Assignment -2

Data Visualization and Pre-processing

Load the dataset

```
import pandas as pd
df=pd.read_csv("/content/Churn_Modelling (2).csv") # import dataset
print(df)
```

```
      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
...         ...         ...        ...          ...       ...     ...  ...
9995       9996    15606229   Obijiaku          771    France    Male   39
9996       9997    15569892  Johnstone          516    France    Male   35
9997       9998    15584532        Liu          709    France  Female   36
9998       9999    15682355  Sabbatini          772   Germany    Male   42
9999      10000    15628319     Walker          792    France  Female   28

      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
...      ...        ...            ...        ...             ...
9995       5       0.00              2          1               0
9996      10   57369.61              1          1               1
9997       7       0.00              1          0               1
9998       3   75075.31              2          1               0
9999       4  130142.79              1          1               0

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

[10000 rows x 14 columns]
```

Perform below visualizations

1.Univarient Analysis

There are three ways to perform univarient analysis

i) Summary statistics

```
# Summary statistics

import pandas as pd
df=pd.read_csv("/content/Churn_Modelling (2).csv")

#mean of CreditScore
M=df['CreditScore'].mean()

#median of CreditScore
Me=df['CreditScore'].median()

# standard deviation of CreditScore
std = df['CreditScore'].std()

print("mean value of CreditScore is {}".format(M))
print("median value of CreditScore is {}".format(Me))
print("Standard deviation of CreditScore is {}".format(std))
```

```
mean value of CreditScore is 650.5288
median value of CreditScore is 652.0
Standard deviation of CreditScore is 96.65329873613035
```

ii) Frequency table

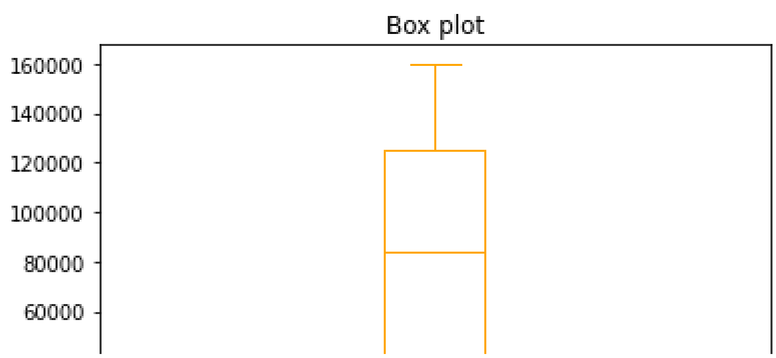
```
#Frequency table
import pandas as pd
df=pd.read_csv("/content/Churn_Modelling (2).csv")

#frequency table for age
ft=df['Age'].value_counts()

print("Frequency table for Age is given below")
print("{}".format(ft))
```

```
Frequency table for Age is given below
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
```

iii) Charts

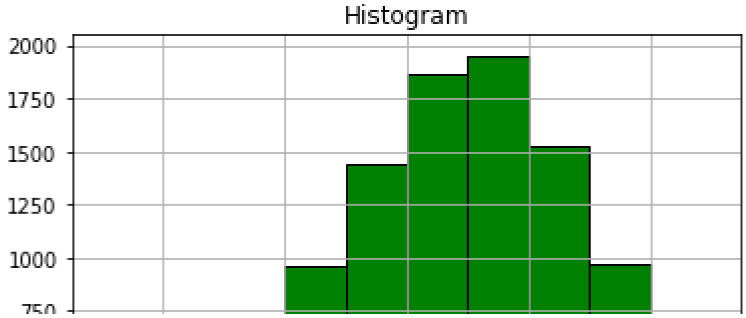
```
#Chart

import matplotlib.pyplot as plt
dfs = df.head() # print first five table from top
print(dfs)

#box plot for Balance column

dfs.boxplot(column="Balance",grid=False,color="orange")
plt.title('Box plot')
```

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

   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
Text(0.5, 1.0, 'Box plot')
```



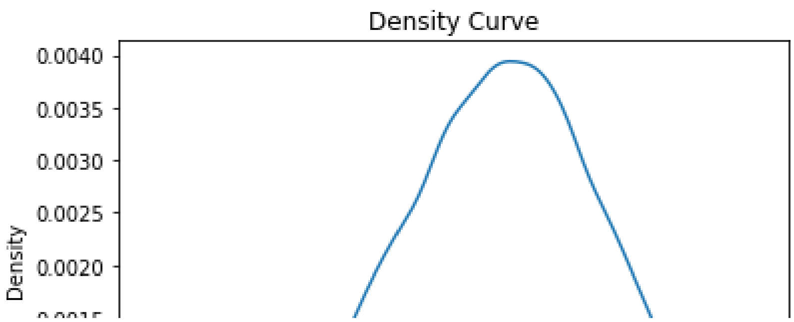

```
# Histogram for Credit Score

df.hist(column="CreditScore" ,grid=True, edgecolor ='black', color ='green')
plt.title('Histogram')
```

```
Text(0.5, 1.0, 'Histogram')
```




```
# Density curve

import seaborn as sns  #statistical data visualization

sns.kdeplot(df['CreditScore'])
plt.title('Density Curve')
```

```
Text(0.5, 1.0, 'Density Curve')
```



2. Bi - Variate Analysis

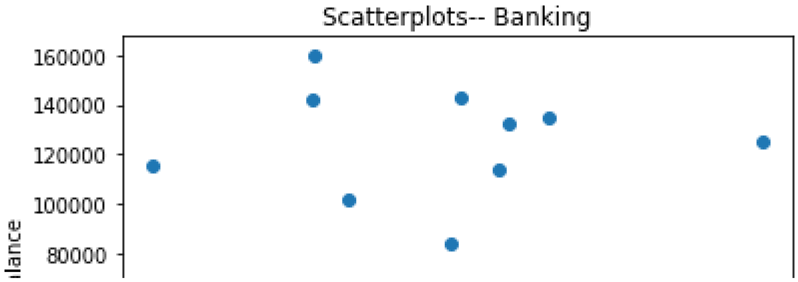
There are three common ways to perform bivariate analysis

i. Scatterplots

```
import matplotlib.pyplot as plt # library for charts

dfs1 = df.head(20)
plt.scatter(dfs1.CreditScore,dfs1.Balance)
plt.title('Scatterplots-- Banking')
```

```
plt.xlabel("CreditScore")
plt.ylabel("Balance")
```

```
Text(0, 0.5, 'Balance')
```



ii.Correlation Coefficient

```
df.corr()
```

	RowNumber	CustomerId	CreditScore	Age	Tenure	Balance	Nu
RowNumber	1.000000	0.004202	0.005840	0.000783	-0.006495	-0.009067	
CustomerId	0.004202	1.000000	0.005308	0.009497	-0.014883	-0.012419	
CreditScore	0.005840	0.005308	1.000000	-0.003965	0.000842	0.006268	
Age	0.000783	0.009497	-0.003965	1.000000	-0.009997	0.028308	
Tenure	-0.006495	-0.014883	0.000842	-0.009997	1.000000	-0.012254	
Balance	-0.009067	-0.012419	0.006268	0.028308	-0.012254	1.000000	
NumOfProducts	0.007246	0.016972	0.012238	-0.030680	0.013444	-0.304180	
HasCrCard	0.000599	-0.014025	-0.005458	-0.011721	0.022583	-0.014858	
IsActiveMember	0.012044	0.001665	0.025651	0.085472	-0.028362	-0.010084	
EstimatedSalary	-0.005988	0.015271	-0.001384	-0.007201	0.007784	0.012797	
Exited	-0.016571	-0.006248	-0.027094	0.285323	-0.014001	0.118533	

iii. Simple Linear Regression

```
import statsmodels.api as sm
# response variable
y = df['CreditScore']

# explanatory variable
x = df[['Balance']]

#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())
```

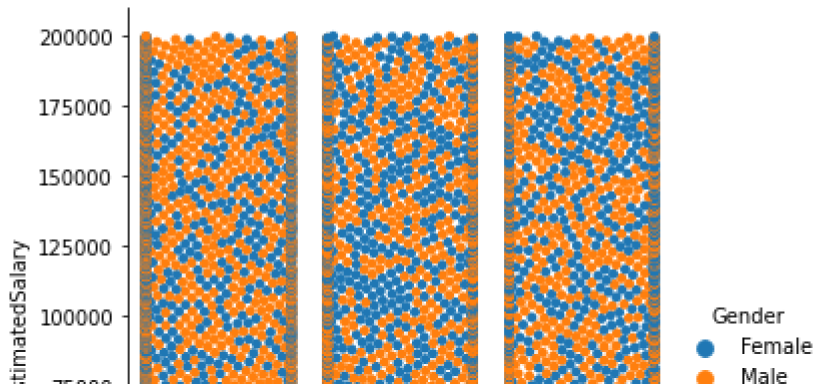
```
                            OLS Regression Results
==============================================================================
Dep. Variable:            CreditScore   R-squared:                       0.000
Model:                            OLS   Adj. R-squared:                 -0.000
Method:                 Least Squares   F-statistic:                    0.3929
Date:                Fri, 30 Sep 2022   Prob (F-statistic):              0.531
Time:                        12:08:20   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        649.7861      1.529    424.948      0.000     646.789     652.783
Balance      9.71e-06   1.55e-05      0.627      0.531   -2.07e-05    4.01e-05
==============================================================================
Omnibus:                      132.594   Durbin-Watson:                   2.014
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               84.114
Skew:                          -0.072   Prob(JB):                     5.43e-19
Kurtosis:                       2.574   Cond. No.                     1.56e+05
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly sp
[2] The condition number is large, 1.56e+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: FutureWarni
  x = pd.concat(x[::order], 1)
```

3. Multi- Variate Analysis

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

```
df=sns.catplot(x="Geography",y="EstimatedSalary",hue="Gender",kind="swarm",data=df)
print(df)
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/categorical.py:129
  warnings.warn(msg, UserWarning)
/usr/local/lib/python3.7/dist-packages/seaborn/categorical.py:129
  warnings.warn(msg, UserWarning)
/usr/local/lib/python3.7/dist-packages/seaborn/categorical.py:129
  warnings.warn(msg, UserWarning)
<seaborn.axisgrid.FacetGrid object at 0x7f7e9e206dd0>
```



4. Perform descriptive statistics on the dataset

```
#load data set into ld
ld= pd.read_csv("/content/Churn_Modelling (2).csv")
five = ld.head() #for print first five rows
```

```
# information about used data set
ld.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 14 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   RowNumber        10000 non-null  int64
 1   CustomerId       10000 non-null  int64
 2   Surname          10000 non-null  object
 3   CreditScore      10000 non-null  int64
 4   Geography        10000 non-null  object
 5   Gender           10000 non-null  object
 6   Age              10000 non-null  int64
 7   Tenure           10000 non-null  int64
```

```
 8   Balance          10000 non-null  float64
 9   NumOfProducts    10000 non-null  int64
 10  HasCrCard        10000 non-null  int64
 11  IsActiveMember   10000 non-null  int64
 12  EstimatedSalary  10000 non-null  float64
 13  Exited           10000 non-null  int64
dtypes: float64(2), int64(9), object(3)
memory usage: 1.1+ MB
```

```
ld.describe() #description of the data in the Dataset
```

	RowNumber	CustomerId	CreditScore	Age	Tenure	Balanc
count	10000.00000	1.000000e+04	10000.000000	10000.000000	10000.000000	10000.00000
mean	5000.50000	1.569094e+07	650.528800	38.921800	5.012800	76485.8892
std	2886.89568	7.193619e+04	96.653299	10.487806	2.892174	62397.4052
min	1.00000	1.556570e+07	350.000000	18.000000	0.000000	0.0000
25%	2500.75000	1.562853e+07	584.000000	32.000000	3.000000	0.0000
50%	5000.50000	1.569074e+07	652.000000	37.000000	5.000000	97198.5400
75%	7500.25000	1.575323e+07	718.000000	44.000000	7.000000	127644.2400
max	10000.00000	1.581569e+07	850.000000	92.000000	10.000000	250898.0900

5. Handle the Missing values

```
ld.isnull().any()
```

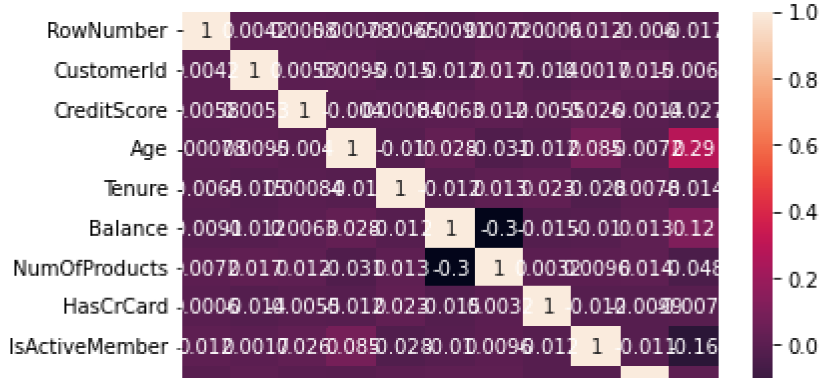
```
RowNumber          False
CustomerId         False
Surname            False
CreditScore        False
Geography          False
Gender             False
Age                False
Tenure             False
Balance            False
NumOfProducts      False
HasCrCard          False
IsActiveMember     False
EstimatedSalary    False
Exited             False
dtype: bool
```

```
ld.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
```

```
sns.heatmap(ld.corr(),annot=True) # heatmap -a plot of rectangular data as a color-encod
```

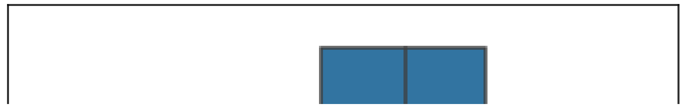
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f7e918d6b90>
```



6. Find the outliers and replace the outliers

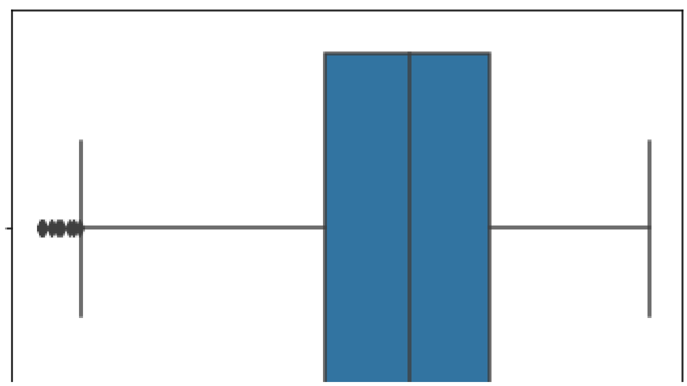
```
#occurence of outliers
ld1= pd.read_csv("/content/Churn_Modelling (2).csv")
sns.boxplot(ld1.CreditScore)
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43:
  FutureWarning
<matplotlib.axes._subplots.AxesSubplot at 0x7f7e8fe10610>
```



```
#Use Mean Detection and Nearest Fill Methods - Outliers

Q1= ld1.CreditScore.quantile(0.25)
Q3=ld1.CreditScore.quantile(0.75)
IQR=Q3-Q1
upper_limit =Q3 + 1.5*IQR
lower_limit =Q1 - 1.5*IQR
ld1['CreditScore'] = np.where(ld1['CreditScore']>upper_limit,30,ld1['CreditScore'])
sns.boxplot(ld1.CreditScore)
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarning
  FutureWarning
<matplotlib.axes._subplots.AxesSubplot at 0x7f7e8fd40550>
```



7. Check for Categorical columns and perform encoding

```
ld1.head(5)
```

	RowNumber	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure
0	1	15634602	Hargrave	619	France	Female	42	2
1	2	15647311	Hill	608	Spain	Female	41	1

```
#label encoder
from sklearn.preprocessing import LabelEncoder
le=LabelEncoder()
ld1.Gender= le.fit_transform(ld1.Gender)
ld1.head(5)
```

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

```
#one hot encoding
ld1_main=pd.get_dummies(ld1,columns=['Geography'])
ld1_main.head()
```

	RowNumber	CustomerId	Surname	CreditScore	Gender	Age	Tenure	Balance	Nu
0	1	15634602	Hargrave	619	0	42	2	0.00	
1	2	15647311	Hill	608	0	41	1	83807.86	
2	3	15619304	Onio	502	0	42	8	159660.80	
3	4	15701354	Boni	699	0	39	1	0.00	
4	5	15737888	Mitchell	850	0	43	2	125510.82	

8. Split the data into dependent and independent variables

```
#Splitting the Dataset into the Independent Feature Matrix
```

```
df=pd.read_csv("/content/Churn_Modelling (2).csv")
X = df.iloc[:, :-1].values
print(X)
```

```
[[1 15634602 'Hargrave' ... 1 1 101348.88]
 [2 15647311 'Hill' ... 0 1 112542.58]
 [3 15619304 'Onio' ... 1 0 113931.57]
 ...
 [9998 15584532 'Liu' ... 0 1 42085.58]
 [9999 15682355 'Sabbatini' ... 1 0 92888.52]
 [10000 15628319 'Walker' ... 1 0 38190.78]]
```

```
#Extracting the Dataset to Get the Dependent Vector
Y = df.iloc[:, -1].values
print(Y)
```

```
[1 0 1 ... 1 1 0]
```

9. Scale the independent variables

```
w = df.head()
q = w[['Age','Balance','EstimatedSalary']] #spliting the dataset into measureable values
q
```

	Age	Balance	EstimatedSalary
0	42	0.00	101348.88
1	41	83807.86	112542.58
2	42	159660.80	113931.57
3	39	0.00	93826.63
4	43	125510.82	79084.10

```
from sklearn.preprocessing import scale # library for scallling
from sklearn.preprocessing import MinMaxScaler
mm = MinMaxScaler()

x_scaled = mm.fit_transform(q)
x_scaled
```

```
array([[0.75      , 0.        , 0.63892099],
       [0.5       , 0.52491194, 0.96014087],
       [0.75      , 1.        , 1.        ],
       [0.        , 0.        , 0.42305883],
       [1.        , 0.78610918, 0.        ]])
```

```
from sklearn.preprocessing import StandardScaler
sc =  StandardScaler()
```

```
x_ss = sc.fit_transform(q)
x_ss
```

```
array([[ 0.44232587, -1.13763618,  0.09337626],
       [-0.29488391,  0.15434425,  0.96285595],
       [ 0.44232587,  1.32369179,  1.07074687],
       [-1.76930347, -1.13763618, -0.49092058],
       [ 1.17953565,  0.79723632, -1.6360585 ]])
```

```
from sklearn.preprocessing import scale
X_scaled=pd.DataFrame(scale(q),columns=q.columns)
X_scale=X_scaled.head()
X_scale
```

	Age	Balance	EstimatedSalary
0	0.442326	-1.137636	0.093376
1	-0.294884	0.154344	0.962856
2	0.442326	1.323692	1.070747
3	-1.769303	-1.137636	-0.490921
4	1.179536	0.797236	-1.636059

10. Split the data into training and testing

```
x= df[['Age','Balance','EstimatedSalary']]
x
```

```
y = df['Balance']
y
```

```
0           0.00
1       83807.86
2      159660.80
3           0.00
4      125510.82
          ...
9995        0.00
9996    57369.61
9997        0.00
9998    75075.31
9999   130142.79
Name: Balance, Length: 10000, dtype: float64
```

```
#scaling
from sklearn.preprocessing import StandardScaler, MinMaxScaler
sc = StandardScaler()
x_scaled1 = sc.fit_transform(x)
x_scaled1
```

```
array([[ 0.29351742, -1.22584767,  0.02188649],
       [ 0.19816383,  0.11735002,  0.21653375],
       [ 0.29351742,  1.33305335,  0.2406869 ],
       ...,
       [-0.27860412, -1.22584767, -1.00864308],
       [ 0.29351742, -0.02260751, -0.12523071],
       [-1.04143285,  0.85996499, -1.07636976]])
```

```
#train and test data
from sklearn.model_selection import train_test_split
x_train, x_test, y_train, y_test = train_test_split(x_scaled1, y, test_size = 0.3, rando
```

```
x_train
```

```
array([[-0.56466489,  1.11721307, -0.77021814],
       [ 0.00745665, -1.22584767, -1.39576675],
       [ 3.53553951,  1.35419118, -1.49965629],
       ...,
       [-0.37395771,  1.35890908,  1.41441489],
       [-0.08789694, -1.22584767,  0.84614739],
       [ 0.86563897,  0.50630343,  0.32630495]])
```

```
x_train.shape
```

```
(7000, 3)
```

```
x_test
```

```
array([[-0.37395771,  0.87532296,  1.61304597],
       [ 0.10281024,  0.42442221,  0.49753166],
```

```
       [ 0.29351742,  0.30292727, -0.4235611 ],
       ...,
       [ 0.10281024,  1.46672809,  1.17045451],
       [ 2.86806437,  1.25761599, -0.50846777],
       [ 0.96099256,  0.19777742, -1.15342685]])
```

```
x_test.shape
```

```
(3000, 3)
```

```
y_train
```

```
7681    146193.60
9031         0.00
3691    160979.68
202          0.00
5625    143262.04
          ...
9225    120074.97
4859    114440.24
3264    161274.05
9845         0.00
2732    108076.33
Name: Balance, Length: 7000, dtype: float64
```

```
y_test
```

```
9394    131101.04
898     102967.41
2398     95386.82
5906    112079.58
2343    163034.82
          ...
4004         0.00
7375     80926.02
9307    168001.34
8394    154953.94
5233     88826.07
Name: Balance, Length: 3000, dtype: float64
```