In [1]:

```
#import libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sb
import plotly.express as px
```

2. Load the dataset into the tool

In [3]:

```
data = pd.read_csv('abalone.csv')
data
```

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	0.1500	15
1	M	0.350	0.265	0.090	0.2255	0.0995	0.0485	0.0700	7
2	F	0.530	0.420	0.135	0.6770	0.2565	0.1415	0.2100	9
3	M	0.440	0.365	0.125	0.5160	0.2155	0.1140	0.1550	10
4	I	0.330	0.255	0.080	0.2050	0.0895	0.0395	0.0550	7
...	...	...	...	...	...	...	...	...	...
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

4177 rows × 9 columns

3. Perform Below Visualizations.

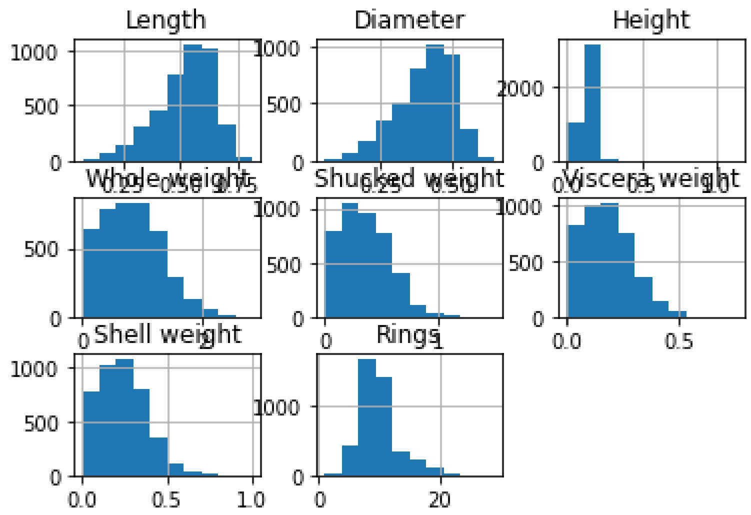
· Univariate Analysis

In [4]:

```
data['Rings'].value_counts()
data.hist()
```

Out[4]:

```
array([[<matplotlib.axes._subplots.AxesSubplot object at 0x7fde9ed90110>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7fde9ed522d0>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7fde9ed0a8d0>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x7fde9ecc0ed0>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7fde9ec84510>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7fde9ec43fd0>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x7fde9ebfe150>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7fde9ebb3750>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7fde9ebbfc50
>]],
      dtype=object)
```



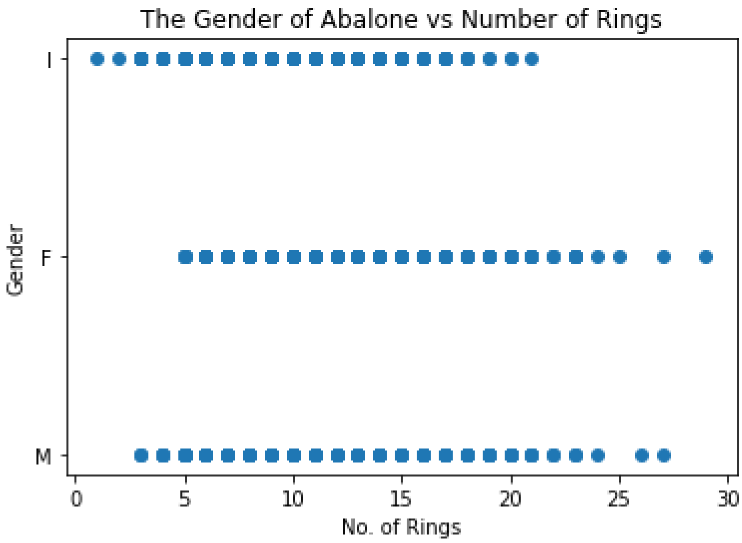
· Bi-Variate Analysis

In [5]:

```
plt.scatter(data.Rings, data.Sex)
plt.title('The Gender of Abalone vs Number of Rings')
plt.xlabel('No. of Rings')
plt.ylabel('Gender')
```

Out[5]:

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



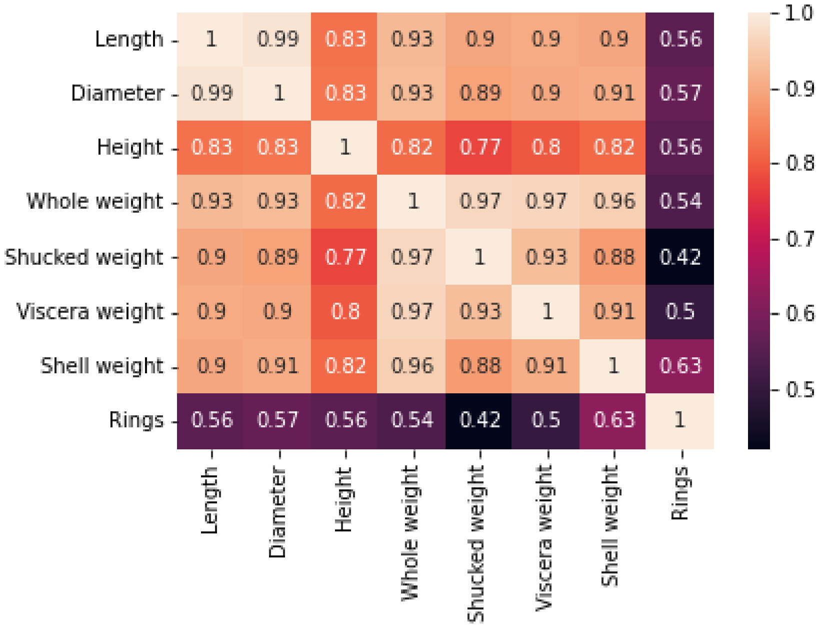
· Multi-Variate Analysis

In [6]:

```
sb.heatmap(data.corr(),annot=True)
```

Out[6]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fde9e451b90>
```



4. Perform descriptive statistics on the dataset.

In [7]:

```
data.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 [8]:

```
data.describe()
```

Out[8]:

	Length	Diameter	Height	Whole weight	Shucked weight	Viscera weight	Shell
count	4177.000000	4177.000000	4177.000000	4177.000000	4177.000000	4177.000000	4177.
mean	0.523992	0.407881	0.139516	0.828742	0.359367	0.180594	0.
std	0.120093	0.099240	0.041827	0.490389	0.221963	0.109614	0.
min	0.075000	0.055000	0.000000	0.002000	0.001000	0.000500	0.
25%	0.450000	0.350000	0.115000	0.441500	0.186000	0.093500	0.
50%	0.545000	0.425000	0.140000	0.799500	0.336000	0.171000	0.
75%	0.615000	0.480000	0.165000	1.153000	0.502000	0.253000	0.
max	0.815000	0.650000	1.130000	2.825500	1.488000	0.760000	1.

5. Check for Missing values and deal with them.

There is no missing values

In [9]:

```
data.isnull().any()
```

Out[9]:

```
Sex               False
Length            False
Diameter          False
Height            False
Whole weight      False
Shucked weight    False
Viscera weight    False
Shell weight      False
Rings             False
dtype: bool
```

6. Find the outliers and replace them outliers

The dataset does not have a outliers

In [10]:

```
fig = px.histogram(data, x='Whole weight')
fig.show()
```

7. Check for Categorical columns and perform encoding.

There is one Categorical column SEX is replaced by an Integer

In [11]:

```
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
data["Sex"] = le.fit_transform(data["Sex"])
data["Sex"]
```

Out[11]:

```
0       2
1       2
2       0
3       2
4       1
       ..
4172    0
4173    2
4174    2
4175    0
4176    2
Name: Sex, Length: 4177, dtype: int64
```

8. Split the data into dependent and independent variables.

In [12]:

```
x=data.iloc[:,0:8].values
y=data.iloc[:,8:9].values
```

In [13]:

```
x
```

Out[13]:

```
array([[2.    , 0.455 , 0.365 , ..., 0.2245, 0.101 , 0.15  ],
       [2.    , 0.35  , 0.265 , ..., 0.0995, 0.0485, 0.07  ],
       [0.    , 0.53  , 0.42  , ..., 0.2565, 0.1415, 0.21  ],
       ...,
       [2.    , 0.6   , 0.475 , ..., 0.5255, 0.2875, 0.308 ],
       [0.    , 0.625 , 0.485 , ..., 0.531 , 0.261 , 0.296 ],
       [2.    , 0.71  , 0.555 , ..., 0.9455, 0.3765, 0.495 ]])
```

In [14]:

```
y
```

Out[14]:

```
array([[15],
       [ 7],
       [ 9],
       ...,
       [ 9],
       [10],
       [12]])
```

9. Scale the independent variables

In [15]:

```
x=data.iloc[:,0:8]
print(x.head())
```

```
   Sex  Length  Diameter  Height  Whole weight  Shucked weight  \
0    2   0.455     0.365   0.095        0.5140          0.2245
1    2   0.350     0.265   0.090        0.2255          0.0995
2    0   0.530     0.420   0.135        0.6770          0.2565
3    2   0.440     0.365   0.125        0.5160          0.2155
4    1   0.330     0.255   0.080        0.2050          0.0895

   Viscera weight  Shell weight
0          0.1010         0.150
1          0.0485         0.070
2          0.1415         0.210
3          0.1140         0.155
4          0.0395         0.055
```

10. Split the data into training and testing

In [16]:

```
from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test = train_test_split(x,y,test_size=0.3,random_state=0)
```

In [17]:

```
x_train.shape
```

Out[17]:

```
(2923, 8)
```

In [18]:

```
x_test.shape
```

Out[18]:

```
(1254, 8)
```

11. Build the Model

In [19]:

```
from sklearn.linear_model import LinearRegression
lr = LinearRegression()
```

12. Train the Model

In [20]:

```
lr.fit(x_train, y_train)
```

Out[20]:

```
LinearRegression()
```

13. Test the Model

In [21]:

```
y_pred = lr.predict(x_test)
print((y_test)[0:6])
print((y_pred)[0:6])
```

```
[[13]
 [ 8]
 [11]
 [ 5]
 [12]
 [11]]
[[13.11640829]
 [ 9.65691091]
 [10.35350972]
 [ 5.63648715]
 [10.67436485]
 [11.95341338]]
```

14. Measure the performance using Metrics.

In [22]:

```
# RMSE(Root Mean Square Error)

from sklearn.metrics import mean_squared_error
mse = mean_squared_error(y_test, y_pred)
rmse = np.sqrt(mse)
print("RMSE value : {:.2f}".format(rmse))
```

```
RMSE value : 2.26
```

In [23]:

```
from sklearn.model_selection import cross_val_score
cv_scores = cross_val_score(lr, x, y, cv=5)
sco=cv_scores.round(4)
print(cv_scores.round(4))
print("Average",sco.sum()/5)
```

```
[0.4113 0.1574 0.4807 0.5046 0.4362]
Average 0.39803999999999995
```