

DATA DESCRIPTION:

This data set contains details of a bank's customers and the target variable is a binary variable reflecting the fact whether the customer left the bank (closed his account) or he continues to be a customer.

RowNumber: Row Numbers from 1 to 10000

CustomerId: Unique Ids for bank customer identification

Surname: Customer's last name

CreditScore: Credit score of the customer

Geography: The country from which the customer belongs

Gender: Male or Female

Age: Age of the customer

Tenure: Number of years for which the customer has been with the bank

Balance: Bank balance of the customer

NumOfProducts: Number of bank products the customer is utilising

HasCrCard: Binary Flag for whether the customer holds a credit card with the bank or not

IsActiveMember: Binary Flag for whether the customer is an active member with the bank or not

EstimatedSalary: Estimated salary of the customer in Dollars

Exited: Binary flag 1 if the customer closed account with bank and 0 if the customer is retained

> Target Column Description: Exited is a class label used to divide into groups (customer closed account or not).

```
In [1]: import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
df=pd.read_csv('Churn_Modelling.csv')
df.head()
```

```
Out[1]:
```

	RowNumber	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure	Balance	EstimatedSalary	Exited
0	1	15634602	Hargrave	619	France	Female	42	2	0.00	84130.63	0
1	2	15647311	Hill	608	Spain	Female	41	1	83807.86	45930.87	1
2	3	15619304	Onio	502	France	Female	42	8	159660.80	101629.52	0
3	4	15701354	Boni	699	France	Female	39	1	0.00	342151.53	0

	RowNumber	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure	Balance	
	4	5	15737888	Mitchell	850	Spain	Female	43	2	125510.82

In [2]: `df.shape`

Out[2]: (10000, 14)

In [3]: `df['HasCrCard'] = df['HasCrCard'].astype('object')`
`df['IsActiveMember'] = df['IsActiveMember'].astype('object')`
`df['Exited'] = df['Exited'].astype('object')`

In [4]: `df_cat = df.select_dtypes('O')`
`df_cat.columns`

Out[4]: Index(['Surname', 'Geography', 'Gender', 'HasCrCard', 'IsActiveMember',
'Exited'],
dtype='object')

In [5]: `df_num = df.select_dtypes(np.number)`
`df_num.columns`

Out[5]: Index(['RowNumber', 'CustomerId', 'CreditScore', 'Age', 'Tenure', 'Balance',
'NumOfProducts', 'EstimatedSalary'],
dtype='object')

In [6]: `df_num.describe()`

Out[6]:

	RowNumber	CustomerId	CreditScore	Age	Tenure	Balance	NumO
count	10000.00000	1.000000e+04	10000.000000	10000.000000	10000.000000	10000.000000	100
mean	5000.50000	1.569094e+07	650.528800	38.921800	5.012800	76485.889288	
std	2886.89568	7.193619e+04	96.653299	10.487806	2.892174	62397.405202	
min	1.00000	1.556570e+07	350.000000	18.000000	0.000000	0.000000	
25%	2500.75000	1.562853e+07	584.000000	32.000000	3.000000	0.000000	
50%	5000.50000	1.569074e+07	652.000000	37.000000	5.000000	97198.540000	
75%	7500.25000	1.575323e+07	718.000000	44.000000	7.000000	127644.240000	
max	10000.00000	1.581569e+07	850.000000	92.000000	10.000000	250898.090000	

In [7]: `df_cat.describe()`

Out[7]:

	Surname	Geography	Gender	HasCrCard	IsActiveMember	Exited
count	10000	10000	10000	10000	10000	10000
unique	2932	3	2	2	2	2
top	Smith	France	Male	1	1	0

	Surname	Geography	Gender	HasCrCard	IsActiveMember	Exited
freq	32	5014	5457	7055	5151	7963

In [8]: `df.isnull().sum()`

Out[8]:

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 [9]: `df.isnull().sum()/len(df)*100`

Out[9]:

RowNumber	0.0
CustomerId	0.0
Surname	0.0
CreditScore	0.0
Geography	0.0
Gender	0.0
Age	0.0
Tenure	0.0
Balance	0.0
NumOfProducts	0.0
HasCrCard	0.0
IsActiveMember	0.0
EstimatedSalary	0.0
Exited	0.0

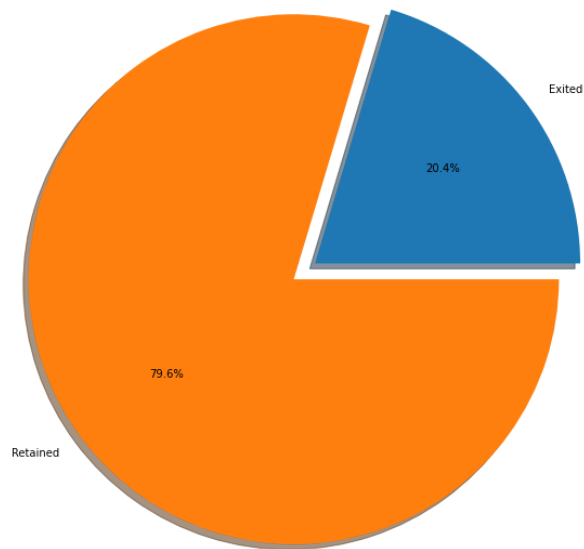
dtype: float64

In [10]: `df['Exited'] = df['Exited'].astype('int')`

In [11]:

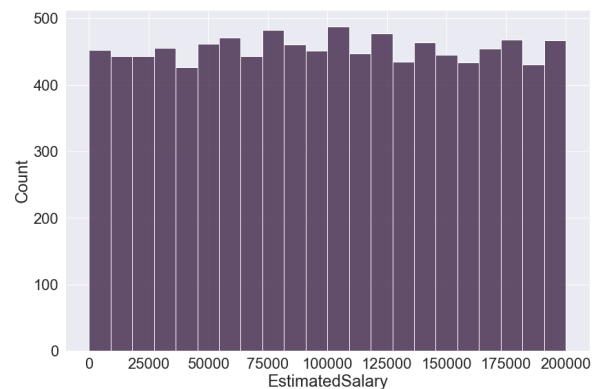
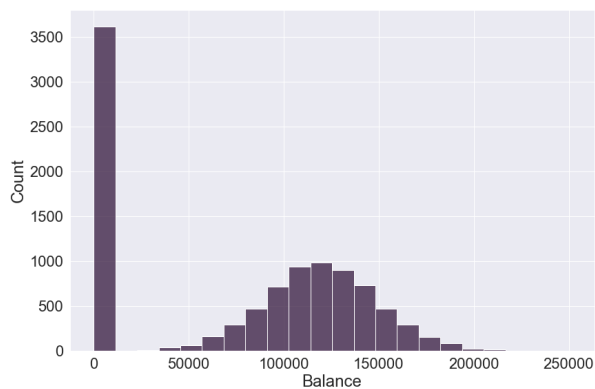
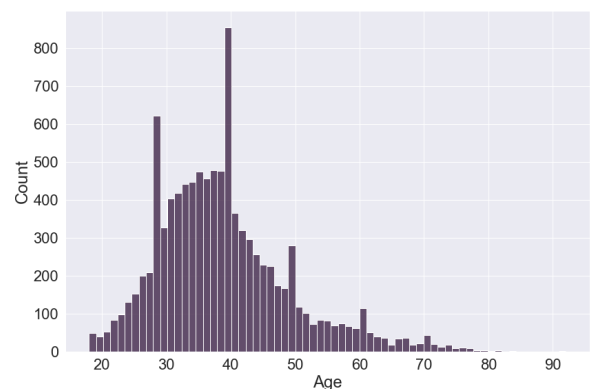
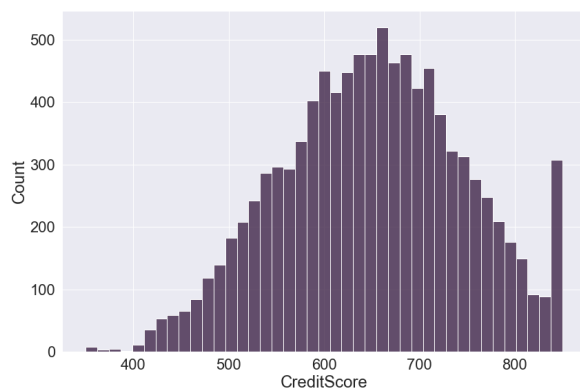
```
fig, axs = plt.subplots(figsize=(20, 10))
sizes = [df.Exited[df['Exited']==1].count(), df.Exited[df['Exited']==0].count()]
axs.pie(sizes, explode=(0, 0.1), labels=['Exited', 'Retained'], autopct='%1.1f%%',sh
axs.axis('equal')
plt.title("Churned and Retained proportion", size = 25)
plt.show()
```

Churned and Retained proportion



In [12]:

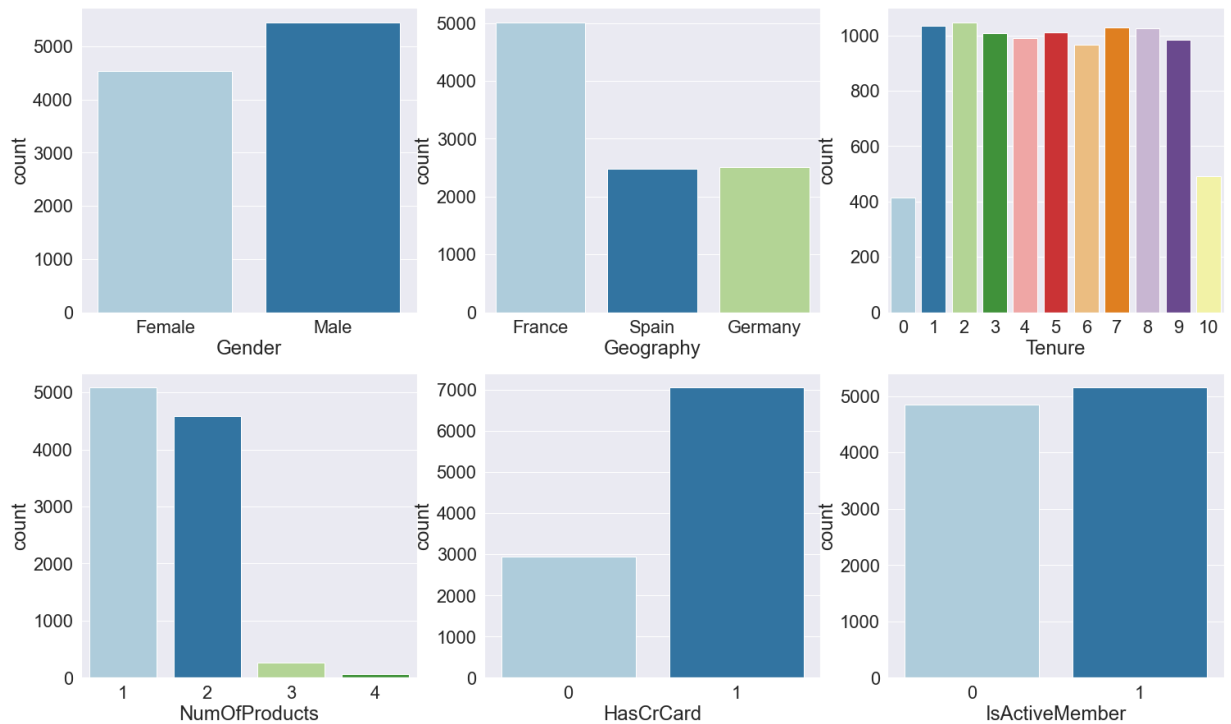
```
sns.set(rc={'figure.figsize':(30,20)})
sns.set(font_scale = 2)
fig,axs = plt.subplots(2,2)
sns.set_theme(palette="rocket")
sns.histplot(data = df,x = "CreditScore",ax=axs[0,0])
sns.histplot(data = df,x = "Age",ax=axs[0,1])
sns.histplot(data = df,x = "Balance",ax=axs[1,0])
sns.histplot(data = df,x = "EstimatedSalary",ax=axs[1,1])
plt.show()
```



In [13]:

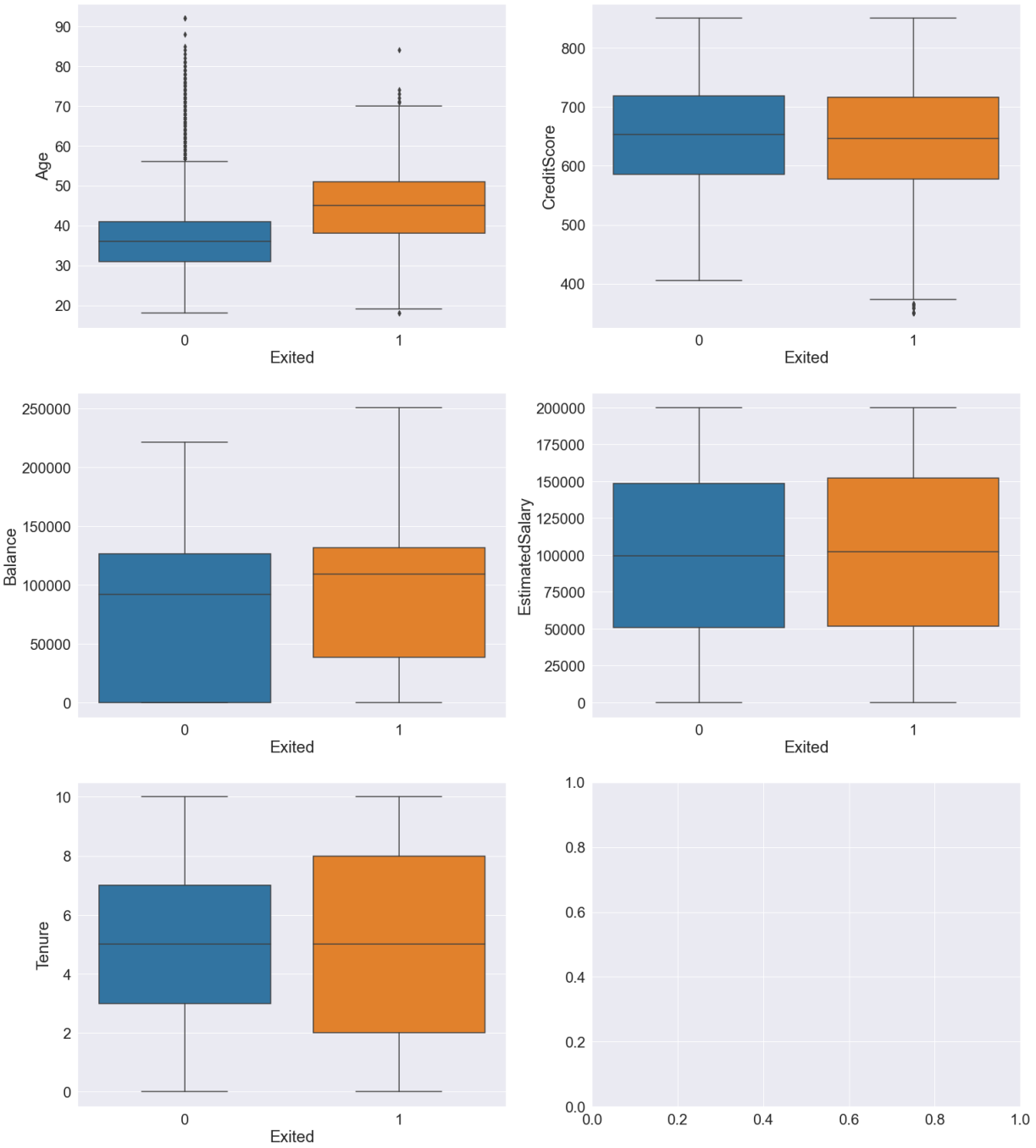
```
sns.set(rc={'figure.figsize':(25,15)})
sns.set(font_scale = 2)
fig,axs = plt.subplots(2,3)
sns.set_theme(palette="Paired")
sns.countplot(data = df,x = 'Gender',ax=axs[0,0])
sns.countplot(data = df,x = 'Geography',ax=axs[0,1])
```

```
sns.countplot(data = df,x = 'Tenure',ax=axes[0,2])
sns.countplot(data = df,x = 'NumOfProducts',ax=axes[1,0])
sns.countplot(data = df,x = 'HasCrCard',ax=axes[1,1])
sns.countplot(data = df,x = 'IsActiveMember',ax=axes[1,2])
plt.show()
```



In [14]:

```
sns.set(rc={'figure.figsize':(25,30)})
sns.set(font_scale = 2)
fig,axes = plt.subplots(3,2)
sns.set_theme(palette="tab10")
sns.boxplot(data = df,x = "Exited",y = "Age",ax = axes[0,0])
sns.boxplot(data = df,x = "Exited",y = "CreditScore",ax = axes[0,1])
sns.boxplot(data = df,x = "Exited",y = "Balance",ax = axes[1,0])
sns.boxplot(data = df,x = "Exited",y = "EstimatedSalary",ax = axes[1,1])
sns.boxplot(data = df,x = "Exited",y = "Tenure",ax=axes[2,0])
plt.show()
```



```
In [15]: df[['Geography', 'Gender', 'Exited']].groupby(['Geography', 'Gender']).agg(['mean', 'count'])
```

Out[15]:

		Exited	
		mean	count
Geography	Gender		
France	Female	0.203450	2261
	Male	0.127134	2753
Germany	Female	0.375524	1193
	Male	0.278116	1316
Spain	Female	0.212121	1089
	Male	0.131124	1388

```
In [16]:
```

```
df['Exited'] = df['Exited'].astype('object')
```

In [17]:

```
from sklearn.preprocessing import StandardScaler

ss = StandardScaler().fit_transform(df_num.values)

df_num = pd.DataFrame(data = ss, index = df_num.index, columns = df_num.columns)

df_num.describe()
```

Out[17]:

	RowNumber	CustomerId	CreditScore	Age	Tenure	Balance
count	1.000000e+04	1.000000e+04	1.000000e+04	1.000000e+04	1.000000e+04	1.000000e+04
mean	-2.338130e-17	7.588219e-15	-4.870326e-16	2.484679e-16	-1.400324e-16	-5.978551e-17
std	1.000050e+00	1.000050e+00	1.000050e+00	1.000050e+00	1.000050e+00	1.000050e+00
min	-1.731878e+00	-1.741069e+00	-3.109504e+00	-1.994969e+00	-1.733315e+00	-1.225848e+00
25%	-8.659388e-01	-8.676501e-01	-6.883586e-01	-6.600185e-01	-6.959818e-01	-1.225848e+00
50%	0.000000e+00	-2.816100e-03	1.522218e-02	-1.832505e-01	-4.425957e-03	3.319639e-01
75%	8.659388e-01	8.659939e-01	6.981094e-01	4.842246e-01	6.871299e-01	8.199205e-01
max	1.731878e+00	1.734255e+00	2.063884e+00	5.061197e+00	1.724464e+00	2.795323e+00

In [18]:

```
#clean df

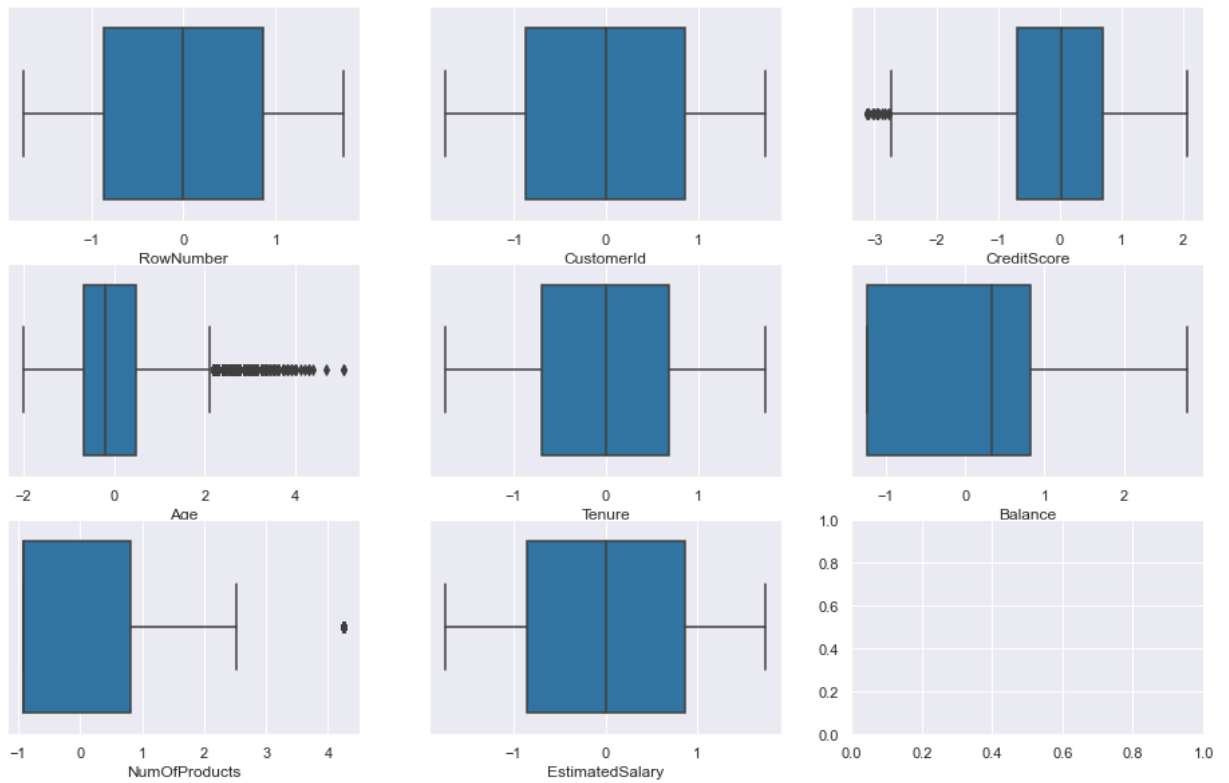
df = pd.concat([df_cat,df_num],axis = 1)
```

In [19]:

```
fig,ax = plt.subplots(nrows = 3, ncols = 3, figsize = (16,10))

df_num = df.select_dtypes(np.number)
for i,j in zip(df_num.columns,ax.flatten()):
    sns.boxplot(df_num[i],ax = j)

plt.show()
```



```
In [20]:
q1 = df_num.quantile(0.25)
q3 = df_num.quantile(0.75)

iqr = q3 - q1

df = df[~((df < (q1 - 1.5 * iqr)) | (df > (q3 + 1.5 * iqr))).any(axis = 1)]
df.shape
```

Out[20]: (9515, 14)

```
In [21]: df['Exited'].value_counts()/len(df)*100
```

```
Out[21]: 0    80.357331
         1    19.642669
         Name: Exited, dtype: float64
```

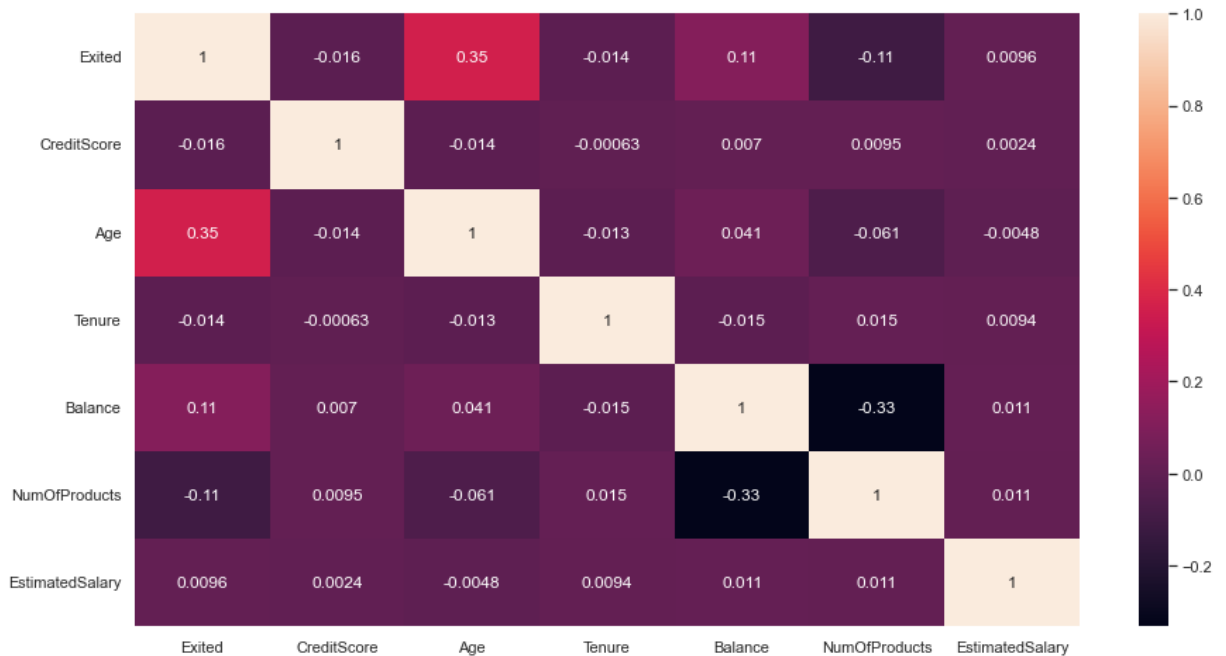
```
In [22]: df = df.drop(['CustomerId', 'Surname', 'RowNumber'], axis = 1)
```

```
In [23]: df['Exited'] = df['Exited'].astype('int')
```

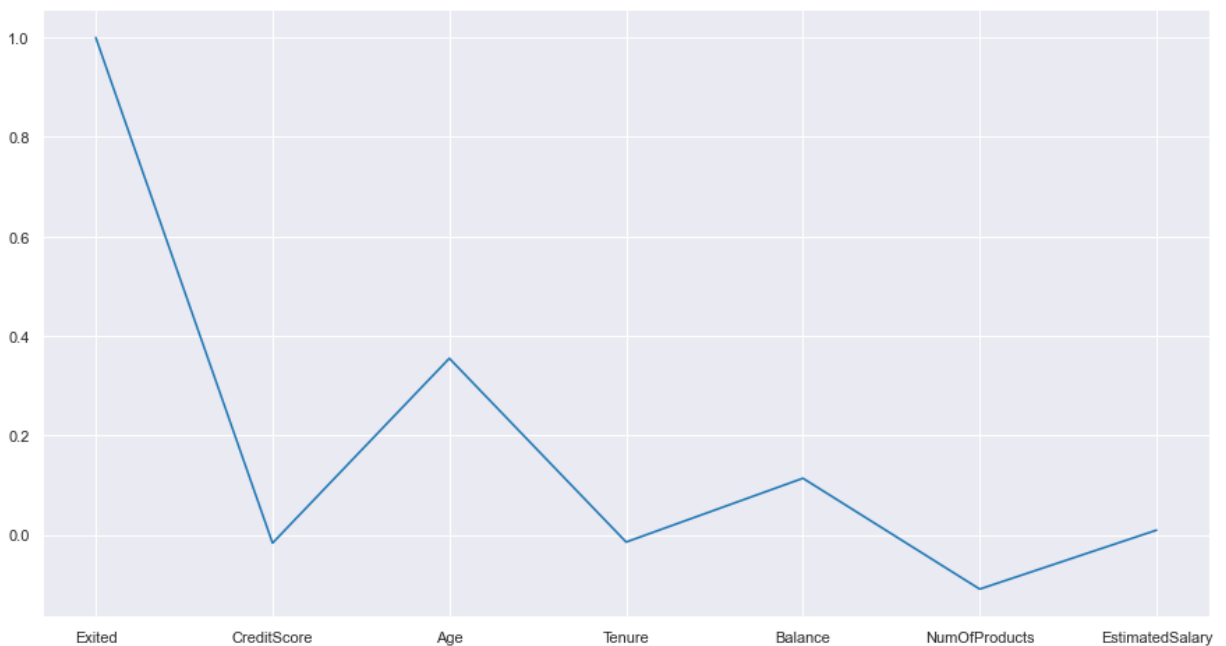
```
In [24]: plt.figure(figsize = (15,8))

         sns.heatmap(df.corr(),annot = True)
```

Out[24]: <AxesSubplot:>



```
In [25]: plt.figure(figsize = (15,8))
df.corr()['Exited'].plot()
plt.show()
```



```
In [26]: #Check for multi-collinearity using VIF

x = df.drop('Exited',axis = 1)
x = pd.get_dummies(x,drop_first = True)
y = df['Exited']

from statsmodels.stats.outliers_influence import variance_inflation_factor
vif = pd.DataFrame()

vif['vif_factor'] = [variance_inflation_factor(x.values,i) for i in range(x.shape[1])]
vif['features'] = x.columns
```

```
multi = vif.sort_values('vif_factor',ascending = False).head()
multi
```

Out[26]:

	vif_factor	features
9	2.185012	HasCrCard_1
8	1.832480	Gender_Male
10	1.714972	IsActiveMember_1
6	1.580130	Geography_Germany
3	1.348576	Balance

In [27]:

```
multi = multi.features.to_list()
multi
```

Out[27]:

```
['HasCrCard_1',
 'Gender_Male',
 'IsActiveMember_1',
 'Geography_Germany',
 'Balance']
```

In [28]:

```
from sklearn.model_selection import train_test_split

x = df.drop('Exited',axis = 1)

x = pd.get_dummies(x,drop_first = True)
y = df['Exited']

x_train,x_test,y_train,y_test = train_test_split(x,y,test_size = 0.3,random_state =
```

In [29]:

```
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score
```

In [30]:

```
dtc = DecisionTreeClassifier(random_state = 1)

model = dtc.fit(x_train,y_train)
```

In [31]:

```
print('The train accuracy is ',model.score(x_train,y_train))
print('The test accuracy is ',model.score(x_test,y_test))
```

```
The train accuracy is  1.0
The test accuracy is  0.8010507880910683
```

In [32]:

```
from sklearn.feature_selection import RFE
dtc = DecisionTreeClassifier(random_state = 1,class_weight = 'balanced')
rfe_model = RFE(estimator = dtc,n_features_to_select = 8)
rfe_model = rfe_model.fit(x_train,y_train)
```

In [33]:

```
df_rfe = pd.DataFrame()
df_rfe['features'] = x.columns
df_rfe['ranking'] = rfe_model.ranking_
```

```
top = df_rfe[df_rfe['ranking']==1]
top = top.features.tolist()
top
```

```
Out[33]: ['CreditScore',
          'Age',
          'Tenure',
          'Balance',
          'NumOfProducts',
          'EstimatedSalary',
          'Geography_Germany',
          'IsActiveMember_1']
```

```
In [34]: x_top = x[top]

          x_train,x_test,y_train,y_test = train_test_split(x_top,y,test_size = 0.3,random_stat
          model_top = dtc.fit(x_train,y_train)
```

```
In [35]: print('The train accuracy is ',model_top.score(x_train,y_train))
          print('The test accuracy is ',model_top.score(x_test,y_test))
```

```
The train accuracy is  1.0
The test accuracy is  0.7950963222416813
```

```
In [36]: from sklearn.model_selection import GridSearchCV

          tuned_params = [{'criterion':['gini','entropy'],'max_depth': range(2,10),'min_sample
          grid = GridSearchCV(estimator = dtc,param_grid = tuned_params,cv = 5)

          grid.fit(x_train,y_train)
```

```
Out[36]: GridSearchCV(cv=5,
                    estimator=DecisionTreeClassifier(class_weight='balanced',
                                                    random_state=1),
                    param_grid=[{'criterion': ['gini', 'entropy'],
                                'max_depth': range(2, 10),
                                'min_samples_split': range(2, 10)}])
```

```
In [37]: grid.best_params_
```

```
Out[37]: {'criterion': 'gini', 'max_depth': 3, 'min_samples_split': 2}
```

```
In [38]: dtc_tuned = DecisionTreeClassifier(random_state = 1,criterion = 'gini',max_depth = 3
          model_final = dtc_tuned.fit(x_train,y_train)
```

```
In [39]: print('The train accuracy is ',model_final.score(x_train,y_train))
          print('The test accuracy is ',model_final.score(x_test,y_test))
```

```
The train accuracy is  0.8361861861861862
The test accuracy is  0.8329246935201401
```

```
In [40]: y_pred = model_final.predict(x_test)
```

```
from sklearn.metrics import classification_report

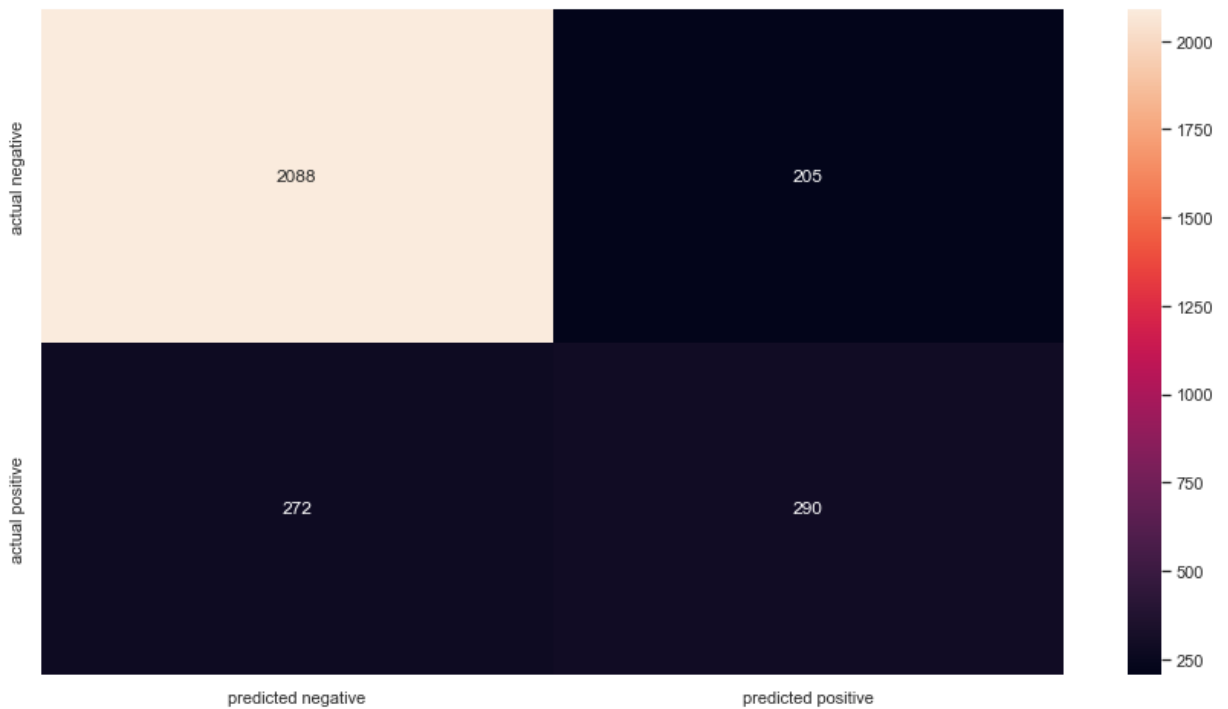
print(classification_report(y_test,y_pred))
```

	precision	recall	f1-score	support
0	0.88	0.91	0.90	2293
1	0.59	0.52	0.55	562
accuracy			0.83	2855
macro avg	0.74	0.71	0.72	2855
weighted avg	0.83	0.83	0.83	2855

In [41]:

```
from sklearn.metrics import confusion_matrix
plt.figure(figsize = (15,8))
cm = confusion_matrix(y_test,y_pred)

conf = pd.DataFrame(data=cm,columns=['predicted negative','predicted positive'],index=
sns.heatmap(conf,annot=True,fmt='g')
plt.show()
```



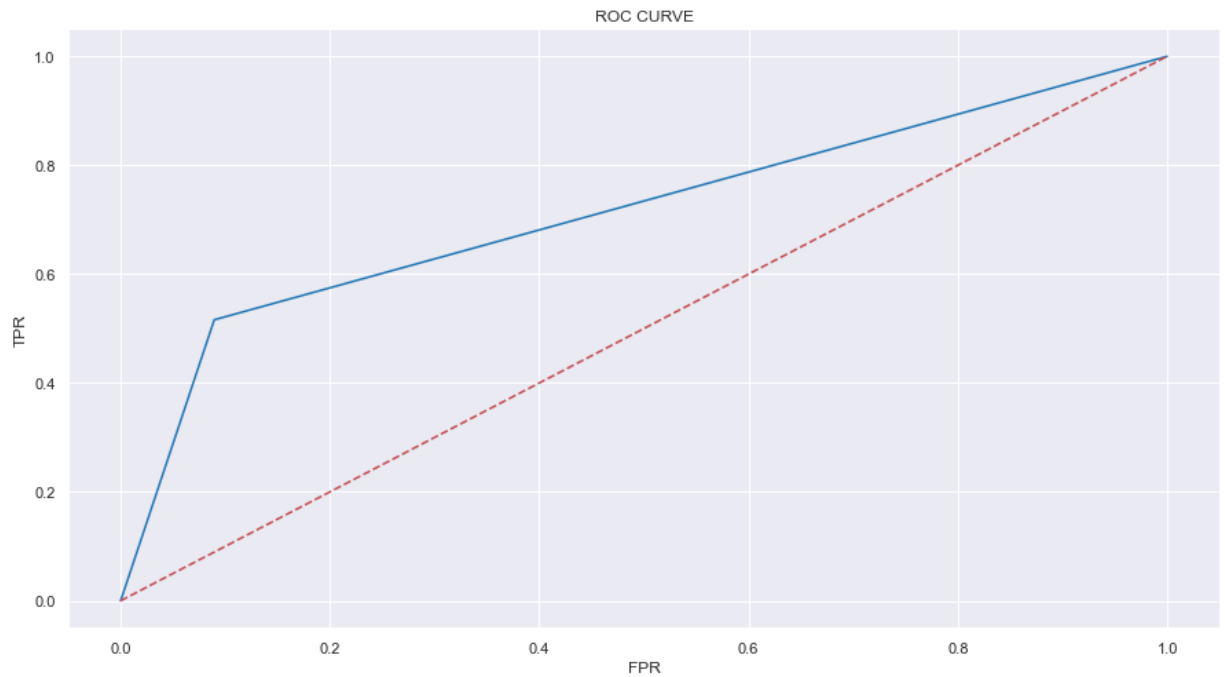
In [42]:

```
from sklearn.metrics import roc_auc_score,roc_curve

y_pred = model_final.predict(x_test)

fpr, tpr, th = roc_curve(y_test, y_pred)
plt.figure(figsize = (15,8))
plt.plot(fpr, tpr, label = 'Decision Tree classifier')

plt.plot([0,1],[0,1], 'r--')
plt.xlabel('FPR')
plt.ylabel('TPR')
plt.title('ROC CURVE')
plt.show()
```



```
In [43]: print(roc_auc_score(y_test,y_pred))
```

0.7133058527190134

```
In [44]: from sklearn.metrics import cohen_kappa_score
print(cohen_kappa_score(y_test,y_pred))
```

0.4467132941002009

```
In [45]: #Random Forest Classifier

from sklearn.model_selection import train_test_split

x = df.drop('Exited',axis = 1)

x = pd.get_dummies(x,drop_first = True)
y = df['Exited']

x_train,x_test,y_train,y_test = train_test_split(x,y,test_size = 0.3,random_state =
```

```
In [46]: from sklearn.ensemble import RandomForestClassifier

rf = RandomForestClassifier(random_state = 1,class_weight = 'balanced')

model_rf = rf.fit(x_train,y_train)
```

```
In [47]: print('The train accuracy is ',model_rf.score(x_train,y_train))
print('The test accuracy is ',model_rf.score(x_test,y_test))
```

The train accuracy is 1.0
The test accuracy is 0.8591943957968476

```
In [48]: from sklearn.feature_selection import RFE
rfc = RandomForestClassifier(random_state = 1,class_weight = 'balanced')
rfe_model = RFE(estimator = rfc,n_features_to_select = 8)
rfe_model = rfe_model.fit(x_train,y_train)
```

```
In [49]: df_rfe = pd.DataFrame()
df_rfe['features'] = x.columns
df_rfe['ranking'] = rfe_model.ranking_

top = df_rfe[df_rfe['ranking']==1]
top = top.features.to_list()
top
```

```
Out[49]: ['CreditScore',
'Age',
'Tenure',
'Balance',
'NumOfProducts',
'EstimatedSalary',
'Geography_Germany',
'IsActiveMember_1']
```

```
In [50]: x_top = x[top]

x_train,x_test,y_train,y_test = train_test_split(x_top,y,test_size = 0.3,random_stat
model_rf_top = dtc.fit(x_train,y_train)
```

```
In [51]: print('The train accuracy is ',model_rf_top.score(x_train,y_train))
print('The test accuracy is ',model_rf_top.score(x_test,y_test))
```

```
The train accuracy is 1.0
The test accuracy is 0.7950963222416813
```

```
In [52]: params = {'max_depth': range(2,10)}

grid = GridSearchCV(estimator = rf, param_grid = params,cv = 5)

grid.fit(x_train, y_train)
```

```
Out[52]: GridSearchCV(cv=5,
estimator=RandomForestClassifier(class_weight='balanced',
random_state=1),
param_grid={'max_depth': range(2, 10)})
```

```
In [53]: grid.best_params_
```

```
Out[53]: {'max_depth': 9}
```

```
In [54]: rf_tuned = RandomForestClassifier(random_state = 1,max_depth =9)

model_rf = rf_tuned.fit(x_train,y_train)
```

```
In [55]: print('The train accuracy is ',model_rf.score(x_train,y_train))
print('The test accuracy is ',model_rf.score(x_test,y_test))
```

```
The train accuracy is 0.8924924924924925
The test accuracy is 0.8644483362521891
```

```
In [56]: y_pred_rf = model_rf.predict(x_test)

from sklearn.metrics import classification_report

print(classification_report(y_test,y_pred_rf))
```

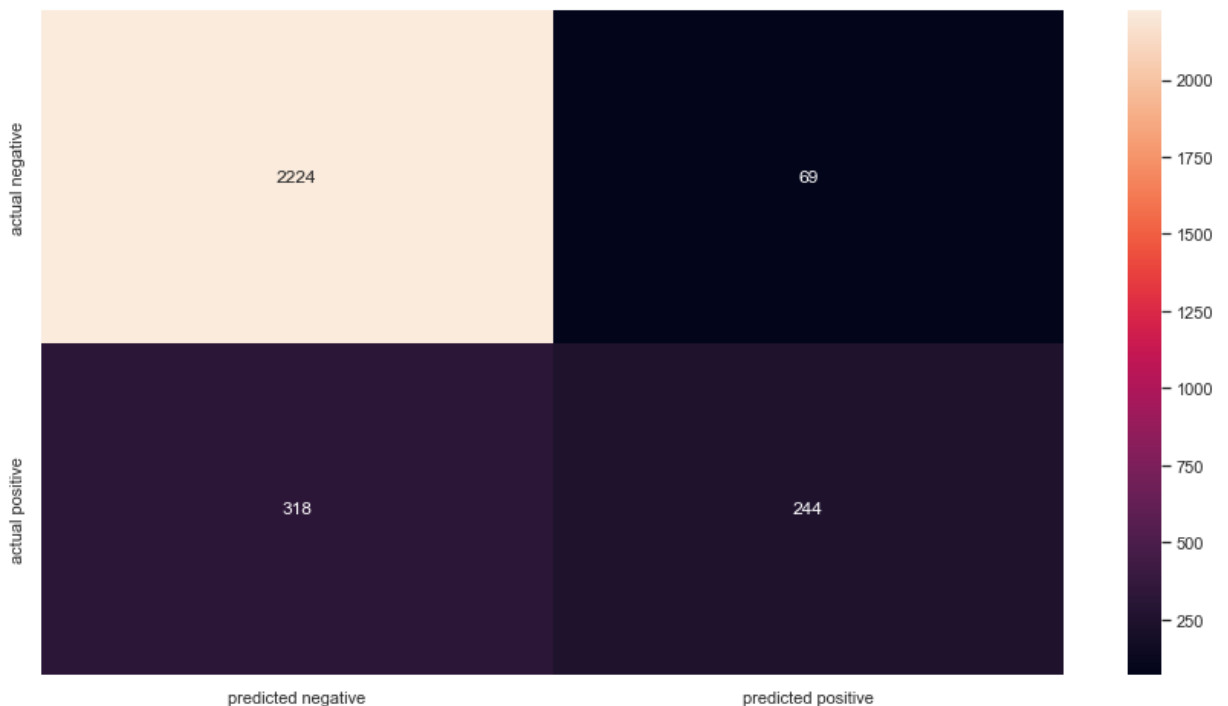
	precision	recall	f1-score	support
0	0.87	0.97	0.92	2293
1	0.78	0.43	0.56	562
accuracy			0.86	2855
macro avg	0.83	0.70	0.74	2855
weighted avg	0.86	0.86	0.85	2855

```
In [57]: from sklearn.metrics import confusion_matrix

cm = confusion_matrix(y_test,y_pred_rf)

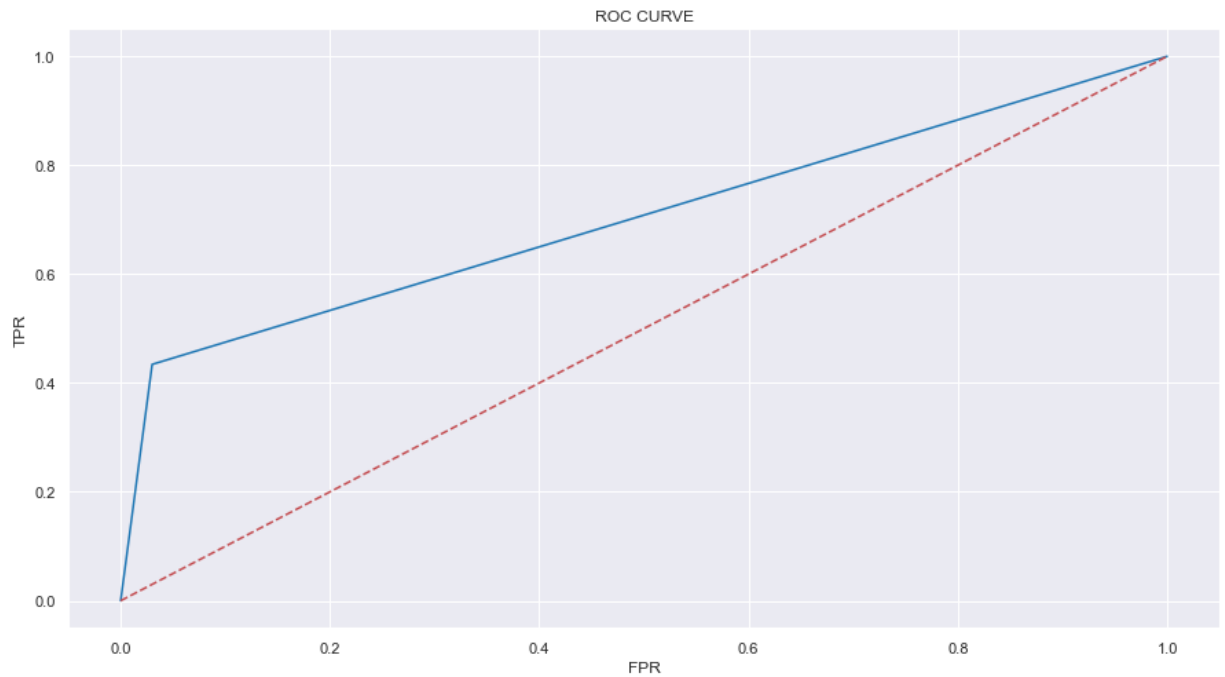
plt.figure(figsize = (15,8))

conf = pd.DataFrame(data=cm,columns=['predicted negative','predicted positive'],index=
sns.heatmap(conf,annot=True,fmt='g')
plt.show()
```



```
In [58]: fpr, tpr, th = roc_curve(y_test, y_pred_rf)
plt.figure(figsize = (15,8))
plt.plot(fpr, tpr, label = 'Random Forest Classifier')

plt.plot([0,1],[0,1], 'r--')
plt.xlabel('FPR')
plt.ylabel('TPR')
plt.title('ROC CURVE')
plt.show()
```



```
In [59]: print(roc_auc_score(y_test,y_pred_rf))
```

0.7020360589943399

```
In [60]: print(cohen_kappa_score(y_test,y_pred_rf))
```

0.48521720736910234

```
In [61]: from sklearn.model_selection import train_test_split

x = df.drop('Exited',axis = 1)

x = pd.get_dummies(x,drop_first = True)
y = df['Exited']

x_train,x_test,y_train,y_test = train_test_split(x,y,test_size = 0.3,random_state =
```

```
In [62]: from sklearn.linear_model import LogisticRegression

lr = LogisticRegression(random_state = 1,C = 0.01,penalty='l2',class_weight = 'balan

model_lr = lr.fit(x_train,y_train)
```

```
In [63]: print('The train accuracy is ',model_lr.score(x_train,y_train))
print('The test accuracy is ',model_lr.score(x_test,y_test))
```

The train accuracy is 0.7273273273273273
The test accuracy is 0.7260945709281962

```
In [64]: y_pred_lr = model_lr.predict(x_test)
```

```
In [65]: from sklearn.metrics import classification_report

print(classification_report(y_test,y_pred_lr))
```


	precision	recall	f1-score	support
0	0.91	0.73	0.81	2293
1	0.39	0.70	0.50	562
accuracy			0.73	2855
macro avg	0.65	0.72	0.66	2855
weighted avg	0.81	0.73	0.75	2855

In [66]:

```

from sklearn.metrics import confusion_matrix

cm = confusion_matrix(y_test,y_pred_lr)

plt.figure(figsize = (15,8))

conf = pd.DataFrame(data=cm,columns=['predicted negative','predicted positive'],index=
sns.heatmap(conf,annot=True,fmt='g')
plt.show()

```



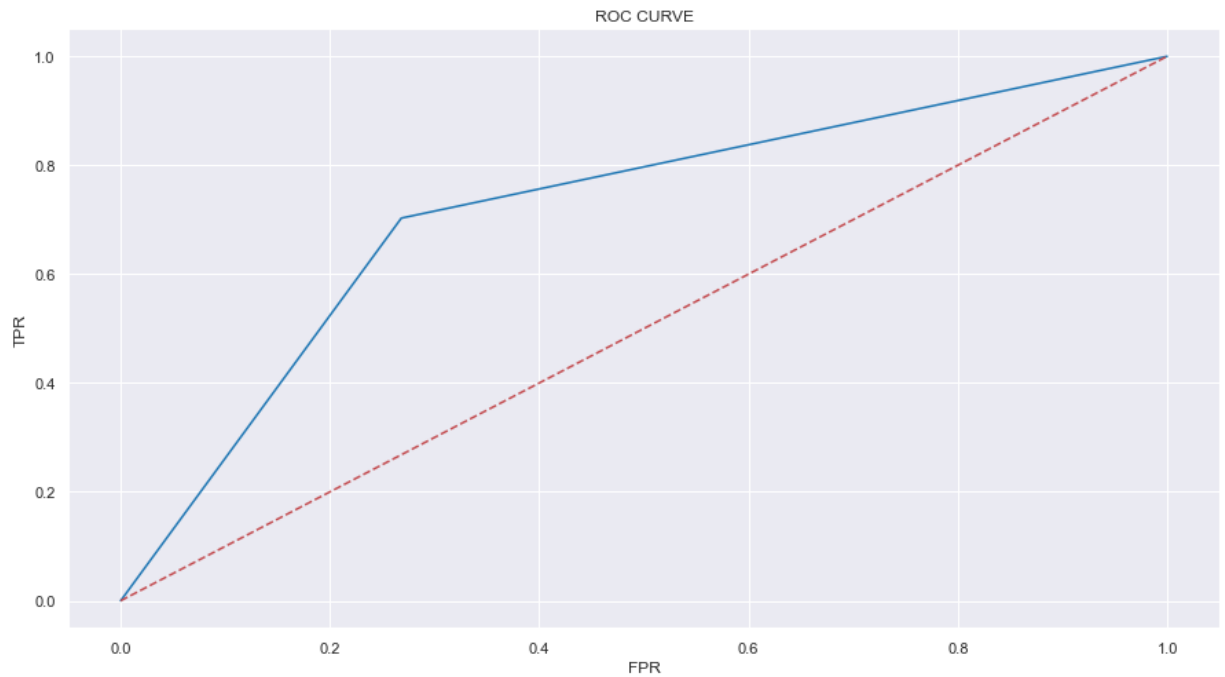
In [67]:

```

fpr,tpr,th = roc_curve(y_test,y_pred_lr)
plt.figure(figsize = (15,8))
plt.plot(fpr,tpr,label = 'Logistic Regression')

plt.plot([0,1],[0,1], 'r--')
plt.xlabel('FPR')
plt.ylabel('TPR')
plt.title('ROC CURVE')
plt.show()

```



```
In [68]: print(roc_auc_score(y_test,y_pred_lr))
```

```
0.7173196933883567
```

```
In [69]: print(cohen_kappa_score(y_test,y_pred_lr))
```

```
0.33410979414343744
```

```
In [70]: comparison = pd.DataFrame(data = [['Decision Tree Classifier',83,290,2088,205,272,0.71,0.44],
      ['Random Forest classifier',86,244,2224,69,318,0.70,0.48],
      columns = ['Algorithm Name','Accuracy','True Positive','True Negative','False Positive','False Negative','ROC-AUC Score','Cohen-Kappa Score'])

comparison
```

```
Out[70]:
```

	Algorithm Name	Accuracy	True Positive	True Negative	False Positive	False Negative	ROC-AUC Score	Cohen-Kappa Score
0	Decision Tree Classifier	83	290	2088	205	272	0.71	0.44
1	Logistic Regression	72	395	1678	615	167	0.71	0.33
2	Random Forest classifier	86	244	2224	69	318	0.70	0.48