


```
import pandas as pd
import numpy as np
import seaborn as sns
```

```
ds = pd.read_csv('Churn_Modelling.csv')
```


```
ds.head()
```




	RowNumber	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure	Balance
0	1	15634602	Hargrave	619	France	Female	42	2	
1	2	15647311	Hill	608	Spain	Female	41	1	8380
2	3	15619304	Onio	502	France	Female	42	8	15966
3	4	15701354	Boni	699	France	Female	39	1	
4	5	15737888	Mitchell	850	Spain	Female	43	2	12551

Next steps:

Generate code with ds


 View recommended plots

```
ds.isna().sum()
```




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

```
ds.shape
```



(10000, 14)

```
ds.info()
```



<class 'pandas.core.frame.DataFrame'>				
RangeIndex: 10000 entries, 0 to 9999				
Data columns (total 14 columns):				
#	Column	Non-Null Count	Dtype	
---	-----	-----	-----	
0	RowNumber	10000 non-null	int64	
1	CustomerId	10000 non-null	int64	
2	Surname	10000 non-null	object	
3	CreditScore	10000 non-null	int64	
4	Geography	10000 non-null	object	
5	Gender	10000 non-null	object	
6	Age	10000 non-null	int64	
7	Tenure	10000 non-null	int64	
8	Balance	10000 non-null	float64	
9	NumOfProducts	10000 non-null	int64	
10	HasCrCard	10000 non-null	int64	
11	IsActiveMember	10000 non-null	int64	
12	EstimatedSalary	10000 non-null	float64	
13	Exited	10000 non-null	int64	
dtypes: float64(2), int64(9), object(3)				
memory usage: 1.1+ MB				

```
ds.describe(include='all')
```

	RowNumber	CustomerId	Surname	CreditScore	Geography	Gender	Age
count	10000.00000	1.000000e+04	10000	10000.000000	10000	10000	10000.0000
unique	NaN	NaN	2932	NaN	3	2	N
top	NaN	NaN	Smith	NaN	France	Male	N
freq	NaN	NaN	32	NaN	5014	5457	N
mean	5000.50000	1.569094e+07	NaN	650.528800	NaN	NaN	38.9218
std	2886.89568	7.193619e+04	NaN	96.653299	NaN	NaN	10.4878
min	1.00000	1.556570e+07	NaN	350.000000	NaN	NaN	18.0000
25%	2500.75000	1.562853e+07	NaN	584.000000	NaN	NaN	32.0000
50%	5000.50000	1.569074e+07	NaN	652.000000	NaN	NaN	37.0000
75%	7500.25000	1.575323e+07	NaN	718.000000	NaN	NaN	44.0000
max	10000.00000	1.581569e+07	NaN	850.000000	NaN	NaN	92.0000

ds.columns

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

ds= ds.drop(columns=['RowNumber', 'CustomerId', 'Surname'])

ds.head()

	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	Exited
0	619	France	Female	42	2	0.00	1	1	1	1503.38	1
1	608	Spain	Female	41	1	83807.86	1	0	0	431604.23	0
2	502	France	Female	42	8	159660.80	3	1	0	330549.59	1
3	699	France	Female	39	1	0.00	2	0	0	0.00	0
4	850	Spain	Female	43	2	125510.82	1	1	1	113562.31	1

Next steps:

[Generate code with ds](#)

[View recommended plots](#)

ds['Geography'].unique()

```
array(['France', 'Spain', 'Germany'], dtype=object)
```

ds['Gender'].unique()

```
array(['Female', 'Male'], dtype=object)
```

ds = pd.get_dummies(ds,columns=["Geography","Gender"],drop_first=True)

ds.head()

	CreditScore	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	Exited
0	619	42	2	0.00	1	1	1	1503.38	1
1	608	41	1	83807.86	1	0	0	431604.23	0
2	502	42	8	159660.80	3	1	0	330549.59	1
3	699	39	1	0.00	2	0	0	0.00	0
4	850	43	2	125510.82	1	1	1	113562.31	1

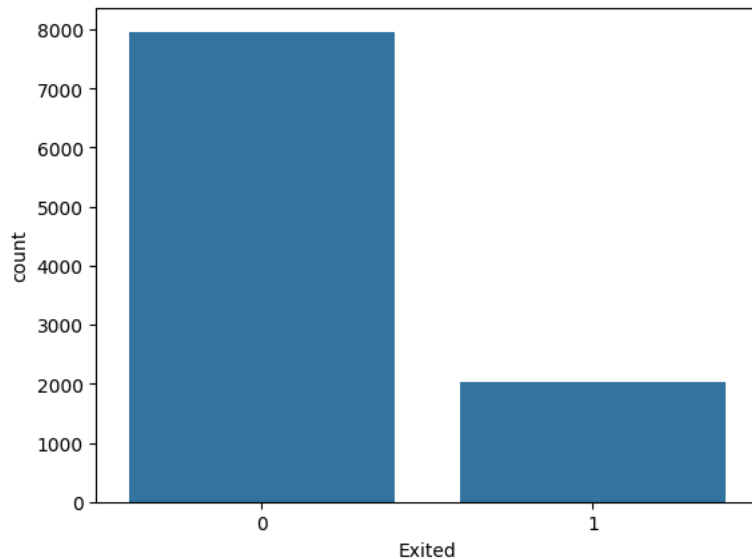
Next steps:

[Generate code with ds](#)

[View recommended plots](#)

sns.countplot(x=ds['Exited']) #dataset is imbalanced

```
<Axes: xlabel='Exited', ylabel='count'>
```



```
X_in = ds.drop('Exited',axis=1)
y_in =ds['Exited']
```

```
y_in.value_counts()
```

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

```
from imblearn.over_sampling import SMOTEN
X,y = SMOTEN().fit_resample(X_in,y_in)
```


```
y.value_counts()
```

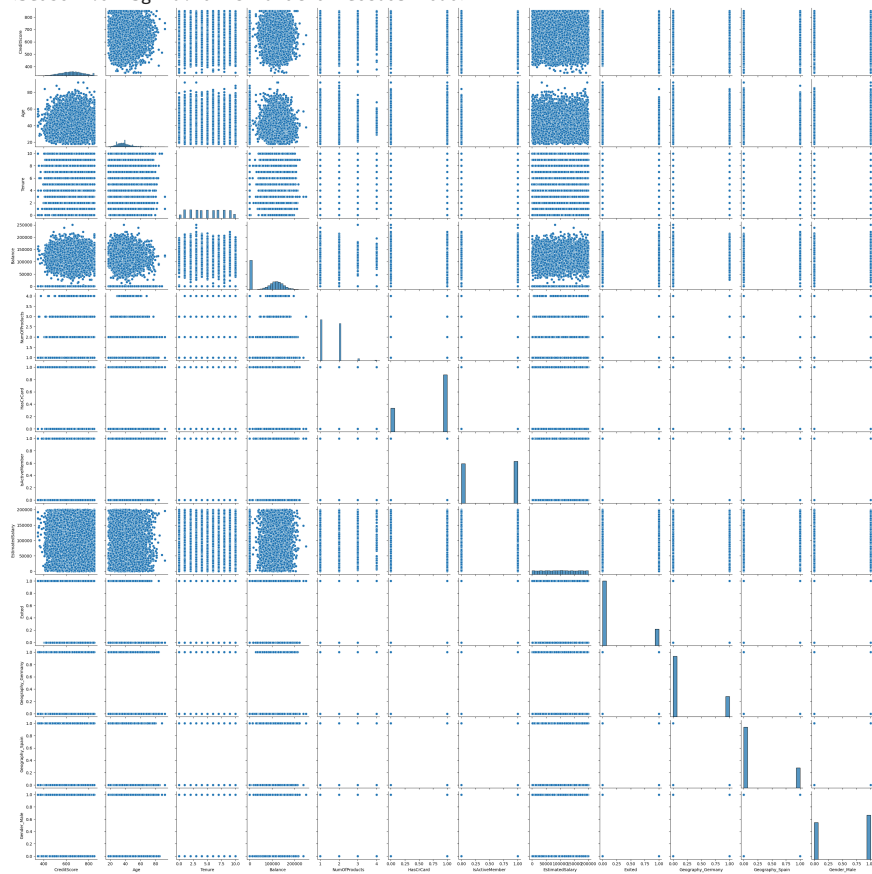
```
Exited
1    7963
0    7963
Name: count, dtype: int64
```

```
ds.corr()
```

	CreditScore	Age	Tenure	Balance	NumOfProducts	HasCrCar
CreditScore	1.000000	-0.003965	0.000842	0.006268	0.012238	-0.005458
Age	-0.003965	1.000000	-0.009997	0.028308	-0.030680	-0.011721
Tenure	0.000842	-0.009997	1.000000	-0.012254	0.013444	0.022583
Balance	0.006268	0.028308	-0.012254	1.000000	-0.304180	-0.014858
NumOfProducts	0.012238	-0.030680	0.013444	-0.304180	1.000000	0.003183
HasCrCard	-0.005458	-0.011721	0.022583	-0.014858	0.003183	1.000000
IsActiveMember	0.025651	0.085472	-0.028362	-0.010084	0.009612	-0.011861
EstimatedSalary	-0.001384	-0.007201	0.007784	0.012797	0.014204	-0.009932
Exited	-0.027094	0.285323	-0.014001	0.118533	-0.047820	-0.007132
Geography_Germany	0.005538	0.046897	-0.000567	0.401110	-0.010419	0.010576
Geography_Spain	0.004780	-0.001685	0.003868	-0.134892	0.009039	-0.013481
Gender_Male	-0.002857	-0.027544	0.014733	0.012087	-0.021859	0.005761

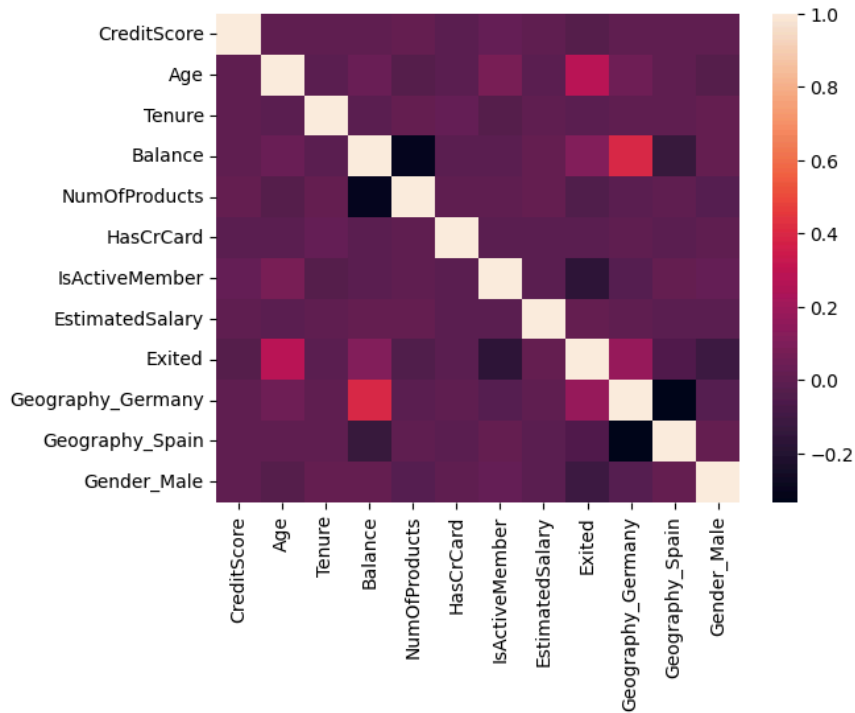
```
sns.pairplot(ds)
```

 <seaborn.axisgrid.PairGrid at 0x7e68da3f70d0>



`sns.heatmap(ds.corr())`

<Axes: >



```
#splitting
from sklearn.model_selection import train_test_split

X_test, X_train, y_test, y_train = train_test_split(X, y, test_size=0.2, random_state=0)
```

```
#Feature Scaling
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)
```

X_train

```
array([[ -1.27858987,  0.32900953,  1.15825177, ...,  1.50588589,
        -0.49892083,  0.99187233],
       [ -0.41459149, -1.15278912,  0.13091599, ...,  1.50588589,
        -0.49892083, -1.00819428],
       [  0.49794612,  0.82294242,  0.81580651, ...,  1.50588589,
        -0.49892083,  0.99187233],
       ...,
       [ -1.10384862, -1.05400255, -1.23886506, ..., -0.66406094,
        -0.49892083, -1.00819428],
       [ -1.12326432,  0.13143638, -1.58131032, ..., -0.66406094,
        -0.49892083, -1.00819428],
       [  0.97363062, -1.2515757 , -0.21152928, ...,  1.50588589,
        -0.49892083,  0.99187233]])
```

```
#Logistic Regression
from sklearn.linear_model import LogisticRegression
lo = LogisticRegression()
lo.fit(X_train,y_train)
```

```
LogisticRegression()
```

```
yp1 = lo.predict(X_test)
```

```
from sklearn.metrics import precision_score, recall_score, accuracy_score, f1_score
from sklearn.metrics import mean_squared_error, mean_absolute_error
```

```

print("LOGISTIC REGRESSION")
print("Accuracy= ",accuracy_score(y_test,yp1))
print("Precision= ",precision_score(y_test,yp1))
print("Recall= ",recall_score(y_test,yp1))
print("F1_Score= ",f1_score(y_test,yp1))
print("MSE= ",mean_squared_error(y_test,yp1))
print("MAE= ",mean_absolute_error(y_test,yp1))

```

LOGISTIC REGRESSION
Accuracy= 0.7827315541601256

```

#Random Forest
from sklearn.ensemble import RandomForestClassifier
rf = RandomForestClassifier()
rf.fit(X_train,y_train)

```

RandomForestClassifier
RandomForestClassifier()

```
yp2 = rf.predict(X_test)
```

```

from sklearn.metrics import precision_score, recall_score, accuracy_score, f1_score
from sklearn.metrics import mean_squared_error, mean_absolute_error

```

```

print("RANDOM FOREST CLASSIFIER")
print("Accuracy= ",accuracy_score(y_test,yp2))
print("Precision= ",precision_score(y_test,yp2))
print("Recall= ",recall_score(y_test,yp2))
print("F1_Score= ",f1_score(y_test,yp2))
print("MSE= ",mean_squared_error(y_test,yp2))
print("MAE= ",mean_absolute_error(y_test,yp2))

```

RANDOM FOREST CLASSIFIER
Accuracy= 0.8793563579277865
Precision= 0.8978583196046128
Recall= 0.8559761269043505
F1_Score= 0.8764171423976843
MSE= 0.1206436420722135
MAE= 0.1206436420722135

```

#Gradient Boosting
from sklearn.ensemble import GradientBoostingClassifier
gb = GradientBoostingClassifier()
gb.fit(X_train,y_train)

```

GradientBoostingClassifier
GradientBoostingClassifier()

```
yp3 = gb.predict(X_test)
```

```

from sklearn.metrics import precision_score, recall_score, accuracy_score, f1_score
from sklearn.metrics import mean_squared_error, mean_absolute_error

```

```

print("GRADIENT BOOSTING")
print("Accuracy= ",accuracy_score(y_test,yp3))
print("Precision= ",precision_score(y_test,yp3))
print("Recall= ",recall_score(y_test,yp3))
print("F1_Score= ",f1_score(y_test,yp3))
print("MSE= ",mean_squared_error(y_test,yp3))
print("MAE= ",mean_absolute_error(y_test,yp3))

```

GRADIENT BOOSTING