Assignment -2

Data Visualization and Pre-processing in ipynb

Assignment Date	21 September 2022
Student Name	NARMADHA.R
Team ID	IBM-29269-1662616381
Maximum Marks	2 Marks

1.Download the dataset

```
import numpy as np import
pandas as pd import seaborn as
sns
import matplotlib.pyplot as plt 2.Load

the dataset

df=pd.read_csv('/content/Churn_Modelling.csv') df.head()
```

	RowNumber	CustomerId	Surname	CreditScore	Geography	Gender	Age	\
1.	1	15634602	Hargrave	619	France	Female	42	
2.	2	15647311	Hill	608	Spain	Female	41	
3.	3	15619304	Onio	502	France	Female	42	
4.	4	15701354	Boni	699	France	Female	39	
5.	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.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999 Data
columns (total 14 columns):
 #   Column          Non-Null Count Dtype
---  ------          -------------- -------------
 0    RowNumber      100    non-    int64
                     00     null
 1    CustomerId     100    non-    int64
                     00     null
 2    Surname        100    non-    obje
                     00     null    ct
 3    CreditScore    100    non-    int64
                     00     null
```

a. Geography 10000 non-null object
b. Gender 10000 non-null object
c. Age 10000 non-null int64
d. Tenure 10000 non-null int64
e. Balance 10000 non-null float64
f. NumOfProducts 10000 non-null int64
g. HasCrCard 10000 non-null int64
h. IsActiveMember 10000 non-null int64
i. EstimatedSalary 10000 non-null float64
j. Exited 10000 non-null int64 dtypes: float64(2), int64(9), object(3) memory usage: 1.1+ MB

1. Perform Below Visualisations Univariate

Analysis df['Geography'].value_counts()

```
France   5014
Germany  2509
Spain    2477
Name: Geography, dtype: int64
```

```
# comparison of geography


plt.hist(x = df.Geography, bins = 6, color = 'lightblue')
plt.title('comparison of Geography') plt.xlabel('Geography')
plt.ylabel('population') plt.show()
```

```
df['IsActiveMember'].value_counts()
```

```
1   5151
0   4849
Name: IsActiveMember, dtype: int64
```

```
# How many active member does the bank have ?


plt.hist(x = df.IsActiveMember, bins = 5, color = 'pink')
plt.title('Active Members')
plt.xlabel('Customers')
plt.ylabel('population') plt.show()
```

```
df['Gender'].value_counts() Male
5457
Female  4543
Name: Gender, dtype: int64

# Plotting the features of the dataset to see the correlation between them
plt.hist(x = df.Gender, bins = 4, color = 'lightgreen') plt.title('comparison of
male and female')
plt.xlabel('Gender')
plt.ylabel('population') plt.show()
```

```
df['Age'].value_counts()

 37     478
 38     477
 35     474
 36     456
 34     447
     ...
 92       2
```

```
82       1
88       1
85       1
83       1
Name:  Age, Length: 70, dtype:
       int64
```

```
# comparison of age in the dataset
```

```
plt.hist(x = df.Age, bins = 10, color = 'red')
plt.title('comparison of Age') plt.xlabel('Age')
plt.ylabel('population') plt.show()
```

```
df['HasCrCard'].value_counts()
```

```
1   7055
0   2945
Name: HasCrCard, dtype: int64
```

```
# comparison of how many customers hold the credit card
```

```
plt.hist(x = df.HasCrCard, bins = 5, color = 'blue') plt.title('how
many people have or not have the credit card') plt.xlabel('customers
holding credit card') plt.ylabel('population')
plt.show()
```

Bi - Variate Analysis

```
# comparing ages in different geographies
```

```
Age = pd.crosstab(df['Age'], df['Geography']) Age.div(Age.sum(1).astype(float),
axis = 0).plot(kind = 'bar', stacked = True, figsize = (15,15))
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fa1a78a13d0>
```

```
# comparison between Geography and Gender

Gender = pd.crosstab(df['Gender'],df['Geography'])
Gender.div(Gender.sum(1).astype(float), axis=0).plot(kind="bar", stacked=True,
figsize=(6, 6))
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fa1a6c48bd0>
```

```
# comparison of active member in differnt geographies

IsActiveMember = pd.crosstab(df['IsActiveMember'], df['Geography'])
IsActiveMember.div(IsActiveMember.sum(1).astype(float), axis = 0).plot(kind =
'bar',stacked = True, figsize= (6, 6))
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fa1a6c36810>
```

```
# calculating total balance in france, germany and spain

total_france = df.Balance[df.Geography == 'France'].sum()
total_germany = df.Balance[df.Geography == 'Germany'].sum()
total_spain = df.Balance[df.Geography == 'Spain'].sum()

print("Total Balance in France :",total_france)
print("Total Balance in Germany :",total_germany)
print("Total Balance in Spain :",total_spain)
```

```
Total Balance in France : 311332479.49 Total
Balance in Germany : 300402861.38 Total Balance
in Spain : 153123552.01
```

```
# plotting a pie chart

labels = 'France', 'Germany', 'Spain' colors =
['green', 'yellow', 'orange'] sizes = [311,
300, 153]
explode = [ 0.01, 0.01, 0.01]
```

```
plt.pie(sizes, colors = colors, labels = labels, explode = explode, shadow
= True)

plt.axis('equal') plt.show()
```

```
# comparison between geography and card holders

HasCrCard = pd.crosstab(df['HasCrCard'], df['Geography'])
HasCrCard.div(HasCrCard.sum(1).astype(float), axis = 0).plot(kind = 'bar',stacked
= True,figsize = (6, 6))
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fa1a6b0c0d0>
```

Multi - Variate Analysis

```
sns.pairplot(data=df, hue='Exited')
```

```
<seaborn.axisgrid.PairGrid at 0x7fa1a1860550>
```

2. Perform descriptive statistics on the dataset

```
df.describe()
```

```
          RowNumber    CustomerId    CreditScore           Age         Tenure
\
count   10000.000    1.000000e+04   10000.000000  10000.000000   10000.0000
        00                                                      00
mean     5000.50000  1.569094e+07     650.528800     38.921800       5.012800
std      2886.89568  7.193619e+04      96.653299     10.487806       2.892174
min         1.00000  1.556570e+07     350.000000     18.000000       0.000000
25%      2500.75000  1.562853e+07     584.000000     32.000000       3.000000
50%      5000.50000  1.569074e+07     652.000000     37.000000       5.000000
75%      7500.25000  1.575323e+07     718.000000     44.000000       7.000000
max     10000.000    1.581569e+07     850.000000     92.000000      10.000000
        00

             Balance    NumOfProducts    HasCrCard   IsActiveMember   \
count    10000.0000     10000.000000  10000.00000     10000.000000
                 00
mean     76485.8892         1.530200      0.70550         0.515100
                 88
std      62397.4052         0.581654      0.45584         0.499797
                 02
min        0.000000         1.000000      0.00000         0.000000
25%        0.000000         1.000000      0.00000         0.000000



50%      97198.540000    1.000000   1.00000      1.000000
75%     127644.240000    2.000000   1.00000      1.000000
max     250898.090000    4.000000   1.00000      1.000000

        EstimatedSala          Exited
        ry
count     10000.000000   10000.000000
mean     100090.239881       0.203700
std       57510.492818       0.402769
min          11.580000       0.000000
25%       51002.110000       0.000000
50%      100193.915000       0.000000
75%      149388.247500       0.000000
max      199992.480000       1.000000
```

3. Handle the Missing values

```
df.isnull().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
```

4. Find the outliers and replace the outliers

```
sns.boxplot(data = df, x = 'EstimatedSalary')
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fa19f13e510>
```

```
sns.boxplot(data = df, x = 'CreditScore')
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fa19f0c2410>
```

```
sns.boxplot(data = df, x = 'Balance')
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fa19f03d1d0>
```

```
sns.boxplot(data = df, x = 'Age')
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fa19d74fb10>
```

```
sns.boxplot(data = df, x = 'RowNumber')
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fa19d7c2b90>
```

```
sns.boxplot(data = df, x = 'Tenure')
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fa19be57c90>
```

5. Check for Categorical columns and perform encoding

```
x = pd.get_dummies(x) x.head()
```

```
    RowNumber    CustomerId   CreditSco     Age   Tenure    Surname_Abazu    \
                              re
0         1.0    15634602.0         619.0     42      2.0                0
                                              .0
1         2.0    15647311.0         608.0     41      1.0                0
                                              .0
2         3.0    15619304.0         502.0     42      8.0                0
                                              .0
3         4.0    15701354.0         699.0     39      1.0                0
                                              .0
4         5.0    15737888.0         850.0     43      2.0                0
                                              .0

    Surname_Abbie     Surname_Abbott    Surname_Abdullah   Surname_Abdulov    ...
\
0               0                  0                   0                  0    ...
```

```
1                  0                  0                  0                  0   ...
2                  0                  0                  0                  0   ...
3                  0                  0                  0                  0   ...
4                  0                  0                  0                  0   ...

     Surname_Zubarev    Surname_Zubareva    Surname_Zuev  Surname_Zuyev    \
0                  0                   0             0                0
1                  0                   0             0                0
2                  0                   0             0                0
3                  0                   0             0                0
4                  0                   0             0                0

     Surname_Zuyeva    Geography_France    Geography_Germa    Geography_Spa    \
                                                ny                 in
0                  0                   1                  0                0
1                  0                   0                  0                1
2                  0                   1                  0                0
3                  0                   1                  0                0
4                  0                   0                  0                1

     Gender_Female    Gender_Male
0                1              0
1                1              0
2                1              0
3                1              0
4                1              0


[5 rows x 2942 columns]
```

6. Split the data into dependent and independent variables

```
# splitting the dataset into x(independent variables) and y(dependent variables)

x = df.iloc[:,0:8]
y = df.iloc[:,8]

print(x.shape) print(y.shape)

print(x.columns)
```

```
(10000, 8)
(10000,)
Index(['RowNumber', 'CustomerId', 'Surname', 'CreditScore', 'Geography',
       'Gender', 'Age', 'Tenure'],
      dtype='object')
```

7. Scale the independent variables

```
from sklearn.preprocessing import StandardScaler

sc = StandardScaler()
x_train = sc.fit_transform(x_train) x_test =
sc.fit_transform(x_test)

x_train = pd.DataFrame(x_train)
x_train.head()
```

```
          0            1           2           3           4           5       6
 \
 0 -0.702176    -          -0.736828    0.042283    0.008860   -0.016332    0.0
               1.343330
 -0.0231
 1 -1.485722     1.5583     1.025257   -0.674496    0.008860   -0.016332    0.0
                 30
 -0.0231
 2 -0.524522    -           0.808861   -0.469702    1.393293   -0.016332    0.0
               0.655156
 -0.0231
 3 -1.167396     1.2005     0.396677   -0.060114    0.008860   -0.016332    0.0
                 94
 -0.0231
 4 -1.451159     0.7787    -0.468908    1.373444    0.701077   -0.016332    0.0
                 98
 -0.0231

    8       9       ...        2932    2933       2934        2935        2936       2
 \
 0
      0.0     0.0   ...   -0.011548     0.0  -           -0.011548   -0.016332   -
                                              0.011548                          1.015
 1    0.0     0.0   ...   -0.011548     0.0  -           -0.011548   -0.016332    0.98
                                              0.011548
```

```
2    0.0    0.0   ...   -0.011548    0.0  -          -0.011548  -0.016332  -
                                          0.011548                         1.015
3    0.0    0.0   ...   -0.011548    0.0  -          -0.011548  -0.016332  -
                                          0.011548                         1.015
4    0.0    0.0   ...   -0.011548    0.0  -          -0.011548  -0.016332   0.984
                                          0.011548


     2938       2939       2940       2941
        0          -   1.087261  -1.087261
 1.760216   0.574682
      1 -          -   1.087261  -1.087261
 0.568112   0.574682
      2 -   1.740094   1.087261  -1.087261
 0.568112
      3 -   1.740094          -   0.919743
 0.568112              0.919743
      4 -          -          -   0.919743
 0.568112   0.574682   0.919743

[5 rows x 2942 columns]
```

8. Split the data into training and testing

```
from sklearn.model_selection import train_test_split
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size = 0.25,
random_state = 0)


print(x_train.shape)


print(y_train.shape)
print(x_test.shape)
print(y_test.shape)
```

```
(7500, 2942)
(7500,)
(2500, 2942)
(2500,)
```