1. Download the dataset: Dataset

2. Load the dataset.

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sbn
%matplotlib inline

file=pd.read_csv("abalone.csv")
df=pd.DataFrame(file)
df.head()
```

```
  Sex  Length  Diameter  Height  Whole weight  Shucked weight  Viscera
weight  \
0   M   0.455     0.365   0.095        0.5140          0.2245
0.1010
1   M   0.350     0.265   0.090        0.2255          0.0995
0.0485
2   F   0.530     0.420   0.135        0.6770          0.2565
0.1415
3   M   0.440     0.365   0.125        0.5160          0.2155
0.1140
4   I   0.330     0.255   0.080        0.2050          0.0895
0.0395

   Shell weight  Rings
0         0.150     15
1         0.070      7
2         0.210      9
3         0.155     10
4         0.055      7
```

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

3. Perform Below Visualizations.

● Univariate Analysis

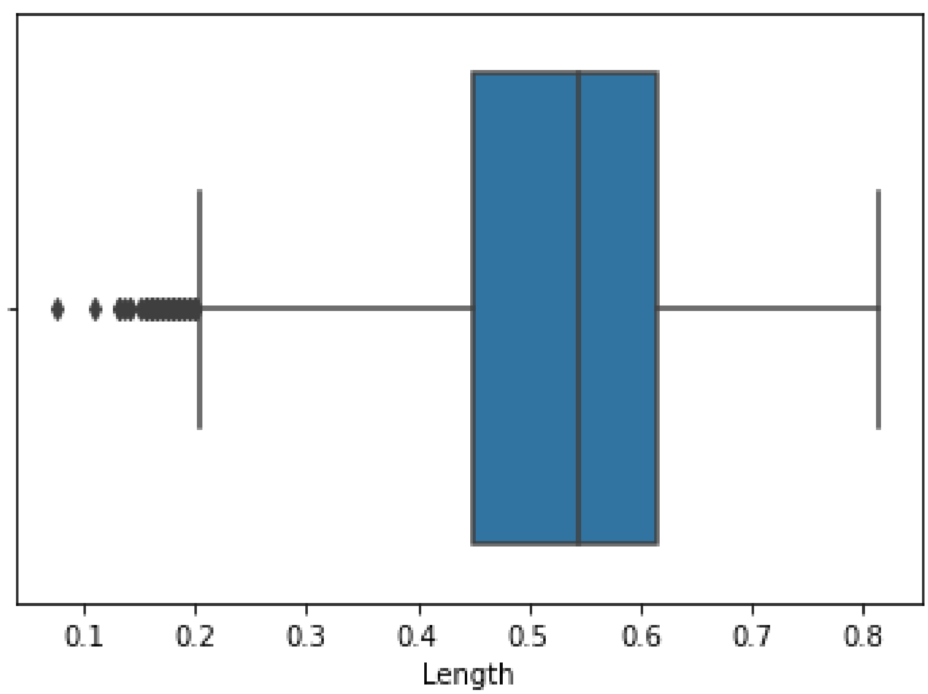
● Bi - Variate Analysis

● Multi - Variate Analysis

```
#Univariate Analysis
sbn.boxplot(df.Length)
```

```
/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 valid positional argument will be `data`, and
passing other arguments without an explicit keyword will result in an
error or misinterpretation.
  FutureWarning
```

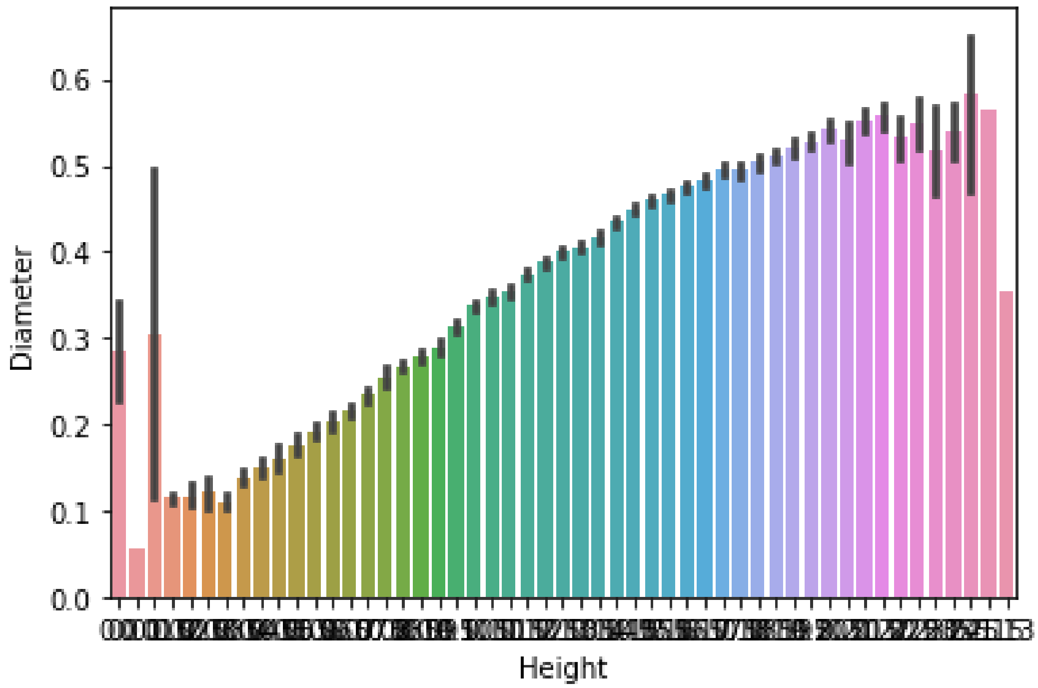
```
<matplotlib.axes._subplots.AxesSubplot at 0x7fe14259ded0>
```



the data is significantly imbalanced

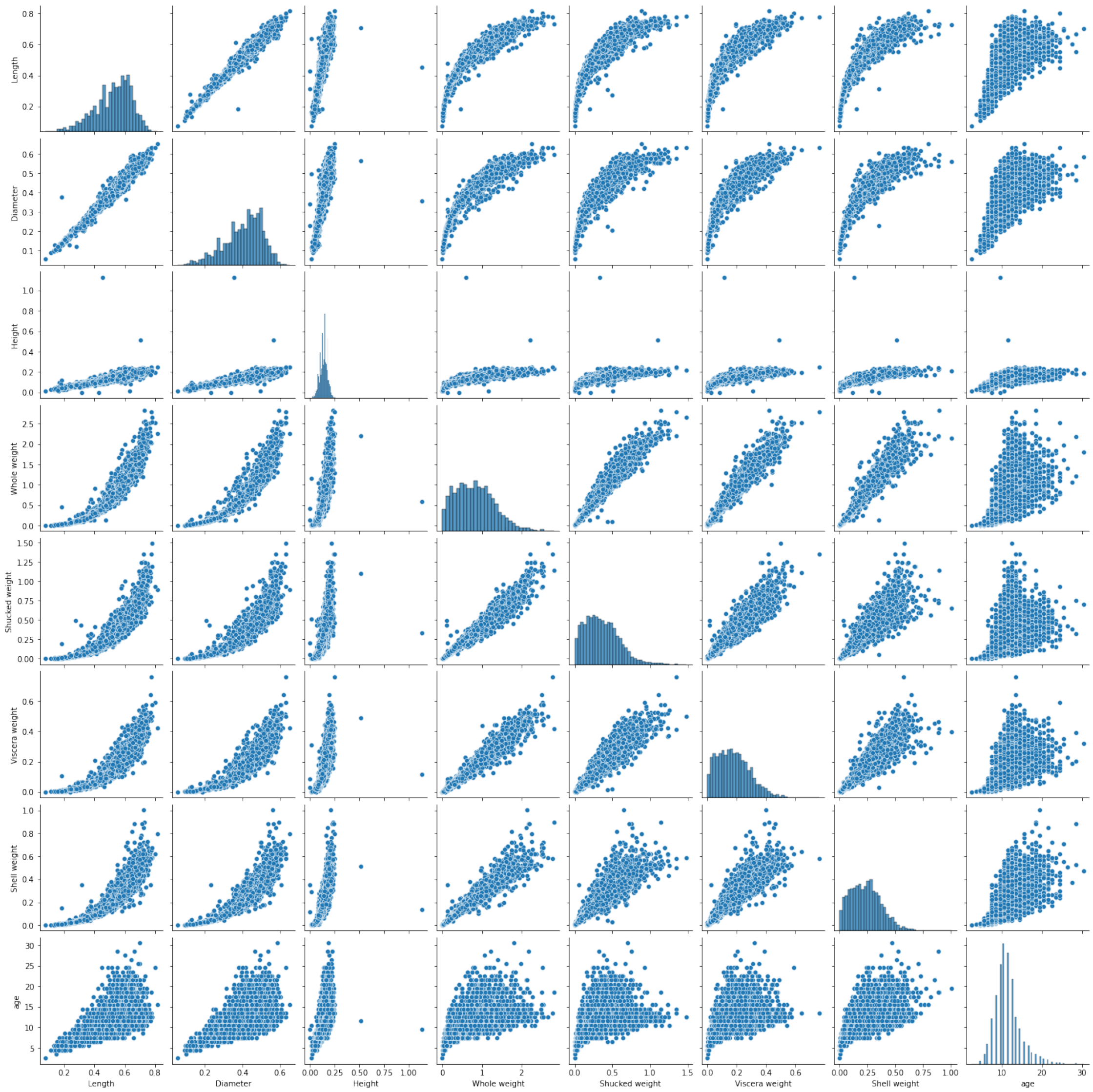
```
#Bi-Variant Analysis
sbn.barplot(x=df.Height,y=df.Diameter)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fe14cb11fd0>
```




```
#Multi-Variant Analysis
sbn.pairplot(df)
```

```
<seaborn.axisgrid.PairGrid at 0x7fe136a92390>
```



4. Perform descriptive statistics on the dataset.

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

```
df.describe()
```

```
            Length     Diameter       Height  Whole weight   Shucked
weight  \
count  4177.000000  4177.000000  4177.000000   4177.000000
4177.000000
mean      0.523992     0.407881     0.139516      0.828742
0.359367
std       0.120093     0.099240     0.041827      0.490389
0.221963
min       0.075000     0.055000     0.000000      0.002000
0.001000
25%       0.450000     0.350000     0.115000      0.441500
0.186000
50%       0.545000     0.425000     0.140000      0.799500
0.336000
75%       0.615000     0.480000     0.165000      1.153000
0.502000
max       0.815000     0.650000     1.130000      2.825500
1.488000

       Viscera weight  Shell weight          age
count     4177.000000   4177.000000  4177.000000
mean         0.180594      0.238831    11.433684
std          0.109614      0.139203     3.224169
min          0.000500      0.001500     2.500000
25%          0.093500      0.130000     9.500000
50%          0.171000      0.234000    10.500000
75%          0.253000      0.329000    12.500000
max          0.760000      1.005000    30.500000
```

5. Handle the Missing values.

```
df.isna().sum()
```

```
Sex               0
Length            0
Diameter          0
Height            0
Whole weight      0
Shucked weight    0
Viscera weight    0
Shell weight      0
age               0
dtype: int64
```

there is no missing values in dataset

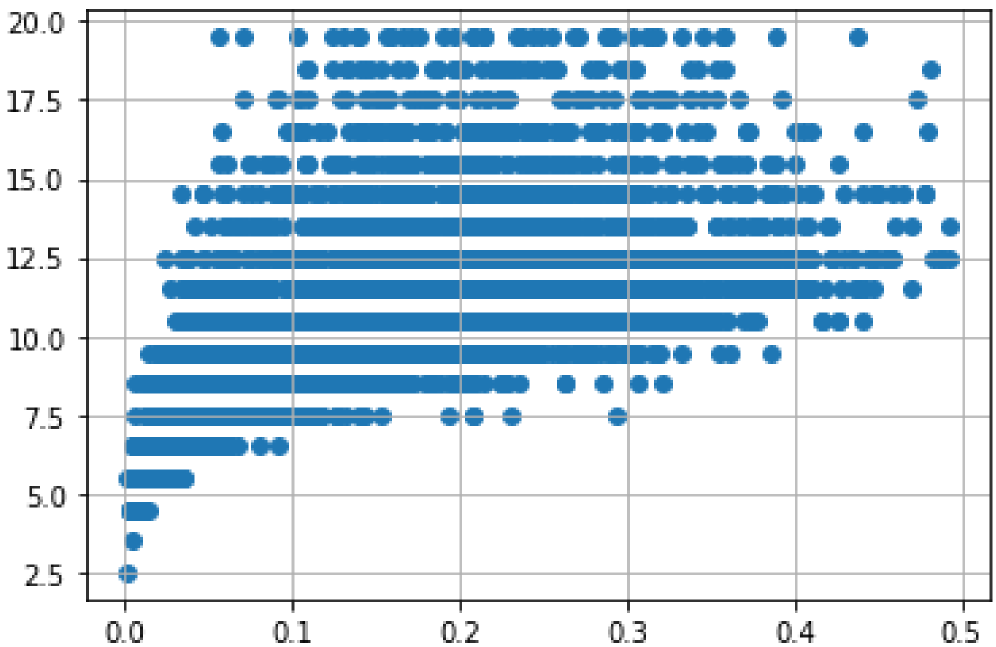
```
for i in df:
    if df[i].dtype=='object' or df[i].dtype=='category':
        print("unique of "+i+" is "+str(len(set(df[i])))+" they are 
"+str(set(df[i])))
```

```
unique of Sex is 3 they are {'F', 'M', 'I'}
```

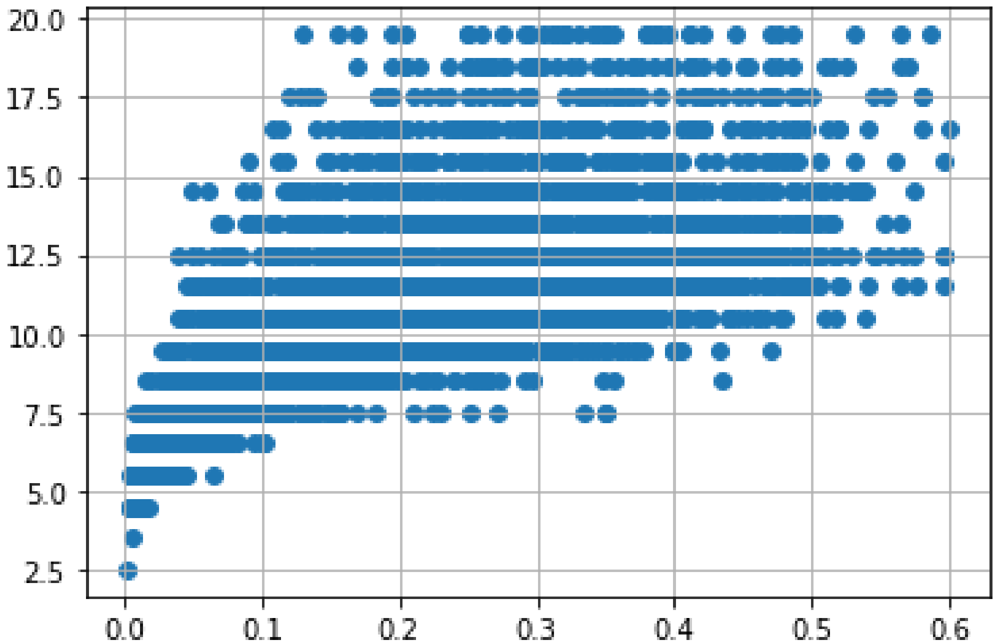
6. Find the outliers and replace the outliers

Checking for outliers

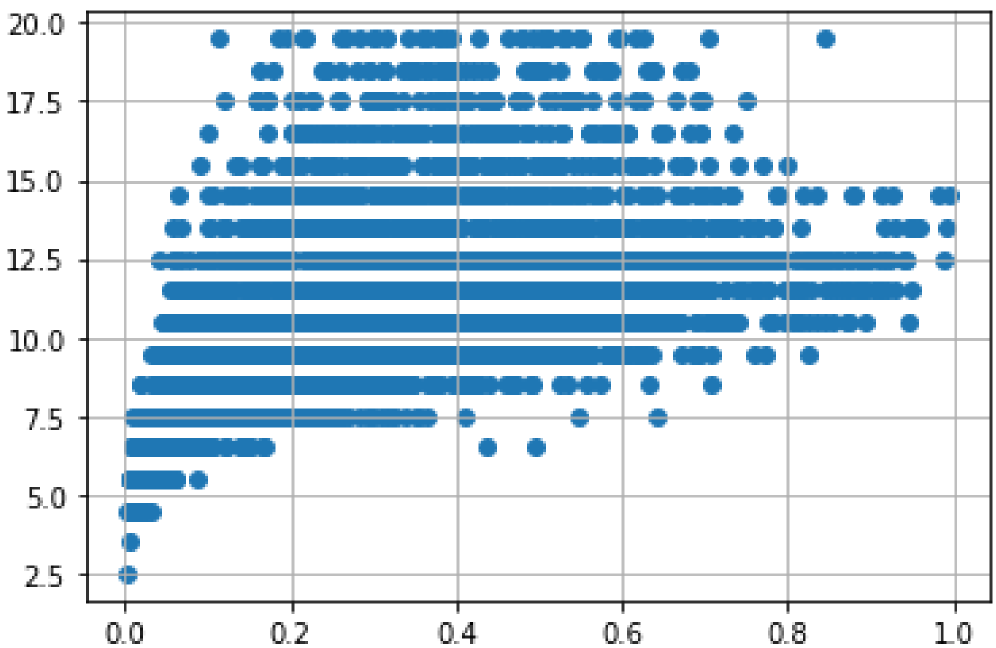
```
#Data Preprocessing
#Outlier handling
df = pd.get_dummies(df)
dummy_df = df

var = 'Viscera weight'
plt.scatter(x = df[var], y = df['age'])
plt.grid(True)
```



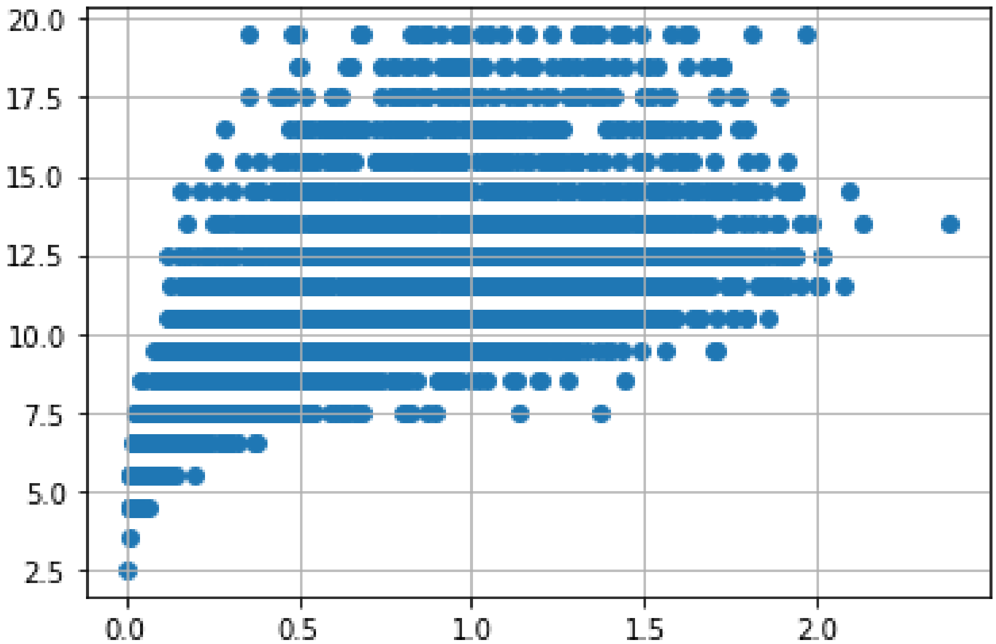

```
var = 'Shell weight'
plt.scatter(x = df[var], y = df['age'])
plt.grid(True)
```



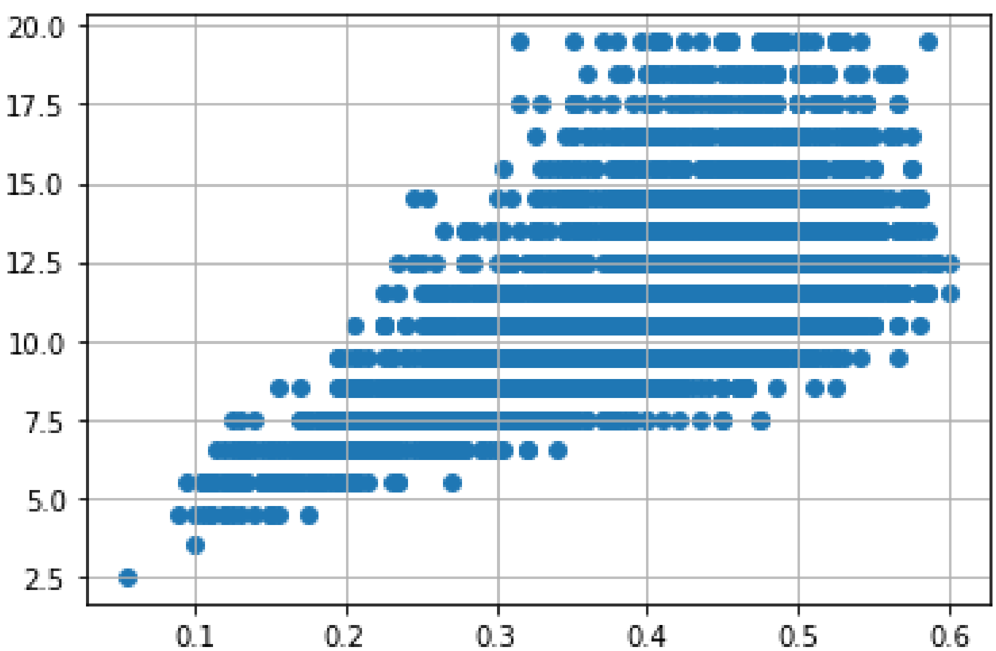

```
var = 'Shucked weight'
plt.scatter(x = df[var], y = df['age'])
plt.grid(True)
```



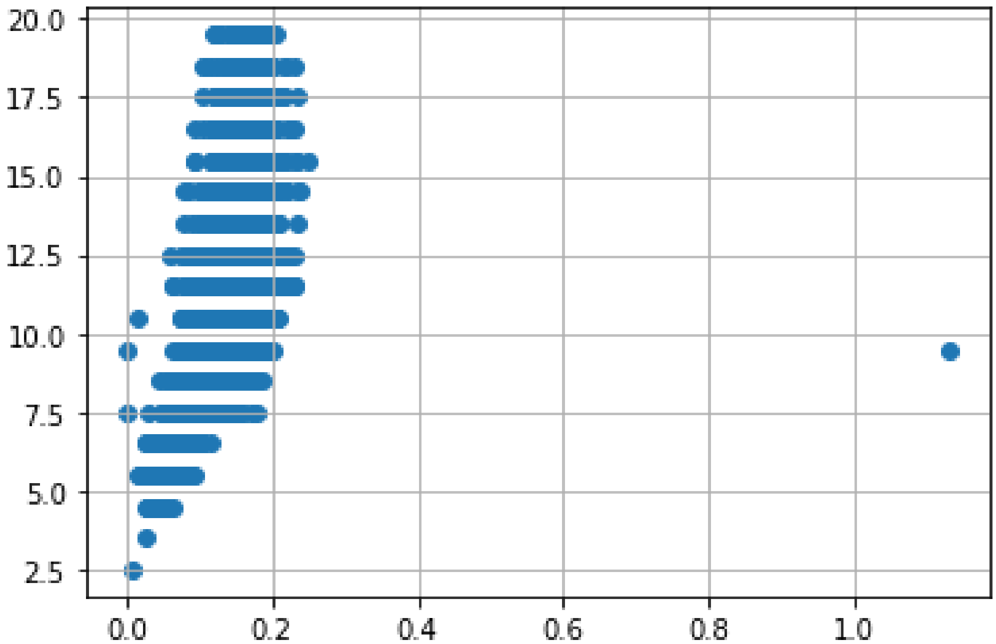

```
var = 'Whole weight'
plt.scatter(x = df[var], y = df['age'])
plt.grid(True)
```



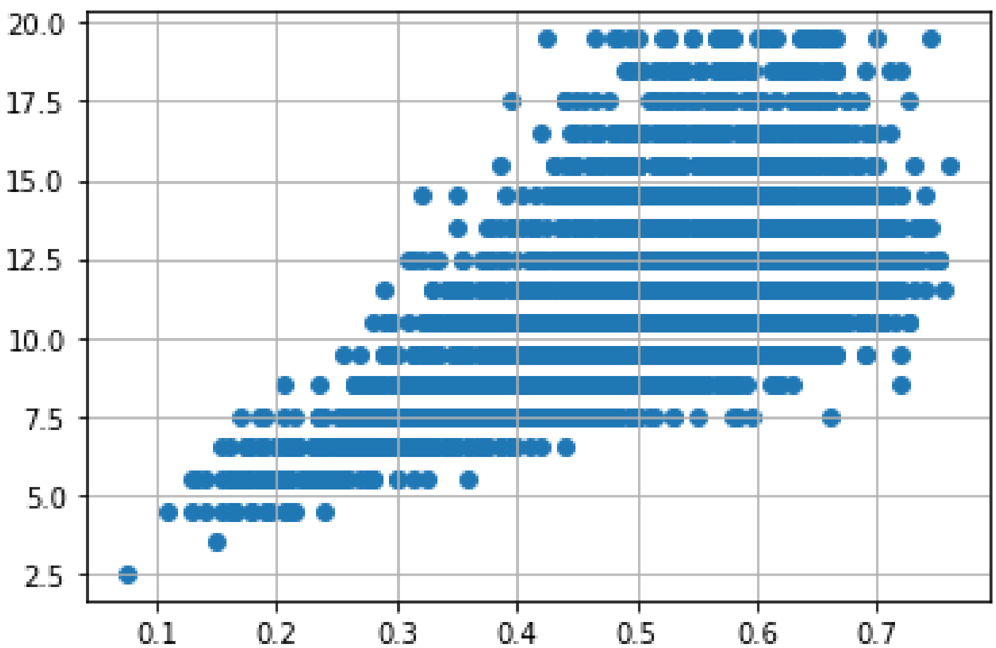

```
var = 'Diameter'
plt.scatter(x = df[var], y = df['age'])
plt.grid(True)
```




```
var = 'Height'
plt.scatter(x = df[var], y = df['age'])
plt.grid(True)
```




```
var = 'Length'
plt.scatter(x = df[var], y = df['age'])
plt.grid(True)
```



Removing outliers

```
df.drop(df[(df['Viscera weight'] > 0.5) &
           (df['age'] < 20)].index, inplace = True)
df.drop(df[(df['Viscera weight']<0.5) & (
df['age'] > 25)].index, inplace = True)
```

```
df.drop(df[(df['Shell weight'] > 0.6) & (df['age'] < 25)].index,
inplace = True)
df.drop(df[(df['Shell weight']<0.8) & (df['age'] > 25)].index, inplace
= True)

df.drop(df[(df['Shucked weight'] >= 1) & (df['age'] < 20)].index,
inplace = True)
df.drop(df[(df['Viscera weight']<1) & (df['age'] > 20)].index, inplace
= True)

df.drop(df[(df['Diameter'] <0.1) & (df['age'] < 5)].index, inplace =
True)
df.drop(df[(df['Diameter']<0.6) & (df['age'] > 25)].index, inplace =
True)
df.drop(df[(df['Diameter']>=0.6) & (df['age'] < 25)].index, inplace =
True)

df.drop(df[(df['Height'] > 0.4) &(df['age'] < 15)].index, inplace =
True)
df.drop(df[(df['Height']<0.4) & (df['age'] > 25)].index, inplace =
True)

df.drop(df[(df['Length'] <0.1) &(df['age'] < 5)].index, inplace =
True)
df.drop(df[(df['Length']<0.8) & (df['age'] > 25)].index, inplace =
True)
df.drop(df[(df['Length']>=0.8) & (df['age'] < 25)].index, inplace =
True)
```

7. Check for Categorical columns and perform encoding.

```
from sklearn.preprocessing import LabelEncoder
encoder=LabelEncoder()
for i in df:
    if df[i].dtype=='object' or df[i].dtype=='category':
        df[i]=encoder.fit_transform(df[i])
```

8. Split the data into dependent and independent variables.

```
x=df.iloc[:,:-1]
x.head()
```

```
   Length  Diameter  Height  Whole weight  Shucked weight  Viscera
weight  \
0   0.455     0.365   0.095        0.5140          0.2245
0.1010
1   0.350     0.265   0.090        0.2255          0.0995
0.0485
2   0.530     0.420   0.135        0.6770          0.2565
0.1415
```

```
3   0.440     0.365   0.125        0.5160          0.2155
0.1140
4   0.330     0.255   0.080        0.2050          0.0895
0.0395

   Shell weight   age  Sex_F  Sex_I
0         0.150  16.5      0      0
1         0.070   8.5      0      0
2         0.210  10.5      1      0
3         0.155  11.5      0      0
4         0.055   8.5      0      1
```

```
y=df.iloc[:,-1]
y.head()
```

```
0    1
1    1
2    0
3    1
4    0
Name: Sex_M, dtype: uint8
```

9. Scale the independent variables

```
from sklearn.preprocessing import StandardScaler
scaler=StandardScaler()
x=scaler.fit_transform(x)
```

```
x
```

```
array([[-0.53701309, -0.39082366, -1.12698145, ...,  1.9433912 ,
        -0.66579302, -0.70803622],
       [-1.42965864, -1.4205279 , -1.26123393, ..., -0.95032771,
        -0.66579302, -0.70803622],
       [ 0.10059087,  0.17551367, -0.05296168, ..., -0.22689798,
         1.50196828, -0.70803622],
       ...,
       [ 0.6956879 ,  0.741851  ,  1.82657293, ..., -0.22689798,
        -0.66579302, -0.70803622],
       [ 0.90822255,  0.84482142,  0.34979574, ...,  0.13481688,
         1.50196828, -0.70803622],
       [ 1.63084038,  1.56561439,  1.55806799, ...,  0.85824661,
        -0.66579302, -0.70803622]])
```

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(x,y,test_size=0.33)
```

```
x_train.shape
```

```
(2676, 10)
```

```
x_test.shape
```

```
(1319, 10)
```

```
y_train.shape
```

```
(2676,)
```

```
y_test.shape
```

```
(1319,)
```

#**MODEL**

Linear regression

```
from sklearn.linear_model import LinearRegression
```

```
lm = LinearRegression()
lm.fit(x_train, y_train)
```

```
LinearRegression()
```

```
y_train_pred = lm.predict(x_train)
y_test_pred = lm.predict(x_test)
```

```
from sklearn.metrics import mean_absolute_error, mean_squared_error
s = mean_squared_error(y_train, y_train_pred)
print('Mean Squared Error of training set :%2f'%s)

p = mean_squared_error(y_test, y_test_pred)
print('Mean Squared Error of testing set :%2f'%p)
```

```
Mean Squared Error of training set :0.000000
Mean Squared Error of testing set :0.000000
```

Note: The Lower the Mean Squared Error,better the forecast.

```
from sklearn.metrics import r2_score
s = r2_score(y_train, y_train_pred)
print('R2 Score of training set:%.2f'%s)

p = r2_score(y_test, y_test_pred)
print('R2 Score of testing set:%.2f'%p)
```

```
R2 Score of training set:1.00
R2 Score of testing set:1.00
```

Note: The ideal value of R-square is 1.

The closer the value of R-square to 1,better is the model fitted.