Assignment-II

Fertilizer recommendation system for disease prediction

Date	5 September 2022
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Maximum marks	2 marks

```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import numpy as np
sns.set_style('darkgrid')
sns.set(font_scale=1.3)

df=pd.read_csv("/content/drive/MyDrive/IBM/Assignment - 2
/Churn_Modelling.csv")

df.head()

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

   Tenure    Balance  NumOfProducts  HasCrCard  IsActiveMember  \
0       2       0.00              1          1               1
1       1   83807.86              1          0               1
2       8  159660.80              3          1               0
3       1       0.00              2          0               0
4       2  125510.82              1          1               1
```

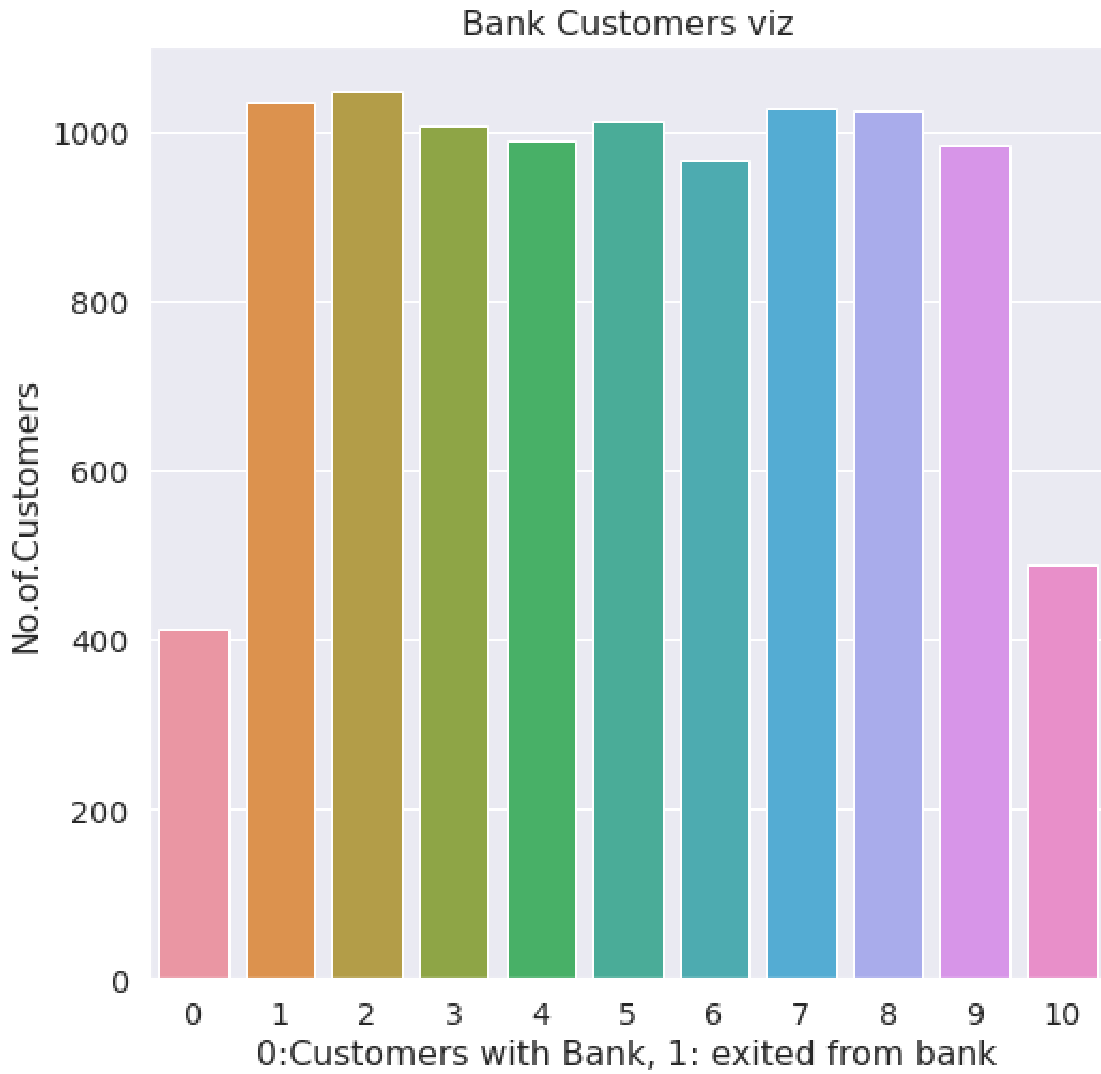
```
   EstimatedSalary  Exited
0        101348.88       1
1        112542.58       0
2        113931.57       1
3         93826.63       0
4         79084.10       0
```

```
df.drop(["RowNumber","CustomerId","Surname"],axis=1,inplace=True)
```

```
df.info()
```

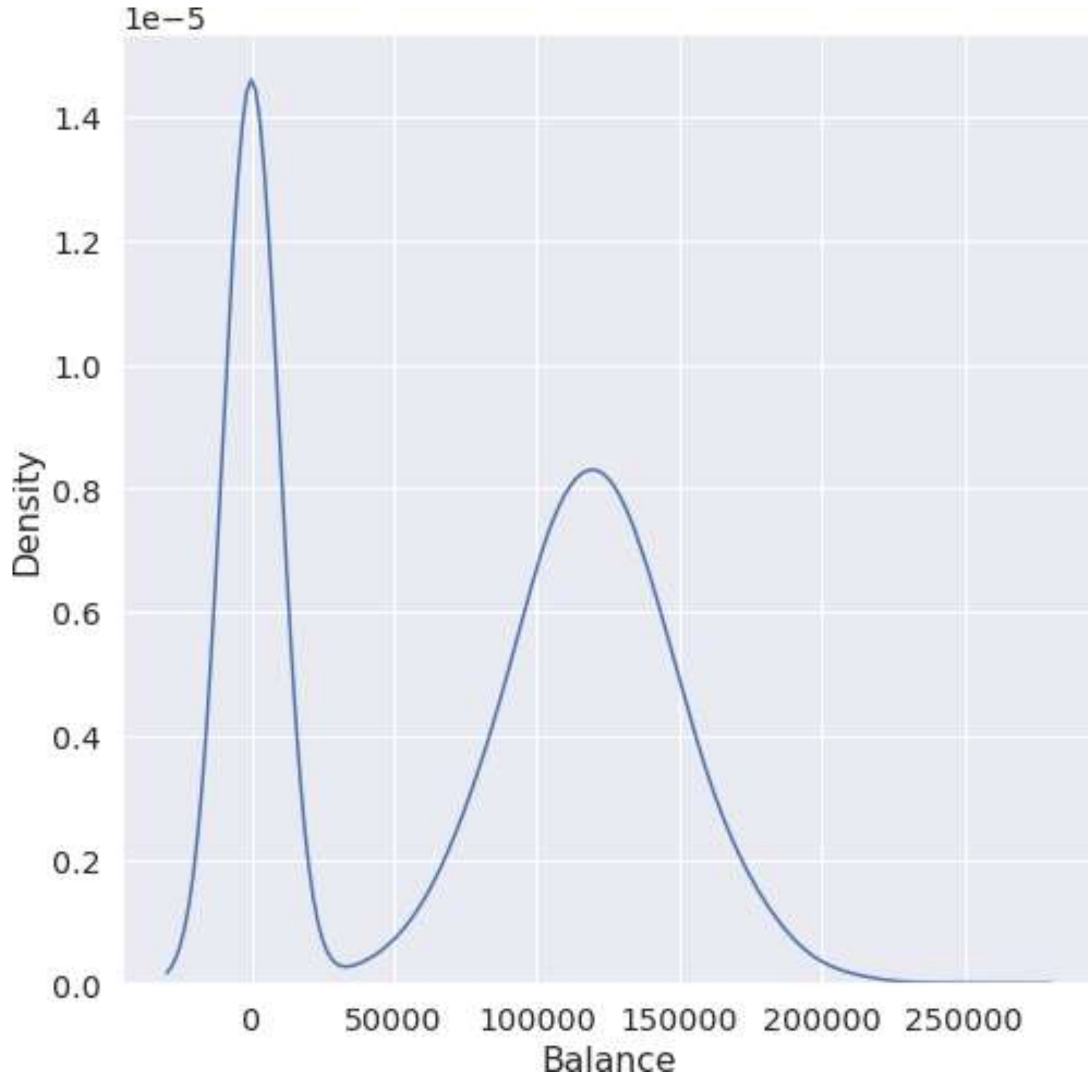
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 11 columns):
 #   Column           Non-Null Count  Dtype
---  ----------       --------------  -----
 0   CreditScore      10000 non-null  int64
 1   Geography        10000 non-null  object
 2   Gender           10000 non-null  object
 3   Age              10000 non-null  int64
 4   Tenure           10000 non-null  int64
 5   Balance          10000 non-null  float64
 6   NumOfProducts    10000 non-null  int64
 7   HasCrCard        10000 non-null  int64
 8   IsActiveMember   10000 non-null  int64
 9   EstimatedSalary  10000 non-null  float64
 10  Exited           10000 non-null int64
dtypes: float64(2), int64(7), object(2)
memory usage: 859.5+ KB
```

```
#Perform Univariate Analysis
plt.figure(figsize=(8,8))
sns.countplot(x='Tenure',data=df)
plt.xlabel('0:Customers with Bank, 1: exited from bank')
plt.ylabel('No.of.Customers')
plt.title("Bank Customers viz")
plt.show()
```



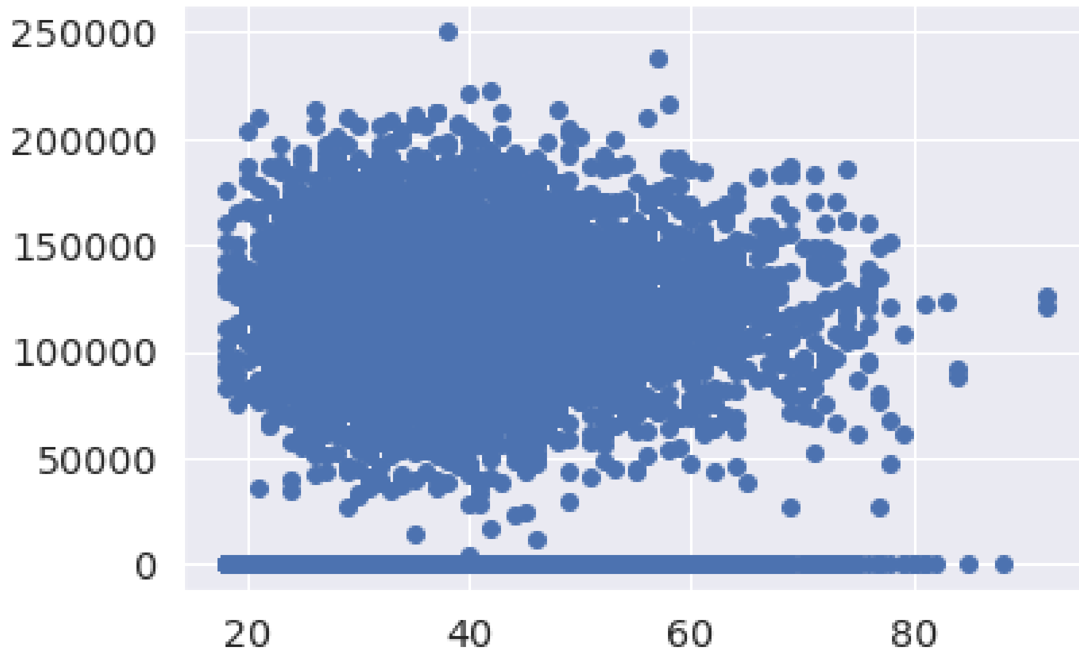

```
#Perform Univariate Analysis
plt.figure(figsize=(8,8))
sns.kdeplot(x=df['Balance'])
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fa0c03906d0>
```




```
#Perform Bivariate Analysis
plt.scatter(df.Age,df.Balance)
```

```
<matplotlib.collections.PathCollection at 0x7fa0d35a7dd0>
```




```python
#Perform Bivariate Analysis
df.corr()
```

```
                 CreditScore    Gender       Age    Tenure   Balance  \
CreditScore         1.000000  0.007888 -0.003965  0.000842  0.006268
Gender              0.007888  1.000000  0.022812  0.003739  0.069408
Age                -0.003965  0.022812  1.000000 -0.009997  0.028308
Tenure              0.000842  0.003739 -0.009997  1.000000 -0.012254
Balance             0.006268  0.069408  0.028308 -0.012254  1.000000
NumOfProducts       0.012238  0.003972 -0.030680  0.013444 -0.304180
HasCrCard          -0.005458 -0.008523 -0.011721  0.022583 -0.014858
IsActiveMember      0.025651  0.006724  0.085472 -0.028362 -0.010084
EstimatedSalary    -0.001384 -0.001369 -0.007201  0.007784  0.012797
Exited             -0.027094  0.035943  0.285323 -0.014001  0.118533

                 NumOfProducts  HasCrCard  IsActiveMember  EstimatedSalary  \
CreditScore           0.012238  -0.005458        0.025651        -0.001384
Gender                0.003972  -0.008523        0.006724        -0.001369
Age                  -0.030680  -0.011721        0.085472        -0.007201
Tenure                0.013444   0.022583       -0.028362         0.007784
Balance              -0.304180  -0.014858       -0.010084         0.012797
NumOfProducts         1.000000   0.003183        0.009612         0.014204
HasCrCard             0.003183   1.000000       -0.011866        -0.009933
IsActiveMember        0.009612  -0.011866        1.000000        -0.011421
EstimatedSalary       0.014204  -0.009933       -0.011421         1.000000
Exited               -0.047820  -0.007138       -0.156128         0.012097

                   Exited
CreditScore     -0.027094
```

```
Gender            0.035943
Age               0.285323
Tenure           -0.014001
Balance           0.118533
NumOfProducts    -0.047820
HasCrCard        -0.007138
IsActiveMember   -0.156128
EstimatedSalary   0.012097
Exited            1.000000
```

```
#Perform Bivariate Analysis
import statsmodels.api as sm

#define response variable
y = df['CreditScore']

#define explanatory variable
x = df[['EstimatedSalary']]

#add constant to predictor variables
x = sm.add_constant(x)

#fit linear regression model
model = sm.OLS(y, x).fit()

#view model summary
print(model.summary())
```

```
                            OLS Regression Results
==============================================================================
=
Dep. Variable:            CreditScore   R-squared:
0.000
Model:                            OLS   Adj. R-squared:                 -
0.000
Method:                 Least Squares   F-statistic:
0.01916
Date:                Sat, 24 Sep 2022   Prob (F-statistic):
0.890
Time:                        05:06:19   Log-Likelihood:                -
59900.
No. Observations:               10000   AIC:
1.198e+05
Df Residuals:                    9998   BIC:
1.198e+05
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
======
                      coef    std err          t      P>|t|      [0.025
```

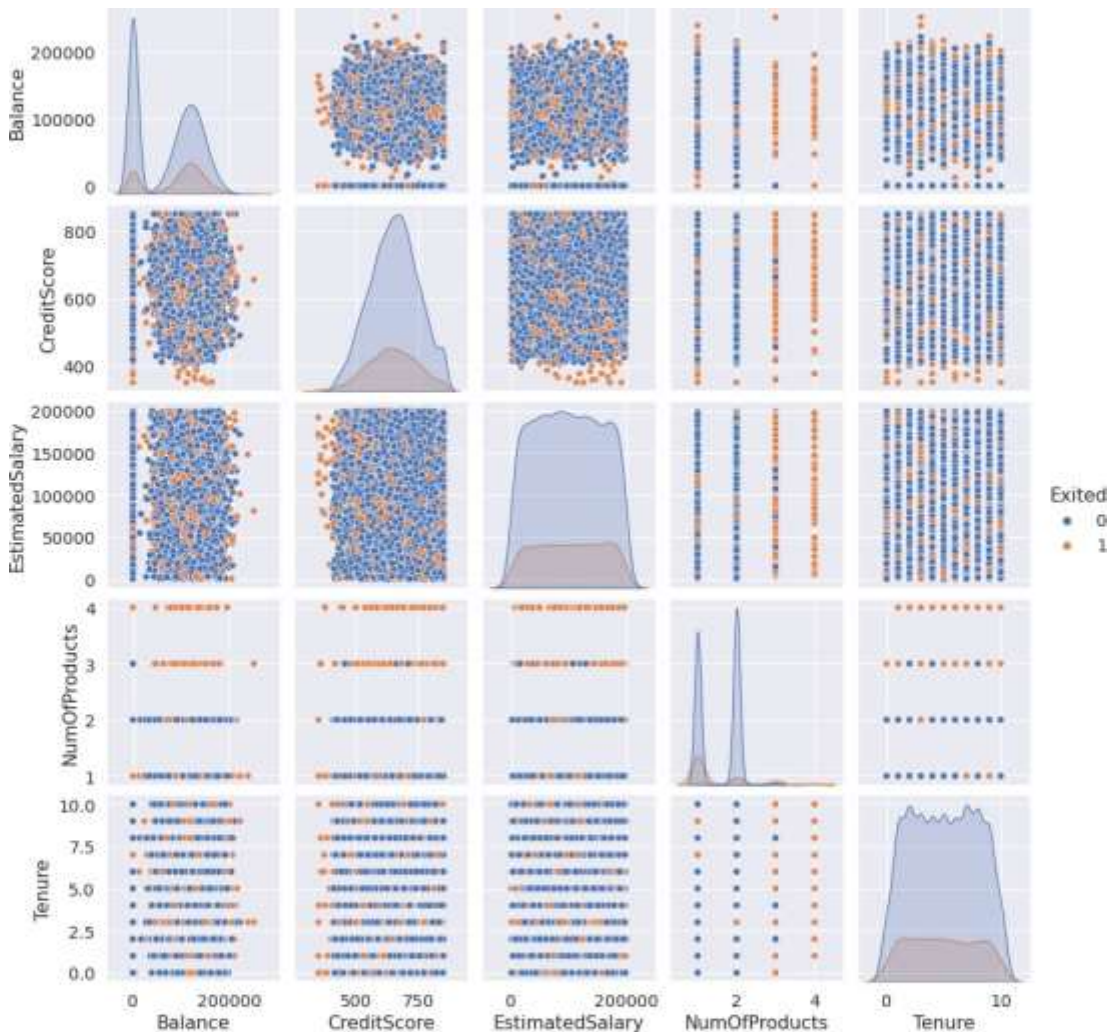
```
0.975]
------------------------------------------------------------------------------------------
------
const             650.7617      1.940    335.407      0.000     646.958
654.565
EstimatedSalary -2.326e-06   1.68e-05     -0.138      0.890   -3.53e-05
3.06e-05
==============================================================================
=
Omnibus:                      132.939   Durbin-Watson:
2.014
Prob(Omnibus):                  0.000   Jarque-Bera (JB):
84.242
Skew:                          -0.072   Prob(JB):                      5.10e-
19
Kurtosis:                       2.574   Cond. No.
2.32e+05
==============================================================================
=

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is
correctly specified.
[2] The condition number is large, 2.32e+05. This might indicate that there
are
strong multicollinearity or other numerical problems.
```

```
/usr/local/lib/python3.7/dist-packages/statsmodels/tsa/tsatools.py:142:
FutureWarning: In a future version of pandas all arguments of concat except
for the argument 'objs' will be keyword-only
  x = pd.concat(x[::order], 1)
```

```
#Perform Multivariate Analysis
plt.figure(figsize=(4,4))
sns.pairplot(data=df[["Balance","CreditScore","EstimatedSalary","NumOfProduct
s","Tenure","Exited"]],hue="Exited")
```

```
<seaborn.axisgrid.PairGrid at 0x7fa0b00a1b10>
```

```
<Figure size 288x288 with 0 Axes>
```




```python
#Perform Descriptive Statistics
df=pd.DataFrame(df)
print(df.sum())
```

```
CreditScore                                                  6505288
Geography          FranceSpainFranceFranceSpainSpainFranceGermany...
Gender             FemaleFemaleFemaleFemaleFemaleMaleMaleFemaleMa...
Age                                                           389218
Tenure                                                         50128
Balance                                                 764858892.88
NumOfProducts                                                  15302
HasCrCard                                                       7055
IsActiveMember                                                  5151
EstimatedSalary                                        1000902398.81
Exited                                                          2037
dtype: object
```

```python
#Perform Descriptive Statistics
print("----Sum Value ---- ")
```

```
print(df.sum(1))
print("--------------------------------------------------")
print("-----Product Value ---- ")
print(df.prod())
print("-------------------------------------------------- ")

----Sum Value-----
0       102015.88
1       197002.44
2       274149.37
3        94567.63
4       205492.92
          ...
9995     97088.64
9996    159633.38
9997     42840.58
9998    168784.83
9999    169159.57
Length: 10000, dtype: float64
--------------------------------------------------
-----Product Value-----
CreditScore        0.0
Age                0.0
Tenure             0.0
Balance            0.0
NumOfProducts      0.0
HasCrCard          0.0
IsActiveMember     0.0
EstimatedSalary    inf
Exited             0.0
dtype: float64
--------------------------------------------------

/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:3:
FutureWarning: Dropping of nuisance columns in DataFrame reductions (with
'numeric_only=None') is deprecated; in a future version this will raise
TypeError.  Select only valid columns before calling the reduction.
  This is separate from the ipykernel package so we can avoid doing imports
until
/usr/local/lib/python3.7/dist-packages/numpy/core/_methods.py:52:
RuntimeWarning: overflow encountered in reduce
  return umr_prod(a, axis, dtype, out, keepdims, initial, where)
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:6:
FutureWarning: Dropping of nuisance columns in DataFrame reductions (with
'numeric_only=None') is deprecated; in a future version this will raise
TypeError.  Select only valid columns before calling the reduction.


#Perform Descriptive Statistics
print("---------------Mean Value----------------")
```

```
print(df.mean())
print("---------------------------------------------------")
print("----------Median Value -------- ")
print(df.median())
print("---------------------------------------------------")
print("-------------Mode Value ----------- ")
print(df.mode())
print("---------------------------------------------------")
```

```
----------------Mean Value-----------------
CreditScore                 [illegible]
Age                    38.921800
Tenure                  5.012800
Balance             76485.889288
NumOfProducts           1.530200
HasCrCard               0.705500
IsActiveMember          0.515100
EstimatedSalary    100090.239881
Exited                  0.203700
dtype: float64
-----------------------------------------------
----------------Median Value--------------
CreditScore           652.000
Age                    37.000
Tenure                  5.000
Balance             97198.540
NumOfProducts           1.000
HasCrCard               1.000
IsActiveMember          1.000
EstimatedSalary    100193.915
Exited                  0.000
dtype: float64
-----------------------------------------------
----------------Mode Value-------------------
   CreditScore Geography Gender  Age  Tenure  Balance  NumOfProducts  \
0          850    France   Male   37       2      0.0              1

   HasCrCard  IsActiveMember  EstimatedSalary  Exited
0          1               1         24924.92       0
-----------------------------------------------

/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:3:
FutureWarning: Dropping of nuisance columns in DataFrame reductions (with
'numeric_only=None') is deprecated; in a future version this will raise
TypeError.  Select only valid columns before calling the reduction.
  This is separate from the ipykernel package so we can avoid doing imports
until
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:6:
FutureWarning: Dropping of nuisance columns in DataFrame reductions (with
'numeric_only=None') is deprecated; in a future version this will raise
```

```
TypeError.  Select only valid columns before calling the reduction.
```

```
#Handling with missing Values
df.isnull()#Checking values are null
```

```
      CreditScore  Geography  Gender    Age  Tenure  Balance  NumOfProducts  \
0           False      False   False  False   False    False          False
1           False      False   False  False   False    False          False
2           False      False   False  False   False    False          False
3           False      False   False  False   False    False          False
4           False      False   False  False   False    False          False
...           ...        ...     ...    ...     ...      ...            ...
9995        False      False   False  False   False    False          False
9996        False      False   False  False   False    False          False
9997        False      False   False  False   False    False          False
9998        False      False   False  False   False    False          False
9999        False      False   False  False   False    False          False

      HasCrCard  IsActiveMember  EstimatedSalary  Exited
0         False           False            False   False
1         False           False            False   False
2         False           False            False   False
3         False           False            False   False
4         False           False            False   False
...         ...             ...              ...     ...
9995      False           False            False   False
9996      False           False            False   False
9997      False           False            False   False
9998      False           False            False   False
9999      False           False            False   False

[10000 rows x 11 columns]
```

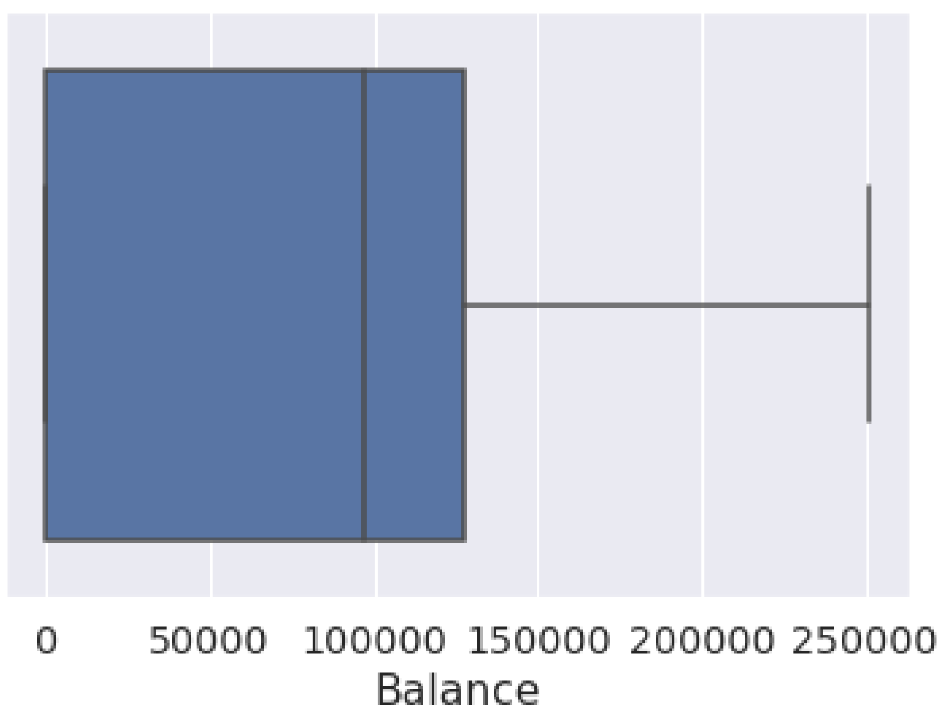
```
#Handling with missing Values
df.notnull()#Checking values are not null
```

```
      CreditScore  Geography  Gender   Age  Tenure  Balance  NumOfProducts  \
0            True       True    True  True    True     True           True
1            True       True    True  True    True     True           True
2            True       True    True  True    True     True           True
3            True       True    True  True    True     True           True
4            True       True    True  True    True     True           True
...           ...        ...     ...   ...     ...      ...            ...
9995         True       True    True  True    True     True           True
9996         True       True    True  True    True     True           True
9997         True       True    True  True    True     True           True
9998         True       True    True  True    True     True           True
9999         True       True    True  True    True     True           True
```

```
      HasCrCard  IsActiveMember  EstimatedSalary  Exited
0          True            True             True    True
1          True            True             True    True
2          True            True             True    True
3          True            True             True    True
4          True            True             True    True
...         ...             ...              ...     ...
9995       True            True             True    True
9996       True            True             True    True
9997       True            True             True    True
9998       True            True             True    True
9999       True            True             True    True

[10000 rows x 11 columns]
```

```python
#Find outliers & replace the outliers
sns.boxplot(df['Balance'])
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43:
FutureWarning: Pass the following variable as a keyword arg: x. From version
0.12, the only valid positional argument will be `data`, and passing other
arguments without an explicit keyword will result in an error or
misinterpretation.
  FutureWarning

<matplotlib.axes._subplots.AxesSubplot at 0x7fa0af6dcf90>
```



```
#Find outliers & replace the outliers
print(np.where(df['Balance']>100000))
```

```
(array([   2,    4,    5, ..., 9987, 9993, 9999]),)
```

```
#Find outliers & replace the outliers
from scipy import stats
import numpy as np

z = np.abs(stats.zscore(df["EstimatedSalary"]))
print(z)
```

```
0       0.021886
1       0.216534
2       0.240687
3       0.108918
4       0.365276
          ...
9995    0.066419
9996    0.027988
9997    1.008643
9998    0.125231
9999    1.076370
Name: EstimatedSalary, Length: 10000, dtype: float64
```

```
#Check for categorical columns & performs encoding
from sklearn.preprocessing import LabelEncoder
df['Gender'].unique()
```

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

```
#Check for categorical columns & performs encoding
df['Gender'].value_counts()
```

```
Male      5457
Female    4543
Name: Gender, dtype: int64
```

```
#Check for categorical columns & performs encoding
encoding=LabelEncoder()
df["Gender"]=encoding.fit_transform(df.iloc[:,1].values)
df
```

```
      CreditScore Geography  Gender  Age  Tenure    Balance  NumOfProducts  \
0             619    France       0   42       2       0.00              1
1             608     Spain       2   41       1   83807.86              1
2             502    France       0   42       8  159660.80              3
3             699    France       0   39       1       0.00              2
4             850     Spain       2   43       2  125510.82              1
...           ...       ...     ...  ...     ...        ...            ...
9995          771    France       0   39       5       0.00              2
9996          516    France       0   35      10   57369.61              1
```

```
9997          709    France       0   36       7       0.00            1
9998          772   Germany       1   42       3   75075.31            2
9999          792    France       0   28       4  130142.79            1

      HasCrCard  IsActiveMember  EstimatedSalary  Exited
0             1               1        101348.88       1
1             0               1        112542.58       0
2             1               0        113931.57       1
3             0               0         93826.63       0
4             1               1         79084.10       0
...         ...             ...              ...     ...
9995          1               0         96270.64       0
9996          1               1        101699.77       0
9997          0               1         42085.58       1
9998          1               0         92888.52       1
9999          1               0         38190.78       0

[10000 rows x 11 columns]
```

```python
#Check for categorical columns & performs encoding

#Split the data into Dependent & Independent Variables
print("----------Dependent Variables ---------")
X=df.iloc[:,1:4]
print(X)
print("----------------------------------------")
print("---------Independent Variables --------")
Y=df.iloc[:,4]
print(Y)
print("----------------------------------------")
```

```
----------Dependent Variables---------
      Age  Tenure    Balance
0      42       2       0.00
1      41       1   83807.86
2      42       8  159660.80
3      39       1       0.00
4      43       2  125510.82
...   ...     ...        ...
9995   39       5       0.00
9996   35      10   57369.61
9997   36       7       0.00
9998   42       3   75075.31
9999   28       4  130142.79

[10000 rows x 3 columns]
----------------------------------------
---------Independent Variables---------
0        1
1        1
```

```
2       3
3       2
4       1
       ..
9995    2
9996    1
9997    1
9998    2
9999    1
Name: NumOfProducts, Length: 10000, dtype: int64
------------------------------------------------
```

```
#Scale the independent Variables
from sklearn.preprocessing import StandardScaler
object= StandardScaler()
# standardization
scale = object.fit_transform(df)
print(scale)
```

```
[[-0.32622142  0.29351742 -1.04175968 ...  0.97024255  0.02188649
   1.97716468]
 [-0.44003595  0.19816383 -1.38753759 ...  0.97024255  0.21653375
  -0.50577476]
 [-1.53679418  0.29351742  1.03290776 ... -1.03067011  0.2406869
   1.97716468]
 ...
 [ 0.60498839 -0.27860412  0.68712986 ...  0.97024255 -1.00864308
   1.97716468]
 [ 1.25683526  0.29351742 -0.69598177 ... -1.03067011 -0.12523071
   1.97716468]
 [ 1.46377078 -1.04143285 -0.35020386 ... -1.03067011 -1.07636976
  -0.50577476]]
```

```
#Split the data into training & testing
from sklearn.model_selection import train_test_split
```

```
#Split the data into training & testing
x_train, x_test, y_train, y_test = train_test_split(x, y,
test_size=4,random_state=4)
x_train
```

```
      const  EstimatedSalary
2558    1.0        137903.54
7642    1.0        121765.00
8912    1.0        109470.34
3319    1.0          2923.61
6852    1.0          7312.25
...     ...              ...
456     1.0          7666.73
6017    1.0          9085.00
709     1.0        147794.63
```

```
8366    1.0        102515.42
1146    1.0         54776.64

[9996 rows x 2 columns]
```

```
#Split the data into training & testing
x_test
```

```
      const  EstimatedSalary
1603    1.0         23305.85
8713    1.0         41248.80
4561    1.0        143317.42
6600    1.0        174123.16
```

```
#Split the data into training & testing
y_train
```

```
2558    727
7642    811
8912    623
3319    430
6852    600
       ...
456     733
6017    487
709     686
8366    637
1146    614
Name: CreditScore, Length: 9996, dtype: int64
```

```
#Split the data into training & testing
y_test
```

```
1603    576
8713    786
4561    562
6600    505
Name: CreditScore, dtype: int64
```