#1
#Dataset downloaded
#Uploading the dataset

from google.colab import files

uploaded = files.upload()

Upload widget is only available when the cell has been executed in the current browser session. Please rerun this cell to enable.

Saving abalone.csv to abalone (1).csv

#2

#Loading the dataset

import pandas as pd
import numpy as np

df = pd.read_csv(r'abalone.csv')
df.head(3)

	Sex	Length	Diameter	Height	Whole weight	Shucked weight	Viscera weight	Shell weight	Rings
0	M	0.455	0.365	0.095	0.5140	0.2245	0.1010	0.15	15
1	M	0.350	0.265	0.090	0.2255	0.0995	0.0485	0.07	7
2	F	0.530	0.420	0.135	0.6770	0.2565	0.1415	0.21	9

#3 Univariate analysis

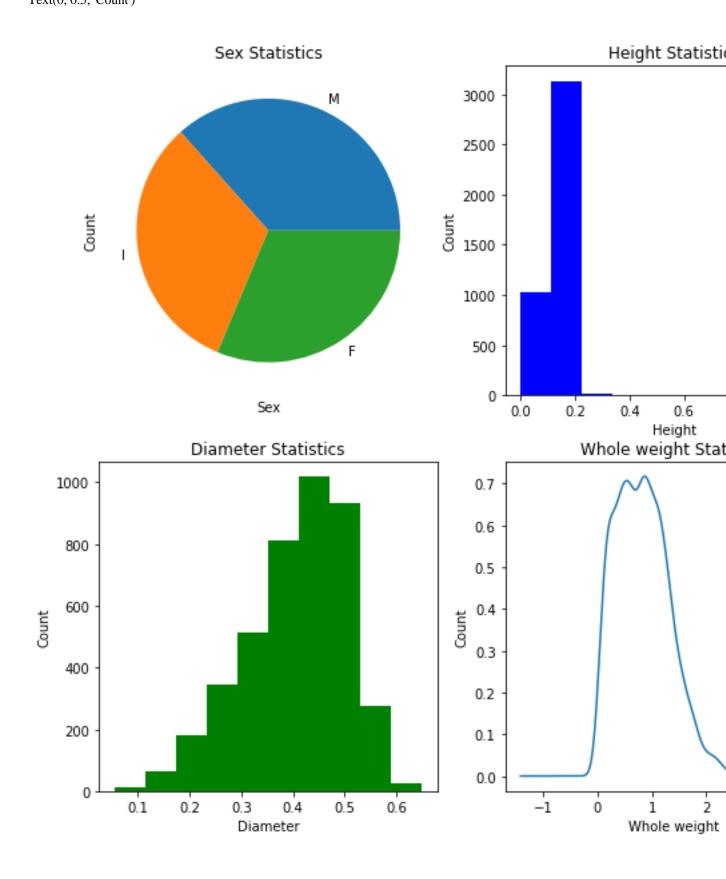
import matplotlib.pyplot as plt

plt.figure(figsize=(10,10))
counts = df['Sex'].value_counts()
plt.subplot(221)
plt.pie(counts, labels = counts.index)
plt.title('Sex Statistics')
plt.vlabel('Sex')
plt.ylabel('Count')

plt.subplot(222) plt.hist(df['Height'],color='blue') plt.title('Height Statistics') plt.xlabel('Height') plt.ylabel('Count')

plt.subplot(223) plt.hist(df['Diameter'],color='green') plt.title('Diameter Statistics') plt.xlabel('Diameter') plt.ylabel('Count')

plt.subplot(224) df['Whole weight'].plot(kind='density') plt.title('Whole weight Statistics')



```
#3 Bivariate Analysis
import seaborn as sns

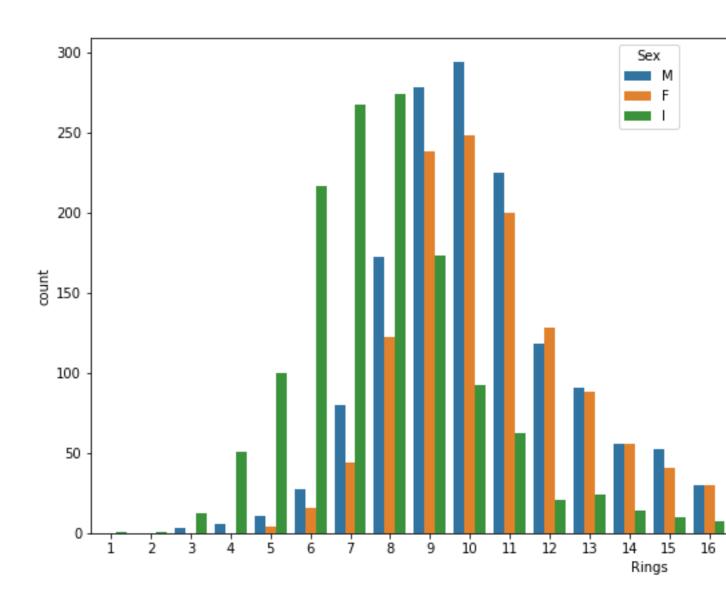
plt.figure(figsize=(15,15))

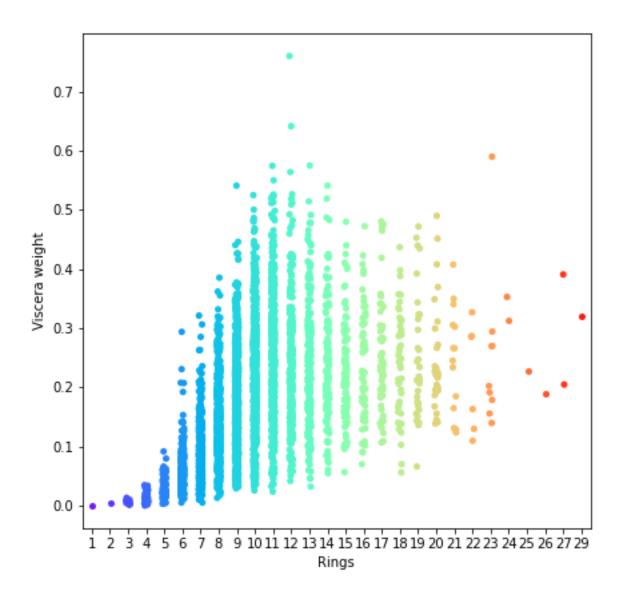
#Categorical vs Categorical
plt.subplot(2,1,1)
sns.countplot(data = df, x = 'Rings', hue = 'Sex')

plt.figure(figsize=(15,15))
#Continuous vs Continuous
plt.subplot(2,2,1)
sns.stripplot(x='Rings', y='Viscera weight', data=df, palette='rainbow')

plt.subplot(2,2,2)
sns.stripplot(x='Rings', y='Height', data=df, palette='rainbow')

<matplotlib.axes._subplots.AxesSubplot at 0x7f68ceeb0d90>
```





1.0

0.8

0.6

0.4

0.2

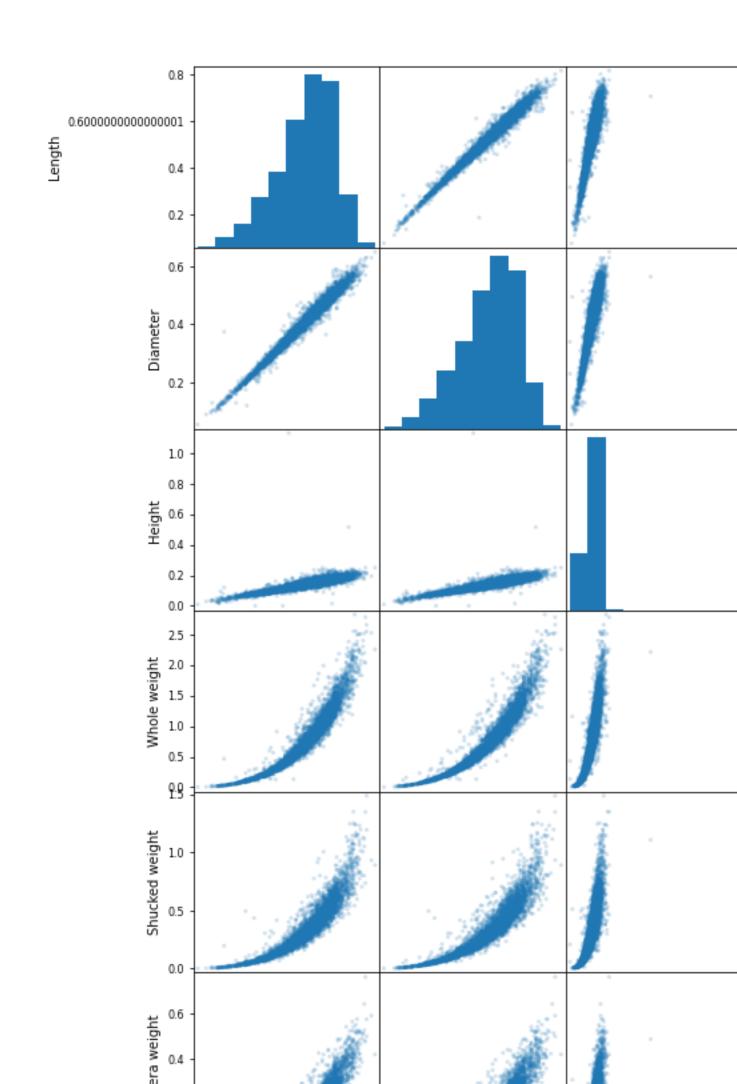
0.0

#3 Multivariate Analysis

pd.plotting.scatter_matrix(df, alpha=0.2, figsize=(20,20))

array([[<matplotlib.axes. subplots.AxesSubplot object at 0x7f68cec9cc50>, <matplotlib.axes._subplots.AxesSubplot object at 0x7f68ceca4690>, <matplotlib.axes._subplots.AxesSubplot object at 0x7f68cd3e8bd0>, <matplotlib.axes._subplots.AxesSubplot object at 0x7f68cd3ad210>, <matplotlib.axes._subplots.AxesSubplot object at 0x7f68cd3e1810>, <matplotlib.axes._subplots.AxesSubplot object at 0x7f68cd39ae10>, <matplotlib.axes._subplots.AxesSubplot object at 0x7f68cd35e450>, <matplotlib.axes._subplots.AxesSubplot object at 0x7f68cd313a50>], [<matplotlib.axes._subplots.AxesSubplot object at 0x7f68cd31cf10>, <matplotlib.axes._subplots.AxesSubplot object at 0x7f68cd2e24d0>, <matplotlib.axes._subplots.AxesSubplot object at 0x7f68cd244910>, <matplotlib.axes._subplots.AxesSubplot object at 0x7f68cd1fee10>, <matplotlib.axes._subplots.AxesSubplot object at 0x7f68cd1c0350>, <matplotlib.axes._subplots.AxesSubplot object at 0x7f68cd177850>, <matplotlib.axes._subplots.AxesSubplot object at 0x7f68cd12ed50>, <matplotlib.axes._subplots.AxesSubplot object at 0x7f68cd0f2290>], [<matplotlib.axes._subplots.AxesSubplot object at 0x7f68cd0a9790>,

```
<matplotlib.axes. subplots.AxesSubplot object at 0x7f68cd0dec90>,
 <matplotlib.axes._subplots.AxesSubplot object at 0x7f68cd0a21d0>,
 <matplotlib.axes._subplots.AxesSubplot object at 0x7f68cd0586d0>,
 <matplotlib.axes. subplots.AxesSubplot object at 0x7f68cd010bd0>,
 <matplotlib.axes._subplots.AxesSubplot object at 0x7f68ccfd2110>,
 <matplotlib.axes._subplots.AxesSubplot object at 0x7f68cecc1f10>,
 <matplotlib.axes._subplots.AxesSubplot object at 0x7f68cd3c71d0>],
[<matplotlib.axes._subplots.AxesSubplot object at 0x7f68cece1710>,
 <matplotlib.axes._subplots.AxesSubplot object at 0x7f68cf0a1c90>,
 <matplotlib.axes._subplots.AxesSubplot object at 0x7f68cecfded0>,
 <matplotlib.axes._subplots.AxesSubplot object at 0x7f68cef23d10>,
 <matplotlib.axes._subplots.AxesSubplot object at 0x7f68cf9010d0>,
 <matplotlib.axes._subplots.AxesSubplot object at 0x7f68cefd8d90>,
 <matplotlib.axes._subplots.AxesSubplot object at 0x7f68ccf943d0>,
 <matplotlib.axes. subplots.AxesSubplot object at 0x7f68ccf4d9d0>],
[<matplotlib.axes._subplots.AxesSubplot object at 0x7f68ccf0f050>,
 <matplotlib.axes._subplots.AxesSubplot object at 0x7f68ccec5610>,
 <matplotlib.axes._subplots.AxesSubplot object at 0x7f68cce7ec10>,
 <matplotlib.axes._subplots.AxesSubplot object at 0x7f68cce41250>,
 <matplotlib.axes._subplots.AxesSubplot object at 0x7f68ccdf7850>,
 <matplotlib.axes._subplots.AxesSubplot object at 0x7f68ccdafe50>,
 <matplotlib.axes. subplots.AxesSubplot object at 0x7f68ccd71490>,
 <matplotlib.axes. subplots.AxesSubplot object at 0x7f68ccd28a90>],
[<matplotlib.axes. subplots.AxesSubplot object at 0x7f68cccec0d0>,
 <matplotlib.axes._subplots.AxesSubplot object at 0x7f68ccd246d0>,
 <matplotlib.axes._subplots.AxesSubplot object at 0x7f68cccd8cd0>,
 <matplotlib.axes. subplots.AxesSubplot object at 0x7f68ccc9d310>,
 <matplotlib.axes._subplots.AxesSubplot object at 0x7f68ccc53990>,
 <matplotlib.axes._subplots.AxesSubplot object at 0x7f68ccc07f90>,
 <matplotlib.axes._subplots.AxesSubplot object at 0x7f68ccbc95d0>,
 <matplotlib.axes._subplots.AxesSubplot object at 0x7f68ccb80bd0>],
[<matplotlib.axes._subplots.AxesSubplot object at 0x7f68ccb46210>,
 <matplotlib.axes. subplots.AxesSubplot object at 0x7f68ccafa810>,
 <matplotlib.axes._subplots.AxesSubplot object at 0x7f68ccab1e10>,
 <matplotlib.axes._subplots.AxesSubplot object at 0x7f68cca7b050>,
 <matplotlib.axes._subplots.AxesSubplot object at 0x7f68cca2f510>,
 <matplotlib.axes._subplots.AxesSubplot object at 0x7f68cc9e6a10>,
 <matplotlib.axes._subplots.AxesSubplot object at 0x7f68cca1cf10>,
 <matplotlib.axes._subplots.AxesSubplot object at 0x7f68cc9e0450>],
[<matplotlib.axes._subplots.AxesSubplot object at 0x7f68cc997950>,
 <matplotlib.axes. subplots.AxesSubplot object at 0x7f68cc94de50>,
 <matplotlib.axes._subplots.AxesSubplot object at 0x7f68cc912390>,
 <matplotlib.axes._subplots.AxesSubplot object at 0x7f68cc8c8890>,
 <matplotlib.axes. subplots.AxesSubplot object at 0x7f68cc880d90>,
 <matplotlib.axes._subplots.AxesSubplot object at 0x7f68cc8442d0>,
 <matplotlib.axes._subplots.AxesSubplot object at 0x7f68cc7f97d0>,
 <matplotlib.axes._subplots.AxesSubplot object at 0x7f68cc7aecd0>]],
dtype=object)
```



	Length	Diameter	Height	Whole weight	Shucked weight	Viscera weight	Shell weight	Rings
coun t	4177.0000 00	4177.0000 00	4177.0000 00	4177.0000 00	4177.0000 00	4177.0000 00	4177.0000 00	4177.0000 00
mea n	0.523992	0.407881	0.139516	0.828742	0.359367	0.180594	0.238831	9.933684
std	0.120093	0.099240	0.041827	0.490389	0.221963	0.109614	0.139203	3.224169
min	0.075000	0.055000	0.000000	0.002000	0.001000	0.000500	0.001500	1.000000
25%	0.450000	0.350000	0.115000	0.441500	0.186000	0.093500	0.130000	8.000000
50%	0.545000	0.425000	0.140000	0.799500	0.336000	0.171000	0.234000	9.000000
75%	0.615000	0.480000	0.165000	1.153000	0.502000	0.253000	0.329000	11.000000
max	0.815000	0.650000	1.130000	2.825500	1.488000	0.760000	1.005000	29.000000

df.info()

<class 'pandas.core.frame.DataFrame'> RangeIndex: 4177 entries, 0 to 4176 Data columns (total 9 columns):

Column Non-Null Count Dtype

0 Sex 4177 non-null object 1 Length 4177 non-null float64

- 2 Diameter 4177 non-null float64
- 3 Height 4177 non-null float64
- 4 Whole weight 4177 non-null float64
- 5 Shucked weight 4177 non-null float64
- 6 Viscera weight 4177 non-null float64
- 7 Shell weight 4177 non-null float64
- 8 Rings 4177 non-null int64

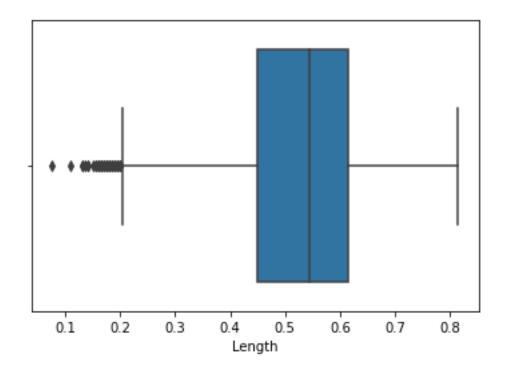
dtypes: float64(7), int64(1), object(1)

memory usage: 293.8+ KB #5 Handling missing values

df.isnull().sum()

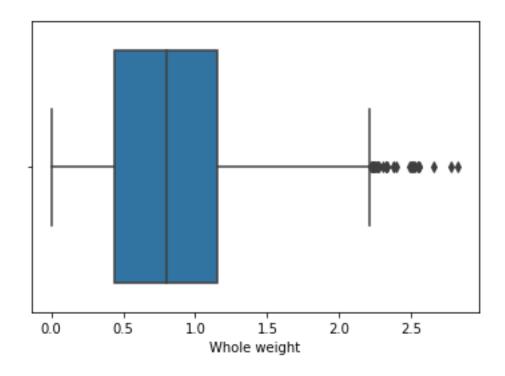
 $\begin{array}{ccc} \text{Sex} & 0 \\ \text{Length} & 0 \\ \text{Diameter} & 0 \\ \text{Height} & 0 \\ \text{Whole weight} & 0 \\ \text{Shucked weight} & 0 \end{array}$

```
Viscera weight 0
Shell weight
Rings
             0
dtype: int64
#For Continuous variables
df['Length'].fillna(df['Length'].mean(), inplace=True)
df['Height'].fillna(df['Height'].mean(), inplace=True)
df['Diameter'].fillna(df['Diameter'].mean(), inplace=True)
df['Whole weight'].fillna(df['Whole weight'].mean(), inplace=True)
df['Shucked weight'].fillna(df['Shucked weight'].mean(), inplace=True)
df['Viscera weight'].fillna(df['Viscera weight'].mean(), inplace=True)
df['Shell weight'].fillna(df['Shell weight'].mean(), inplace=True)
df['Rings'].fillna(df['Rings'].mean(), inplace=True)
#For Categorical variables
df['Sex'].fillna(df['Sex'].mode(), inplace=True)
#Ensuring again
print(df.isnull().sum())
print('\n\Sex : ', df['Sex'].unique())
Sex
              0
Length
Diameter
               0
              0
Height
Whole weight
Shucked weight 0
Viscera weight 0
Shell weight
              0
Rings
             0
dtype: int64
\Sex : ['M' 'F' 'I']
#6 Outlier detection - box plot
import seaborn as sns
sns.boxplot(df['Length'])
print('No. of Outliers: ', (df['Length'] < 0.2).sum())
No. of Outliers: 43
```



```
#6 Outlier detection - zscore
from scipy import stats
zscore = np.abs(stats.zscore(df['Diameter']))
print(zscore)
print('No. of Outliers : ', np.shape(np.where(zscore>3)))
     0.432149
0
     1.439929
1
2
     0.122130
3
     0.432149
4
     1.540707
4172 0.424464
4173 0.323686
4174 \quad 0.676409
4175 0.777187
4176 1.482634
Name: Diameter, Length: 4177, dtype: float64
No. of Outliers: (1, 13)
#6 Outlier detection - box plot
sns.boxplot(df['Whole weight'])
print('No. of Outliers: ', (df['Whole weight'] > 2.2).sum())
```

No. of Outliers: 33

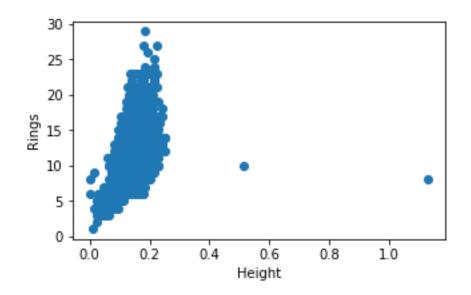


#6 Outlier detection - Scatter plot import matplotlib.pyplot as plt

fig, ax = plt.subplots(figsize = (5,3)) ax.scatter(df['Height'], df['Rings'])

x-axis label
ax.set_xlabel('Height')

y-axis label
ax.set_ylabel('Rings')
plt.show()



```
#6 Outlier detection - IQR
Q1 = df['Shucked weight'].quantile(0.25)
Q3 = df['Shucked weight'].quantile(0.75)
IQR = Q3 - Q1
print(IQR)
upper=Q3 + 1.5 * IQR
lower=Q1 - 1.5 * IQR
count = np.size(np.where(df['Shucked weight'] >upper))
count = count + np.size(np.where(df['Shucked weight'] <lower))</pre>
print('No. of outliers : ', count)
0.316
No. of outliers: 48
0.316
No. of outliers: 48
#6 Outlier detection - 3 sigma
upper = df['Viscera weight'].mean() + (3 * df['Viscera weight'].std())
lower = df['Viscera weight'].mean() - (3 * df['Viscera weight'].std())
columns = df[ ( df['Viscera weight'] > upper ) | ( df['Viscera weight'] < lower ) ]
print('Upper range : ', upper)
print('Lower range : ', lower)
print('No. of Outliers : ', len(columns))
Upper range: 0.5094363586315791
Lower range: -0.1482491429265277
No. of Outliers: 22
#6 Outlier detection - 3 sigma
upper = df['Shell weight'].mean() + (3 * df['Shell weight'].std())
lower = df['Shell weight'].mean() - (3 * df['Shell weight'].std())
columns = df[ ( df['Shell weight'] > upper ) | ( df['Shell weight'] < lower ) ]</pre>
print('Upper range : ', upper)
print('Lower range : ', lower)
print('No. of Outliers : ', len(columns))
Upper range: 0.6564388680356763
Lower range: -0.17877714909864026
No. of Outliers: 27
#6 Removing Outliers
columns = ['Diameter', 'Length', 'Whole weight', 'Height', 'Shucked weight', 'Viscera weight', 'Shell weight']
for i in columns:
     Q1=df[i].quantile(0.25)
     Q3=df[i].quantile(0.75)
     IQR=Q3-Q1
     upper=Q3+1.5*IQR
     lower=Q1-1.5*IQR
     df[i]=np.where(df[i] >upper, upper, df[i])
     df[i]=np.where(df[i] < lower, lower, df[i])
#After outlier removal
columns = ['Diameter', 'Length', 'Whole weight', 'Height', 'Shucked weight', 'Viscera weight', 'Shell weight']
for i in columns:
 Q1 = df[i].quantile(0.25)
 Q3 = df[i].quantile(0.75)
```

```
IQR = Q3 - Q1
 upper=Q3 + 1.5 * IQR
 lower=Q1 - 1.5 * IQR
 count = np.size(np.where(df[i] >upper))
 count = count + np.size(np.where(df[i] <lower))</pre>
 print('No. of outliers in ', i, ': ', count)
No. of outliers in Diameter: 0
No. of outliers in Length: 0
No. of outliers in Whole weight: 0
No. of outliers in Height: 0
No. of outliers in Shucked weight: 0
No. of outliers in Viscera weight: 0
No. of outliers in Shell weight: 0
#7 Label Encoding
print('Before encoding : ', df['Sex'][0])
df['Sex'] = df['Sex'].astype('category')
df['Sex'] = df['Sex'].cat.codes
print('After encoding : ', df['Sex'][0])
df['Sex'].dtype
Before encoding: M
After encoding: 2
dtype('int8')
df.dtypes
Sex
              int8
Length
              float64
Diameter
               float64
Height
              float64
Whole weight
                 float64
Shucked weight float64
Viscera weight float64
Shell weight
               float64
Rings
               int64
dtype: object
#Changing target column(Exited) as the last column
Exit = df['Rings']
```

	Sex	Length	Diameter	Height	Whole weight	Shucked weight	Viscera weight	Shell weight	Rings
0	2	0.455	0.365	0.095	0.514	0.2245	0.101	0.15	15

#8 Splitting dependent and independent variables

X = df.iloc[:, :-1]

 $df = df \cdot join(Exit)$

df.head(1)

print('Independent : \n', X.head(2))

df = df.drop('Rings', axis=1)

Y = df.iloc[:, -1]

 $print('Dependent: \ \ \ \ ', \ Y.head(2))$

Independent:

```
Sex Length Diameter Height Whole weight Shucked weight \
0 2 0.455
              0.365 0.095
                               0.5140
                                            0.2245
                                            0.0995
  2 0.350
             0.265 0.090
                               0.2255
 Viscera weight Shell weight
0
      0.1010
                   0.15
       0.0485
                   0.07
1
Dependent:
0 15
1
Name: Rings, dtype: int64
#9 Scaling
from sklearn.preprocessing import RobustScaler
scaler=RobustScaler()
print('Before scaling : \n', X[1:3])
X = scaler.fit_transform(X)
print(\n After scaling : \n', X[1:3])
Before scaling:
  Sex Length Diameter Height Whole weight Shucked weight \
  2 0.35
             0.265 0.090
                              0.2255
                                           0.0995
             0.420 0.135
2 0 0.53
                               0.6770
                                           0.2565
 Viscera weight Shell weight
       0.0485
                   0.07
1
2
       0.1415
                   0.21
After scaling:
          -1.18181818 -1.23076923 -1.
[[0.5]]
                                           -0.80674631 -0.74841772
 -0.76802508 -0.8241206 ]
[-0.5]
         -0.09090909 -0.03846154 -0.1
                                           -0.17217147 -0.25158228
 -0.18495298 -0.12060302]]
#10 Splitting data into training and test set
from sklearn.model_selection import train_test_split
X_train, X_test, Y_train, Y_test = train_test_split(X,Y,test_size = 0.2)
print(X_train.shape, X_test.shape, Y_train.shape, Y_test.shape)
(3341, 8) (836, 8) (3341,) (836,)
#11 Build the model
from sklearn import linear_model as lin_mod
model = lin_mod.LinearRegression()
#12 Training the model
LinearRegression = model.fit(X_train, Y_train)
r_sq = model.score(X_train, Y_train)
print(f"Determination coeeficient: {r_sq}")
Determination coeeficient: 0.5394019894190405
#13 Testing the model
Y_pred = model.predict(X_test)
print('Predicted values : ', Y_pred[:5])
Predicted values: [13.18842068 14.21223424 8.63255896 5.61492745 9.05210334]
#Metrics
from sklearn.metrics import r2_score
from sklearn.metrics import mean_squared_error
```

r2 = r2_score(Y_test, Y_pred) mean_squared_error = mean_squared_error(Y_test, Y_pred) rmse = (np.sqrt(mean_squared_error))

print('R2 score : ', r2)

print('Mean squared error : ', mean_squared_error)

print('Root Mean squared error : ', rmse)

R2 score: 0.5244781220124035

Mean squared error: 4.597226769271034 Root Mean squared error: 2.144114448734263