### UNIVERSITY ADMIT ELIGIBILITY PREDICTOR

## **ASSIGNMENT - 2**

| Date          | 26th September 2022                    |
|---------------|--|
| Team ID       | PNT2022TMID27839                       |
| Student Name  | Prem B (311519104047)                  |
| Domain Name   | Education                              |
| Project Name  | University Admit Eligibility Predictor |
| Maximum Marks | 2 Marks                                |

## 1.) IMPORT THE REQUIRED LIBRARIES

```
In [1]:
    import pandas as pd
    import numpy as np
    import matplotlib.pyplot as plt
    import seaborn as sns
```

## 2.)DOWNLOAD AND UPLOAD THE DATASET

|   | = pd.read_<br>.head() | csv('Churn | _Modellir | g.csv')     |           |        |     |        |           |               |           |                |                  |
|---|-----------------------|------------|-----------|-------------|-----------|--------|-----|--------|-----------|---------------|-----------|----------------|------------------|
|   | RowNumber             | CustomerId | Surname   | CreditScore | Geography | Gender | Age | Tenure | Balance   | NumOfProducts | HasCrCard | IsActiveMember | Estimated Salary |
| 0 | 1                     | 15634602   | Hargrave  | 619         | France    | Female | 42  | 2      | 0.00      | 1             | 1         | 1              | 101348.8         |
| 1 | 2                     | 15647311   | Hill      | 608         | Spain     | Female | 41  | 1      | 83807.86  | 1             | 0         | 1              | 112542.5         |
| 2 | 3                     | 15619304   | Onio      | 502         | France    | Female | 42  | 8      | 159660.80 | 3             | 1         | 0              | 113931.5         |
| 3 | 4                     | 15701354   | Boni      | 699         | France    | Female | 39  | 1      | 0.00      | 2             | 0         | 0              | 93826.6          |
| 4 | 5                     | 15737888   | Mitchell  | 850         | Snain     | Female | 43  | 2      | 125510.82 | 1             | 1         | 1              | 79084.1          |

## 3.)HANDLE MISSING VALUES IN THE DATASET

```
Handle the Missing Values in the Dataset

In [3]: #Removing Unwanted Values df = df.drop(columns=['RowNumber','CustomerId','Surname'])

In [4]: df.isnull().sum()

Out[4]: CreditScore 0 Geography 0 Gender 0 Age 0 Tenure 0 Balance NumofProducts 0 HascrCard 0 ISActiveMember 0 EstimatedSalary 0 Exited 0 dtype: int64

In [5]: df.shape

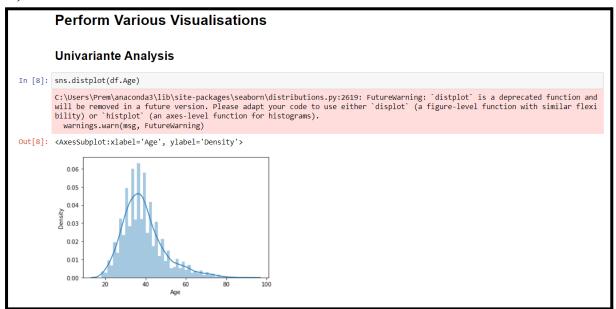
Out[5]: (10000, 11)
```

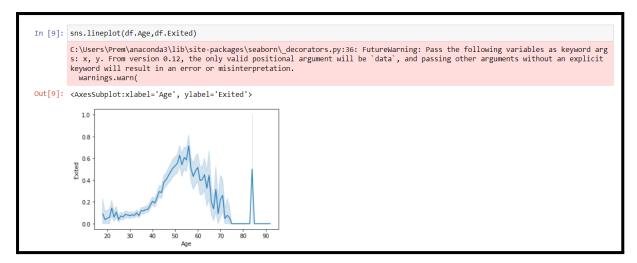
### 4.) PERFORM THE DESCRIPTIVE STATISTICS ON THE DATASET

| ]:   |  |   | _  |  |               |             |                |                  |              |
|--|--|---|--|--|---------------|-------------|----------------|------------------|--------------|
|  | CreditScore  | Age   | Tenure   | Balance                                    | NumOfProducts | HasCrCard   | IsActiveMember | Estimated Salary | Exited       |
| count  | 10000.000000   | 10000.000000  | 10000.000000   | 10000.000000                               | 10000.000000  | 10000.00000 | 10000.000000   | 10000.000000     | 10000.000000 |
| mean   | 650.528800   | 38.921800   | 5.012800   | 76485.889288                               | 1.530200      | 0.70550     | 0.515100       | 100090.239881    | 0.203700     |
| std  | 96.653299  | 10.487806   | 2.892174   | 62397.405202                               | 0.581654      | 0.45584     | 0.499797       | 57510.492818     | 0.402769     |
| min  | 350.000000   | 18.000000   | 0.000000   | 0.000000                                   | 1.000000      | 0.00000     | 0.000000       | 11.580000        | 0.000000     |
| 25%  | 584.000000   | 32.000000   | 3.000000   | 0.000000                                   | 1.000000      | 0.00000     | 0.000000       | 51002.110000     | 0.000000     |
| 50%  | 652.000000   | 37.000000   | 5.000000   | 97198.540000                               | 1.000000      | 1.00000     | 1.000000       | 100193.915000    | 0.000000     |
| 75%  | 718.000000   | 44.000000   | 7.000000   | 127644.240000                              | 2.000000      | 1.00000     | 1.000000       | 149388.247500    | 0.000000     |
| max  |  | 92.000000   |  | 250898.090000                              | 4.000000      | 1.00000     | 1.000000       | 199992.480000    | 1.000000     |
|  | s 'pandas.com  |   |  |  |               |             |                |                  |              |
| Range<br>Data<br>#                                   | Index: 10000<br>columns (tota<br>Column                            | entries, 0<br>al 11 column<br>Non-Nul   | to 9999<br>s):<br>l Count Dty  |  |               |             |                |                  |              |
| Range<br>Data<br>#<br><br>0<br>1<br>2                | Index: 10000 columns (tota Column CreditScore Geography Gender Age | entries, 0<br>al 11 column<br>Non-Nul<br><br>10000 n<br>10000 n<br>10000 n      | to 9999 s): l Count Dty on-null inf on-null ob on-null inf on-null inf | t64<br>ject<br>ject<br>ject                |               |             |                |                  |              |
| Range<br>Data<br>#<br><br>0<br>1<br>2<br>3<br>4<br>5 | Index: 10000 columns (tota Column CreditScore Geography Gender     | entries, 0 al 11 column Non-Nul 10000 r 10000 r 10000 r 10000 r 10000 r 10000 r | to 9999 s): l Count Dty on-null infon-null obj on-null obj             | 564<br>ject<br>ject<br>664<br>664<br>pat64 |               |             |                |                  |              |

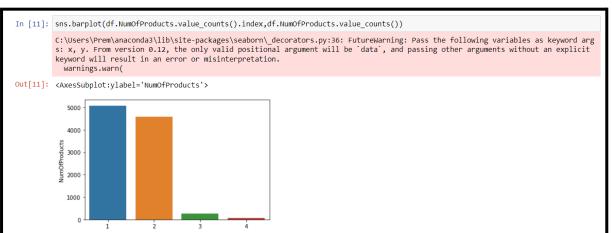
# 5.) PERFORM VARIOUS VISUALISATIONS

### a.) UNIVARIANTE ANALYSIS

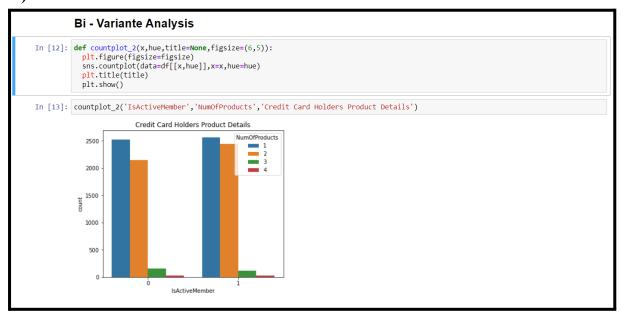




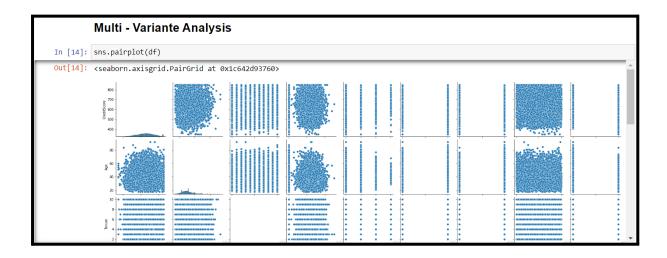


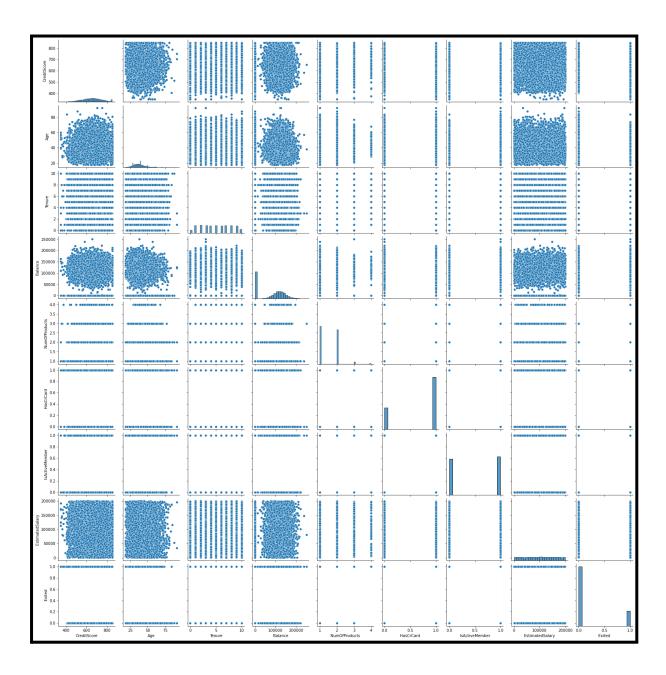


### **b.) BI - VARIANTE ANALYSIS**



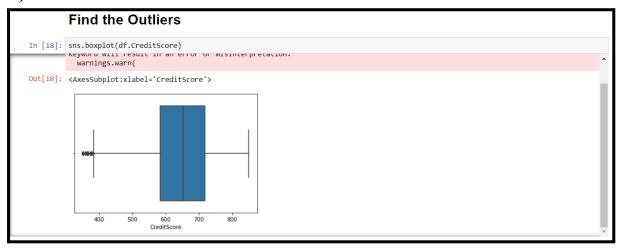
# c.) MULTI - VARIANTE ANALYSIS

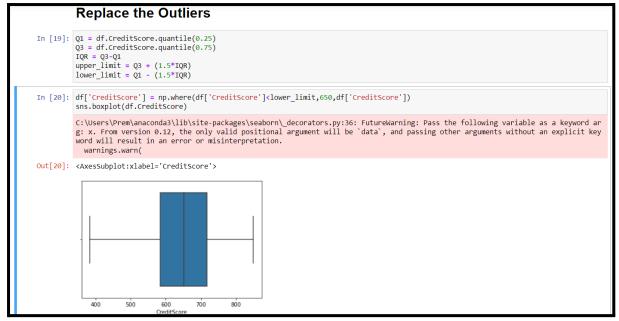




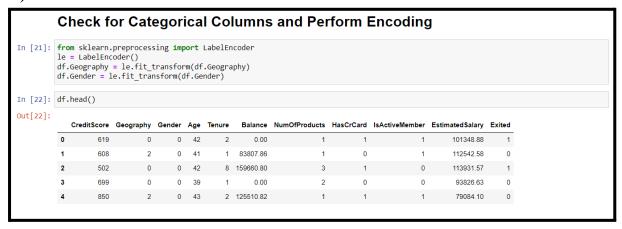
|                 | CreditScore | Age       | Tenure    | Balance   | NumOfProducts | HasCrCard | IsActiveMember | <b>Estimated Salary</b> | Exited    |
|-----------------|-------------|-----------|-----------|-----------|---------------|-----------|----------------|-------------------------|-----------|
| CreditScore     | 1.000000    | -0.003965 | 0.000842  | 0.006268  | 0.012238      | -0.005458 | 0.025651       | -0.001384               | -0.027094 |
| Age             | -0.003965   | 1.000000  | -0.009997 | 0.028308  | -0.030680     | -0.011721 | 0.085472       | -0.007201               | 0.285323  |
| Tenure          | 0.000842    | -0.009997 | 1.000000  | -0.012254 | 0.013444      | 0.022583  | -0.028362      | 0.007784                | -0.014001 |
| Balance         | 0.006268    | 0.028308  | -0.012254 | 1.000000  | -0.304180     | -0.014858 | -0.010084      | 0.012797                | 0.118533  |
| NumOfProducts   | 0.012238    | -0.030680 | 0.013444  | -0.304180 | 1.000000      | 0.003183  | 0.009612       | 0.014204                | -0.047820 |
| HasCrCard       | -0.005458   | -0.011721 | 0.022583  | -0.014858 | 0.003183      | 1.000000  | -0.011866      | -0.009933               | -0.007138 |
| IsActiveMember  | 0.025651    | 0.085472  | -0.028362 | -0.010084 | 0.009612      | -0.011866 | 1.000000       | -0.011421               | -0.156128 |
| EstimatedSalary | -0.001384   | -0.007201 | 0.007784  | 0.012797  | 0.014204      | -0.009933 | -0.011421      | 1.000000                | 0.012097  |
| Exited          | -0.027094   | 0.285323  | -0.014001 | 0.118533  | -0.047820     | -0.007138 | -0.156128      | 0.012097                | 1.000000  |

#### 6.) FIND AND REPLACE THE OUTLIERS





#### 7.) CHECK FOR CATEGORICAL COLUMNS AND ENCODE THEM



### 8.) SPLIT DATA INTO DEPENDENT AND INDEPENDENT VARIABLES

| X.I                            | <pre>X = df.drop(columns=['Exited']) X.head()</pre>           |           |        |     |        |           |               |           |                |                 |
|--------------------------------|---|-----------|--------|-----|--------|-----------|---------------|-----------|----------------|-----------------|
| :                              | CreditScore   | Geography | Gender | Age | Tenure | Balance   | NumOfProducts | HasCrCard | IsActiveMember | EstimatedSalary |
| 0                              | 619   | 0         | 0      | 42  | 2      | 0.00      | 1             | 1         | 1              | 101348.88       |
| 1                              | 608   | 2         | 0      | 41  | 1      | 83807.86  | 1             | 0         | 1              | 112542.58       |
| 2                              | 502   | 0         | 0      | 42  | 8      | 159660.80 | 3             | 1         | 0              | 113931.57       |
| 3                              | 699   | 0         | 0      | 39  | 1      | 0.00      | 2             | 0         | 0              | 93826.63        |
| 4                              | 850   | 2         | 0      | 43  | 2      | 125510.82 | 1             | 1         | 1              | 79084.10        |
| Y.I<br>: 0<br>1<br>2<br>3<br>4 | = df.Exited<br>head()<br>1<br>0<br>1<br>0<br>0<br>me: Exited, |           | -1-54  |     |        |           |               |           |                |                 |

## 9.) SCALE THE INDEPENDENT VARIABLES

```
Scale the Independent Variables

In [25]: from sklearn.preprocessing import MinMaxScaler
scale = MinMaxScaler()
X_scaled = pd.DataFrame(scale.fit_transform(X),columns=X.columns)
```

## 10.) SPLIT THE DATA INTO TRAINING AND TESTING