Bank Churn Analysis & Modeling

Churn refers to customers leaving a bank or discontinuing their banking services.

Our goal is to forecast whether a client will leave the bank soon.

Importing Libraries

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pylab as plt
import seaborn as sns
import warnings as w
import plotly.express as px
import plotly.graph_objects as go
w.filterwarnings("ignore")
plt.style.use('ggplot')
```

`Loading Data`

In [2]:
```
df = pd.read_csv(r'C:\Users\singh\Downloads\Bank_Churn_14.csv')
```

Data Understanding

- Dataframe `shape`
- `head` and `tail`
- `dtypes`
- `describe`

`Checking the number of rows & columns present in dataframe`

In [3]:
```
df.shape
```

Out[3]:
```
(10000, 14)
```

The Df has 10000 rows with 14 attributes.

See top 5 Rows

In [4]:
```
df.head()
```

Out[4]:

	RowNumber	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure	Balance	Num(
0	1	15634602	Hargrave	619	France	Female	42	2	0.00	
1	2	15647311	Hill	608	Spain	Female	41	1	83807.86	
2	3	15619304	Onio	502	France	Female	42	8	159660.80	
3	4	15701354	Boni	699	France	Female	39	1	0.00	
4	5	15737888	Mitchell	850	Spain	Female	43	2	125510.82	

All Columns/Features in the Dataframe

In [5]:
```
df.columns
```

Out[5]:
```
Index(['RowNumber', 'CustomerId', 'Surname', 'CreditScore', 'Geography',
       'Gender', 'Age', 'Tenure', 'Balance', 'NumOfProducts', 'HasCrCard',
       'IsActiveMember', 'EstimatedSalary', 'Exited'],
      dtype='object')
```

There are total 14 columns in our dataset

Column Data Types

In [6]:
```
df.dtypes
```

Out[6]:
```
RowNumber            int64
CustomerId           int64
Surname             object
CreditScore          int64
Geography           object
Gender              object
Age                  int64
Tenure               int64
Balance            float64
NumOfProducts        int64
HasCrCard            int64
IsActiveMember       int64
EstimatedSalary    float64
Exited               int64
dtype: object
```

Our dataset mostly consists of numerical columns.

Basic Statistics of Numerical Columns

In [7]:
```
df.describe().round(3).T
```

Out[7]:

	count	mean	std	min	25%	50%	75%
RowNumber	10000.0	5.000500e+03	2886.896	1.00	2500.75	5.000500e+03	7.500250e+03
CustomerId	10000.0	1.569094e+07	71936.186	15565701.00	15628528.25	1.569074e+07	1.575323e+07
CreditScore	10000.0	6.505290e+02	96.653	350.00	584.00	6.520000e+02	7.180000e+02
Age	10000.0	3.892200e+01	10.488	18.00	32.00	3.700000e+01	4.400000e+01
Tenure	10000.0	5.013000e+00	2.892	0.00	3.00	5.000000e+00	7.000000e+00
Balance	10000.0	7.648589e+04	62397.405	0.00	0.00	9.719854e+04	1.276442e+05
NumOfProducts	10000.0	1.530000e+00	0.582	1.00	1.00	1.000000e+00	2.000000e+00
HasCrCard	10000.0	7.060000e-01	0.456	0.00	0.00	1.000000e+00	1.000000e+00
IsActiveMember	10000.0	5.150000e-01	0.500	0.00	0.00	1.000000e+00	1.000000e+00
EstimatedSalary	10000.0	1.000902e+05	57510.493	11.58	51002.11	1.001939e+05	1.493882e+05
Exited	10000.0	2.040000e-01	0.403	0.00	0.00	0.000000e+00	0.000000e+00

`Basic Statistics of Categorical Columns using Transpose`

In [8]:
```
df.describe(include='object').T
```

Out[8]:

	count	unique	top	freq
Surname	10000	2932	Smith	32
Geography	10000	3	France	5014
Gender	10000	2	Male	5457

`Checking for missing values`

In [9]:
```
df.isnull().sum()
```

Out[9]:
```
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
```

Well isn't that a rare find; no missing values!

`Removing unnecessary column`

`RowNumber`, `Surname` and `CustomerId` columns are not relevant for predicting customer churned or not. So we can simply drop these features.

In [10]:
```
df.drop(['RowNumber','Surname','CustomerId'],axis=1,inplace=True)
```

Exploratory Data Analysis

`Separate Numeric Columns`

In [11]:
```
num_cols = df.select_dtypes(['int','float64']).columns
num_cols
```

Out[11]:
```
Index(['CreditScore', 'Age', 'Tenure', 'Balance', 'NumOfProducts', 'HasCrCard',
       'IsActiveMember', 'EstimatedSalary', 'Exited'],
      dtype='object')
```

There are 10 Numeric Columns in the dataset and we store it in a variable name 'num_cols'.

`Separate Categorical Columns`

In [12]:
```
cols = df.select_dtypes('object').columns
cols
```

Out[12]:
```
Index(['Geography', 'Gender'], dtype='object')
```

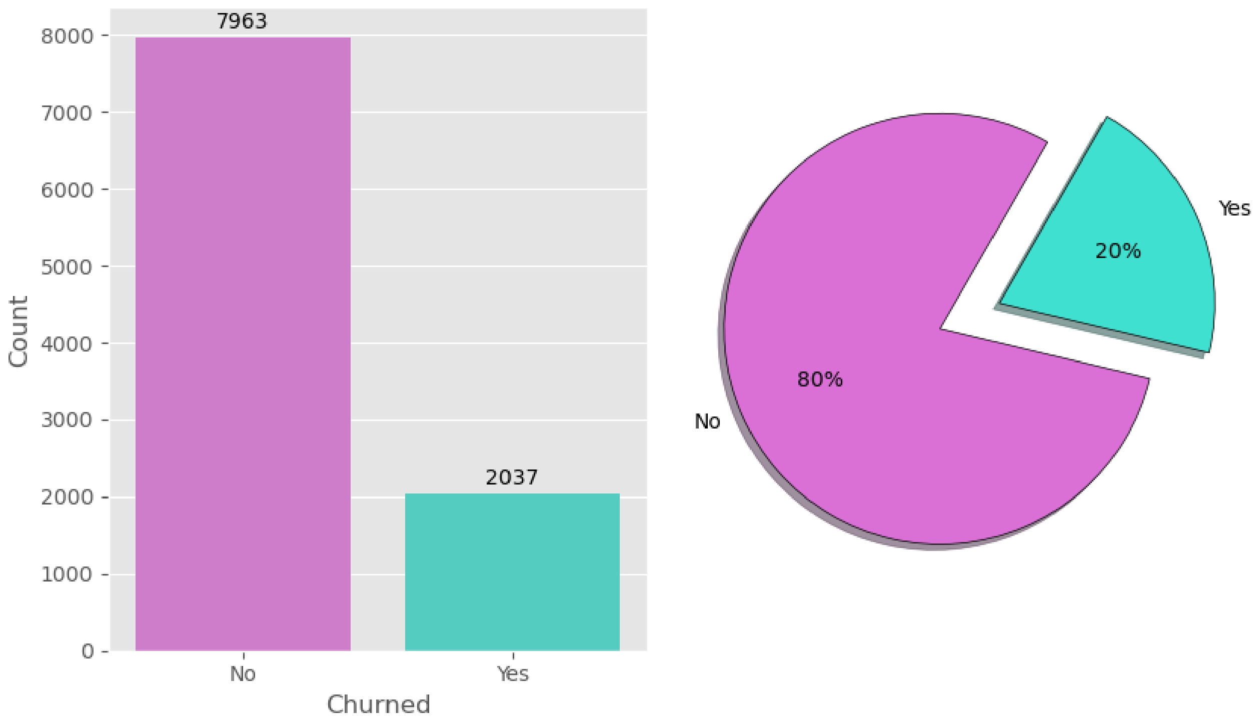
There are 2 Categorical Columns in the dataset and we store it in a variable name 'cols'.

`Target Distribution`

In [13]:
```
df['Exited'].value_counts()
```

Out[13]:
```
0    7963
1    2037
Name: Exited, dtype: int64
```

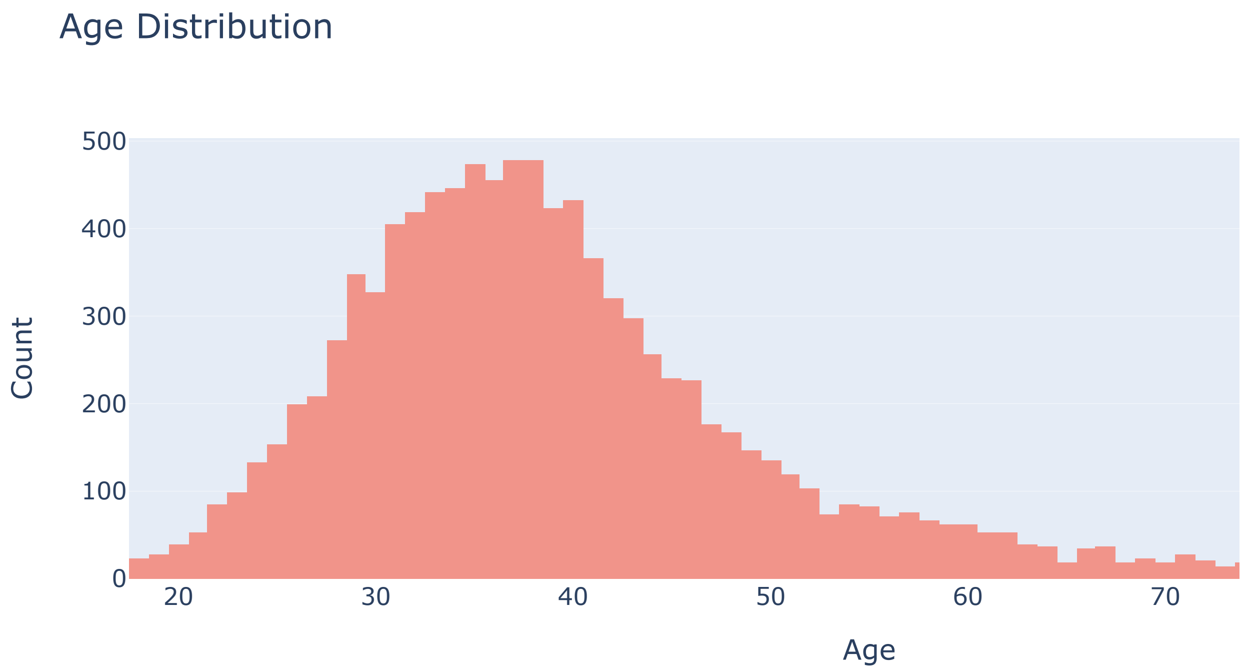
In [14]:
```
fig, axes = plt.subplots(1, 2, figsize=(8.5, 5))

sns.countplot(x="Exited", data=df, palette=['orchid', 'turquoise'], ax=axes[0])
axes[0].set_xlabel("Churned")
axes[0].set_ylabel("Count")
ax = axes[0]
ax.bar_label(ax.containers[0], padding = 2)
axes[0].set_xticklabels(["No", "Yes"])


colors = ['orchid', 'turquoise']
count = df["Exited"].value_counts()
labels = ["No", "Yes"]
axes[1].pie(count, labels=labels, autopct='%1.f%%', startangle=60, explode=[0, 0.3], col
            wedgeprops={'edgecolor': 'black'}, shadow=True)

plt.tight_layout()
plt.show()
```



Out of a total of `9,730` customers, `2,037` have decided to Exit the bank, while `7,693` have chosen to Stay.

`Age Distribution`

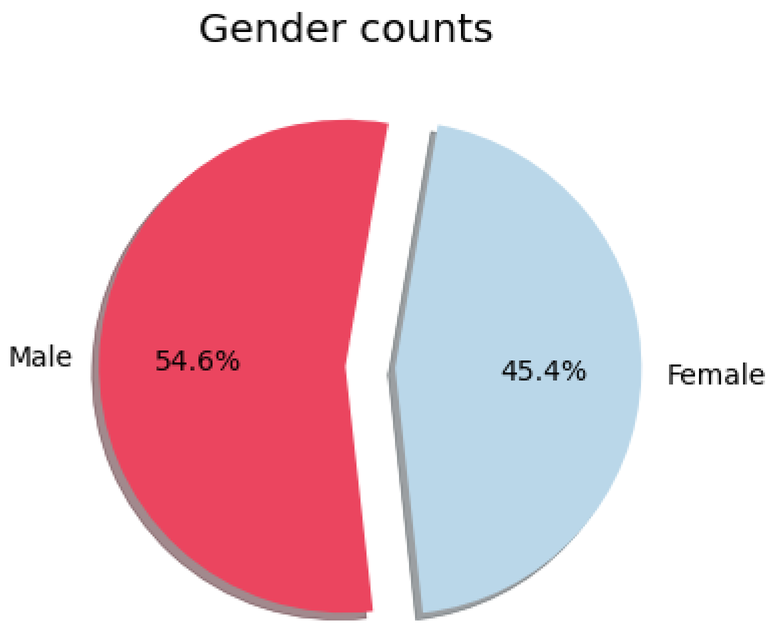
In [15]:
```
fig = px.histogram(df, x="Age", title="Age Distribution", color_discrete_sequence=['#F19
fig.update_layout(
    xaxis_title="Age",
    yaxis_title="Count",
    height=400,
    width=900
)
fig.show()
```



Most customers are between ages `30` and `40`

`Understanding Gender Distribution`

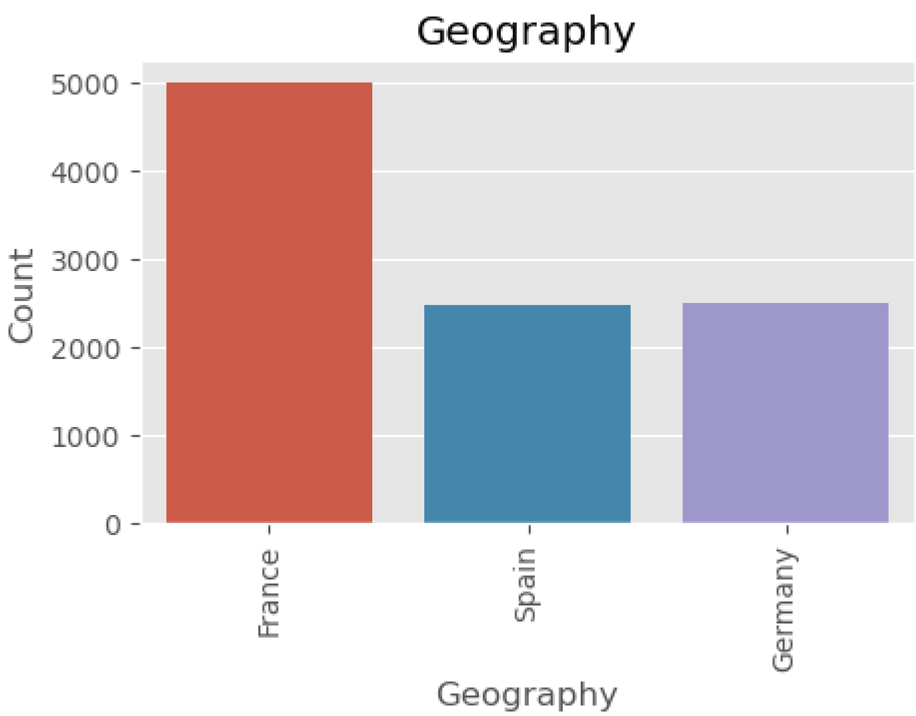
In [16]:
```
plt.figure(figsize=(4,4))
plt.pie(df['Gender'].value_counts(),
        labels=df['Gender'].value_counts().index,
        rotatelabels=False,
        autopct='%1.1f%%',
        colors=['#EB455F','#BAD7E9'],
        shadow=True,
        startangle=80,
        explode=(0,0.2))
plt.title('Gender counts')
plt.show()
```



`54.6%` of the individuals are male, while the remaining `45.4%` are female.

`Country Counts`

In [17]:
```
plt.figure(figsize=(5,3))
sns.countplot(data=df, x='Geography')
plt.title('Geography')
plt.xticks(rotation=90)
plt.xlabel('Geography')
plt.ylabel('Count')
plt.show()
```

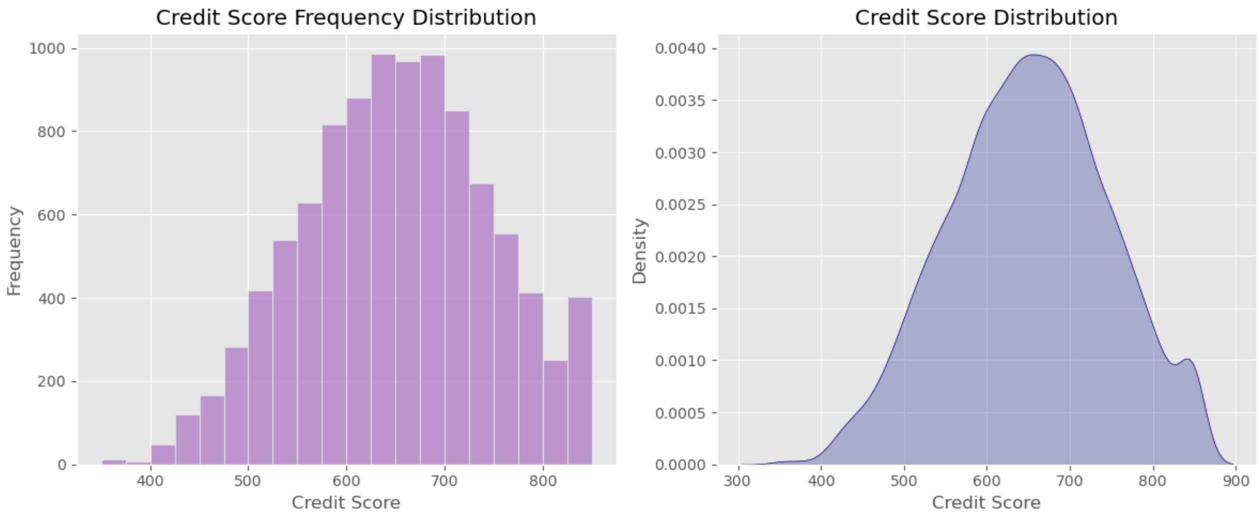


The dataset comprises three countries: `France`, `Spain`, and `Germany`, listed in the order of their respective counts

`Credit Score Distribution`

In [18]:

```
fig, axes = plt.subplots(1, 2, figsize=(12, 5))

# Plot the histogram on the first subplot
sns.histplot(df['CreditScore'], bins=20, color='#AF7AC5', ax=axes[0])
axes[0].set_title('Credit Score Frequency Distribution')
axes[0].set_xlabel('Credit Score')
axes[0].set_ylabel('Frequency')
axes[0].grid(True)

# Plot the kernel density plot on the second subplot
sns.kdeplot(df['CreditScore'], shade=True, color='navy', ax=axes[1])
axes[1].set_title('Credit Score Distribution')
axes[1].set_xlabel('Credit Score')
axes[1].set_ylabel('Density')
axes[1].grid(True, alpha=0.7)

plt.tight_layout()
plt.show()
```

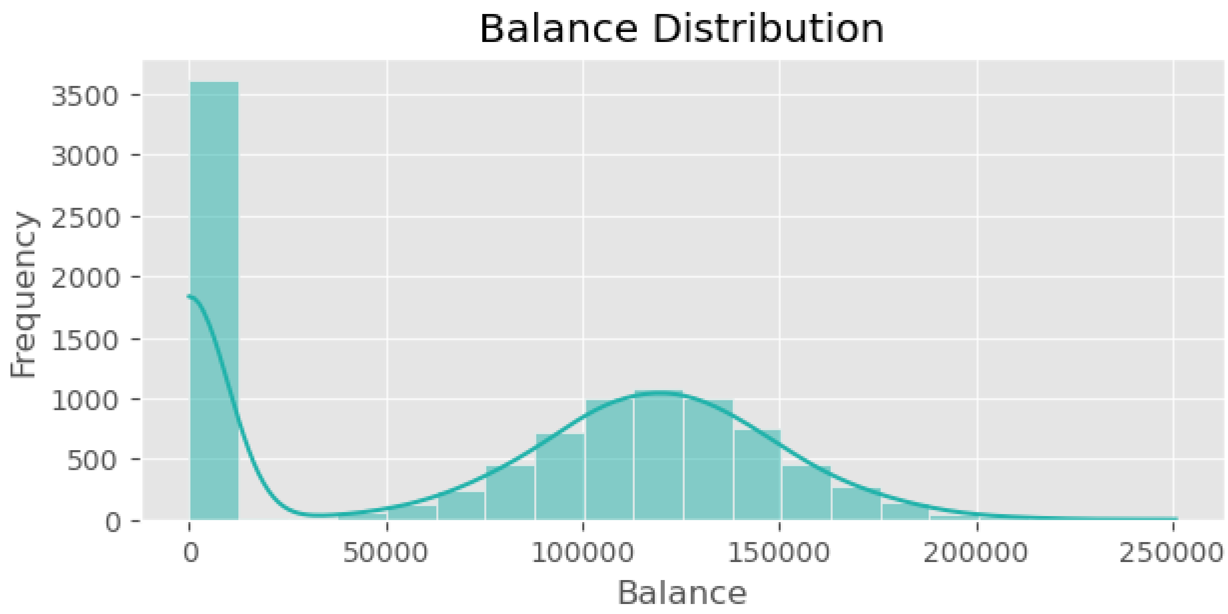


Most accounts have a credit score between `550` and `700`

`Balance distribution across accounts`

In [19]:

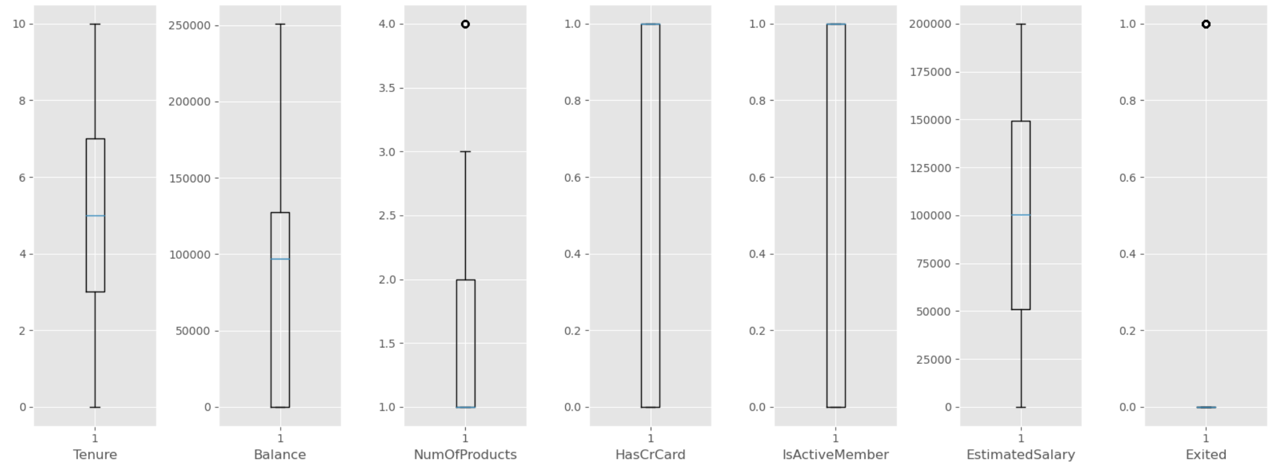
```
plt.figure(figsize=(7,3))
sns.histplot(df['Balance'], bins=20, kde=True, color='lightseagreen')
plt.title('Balance Distribution')
plt.xlabel('Balance')
plt.ylabel('Frequency')
plt.grid(True, alpha=0.7)
plt.show()
```



A lot of customers have `0` balance and the rest have balance between `50k` and `200k`

`Boxplots for Numerical Columns`

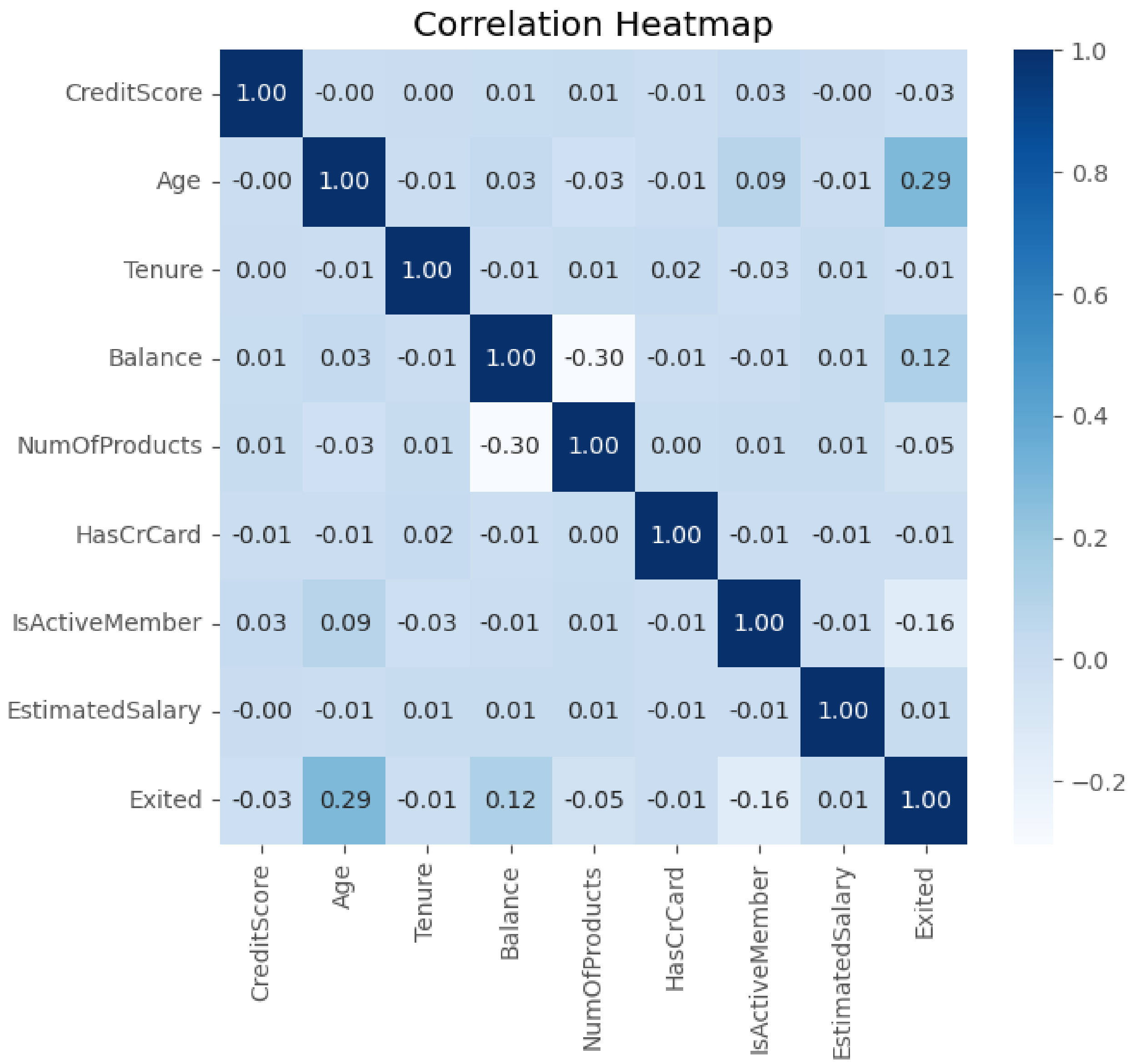
In [20]:
```python
fig, axes = plt.subplots(1,7, figsize=(16, 6))

# Box plot for each numerical column
for i, col in enumerate(num_cols[2:]):
    axes[i].boxplot(df[col])
    axes[i].set_xlabel(col.replace('_',' '))

plt.tight_layout()
plt.show()
```



We see that our dataframe does not have too many outliers. Only NumOfProducts have a few outliers. Fortunately, these outliers are not expected to influence our predictions, we can ignore them.

`Correlation Heatmap`

In [21]:
```python
plt.figure(figsize=(7,6))
plt.title('Correlation Heatmap')
sns.heatmap(df[num_cols].corr(), annot=True,fmt = ".2f",cmap='Blues')
plt.show()
```



Most of the features don't show any significant correlation. `Age` has a correlation of `0.29` with the target. We will analyse it further.

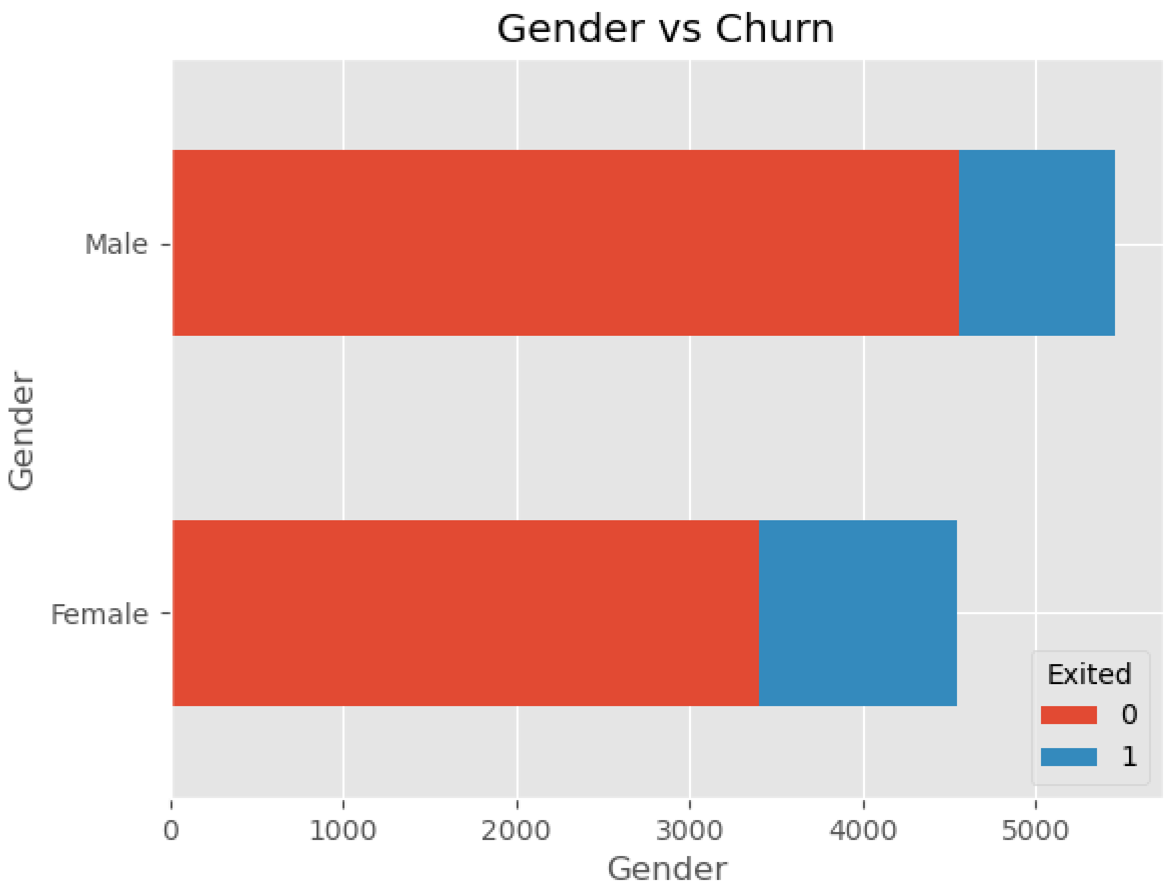
`Does Gender play a role in customer churn?`

- Yes, Females are `more likely` to churn

In [22]:

```
plt.figure(figsize=(4,3))
plot_data = df.groupby('Gender')['Exited'].value_counts().unstack()
plot_data.plot(kind='barh', stacked=True)
plt.title('Gender vs Churn')
plt.xlabel('Gender')
plt.show()
```

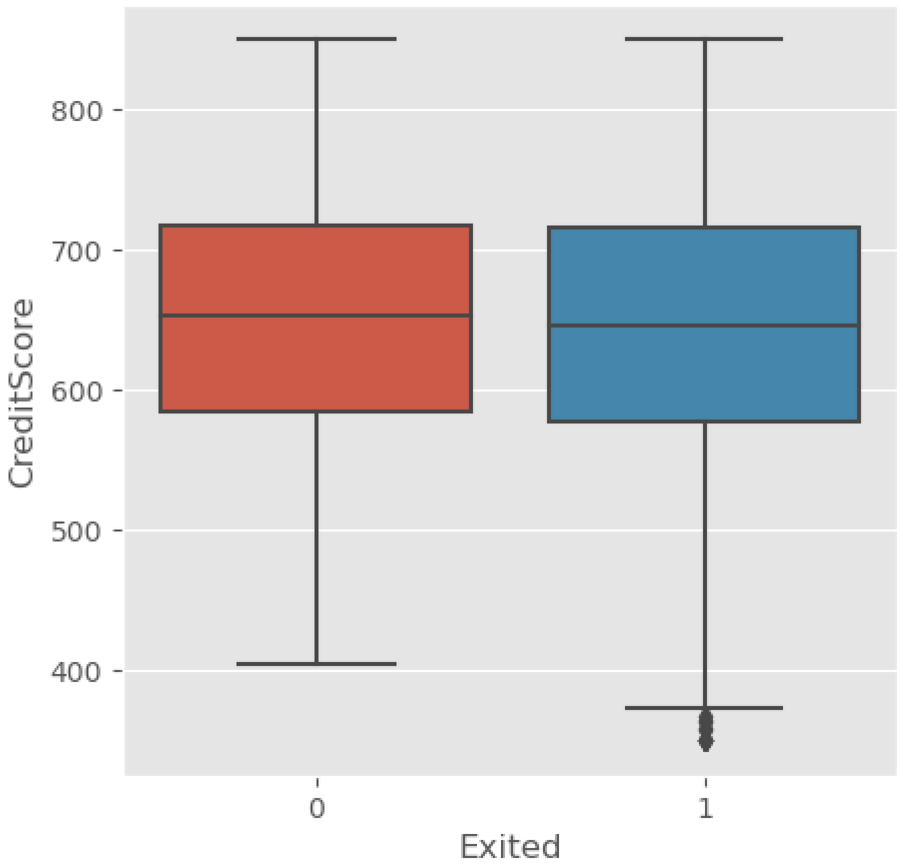
```
<Figure size 400x300 with 0 Axes>
```



`Credit Score vs Churn`

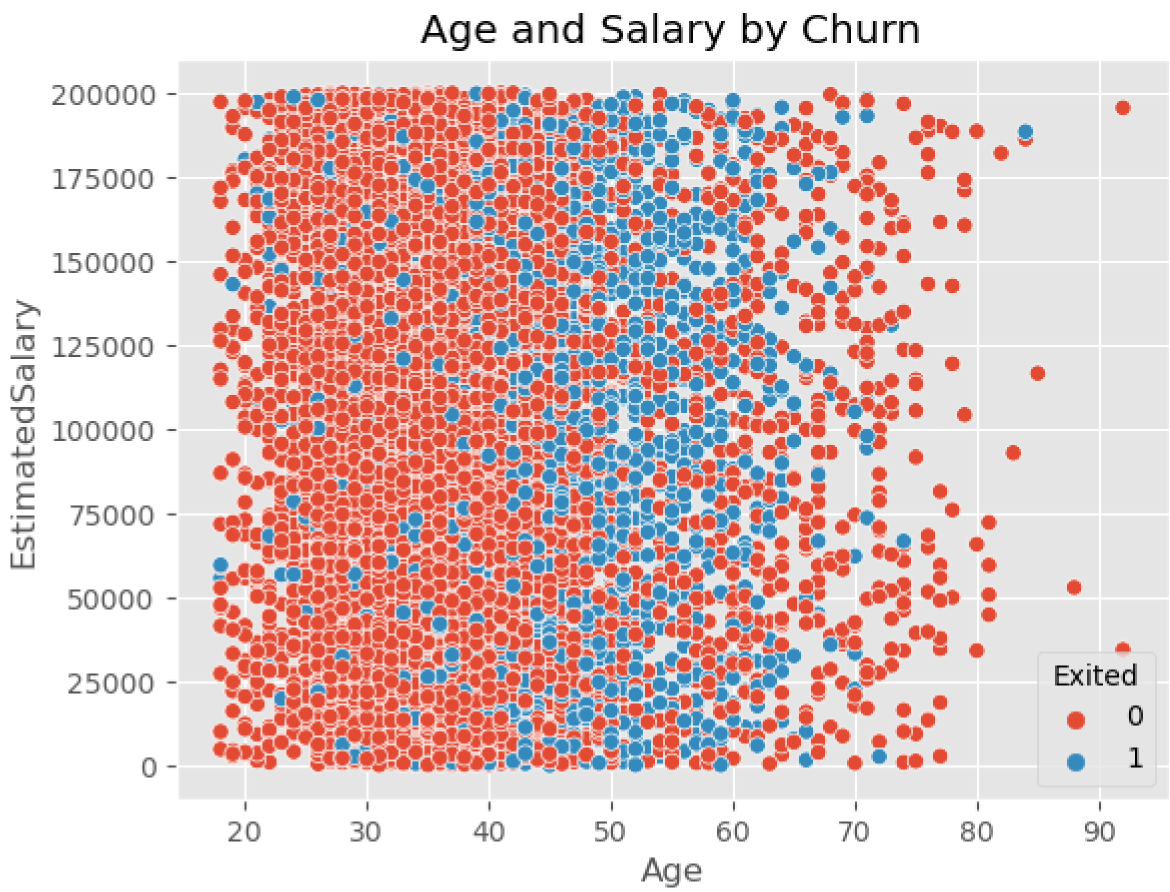
- Churned customers have `lower` median credit

In [23]:
```
plt.figure(figsize=(5,5))
sns.boxplot(data=df,x='Exited',y='CreditScore')
plt.show()
```



```
Age and Salary's impact on churn
```

In [24]:
```
ax = sns.scatterplot(x='Age',y='EstimatedSalary',hue='Exited',data=df)
ax.set_title('Age and Salary by Churn')
plt.show()
```



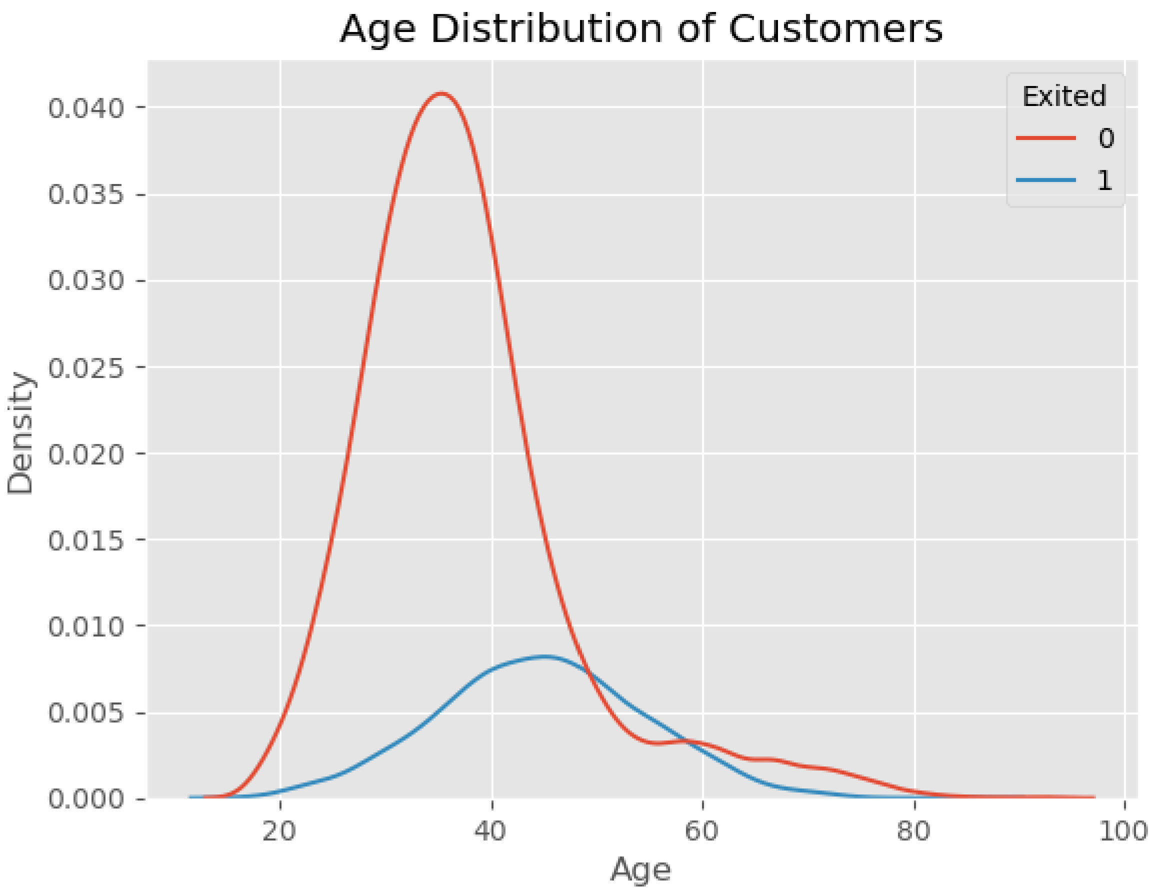
We can see that the Churned customers are concentrated around ages `50` and `60`

```
Exits vs Age
```

Does age play a role in churn?

- Older people are more likey to churn

In [25]:
```
sns.kdeplot(x=df['Age'],hue=df['Exited'])
plt.title("Age Distribution of Customers")
plt.xlabel('Age')
plt.ylabel('Density')
plt.show()
```

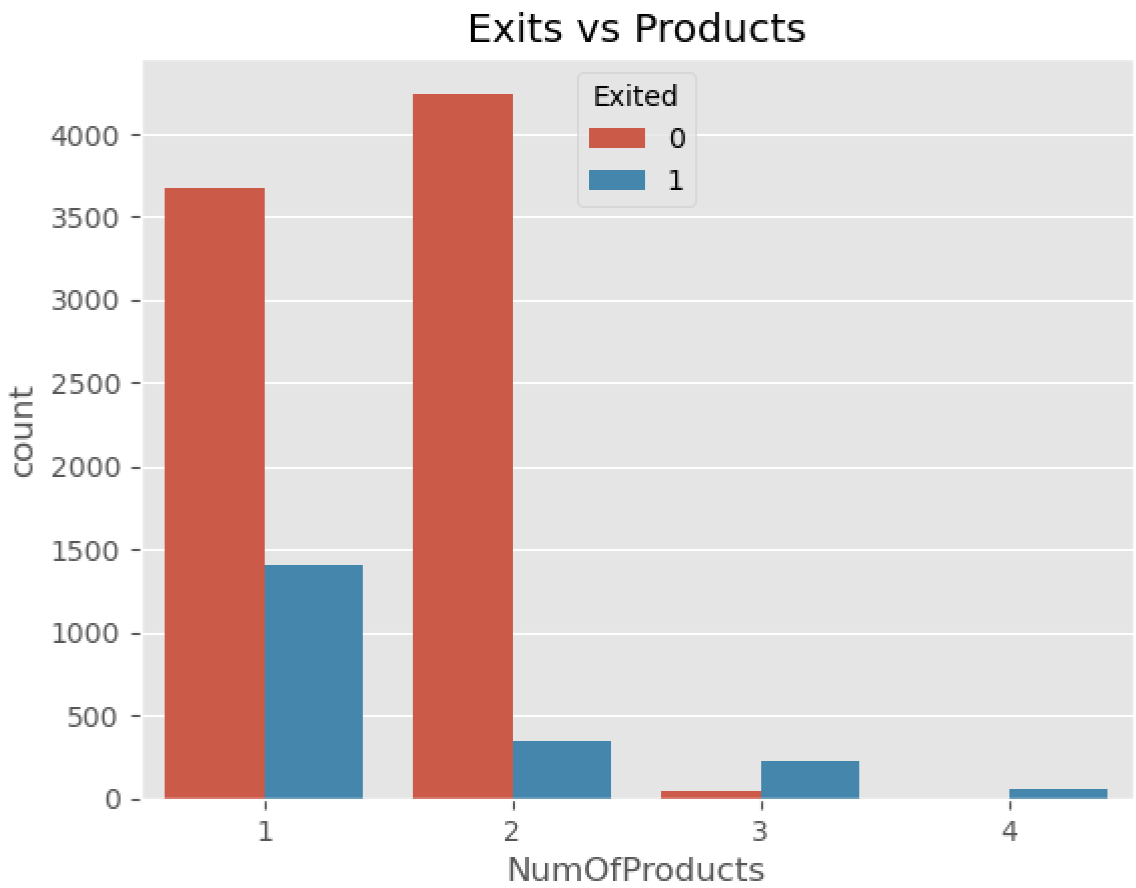


`Exits vs Products`

Does number of products matter?

- Customers with 3-4 products are more likely to churn

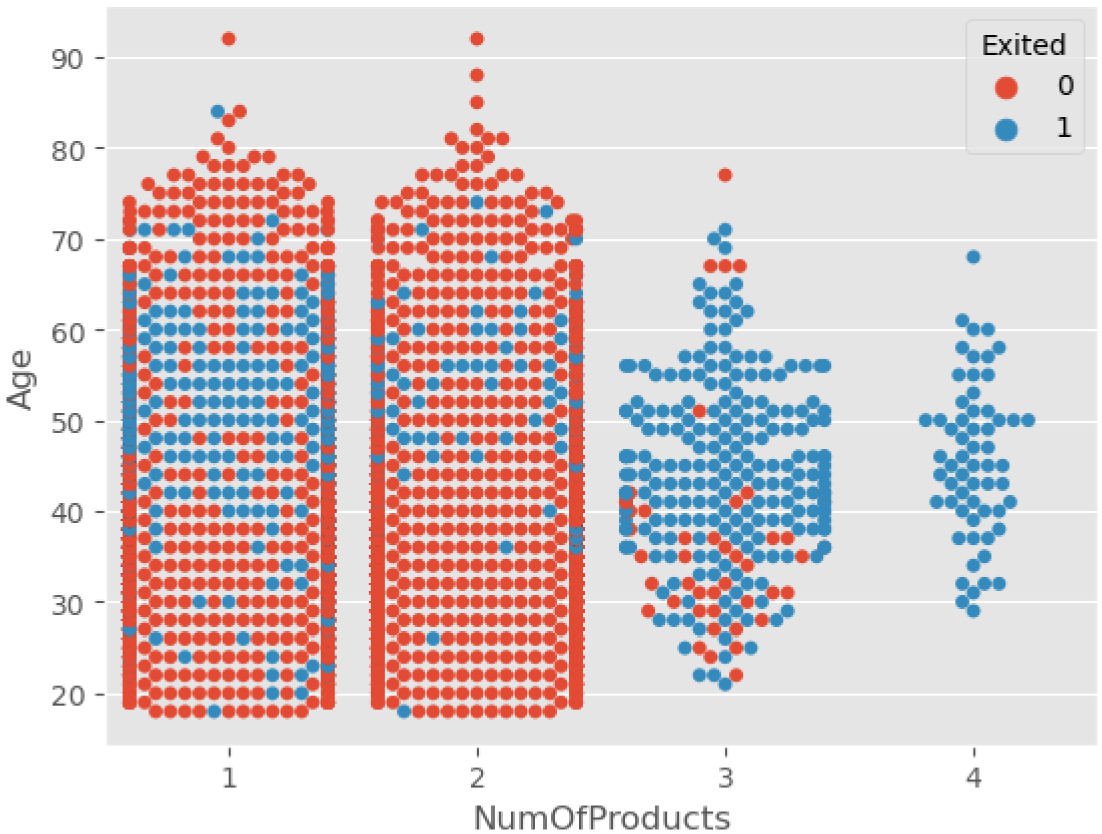
In [26]:
```
sns.countplot(x = "NumOfProducts", hue="Exited", data = df)
plt.title("Exits vs Products")
plt.show()
```



`Age and Products combined`

- We see that the middle aged people are most likely to churn especially if they own multiple products

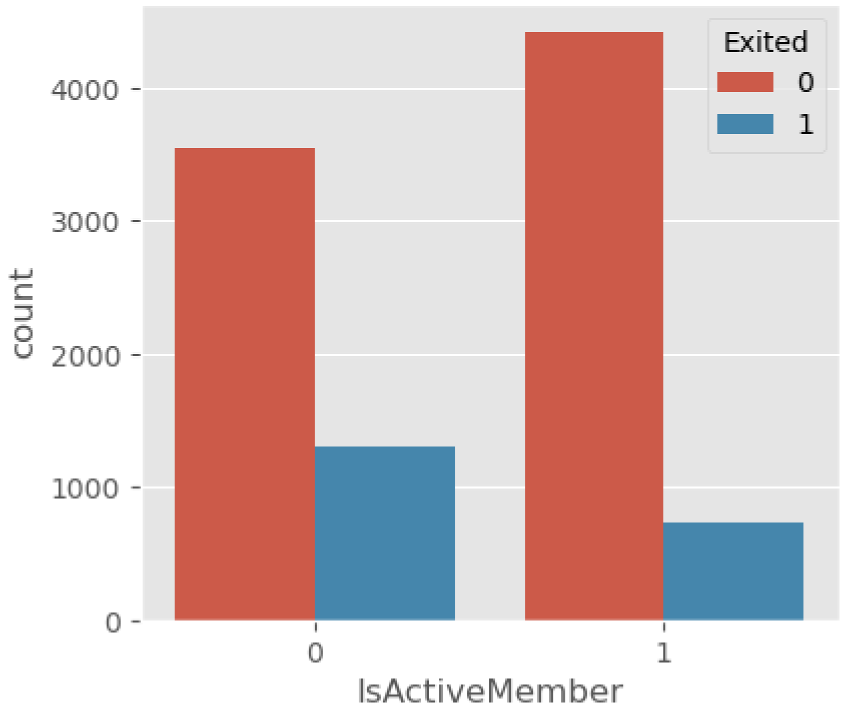
In [27]:
```
sns.swarmplot(x = "NumOfProducts", y = "Age", hue="Exited", data = df)
plt.show()
```



`Activity Status vs Churn`

- Inactive members are more likely to churn

In [28]:
```
plt.figure(figsize=(4.5,4))
sns.countplot(x = "IsActiveMember", hue="Exited", data = df)
plt.show()
```



IsInactive and Age vs Churn

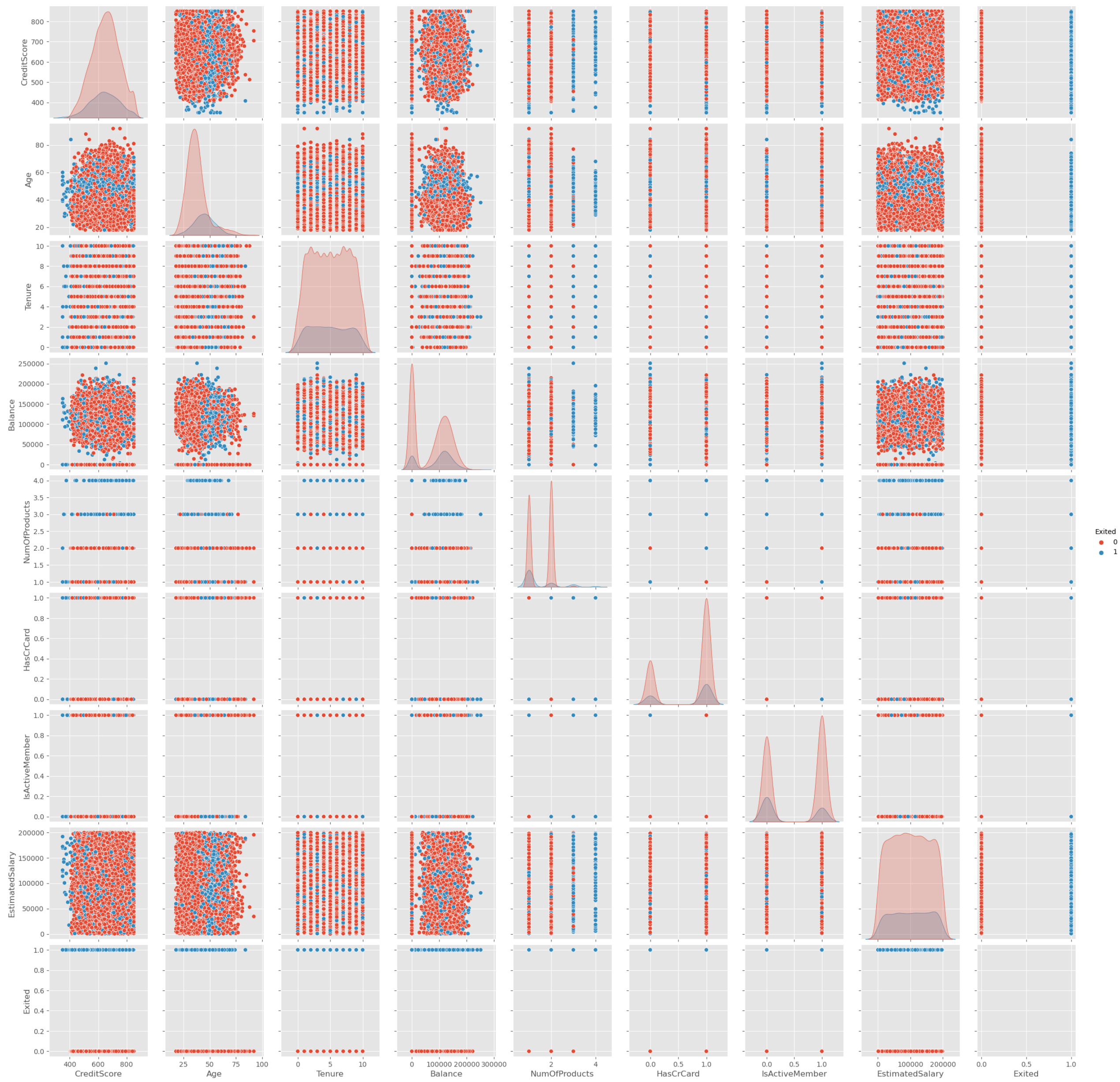
- Inactive senior customers have higher churn

In [29]:
```
sns.swarmplot(x = "IsActiveMember", y = "Age", hue="Exited", data = df)
```

Out[29]:
```
<AxesSubplot:xlabel='IsActiveMember', ylabel='Age'>
```

Graphical representation of numerical data using Pairplot

In [30]:
```
sns.pairplot(df,vars=num_cols,hue='Exited')
plt.show()
```



Data Preprocessing

- Splitting `Features` and `Target`
- `Encoding`
- `Scaling`

`Splitting data into features(x) and target(y)`

In [31]:
```
x = df.iloc[:,:-1]
y = df['Exited']
```

Encoding

Encoding is the process of converting `categorical` data into `numerical` form

- `OneHot` : Encoded categorical `Geography` data into binary variables and renamed them for analysis
- `Label` : Applied label encoding to transform `Gender` into numerical values `0` and `1`.

In [32]:
```
#OneHot
x = pd.get_dummies(x, columns=['Geography'], drop_first=True)
x.rename(columns={'Geography_Germany': 'Geo_Germany','Geography_Spain': 'Geo_Spain'}, in
```

In [33]:
```
#Label Encoding
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
x['Gender'] = le.fit_transform(x['Gender'])
```

In [34]:
```
x.head()
```

Out[34]:

	CreditScore	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	Estimate
0	619	0	42	2	0.00	1	1	1	10
1	608	0	41	1	83807.86	1	0	1	11
2	502	0	42	8	159660.80	3	1	0	11
3	699	0	39	1	0.00	2	0	0	9
4	850	0	43	2	125510.82	1	1	1	7

Scaling

Scaling ensures that all features have the same scale or range. This is important because many machine learning algorithms are sensitive to the scale of the input features. Without scaling, some features might dominate others in terms of their impact on the model

- StandardScaler: Data is transformed such that it has a `mean` of `0` and a `standard deviation` of `1`

In [35]:
```
from sklearn.preprocessing import StandardScaler
sc=StandardScaler()
cols_to_scale = num_cols[:-1] #Leaving out the exited column
x[cols_to_scale]=sc.fit_transform(x[cols_to_scale])
x.head()
```

Out[35]:

	CreditScore	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	Es
0	-0.326221	0	0.293517	-1.041760	-1.225848	-0.911583	0.646092	0.970243	
1	-0.440036	0	0.198164	-1.387538	0.117350	-0.911583	-1.547768	0.970243	
2	-1.536794	0	0.293517	1.032908	1.333053	2.527057	0.646092	-1.030670	
3	0.501521	0	0.007457	-1.387538	-1.225848	0.807737	-1.547768	-1.030670	
4	2.063884	0	0.388871	-1.041760	0.785728	-0.911583	0.646092	0.970243	

Modelling

- Splitting data into `Train` and `Test`
- Training `Models`
- `Hyperparameter Tuning`

Train Test split

Using the 'train_test_split' function to split the data into training and testing sets, allocating 20% of the data to testing.

In [36]:
```
from sklearn.model_selection import train_test_split
xtrain,xtest,ytrain,ytest = train_test_split(x,y,test_size=0.20,random_state=1)
```

Model Metrics

Creating blank lists to hold data for plotting model performance

In [37]:
```
model_list = [] # Model Name
model_train_acc = [] # Training Accuracy
model_test_acc = [] # Test Accuracy
```

Logistic Regression

In [38]:
```
from sklearn.linear_model import LogisticRegression
lreg = LogisticRegression()
lreg.fit(xtrain,ytrain)
ypred_train = lreg.predict(xtrain)
ypred_test = lreg.predict(xtest)
```

In [39]:
```
# Adding to model metrics
lr_train_acc = lreg.score(xtrain, ytrain)
lr_test_acc = lreg.score(xtest, ytest)

print("Train set accuracy:", lr_train_acc)
print("Test set accuracy:", lr_test_acc)
model_list.append('LR')
model_train_acc.append(lr_train_acc)
model_test_acc.append(lr_test_acc)
```

```
Train set accuracy: 0.812125
Test set accuracy: 0.8125
```

In [40]:
```
from sklearn.metrics import confusion_matrix,accuracy_score,r2_score,mean_squared_error
print("Train Data")
print(confusion_matrix(ytrain,ypred_train))
print("Test Data")
print(confusion_matrix(ytest,ypred_test))
```

```
Train Data
[[6166  212]
 [1291  331]]
Test Data
[[1533   52]
 [ 323   92]]
```

A `Confusion Matrix` provides a summary of a classification model's performance.

It contains four key metrics:

- **True Positives (TP): Correctly predicted positive cases.**
- **True Negatives (TN): Correctly predicted negative cases.**
- **False Positives (FP): Incorrectly predicted positive cases (Type I error).**
- **False Negatives (FN): Incorrectly predicted negative cases (Type II error).**

These metrics help assess the model's accuracy, precision, recall etc.

Precision Recall Curve

In [41]:
```
#using slicing to check probability of 1
ytrain_prob = lreg.predict_proba(xtrain)[:,1]
ytrain_prob
```

Out[41]:
```
array([0.08039676, 0.16774223, 0.3476632 , ..., 0.12807334, 0.08334479,
       0.3572384 ])
```

In [42]:
```
ytest_prob = lreg.predict_proba(xtest)[:,1]
ytest_prob
```

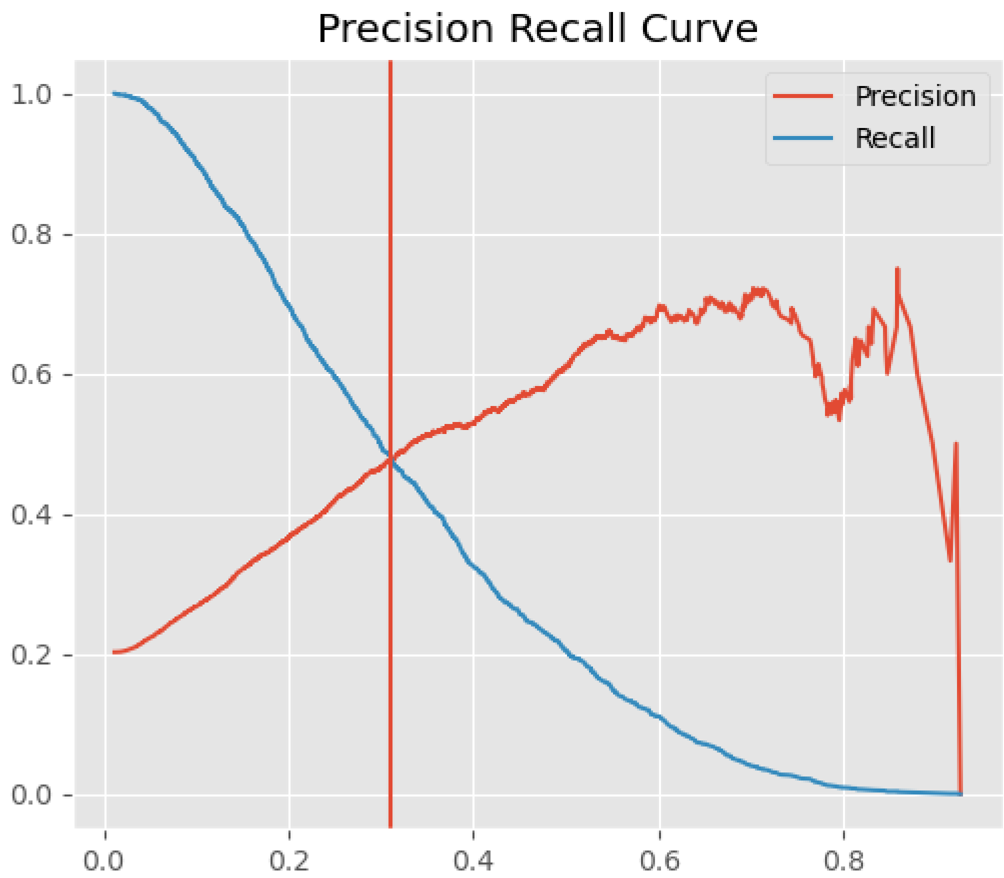
Out[42]:
```
array([0.09628867, 0.15458893, 0.12183095, ..., 0.04358637, 0.12753935,
       0.30661994])
```

In [43]:
```
from sklearn.metrics import classification_report
print("Train Data")
print(classification_report(ytrain,ypred_train))
print("Test Data")
print(classification_report(ytest,ypred_test))
```

```
Train Data
              precision    recall  f1-score   support

           0       0.83      0.97      0.89      6378
           1       0.61      0.20      0.31      1622

    accuracy                           0.81      8000
   macro avg       0.72      0.59      0.60      8000
weighted avg       0.78      0.81      0.77      8000

Test Data
              precision    recall  f1-score   support

           0       0.83      0.97      0.89      1585
           1       0.64      0.22      0.33       415

    accuracy                           0.81      2000
   macro avg       0.73      0.59      0.61      2000
weighted avg       0.79      0.81      0.77      2000
```

In [44]:
```
from sklearn.metrics import precision_recall_curve
p,r,th = precision_recall_curve(ytrain,ytrain_prob)
```

In [45]:
```
plt.figure(figsize=(6,5))
sns.lineplot(x=th,y=p[:-1],label='Precision')
sns.lineplot(x=th,y=r[:-1],label='Recall')
plt.title('Precision Recall Curve')
plt.axvline(0.310)
plt.show()
```



`Precision` **measures the accuracy of positive predictions made by a model.**
`Recall` **measures the completeness of positive predictions.**

ROC-AUC Curve

In [46]:
```
from sklearn.metrics import classification_report,accuracy_score
ac = accuracy_score(ytest,ypred_test)
cr = classification_report(ytest,ypred_test)

print(f'Accuracy Score: {ac}')
print(f'\n\n {cr}')
```

```
Accuracy Score: 0.8125


              precision    recall  f1-score   support

           0       0.83      0.97      0.89      1585
           1       0.64      0.22      0.33       415

    accuracy                           0.81      2000
   macro avg       0.73      0.59      0.61      2000
weighted avg       0.79      0.81      0.77      2000
```

In [47]:
```
print(f'Actual Values:  {ytest[:25].values}')
print(f'Predicted Values:  {ypred_test[:25]}')
```

```
Actual Values:  [0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0]
Predicted Values:  [0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0]
```

In [48]:
```
#finding xtest probability values
ypred_prob = lreg.predict_proba(xtest)[:,1]
ypred_prob
```

Out[48]:
```
array([0.09628867, 0.15458893, 0.12183095, ..., 0.04358637, 0.12753935,
       0.30661994])
```

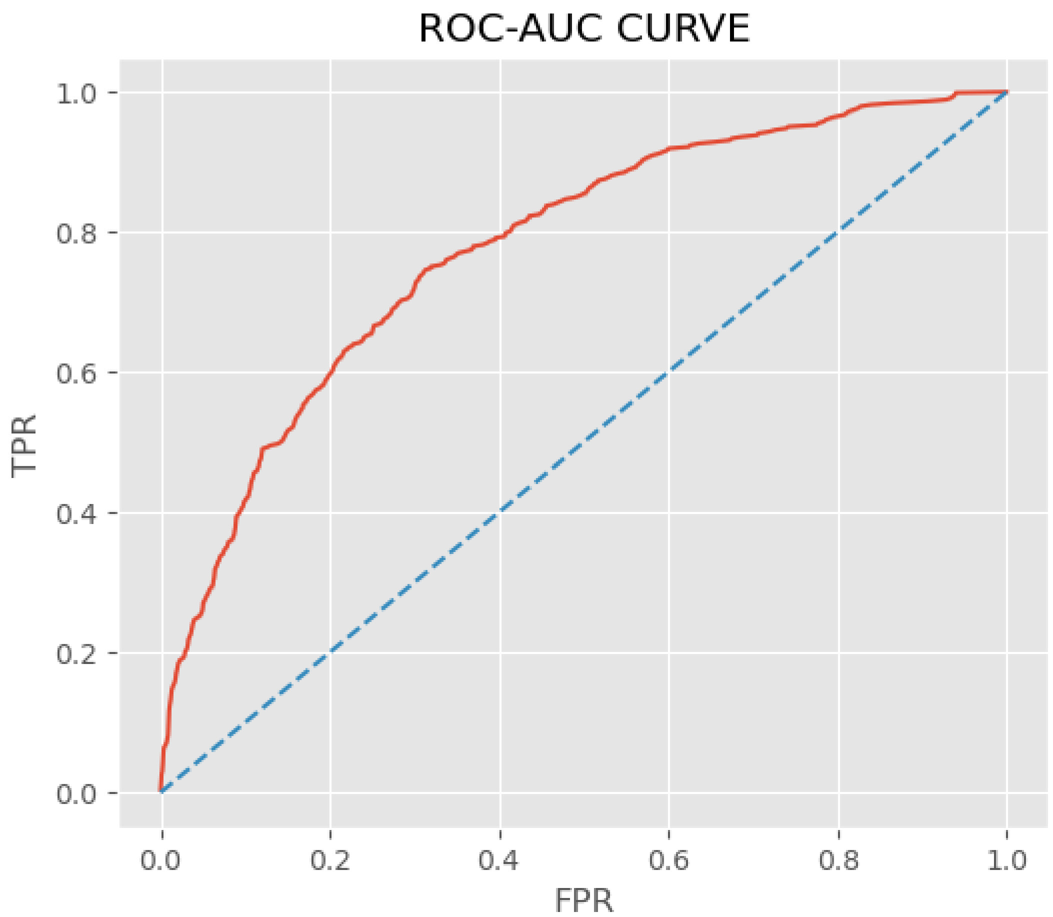
In [49]:
```
#Binary function convert countinues values into binary form
from sklearn.preprocessing import binarize
ypred = binarize([ypred_prob],threshold=0.310)[0]
```

In [50]:
```
print(f'Actual Values:     {ytest[:25].values}')
print(f'Predicted Values:  {ypred[:25]}')
```

```
Actual Values:     [0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0]
Predicted Values:  [0. 0. 0. 0. 0. 0. 0. 0. 1. 0. 1. 0. 0. 0. 1. 0. 0. 0. 0. 1. 0. 0. 0.
0.
 0.]
```

In [51]:
```
from sklearn.metrics import roc_curve
fpr,tpr,th = roc_curve(ytest,ypred_prob)
```

In [52]:
```
plt.figure(figsize=(6,5))
plt.title('ROC-AUC CURVE')
sns.lineplot(x=fpr,y=tpr)
sns.lineplot(x=[0.0,1],y=[0.0,1],linestyle='--')
plt.xlabel('FPR')
plt.ylabel('TPR')
plt.grid(True)
plt.show()
```



K-Nearest Neighbours

In [53]:
```
from sklearn.neighbors import KNeighborsClassifier
```

In [54]:
```
knn = KNeighborsClassifier(n_neighbors=3,)
knn.fit(xtrain,ytrain)
```

```
ypred=knn.predict(xtest)
print(classification_report(ytest,ypred))
```

```
              precision    recall  f1-score   support

           0       0.87      0.95      0.90      1585
           1       0.68      0.45      0.54       415

    accuracy                           0.84      2000
   macro avg       0.77      0.70      0.72      2000
weighted avg       0.83      0.84      0.83      2000
```

Hyperparameter Tuning

In [55]:
```
param_grid = {'n_neighbors':[2,4,5,7,9],
              'metric':['euclidean','manhattan','minkowski'],
              'weights':['uniform','distance']}
```

In [56]:
```
from sklearn.model_selection import GridSearchCV
model=GridSearchCV(knn,param_grid,cv=3,n_jobs=1,scoring='accuracy')
model.fit(xtrain,ytrain)
```

Out[56]:
```
GridSearchCV(cv=3, estimator=KNeighborsClassifier(n_neighbors=3), n_jobs=1,
             param_grid={'metric': ['euclidean', 'manhattan', 'minkowski'],
                         'n_neighbors': [2, 4, 5, 7, 9],
                         'weights': ['uniform', 'distance']},
             scoring='accuracy')
```

In [57]:
```
model.best_score_
```

Out[57]:
```
0.8412502919505654
```

In [58]:
```
#giving best parameters
model.best_params_
```

Out[58]:
```
{'metric': 'euclidean', 'n_neighbors': 9, 'weights': 'uniform'}
```

In [59]:
```
knn = KNeighborsClassifier(n_neighbors=4,metric='manhattan',weights='uniform')
knn.fit(xtrain,ytrain)
ypred=knn.predict(xtest)
print(classification_report(ytest,ypred))
```

```
              precision    recall  f1-score   support

           0       0.84      0.97      0.90      1585
           1       0.75      0.29      0.41       415

    accuracy                           0.83      2000
   macro avg       0.79      0.63      0.66      2000
weighted avg       0.82      0.83      0.80      2000
```

In [60]:
```
from sklearn.metrics import confusion_matrix
confusion_matrix(ytest,ypred)
```

Out[60]:
```
array([[1545,   40],
       [ 296,  119]], dtype=int64)
```

In [61]:
```
# Adding to model metrics
knn_train_acc = knn.score(xtrain, ytrain)
knn_test_acc = knn.score(xtest, ytest)

print("Train set accuracy:", knn_train_acc)
print("Test set accuracy:", knn_test_acc)
```

```
model_list.append('KNN')
model_train_acc.append(knn_train_acc)
model_test_acc.append(knn_test_acc)
```

```
Train set accuracy: 0.874
Test set accuracy: 0.832
```

Support Vector Machine

In [62]:
```
from sklearn.svm import SVC
from sklearn.model_selection import cross_val_score, GridSearchCV
```

In [63]:
```
svm_model = SVC()
svm_model.fit(xtrain,ytrain)
svm_train_acc_b_ht = svm_model.score(xtrain, ytrain)
svm_test_acc_b_ht = svm_model.score(xtest, ytest)
print("Train set accuracy:", svm_train_acc_b_ht)
print("Test set accuracy:", svm_test_acc_b_ht)
```

```
Train set accuracy: 0.86275
Test set accuracy: 0.859
```

In [64]:
```
param_grid = {
    'kernel': ['linear', 'rbf',],
    'C': [1, 10],
    'gamma': [1, 10]}
```

Hyperparameter Tuning

In [65]:
```
gd = GridSearchCV(svm_model, param_grid, cv=3, scoring='accuracy')
gd.fit(xtrain,ytrain)
ypred = gd.predict(xtest)
```

In [66]:
```
best_svm_model = gd.best_estimator_
best_parameters = gd.best_params_
best_score = gd.best_score_

print("Best Parameters:", best_parameters)
print("Best Cross-Validation Accuracy:", best_score)
```

```
Best Parameters: {'C': 1, 'gamma': 1, 'kernel': 'rbf'}
Best Cross-Validation Accuracy: 0.8194999631047618
```

In [67]:
```
# Adding to model metrics
svc_train_acc = best_svm_model.score(xtrain, ytrain)
svc_test_acc = best_svm_model.score(xtest, ytest)

print("Train set accuracy:", svc_train_acc)
print("Test set accuracy:", svc_test_acc)
model_list.append('SVC')
model_train_acc.append(svc_train_acc)
model_test_acc.append(svc_test_acc)
```

```
Train set accuracy: 0.939375
Test set accuracy: 0.822
```

Decision Tree Classifier

In [68]:
```
from sklearn.tree import DecisionTreeClassifier
```

In [69]:
```
dt = DecisionTreeClassifier()
dt.fit(xtrain,ytrain)
```

Out[69]:
```
DecisionTreeClassifier()
```

In [70]:
```python
from sklearn.metrics import classification_report
```

In [71]:
```python
ytrain_pred = dt.predict(xtrain)
ytest_pred = dt.predict(xtest)
```

In [72]:
```python
train = dt.score(xtrain,ytrain)
test = dt.score(xtest,ytest)
print(f'Training result: {train}')
print(f'Testing result: {test}')
```

```
Training result: 1.0
Testing result: 0.797
```

Hyperparameter Tuning

In [73]:
```python
param_grid = {
    'max_depth': [None, 10, 20, 30],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4],
    'criterion': ['gini', 'entropy']}
```

In [74]:
```python
grid_search = GridSearchCV(dt, param_grid, cv=5, scoring='accuracy', n_jobs=-1)
grid_search.fit(xtrain,ytrain)
```

Out[74]:
```
GridSearchCV(cv=5, estimator=DecisionTreeClassifier(), n_jobs=-1,
             param_grid={'criterion': ['gini', 'entropy'],
                         'max_depth': [None, 10, 20, 30],
                         'min_samples_leaf': [1, 2, 4],
                         'min_samples_split': [2, 5, 10]},
             scoring='accuracy')
```

In [75]:
```python
best_dt_model = grid_search.best_estimator_
best_parameters = grid_search.best_params_
best_score = grid_search.best_score_

print("Best Parameters:", best_parameters)
print("Best Cross-Validation Accuracy:", best_score)
```

```
Best Parameters: {'criterion': 'entropy', 'max_depth': 10, 'min_samples_leaf': 4, 'min_s
amples_split': 10}
Best Cross-Validation Accuracy: 0.844625
```

In [76]:
```python
best_dt_model.fit(xtrain, ytrain)
train_accuracy = best_dt_model.score(xtrain, ytrain)
test_accuracy = best_dt_model.score(xtest, ytest)

print("Train accuracy:",train_accuracy)
print("Test accuracy:", test_accuracy)
```

```
Train accuracy: 0.888125
Test accuracy: 0.843
```

In [77]:
```python
# Adding to model metrics
dt_train_acc = best_dt_model.score(xtrain, ytrain)
dt_test_acc = best_dt_model.score(xtest, ytest)

print("Train set accuracy:", dt_train_acc)
print("Test set accuracy:", dt_test_acc)
model_list.append('DT')
model_train_acc.append(dt_train_acc)
model_test_acc.append(dt_test_acc)
```

```
Train set accuracy: 0.888125
Test set accuracy: 0.843
```

Random Forest Classifier

In [78]:
```python
from sklearn.ensemble import RandomForestClassifier
```

In [79]:
```python
rf = RandomForestClassifier()
rf.fit(xtrain,ytrain)
ypred = rf.predict(xtest)
```

In [80]:
```python
train_accuracy = rf.score(xtrain, ytrain)
test_accuracy = rf.score(xtest, ytest)

print("Train accuracy:",train_accuracy)
print("Test accuracy:", test_accuracy)
```

```
Train accuracy: 1.0
Test accuracy: 0.864
```

Hyperparameter Tuning

In [81]:
```python
param_grid = {
    'n_estimators': [100,200],
    'max_depth': [5,8],
    'min_samples_split': [2,5],
    'min_samples_leaf': [1,2],
    'max_features': ['sqrt']}
```

In [82]:
```python
from sklearn.model_selection import GridSearchCV
```

In [83]:
```python
rs = GridSearchCV(rf, param_grid ,cv=5, scoring='accuracy', n_jobs=-1)
rs.fit(xtrain,ytrain)
```

Out[83]:
```
GridSearchCV(cv=5, estimator=RandomForestClassifier(), n_jobs=-1,
             param_grid={'max_depth': [5, 8], 'max_features': ['sqrt'],
                         'min_samples_leaf': [1, 2],
                         'min_samples_split': [2, 5],
                         'n_estimators': [100, 200]},
             scoring='accuracy')
```

In [84]:
```python
rs.best_params_
```

Out[84]:
```
{'max_depth': 8,
 'max_features': 'sqrt',
 'min_samples_leaf': 1,
 'min_samples_split': 5,
 'n_estimators': 100}
```

In [85]:
```python
best_random_forest_model = rs.best_estimator_
best_parameters = rs.best_params_
best_score = rs.best_score_

print("Best Parameters:", best_parameters)
print("Best Cross-Validation Accuracy:", best_score)
```

```
Best Parameters: {'max_depth': 8, 'max_features': 'sqrt', 'min_samples_leaf': 1, 'min_sa
mples_split': 5, 'n_estimators': 100}
Best Cross-Validation Accuracy: 0.8602500000000001
```

In [86]:
```python
best_random_forest_model.fit(xtrain, ytrain)
train_accuracy = best_random_forest_model.score(xtrain, ytrain)
test_accuracy = best_random_forest_model.score(xtest, ytest)
```

```
print("Train accuracy:", train_accuracy)
print("Test accuracy:", test_accuracy)
```

```
Train accuracy: 0.879
Test accuracy: 0.8665
```

In [87]:
```
# Adding to model metrics
rf_train_acc = best_random_forest_model.score(xtrain, ytrain)
rf_test_acc = best_random_forest_model.score(xtest, ytest)

print("Train set accuracy:", rf_train_acc)
print("Test set accuracy:", rf_test_acc)
model_list.append('RF')
model_train_acc.append(rf_train_acc)
model_test_acc.append(rf_test_acc)
```

```
Train set accuracy: 0.879
Test set accuracy: 0.8665
```

Boosting

- **Adaboost**
- **Gradientboost**
- **XGBoost**

Adaboost

In [88]:
```
from sklearn.ensemble import AdaBoostClassifier
```

In [89]:
```
ada = AdaBoostClassifier(n_estimators=200)
ada.fit(xtrain,ytrain)
ypred_train = ada.predict(xtrain)
ypred_test = ada.predict(xtest)
```

In [90]:
```
print('Train Data')
print(classification_report(ytrain,ypred_train))
print('Test Data')
print(classification_report(ytest,ypred_test))
```

```
Train Data
              precision    recall  f1-score   support

           0       0.88      0.96      0.92      6378
           1       0.75      0.48      0.58      1622

    accuracy                           0.86      8000
   macro avg       0.81      0.72      0.75      8000
weighted avg       0.85      0.86      0.85      8000

Test Data
              precision    recall  f1-score   support

           0       0.87      0.96      0.92      1585
           1       0.76      0.47      0.58       415

    accuracy                           0.86      2000
   macro avg       0.82      0.72      0.75      2000
weighted avg       0.85      0.86      0.85      2000
```

In [91]:
```
param_dist = {
    'n_estimators': [50, 100, 200],
```

```
    'learning_rate': [0.01, 0.1, 1.0]}
```

Hyperparameter Tuning

In [92]:
```
clf = GridSearchCV(ada, param_dist, cv=5, scoring='accuracy', n_jobs=-1)
clf.fit(xtrain,ytrain)
```

Out[92]:
```
GridSearchCV(cv=5, estimator=AdaBoostClassifier(n_estimators=200), n_jobs=-1,
             param_grid={'learning_rate': [0.01, 0.1, 1.0],
                         'n_estimators': [50, 100, 200]},
             scoring='accuracy')
```

In [93]:
```
clf.best_params_
```

Out[93]:
```
{'learning_rate': 0.1, 'n_estimators': 200}
```

In [94]:
```
grid_train_predictions = clf.predict(xtrain)
grid_test_predictions = clf.predict(xtest)
```

In [95]:
```
print(classification_report(ytrain,grid_train_predictions))
print(classification_report(ytest,grid_test_predictions))
```

```
              precision    recall  f1-score   support

           0       0.87      0.97      0.92      6378
           1       0.79      0.43      0.56      1622

    accuracy                           0.86      8000
   macro avg       0.83      0.70      0.74      8000
weighted avg       0.85      0.86      0.85      8000

              precision    recall  f1-score   support

           0       0.86      0.97      0.91      1585
           1       0.79      0.41      0.54       415

    accuracy                           0.85      2000
   macro avg       0.82      0.69      0.73      2000
weighted avg       0.85      0.85      0.84      2000
```

In [96]:
```
# Adding to model metrics
ada_train_acc = clf.score(xtrain, ytrain)
ada_test_acc = clf.score(xtest, ytest)

print("Train set accuracy:", ada_train_acc)
print("Test set accuracy:", ada_test_acc)
model_list.append('Ada')
model_train_acc.append(ada_train_acc)
model_test_acc.append(ada_test_acc)
```

```
Train set accuracy: 0.8615
Test set accuracy: 0.855
```

Gradient Boosting Classifier

In [97]:
```
from sklearn.ensemble import GradientBoostingClassifier
```

In [98]:
```
gdc = GradientBoostingClassifier(n_estimators=200)
gdc.fit(xtrain,ytrain)
y_pred_train = gdc.predict(xtrain)
y_pred_test = gdc.predict(xtest)
```

In [99]:
```python
print('Train Data')
print(classification_report(ytrain,y_pred_train))
print('Test Data')
print(classification_report(ytest,y_pred_test))
```

```
Train Data
              precision    recall  f1-score   support

           0       0.89      0.97      0.93      6378
           1       0.84      0.53      0.65      1622

    accuracy                           0.88      8000
   macro avg       0.86      0.75      0.79      8000
weighted avg       0.88      0.88      0.87      8000

Test Data
              precision    recall  f1-score   support

           0       0.88      0.96      0.92      1585
           1       0.77      0.48      0.59       415

    accuracy                           0.86      2000
   macro avg       0.82      0.72      0.75      2000
weighted avg       0.85      0.86      0.85      2000
```

In [100…
```python
param_dist = {
    'n_estimators': [50, 100, 200],
    'learning_rate': [0.01, 0.1, 1.0],
    'max_depth': [3, 4, 5],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4],
    'subsample': [0.8, 0.9, 1.0]}
```

Hyperparameter Tuning

In [101…
```python
rsc = GridSearchCV(gdc, param_dist, cv=5, scoring='accuracy', n_jobs=-1)
rsc.fit(xtrain,ytrain)
```

Out[101]:
```
GridSearchCV(cv=5, estimator=GradientBoostingClassifier(n_estimators=200),
             n_jobs=-1,
             param_grid={'learning_rate': [0.01, 0.1, 1.0],
                         'max_depth': [3, 4, 5], 'min_samples_leaf': [1, 2, 4],
                         'min_samples_split': [2, 5, 10],
                         'n_estimators': [50, 100, 200],
                         'subsample': [0.8, 0.9, 1.0]},
             scoring='accuracy')
```

In [102…
```python
rsc.best_params_
```

Out[102]:
```
{'learning_rate': 0.1,
 'max_depth': 3,
 'min_samples_leaf': 1,
 'min_samples_split': 5,
 'n_estimators': 100,
 'subsample': 0.9}
```

In [103…
```python
grid_train_predictions = rsc.predict(xtrain)
grid_test_predictions = rsc.predict(xtest)
```

In [104…
```python
print('Train Data')
print(classification_report(ytrain,grid_train_predictions))
print('Test Data')
print(classification_report(ytest,grid_test_predictions))
```

```
Train Data
              precision    recall  f1-score   support

           0       0.88      0.97      0.92      6378
           1       0.81      0.49      0.61      1622

    accuracy                           0.87      8000
   macro avg       0.84      0.73      0.77      8000
weighted avg       0.87      0.87      0.86      8000

Test Data
              precision    recall  f1-score   support

           0       0.87      0.97      0.92      1585
           1       0.79      0.47      0.59       415

    accuracy                           0.86      2000
   macro avg       0.83      0.72      0.75      2000
weighted avg       0.86      0.86      0.85      2000
```

In [105…

```python
# Adding to model metrics
gb_train_acc = clf.score(xtrain, ytrain)
gb_test_acc = clf.score(xtest, ytest)

print("Train set accuracy:", gb_train_acc)
print("Test set accuracy:", gb_test_acc)
model_list.append('GB')
model_train_acc.append(gb_train_acc)
model_test_acc.append(gb_test_acc)
```

```
Train set accuracy: 0.8615
Test set accuracy: 0.855
```

Extreme Gradient Boosting

In [106…

```python
from xgboost import XGBClassifier
```

In [107…

```python
from xgboost import XGBClassifier
xg = XGBClassifier()
xg.fit(xtrain,ytrain)
ypred_train = xg.predict(xtrain)
ypred_test = xg.predict(xtest)
print(classification_report(ytrain,ypred_train))
print(classification_report(ytest,ypred_test))
```

```
              precision    recall  f1-score   support

           0       0.96      0.99      0.98      6378
           1       0.97      0.84      0.90      1622

    accuracy                           0.96      8000
   macro avg       0.97      0.92      0.94      8000
weighted avg       0.96      0.96      0.96      8000

              precision    recall  f1-score   support

           0       0.88      0.95      0.91      1585
           1       0.73      0.50      0.60       415

    accuracy                           0.86      2000
   macro avg       0.81      0.73      0.76      2000
weighted avg       0.85      0.86      0.85      2000
```

In [108…

```
train_accuracy = xg.score(xtrain, ytrain)
test_accuracy = xg.score(xtest, ytest)

print("Train accuracy:",train_accuracy)
print("Test accuracy:", test_accuracy)
```

```
Train accuracy: 0.96225
Test accuracy: 0.8585
```

In [109…

```
param_dist = {
    'n_estimators': [100, 200,],
    'learning_rate': [0.01, 0.1],
    'max_depth': [3, 4],
    'min_child_weight': [1, 2],
    'subsample': [0.8, 0.9]}
```

Hyperparameter Tuning

In [110…

```
rsc_xb = GridSearchCV(xg, param_dist, cv=5, scoring='accuracy', n_jobs=-1)
rsc_xb.fit(xtrain,ytrain)
```

Out[110]:

```
GridSearchCV(cv=5,
             estimator=XGBClassifier(base_score=None, booster=None,
                                     callbacks=None, colsample_bylevel=None,
                                     colsample_bynode=None,
                                     colsample_bytree=None, device=None,
                                     early_stopping_rounds=None,
                                     enable_categorical=False, eval_metric=None,
                                     feature_types=None, gamma=None,
                                     grow_policy=None, importance_type=None,
                                     interaction_constraints=None,
                                     learning_rate=None,...
                                     max_delta_step=None, max_depth=None,
                                     max_leaves=None, min_child_weight=None,
                                     missing=nan, monotone_constraints=None,
                                     multi_strategy=None, n_estimators=None,
                                     n_jobs=None, num_parallel_tree=None,
                                     random_state=None, ...),
             n_jobs=-1,
             param_grid={'learning_rate': [0.01, 0.1, 1.0],
                         'max_depth': [3, 4, 5], 'min_child_weight': [1, 2, 4],
                         'n_estimators': [100, 200, 300],
                         'subsample': [0.8, 0.9, 1.0]},
             scoring='accuracy')
```

In [111…

```
best_xgboost_model = rsc_xb.best_estimator_
best_parameters = rsc_xb.best_params_
best_score = rsc_xb.best_score_

print("Best Parameters:", best_parameters)
print("Best Cross-Validation Accuracy:", best_score)
```

```
Best Parameters: {'learning_rate': 0.1, 'max_depth': 3, 'min_child_weight': 1, 'n_estima
tors': 200, 'subsample': 0.9}
Best Cross-Validation Accuracy: 0.86675
```

In [112…

```
best_xgboost_model.fit(xtrain,ytrain)
train_accuracy = best_xgboost_model.score(xtrain, ytrain)
test_accuracy = best_xgboost_model.score(xtest, ytest)

print("Train accuracy:",train_accuracy)
print("Test accuracy:", test_accuracy)
```

```
Train accuracy: 0.8805
Test accuracy: 0.864
```

In [113…
```python
# Adding to model metrics
xgb_train_acc = best_xgboost_model.score(xtrain, ytrain)
xgb_test_acc = best_xgboost_model.score(xtest, ytest)

print("Train set accuracy:", xgb_train_acc)
print("Test set accuracy:", xgb_test_acc)
model_list.append('XGB')
model_train_acc.append(xgb_train_acc)
model_test_acc.append(xgb_test_acc)
```

```
Train set accuracy: 0.8805
Test set accuracy: 0.864
```

Creating a Model Metrics Dataframe

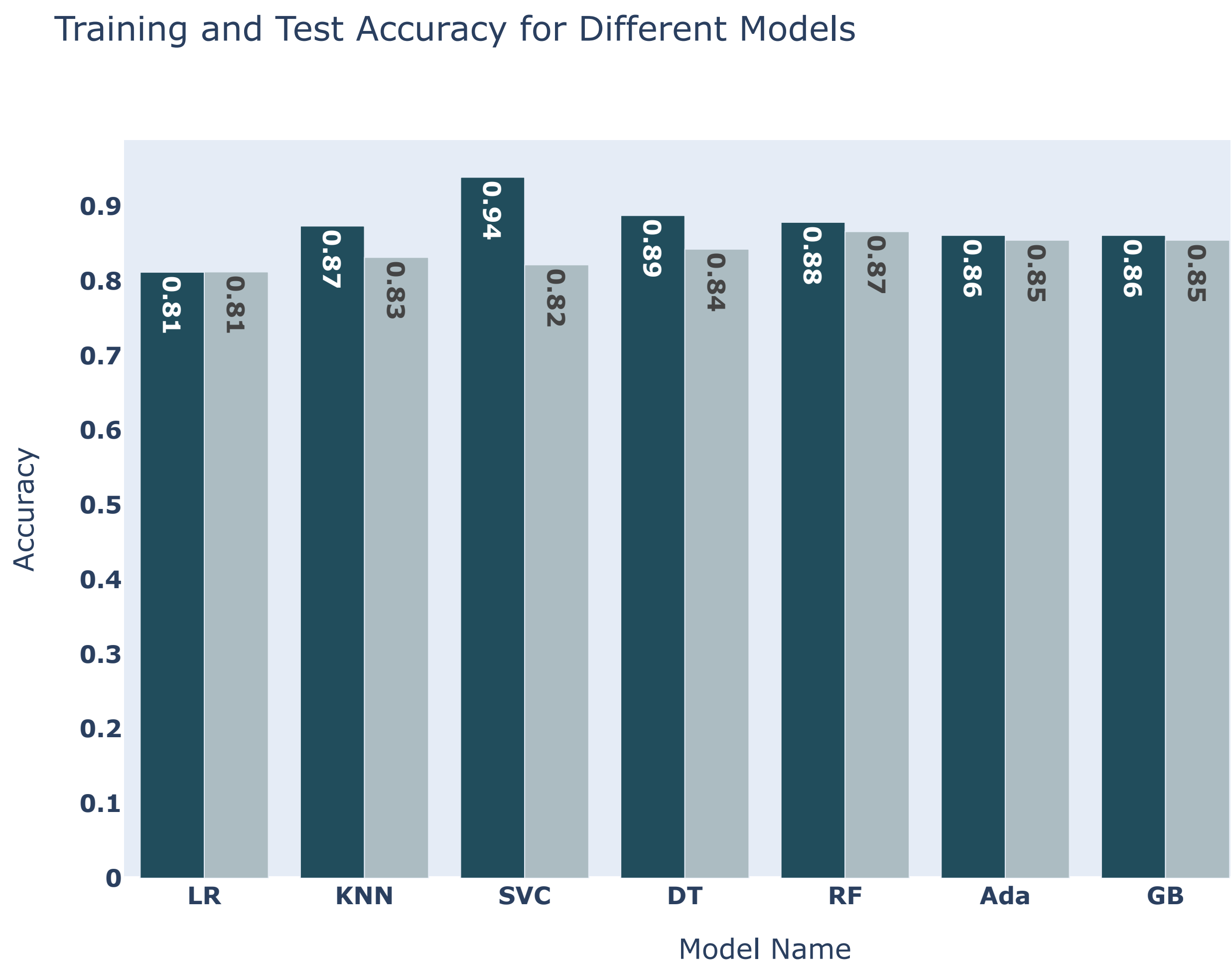
In [114…
```python
model_data = {'Model Name': model_list, 'Training Accuracy': model_train_acc, 'Test Accu
model_df = pd.DataFrame(model_data)
model_df
```

Out[114]:

	Model Name	Training Accuracy	Test Accuracy
0	LR	0.812125	0.8125
1	KNN	0.874000	0.8320
2	SVC	0.939375	0.8220
3	DT	0.888125	0.8430
4	RF	0.879000	0.8665
5	Ada	0.861500	0.8550
6	GB	0.861500	0.8550
7	XGB	0.880500	0.8640

In [115…
```python
fig = go.Figure()

# Add the training accuracy bars with style
fig.add_trace(go.Bar(
    x=model_df['Model Name'],
    y=model_df['Training Accuracy'],
    name='Training Accuracy',
    marker_color='#214D5C',
    hovertemplate='Model: %{x}<br>Training Accuracy: %{y:.4f}',
    text=model_df['Training Accuracy'].apply(lambda x: f'{x:.2f}'),  # Format score to 4
    textposition='auto',  # Show text above bars
    showlegend=True,
))

# Add the test accuracy bars with style
fig.add_trace(go.Bar(
    x=model_df['Model Name'],
    y=model_df['Test Accuracy'],
    name='Test Accuracy',
    marker_color='#ACBCC2',
    hovertemplate='Model: %{x}<br>Test Accuracy: %{y:.4f}',
    text=model_df['Test Accuracy'].apply(lambda x: f'{x:.2f}'),  # Format score to 4 dec
    textposition='auto',
    showlegend=True,
))

# Customize the layout to match the style
fig.update_layout(
```

```python
    xaxis_title='Model Name',
    yaxis_title='Accuracy',
    title='Training and Test Accuracy for Different Models',
    barmode='group',
    width=900,
    height=550,
    xaxis=dict(showgrid=False),
    yaxis=dict(showgrid=False)
)

# Show the chart
fig.show()
```



Hyperparameter tuned Random Forest Classifier performed the best on test data

Project by Priyanka Singh