```
import numpy as np
import pandas as pd

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

#univariate analysis-1)summary statistics

df['Balance'].mean()
```

```
76485.889288
```

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

```
37.0
```

```
df['CreditScore'].std()
```

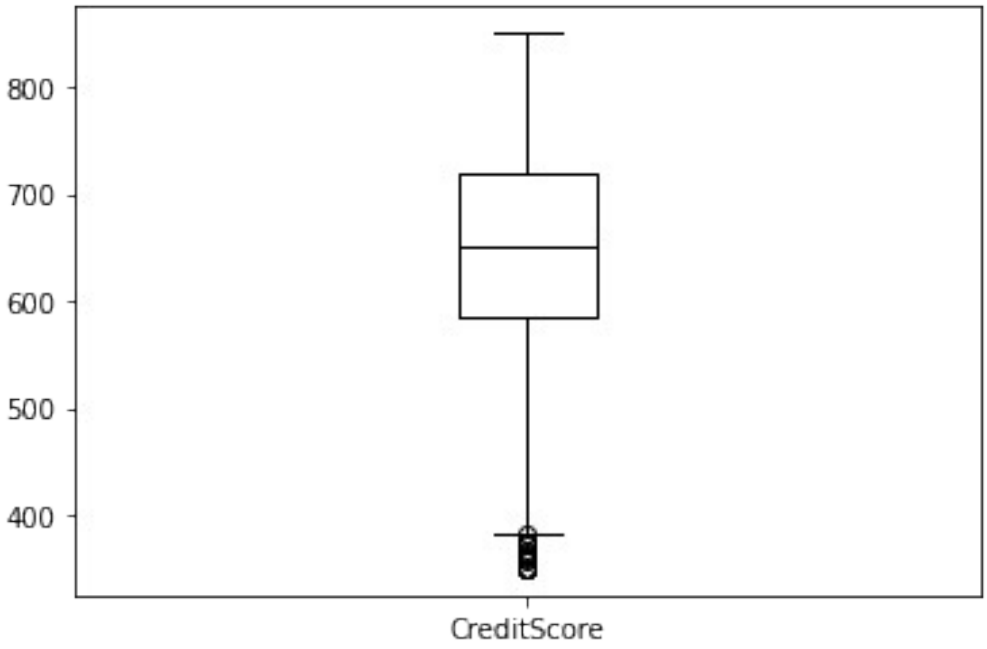
```
96.65329873613035
```

```
#2)Create frequency table

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
```

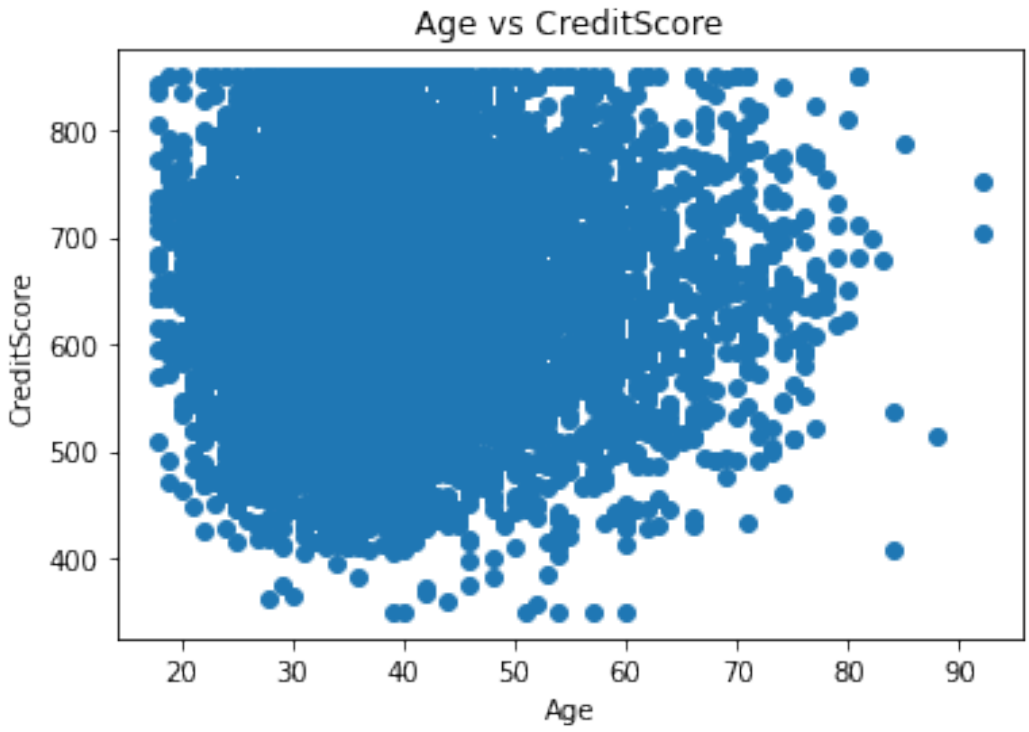
```
#3)create charts
import matplotlib.pyplot as plt
df.boxplot(column=['CreditScore'],grid=False, color='black')
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f89bc881250>
```




```
#Bivariate analysis-
#1)Scatterplots
import matplotlib.pyplot as plt
plt.scatter(df.Age,df.CreditScore)
plt.title('Age vs CreditScore')
plt.xlabel('Age')
plt.ylabel('CreditScore')
```

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




```
#2)Correlation Coefficients
df.corr()
```

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

```
                  Balance  NumOfProducts  HasCrCard  IsActiveMember  \
RowNumber       -0.009067       0.007246   0.000599        0.012044
CustomerId      -0.012419       0.016972  -0.014025        0.001665
CreditScore      0.006268       0.012238  -0.005458        0.025651
Age              0.028308      -0.030680  -0.011721        0.085472
Tenure          -0.012254       0.013444   0.022583       -0.028362
Balance          1.000000      -0.304180  -0.014858       -0.010084
NumOfProducts   -0.304180       1.000000   0.003183        0.009612
HasCrCard       -0.014858       0.003183   1.000000       -0.011866
IsActiveMember  -0.010084       0.009612  -0.011866        1.000000
EstimatedSalary  0.012797       0.014204  -0.009933       -0.011421
Exited           0.118533      -0.047820  -0.007138       -0.156128

                 EstimatedSalary    Exited
RowNumber              -0.005988 -0.016571
CustomerId              0.015271 -0.006248
CreditScore            -0.001384 -0.027094
Age                    -0.007201  0.285323
Tenure                  0.007784 -0.014001
Balance                 0.012797  0.118533
NumOfProducts           0.014204 -0.047820
HasCrCard              -0.009933 -0.007138
IsActiveMember         -0.011421 -0.156128
EstimatedSalary         1.000000  0.012097
Exited                  0.012097  1.000000
```

```
#3)Simple Linear Regressiion
import statsmodels.api as sm
y=df['CreditScore']
x=df[['Age']]
x=sm.add_constant(x)
model=sm.OLS(y,x).fit()
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:
0.1572
Date:                Mon, 03 Oct 2022   Prob (F-statistic):
0.692
Time:                        06:05:58   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        651.9510      3.715    175.481      0.000     644.668
659.234
Age           -0.0365      0.092     -0.396      0.692      -0.217
0.144
==============================================================================
========
Omnibus:                      133.033   Durbin-Watson:
2.014
Prob(Omnibus):                  0.000   Jarque-Bera (JB):
84.280
Skew:                          -0.071   Prob(JB):
5.00e-19
Kurtosis:                       2.574   Cond. No.
155.
==============================================================================
========

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is
correctly specified.

/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)
```

```
#Descriptive Analysis
df.describe()
```

```
         RowNumber    CustomerId   CreditScore           Age
Tenure  \
count  10000.00000  1.000000e+04  10000.000000  10000.000000
10000.000000
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    10000.00000  1.581569e+07    850.000000     92.000000
10.000000

             Balance  NumOfProducts    HasCrCard  IsActiveMember  \
count   10000.000000   10000.000000  10000.00000    10000.000000
mean    76485.889288       1.530200      0.70550        0.515100
std     62397.405202       0.581654      0.45584        0.499797
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

       EstimatedSalary        Exited
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
```

```
df.describe(include=['object'])
```

```
       Surname Geography Gender
count    10000     10000  10000
unique    2932         3      2
top      Smith    France   Male
freq        32      5014   5457
```

```
df.std()
```

```
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:1:
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.
  """Entry point for launching an IPython kernel.

RowNumber          2886.895680
CustomerId        71936.186123
CreditScore          96.653299
```

```
Age                   10.487806
Tenure                 2.892174
Balance            62397.405202
NumOfProducts          0.581654
HasCrCard              0.455840
IsActiveMember         0.499797
EstimatedSalary    57510.492818
Exited                 0.402769
dtype: float64
```

```
df.sum()
```

```
RowNumber                                                     50005000
CustomerId                                                156909405694
Surname            HargraveHillOnioBoniMitchellChuBartlettObinnaH...
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
```

```
df.count()
```

```
RowNumber          10000
CustomerId         10000
Surname            10000
CreditScore        10000
Geography          10000
Gender             10000
Age                10000
Tenure             10000
Balance            10000
NumOfProducts      10000
HasCrCard          10000
IsActiveMember     10000
EstimatedSalary    10000
Exited             10000
dtype: int64
```

```
#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
```

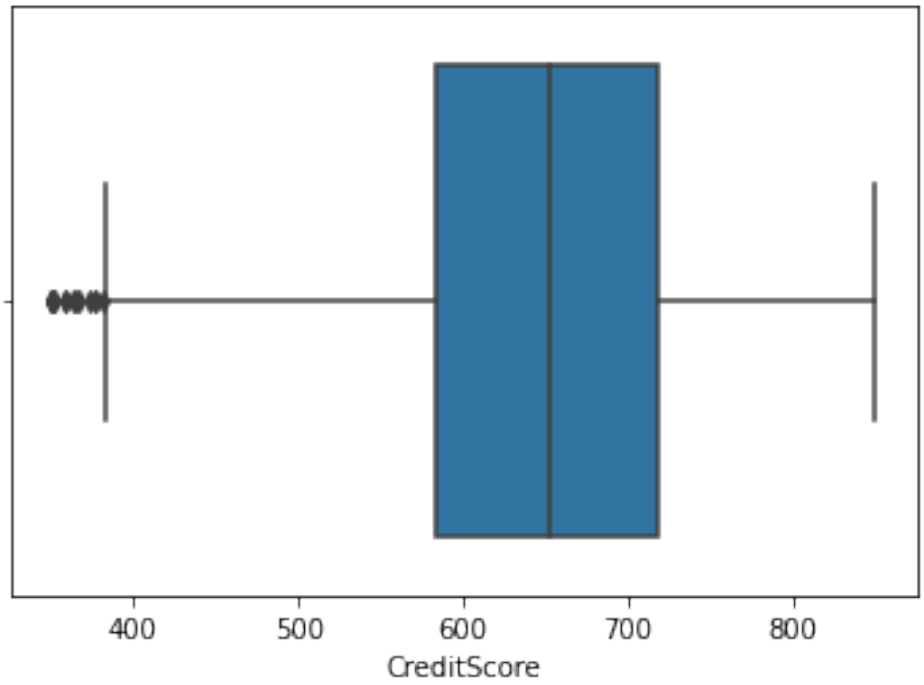
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 14 columns):
 #   Column           Non-Null Count  Dtype  
---  ------           --------------  -----  
 0   RowNumber        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
```

```
#there are no missing values in the given dataset
import seaborn as sns
sns.boxplot(df['CreditScore'])
```

```
/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 0x7f89bc1b3350>
```




```
np.where(df['CreditScore']<400)
```

```
(array([   7,  942, 1193, 1201, 1405, 1631, 1838, 1962, 2473, 2579,
5285,
        5494, 6253, 8154, 8723, 8762, 9210, 9356, 9624]),)
```

```
df['CreditScore'].mean()
```

```
650.5288
```

```
df['CreditScore']=np.where(df['CreditScore']<400,650.5288,df['CreditSc
ore'])
df.head(10)
```

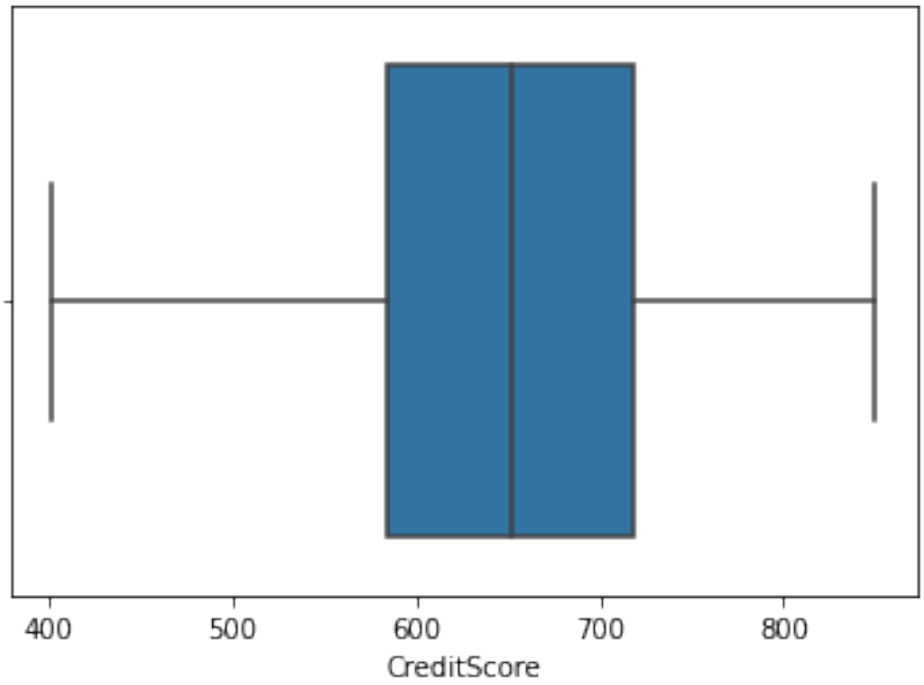
```
   RowNumber  CustomerId   Surname  CreditScore Geography  Gender  Age
\
0          1    15634602  Hargrave     619.0000    France  Female   42

1          2    15647311      Hill     608.0000     Spain  Female   41

2          3    15619304      Onio     502.0000    France  Female   42

3          4    15701354      Boni     699.0000    France  Female   39

4          5    15737888  Mitchell     850.0000     Spain  Female   43

5          6    15574012       Chu     645.0000     Spain    Male   44

6          7    15592531  Bartlett     822.0000    France    Male   50
```

```
7          8    15656148    Obinna     650.5288   Germany  Female   29

8          9    15792365        He     501.0000    France    Male   44

9         10    15592389        H?     684.0000    France    Male   27
```

```
   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
5       8  113755.78              2          1               0
6       7       0.00              2          1               1
7       4  115046.74              4          1               0
8       4  142051.07              2          0               1
9       2  134603.88              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
5        149756.71       1
6         10062.80       0
7        119346.88       1
8         74940.50       0
9         71725.73       0
```

```
#boxplot after identifying and replacing the outliers with the mean
value of the column

sns.boxplot(df['CreditScore'])
```

```
/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 0x7f89bc2d5610>
```




```
#Check for Categorical columns and perform encoding.
df_categorical=df[['Geography','Gender']]
df['Gender'].unique()
#two unique values

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

df['Geography'].unique()
#three unique values

array(['France', 'Spain', 'Germany'], dtype=object)

#encoding categorical values with two distinct values
from sklearn.preprocessing import LabelEncoder
en_gen = LabelEncoder()

en_gen.fit(df_categorical['Gender'])
LabelEncoder()
values_gen=en_gen.transform(df_categorical['Gender'])
"After encoding",values_gen

('After encoding', array([0, 0, 0, ..., 0, 1, 0]))

#encoding categorical values with more than two distinct values
from sklearn.preprocessing import OneHotEncoder
import numpy as np
geo_encoder = OneHotEncoder()
geo_reshaped = np.array(df_categorical['Geography']).reshape(-1, 1)
geo_values = geo_encoder.fit_transform(geo_reshaped)
print(geo_values.toarray())
```

```
print()
print(geo_encoder.inverse_transform(geo_values))
```

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

[['France']
 ['Spain']
 ['France']
 ...
 ['France']
 ['Germany']
 ['France']]
```

```
#independent variable
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]]
```

```
#dependent variable
Y = df.iloc[:,-1].values
print(Y)
```

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

```
#Scale the independent variables
X = df[["CreditScore", "Age", "Tenure", "EstimatedSalary"]].values
y=df[["Exited"]]
from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()
scaler.fit(X)
X
```

```
array([[6.1900000e+02, 4.2000000e+01, 2.0000000e+00, 1.0134888e+05],
       [6.0800000e+02, 4.1000000e+01, 1.0000000e+00, 1.1254258e+05],
       [5.0200000e+02, 4.2000000e+01, 8.0000000e+00, 1.1393157e+05],
       ...,
```

```
       [7.0900000e+02, 3.6000000e+01, 7.0000000e+00, 4.2085580e+04],
       [7.7200000e+02, 4.2000000e+01, 3.0000000e+00, 9.2888520e+04],
       [7.9200000e+02, 2.8000000e+01, 4.0000000e+00, 3.8190780e+04]])
```

```
#Split the data into training and testing
from sklearn.model_selection import train_test_split
xtrain,xtest,ytrain,ytest =
train_test_split(X,Y,test_size=0.3,random_state=10)
```

```
xtrain.shape,xtest.shape
```

```
((7000, 4), (3000, 4))
```

```
ytrain.shape,ytest.shape
```

```
((7000,), (3000,))
```