

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from wordcloud import WordCloud
import nltk
import re
nltk.download('stopwords')
from nltk.corpus import stopwords
from nltk.stem.porter import PorterStemmer
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC
from sklearn.naive_bayes import MultinomialNB

[nltk_data] Downloading package stopwords to /root/nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
```

```
df = pd.read_csv('/content/drive/MyDrive/Subway/Churn_Modelling.csv')
```

```
df.columns

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

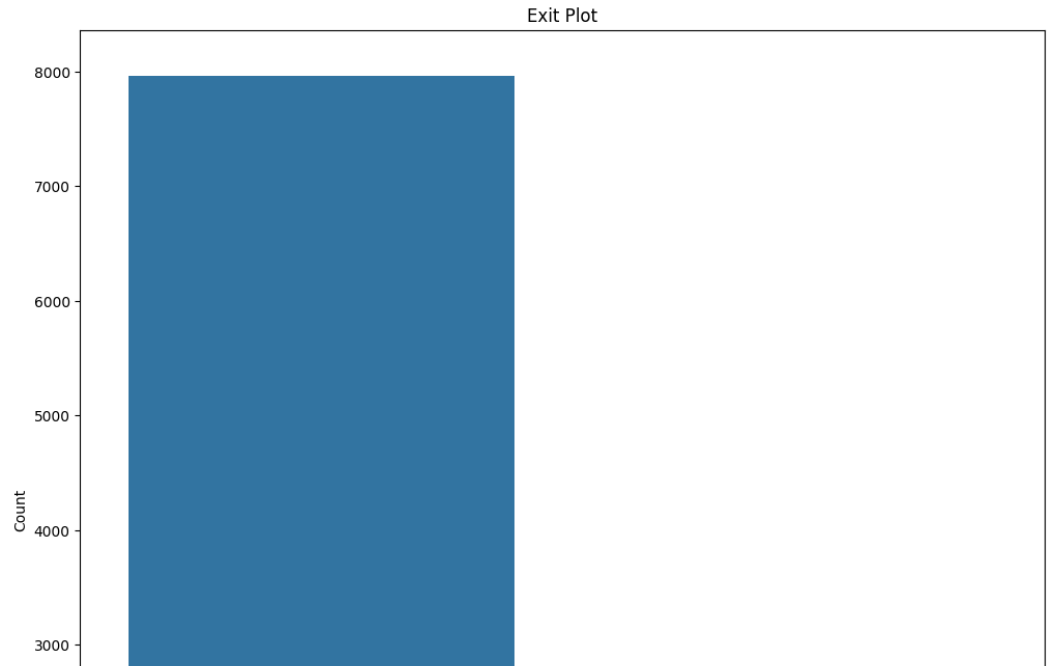
```
df.shape

(10000, 14)
```

```
df.head(5)
```

	RowNumber	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProduct
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	

```
plt.figure(figsize=(12,12))
sns.countplot(x='Exited', data=df)
plt.xlabel('Exits')
plt.ylabel('Count')
plt.title('Exit Plot')
plt.show()
```



```
exits = list(df['Exited'].unique())
exits.sort()
exits
```

[0, 1]



```
df.isna().any()
```

RowNumber	False
CustomerId	False
Surname	False
CreditScore	False
Geography	False
Gender	False
Age	False
Tenure	False
Balance	False
NumOfProducts	False
HasCrCard	False
IsActiveMember	False
EstimatedSalary	False
Exited	False
dtype:	bool

```
df.drop('RowNumber', axis=1, inplace=True)
df.drop('CustomerId', axis=1, inplace=True)
df.drop('Surname', axis=1, inplace=True)
```

```
import pandas as pd
from sklearn.preprocessing import OrdinalEncoder
from sklearn.naive_bayes import CategoricalNB
from sklearn import metrics

data = df
le = OrdinalEncoder()
data[['CreditScore', 'Geography', 'Gender', 'Age', 'Tenure', 'Balance', 'NumOfProducts', 'HasCrCard', 'IsActiveMember', 'EstimatedSalary',
      'CreditScore', 'Geography', 'Gender', 'Age', 'Tenure', 'Balance', 'NumOfProducts', 'HasCrCard', 'IsActiveMember', 'EstimatedSala

Features = ['CreditScore', 'Geography',
            'Gender', 'Age', 'Tenure', 'Balance', 'NumOfProducts', 'HasCrCard',
            'IsActiveMember', 'EstimatedSalary']
X = data[Features]
Y = data['Exited']

clf_nb = CategoricalNB()
clf_nb.fit(X,Y)
```

▼ CategoricalNB

CategoricalNB()

```
from sklearn.ensemble import RandomForestClassifier
clf_rf = RandomForestClassifier(n_estimators=100, random_state=0) # You can adjust n_estimators as needed
clf_rf.fit(X, Y)
```

```
▼ RandomForestClassifier
RandomForestClassifier(random_state=0)
```

```
from sklearn.ensemble import GradientBoostingClassifier
```

```
clf_gb = GradientBoostingClassifier(n_estimators=100, random_state=0) # You can adjust n_estimators as needed
clf_gb.fit(X, Y)
```

```
▼ GradientBoostingClassifier
GradientBoostingClassifier(random_state=0)
```

```
y_pred = clf_nb.predict(X)
print(Y)
print(y_pred)

print("Accuracy : " , metrics.accuracy_score(y_pred,Y) * 100)
```

```
0      1.0
1      0.0
2      1.0
3      0.0
4      0.0
...
9995   0.0
9996   0.0
9997   1.0
9998   1.0
9999   0.0
Name: Exited, Length: 10000, dtype: float64
[0. 0. 1. ... 0. 1. 0.]
Accuracy : 94.22
```

```
y_pred = clf_rf.predict(X)
print(Y)
print(y_pred)

print("Accuracy : " , metrics.accuracy_score(y_pred,Y) * 100)
```

```
0      1.0
1      0.0
2      1.0
3      0.0
4      0.0
...
9995   0.0
9996   0.0
9997   1.0
9998   1.0
9999   0.0
Name: Exited, Length: 10000, dtype: float64
[1. 0. 1. ... 1. 1. 0.]
Accuracy : 100.0
```

```
y_pred = clf_gb.predict(X)
print(Y)
print(y_pred)

print("Accuracy : " , metrics.accuracy_score(y_pred,Y) * 100)
```

```
0      1.0
1      0.0
2      1.0
3      0.0
4      0.0
...
9995   0.0
9996   0.0
9997   1.0
9998   1.0
9999   0.0
Name: Exited, Length: 10000, dtype: float64
[0. 0. 1. ... 0. 0. 0.]
Accuracy : 87.15
```

✓ 0s completed at 18:00

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