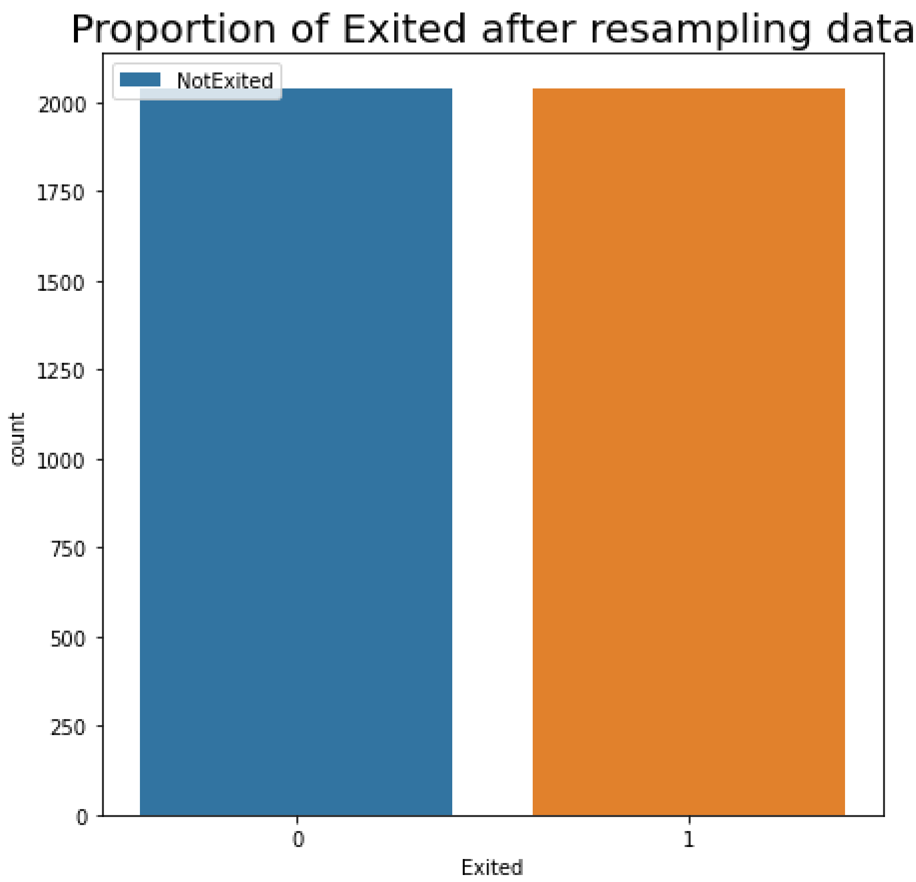
```
Percentage of NotExited:  2037
Percentage of Exited:  2037
Total number of  resampled data:  4074
```

In [44]:

```
under_sample_Exited_Real = [under_sample_data.Exited[under_sample_data['Exited'] == 0].coun

# Plot the proportion
plt.subplots(figsize = (7, 7))
plt.title("Proportion of Exited after resampling data", size = 20)
ax = sns.countplot(x = under_sample_data['Exited'], data= under_sample_data)
ax.legend(labels=['NotExited', 'Exited'], loc = 'upper left')
```

Out[44]:

```
<matplotlib.legend.Legend at 0x13608dc9ca0>
```



In [46]:

```
# Split the 'features_undersample' and 'target_anderSample' data into training and testing
X_train_sampled, X_test_sampled, y_train_sampled, y_test_sampled = train_test_split(feature
                                                                                    target_
                                                                                    test_si
                                                                                    random_

# Show the results of the split
print("Training set has {} samples.".format(X_train_sampled.shape[0]))
print("Testing set has {} samples.".format(X_test_sampled.shape[0]))
```

```
Training set has 3666 samples.
Testing set has 408 samples.
```

In [47]:

```
# using Logistic Regresiion algorithm to fit it on the resampled data
logreg_model = LogisticRegression(solver='liblinear')
fit = logreg_model.fit(X_train_sampled, y_train_sampled)
fit_prediction_train_sampled = fit.predict(X_train_sampled)
fit_prediction_test_sampled = fit.predict(X_test_sampled)

#validation of  Logistic Regresiion
print('Accuracy Score for testing set :' +'{}'.format(accuracy_score(fit_prediction_test_sa
print('Accuracy Score for training set :' +'{}'.format(accuracy_score(fit_prediction_train_

print('\nF1 score for testing set :'+'{}'.format(f1_score(fit_prediction_test_sampled, y_te
print('F1 score for training set:'+'{}'.format(f1_score(fit_prediction_train_sampled, y_tra


print('\nROC AUC Score for testing set: ' +'{}'.format(roc_auc_score(y_test_sampled, fit.pr
print('ROC AUC Score for train set: ' +'{}'.format(roc_auc_score(y_train_sampled, fit.predi

confusion_matrix(y_test_sampled, fit.predict(X_test_sampled))
```

```
Accuracy Score for testing set :0.6666666666666666
Accuracy Score for training set :0.665848336061102

F1 score for testing set :0.6582914572864321
F1 score for training set:0.6700781039590628

ROC AUC Score for testing set: 0.712360415864459
ROC AUC Score for train set: 0.707489229349743
```

Out[47]:

```
array([[141,  71],
       [ 65, 131]], dtype=int64)
```

In [48]:

```
# using RandomForestClassifier algorithm to to fit it on the resampled data
rf = RandomForestClassifier(n_estimators=100)
rf_fit = rf.fit(X_train_sampled, y_train_sampled)
rf_prediction_train_sampled = rf_fit.predict(X_train_sampled)
rf_prediction_test_sampled= rf_fit.predict(X_test_sampled)

#validation of RandomForestClassifier
print('Accuracy Score for testing set :' +'{}'.format(accuracy_score(rf_prediction_test_sam
print('Accuracy Score for training set :' +'{}'.format(accuracy_score(rf_prediction_train_s

print('\nF1 score for testing set :'+'{}'.format(f1_score(rf_prediction_test_sampled, y_tes
print('F1 score for training set:'+'{}'.format(f1_score(rf_prediction_train_sampled, y_trai


print('\nROC AUC Score for testing set: ' +'{}'.format(roc_auc_score(y_test_sampled, fit.pr
print('ROC AUC Score for train set: ' +'{}'.format(roc_auc_score(y_train_sampled, fit.predi

confusion_matrix(y_test_sampled, fit.predict(X_test_sampled))
```

```
Accuracy Score for testing set :0.7745098039215687
Accuracy Score for training set :1.0

F1 score for testing set :0.766497461928934
F1 score for training set:1.0

ROC AUC Score for testing set: 0.712360415864459
ROC AUC Score for train set: 0.707489229349743
```

Out[48]:

```
array([[141,  71],
       [ 65, 131]], dtype=int64)
```

In [49]:

```
gb = GradientBoostingClassifier(n_estimators=100)
gb_fit = gb.fit(X_train, y_train)
gb_prediction_train_sampled = gb_fit.predict(X_train_sampled)
gb_prediction_test_sampled = gb_fit.predict(X_test_sampled)

#validation of GradientBoostingClassifier
print('Accuracy Score for testing set :' +'{}'.format(accuracy_score(gb_prediction_test_sam
print('Accuracy Score for training set :' +'{}'.format(accuracy_score(gb_prediction_train_s

print('\nF1 score for testing set :'+'{}'.format(f1_score(gb_prediction_test_sampled, y_tes
print('F1 score for training set:'+'{}'.format(f1_score(gb_prediction_train_sampled, y_trai


print('\nROC AUC Score for testing set: ' +'{}'.format(roc_auc_score(y_test_sampled, fit.pr
print('ROC AUC Score for train set: ' +'{}'.format(roc_auc_score(y_train_sampled, fit.predi

confusion_matrix(y_test_sampled, fit.predict(X_test_sampled))
```

```
Accuracy Score for testing set :0.7794117647058824
Accuracy Score for training set :0.7334969994544462

F1 score for testing set :0.7169811320754718
F1 score for training set:0.6504472271914132

ROC AUC Score for testing set: 0.712360415864459
ROC AUC Score for train set: 0.707489229349743
```

Out[49]:

```
array([[141,  71],
       [ 65, 131]], dtype=int64)
```

In [50]:

```
# Use the logistic Regresiion model to predict the training and testing set of whole datase
fit_prediction_train_after_sampled = fit.predict(X_train)
fit_prediction_test_after_sampled = fit.predict(X_test)

print('Accuracy Score for testing set :' +'{}'.format(accuracy_score(fit_prediction_test_af
print('Accuracy Score for training set :' +'{}'.format(accuracy_score(fit_prediction_train_

print('\nF1 score for testing set :'+'{}'.format(f1_score(fit_prediction_test_after_sampled
print('F1 score for training set:'+'{}'.format(f1_score(fit_prediction_train_after_sampled,


print('\nROC AUC Score for testing set: ' +'{}'.format(roc_auc_score(y_test, fit_prediction
print('ROC AUC Score for train set: ' +'{}'.format(roc_auc_score(y_train,fit_prediction_tra
```

```
Accuracy Score for testing set :0.65
Accuracy Score for training set :0.662

F1 score for testing set :0.45652173913043487
F1 score for training set:0.4443074393752569

ROC AUC Score for testing set: 0.6640334330349233
ROC AUC Score for train set: 0.6655264922870556
```

In [51]:

```
#Random ForestClassifier model to predict the training and testing set of whole dataset
rf_fit_prediction_train_after_sampled = rf_fit.predict(X_train)
rf_fit_prediction_test_after_sampled = rf_fit.predict(X_test)

print('Accuracy Score for testing set :' +'{}'.format(accuracy_score(rf_fit_prediction_test
print('Accuracy Score for training set :' +'{}'.format(accuracy_score(rf_fit_prediction_tra

print('\nF1 score for testing set :'+'{}'.format(f1_score(rf_fit_prediction_test_after_samp
print('F1 score for training set:'+'{}'.format(f1_score(rf_fit_prediction_train_after_sampl


print('\nROC AUC Score for testing set: ' +'{}'.format(roc_auc_score(y_test, rf_fit_predict
print('ROC AUC Score for train set: ' +'{}'.format(roc_auc_score(y_train,rf_fit_prediction_
```

```
Accuracy Score for testing set :0.8635
Accuracy Score for training set :0.86625

F1 score for testing set :0.7538322813345356
F1 score for training set:0.7463252726410622

ROC AUC Score for testing set: 0.9055452743977335
ROC AUC Score for train set: 0.9079122075447856
```

In [52]:

```
#GradientBoostingClassifier model to predict the training and testing set of whole dataset

gb_fit_prediction_train_after_sampled = gb_fit.predict(X_train)
gb_fit_prediction_test_after_sampled = gb_fit.predict(X_test)

print('Accuracy Score for testing set :' +'{}'.format(accuracy_score(gb_fit_prediction_test
print('Accuracy Score for training set :' +'{}'.format(accuracy_score(gb_fit_prediction_tra

print('\nF1 score for testing set :'+'{}'.format(f1_score(gb_fit_prediction_test_after_samp
print('F1 score for training set:'+'{}'.format(f1_score(gb_fit_prediction_train_after_sampl


print('\nROC AUC Score for testing set: ' +'{}'.format(roc_auc_score(y_test, gb_fit_predict
print('ROC AUC Score for train set: ' +'{}'.format(roc_auc_score(y_train,gb_fit_prediction_
```

```
Accuracy Score for testing set :0.851
Accuracy Score for training set :0.879625

F1 score for testing set :0.556547619047619
F1 score for training set:0.6345351043643265

ROC AUC Score for testing set: 0.7005334456899286
ROC AUC Score for train set: 0.7448385967981804
```

In [ ]:

```
#Conclusion

##Random forest is giving better results in whole dataset(even in sample dataset) with accu
```