Assignment Date	01-October-2022
Student Name	MONIKA K
Student Roll No	61771931034
Maximum marks	2 marks

Assignment -3

Python Programming

1. Download the dataset

In [1]:
```
#importing the libraries

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
```

2. Load the dataset into the tool.

In [2]:
```
#Loading the dataset

d = pd.read_csv(r'Downloads/abalone.csv')
```

3. Perform Below Visualizations.

· Univariate Analysis

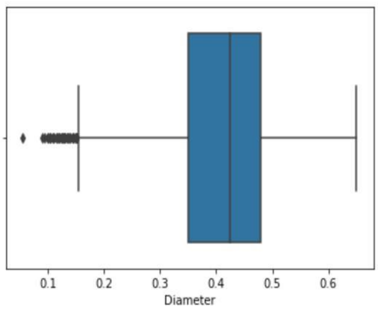
In [3]:
```
d.head()
```

Out[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	0.150	15
1	M	0.350	0.265	0.090	0.2255	0.0995	0.0485	0.070	7
2	F	0.530	0.420	0.135	0.6770	0.2565	0.1415	0.210	9
3	M	0.440	0.365	0.125	0.5160	0.2155	0.1140	0.155	10
4	I	0.330	0.255	0.080	0.2050	0.0895	0.0395	0.055	7

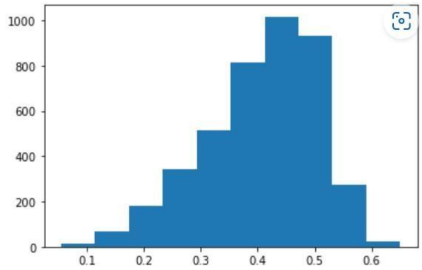
In [4]:
```
#BoxPlot

sns.boxplot(d['Diameter'])
```

Out[4]: <AxesSubplot:xlabel='Diameter'>



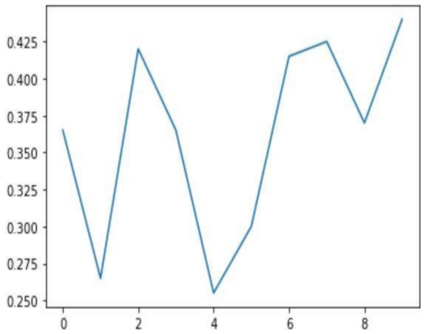
In [5]:
```
#histogram

plt.hist(d['Diameter'])
```

Out[5]:
```
(array([  13.,   66.,  180.,  344.,  513.,  812., 1017.,  934.,  275.,
          23.]),
 array([0.055 , 0.1145, 0.174 , 0.2335, 0.293 , 0.3525, 0.412 , 0.4715,
        0.531 , 0.5905, 0.65  ]),
 <BarContainer object of 10 artists>)
```



In [6]:
```
#line plot

plt.plot(d['Diameter'].head(10))
```

Out[6]:
```
[<matplotlib.lines.Line2D at 0x1c2ed71d130>]
```

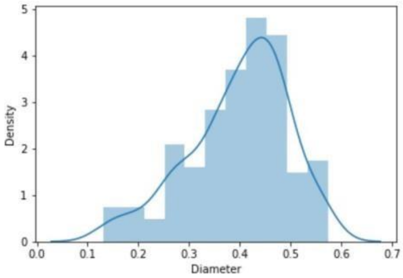


In [7]:
```
#piechart

plt.pie(d['Diameter'].head(),autopct='%.2f')
```

Out[7]:
```
([<matplotlib.patches.Wedge at 0x1c2ed77fd00>,
  <matplotlib.patches.Wedge at 0x1c2ed78d460>,
  <matplotlib.patches.Wedge at 0x1c2ed78db80>,
  <matplotlib.patches.Wedge at 0x1c2ed7992e0>,
  <matplotlib.patches.Wedge at 0x1c2ed799a30>],
 [Text(0.8507215626110558, 0.6973326486753676, ''),
  Text(-0.32611344931648134, 1.0505474849691026, ''),
  Text(-1.0998053664078908, -0.02069193128747144, ''),
  Text(-0.08269436219656089, -1.096887251480709, ''),
  Text(0.9758446362287218, -0.5076684409569241, '')],
 [Text(0.464029943242394, 0.3803632629138369, '21.86'),
  Text(-0.17788006326353525, 0.5730259008922377, '15.87'),
  Text(-0.5998938362224858, -0.011286507974984419, '25.15'),
  Text(-0.045106015743578656, -0.5983021371712958, '21.86'),
  Text(0.5322788924883937, -0.2769100587037768, '15.27')])
```

In [8]:
```
#distplot

sns.distplot(d['Diameter'].head(200))
```

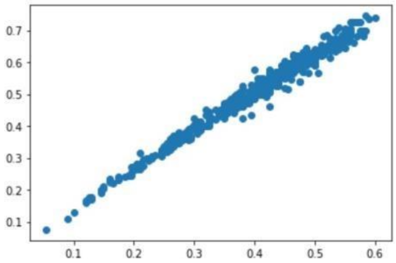
Out[8]: <AxesSubplot:xlabel='Diameter', ylabel='Density'>



● Bi - Variate Analysis

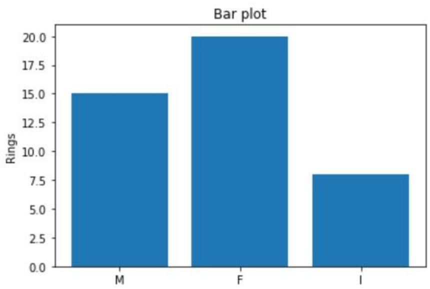
In [9]:
```
#scatter plot

plt.scatter(d['Diameter'].head(500),d['Length'].head(500))
```

Out[9]: <matplotlib.collections.PathCollection at 0x1c2edcc2d60>



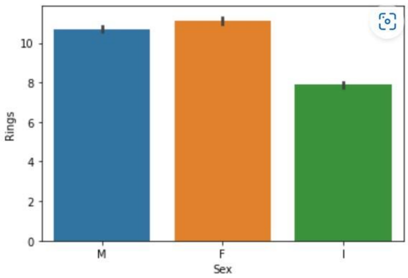
In [10]:
```
#bar plot

plt.bar(d['Sex'].head(10),d['Rings'].head(10))

#labelling of x,y and result

plt.title('Bar plot')
plt.xlabel('Diameter')
plt.ylabel('Rings')
```

Out[10]: Text(0, 0.5, 'Rings')



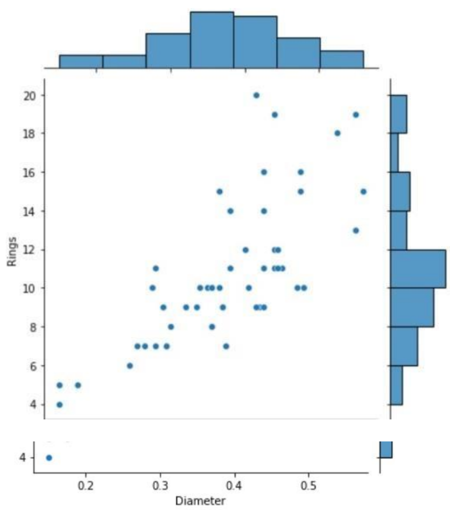
In [11]:
```
sns.barplot(d['Sex'], d['Rings'])
```

Out[11]: <AxesSubplot:xlabel='Sex', ylabel='Rings'>



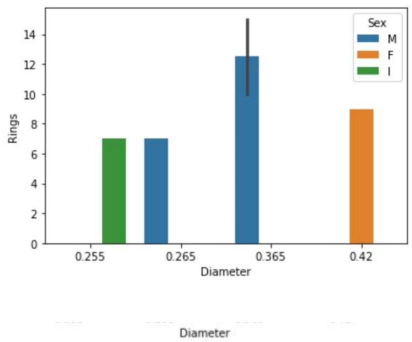
In [12]:
```python
#joint plot

sns.jointplot(d['Diameter'].head(50),d['Rings'].head(50))
```

Out[12]: <seaborn.axisgrid.JointGrid at 0x1c2edde3160>



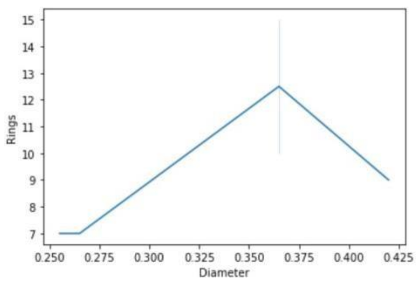
In [13]:
```python
#bar plot

sns.barplot('Diameter','Rings',hue='Sex',data=d.head())
```

Out[13]: <AxesSubplot:xlabel='Diameter', ylabel='Rings'>



In [14]:
```python
sns.lineplot(d['Diameter'].head(),d['Rings'].head())
```

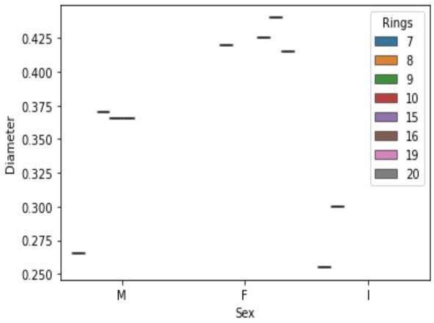
Out[14]: <AxesSubplot:xlabel='Diameter', ylabel='Rings'>



● Multi - Variate Analysis

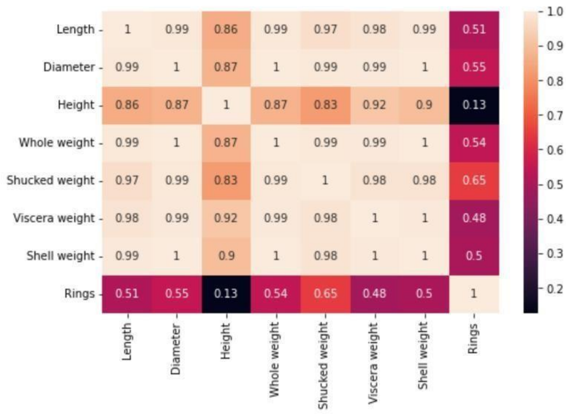
In [15]:
```
#boxplot

sns.boxplot(d['Sex'].head(10),d['Diameter'].head(10),d['Rings'].head(10))
```

Out[15]:
```
<AxesSubplot:xlabel='Sex', ylabel='Diameter'>
```



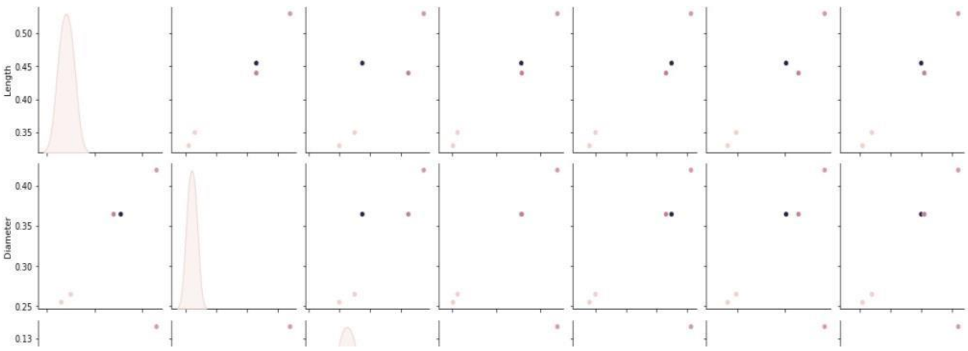
In [16]:
```
#heat map

fig=plt.figure(figsize=(8,5))
sns.heatmap(d.head().corr(),annot=True)
```

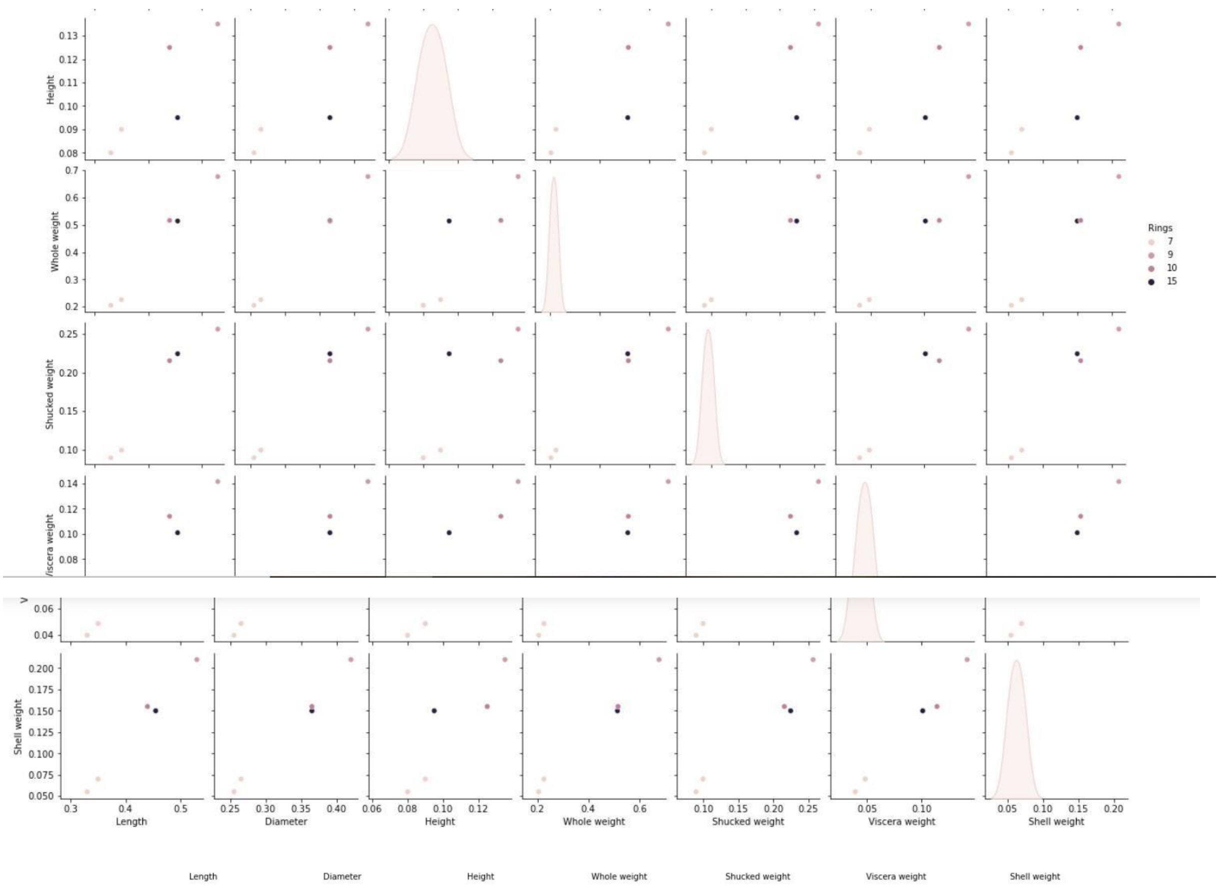
Out[16]:
```
<AxesSubplot:>
```



In [17]:
```
#pair plot

sns.pairplot(d.head(),hue='Rings')
```

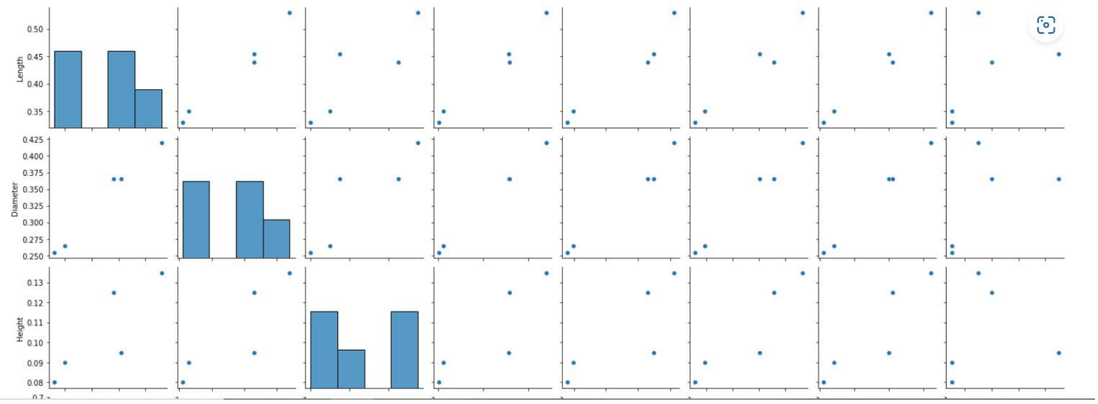
Out[17]:
```
<seaborn.axisgrid.PairGrid at 0x1c2edd07fd0>
```

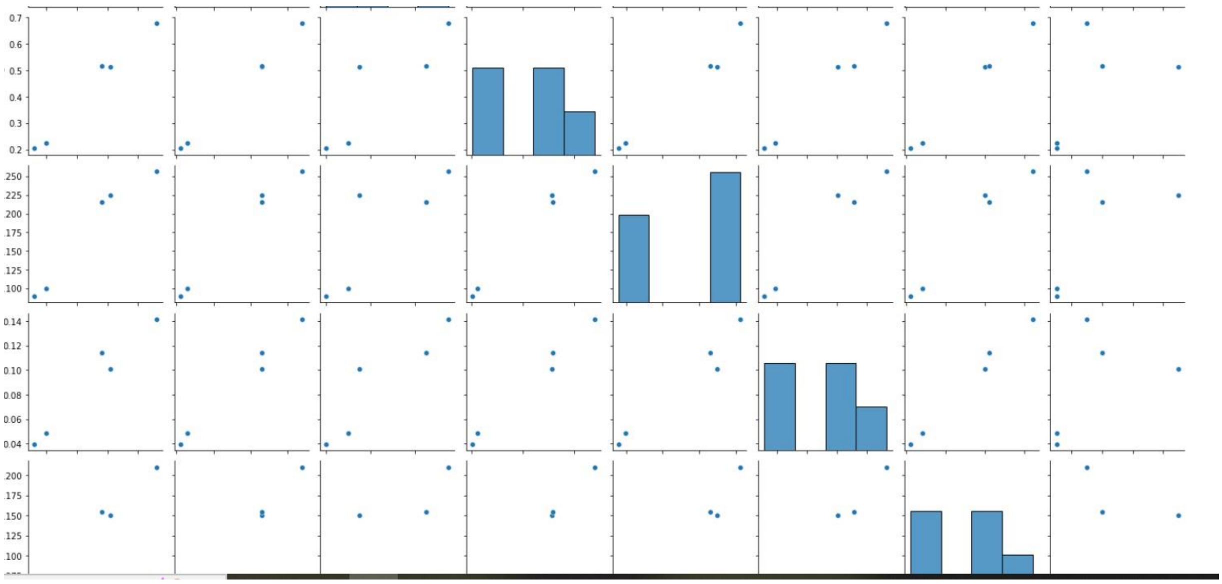


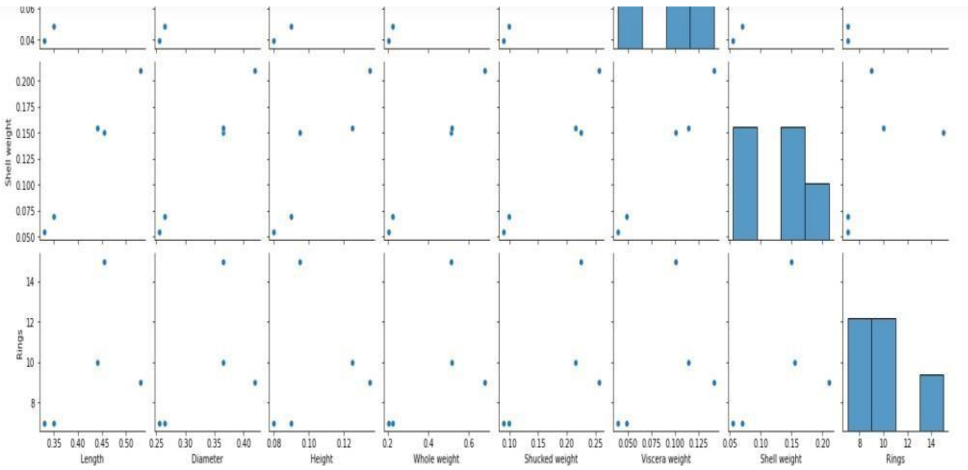



```
In [18]: sns.pairplot(d.head())
```

Out[18]: <seaborn.axisgrid.PairGrid at 0x1c2f243e910>







4. Perform descriptive statistics on the dataset.

In [19]:
```
#head
d.head()
```

Out[19]:

	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	0.150	15
1	M	0.350	0.265	0.090	0.2255	0.0995	0.0485	0.070	7
2	F	0.530	0.420	0.135	0.6770	0.2565	0.1415	0.210	9
3	M	0.440	0.365	0.125	0.5160	0.2155	0.1140	0.155	10
4	I	0.330	0.255	0.080	0.2050	0.0895	0.0395	0.055	7

In [20]:
```
#tail
d.tail()
```

Out[20]:

	Sex	Length	Diameter	Height	Whole weight	Shucked weight	Viscera weight	Shell weight	Rings
4172	F	0.565	0.450	0.165	0.8870	0.3700	0.2390	0.2490	11
4173	M	0.590	0.440	0.135	0.9660	0.4390	0.2145	0.2605	10

4174	M	0.600	0.475	0.205	1.1760	0.5255	0.2875	0.3080	9
4175	F	0.625	0.485	0.150	1.0945	0.5310	0.2610	0.2960	10
4176	M	0.710	0.555	0.195	1.9485	0.9455	0.3765	0.4950	12

In [21]:
```
d.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
```

In [22]:
```
d.describe()
```

Out[22]:

	Length	Diameter	Height	Whole weight	Shucked weight	Viscera weight	Shell weight	Rings
count	4177.000000	4177.000000	4177.000000	4177.000000	4177.000000	4177.000000	4177.000000	4177.000000
mean	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

In [23]:
```
#mode

d.mode().T
```

Out[23]:

	0	1
Sex	M	NaN
Length	0.55	0.625
Diameter	0.45	NaN
Height	0.15	NaN
Whole weight	0.2225	NaN
Shucked weight	0.175	NaN
Viscera weight	0.1715	NaN
Shell weight	0.275	NaN
Rings	9.0	NaN

In [24]:
```
d.shape
```

Out[24]: (4177, 9)

In [25]: #kurtosis

```
d.kurt()
```

Out[25]:
```
Length             0.064621
Diameter          -0.045476
Height            76.025509
Whole weight      -0.023644
Shucked weight     0.595124
Viscera weight     0.084012
Shell weight       0.531926
Rings              2.330687
dtype: float64
```

In [26]: #skewness

```
d.skew()
```

Out[26]:
```
Length           -0.639873
Diameter         -0.609198
Height            3.128817
Whole weight      0.530959
Shucked weight    0.719098
Viscera weight    0.591852
Shell weight      0.620927
Rings             1.114102
dtype: float64
```

In [27]: #variance

```
d.var()
```

Out[27]:
```
Length             0.014422
Diameter           0.009849
Height             0.001750
Whole weight       0.240481
Shucked weight     0.049268
Viscera weight     0.012015
Shell weight       0.019377
Rings             10.395266
dtype: float64
```

In [28]: #finding unique values for columns

```
d.nunique()
```

Out[28]:
```
Sex                  3
Length             134
Diameter           111
Height              51
Whole weight      2429
Shucked weight    1515
Viscera weight     880
Shell weight       926
Rings               28
dtype: int64
```

5. Check for Missing values and deal with them.

In [29]: #finding missing values

```
d.isna()
```

Out[29]:

	Sex	Length	Diameter	Height	Whole weight	Shucked weight	Viscera weight	Shell weight	Rings
0	False	False	False	False	False	False	False	False	False
1	False	False	False	False	False	False	False	False	False
2	False	False	False	False	False	False	False	False	False
3	False	False	False	False	False	False	False	False	False
4	False	False	False	False	False	False	False	False	False
...	...	...	...	...	...	...	...	...	...
4172	False	False	False	False	False	False	False	False	False
4173	False	False	False	False	False	False	False	False	False
4174	False	False	False	False	False	False	False	False	False
4175	False	False	False	False	False	False	False	False	False
4176	False	False	False	False	False	False	False	False	False

4177 rows × 9 columns

In [30]:
```
d.isna().any()
```

Out[30]:
```
Sex               False
Length            False
Diameter          False
Height            False
Whole weight      False
Shucked weight    False
Viscera weight    False
Shell weight      False
Rings             False
dtype: bool
```

In [31]:
```
d.isna().sum()
```

Out[31]:
```
Sex               0
Length            0
Diameter          0
Height            0
Whole weight      0
Shucked weight    0
Viscera weight    0
Shell weight      0
Rings             0
dtype: int64
```


```
dtype: bool
```

In [31]:
```
d.isna().sum()
```

Out[31]:
```
Sex               0
Length            0
Diameter          0
Height            0
Whole weight      0
Shucked weight    0
Viscera weight    0
Shell weight      0
Rings             0
dtype: int64
```

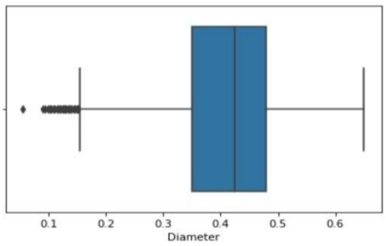

In [32]:
```
d.isna().any().sum()
#no missing values
```

Out[32]: 0

6. Find the outliers and replace them outliers

In [33]:
```
#finding outliers

sns.boxplot(d['Diameter'])
```

Out[33]: <AxesSubplot:xlabel='Diameter'>



In [34]:
```
#handling outliers

qnt=d.quantile(q=[0.25,0.75])
qnt
```

Out[34]:

	Length	Diameter	Height	Whole weight	Shucked weight	Viscera weight	Shell weight	Rings
0.25	0.450	0.35	0.115	0.4415	0.186	0.0935	0.130	8.0
0.75	0.615	0.48	0.165	1.1530	0.502	0.2530	0.329	11.0

In [35]:
```
iqr=qnt.loc[0.75]-qnt.loc[0.25]

iqr
```

Out[35]:
```
Length            0.1650
Diameter          0.1300
Height            0.0500
Whole weight      0.7115
Shucked weight    0.3160
Viscera weight    0.1595
Shell weight      0.1990
Rings             3.0000
dtype: float64
```

In [36]:
```
lower=qnt.loc[0.25]-(1.5*iqr)
lower
```

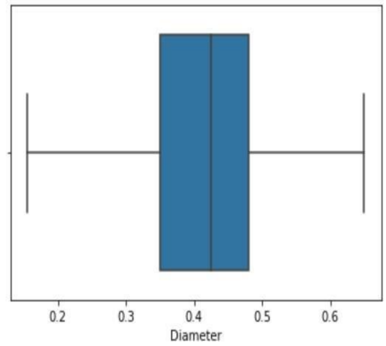
```
Out[36]: Length            0.20250
         Diameter          0.15500
         Height            0.04000
         Whole weight     -0.62575
         Shucked weight   -0.28800
         Viscera weight   -0.14575
         Shell weight     -0.16850
         Rings             3.50000
         dtype: float64
```

```python
In [37]: upper=qnt.loc[0.75]+(1.5*iqr)
         upper
```

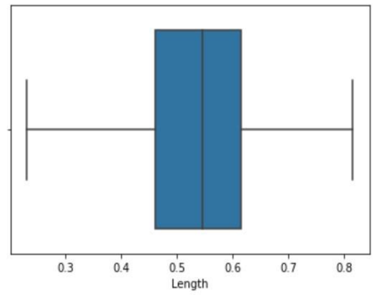
```
Out[37]: Length             0.86250
         Diameter           0.67500
         Height             0.24000
         Whole weight       2.22025
         Shucked weight     0.97600
         Viscera weight     0.49225
         Shell weight       0.62750
         Rings             15.50000
         dtype: float64
```

```python
In [38]: # replacing outliers

         ##Diameter
         d['Diameter']=np.where(d['Diameter']<0.155,0.4078,d['Diameter'])
         sns.boxplot(d['Diameter'])
```

Out[38]: <AxesSubplot:xlabel='Diameter'>



Out[41]: <AxesSubplot:xlabel='Length'>

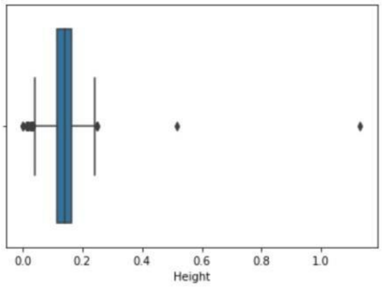



```python
In [42]: ## Height

         sns.boxplot(d['Height'])
```

Out[42]: <AxesSubplot:xlabel='Height'>

In [42]:
```
## Height

sns.boxplot(d['Height'])
```

Out[42]: <AxesSubplot:xlabel='Height'>

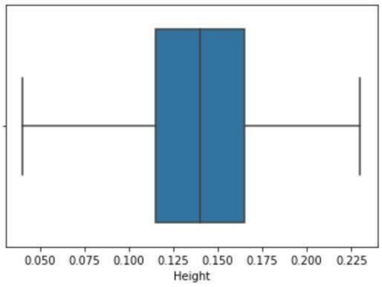


In [43]:
```
d['Height']=np.where(d['Height']<0.04,0.139, d['Height'])
d['Height']=np.where(d['Height']>0.23,0.139, d['Height'])
```


```
d['Height']=np.where(d['Height']>0.23,0.139, d['Height'])
```


In [44]:
```
sns.boxplot(d['Height'])
```

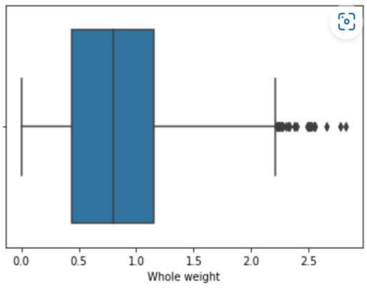
Out[44]: <AxesSubplot:xlabel='Height'>



In [45]:
```
## Whole weight

sns.boxplot(d['Whole weight'])
```

Out[45]: <AxesSubplot:xlabel='Whole weight'>

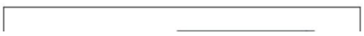
Out[45]: <AxesSubplot:xlabel='Whole weight'>



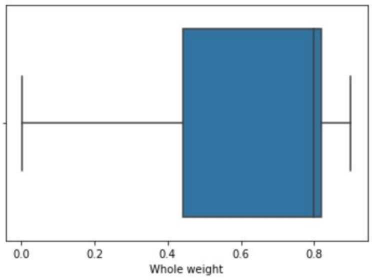
In [46]:
```
d['Whole weight']=np.where(d['Whole weight']>0.9,0.82, d['Whole weight'])
```

In [47]:
```
sns.boxplot(d['Whole weight'])
```

Out[47]: <AxesSubplot:xlabel='Whole weight'>

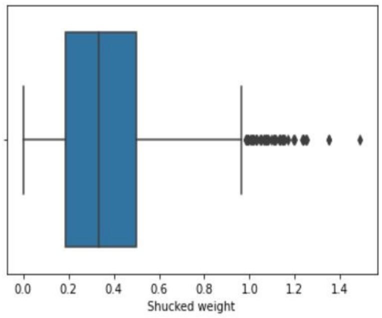


In [47]:
```
sns.boxplot(d['Whole weight'])
```
Out[47]: <AxesSubplot:xlabel='Whole weight'>



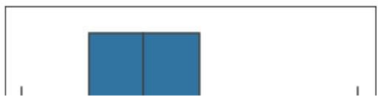
In [48]:
```
## Shucked weight

sns.boxplot(d['Shucked weight'])
```
Out[48]: <AxesSubplot:xlabel='Shucked weight'>

Out[48]: <AxesSubplot:xlabel='Shucked weight'>

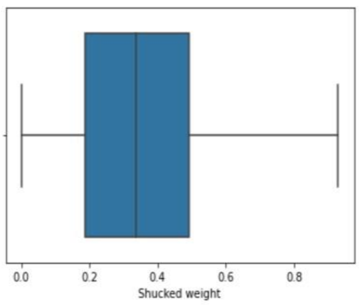


In [49]:
```
d['Shucked weight']=np.where(d['Shucked weight']>0.93,0.35, d['Shucked weight'])
```

In [50]:
```
sns.boxplot(d['Shucked weight'])
```
Out[50]: <AxesSubplot:xlabel='Shucked weight'>

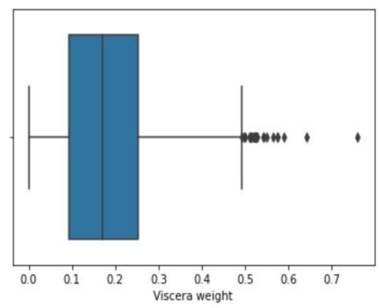


Out[50]: <AxesSubplot:xlabel='Shucked weight'>



In [51]:
```
## Viscera weight

sns.boxplot(d['Viscera weight'])
```
Out[51]: <AxesSubplot:xlabel='Viscera weight'>

Out[51]: <AxesSubplot:xlabel='Viscera weight'>



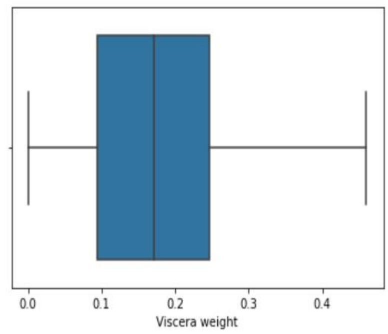
In [52]:
```
d['Viscera weight']=np.where(d['Viscera weight']>0.46,0.18, d['Viscera weight'])
```

In [53]:
```
sns.boxplot(d['Viscera weight'])
```

Out[53]: <AxesSubplot:xlabel='Viscera weight'>

In [53]: sns.boxplot(d['Viscera weight'])

Out[53]: <AxesSubplot:xlabel='Viscera weight'>



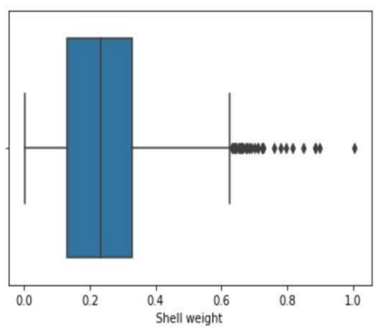
In [54]:
```
## Shell weight

sns.boxplot(d['Shell weight'])
```

Out[54]: <AxesSubplot:xlabel='Shell weight'>

In [54]: ## Shell weight

sns.boxplot(d['Shell weight'])

Out[54]: <AxesSubplot:xlabel='Shell weight'>

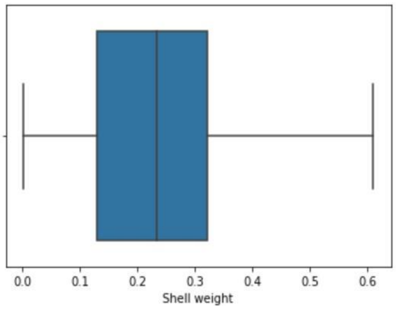


In [55]:
```
d['Shell weight']=np.where(d['Shell weight']>0.61,0.2388, d['Shell weight'])
```

In [56]:
```
sns.boxplot(d['Shell weight'])
```

Out[56]: <AxesSubplot:xlabel='Shell weight'>

In [56]:
```
sns.boxplot(d['Shell weight'])
```
Out[56]: <AxesSubplot:xlabel='Shell weight'>



7. Check for Categorical columns and perform encoding.

In [57]:
```
#one hot encoding

d['Sex'].replace({'M':1,'F':0,'I':2},inplace=True)
d
```
Out[57]:

	Sex	Length	Diameter	Height	Whole weight	Shucked weight	Viscera weight	Shell weight	Rings
0	1	0.455	0.365	0.095	0.5140	0.2245	0.1010	0.1500	15
1	1	0.350	0.265	0.090	0.2255	0.0995	0.0485	0.0700	7
2	0	0.530	0.420	0.135	0.6770	0.2565	0.1415	0.2100	9
3	1	0.440	0.365	0.125	0.5160	0.2155	0.1140	0.1550	10
4	2	0.330	0.255	0.080	0.2050	0.0895	0.0395	0.0550	7
...	...	...	...	...	...	...	...	...	...
4172	0	0.565	0.450	0.165	0.8870	0.3700	0.2390	0.2490	11
4173	1	0.590	0.440	0.135	0.8200	0.4390	0.2145	0.2605	10
4174	1	0.600	0.475	0.205	0.8200	0.5255	0.2875	0.3080	9
4175	0	0.625	0.485	0.150	0.8200	0.5310	0.2610	0.2960	10
4176	1	0.710	0.555	0.195	0.8200	0.3500	0.3765	0.4950	12

4177 rows × 9 columns

8. Split the data into dependent and independent variables.

In [58]:
```
x=d.drop(columns= ['Rings'])
y=d['Rings']
x
```
Out[58]:

	Sex	Length	Diameter	Height	Whole weight	Shucked weight	Viscera weight	Shell weight
0	1	0.455	0.365	0.095	0.5140	0.2245	0.1010	0.1500
1	1	0.350	0.265	0.090	0.2255	0.0995	0.0485	0.0700
2	0	0.530	0.420	0.135	0.6770	0.2565	0.1415	0.2100
3	1	0.440	0.365	0.125	0.5160	0.2155	0.1140	0.1550
4	2	0.330	0.255	0.080	0.2050	0.0895	0.0395	0.0550
...	...	...	...	...	...	...	...	...
4172	0	0.565	0.450	0.165	0.8870	0.3700	0.2390	0.2490
4173	1	0.590	0.440	0.135	0.8200	0.4390	0.2145	0.2605
4174	1	0.600	0.475	0.205	0.8200	0.5255	0.2875	0.3080
4175	0	0.625	0.485	0.150	0.8200	0.5310	0.2610	0.2960
4176	1	0.710	0.555	0.195	0.8200	0.3500	0.3765	0.4950

4177 rows × 8 columns

4177 rows × 8 columns

In [59]:
```
y
```

Out[59]:
```
0       15
1        7
2        9
3       10
4        7
        ..
4172    11
4173    10
4174     9
4175    10
4176    12
Name: Rings, Length: 4177, dtype: int64
```

9. Scale the independent variables

In [60]:
```
from sklearn.preprocessing import scale  #StandardScaler
```

In [61]:
```
#Scaling the independent variables

x = scale(x)
x
```

Out[61]:
```
array([[-0.0105225 , -0.67088921, -0.50179694, ..., -0.61037964,
        -0.7328165 , -0.64358742],
       [-0.0105225 , -1.61376082, -1.57304487, ..., -1.22513334,
        -1.24343929, -1.25742181],
       [-1.26630752,  0.00259051,  0.08738942, ..., -0.45300269,
        -0.33890749, -0.18321163],
       ...,
       [-0.0105225 ,  0.63117159,  0.67657577, ...,  0.86994729,
         1.08111018,  0.56873549],
       [-1.26630752,  0.85566483,  0.78370057, ...,  0.89699645,
         0.82336724,  0.47666033],
       [-0.0105225 ,  1.61894185,  1.53357412, ...,  0.00683308,
         1.94673739,  2.00357336]])
```

10. Split the data into training and testing

In [62]:
```
from sklearn.model_selection import train_test_split
```

In [63]:
```
#spliting data to train and test

x_train, x_test, y_train, y_test = train_test_split(x,y, test_size = 0.2)
print(x_train.shape, x_test.shape)
```

```
(3341, 8) (836, 8)
```

11. Build the Model

In [64]:
```
#Multiple Regression

from sklearn.linear_model import LinearRegression

MLR=LinearRegression()
```

12. Train the Model

In [65]:
```
MLR.fit(x_train,y_train)
```
Out[65]:
```
LinearRegression()
```

13. Test the Model

In [66]:
```
#predcition on the test data
y_pred=MLR.predict(x_test)
y_pred
```
Out[66]:
```
array([11.46655124,  9.2166091 ,  6.59967857,  7.81824648, 12.18984569,
       11.44220895, 11.20545145,  8.71621092, 10.98237601,  6.83381457,
       10.46227495,  9.10809044, 12.39359143, 14.54491772, 13.54791716,
       10.12045364, 11.48597397,  7.73511543, 12.86466796,  8.37939955,
        6.51920876,  8.16682072,  8.05416099, 10.22713858, 10.57995698,
       11.31009826,  7.52742935,  9.88582514, 11.25644638, 11.38973324,
       10.95569239, 10.28552912, 10.40475249, 10.44887526, 11.03343746,
       10.15213587, 10.04733695,  6.54448931, 11.86305246,  6.73817965,
        4.07354447, 11.09033543,  7.69897797,  9.56311429, 11.63006462,
       13.17063754,  6.34451832,  7.27896893, 15.31511539,  6.92860099,
        3.63485054,  6.80184256, 11.451762  , 10.69664795,  8.59383781,
        7.50446583, 10.33994154, 11.85072027, 13.544946  , 10.27236403,
```


13. Test the Model

In [66]:
```
#predcition on the test data
y_pred=MLR.predict(x_test)
y_pred
```
Out[66]:
```
array([11.46655124,  9.2166091 ,  6.59967857,  7.81824648, 12.18984569,
       11.44220895, 11.20545145,  8.71621092, 10.98237601,  6.83381457,
       10.46227495,  9.10809044, 12.39359143, 14.54491772, 13.54791716,
       10.12045364, 11.48597397,  7.73511543, 12.86466796,  8.37939955,
        6.51920876,  8.16682072,  8.05416099, 10.22713858, 10.57995698,
       11.31009826,  7.52742935,  9.88582514, 11.25644638, 11.38973324,
       10.95569239, 10.28552912, 10.40475249, 10.44887526, 11.03343746,
       10.15213587, 10.04733695,  6.54448931, 11.86305246,  6.73817965,
        4.07354447, 11.09033543,  7.69897797,  9.56311429, 11.63006462,
       13.17063754,  6.34451832,  7.27896893, 15.31511539,  6.92860099,
        3.63485054,  6.80184256, 11.451762  , 10.69664795,  8.59383781,
        7.50446583, 10.33994154, 11.85072027, 13.544946  , 10.27236403,
```


```
        9.18410191,  7.7208794 , 12.33421272,  6.527156  , 11.17483778,
        7.97617745,  9.31452692,  9.56473016,  9.51077399, 12.20917888,
       12.10672271,  4.70427674,  6.38943267, 10.02410014, 11.97786002,
       12.77246335,  6.50139525, 10.64829499,  7.7058727 ,  6.05475715,
       11.28248424, 10.75341994, 17.22835762,  9.53819376,  8.96368426,
        6.61412036, 12.00162611,  5.85400348,  4.07058709, 10.08426584,
       10.15760235, 11.50892785, 10.58412873, 10.32113545, 12.98841501,
```

```
       13.17063754,  6.54451832,  7.27896895, 15.31511539,  6.92860099,
        3.63485054,  6.80184256, 11.451762  , 10.69664795,  8.59383781,
        7.50446583, 10.33994154, 11.85072027, 13.544946  , 10.27236403,
        9.18410191,  7.7208794 , 12.33421272,  6.527156  , 11.17483778,
        7.97617745,  9.31452692,  9.56473016,  9.51077399, 12.20917888,
       12.10672271,  4.70427674,  6.38943267, 10.02410014, 11.97786002,
       12.77246335,  6.50139525, 10.64829499,  7.7058727 ,  6.05475715,
       11.28248424, 10.75341994, 17.22835762,  9.53819376,  8.96368426,
        6.61412036, 12.00162611,  5.85400348,  4.07058709, 10.08426584,
       10.15760235, 11.50892785, 10.58412873, 10.32113545, 12.98841501,
```

In [67]:
```
#prediction in the train data
pred=MLR.predict(x_train)
pred
```

Out[67]:
```
array([10.64104453, 11.72955404,  9.71670847, ...,  9.33031288,
       11.94411399,  9.8609076 ])
```

In [68]:
```
from sklearn.metrics import r2_score

acc=r2_score(y_test,y_pred)

acc
```

Out[68]:
```
0.4331576346139585
```

In [69]:
```
#test this model
```


Out[68]:
```
0.4331576346139585
```


In [69]:
```
#test this model

MLR.predict([[1,0.455,0.365,0.095,0.5140,0.2245,0.1010,0.150]])
```

Out[69]:
```
array([9.91033204])
```

14. Measure the performance using Metrics.¶

In [70]:
```
from sklearn import metrics
from sklearn.metrics import mean_squared_error
```

In [71]:
```
np.sqrt(mean_squared_error(y_test,y_pred))
```

Out[71]:
```
2.4905110779015462
```

LASSO

In [72]:
```
from sklearn.linear_model import Lasso, Ridge
```

In [73]:
```
#intialising model
```

In [73]:
```
#intialising model

lso=Lasso(alpha=0.01,normalize=True)
```

In [74]:
```
#fit the model
lso.fit(x_train,y_train)
```

Out[74]:
```
Lasso(alpha=0.01, normalize=True)
```

In [75]:
```
#predcition on test data

lso_pred=lso.predict(x_test)
```

In [76]:
```
#coef
coef=lso.coef_
coef
```

Out[76]:
```
array([-0.        ,  0.        ,  0.        ,  0.4751529 ,  0.18634695,
        0.        ,  0.        ,  0.8021721 ])
```

In [77]:
```
#accuracy

from sklearn import metrics
from sklearn.metrics import mean_squared_error
metrics.r2_score(y_test,lso_pred)
```

Out[77]:
```
0.3260900261255968
```

In [78]:
```
#error

np.sqrt(mean_squared_error(y_test,lso_pred))
```

Out[78]:
```
2.715552909824135
```

RIDGE

In [79]:
```
rg=Ridge(alpha=0.01,normalize=True)
```

In [80]:
```
#fit
rg.fit(x_train,y_train)
```

Out[80]:
```
Ridge(alpha=0.01, normalize=True)
```

In [81]:
```
#predcition

rg_pred=rg.predict(x_test)
rg_pred
```

Out[81]:
```
array([11.49838542,  9.22452452,  6.72241086,  7.80010402, 12.09475499,
       11.33701357, 11.13313   ,  8.85299136, 10.95426872,  6.83332623,
       10.48221326,  9.08348674, 12.3098871 , 14.39846005, 13.62343834,
       10.11925891, 11.53997639,  7.75730522, 12.85320604,  8.43018605,
        6.53855123,  8.20224034,  7.58755052, 10.2671289 , 10.65653767,
       11.30141111,  7.50735436,  9.91086293, 11.27856902, 11.29021902,
       10.93344581, 10.32246436, 10.4456454 , 10.47230589, 11.05682097,
       10.1640513 , 10.10050704,  6.5623351 , 11.84100809,  6.75171646,
        4.18665064, 11.0291328 ,  7.72116038,  9.60080953, 11.57691909,
       13.01362452,  6.35434964,  7.30414243, 15.1541625 ,  6.91515291,
        4.16356146,  6.81943931, 11.43766939, 10.62078881,  8.65255458,
        7.53582353, 10.44494347, 11.86697333, 13.45239251, 10.40153892,
        9.1961334 ,  7.75332002, 12.25958727,  6.54710958, 11.17149665,
        7.96864693,  9.37526527,  9.69298327,  9.54666379, 12.19633696,
       12.1127204 ,  4.82993146,  6.43644112,  9.93303646, 12.00590353,
       12.76127566,  6.53636246, 10.58092597,  7.71945979,  5.98307484,
       11.30567761, 10.77297947, 16.83531384,  9.62951405,  9.07577717,
        6.65047637, 11.98056215,  5.83715385,  4.18471904, 10.06479866,
       10.18956629, 11.5066688 , 10.63940289, 10.38796727, 12.94599046,
```

In [82]:
```
#coef
rg.coef_
```

Out[82]:
```
array([-0.30797338, -0.75443399,  0.34843757,  0.94370227,  0.96851431,
       -1.38791368, -0.04943813,  1.70772786])
```


In [82]:
```
#coef
rg.coef_
```

Out[82]:
```
array([-0.30797338, -0.75443399,  0.34843757,  0.94370227,  0.96851431,
       -1.38791368, -0.04943813,  1.70772786])
```


In [83]:
```
#accuracy

metrics.r2_score(y_test,rg_pred)
```

Out[83]:
```
0.43177328549243543
```

In [84]:
```
#error

np.sqrt(mean_squared_error(y_test,rg_pred))
```

Out[84]:
```
2.4935504011542577
```

In [ ]:
```
# 1. Download the dataset

#importing the libraries

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

```
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')

# 2. Load the dataset into the tool.

#Loading the dataset

d = pd.read_csv(r'Downloads/abalone.csv')

# 3. Perform Below Visualizations.

# · Univariate Analysis

d.head()

#Boxplot

sns.boxplot(d['Diameter'])

#histogram

plt.hist(d['Diameter'])

#Line plot
```

```
#Line plot

plt.plot(d['Diameter'].head(10))

#piechart

plt.pie(d['Diameter'].head(),autopct='%.2f')

#distplot

sns.distplot(d['Diameter'].head(200))

# ● Bi - Variate Analysis

#scatter plot

plt.scatter(d['Diameter'].head(500),d['Length'].head(500))

#bar plot

plt.bar(d['Sex'].head(10),d['Rings'].head(10))

#labelling of x,y and result

plt.title('Bar plot')
```

```
plt.xlabel('Diameter')
plt.ylabel('Rings')

sns.barplot(d['Sex'], d['Rings'])

#joint plot

sns.jointplot(d['Diameter'].head(50),d['Rings'].head(50))

#bar plot

sns.barplot('Diameter','Rings',hue='Sex',data=d.head())

sns.lineplot(d['Diameter'].head(),d['Rings'].head())

# ● Multi - Variate Analysis

#boxplot

sns.boxplot(d['Sex'].head(10),d['Diameter'].head(10),d['Rings'].head(10))

#heat map

fig=plt.figure(figsize=(8,5))
sns.heatmap(d.head().corr(),annot=True)

#pair plot

sns.pairplot(d.head(),hue='Rings')
```

```
sns.pairplot(d.head(),hue='Rings')

sns.pairplot(d.head())

# 4. Perform descriptive statistics on the dataset.

#head

d.head()

#tail

d.tail()

d.info()

d.describe()

#mode

d.mode().T

d.shape

#kurtosis
```

```
d.kurt()

#skewness

d.skew()

#variance

d.var()

#finding unique values for columns

d.nunique()

# 5. Check for Missing values and deal with them.

#finding missing values

d.isna()

d.isna().any()

d.isna().sum()

d.isna().any().sum()
#no missing values
```

```
# 6. Find the outliers and replace them outliers

#finding outliers

sns.boxplot(d['Diameter'])

#handling outliers

qnt=d.quantile(q=[0.25,0.75])
qnt

iqr=qnt.loc[0.75]-qnt.loc[0.25]

iqr

lower=qnt.loc[0.25]-(1.5*iqr)
lower

upper=qnt.loc[0.75]+(1.5*iqr)
upper

# replacing outliers

##Diameter
d['Diameter']=np.where(d['Diameter']<0.155,0.4078,d['Diameter'])
sns.boxplot(d['Diameter'])
```

```
## Length

sns.boxplot(d['Length'])

d['Length']=np.where(d['Length']<0.23,0.52, d['Length'])

sns.boxplot(d['Length'])

## Height

sns.boxplot(d['Height'])

d['Height']=np.where(d['Height']<0.04,0.139, d['Height'])
d['Height']=np.where(d['Height']>0.23,0.139, d['Height'])

sns.boxplot(d['Height'])

## Whole weight

sns.boxplot(d['Whole weight'])

d['Whole weight']=np.where(d['Whole weight']>0.9,0.82, d['Whole weight'])

sns.boxplot(d['Whole weight'])

## Shucked weight
```



```
## Shucked weight
```



```
sns.boxplot(d['Shucked weight'])

d['Shucked weight']=np.where(d['Shucked weight']>0.93,0.35, d['Shucked weight'])

sns.boxplot(d['Shucked weight'])

## Viscera weight

sns.boxplot(d['Viscera weight'])

d['Viscera weight']=np.where(d['Viscera weight']>0.46,0.18, d['Viscera weight'])

sns.boxplot(d['Viscera weight'])

## Shell weight

sns.boxplot(d['Shell weight'])

d['Shell weight']=np.where(d['Shell weight']>0.61,0.2388, d['Shell weight'])

sns.boxplot(d['Shell weight'])

# 7. Check for Categorical columns and perform encoding.

#one hot encoding
```

```
# 8. Split the data into dependent and independent variables.

x=d.drop(columns= ['Rings'])
y=d['Rings']
x

y

# 9. Scale the independent variables

from sklearn.preprocessing import scale  #StandardScaler

#Scaling the independent variables

x = scale(x)
x

# 10. Split the data into training and testing

from sklearn.model_selection import train_test_split
```

```
# 10. Split the data into training and testing

from sklearn.model_selection import train_test_split

#spliting data to train and test

x_train, x_test, y_train, y_test = train_test_split(x,y, test_size = 0.2)
print(x_train.shape, x_test.shape)

# 11. Build the Model

#Multiple Regression

from sklearn.linear_model import LinearRegression

MLR=LinearRegression()

# 12. Train the Model

MLR.fit(x_train,y_train)

# 13. Test the Model

#predcition on the test data
y_pred=MLR.predict(x_test)
y_pred
```

```
#prediction in the train data
pred=MLR.predict(x_train)
pred

from sklearn.metrics import r2_score

acc=r2_score(y_test,y_pred)

acc

#test this model

MLR.predict([[1,0.455,0.365,0.095,0.5140,0.2245,0.1010,0.150]])

# 14. Measure the performance using Metrics.¶

from sklearn import metrics
from sklearn.metrics import mean_squared_error

np.sqrt(mean_squared_error(y_test,y_pred))

# LASSO

from sklearn.linear_model import Lasso, Ridge

#intialising model

lso=Lasso(alpha=0.01,normalize=True)
```


```
# LASSO

from sklearn.linear_model import Lasso, Ridge

#intialising model

lso=Lasso(alpha=0.01,normalize=True)
```


```
#fit the model
lso.fit(x_train,y_train)

#predcition on test data

lso_pred=lso.predict(x_test)

#coef
coef=lso.coef_
coef

#accuracy

from sklearn import metrics
from sklearn.metrics import mean_squared_error
metrics.r2_score(y_test,lso_pred)

#error
```