ASSIGNMENT-3
ABALONE AGE PREDICTION

Assignment Date	21 /10/2022
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Student Roll Number	61772021T306
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.

<u>Task-1</u>

Download and Load Dataset

Download the data set:

abalone.csv

<u>Task-2:</u>

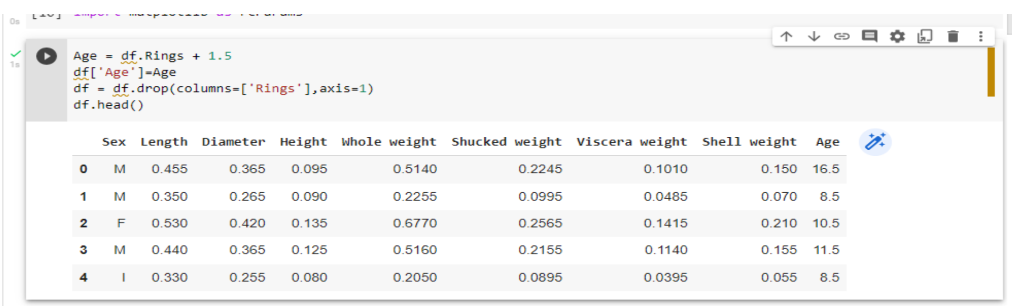
Load the Dataset:

Solution:

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(

)



```
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

ASSIGNMENT-3
DATA VISUALIZATION AND

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

```
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

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

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

```
df.shape

(4177, 9)
```

df.info()

```
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
```

df.Sex.unique()

```
[21] 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
```

ASSIGNMENT-3
ABALONE AGE PREDICTION

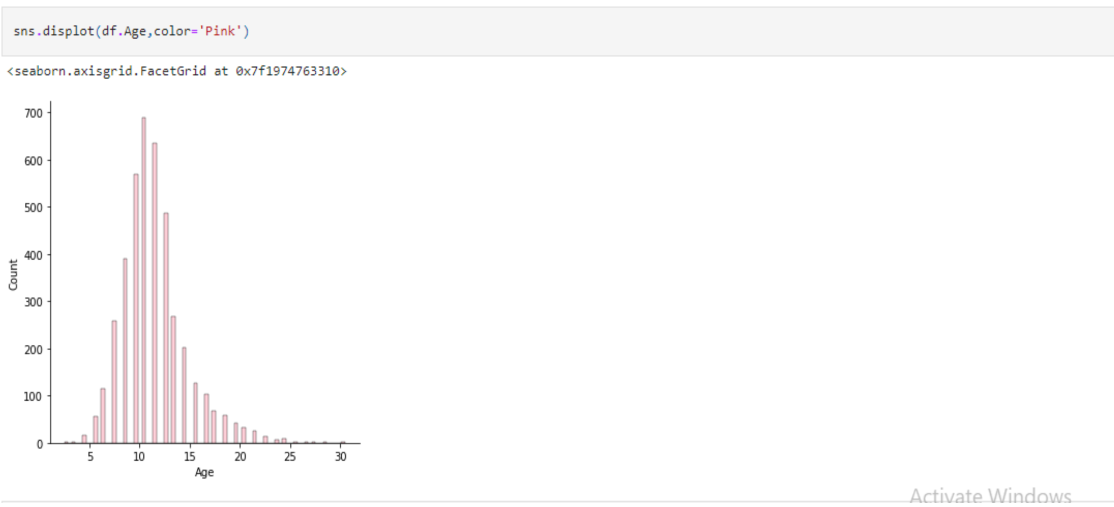
Task-3:

3. Perform Below Visualizations.

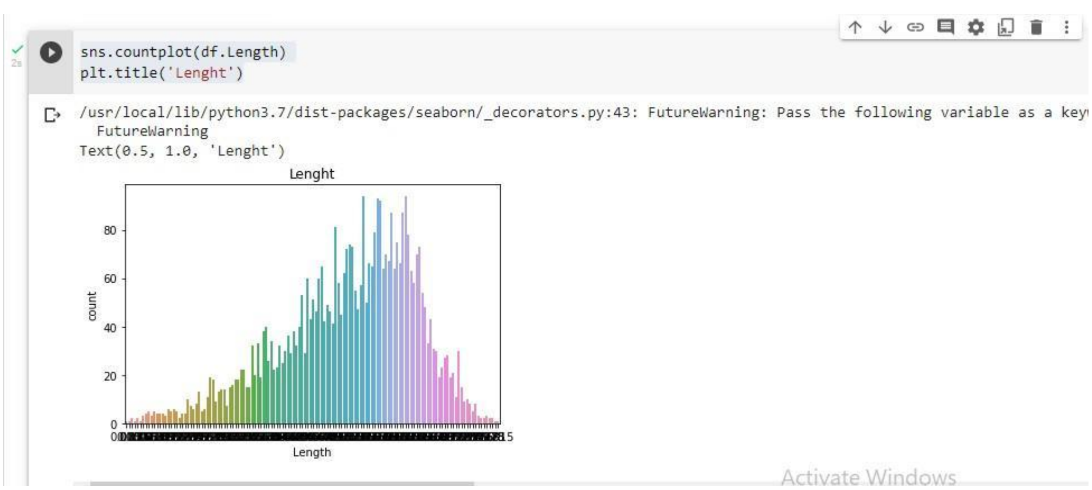
- Univariate Analysis
- Bi - Variate Analysis
- Multi - Variate Analysis

Univariate Analysis:

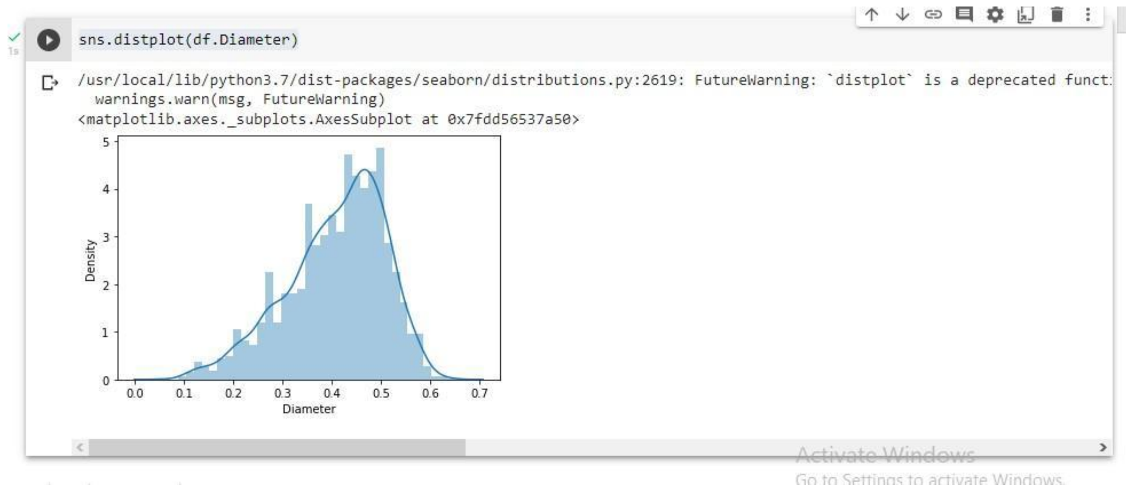
SOLUTION:




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

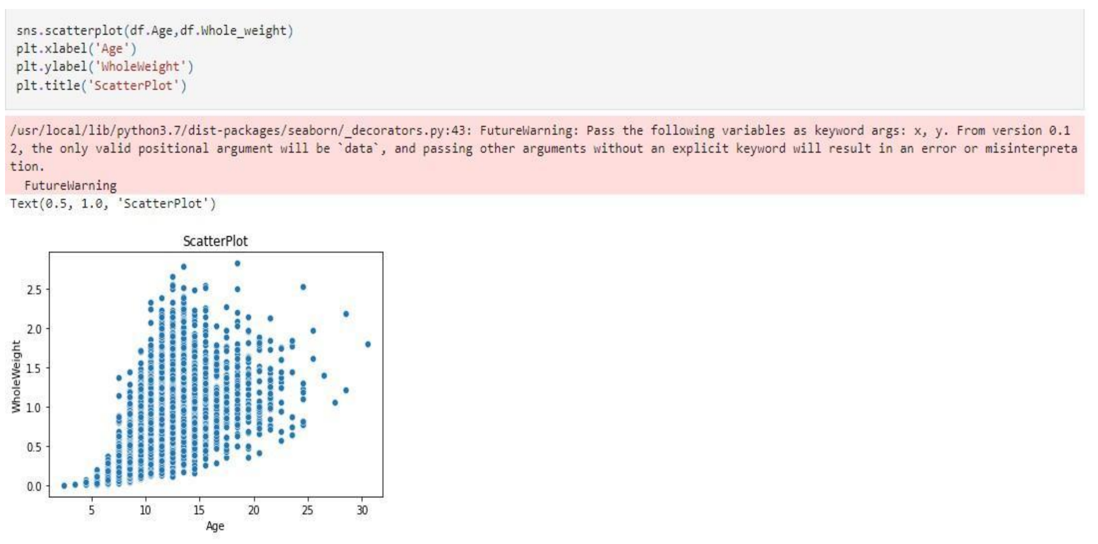


sns.distplot(df.Diameter)

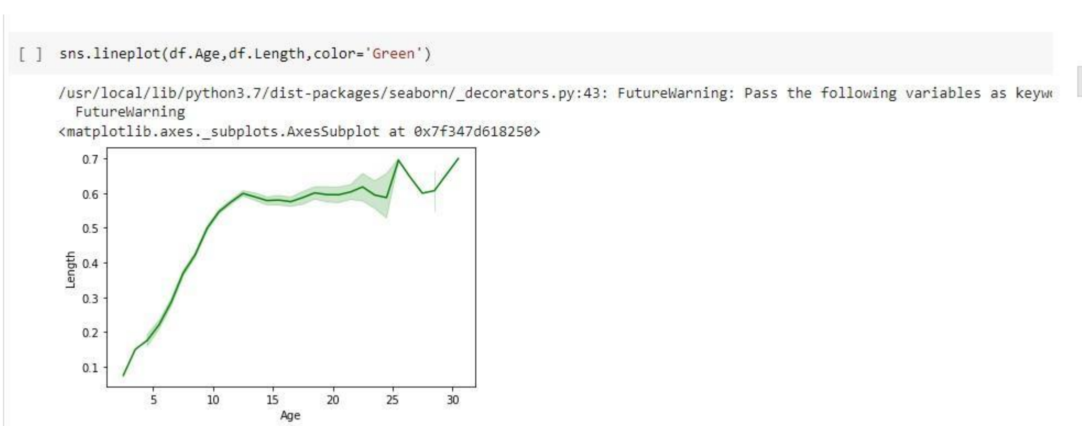


Bi-Variate Analysis:

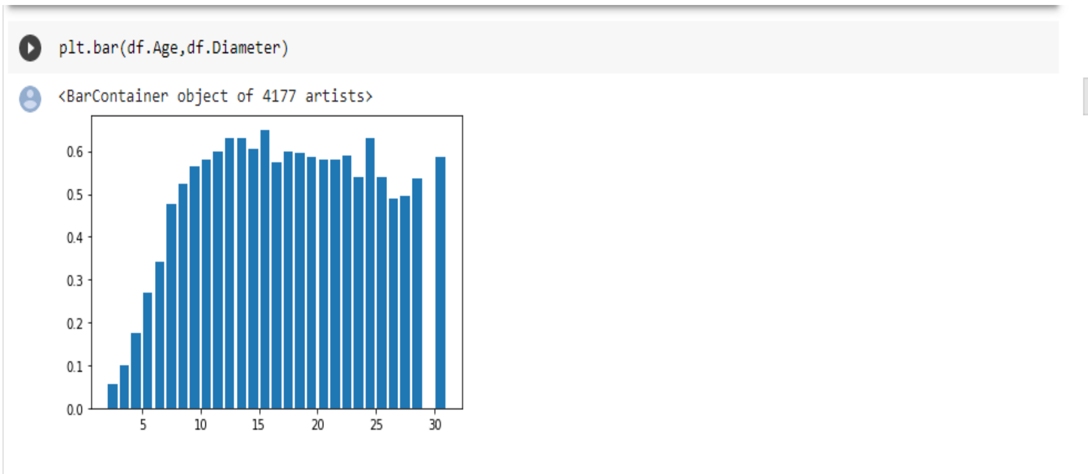
sns.scatterplot(df.Age,df.Whole_weight)
plt.xlabel('Age')
plt.ylabel('WholeWeight')
plt.title('ScatterPlot')



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

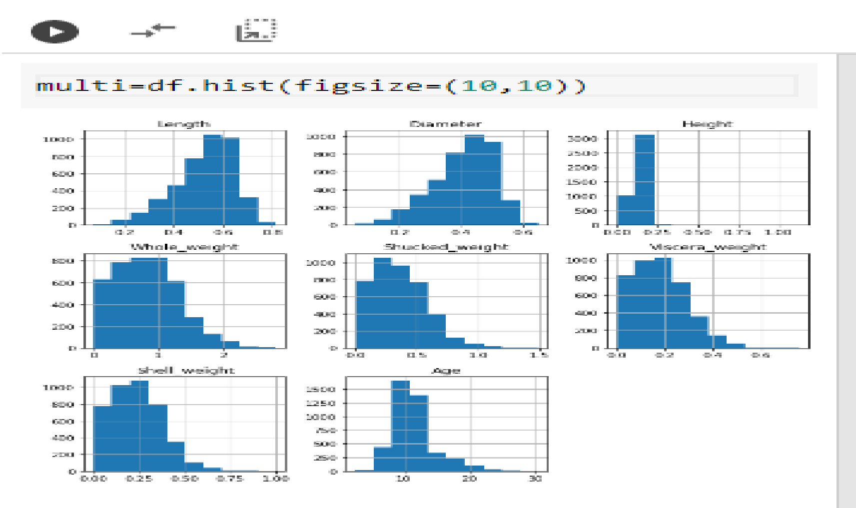


plt.bar(df.Age,df.Diameter)

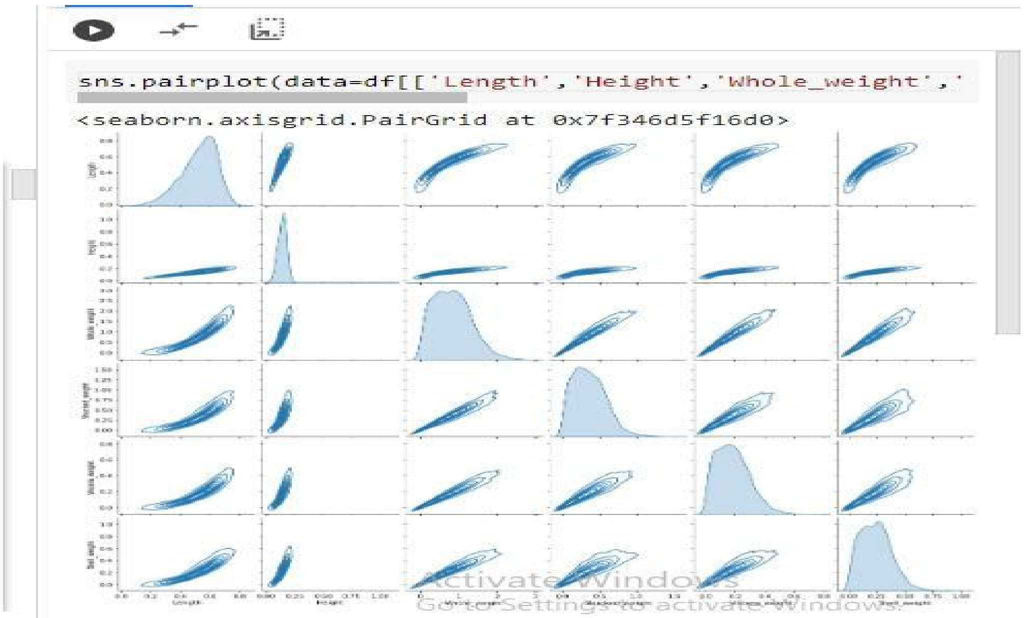


Multi-Variate Analysis:

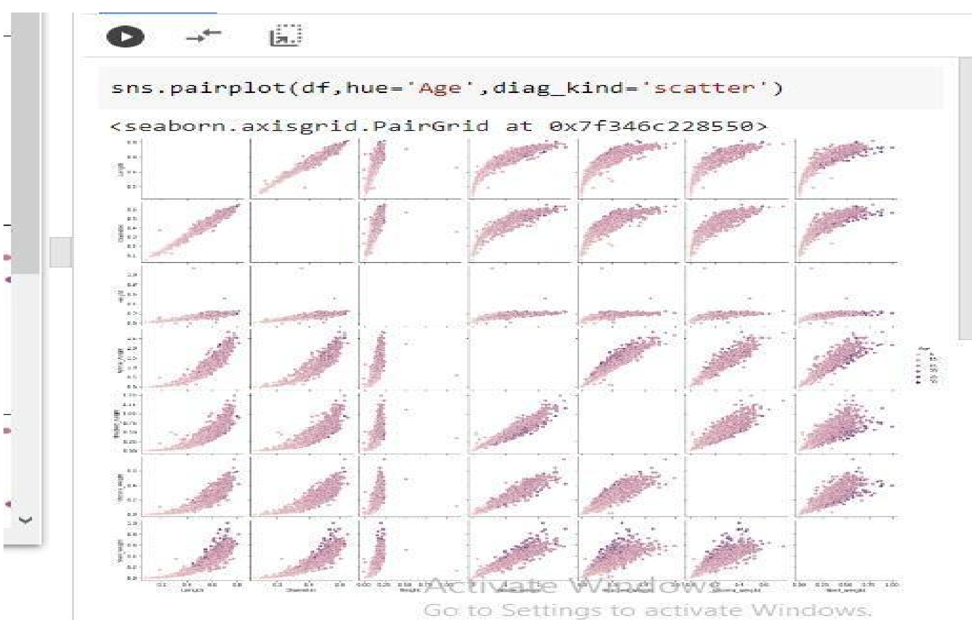
multi=df.hist(figsize=(10,10))



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



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



ASSIGNMENT-3
DATA VISUALIZATION AND
PREPROCESSING

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

Handle missing data

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

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

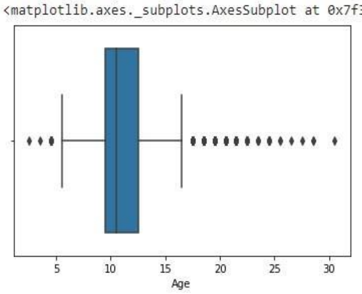
```
Sex               False
Length            False
Diameter          False
Height            False
Whole_weight      False
Shucked_weight    False
Viscera_weight    False
Shell_weight      False
Age               False
dtype: bool
```

Outliers Replacement

sns.boxplot(df.Age)

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

```
/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
  FutureWarning
<matplotlib.axes._subplots.AxesSubplot at 0x7f346ad34710>
```



```
In [ ]: q1=df.Age.quantile(0.25)
        q3=df.Age.quantile(0.75)
```

```
In [ ]: IQR = q3-q1
```

```
In [ ]: upper_limit=q3 + 1.5 * IQR
        lower_limit=q1 - 1.5 * IQR
```

```
In [ ]: upper_limit,lower_limit
Out[ ]: (17.0, 5.0)
```

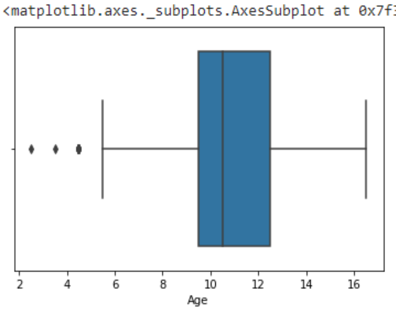
```
In [ ]: df.Age.median()
Out[ ]: 10.5
```

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

```
In [ ]: sns.boxplot(df.Age)
```

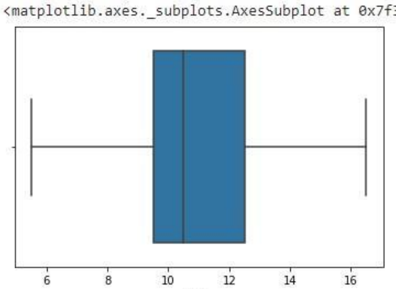
sns.boxplot(df.Age)

```
sns.boxplot(df.Age)
/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
  FutureWarning
<matplotlib.axes._subplots.AxesSubplot at 0x7f346ac51b50>
```



df.Age=np.where(df.Age<lower_limit,10.5,df.Age) #Median=10.5

```
sns.boxplot(df.Age)
/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, th
  FutureWarning
<matplotlib.axes._subplots.AxesSubplot at 0x7f346ac3ad50>
```



```
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
df.Sex=le.fit_transform(df.Sex)
df.head()
```

```
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

Split the data into dependent and independent variables

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

```
#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()
```

```
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

Scale the independent variables

from sklearn.preprocessing import scale
df2=pd.DataFrame(scale(X),columns=X.columns)
df2.head()

```
[ ] 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

Split the data 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

```
y_train.shape,y_test.shape
```

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

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

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

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

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

Train the model

lr.fit(X_train,y_train) #Training lr model
pred1_train=lr.predict(X_train)
pred1_train
r.fit(X_train,y_train) #Training r model
pred2_train=r.predict(X_train)
pred2_train
l.fit(X_train,y_train) #Training l 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

```
pred3_train=l.predict(X_train)
pred3_train

array([10.90661081, 10.94589013, 10.96552979, ..., 10.19958302,
       10.86733149, 10.14066404])
```

Test the model

y_test

```
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
pred2=r.predict(X_test)
pred2
pred3=l.predict(X_test)
pred3

```
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()

```
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

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))

```
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))

```
#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
```

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))

```
## 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)))

```
## 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
```