ASSIGNMENT-3

Assignment Date	21 October 2022
Student Name	ABIRAMI P.
Student Roll Number	61771921001
Maximum Marks	2 Marks

Description:- Predicting the age of abalone from physical measurements. The age of abalone is determined by cutting the shell through the cone, staining it, and counting the number of rings through a microscope -- a boring and time-consuming task. Other measurements, which are easier to obtain, are used to predict age. Further information, such as weather patterns and location (hence food availability) may be required to solve the problem.

Attribute Information:

Given is the attribute name, attribute type, measurement unit, and a brief description. The number of rings is the value to predict: either as a continuous value or as a classification problem.

Name / Data Type / Measurement Unit / Description

1- Sex / nominal / -- / M, F, and I (infant)

2- Length / continuous / mm / Longest shell measurement

3- Diameter / continuous / mm / perpendicular to length

4- Height / continuous / mm / with meat in shell

5- Whole weight / continuous / grams / whole abalone

6- Shucked weight / continuous / grams / weight of meat

7- Viscera weight / continuous / grams / gut weight (after bleeding)

8- Shell weight / continuous / grams / after being dried

9- Rings / integer / -- / +1.5 gives the age in years

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Building a Regression Model

1. Download the dataset: Dataset
2. Load the dataset into the tool.
3. Perform Below Visualizations.
    · Univariate Analysis
    · Bi-Variate Analysis
    · Multi-Variate Analysis
4. Perform descriptive statistics on the dataset.
5. Check for Missing values and deal with them.
6. Find the outliers and replace them outliers
7. Check for Categorical columns and perform encoding. 8. Split the data into dependent and independent variables. 9. Scale the independent variables
10. Split the data into training and testing
11. Build the Model
12. Train the Model
13. Test the Model
14. Measure the performance using Metrics.

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TASK 1

DOWNLOAD AND LOAD THE DATASET

TASK 2

Albalone.csv

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

df=pd.read_csv('abalone.csv')
df.head()
```

	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

```
Age = df.Rings + 1.5
df['Age']=Age
df = df.drop(columns=['Rings'],axis=1)
df.head()
```

	Sex	Length	Diameter	Height	Whole weight	Shucked weight	Viscera weight	Shell weight	Age
0	M	0.455	0.365	0.095	0.5140	0.2245	0.1010	0.150	16.5
1	M	0.350	0.265	0.090	0.2255	0.0995	0.0485	0.070	8.5
2	F	0.530	0.420	0.135	0.6770	0.2565	0.1415	0.210	10.5
3	M	0.440	0.365	0.125	0.5160	0.2155	0.1140	0.155	11.5
4	I	0.330	0.255	0.080	0.2050	0.0895	0.0395	0.055	8.5

```
df = df.rename(columns = {'Whole weight': 'Whole_weight','Shucked weight':
'Shucked_weight','Viscera weight': 'Viscera_weight',
                     'Shell weight': 'Shell_weight'})
```

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df.shape

```
df.shape
```

```
(4177, 9)
```

df.info()

```
df.info()
```

```
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   Age             4177 non-null   float64
dtypes: float64(8), object(1)
memory usage: 293.8+ KB
```

df.Sex.unique()

```
df.Sex.unique()
```

```
array(['M', 'F', 'I'], dtype=object)
```

df.Sex.value_counts()

```
df.Sex.value_counts()
```

```
M    1528
I    1342
F    1307
Name: Sex, dtype: int64
```

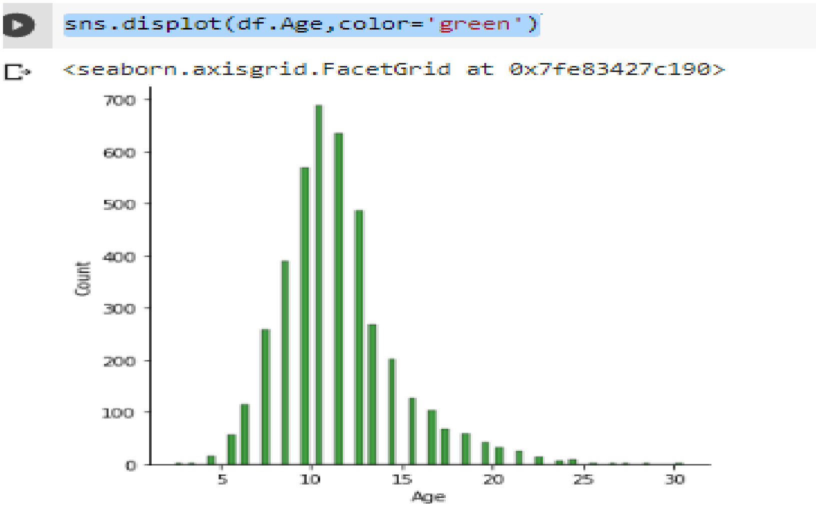
TASK 3

Perform Below Visualizations

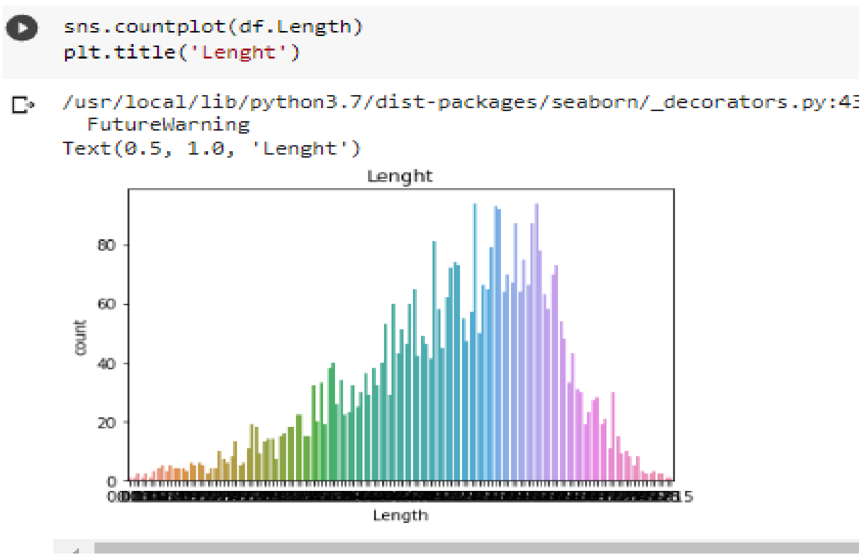
- ❖ Univariate Analysis
- ❖ Bi - Variate Analysis
- ❖ Multi - Variate Analysis

Univariate Analysis

sns.displot(df.Age,color='green')



sns.countplot(df.Length)
plt.title('Lenght')



sns.distplot(df.Diameter)

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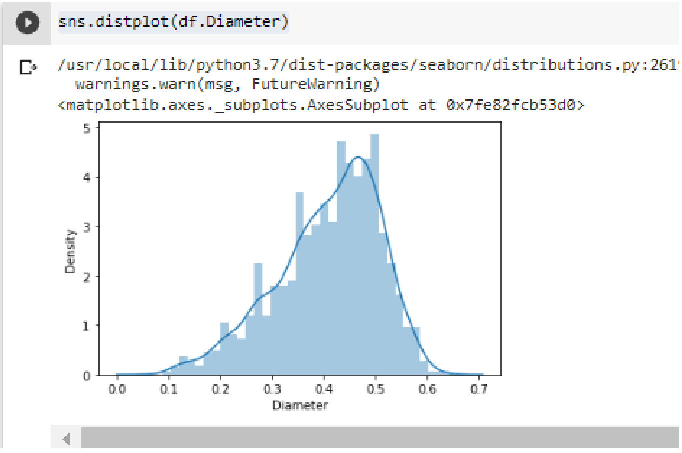
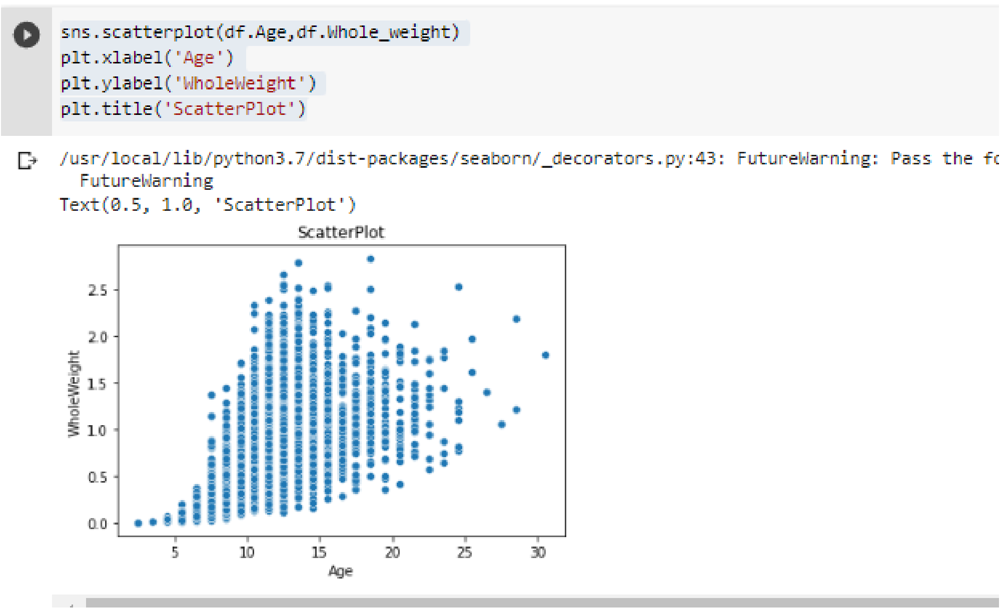
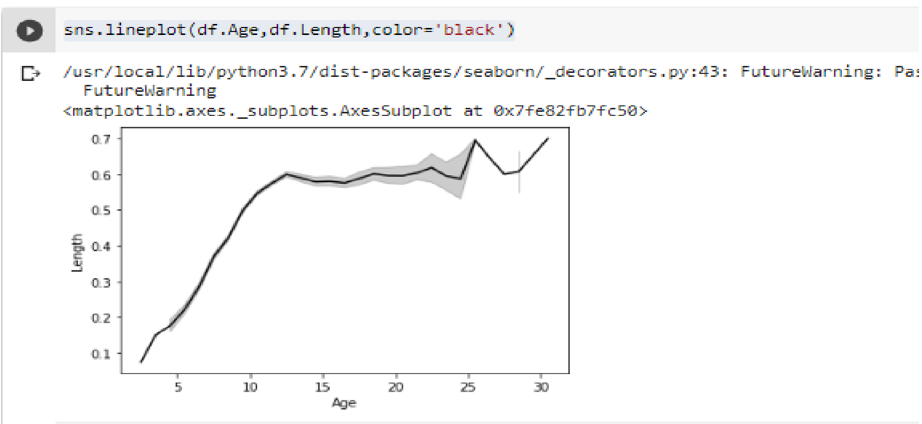


Bi-Variate Analysis

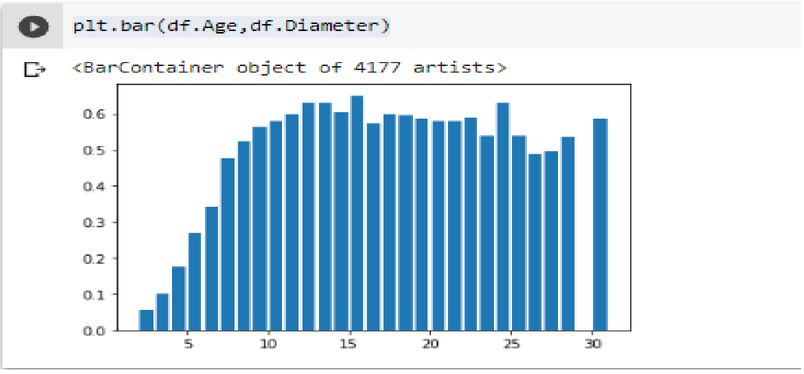
sns.scatterplot(df.Age,df.Whole_weight)
plt.xlabel('Age')
plt.ylabel('WholeWeight')
plt.title('ScatterPlot')



sns.lineplot(df.Age,df.Length,color='black')

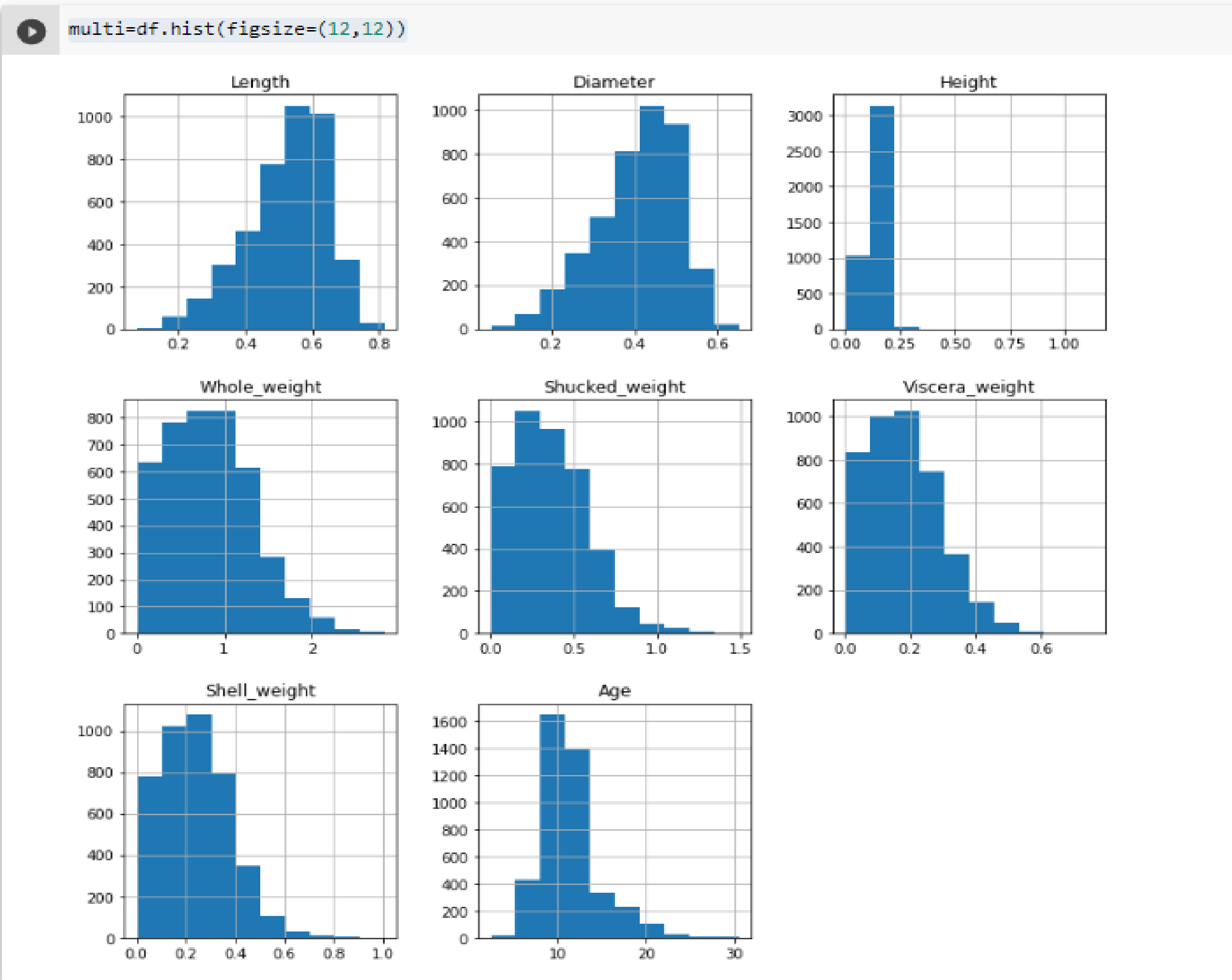


plt.bar(df.Age,df.Diameter)



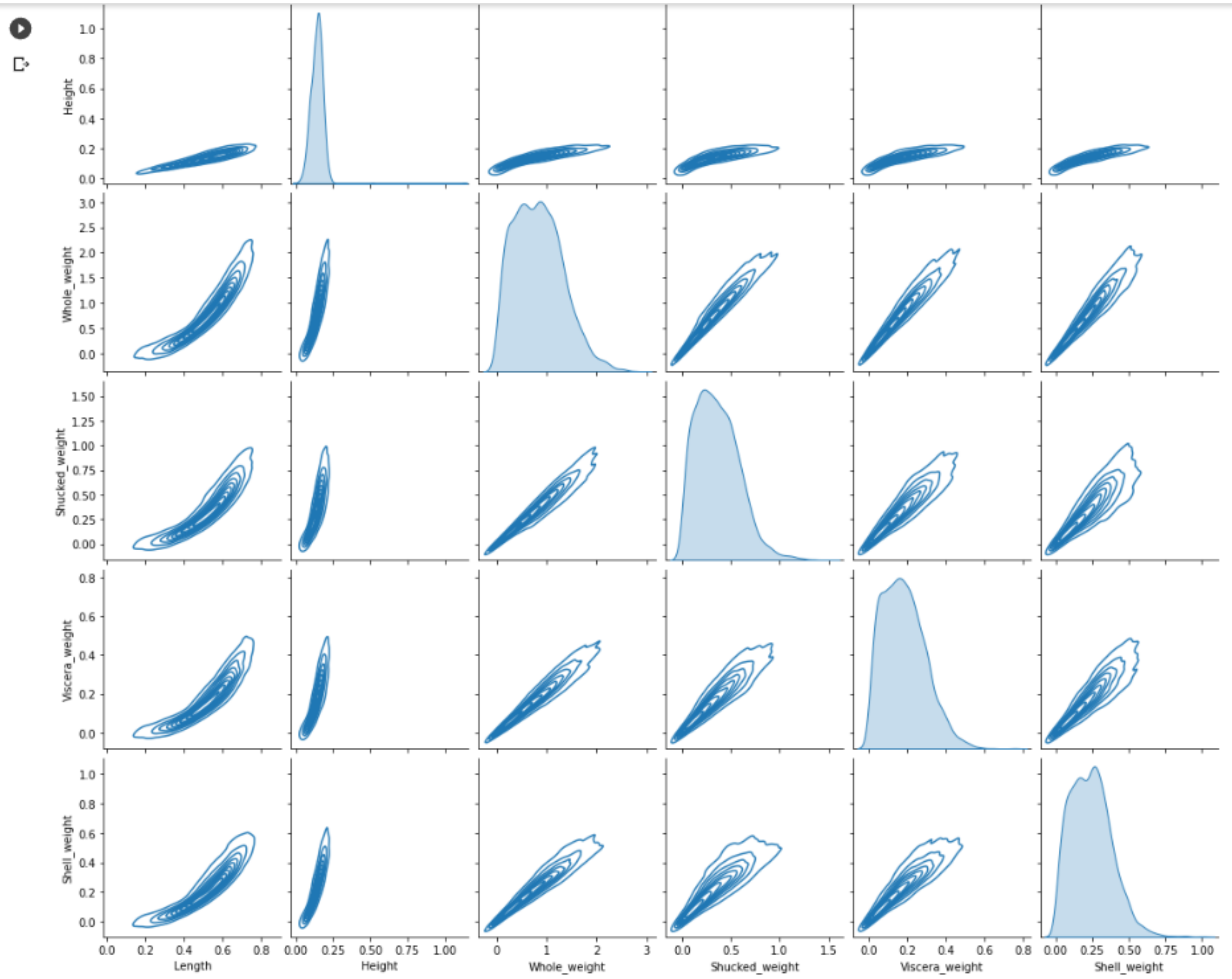
Multi-Variate Analysis

multi=df.hist(figsize=(12,12))



sns.pairplot(data=df[['Length','Height','Whole_weight','Shucked_weight','Viscera_weight','Shell_weight']],kind='kde')

sns.pairplot(df,hue='Age',diag_kind='scatter')



TASK 4

Descriptive statistics

df.describe()

```
df.describe()
```

	Length	Diameter	Height	Whole_weight	Shucked_weight	Viscera_weight	Shell_weight	Age
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	11.433684
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	2.500000
25%	0.450000	0.350000	0.115000	0.441500	0.186000	0.093500	0.130000	9.500000
50%	0.545000	0.425000	0.140000	0.799500	0.336000	0.171000	0.234000	10.500000
75%	0.615000	0.480000	0.165000	1.153000	0.502000	0.253000	0.329000	12.500000
max	0.815000	0.650000	1.130000	2.825500	1.488000	0.760000	1.005000	30.500000

TASK 5

Handle missing data

df.isnull().any()   #no missing data

```
df.isnull().any()    #no missing data
```

```
Sex               False
Length            False
Diameter          False
Height            False
Whole_weight      False
Shucked_weight    False
Viscera_weight    False
Shell_weight      False
Age               False
dtype: bool
```

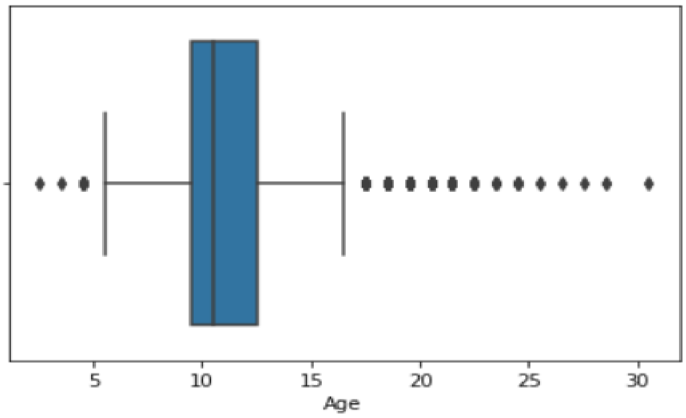
TASK 6

Outliers Replacement

sns.boxplot(df.Age)

```
sns.boxplot(df.Age)
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators
  FutureWarning
<matplotlib.axes._subplots.AxesSubplot at 0x7fe829463650>
```



q1=df.Age.quantile(0.25)
q3=df.Age.quantile(0.75)
IQR = q3-q1
upper_limit=q3 + 1.5 * IQR
lower_limit=q1 - 1.5 * IQR

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```
upper_limit,lower_limit
```

```
(17.0, 5.0)
```

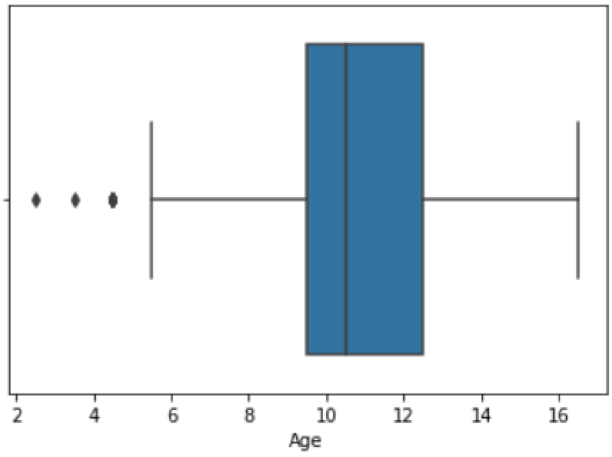
```
df.Age.median()
```

```
10.5
```

```
[ ] df.Age=np.where(df.Age>upper_limit,10.5,df.Age) #Median=10.5
```

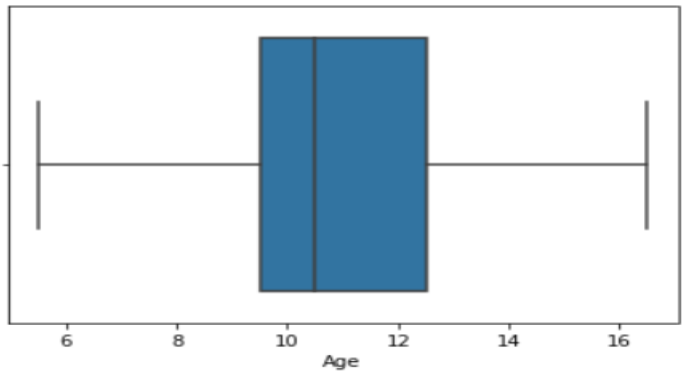
```
sns.boxplot(df.Age)
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarning
  FutureWarning
<matplotlib.axes._subplots.AxesSubplot at 0x7fe829410390>
```




```
sns.boxplot(df.Age)
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: Fu
  FutureWarning
<matplotlib.axes._subplots.AxesSubplot at 0x7fe829313110>
```



TASK 7

Check for Categorical column and perform encoding

Label Encoding for Gender column

```
[ ] from sklearn.preprocessing import LabelEncoder
```

```
[ ] le = LabelEncoder()
```

```
[ ] df.Sex=le.fit_transform(df.Sex)
```

```
[ ] df.head()
```

	Sex	Length	Diameter	Height	Whole_weight	Shucked_weight	Viscera_weight	Shell_weight	Age
0	2	0.455	0.365	0.095	0.5140	0.2245	0.1010	0.150	16.5
1	2	0.350	0.265	0.090	0.2255	0.0995	0.0485	0.070	8.5
2	0	0.530	0.420	0.135	0.6770	0.2565	0.1415	0.210	10.5
3	2	0.440	0.365	0.125	0.5160	0.2155	0.1140	0.155	11.5
4	1	0.330	0.255	0.080	0.2050	0.0895	0.0395	0.055	8.5

TASK 8

Split the data into dependent and independent variables

```
[ ] #y - target columns
    #X - predicting columns
```

```
[ ] y=df['Age']
    y
```

```
0       16.5
1        8.5
2       10.5
3       11.5
4        8.5
        ...
4172    12.5
4173    11.5
4174    10.5
4175    11.5
4176    13.5
Name: Age, Length: 4177, dtype: float64
```

```
[ ] X=df.drop(columns=['Age'],axis=1)
    X.head()
```

	Sex	Length	Diameter	Height	Whole_weight	Shucked_weight	Viscera_weight	Shell_weight
0	2	0.455	0.365	0.095	0.5140	0.2245	0.1010	0.150
1	2	0.350	0.265	0.090	0.2255	0.0995	0.0485	0.070
2	0	0.530	0.420	0.135	0.6770	0.2565	0.1415	0.210
3	2	0.440	0.365	0.125	0.5160	0.2155	0.1140	0.155
4	1	0.330	0.255	0.080	0.2050	0.0895	0.0395	0.055

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TASK 9

Scale the independent variables

```
[ ] from sklearn.preprocessing import scale
```

```
df2=pd.DataFrame(scale(X),columns=X.columns)
df2.head()
```

	Sex	Length	Diameter	Height	Whole_weight	Shucked_weight	Viscera_weight	Shell_weight
0	1.151980	-0.574558	-0.432149	-1.064424	-0.641898	-0.607685	-0.726212	-0.638217
1	1.151980	-1.448986	-1.439929	-1.183978	-1.230277	-1.170910	-1.205221	-1.212987
2	-1.280690	0.050033	0.122130	-0.107991	-0.309469	-0.463500	-0.356690	-0.207139
3	1.151980	-0.699476	-0.432149	-0.347099	-0.637819	-0.648238	-0.607600	-0.602294
4	-0.064355	-1.615544	-1.540707	-1.423087	-1.272086	-1.215968	-1.287337	-1.320757

TASK 10

Split the data into training and testing

```
[ ] from sklearn.model_selection import train_test_split
    X_train,X_test,y_train,y_test=train_test_split(df2,y,test_size=0.3,random_state=1)
```

```
[ ] X_train.shape,X_test.shape

    ((2923, 8), (1254, 8))
```

```
[ ] y_train.shape,y_test.shape

    ((2923,), (1254,))
```

TASK 11

Build the model

```
[ ] from sklearn.linear_model import LinearRegression
    lr=LinearRegression() #Linear Regression Model
```

```
[ ] from sklearn.linear_model import Ridge
    r=Ridge() #Ridge Regression Model
```

```
[ ] from sklearn.linear_model import Lasso
    l=Lasso() #Lasso Regression Model
```

TASK 12

Train the model

```
lr.fit(X_train,y_train) #Training lr model
LinearRegression()
```

```
pred1_train=lr.predict(X_train)
pred1_train
array([11.37532295, 10.8623978 , 10.98473747, ...,  8.47235413,
       10.0771839 ,  8.2997195 ])
```

```
r.fit(X_train,y_train) #Training r model
Ridge()
```

```
pred2_train=r.predict(X_train)
pred2_train
array([11.37024121, 10.86610153, 10.98923414, ...,  8.47158189,
       10.08029538,  8.29939996])
```

```
l.fit(X_train,y_train) #Training l model
Lasso()
```

```
pred3_train=l.predict(X_train)
pred3_train
array([10.90661081, 10.94589013, 10.96552979, ..., 10.19958302,
       10.86733149, 10.14066404])
```

TASK 12

Test the model

```
y_test
17      11.5
1131     9.5
299     10.5
1338    11.5
2383    10.5
        ...
802     10.5
3016     8.5
2886     9.5
2580     9.5
2814     5.5
Name: Age, Length: 1254, dtype: float64
```

```
[ ] pred1=lr.predict(X_test)
    pred1                    #Testing data using linear regression model

    array([ 9.82570208, 10.03404396,  9.28563548, ..., 10.0965599 ,
           10.66920195,  7.77742412])
```

```
pred2=r.predict(X_test)
pred2                    #Testing data using ridge model

array([ 9.82297354, 10.04038957,  9.28565669, ..., 10.10174311,
       10.66576784,  7.77789848])
```

```
[ ] pred3=l.predict(X_test)
    pred3                    #Testing data using lasso model

    array([10.59237624, 10.96552979, 10.35670031, ..., 10.69057454,
           10.92625047, 10.04246574])
```

```
[ ] age_pred = pd.DataFrame({'Actual_value':y_test,'Predicted_value_using_lr':pred1,'Predicted_value_using_r':pred2,'Predicted_value_using_l':pred3})
    age_pred.head()
```

	Actual_value	Predicted_value_using_lr	Predicted_value_using_r	Predicted_value_using_l
17	11.5	9.825702	9.822974	10.592376
1131	9.5	10.034044	10.040390	10.965530
299	10.5	9.285635	9.285657	10.356700
1338	11.5	11.109891	11.111671	11.044088
2383	10.5	10.901944	10.905969	10.788773

TASK 14

Measure the performance using metrics

```
[ ] from sklearn import metrics
```

```
[ ] #R2-square
    #Testing accuracy of linear regression, ridge, lasso

    print(metrics.r2_score(y_test,pred1))
    print(metrics.r2_score(y_test,pred2))
    print(metrics.r2_score(y_test,pred3))

    0.4162940378151394
    0.41640627795250973
    0.17272068414915298
```

```
#R2-square
#Training accuracy of linear regression, ridge, lasso

print(metrics.r2_score(y_train,pred1_train))
print(metrics.r2_score(y_train,pred2_train))
print(metrics.r2_score(y_train,pred3_train))

0.40173116413670873
0.40172280022100826
0.17472314547809642
```

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```
## MSE(Mean square error)
#Testing accuracy of linear regression, ridge, lasso

print(metrics.mean_squared_error(y_test,pred1))
print(metrics.mean_squared_error(y_test,pred2))
print(metrics.mean_squared_error(y_test,pred3))
```

```
3.066910254318059
3.0663205217291396
4.346694365552255
```

```
## RMSE
#Testing accuracy of linear regression, ridge, lasso


print(np.sqrt(metrics.mean_squared_error(y_test,pred1)))
print(np.sqrt(metrics.mean_squared_error(y_test,pred2)))
print(np.sqrt(metrics.mean_squared_error(y_test,pred3)))
```

```
1.751259619336339
1.7510912374085879
2.084872745649541
```