Customer Churn Prediction for Banks usinf Logistic Regression

In [1]:
```
import numpy as np
import pandas as pd
#for data visualization
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
```

In [2]:
```
df = pd.read_csv('Churn_Modelling.csv')
```

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

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

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

Out[4]:

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

In [5]:
```
# Checking duplicate and missing values
df.nunique()
```

Out[5]:
```
RowNumber          10000
CustomerId         10000
Surname             2932
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 [6]:
```
df.isnull().sum()
```

Out[6]:
```
RowNumber          0
CustomerId         0
Surname            0
CreditScore        0
Geography          0
Gender             0
Age                0
Tenure             0
Balance            0
NumOfProducts      0
HasCrCard          0
IsActiveMember     0
EstimatedSalary    0
Exited             0
dtype: int64
```

In [7]:
```
df.dtypes
```

Out[7]:
```
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
```

In [8]:
```
#Let's get the summary statistics for the numeric variables
#We will omit Row Number and Customer Id as they are identification numbers and
#will omit Exited, HasCrCard and IsActiveMember as they are just categories

#These are more relevant and can give us an idea on our data in terms of mean and std
numeric_cols = ['CreditScore', 'Age', 'Tenure', 'Balance', 'NumOfProducts', 'EstimatedSalary']

# The summary statistics for the selected columns are;
df[numeric_cols].describe()
```

Out[8]:

	CreditScore	Age	Tenure	Balance	NumOfProducts	EstimatedSalary
count	10000.000000	10000.000000	10000.000000	10000.000000	10000.000000	10000.000000
mean	650.528800	38.921800	5.012800	76485.889288	1.530200	100090.239881
std	96.653299	10.487806	2.892174	62397.405202	0.581654	57510.492818
min	350.000000	18.000000	0.000000	0.000000	1.000000	11.580000
25%	584.000000	32.000000	3.000000	0.000000	1.000000	51002.110000
50%	652.000000	37.000000	5.000000	97198.540000	1.000000	100193.915000
75%	718.000000	44.000000	7.000000	127644.240000	2.000000	149388.247500
max	850.000000	92.000000	10.000000	250898.090000	4.000000	199992.480000

In [9]:
```
df.head()
```

Out[9]:

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

EDA

Firstly, to be effective as possible, we only want to work with relevant data and weed out what is not going to be useful to us. The following columns will be definetly dropped; 'Row Number' as it is just a number, 'CustomerId' as it is just a serial number that will not really help us in knowing if a customer is going to churn or not and lastly 'Surname' because I do not see how your name will influence the decision you going to take in this context. It just leads to unnecessary profiling if we include it in our data

In [10]:
```
# Dropping the columns
df = df.drop(['RowNumber','CustomerId','Surname'],axis=1)
```

In [11]:
```
#Let's recheck our data
df.head()
```

Out[11]:

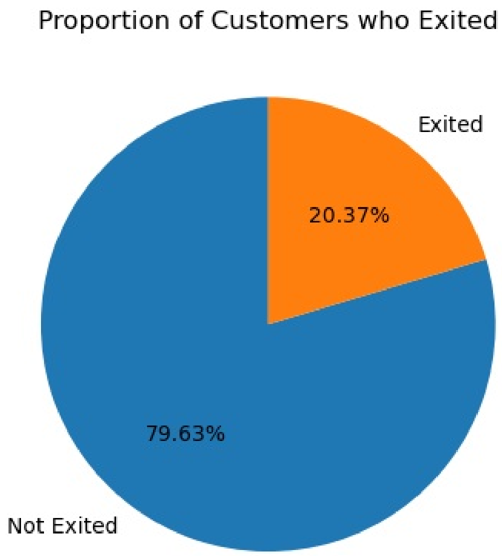
	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	Exited
0	619	France	Female	42	2	0.00	1	1	1	101348.88	1
1	608	Spain	Female	41	1	83807.86	1	0	1	112542.58	0
2	502	France	Female	42	8	159660.80	3	1	0	113931.57	1
3	699	France	Female	39	1	0.00	2	0	0	93826.63	0
4	850	Spain	Female	43	2	125510.82	1	1	1	79084.10	0

In [12]:
```
#What is the retention rate of our bank?
# The best way to see the ratio between churned and not churned is a pie chart
#Let's count the number of unique values in the Exited column
df['Exited'].value_counts()
```

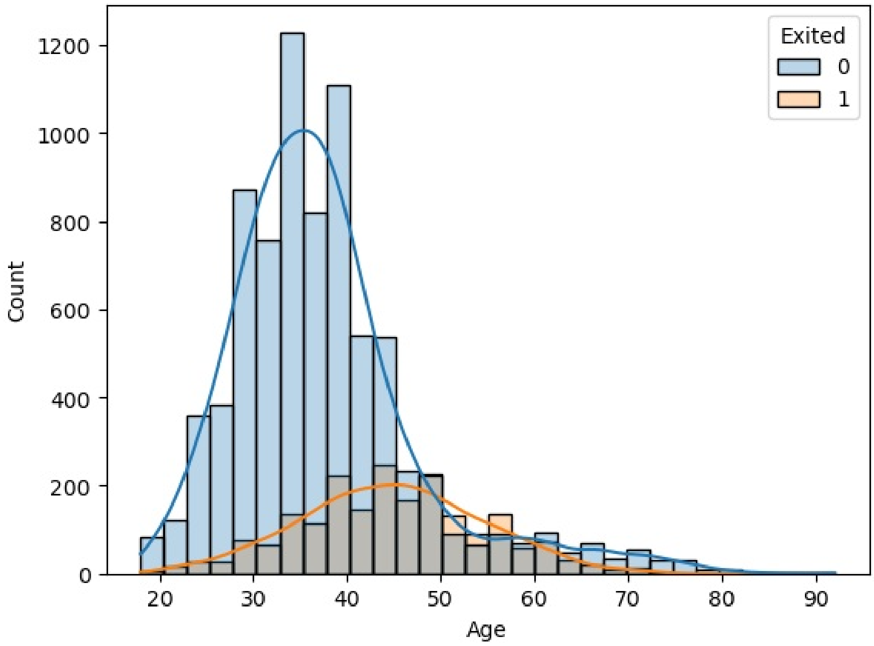
Out[12]:
```
0    7963
1    2037
Name: Exited, dtype: int64
```

In [13]:
```
#We can already visualize what the percentages are going to be.
#Let's create our diagram

ratios = df['Exited'].value_counts()
plt.pie(ratios,labels=['Not Exited','Exited'], autopct = '%0.2f%%',
        startangle=90)

plt.title('Proportion of Customers who Exited')
```

Out[13]:
```
Text(0.5, 1.0, 'Proportion of Customers who Exited')
```

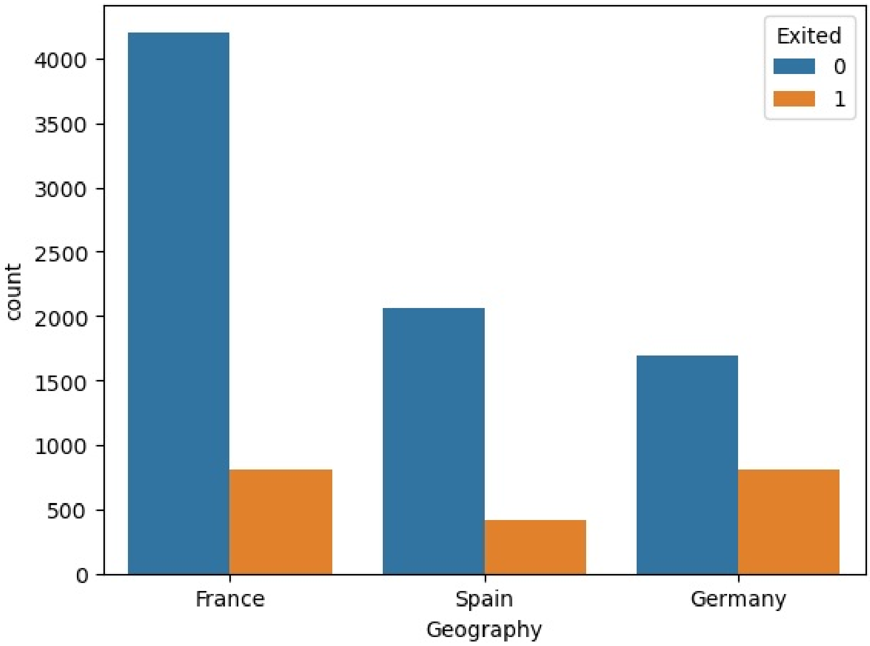


In [14]:
```
#Histplot allows us to see the distribution of our data
# Our KDE curves shows the distribution and alpha is our transparency parameter
sns.histplot(x = 'Age', data = df, hue='Exited',bins=30,kde=True,alpha=0.3)
plt.show()
```



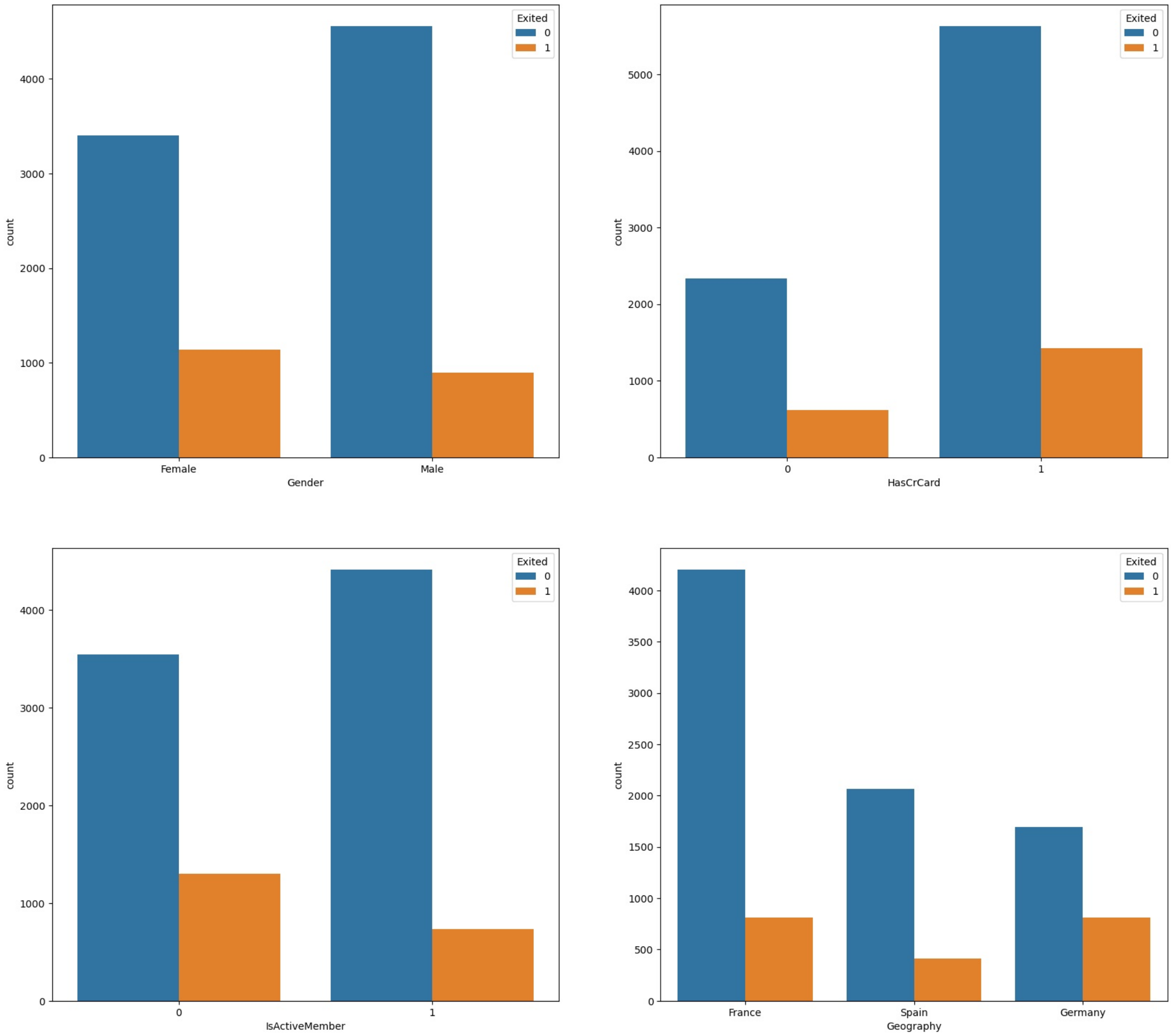
In [15]:
```
sns.countplot(x='Geography', hue='Exited', data=df)
```

Out[15]:
```
<Axes: xlabel='Geography', ylabel='count'>
```



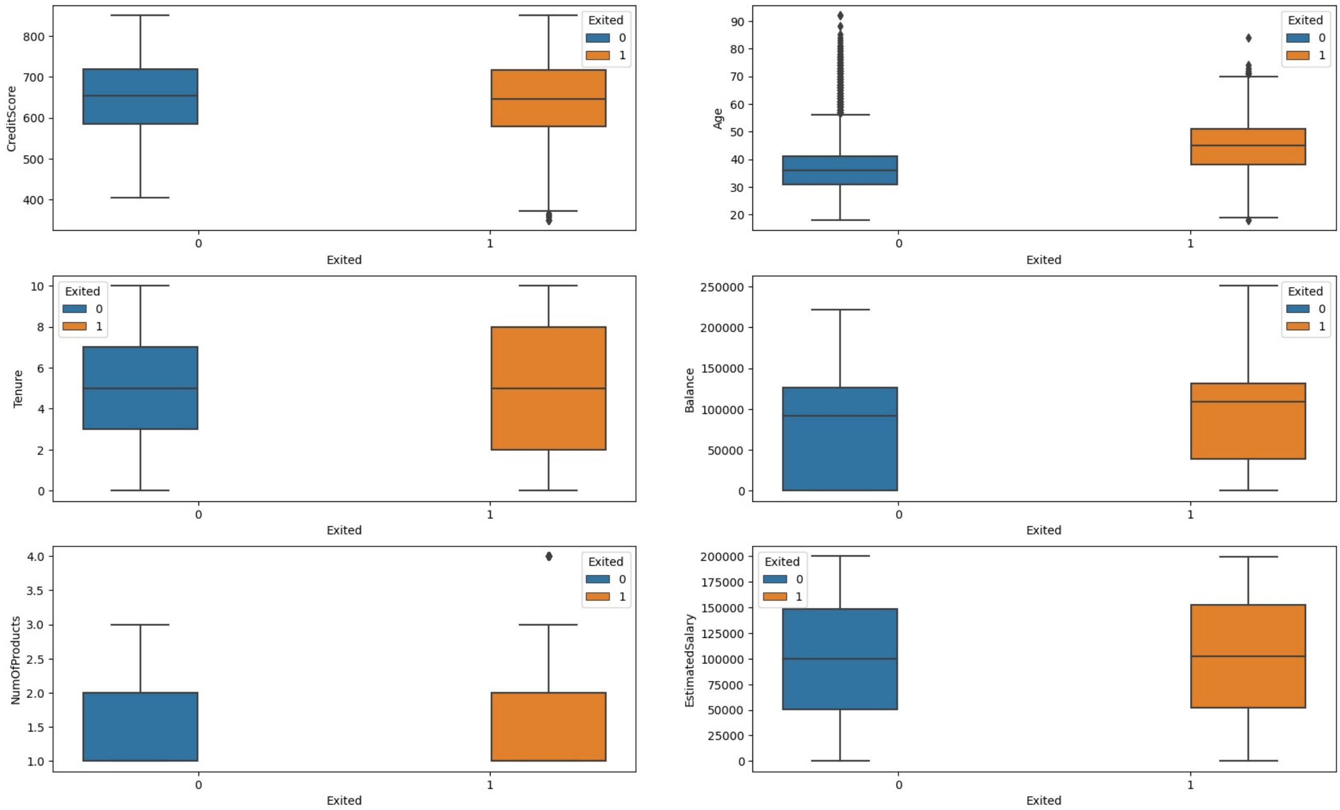
In [16]:
```
fig, axarr = plt.subplots(2, 2, figsize=(20, 18))
sns.countplot(x='Gender', hue = 'Exited',data = df, ax=axarr[0][0])
sns.countplot(x='HasCrCard', hue = 'Exited',data = df, ax=axarr[0][1])
sns.countplot(x='IsActiveMember', hue = 'Exited',data = df, ax=axarr[1][0])
sns.countplot(x='Geography', hue = 'Exited',data = df, ax=axarr[1][1])
```

Out[16]:
```
<Axes: xlabel='Geography', ylabel='count'>
```



In [17]:
```python
fig, axarr = plt.subplots(3, 2, figsize=(20, 12))
sns.boxplot(y='CreditScore',x = 'Exited', hue = 'Exited',data = df, ax=axarr[0][0])
sns.boxplot(y='Age',x = 'Exited', hue = 'Exited',data = df , ax=axarr[0][1])
sns.boxplot(y='Tenure',x = 'Exited', hue = 'Exited',data = df, ax=axarr[1][0])
sns.boxplot(y='Balance',x = 'Exited', hue = 'Exited',data = df, ax=axarr[1][1])
sns.boxplot(y='NumOfProducts',x = 'Exited', hue = 'Exited',data = df, ax=axarr[2][0])
sns.boxplot(y='EstimatedSalary',x = 'Exited', hue = 'Exited',data = df, ax=axarr[2][1])
```

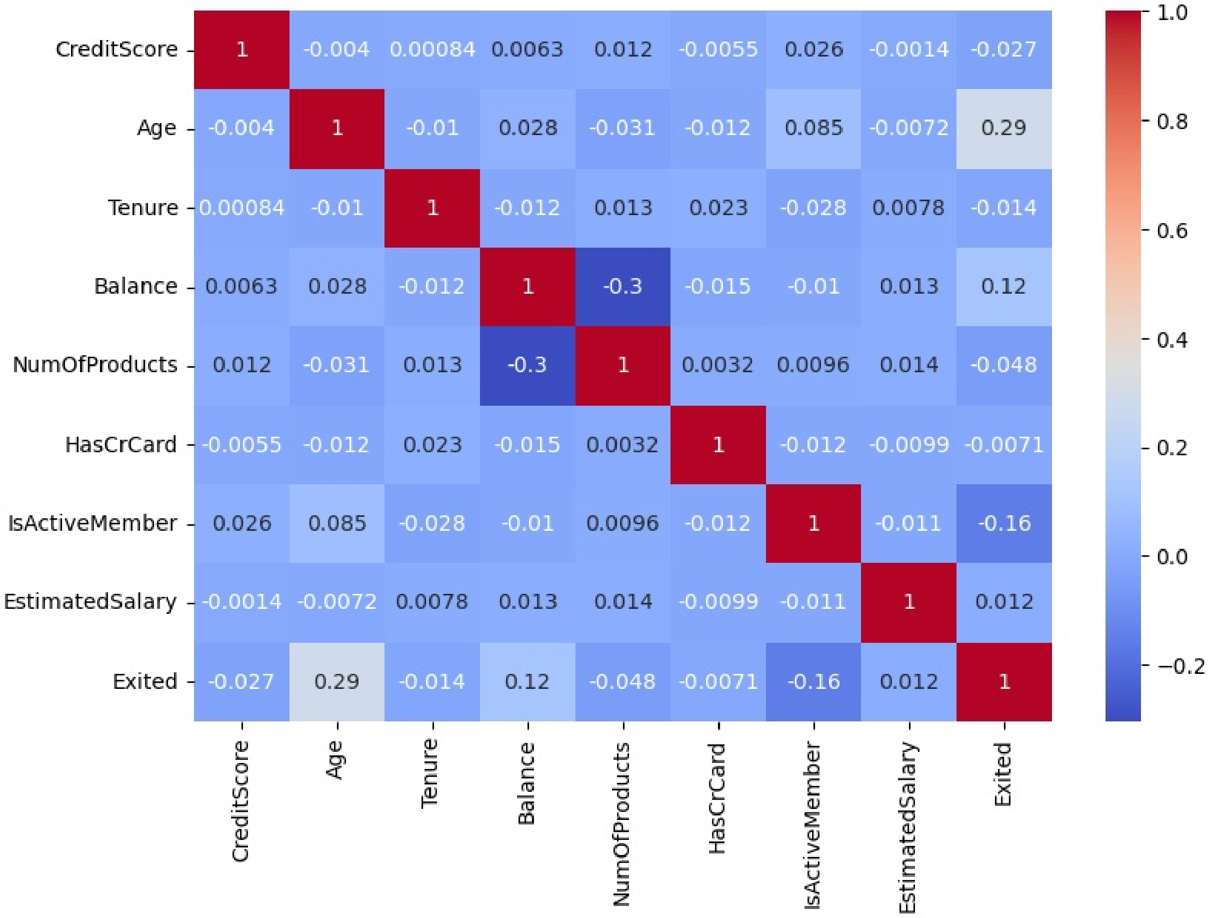
Out[17]:
```
<Axes: xlabel='Exited', ylabel='EstimatedSalary'>
```



In [18]:
```python
corr = df.corr(numeric_only=True)
```

In [19]:
```python
fig, ax = plt.subplots(figsize=(9,6))

sns.heatmap(corr,annot=True,cmap='coolwarm')
```

Out[19]:
```
<Axes: >
```



Logistic Regression

In [20]:
```python
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
```

```python
from sklearn.metrics import classification_report,confusion_matrix, accuracy_score
```

In [21]:

```python
#Let's convert categorical variables to numerical values
from sklearn.preprocessing import LabelEncoder

#Application of the LabelEncoder
le = LabelEncoder()

# encode Country column
df['Geography'] = le.fit_transform(df['Geography'])

# encode Gender column
df['Gender'] = le.fit_transform(df['Gender'])
```

In [22]:

```python
df.head()
```

Out[22]:

	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	Exited
0	619	0	0	42	2	0.00	1	1	1	101348.88	1
1	608	2	0	41	1	83807.86	1	0	1	112542.58	0
2	502	0	0	42	8	159660.80	3	1	0	113931.57	1
3	699	0	0	39	1	0.00	2	0	0	93826.63	0
4	850	2	0	43	2	125510.82	1	1	1	79084.10	0

In [23]:

```python
# Let's define our X and y
# We will drop 'Exited' from our X because it is our target variable

X= df.drop(['Exited'],axis=1)
y= df['Exited']
```

In [24]:

```python
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

In [25]:

```python
logmodel = LogisticRegression(random_state=42)
logmodel.fit(X_train, y_train)
```

Out[25]:

```
▾ LogisticRegression
LogisticRegression(random_state=42)
```

In [26]:

```python
y_pred = logmodel.predict(X_test)
```

In [27]:

```python
accuracy = accuracy_score(y_test, y_pred)

print(f"Accuracy: {accuracy}")
```

```
Accuracy: 0.8005
```

In [28]:

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

```
              precision    recall  f1-score   support

           0       0.81      0.98      0.89      1607
           1       0.45      0.07      0.12       393

    accuracy                           0.80      2000
   macro avg       0.63      0.53      0.51      2000
weighted avg       0.74      0.80      0.74      2000

[[1573   34]
 [ 365   28]]
```

In [ ]:

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