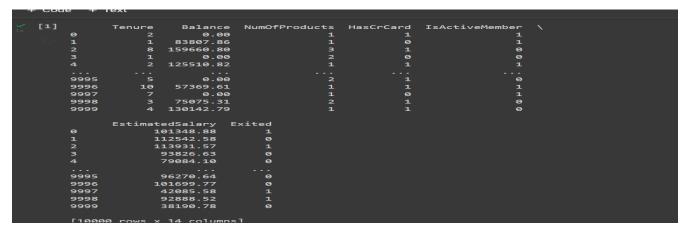
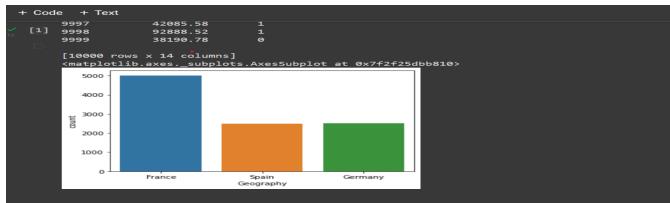
# **ASSIGNMENT - 02**

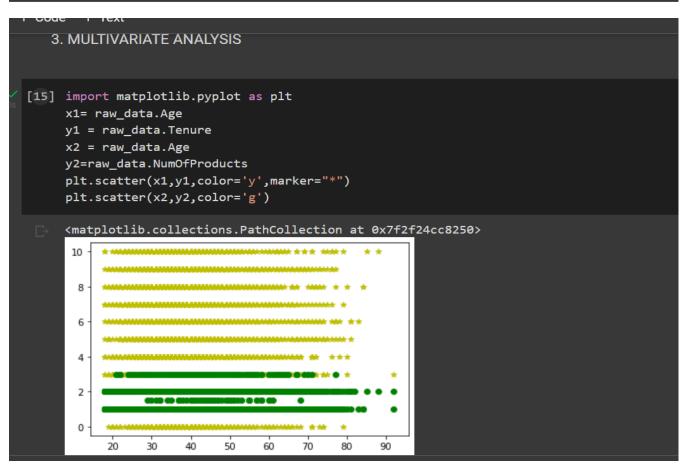
### DATA VISUALIZATION AND PRE-PROCESSING

Assignment Date	19-09-2022
Student Name	VALLIAMMAI S
Student Roll Number	311519106105
Maximum Marks	2





```
2. BIVARIATE ANALYSIS
[2] sns.barplot(x="Geography",y="EstimatedSalary",data=raw_data)
     plt.title('Geography vs EstimatedSalary')
     plt.xlabel('Geography')
     plt.ylabel('EstimatedSalary')
     Text(0, 0.5, 'EstimatedSalary')
                         Geography vs EstimatedSalary
        100000
         80000
      EstimatedSalary
         60000
         40000
         20000
                    France
                                     Spain
                                                    Germany
                                   Geography
```



## 4.DESCRIPTIVE STATISTICS

## [5] print(raw\_data['CreditScore'].describe())

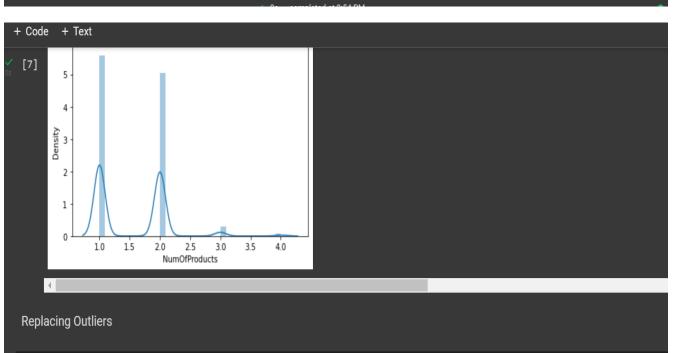
10000.000000 count mean 650.528800 96.653299 std 350.000000 min 25% 584.000000 50% 652.000000 718.000000 75% 850.000000 max

Name: CreditScore, dtype: float64

													DISK	
5.MIS	5.MISSING VALUES													
[6]	[6] raw_data.isnull()													
		RowNumber	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary
	0	False	False	False	False	False	False	False	False	False	False	False	False	False
	1	False	False	False	False	False	False	False	False	False	False	False	False	False
	2	False	False	False	False	False	False	False	False	False	False	False	False	False
	3	False	False	False	False	False	False	False	False	False	False	False	False	False
	4	False	False	False	False	False	False	False	False	False	False	False	False	False
	9995	False	False	False	False	False	False	False	False	False	False	False	False	False
	9996	False	False	False	False	False	False	False	False	False	False	False	False	False
	9997	False	False	False	False	False	False	False	False	False	False	False	False	False
	9998	False	False	False	False	False	False	False	False	False	False	False	False	False
	9999	False	False	False	False	False	False	False	False	False	False	False	False	False



6.0UT	TLIERS										5.9.0	<b>↑</b> ↓	s <b>目 / ∏ Î</b> :
:	7] sns.distplot(raw_data["NumOfProducts"]) ul=raw_data["NumOfProducts"].mean()+3*raw_data["NumOfProducts"].std() ll=raw_data["NumOfProducts"].mean()-3*raw_data["NumOfProducts"].std() raw_data.loc[(raw_data["NumOfProducts"]>ul)   (raw_data["NumOfProducts"] <ll)]< td=""><td></td><td></td></ll)]<>												
	6279	6280	15608338	Chiemenam	757	Spain	Female	55	9	117294.12	4		0
	6750	6751	15690546	Riley	618	France	Female	42	2	0.00	4		0
	6875	6876	15665283	Brookes	610	France	Female	57	7	72092.95	4	0	1
	7257	7258	15648681	Voronoff	747	France	Female	47	5	139914.60	4		1
	7457	7458	15668889	Galgano	665	Germany	Female	43	2	116322.27	4		0
	7567	7568	15750545	Chidiebere	629	France	Male	44	5	0.00	4		0
	7698	7699	15691513	Dawkins	592	France	Male	60	9	0.00	4		1
	7724	7725	15673591	Oluchukwu	842	France	Male	44	3	141252.18	4		1
	7729	7730	15681007	Yen	850	France	Female	35	2	128548.49	4		0
	8041	8042	15701439	Fanucci	698	Spain	Female	50		0.00	4		0



raw\_data['NumOfProducts']=np.where(raw\_data['NumOfProducts']==4,mean,raw\_data['NumOfProducts'])

[8] import statistics

1.0

mean=statistics.mean(raw\_data.NumOfProducts)

print(raw\_data.NumOfProducts[9])

#### 7.CATEGORICAL COLUMNS AND ENCODING [9] print(pd.Categorical(raw\_data.Gender)) ['Female', 'Female', 'Female', 'Female', 'Male', 'Male', 'Female', 'Male', 'Female'] Length: 10000 Categories (2, object): ['Female', 'Male'] 8.Encoding [10] from sklearn.preprocessing import LabelEncoder,OneHotEncoder x=raw\_data.iloc[:,:].values labelencoder\_x=LabelEncoder() x[:,5]=labelencoder\_x.fit\_transform(x[:,5]) y=pd.DataFrame(x) print(y) 4 5 6 7 8 9 France 0 42 2 0.0 1.0 Spain 0 41 1 83807.86 1.0 9 10 1 15634602 Hargrave 619 2 15647311 Hill 608 3 15619304 Onio 502 4 15701354 Boni 699 5 15737888 Mitchell 850 0 France 0 42 8 159660.8 3.0 France 0 39 1 0.0 2.0 Spain 0 43 2 125510.82 1.0 9996 15606229 Obijiaku 771 France 1 39 5 0.0 2.0 9997 15569892 Johnstone 516 France 1 35 10 57369.61 1.0 9998 15584532 Liu 709 France 0 36 7 0.0 1.0 9999 15682355 Sabbatini 772 Germany 1 42 3 75075.31 2.0 10000 15628319 Walker 792 France 0 28 4 130142.79 1.0 ... ... 9996 15606229 Obijiaku 771 9995 9996 9998 9999 10000 15628319 12 13 11 12 13 1 101348.88 1 1 112542.58 0 4 15701354 Boni 699 France 0 39 0.0 2.0 0 [10] 4 5 15737888 Mitchell 850 Spain 0 43 2 125510.82 1.0 1 ... .. 0 2.0 France 1 39 5 0.0 2.0 France 1 35 10 57369.61 1.0 France 0 36 7 0.0 1.0 ... ... 9996 15606229 Obijiaku 771 9997 15569892 Johnstone 516 9996 Liu 709 9998 15584532 9997 0 9999 15682355 Sabbatini 772 Germany 1 42 3 75075.31 2.0 9998 Walker 792 France 0 28 4 130142.79 1.0 1 9999 10000 15628319 12 13 1 101348.88 1 0 1 112542.58 0 0 113931.57 0 93826.63 4 79084.1 0 9995 0 96270.64 0 9996 1 101699.77 0 9997 1 42085.58 1 9998 0 92888.52 1 9999 0 38190.78 0

[10000 rows x 14 columns]

```
Split the data into dependent and independent variables
[11] print("Dependent variables")
          x= raw_data.iloc[ : ,[4,5,10,11,13]].values
          print(x)
          print("Independent variables")
          y= raw_data.iloc[ : ,[1,2,3,6,7,8,9,12]].values
          print(y)
          Dependent variables
          [['France' 'Female' 1 1 1]
            ['Spain' 'Female' 0 1 0]
            ['France' 'Female' 1 0 1]
            ['France' 'Female' 0 1 1]
             ['Germany' 'Male' 1 0 1]
            ['France' 'Female' 1 0 0]]
          Independent variables
          [[15634602 'Hargrave' 619 ... 0.0 1.0 101348.88]
            [15647311 'Hill' 608 ... 83807.86 1.0 112542.58]
            [15619304 'Onio' 502 ... 159660.8 3.0 113931.57]
            [15584532 'Liu' 709 ... 0.0 1.0 42085.58]
            [15682355 'Sabbatini' 772 ... 75075.31 2.0 92888.52]
             [15628319 'Walker' 792 ... 130142.79 1.0 38190.78]]
 10. Scale the independent variables
[12] from sklearn.preprocessing import MinMaxScaler
          min_max_scaler = MinMaxScaler()
          print("Scaled Independent Variable CreditScore")
          raw_data[["CreditScore"]] = min_max_scaler.fit_transform(raw_data[["CreditScore"]])
          print(raw_data)
          Scaled Independent Variable CreditScore
                     RowNumber CustomerId Surname CreditScore Geography Gender Age \

        owNumber
        CustomerId
        Surname
        CreditScore Geography
        Gender
        Age

        1
        15634602
        Hargrave
        0.538
        France
        Female
        42

        2
        15647311
        Hill
        0.516
        Spain
        Female
        41

        3
        15619304
        Onio
        0.304
        France
        Female
        42

        4
        15701354
        Boni
        0.698
        France
        Female
        39

        5
        15737888
        Mitchell
        1.000
        Spain
        Female
        43

        ...
        ...
        ...
        ...
        ...
        ...
        ...

        9996
        15606229
        Obijiaku
        0.842
        France
        Male
        39

        9997
        15569892
        Johnstone
        0.332
        France
        Male
        35

        9998
        15584532
        Liu
        0.718
        France
        Female
        36

        9999
        15682355
        Sabbatini
        0.844
        Germany
        Male
        42

        10000
        15628319
        Walker<
          9996
```

Balance NumOfProducts HasCrCard IsActiveMember \

0

1.0

9997 9998 9999

0

Tenure

2 0.00 1.0

83807.86

```
Balance NumOfProducts HasCrCard IsActiveMember
         Tenure
[12]
                  0.00
                             1.0
           2
                                             1
                                                            1
             1 83807.86
                                  1.0
                                             0
    1
             8 159660.80
    2
                                  3.0
                                             1
                                                            0
    3
                 0.00
                                  2.0
                                              0
                                                            0
    4
             2 125510.82
                                  1.0
                 0.00
            5
                                 2.0
                                                            0
                                             1
             10 57369.61
                                 1.0
                                             1
    9996
                                  1.0
                                             0
                                                            1
    9997
                  0.00
    9998
             3
                75075.31
                                  2.0
                                             1
                                                            0
    9999
             4 130142.79
                                  1.0
                                                            0
         EstimatedSalary Exited
    0
             101348.88
              112542.58
                            0
    1
    2
              113931.57
                             1
    3
               93826.63
                            0
               79084.10
                            0
              96270.64
                           0
                           0
    9996
              101699.77
    9997
               42085.58
                            1
    9998
               92888.52
    9999
              38190.78
                           0
    [10000 rows x 14 columns]
```

#### 11. Split the data into training and testing

```
[13] import pandas as pd
    from sklearn.linear_model import LinearRegression
    from sklearn.model_selection import train_test_split
    X = raw_data.iloc[:, :-1]
    y = raw_data.iloc[:, -1]
    X_train, X_test, y_train, y_test = train_test_split(
        X, y, test_size=0.05, random_state=0)
    print(X_train)
    print(X_test)
    print(y_train)
    print(y_test)
                                 ...
0.686
                                                   Spain
                             Ritchie
             8939 15722409
    8938
                                                              Male
                                                                    47
              9292
                     15679804 Esquivel
                                             0.572
    9291
                                                     France
                                                              Male
                                                                     36
              492
    491
                     15699005
                               Martin
                                            0.720 France Female
                                                                     41
    2021
              2022
                     15795519 Vasiliev
                                            0.732
                                                     Germany Female
                                                                     18
             4300 15711991 Chiawuotu
                                             0.530
    4299
                                                    France
                                                               Male 30
          Tenure Balance NumOfProducts HasCrCard IsActiveMember \
              8 131101.04
    9394
                              1.0
    898
              2 102967.41
                                   1.0
                                               1
                                                              0
    2398
              8 95386.82
                                   1.0
                                               1
```

```
Tenure Balance
8 131101.04
2 102967.41
8 95386.82
                   Balance NumOfProducts HasCrCard IsActiveMember
[13] <sub>9394</sub>
                             1.0
                                                                     1
    898
                                        1.0
                                                                     0
                                       1.0
    2398
              4 112079.58
    5906
                                       1.0
                                                   ø
                                                                    ø
    2343
              5 163034.82
                                       2.0
                                      1.0
2.0
1.0
             8 107604.66
5 117559.05
2 156067.05
    8938
    9291
                                                   1
    491
             3 128743.80
                                      1.0
                                                                   0
    2021
                                      2.0
    4299
                     0.00
                                                   0
          EstimatedSalary
           192852.67
128702.10
    9394
    898
    2398
                 75732.<u>25</u>
                89368.59
    5906
    2343
               135662.17
               80149.27
    8938
               111573.30
     9291
                 9983.88
    491
    2021
               197322.13
    4299
                 3183.15
```

```
[13] [500 rows x 13 columns]
    799
          0
    1069
          1
    8410
          0
    9436
          0
    5099
          1
    9225 0
    4859
          0
    3264
          0
    9845
          0
          1
    2732
    Name: Exited, Length: 9500, dtype: int64
    9394
          0
    898
          1
    2398
          0
    5906
          0
          0
    2343
    8938
          0
          0
    9291
    491
          0
    2021
          0
    4299
           0
    Name: Exited, Length: 500, dtype: int64
```