

# Logistic Regression on Bank churn dataset.

In [1]: *#importing the Libraries*

```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
```

In [2]: *# Lets Load the dataset*

```
bank_data = pd.read_csv("G:/dataset files/Bank_churn_modelling.csv")
```

In [3]: *#viewing the data using head by which we can see the top 5 rows.*

```
bank_data.head()
```

Out[3]:

	RowNumber	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure	Balan
0	1	15634602	Hargrave	619	France	Female	42	2	0.
1	2	15647311	Hill	608	Spain	Female	41	1	83807.
2	3	15619304	Onio	502	France	Female	42	8	159660.
3	4	15701354	Boni	699	France	Female	39	1	0.
4	5	15737888	Mitchell	850	Spain	Female	43	2	125510.

In [4]: *# to see the columns in dataset*

```
bank_data.columns
```

Out[4]: Index(['RowNumber', 'CustomerId', 'Surname', 'CreditScore', 'Geography', 'Gender', 'Age', 'Tenure', 'Balance', 'NumOfProducts', 'HasCrCard', 'IsActiveMember', 'EstimatedSalary', 'Exited'], dtype='object')

In [5]: *# Lets check the datatypes for each columns*

```
bank_data.dtypes
```

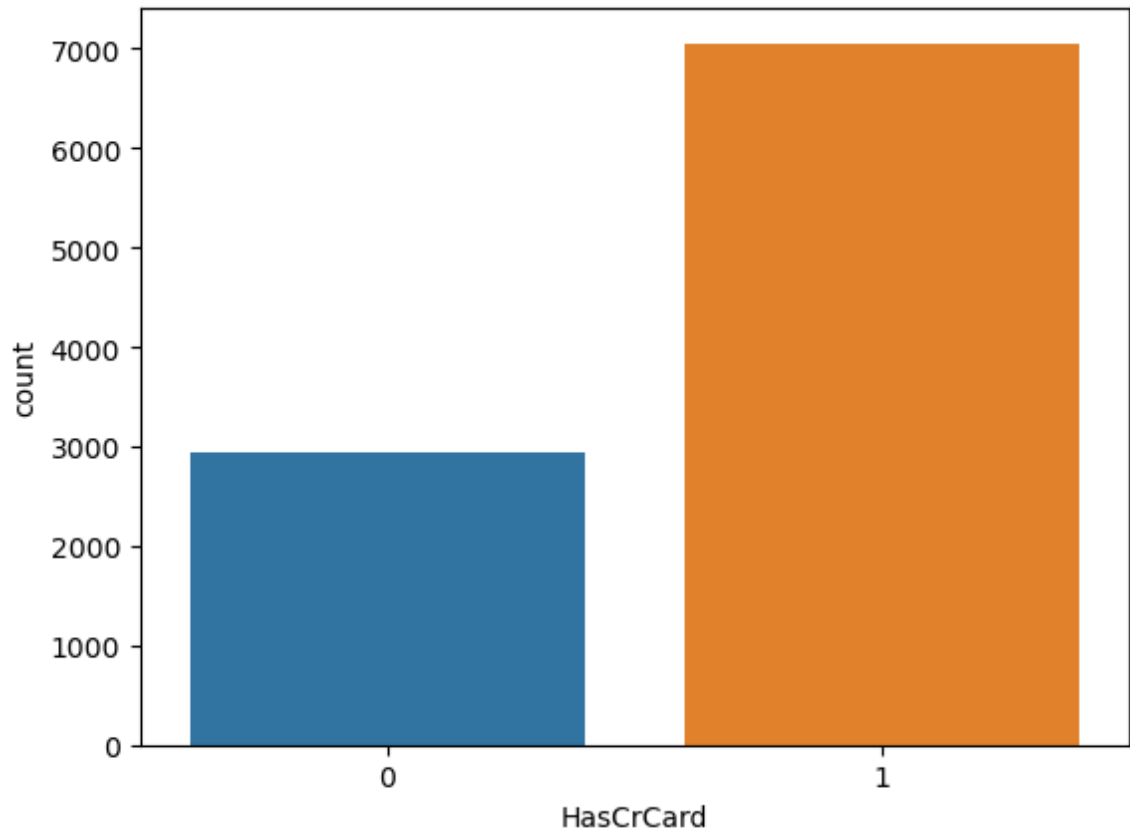
Out[5]:

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

# DATA ANALYSIS

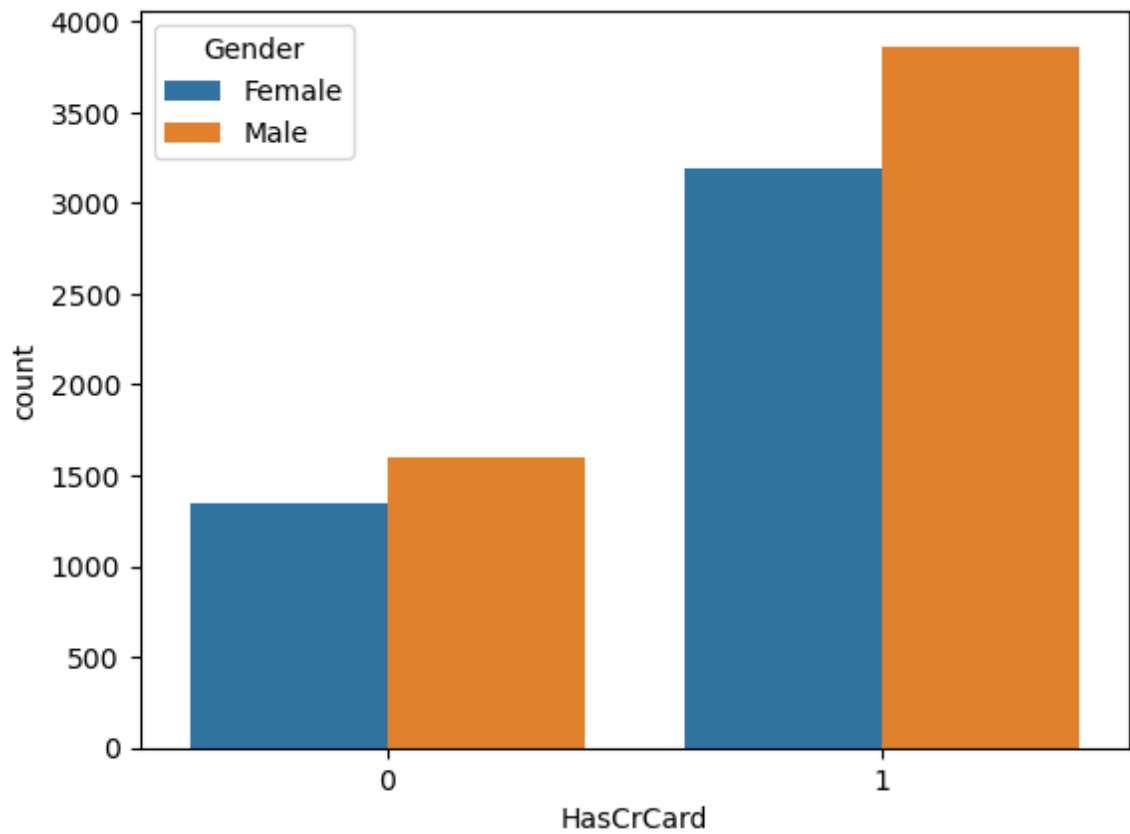
```
In [6]: # plotting between having Creditcard Vs not having credit card Customers

sns.countplot(x='HasCrCard', data = bank_data )
plt.show()
```



```
In [7]: # Male Vs Female customers
```

```
In [8]: sns.countplot(x='HasCrCard', data = bank_data, hue='Gender')
plt.show()
```



In [9]: *# checking the null values*

```
bank_data.isnull().sum()
```

Out[9]:

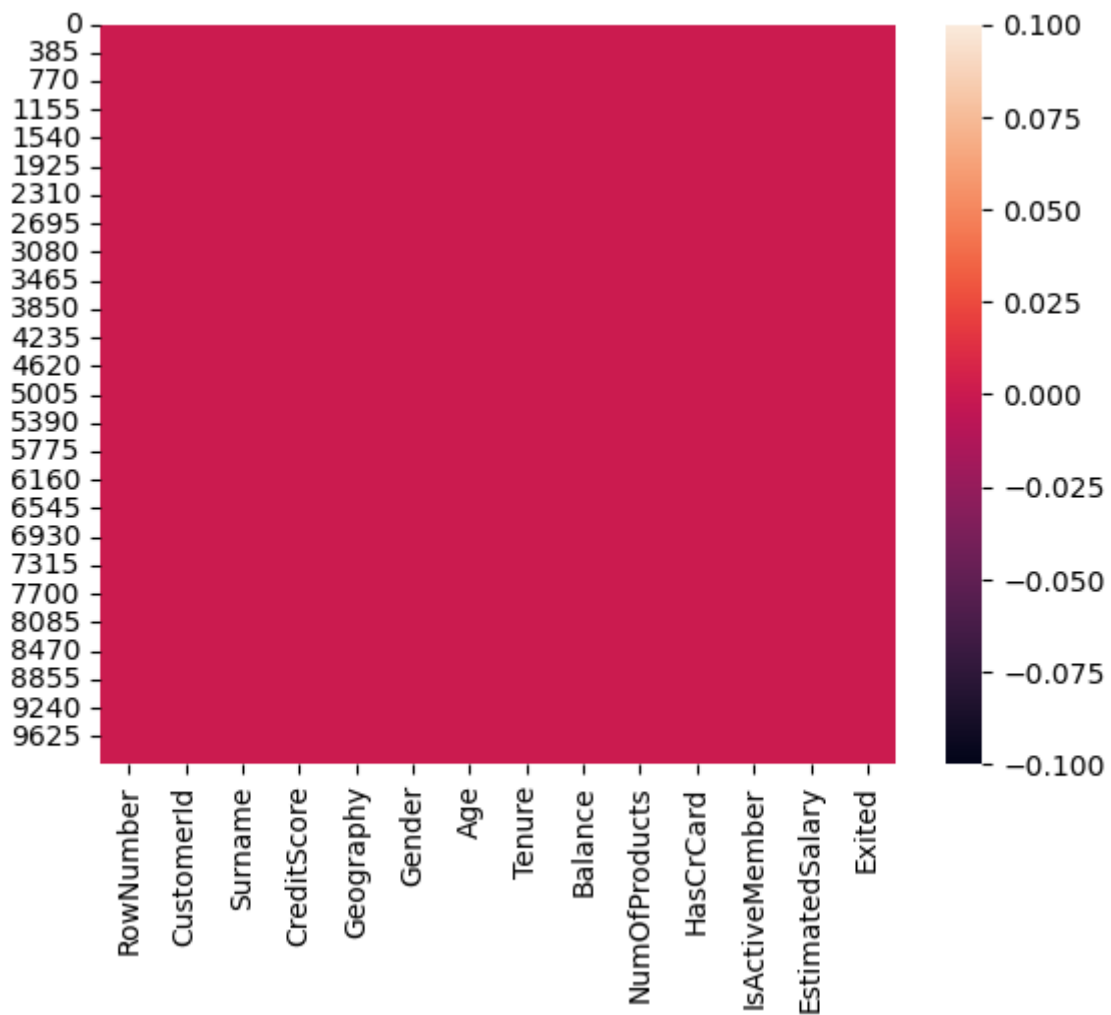
RowNumber	0
CustomerId	0
Surname	0
CreditScore	0
Geography	0
Gender	0
Age	0
Tenure	0
Balance	0
NumOfProducts	0
HasCrCard	0
IsActiveMember	0
EstimatedSalary	0
Exited	0

dtype: int64

In [10]: *#visualization for Null Values*

```
sns.heatmap(bank_data.isnull())
```

Out[10]: <Axes: >



```
In [11]: # conclusion: there is no null values in our dataset
```

## DATA CLEANING

```
In [12]: # lets check for the non numerical columns  
bank_data.dtypes
```

```
Out[12]: 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 [13]: # we can see Geography and Gender are non numerical columns.  
# It seems that there is no need for Geography column for further predictions.
```

```
In [14]: # Now the column Gender we are going to make non-numerical to numerical category
```

```
In [15]: # Lets convert the Gender column into numerical values.
```

```
gender = pd.get_dummies(bank_data['Gender'], drop_first=True)
bank_data['Gender'] = gender
```

```
In [16]: bank_data.head()
```

```
Out[16]:
```

	RowNumber	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure	Balan
0	1	15634602	Hargrave	619	France	0	42	2	0.
1	2	15647311	Hill	608	Spain	0	41	1	83807.
2	3	15619304	Onio	502	France	0	42	8	159660.
3	4	15701354	Boni	699	France	0	39	1	0.
4	5	15737888	Mitchell	850	Spain	0	43	2	125510.

```
In [17]: # Lets drop some unwanted columns from our dataset.
```

```
bank_data=bank_data.drop(['Surname'],axis=1)
bank_data.head()
```

```
Out[17]:
```

	RowNumber	CustomerId	CreditScore	Geography	Gender	Age	Tenure	Balance	NumO
0	1	15634602	619	France	0	42	2	0.00	
1	2	15647311	608	Spain	0	41	1	83807.86	
2	3	15619304	502	France	0	42	8	159660.80	
3	4	15701354	699	France	0	39	1	0.00	
4	5	15737888	850	Spain	0	43	2	125510.82	

```
In [18]: # separate the dependent variable and non dependent variable
```

```
In [19]: x=bank_data[['RowNumber','CustomerId','CreditScore','Gender','Age','Tenure','Bal
            'NumOfProducts','HasCrCard','IsActiveMember','EstimatedSalary']]
y=bank_data[['Exited']]]
```

## DATA MODELLING

### building model using logistic regression

```
In [20]: # importing Train test function
```

```
from sklearn.model_selection import train_test_split
```

```
In [30]: xtrain, xtest, ytrain, ytest = train_test_split(x, y, train_size=0.8)
```

In [31]: `# importing Logistic regression`

```
from sklearn.linear_model import LogisticRegression
```

In [32]: `model=LogisticRegression()`

In [33]: `model.fit(xtrain, ytrain)`

C:\Users\LENOVO\anaconda3\lib\site-packages\sklearn\utils\validation.py:1143: DataConversionWarning: A column-vector y was passed when a 1d array was expected. Please change the shape of y to (n\_samples, ), for example using ravel().  
y = column\_or\_1d(y, warn=True)

Out[33]: `▼ LogisticRegression`  
`LogisticRegression()`

In [34]: `# Lets predict`

```
predict = model.predict(xtest)
```

In [35]: `predict`

Out[35]: `array([0, 0, 0, ..., 0, 0, 0], dtype=int64)`

In [ ]: `# TESTING`  
`# To see how our model is performing`

In [51]: `from sklearn.metrics import classification_report`

In [52]: `print(classification_report(ytest, predict))`

	precision	recall	f1-score	support
0	0.78	1.00	0.88	1562
1	0.00	0.00	0.00	438
accuracy			0.78	2000
macro avg	0.39	0.50	0.44	2000
weighted avg	0.61	0.78	0.68	2000

C:\Users\LENOVO\anaconda3\lib\site-packages\sklearn\metrics\\_classification.py:1344: UndefinedMetricWarning: Precision and F-score are ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero\_division` parameter to control this behavior.

```
_warn_prf(average, modifier, msg_start, len(result))
```

C:\Users\LENOVO\anaconda3\lib\site-packages\sklearn\metrics\\_classification.py:1344: UndefinedMetricWarning: Precision and F-score are ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero\_division` parameter to control this behavior.

```
_warn_prf(average, modifier, msg_start, len(result))
```

C:\Users\LENOVO\anaconda3\lib\site-packages\sklearn\metrics\\_classification.py:1344: UndefinedMetricWarning: Precision and F-score are ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero\_division` parameter to control this behavior.

```
_warn_prf(average, modifier, msg_start, len(result))
```

In [ ]: `# thanks....`