A : Business Understanding

According to the dataset we used, we have realized that many factors caused the churn for bank clients. Churn rate is important to banks because high churn rates or increasing churn rates over time can damage a company's profitability and limit its growth potential. Therefore, the ability to predict customer churn is critical to the company's success. As we know in the management of any business, it is always better and advantageous for the business to have a well understanding and know what leads a client towards the decision to leave the company. So based on the dataset, we can analyze and figure out the problems and allow companies to develop loyalty programs and retention activities to keep as many customers as possible. Hence, we are able to identify and classify the facts that caused churn for bank customers.

Then, the purpose of doing churn rate prediction towards a bank is to get know what causes the churn rate the most to the bank. Hence, the bank is able to reduce the churn rate by doing precautions to minimize the causes.

In [63]:

```
#import google drive
#from google.colab import drive
#drive.mount('/content/datascience')
```

In [64]:

```
import pandas as pd
import numpy as np
import seaborn as sns
sns.set(style="white")
import matplotlib.pyplot as plt
```

The above codes are meant to import libraries and use their function for our program.

B : Data Understanding

Based on the dataset we used, the columns of the dataset have 13 variables, and the rows of the dataset have 10000 data. After that, the variables in the columns are used to know the information about the customers such as customerID, Surname, CreditScore, Geography and others. Then, these variables in the columns are used to analyze and figure out the churn rate like the ‘Age’ variable can figure out older customers are less likely to leave their bank than younger ones based on the data of variables. Besides, the dataset we used has no missing value.

Lastly, each variable stands for different meanings. RowNumber stands for the record (row) number and has no effect on the output. CustomerId stands for contains random values and has no effect on customers leaving the bank. Then, Surname stands for the customer's last name and will not affect their decision to leave the bank. CreditScore is to know the score of credit can have an effect on customer churn, since a customer with a higher credit score is less likely to leave the bank. Geography is to determine a customer’s location can affect their decision to leave the bank. Next, the Gender variable is to explore if gender plays a role in customers leaving the bank. Besides, Age variables are of course relevant, because older customers are less likely to leave the bank than younger customers. Additionally, Tenure variable refers to the number of years the customer has become a bank customer. Generally, older customers are more loyal and less likely to leave the bank. Within the Tenure variable, there are many variables inside. Balance variable is also a good indicator of customer churn, because people with higher account balances are less likely to leave the bank than those with lower balances. Then, NumOfProducts variable refers to the number of products purchased by customers through the bank. HasCrCard indicates whether the customer has a credit card. This column is also important because the person with the credit card is less likely to leave the bank. Next, IsActiveMember variables can know active customers are seldom to leave the bank. EstimatedSalary variable is compared with people with higher salaries, people with lower salaries are more likely to leave the bank.

In [65]:

```
#import dataset
dataset = pd.read_csv('churn.csv', index_col='RowNumber')\
    .drop(['Surname', 'CustomerId'], axis=1)
dataset
```

Out[65]:

	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	Has
RowNumber								
1	619	France	Female	42	2	0.00	1	
2	608	Spain	Female	41	1	83807.86	1	
3	502	France	Female	42	8	159660.80	3	
4	699	France	Female	39	1	0.00	2	
5	850	Spain	Female	43	2	125510.82	1	
...	...	...	...	...	...	...	...	
9996	771	France	Male	39	5	0.00	2	
9997	516	France	Male	35	10	57369.61	1	
9998	709	France	Female	36	7	0.00	1	
9999	772	Germany	Male	42	3	75075.31	2	
10000	792	France	Female	28	4	130142.79	1	

10000 rows × 11 columns

The above code is meant to extract the dataset from google drive, then drop and ignore the 'Surname' and 'CustomerId' variables.

In [66]:

```
#check null value of dataset
dataset.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 10000 entries, 1 to 10000
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: 937.5+ KB
```

The above code is meant to show the data and information from the dataset.

In [67]:

```
#check data type of dataset
dataset.dtypes
```

Out[67]:

```
CreditScore          int64
Geography           object
Gender              object
Age                  int64
Tenure               int64
Balance            float64
NumOfProducts        int64
HasCrCard            int64
IsActiveMember       int64
EstimatedSalary    float64
Exited               int64
dtype: object
```

The above code is meant to check and verify the data type of variables.

In [68]:

```
#check information of dataset
print ("Rows     :" ,dataset.shape[0])
print ("Columns  : " ,dataset.shape[1])
print ("\nFeatures : \n" ,dataset.columns.tolist())
print ("\nMissing values :  \n",dataset.isnull().sum())
print ("\nUnique values :  \n",dataset.nunique())
```

```
Rows     : 10000
Columns  :  11

Features : 
 ['CreditScore', 'Geography', 'Gender', 'Age', 'Tenure', 'Balance', 'NumOf
Products', 'HasCrCard', 'IsActiveMember', 'EstimatedSalary', 'Exited']

Missing values :  
 CreditScore        0
Geography          0
Gender             0
Age                0
Tenure             0
Balance            0
NumOfProducts      0
HasCrCard          0
IsActiveMember     0
EstimatedSalary    0
Exited             0
dtype: int64

Unique values :  
 CreditScore         460
Geography             3
Gender                2
Age                  70
Tenure               11
Balance            6382
NumOfProducts         4
HasCrCard             2
IsActiveMember        2
EstimatedSalary    9999
Exited                2
dtype: int64
```

In [69]:

```
#show the unique value of category columns
for i in dataset.columns:
  if len(dataset[i].unique()) < 5:
    print(i)
    print (dataset[i].unique())
```

```
Geography
['France' 'Spain' 'Germany']
Gender
['Female' 'Male']
NumOfProducts
[1 3 2 4]
HasCrCard
[1 0]
IsActiveMember
[1 0]
Exited
[1 0]
```

In [70]:

```
#convert category columns into binary value
convertGeography = ['Geography']
for i in convertGeography:
  dataset[i].replace(to_replace='France',value=0,inplace=True)
  dataset[i].replace(to_replace='Spain',value=1,inplace=True)
  dataset[i].replace(to_replace='Germany',value=2,inplace=True)

convertGender = ['Gender']
for i in convertGender:
  dataset[i].replace(to_replace='Female',value=0,inplace=True)
  dataset[i].replace(to_replace='Male',value=1,inplace=True)

dataset
```

Out[70]:

	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	Has
RowNumber								
1	619	0	0	42	2	0.00	1	
2	608	1	0	41	1	83807.86	1	
3	502	0	0	42	8	159660.80	3	
4	699	0	0	39	1	0.00	2	
5	850	1	0	43	2	125510.82	1	
...	...	...	...	...	...	...	...	
9996	771	0	1	39	5	0.00	2	
9997	516	0	1	35	10	57369.61	1	
9998	709	0	0	36	7	0.00	1	
9999	772	2	1	42	3	75075.31	2	
10000	792	0	0	28	4	130142.79	1	

10000 rows × 11 columns

In [71]:

```
#check the count,mean,min and etc of dataset
dataset.describe().T
```

Out[71]:

	count	mean	std	min	25%	50%	
CreditScore	10000.0	650.528800	96.653299	350.00	584.00	652.000	718
Geography	10000.0	0.749500	0.830433	0.00	0.00	0.000	2
Gender	10000.0	0.545700	0.497932	0.00	0.00	1.000	1
Age	10000.0	38.921800	10.487806	18.00	32.00	37.000	44
Tenure	10000.0	5.012800	2.892174	0.00	3.00	5.000	7
Balance	10000.0	76485.889288	62397.405202	0.00	0.00	97198.540	127644
NumOfProducts	10000.0	1.530200	0.581654	1.00	1.00	1.000	2
HasCrCard	10000.0	0.705500	0.455840	0.00	0.00	1.000	1
IsActiveMember	10000.0	0.515100	0.499797	0.00	0.00	1.000	1
EstimatedSalary	10000.0	100090.239881	57510.492818	11.58	51002.11	100193.915	149388
Exited	10000.0	0.203700	0.402769	0.00	0.00	0.000	0

In [72]:

```
#check
dataset["Exited"].value_counts()
```

Out[72]:

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

In [73]:

```
from sklearn.model_selection import train_test_split
```

In [74]:

```
#Classify dataset into train dataset and test dataset
trainDataset,testDataset = train_test_split(dataset,test_size=0.3,random_state=100)
trainDataset
```

Out[74]:

	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	Has
RowNumber								
1192	639	2	1	27	3	150795.81	1	
4459	633	0	1	37	2	0.00	2	
1132	500	1	1	37	9	125822.21	1	
9563	738	0	1	39	5	0.00	2	
6580	496	0	0	36	7	0.00	2	
...	...	...	...	...	...	...	...	
351	659	1	1	32	3	107594.11	2	
80	416	2	0	41	10	122189.66	2	
8040	672	0	0	43	4	92599.55	2	
6937	592	0	0	31	2	84102.11	2	
5641	477	2	0	24	2	95675.62	2	

7000 rows × 11 columns

C. EDA

In [75]:

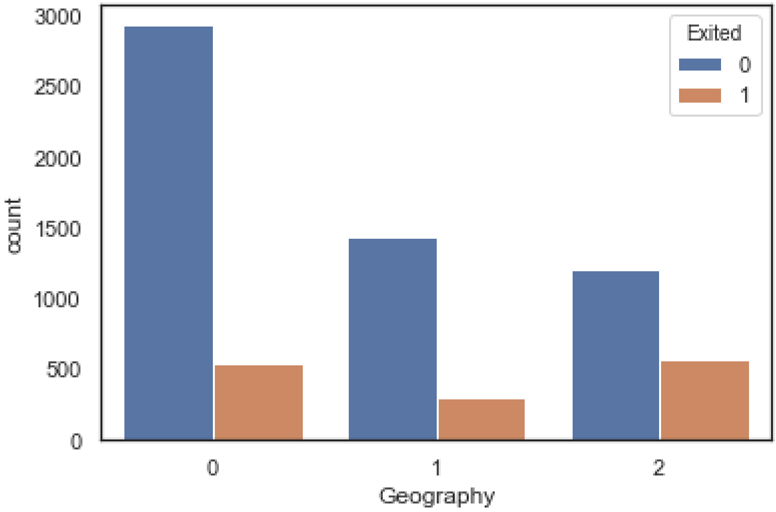
```
exited = trainDataset[trainDataset["Exited"]==1]
non_exited = trainDataset[trainDataset["Exited"]==0]
```

In [76]:

```
sns.countplot(x = 'Geography', hue = 'Exited',data = trainDataset)

#0 = France
#1 = Spain
#2 = Germany
```

Out[76]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1e684fbb7c8>
```



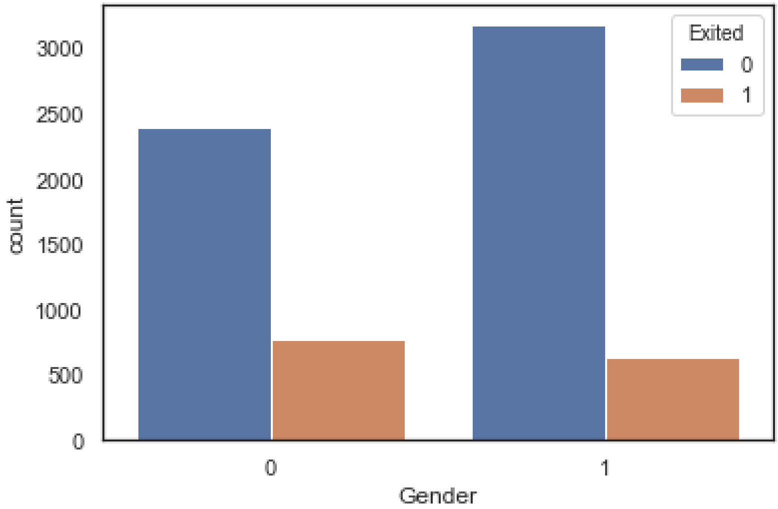
Geography : Based on the bar chart, France has the highest number of non-exited customers and Spain is the second highest. Germany has the lowest number non-exited customers. Then, Germany has the highest exited customers and France is the second highest. Lastly, Spain has the lowest number of exited customers.

In [77]:

```
sns.countplot(x = 'Gender', hue = 'Exited',data = trainDataset)
#0 = Female
#1 = Male
```

Out[77]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1e68502b1c8>
```



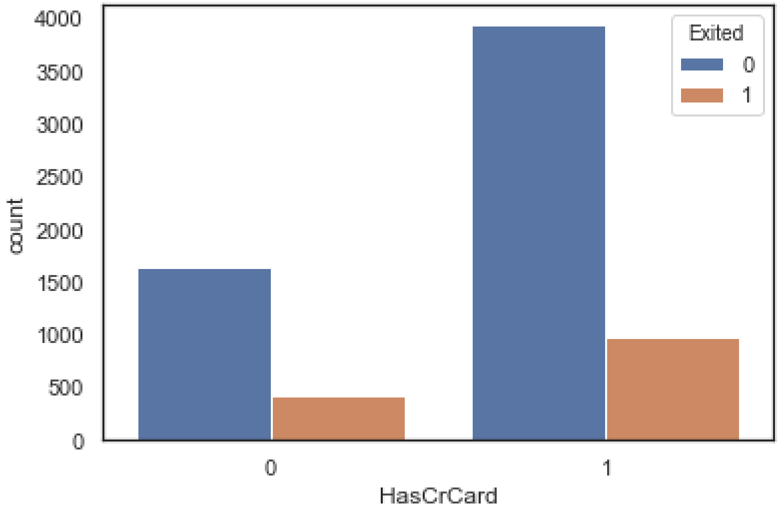
Gender : According to the bar chart, female has the highest number of exited customers while male has the lowest number of exited customers. Then, male has the highest non-exited customers while female has the lowest non-exited customers.

In [78]:

```
sns.countplot(x = 'HasCrCard', hue = 'Exited',data = trainDataset)
#0 = No Credit Card
#1 = Has Credit Card
```

Out[78]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1e6857accc8>
```



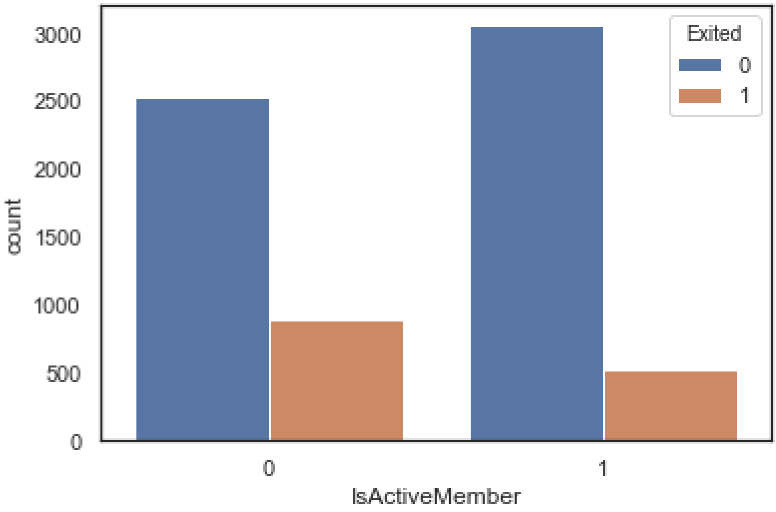
HasCrCard : Based on the bar chart, the customers without credit cards have the lowest number of non-exited and exited customers. In the same time, the customers with credit cards have the highest number of non-exited and exited customers.

In [79]:

```
sns.countplot(x = 'IsActiveMember', hue = 'Exited',data = trainDataset)
```

Out[79]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1e68584dc88>
```



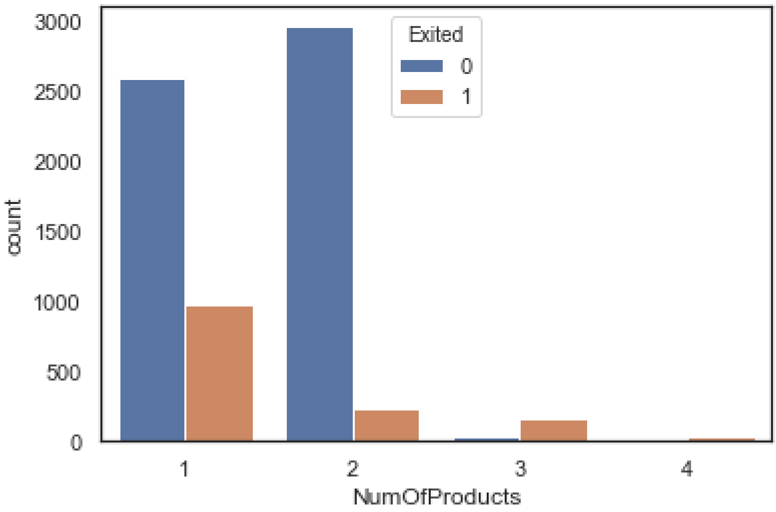
IsActiveMember : According to the bar chart, inactive members have the lowest number of non-exited customers but active members have the highest number of non-exited numbers. Meanwhile, inactive members have the highest exited number of customers while active members have the lowest exited number of customers.

In [80]:

```
sns.countplot(x = 'NumOfProducts', hue = 'Exited',data = trainDataset)
```

Out[80]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1e6859076c8>
```



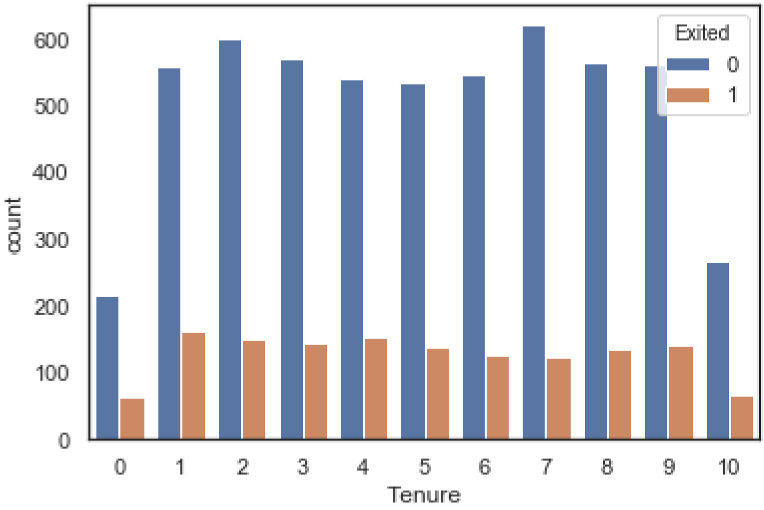
NumOfProducts : Based on the bar chart, the number of products that a customer has purchased through the bank is 1 has the highest of exited number of customers. Then, with 2 purchased is the second highest and 3 purchased is the third highest of exited number of customers. Lastly, 4 purchased is the lowest number of exited customers. Besides, customers with 2 purchased are the highest number of non-exited while 1 purchased is the second highest. Then, with 3 purchased is the third highest and 4 purchased is the lowest number of non-exited.

In [81]:

```
sns.countplot(x = 'Tenure', hue = 'Exited',data = trainDataset)
```

Out[81]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1e68597c548>
```



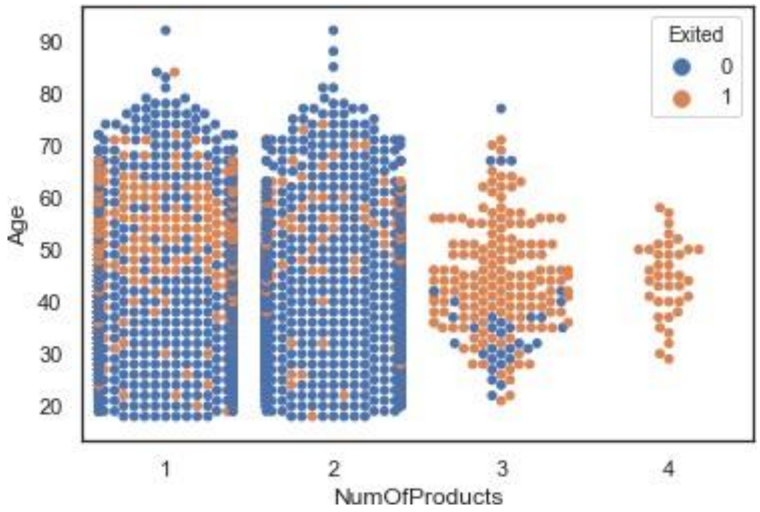
Tenure : According to the bar chart, the customers who have been a client of the bank for 7 years have the highest number of non-exited customers while those with 0 years have the lowest number of non-exited customers. Then, customers who have been a client of the bank for 1 year have the highest number of exited customers while those with 0 years have the lowest number of exited customers.

In [82]:

```
sns.swarmplot(x = "NumOfProducts", y = "Age", hue="Exited", data = trainDataset)
```

Out[82]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1e685a2ae48>
```



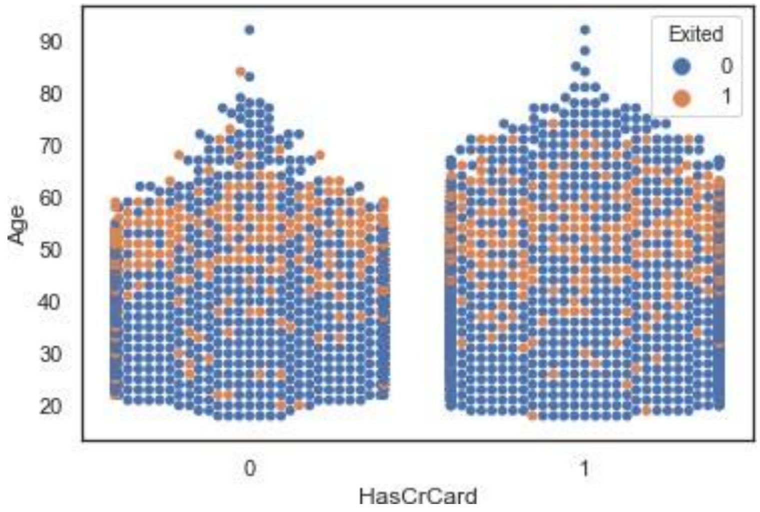
Swarmplot 1 : According to the swarmplot diagram, it shows the relationship of y value 'Age' and x value 'NumOfProducts' and 'Exited' variables.

In [83]:

```
sns.swarmplot(x = "HasCrCard", y = "Age", data = trainDataset, hue="Exited")
```

Out[83]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1e685a30548>
```



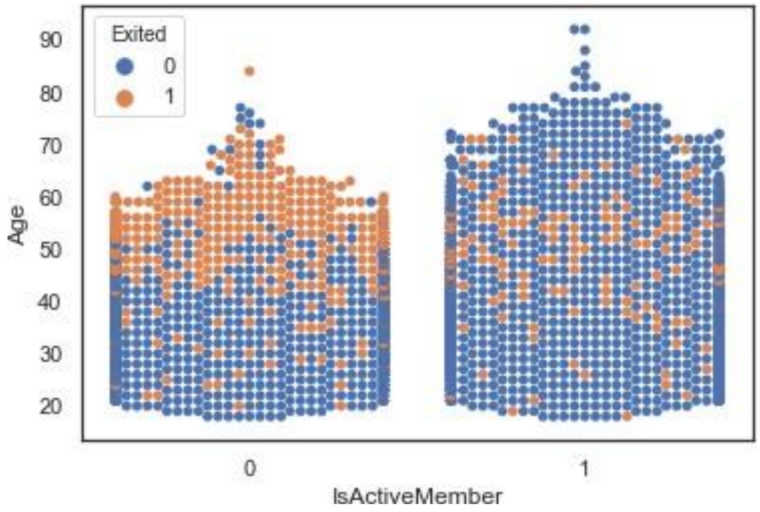
Swarmplot 2 : Based on the swarmplot diagram, it shows the relationship of y value 'Age' and x value 'HasCrCard' and 'Exited' variables.

In [84]:

```
sns.swarmplot(x = "IsActiveMember", y = "Age", hue="Exited", data = trainDataset)
```

Out[84]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1e686afbc48>
```



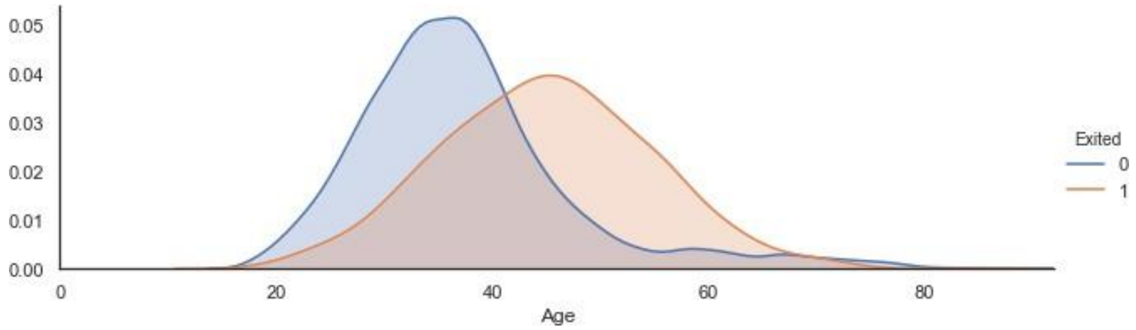
Swarmplot 3 : According to the swarmplot diagram, it shows the relationship of y value ‘Age’ and x value ‘IsActiveMember’ and ‘Exited’ variables.

In [85]:

```
facet = sns.FacetGrid(trainDataset, hue = "Exited", aspect = 3)
facet.map(sns.kdeplot, "Age", shade = True)
facet.set(xlim = (0, trainDataset["Age"].max()))
facet.add_legend()

#plt.show();
```

Out[85]:

```
<seaborn.axisgrid.FacetGrid at 0x1e686bdd848>
```



FacetGrid : Based on this diagram, it shows the relationship of ‘Age’ and ‘Exited’ variables.

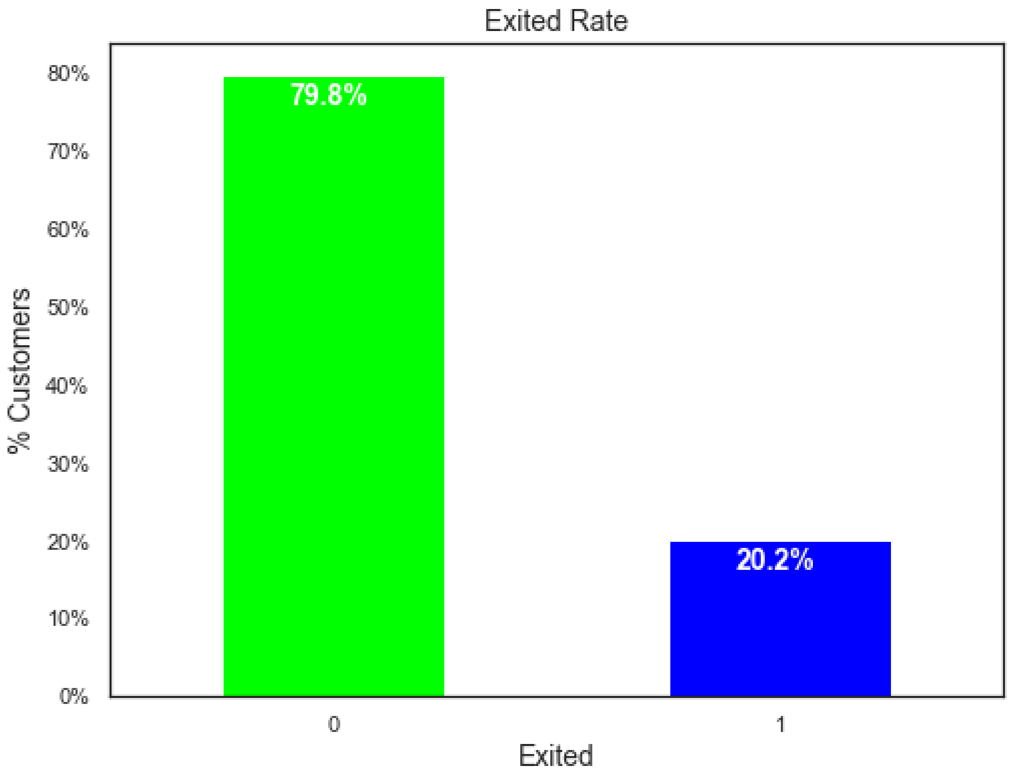
In [86]:

```
import matplotlib.ticker as mtick
```

Balance the number of churners and non-churners

In [87]:

```
colors = ['#00FF00','#0000FF']
ax = (trainDataset['Exited'].value_counts()*100.0 /len(trainDataset)).plot(kind='bar',
stacked=True,rot =0, color = colors, figsize = (8,6))


ax.yaxis.set_major_formatter(mtick.PercentFormatter())
ax.set_ylabel('% Customers',size = 14)
ax.set_xlabel('Exited',size = 14)
ax.set_title('Exited Rate', size = 14)

totals = []

for i in ax.patches:
  totals.append(i.get_width())


total = sum(totals)

for i in ax.patches:
  ax.text(i.get_x()+.15, i.get_height()-4.0, \
          str(round((i.get_height()/total),1))+'%',
          fontsize = 12,
          color='white',
          weight = 'bold',
          size = 14)
```



In [88]:

```
#Let the exited and non exited have the same value
exited_number = len(trainDataset[trainDataset['Exited'] ==1])
print("Number of Exited:",exited_number)

exitNum = (trainDataset[trainDataset['Exited']==1])

noExit = trainDataset[trainDataset['Exited']==0].sample(n=exited_number)
print("Number of not exited: ",len(noExit))
balance_trainDataset = exitNum.append(noExit)
```

```
Number of Exited: 1413
Number of not exited:  1413
```

In [89]:

```
X_train = balance_trainDataset.drop('Exited',axis=1)
X_test = testDataset.drop('Exited',axis=1)
Y_train = balance_trainDataset['Exited']
Y_test = testDataset['Exited']
X_train.head()
```

Out[89]:

	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	Has
RowNumber								
139	584	1	0	48	2	213146.20	1	
36	475	0	0	45	0	134264.04	1	
552	674	2	1	47	6	106901.94	1	
3164	649	2	0	37	8	114737.26	1	
4713	474	0	1	54	3	0.00	1	

D. Data Preprocessing

According to the EDA, we use the integer ‘0’ for France, ‘1’ for Spain and ‘2’ for Germany in the Geography column. Then, we also use the integer ‘0’ for female and ‘1’ for male in the Gender column. Additionally, we use StandardScaler function () to scale the CreditScore, Age, Ternure, Balance and EstimatedSalary variables.

In [90]:

```
import sklearn
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn import preprocessing
```

In [91]:

```
#use standard scaler to scale the continuous value
ss = StandardScaler()

X_train['CreditScore'] = ss.fit_transform(X_train[['CreditScore']])
X_test['CreditScore'] = ss.transform(X_test[['CreditScore']])

X_train['Age'] = ss.fit_transform(X_train[['Age']])
X_test['Age'] = ss.transform(X_test[['Age']])

X_train['Tenure'] = ss.fit_transform(X_train[['Tenure']])
X_test['Tenure'] = ss.transform(X_test[['Tenure']])

X_train['Balance'] = ss.fit_transform(X_train[['Balance']])
X_test['Balance'] = ss.transform(X_test[['Balance']])

X_train['EstimatedSalary'] = ss.fit_transform(X_train[['EstimatedSalary']])
X_test['EstimatedSalary'] = ss.transform(X_test[['EstimatedSalary']])

X_train
```

Out[91]:

	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProduc
RowNumber							
139	-0.668098	1	0	0.630320	-1.003741	2.125721	
36	-1.782743	0	0	0.351239	-1.693233	0.834359	
552	0.252251	2	1	0.537293	0.375244	0.386420	
3164	-0.003401	2	0	-0.392979	1.064736	0.514691	
4713	-1.792969	0	1	1.188484	-0.658995	-1.363647	
...	...	...	...	...	...	...	
2945	-0.749907	0	1	-0.858115	0.719990	-1.363647	
5304	-0.156793	1	1	-1.509306	1.409482	-1.363647	
4421	0.661295	2	0	-0.579034	0.375244	0.700338	
1973	0.855591	1	0	-1.044170	-1.693233	0.000354	
7677	-1.966812	0	0	-0.765088	0.719990	0.729152	

2826 rows × 10 columns

E. Data preparation

Based on our EDA, the variable that affects the churn rate the most is ‘IsActiveMember’, ‘Gender’ and ‘Geography’ . Besides, the first time we do the modelling is to use all the columns above to test the modelling. Then, the second time we do is to use the only one variable that affects churn rate the most to do the modelling which is ‘IsActiveMember’, ‘Gender’ and ‘Geography’ .

F. Modelling

Based on the dataset, we have used 4 models to do the modelling which are KNN, SVM, Logistic Regression and Gausian Naive Bayes. Then, we have realized that with using all columns to do these 4 models, SVM is the highest overall accuracy, precision and recall among the other three models.

K-Nearest Neighbour *(with all variables)*

In [92]:

```
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import confusion_matrix
from sklearn.model_selection import GridSearchCV

from sklearn.preprocessing import LabelEncoder, StandardScaler, normalize
from sklearn.model_selection import train_test_split, KFold
from sklearn.metrics import accuracy_score, roc_auc_score, f1_score, recall_score
```

In [93]:

```
KNN_before = KNeighborsClassifier(n_neighbors=5)
KNN_before.fit(X_train, Y_train)

KNN_Y_predict_before = KNN_before.predict(X_test)
KNN_acc_score_before = accuracy_score(Y_test,KNN_Y_predict_before)
KNN_conf_matrix_before = confusion_matrix(Y_test, KNN_Y_predict_before)
print(KNN_acc_score_before, "\n", KNN_conf_matrix_before)
```

```
0.7553333333333333
 [[1822  554]
 [ 180  444]]
```

In [94]:

```
parameter = dict(n_neighbors = list(range(3,50)), weights = ["uniform", "distance"])

grid_search = GridSearchCV(KNN_before, parameter, cv = 10, scoring = 'accuracy')
grid_search.fit(X_train,Y_train)
best_params = grid_search.best_params_
print(best_params)
```

```
{'n_neighbors': 10, 'weights': 'distance'}
```

In [95]:

```
KNN_after = KNeighborsClassifier(n_neighbors=best_params['n_neighbors'], weights=best_p
arams['weights'])
KNN_after.fit(X_train, Y_train)

KNN_Y_predict_after = KNN_after.predict(X_test)
KNN_acc_score_after = accuracy_score(Y_test, KNN_Y_predict_after)
KNN_conf_matrix_after = confusion_matrix(Y_test, KNN_Y_predict_after)
print(KNN_acc_score_after, "\n", KNN_conf_matrix_after)
```

```
0.772
 [[1867  509]
 [ 175  449]]
```

Support Vector Machine *(with all variables)*

In [96]:

```
from sklearn import svm
from sklearn.model_selection import GridSearchCV
from sklearn.svm import SVC
```

In [97]:

```
SVC_before = SVC(kernel='linear',degree=3,gamma='scale')

SVC_before.fit(X_train, Y_train)

SVC_Y_predict_before = SVC_before.predict(X_test)
SVC_acc_score_before = accuracy_score(Y_test,SVC_Y_predict_before)
SVC_conf_matrix_before = confusion_matrix(Y_test,SVC_Y_predict_before)
print(SVC_acc_score_before, "\n", SVC_conf_matrix_before)
```

```
0.7236666666666667
 [[1738  638]
 [ 191  433]]
```

In [98]:

```
param_grid = {'C': [0.1, 1, 10, 100, 1000],
              'gamma': [1, 0.1, 0.01, 0.001, 0.0001]}

grid = GridSearchCV(SVC_before, param_grid, refit = True)

#fitting the model for grid search
grid = grid.fit(X_train, Y_train)
grid = grid.best_params_
print(grid)
```

```
{'C': 1000, 'gamma': 1}
```

In [99]:

```
SVC_after = SVC(C=grid["C"],gamma=grid["gamma"])
SVC_after.fit(X_train, Y_train)

SVC_Y_predict_after = SVC_after.predict(X_test)
SVC_acc_score_after = accuracy_score(Y_test,SVC_Y_predict_after)
SVC_conf_matrix_after = confusion_matrix(Y_test,SVC_Y_predict_after)
print(SVC_acc_score_after, "\n", SVC_conf_matrix_after)
```

```
0.7106666666666667
 [[1678  698]
 [ 170  454]]
```

Gaussian Naive Bayes *(with all variables)*

In [100]:

```
from sklearn.naive_bayes import GaussianNB

GNB = GaussianNB()
GNB.fit(X_train, Y_train)

GNB_Y_predict = GNB.predict(X_test)
GNB_acc_score = accuracy_score(Y_test,GNB_Y_predict)
GNB_conf_matrix = confusion_matrix(Y_test,GNB_Y_predict)

print(GNB_acc_score, "\n", GNB_conf_matrix)
```

```
0.7503333333333333
 [[1822  554]
 [ 195  429]]
```

LogisticRegression *(with all variables)*

In [101]:

```
from sklearn.linear_model import  LogisticRegression
```

In [102]:

```
LR_before = LogisticRegression()
LR_before.fit(X_train,Y_train)


LR_Y_predict_before = LR_before.predict(X_test)
LR_acc_score_before = accuracy_score(Y_test,LR_Y_predict_before)
LR_conf_matrix_before = confusion_matrix(Y_test,LR_Y_predict_before)

print(LR_acc_score_before, "\n", LR_conf_matrix_before)
```

```
0.7136666666666667
 [[1715  661]
 [ 198  426]]
```

In [103]:

```
param_grid = {'penalty' : ['l2'],'C': np.logspace(0, 4, 10), 'solver':['lbfgs', 'liblin
ear', 'sag', 'saga']}

grid = GridSearchCV(LR_before, param_grid,cv=5)

#fitting the model for grid search
best_model = grid.fit(X_train,Y_train)
grid = best_model.best_params_
print(grid)
```

```
{'C': 1.0, 'penalty': 'l2', 'solver': 'liblinear'}
```

In [104]:

```
LR_after = LogisticRegression(C = grid['C'], penalty = grid['penalty'],solver = grid['s
olver'])
LR_after.fit(X_train,Y_train)


LR_Y_predict_after = LR_after.predict(X_test)
LR_acc_score_after = accuracy_score(Y_test,LR_Y_predict_after)
LR_conf_matrix_after = confusion_matrix(Y_test,LR_Y_predict_after)

print(LR_acc_score_before, "\n", LR_conf_matrix_before)
```

```
0.7136666666666667
 [[1715  661]
 [ 198  426]]
```

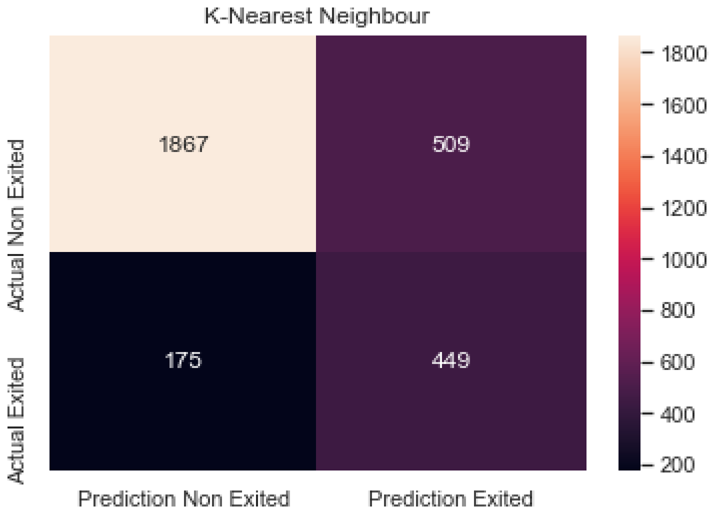
Confusion Matrix *(with all variables)*

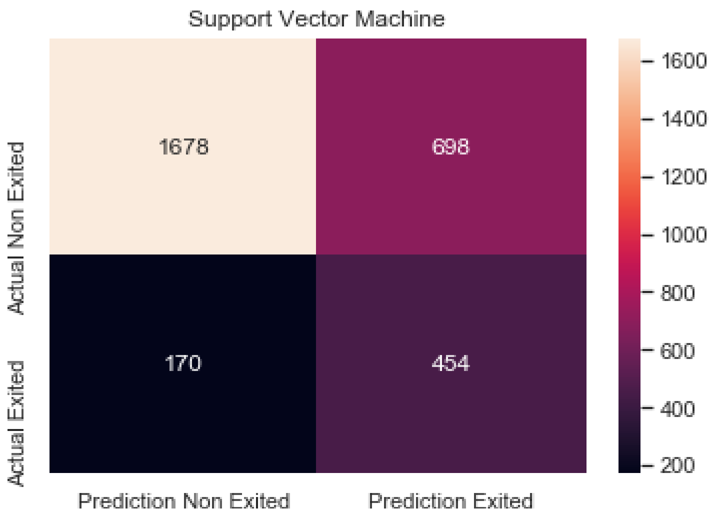
In [105]:

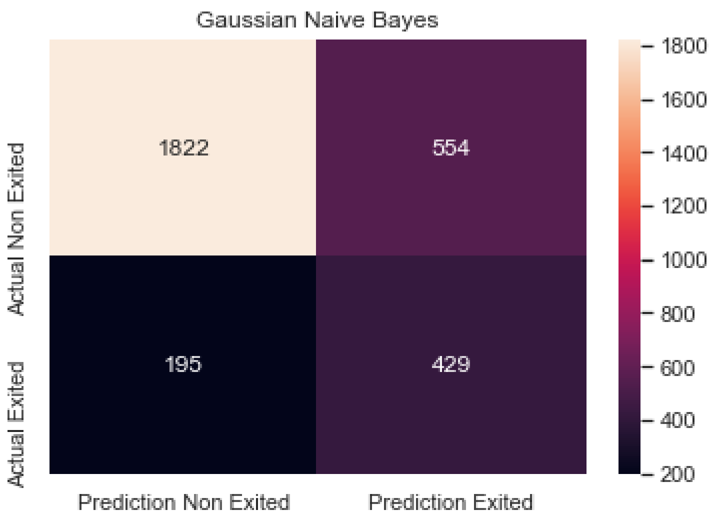
```
import seaborn as sn
```

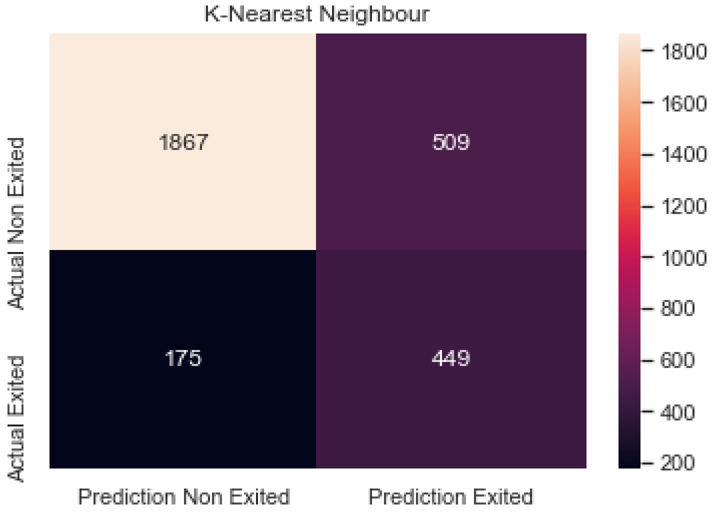
In [106]:

```
sn.heatmap(KNN_conf_matrix_after, annot=True,fmt = '.4g', xticklabels=["Prediction Non
 Exited","Prediction Exited"], yticklabels=["Actual Non Exited","Actual Exited"])
plt.title("K-Nearest Neighbour")
plt.show()
sn.heatmap(SVC_conf_matrix_after, annot=True,fmt = '.4g', xticklabels=["Prediction Non
 Exited","Prediction Exited"], yticklabels=["Actual Non Exited","Actual Exited"])
plt.title("Support Vector Machine")
plt.show()
sn.heatmap(GNB_conf_matrix, annot=True,fmt = '.4g', xticklabels=["Prediction Non Exite
d","Prediction Exited"], yticklabels=["Actual Non Exited","Actual Exited"])
plt.title("Gaussian Naive Bayes")
plt.show()
sn.heatmap(LR_conf_matrix_after, annot=True,fmt = '.4g', xticklabels=["Prediction Non E
xited","Prediction Exited"], yticklabels=["Actual Non Exited","ActualExited"])
plt.title("LogisticRegression")
plt.show()
```


K-Nearest Neighbour
1867
509
175
449
Actual Non Exited
Actual Exited
Prediction Non Exited
Prediction Exited
1800
1600
1400
1200
1000
800
600
400
200


Support Vector Machine
1678
698
170
454
Actual Non Exited
Actual Exited
Prediction Non Exited
Prediction Exited
1600
1400
1200
1000
800
600
400
200


Gaussian Naive Bayes
1822
554
195
429
Actual Non Exited
Actual Exited
Prediction Non Exited
Prediction Exited
1800
1600
1400
1200
1000
800
600
400
200



Modal Comparison Table *(with all variables)*

In [107]:

```
from sklearn.metrics import accuracy_score, roc_auc_score, f1_score, recall_score, prec
ision_score
import plotly.figure_factory as ff
import plotly.offline as py
```

Modelling with usable column *('IsActiveMember', 'Gender' and 'Geography')*

In [108]:

```
X_train_usable = X_train[['IsActiveMember','Gender','Geography']]
X_test_usable = X_test[['IsActiveMember','Gender','Geography']]
X_train_usable
```

Out[108]:

	IsActiveMember	Gender	Geography
RowNumber			
139	0	0	1
36	0	0	0
552	1	1	2
3164	1	0	2
4713	0	1	0
...	...	...	...
2945	0	1	0
5304	1	1	1
4421	1	0	2
1973	0	0	1
7677	1	0	0

2826 rows × 3 columns

K-Nearest Neighbour *('IsActiveMember', 'Gender' and 'Geography')*

In [109]:

```
KNN2_before = KNeighborsClassifier(n_neighbors=5)
KNN2_before.fit(X_train_usable, Y_train)

KNN2_Y_predict_before = KNN2_before.predict(X_test_usable)
KNN2_acc_score_before = accuracy_score(Y_test,KNN2_Y_predict_before)
KNN2_conf_matrix_before = confusion_matrix(Y_test, KNN2_Y_predict_before)
print(KNN2_acc_score_before, "\n", KNN2_conf_matrix_before)
```

```
0.434
 [[ 844 1532]
 [ 166  458]]
```

In [110]:

```
parameter = dict(n_neighbors = list(range(3,50)), weights = ["uniform", "distance"])

grid_search = GridSearchCV(KNN2_before, parameter, cv = 10, scoring = 'accuracy')
grid_search.fit(X_train_usable,Y_train)
best_params = grid_search.best_params_
print(best_params)
```

```
{'n_neighbors': 36, 'weights': 'uniform'}
```

In [111]:

```
KNN2_after = KNeighborsClassifier(n_neighbors=best_params['n_neighbors'], weights=best_
params['weights'])
KNN2_after.fit(X_train_usable, Y_train)

KNN2_Y_predict_after = KNN2_after.predict(X_test_usable)
KNN2_acc_score_after = accuracy_score(Y_test, KNN2_Y_predict_after)
KNN2_conf_matrix_after = confusion_matrix(Y_test, KNN2_Y_predict_after)
print(KNN2_acc_score_after, "\n", KNN2_conf_matrix_after)
```

```
0.5733333333333334
 [[1289 1087]
 [ 193  431]]
```

Support Vector Machine *('IsActiveMember', 'Gender' and 'Geography')*

In [112]:

```
SVC2_before = SVC(kernel='linear',degree=3,gamma='scale')
SVC2_before.fit(X_train_usable, Y_train)

SVC2_Y_predict_before = SVC2_before.predict(X_test_usable)
SVC2_acc_score_before = accuracy_score(Y_test,SVC2_Y_predict_before)
SVC2_conf_matrix_before = confusion_matrix(Y_test,SVC2_Y_predict_before)
print(SVC2_acc_score_before, "\n", SVC2_conf_matrix_before)
```

```
0.588
 [[1356 1020]
 [ 216  408]]
```

In [113]:

```
param_grid = {'C': [0.1, 1, 10, 100, 1000],
              'gamma': [1, 0.1, 0.01, 0.001, 0.0001]}

grid = GridSearchCV(SVC2_before, param_grid, refit = True)

#fitting the model for grid search
grid = grid.fit(X_train_usable, Y_train)
grid = grid.best_params_
print(grid)
```

```
{'C': 0.1, 'gamma': 1}
```

In [114]:

```
SVC2_after = SVC(C=grid["C"],gamma=grid["gamma"])
SVC2_after.fit(X_train_usable, Y_train)

SVC2_Y_predict_after = SVC2_after.predict(X_test_usable)
SVC2_acc_score_after = accuracy_score(Y_test,SVC2_Y_predict_after)
SVC2_conf_matrix_after = confusion_matrix(Y_test,SVC2_Y_predict_after)
print(SVC2_acc_score_after, "\n", SVC2_conf_matrix_after)
```

```
0.611
 [[1419  957]
 [ 210  414]]
```

Gaussian Naive Bayes *('IsActiveMember', 'Gender' and 'Geography')*

In [115]:

```
GNB2 = GaussianNB()
GNB2.fit(X_train_usable, Y_train)

GNB2_Y_predict = GNB2.predict(X_test_usable)
GNB2_acc_score = accuracy_score(Y_test,GNB2_Y_predict)
GNB2_conf_matrix = confusion_matrix(Y_test,GNB2_Y_predict)

print(GNB2_acc_score, "\n", GNB2_conf_matrix)
```

```
0.654
 [[1585  791]
 [ 247  377]]
```

LogisticRegression *('IsActiveMember', 'Gender' and 'Geography')*

In [116]:

```
LR2_before = LogisticRegression()
LR2_before.fit(X_train_usable,Y_train)


LR2_Y_predict_before = LR2_before.predict(X_test_usable)
LR2_acc_score_before = accuracy_score(Y_test,LR2_Y_predict_before)
LR2_conf_matrix_before = confusion_matrix(Y_test,LR2_Y_predict_before)

print(LR2_acc_score_before, "\n", LR2_conf_matrix_before)
```

```
0.654
 [[1585  791]
 [ 247  377]]
```

In [117]:

```
param_grid = {'penalty' : ['l2'],'C': np.logspace(0, 4, 10)}

grid = GridSearchCV(LR_before, param_grid,cv=5)

#fitting the model for grid search
best_model = grid.fit(X_train,Y_train)
grid = best_model.best_params_
print(grid)
```

```
{'C': 2.7825594022071245, 'penalty': 'l2'}
```

In [118]:

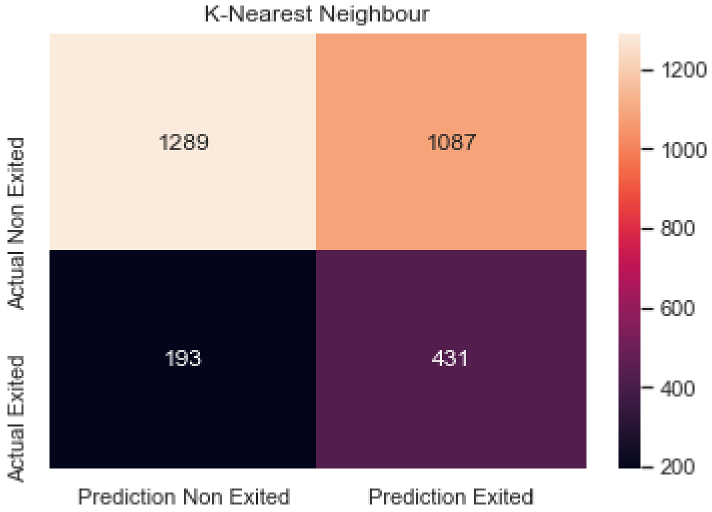
```
LR2_after = LogisticRegression(C = grid['C'], penalty = grid['penalty'])
LR2_after.fit(X_train_usable,Y_train)


LR2_Y_predict_after = LR2_after.predict(X_test_usable)
LR2_acc_score_after = accuracy_score(Y_test,LR2_Y_predict_after)
LR2_conf_matrix_after = confusion_matrix(Y_test,LR2_Y_predict_after)

print(LR2_acc_score_after, "\n", LR2_conf_matrix_after)
```

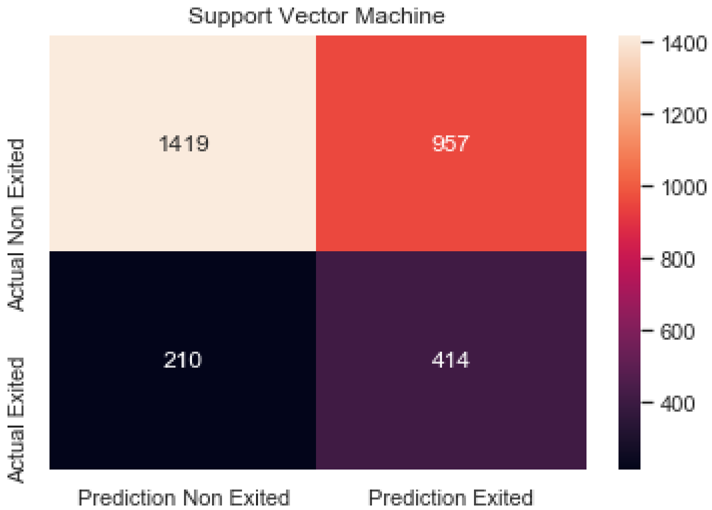
```
0.654
 [[1585  791]
 [ 247  377]]
```

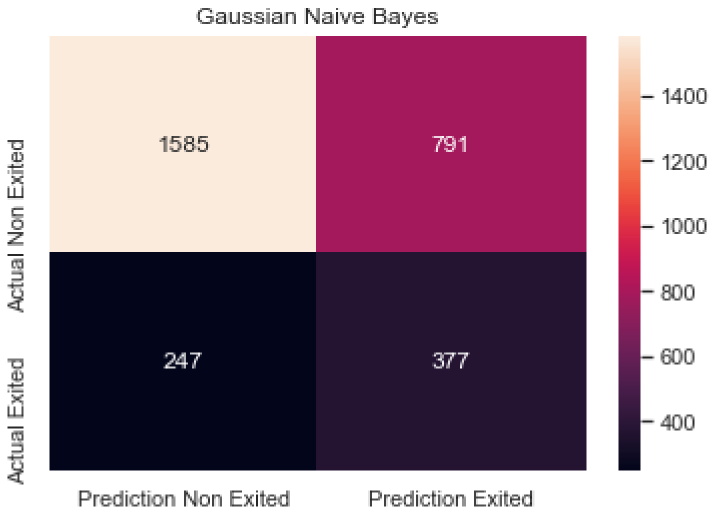
Confusion Matrix *('IsActiveMember', 'Gender' and 'Geography')*

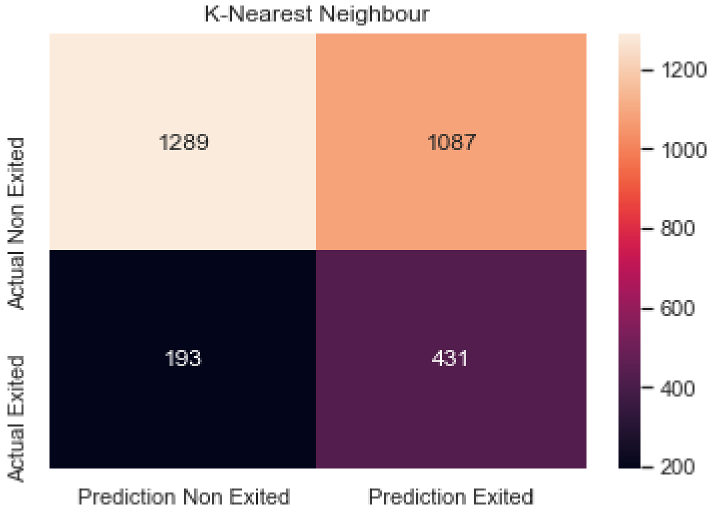
In [119]:

```
sn.heatmap(KNN2_conf_matrix_after, annot=True,fmt = '.4g', xticklabels=["Prediction Non Exited","Prediction Exited"], yticklabels=["Actual Non Exited","Actual Exited"])
plt.title("K-Nearest Neighbour")
plt.show()
sn.heatmap(SVC2_conf_matrix_after, annot=True,fmt = '.4g', xticklabels=["Prediction Non Exited","Prediction Exited"], yticklabels=["Actual Non Exited","Actual Exited"])
plt.title("Support Vector Machine")
plt.show()
sn.heatmap(GNB2_conf_matrix, annot=True,fmt = '.4g', xticklabels=["Prediction Non Exited","Prediction Exited"], yticklabels=["Actual Non Exited","Actual Exited"])
plt.title("Gaussian Naive Bayes")
plt.show()
sn.heatmap(LR2_conf_matrix_after, annot=True,fmt = '.4g', xticklabels=["Prediction Non Exited","Prediction Exited"], yticklabels=["Actual Non Exited","ActualExited"])
plt.title("LogisticRegression")
plt.show()
```


K-Nearest Neighbour
1289
1087
193
431
Actual Non Exited
Actual Exited
Prediction Non Exited
Prediction Exited
1200
1000
800
600
400
200


Support Vector Machine
1419
957
210
414
Actual Non Exited
Actual Exited
Prediction Non Exited
Prediction Exited
1400
1200
1000
800
600
400


Gaussian Naive Bayes
1585
791
247
377
Actual Non Exited
Actual Exited
Prediction Non Exited
Prediction Exited
1400
1200
1000
800
600
400



Modal Comparison Table *(all variables and usable variables)*

In [120]:

```
model_name = ["KNN(all variables)","SVM(all variables)"
,"GNB(all variables)","LR(all variables)"
,"KNN(usable variables)","SVM(usable variables)"
,"GNB(usable variables)","LR(usable variables)"]
model_acc_score = [KNN_acc_score_after,SVC_acc_score_after,GNB_acc_score,LR_acc_score_a
fter,KNN2_acc_score_after,SVC2_acc_score_after,GNB2_acc_score,LR2_acc_score_after]
model_Y_predict = [KNN_Y_predict_after,SVC_Y_predict_after,GNB_Y_predict,LR_Y_predict_a
fter,KNN2_Y_predict_after,SVC2_Y_predict_after,GNB2_Y_predict,LR2_Y_predict_after]

model_rec_score = []
model_pre_score = []
model_f1_score = []
model_roc_auc_score = []

for i in range(0,len(model_name),1):
  model_rec_score.append(recall_score(Y_test,model_Y_predict[i]))
  model_pre_score.append(precision_score(Y_test, model_Y_predict[i]))
  model_f1_score.append(f1_score(Y_test, model_Y_predict[i]))
  model_roc_auc_score.append(roc_auc_score(Y_test, model_Y_predict[i]))

model_table = pd.DataFrame({"Model":model_name,"Accuracy_score":model_acc_score,"Recall
_score":model_rec_score,"Precision":model_pre_score,"f1_score":model_f1_score,"Area_und
er_curve":model_roc_auc_score})

model_table = ff.create_table(np.round(model_table,8))

py.iplot(model_table)
print("LR= LogisticRegression")
```

```
LR= LogisticRegression
```

K-FLow

Based on our project, we have used K-fold cross validation to determine whether the selected model has overfitting problems. Then, we have to ensure that the model will provide us with consistent results when forecasting different datasets. When a model provides us with accurate and precise results during the modeling process, but provides poor results when using another set of data for modeling, it means that the model is essential as overfitting may occur.This is because the model is only applicable to specific data sets.

In [121]:

```
from sklearn.model_selection import KFold
```

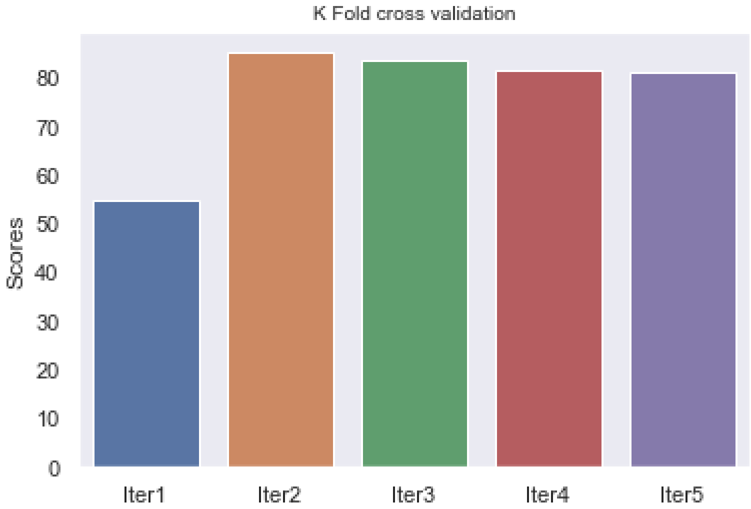
In [127]:

```
X = X_train.append(X_test)
Y = np.concatenate((Y_train,Y_test))

# KFold Cross Validation approach
kf = KFold(n_splits=5,shuffle=False)
kf.split(X)

# Initialize the accuracy of the models to blank list. The accuracy of each model will
 be appended to this list
accuracy_model = []

# Iterate over each train-test split
for train_No, test_No in kf.split(X):
    # Split train-test
    X_train, X_test = X.iloc[train_No], X.iloc[test_No]
    Y_train, Y_test = Y[train_No], Y[test_No]
    # Train the model
    model = SVC().fit(X_train, Y_train)
    # Append to accuracy_model the accuracy of the model
    accuracy_model.append(accuracy_score(Y_test, model.predict(X_test), normalize=True)
*100)

# Print the accuracy
print(accuracy_model)
```

```
[54.71698113207547, 85.23605150214593, 83.86266094420601, 81.7167381974248
9, 81.11587982832617]
```

In [128]:

```
# Visualize accuracy for each iteration

scores = pd.DataFrame(accuracy_model,columns=['Scores'])

sns.set(style="dark", rc={"lines.linewidth": 4})
sns.barplot(x=['Iter1','Iter2','Iter3','Iter4','Iter5'],y="Scores",data=scores)
plt.title('K Fold cross validation', fontsize=10)


plt.show()
sns.set()
```



Conclusion

According to the chart above, the accuracy score of the five iterations are in the acceptable range. As a conclusion, we can know that the SVM model does not has any overfit problems. The advantages of SVM is it works relatively well when there is clear margin of separation between classes. Besides,SVM is more effective in high dimensional spaces. SVM is effective in cases where number of dimensions is greater than the number of samples. SVM is relatively memory efficient. But, SVM also got its limition, SVM is not suitable for large dataset because the when we use svm to find the best parameter, it take long time to search because SVM has many parameters, so it will take a long time.

In [ ]:

```
```