Assignment -3
Python Programming

Assignment Date	6 October 2022
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Student Roll Number	910619104045
Maximum Marks	2 Marks

Abalone Age Prediction

1. Download the dataset

In [1]:

```
#Dataset Downloaded
```

2. Load the Dataset

In [3]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
df = pd.read_csv('abalone.csv')
```

In [4]:

```
df.head()
```

Out[4]:

	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 [5]:

```
#Modifying the given dataset
Age=1.5+df.Rings
df["Age"]=Age
```

```
df=df.rename(columns = {'Whole weight':'Whole_weight','Shucked weight':
'Shucked_weight','Viscera weight': 'Viscera_weight','Shell weight':
'Shell_weight'})
df=df.drop(columns=["Rings"],axis=1)
df.head()
```

Out[5]:

	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

In [6]:

```
df.tail()
```

Out[6]:

	Sex	Length	Diameter	Height	Whole_weight	Shucked_weight	Viscera_weight	Shell_weight	Age
4172	F	0.565	0.450	0.165	0.8870	0.3700	0.2390	0.2490	12.5
4173	M	0.590	0.440	0.135	0.9660	0.4390	0.2145	0.2605	11.5
4174	M	0.600	0.475	0.205	1.1760	0.5255	0.2875	0.3080	10.5
4175	F	0.625	0.485	0.150	1.0945	0.5310	0.2610	0.2960	11.5
4176	M	0.710	0.555	0.195	1.9485	0.9455	0.3765	0.4950	13.5

In [7]:

```
df.shape
```

Out[7]:

```
(4177, 9)
```

In [8]:

```
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
```

3. Perform Visualizations

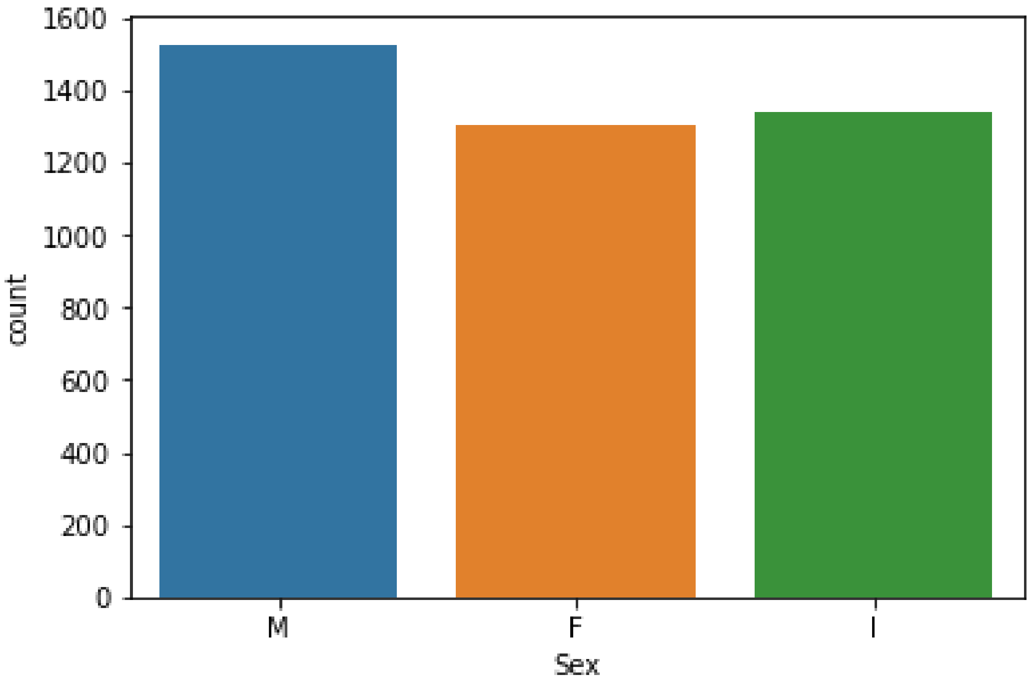
Univariate Analysis

In [10]:

```
sns.countplot(x='Sex',data=df)
```

Out[10]:

```
<AxesSubplot:xlabel='Sex', ylabel='count'>
```

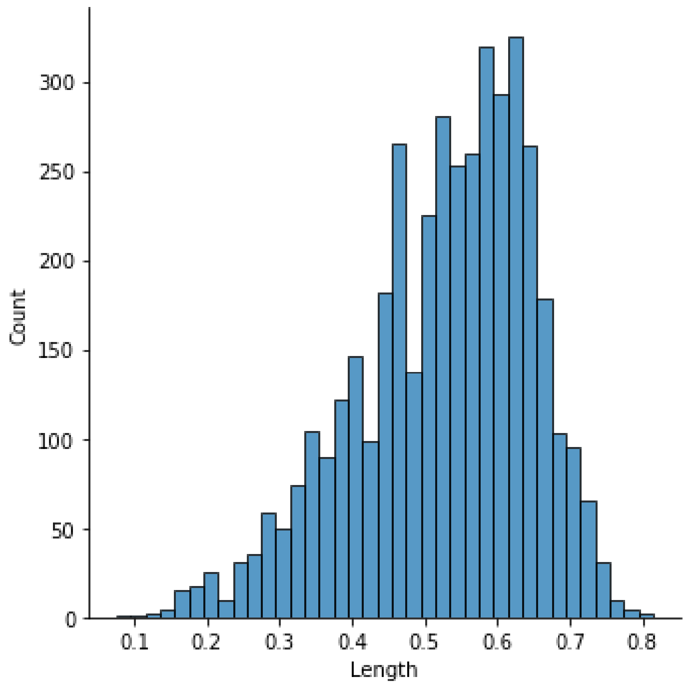


In [12]:

```
sns.displot(df["Length"])
```

Out[12]:

```
<seaborn.axisgrid.FacetGrid at 0x2d750617c10>
```

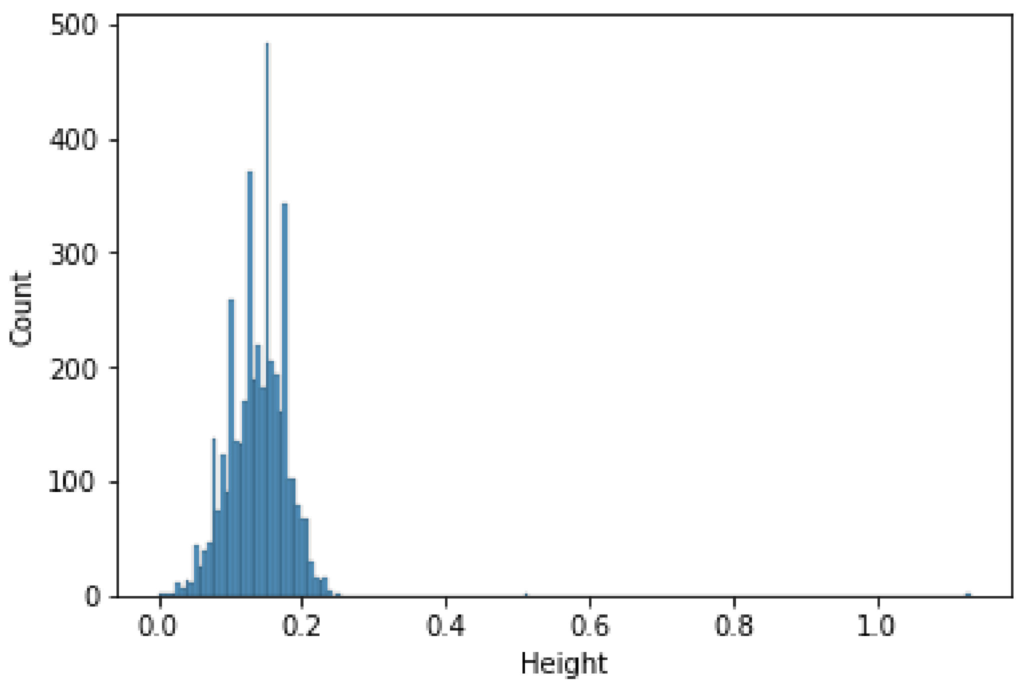


In [13]:

```
sns.histplot(x='Height',data=df)
```

Out[13]:

```
<AxesSubplot:xlabel='Height', ylabel='Count'>
```

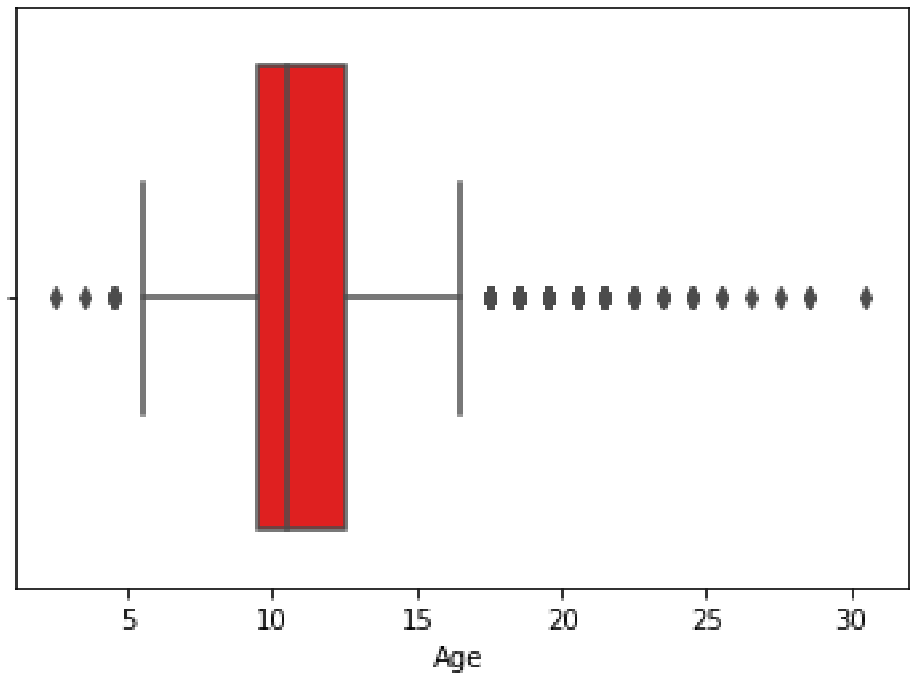


In [15]:

```
sns.boxplot(df["Age"],color='red')
```

Out[15]:

```
<AxesSubplot:xlabel='Age'>
```



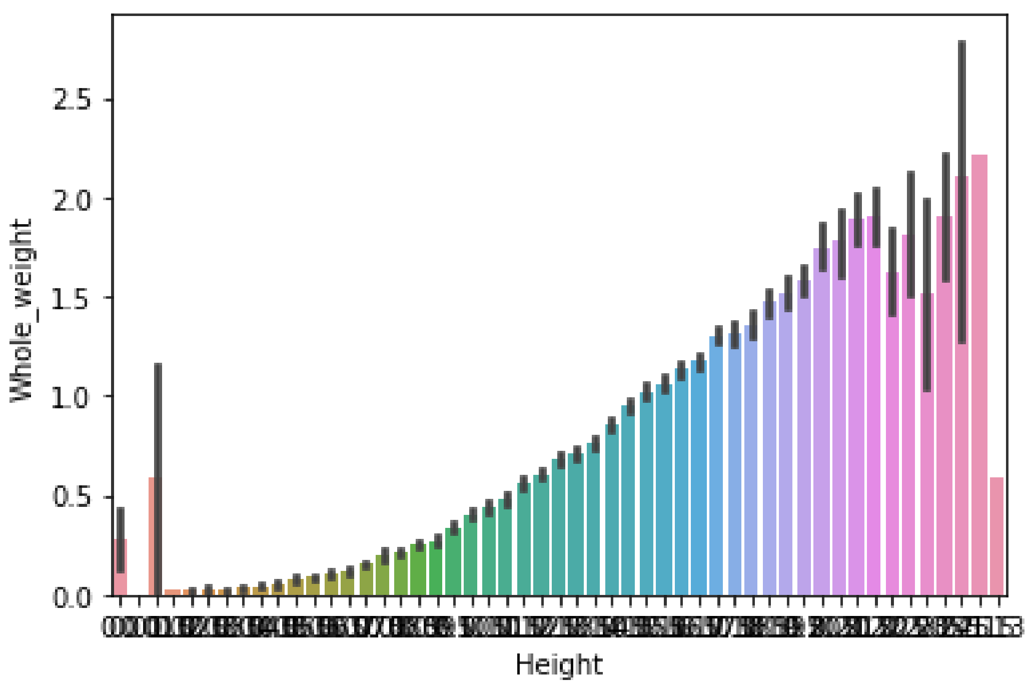
Bivariate Analysis

In [17]:

```
sns.barplot(x=df["Height"],y=df["Whole_weight"])
```

Out[17]:

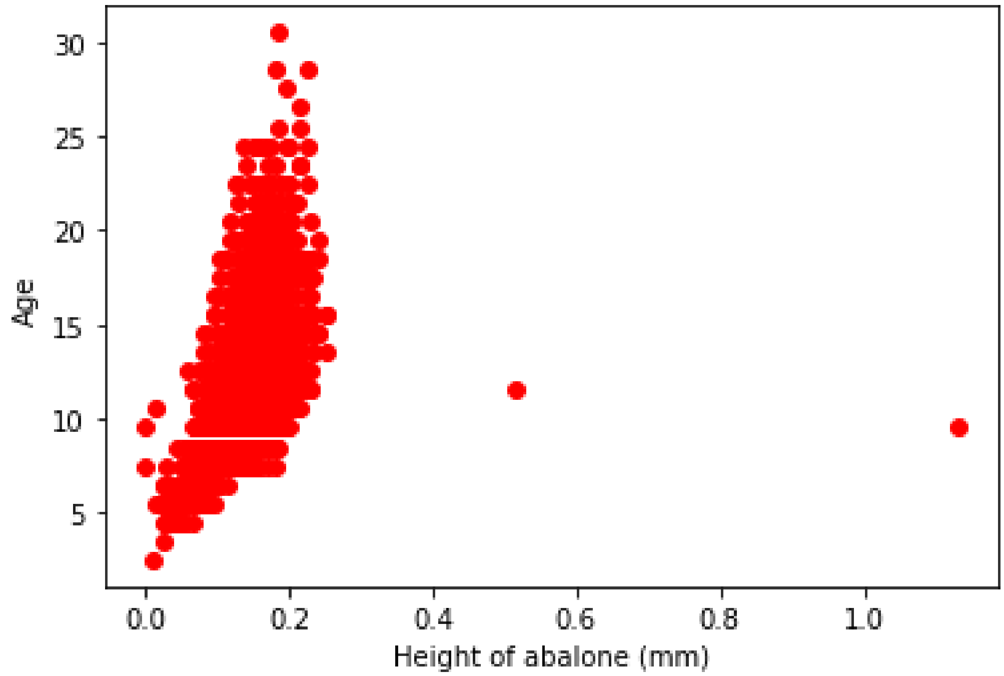
```
<AxesSubplot:xlabel='Height', ylabel='Whole_weight'>
```



In [21]:

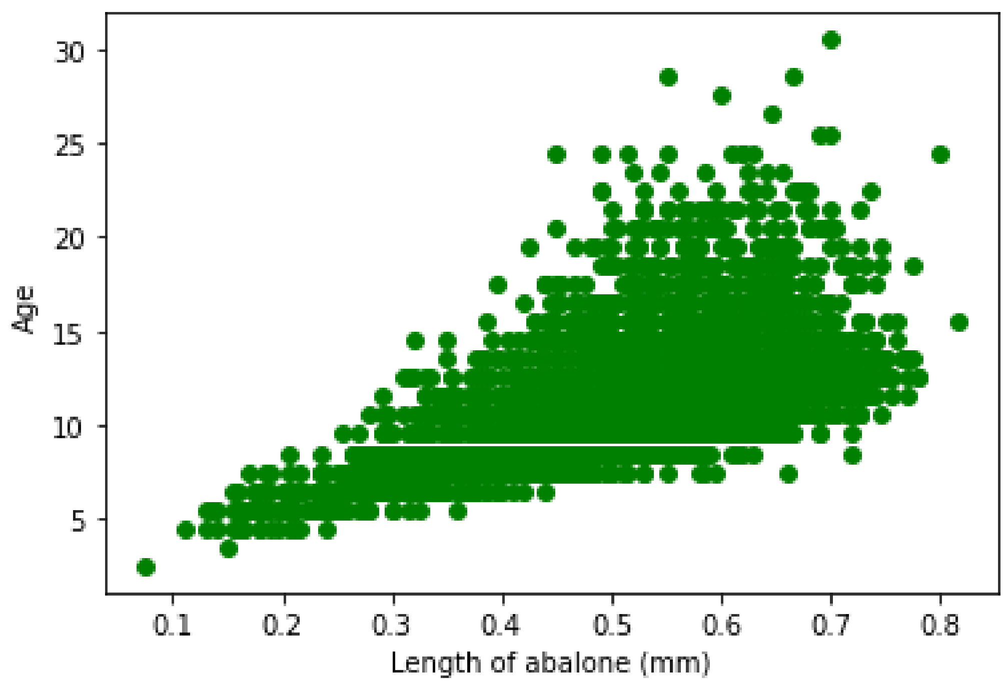
```
plt.scatter(df['Height'], df['Age'], c='red')
```

```
plt.xlabel('Height of abalone (mm)')
plt.ylabel('Age')
plt.show()
```



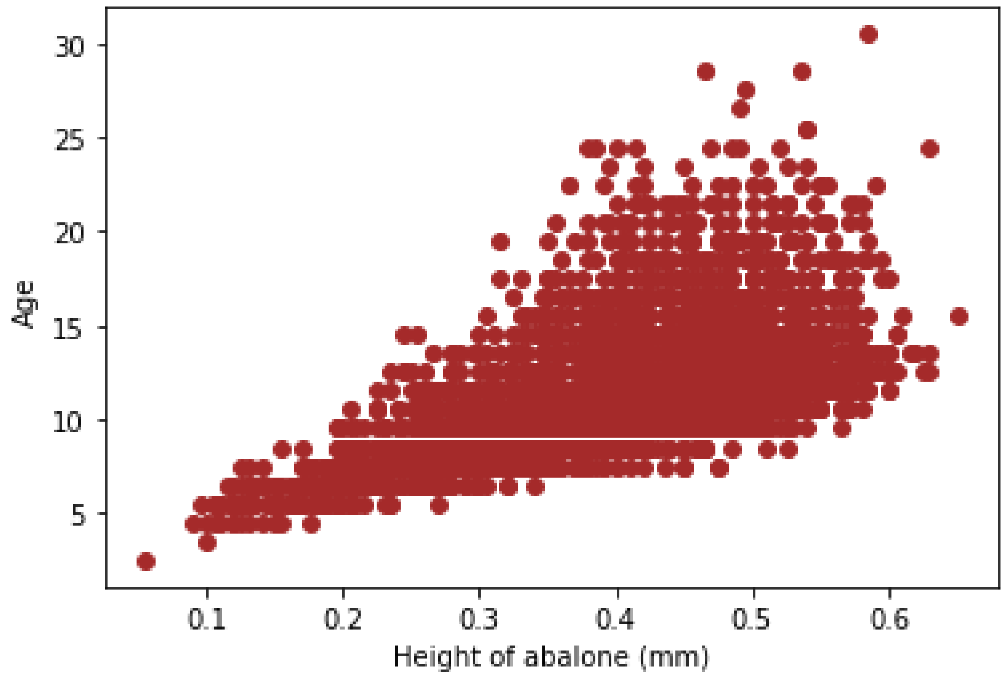
In [20]:

```
plt.scatter(df['Length'], df['Age'], c='green')
plt.xlabel('Length of abalone (mm)')
plt.ylabel('Age')
plt.show()
```



In [23]:

```
plt.scatter(df['Diameter'], df['Age'],c='brown')
plt.xlabel('Height of abalone (mm)')
plt.ylabel('Age')
plt.show()
```



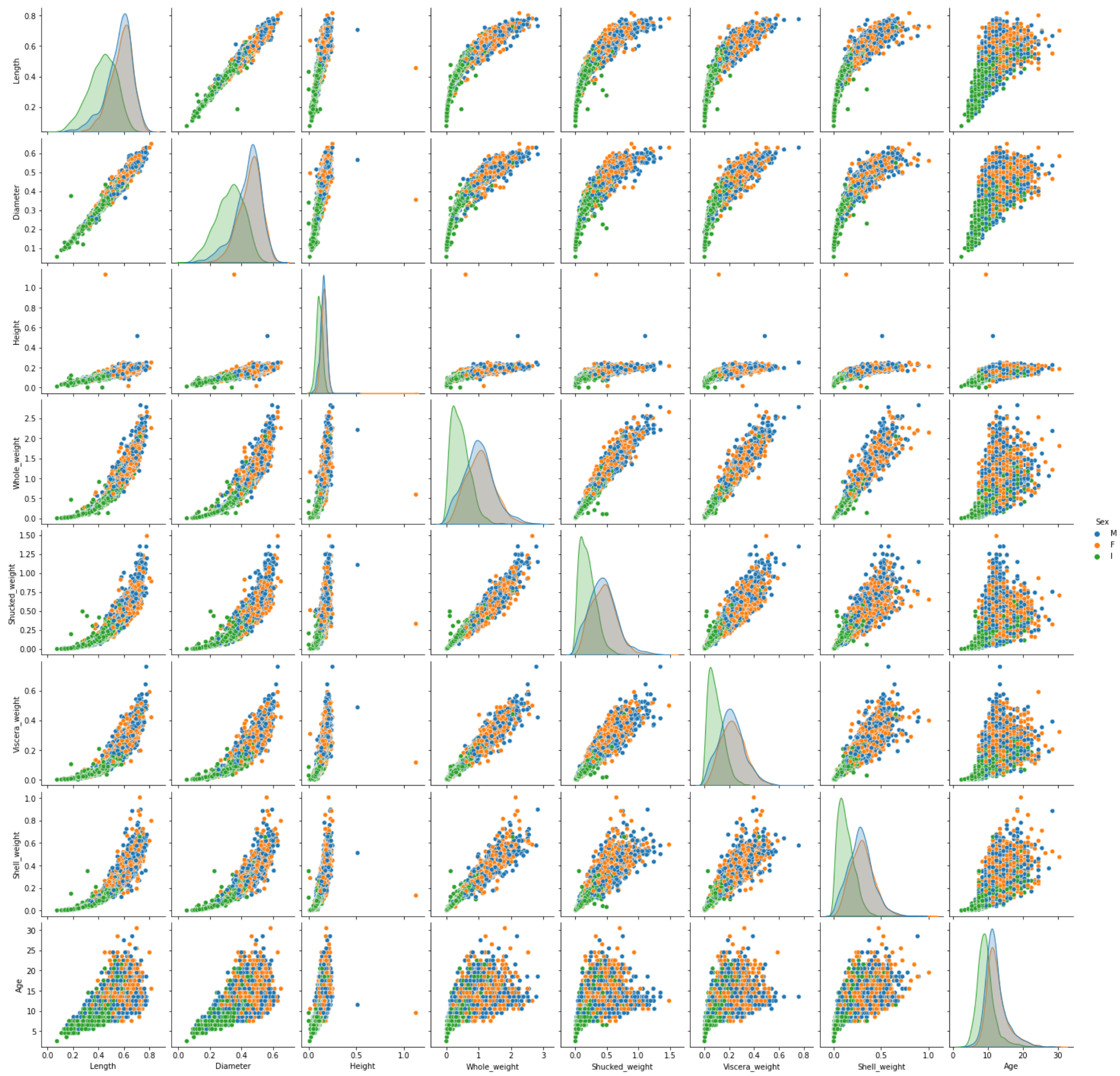
Multi-Variate Analysis

In [24]:

```
sns.pairplot(df,hue='Sex')
```

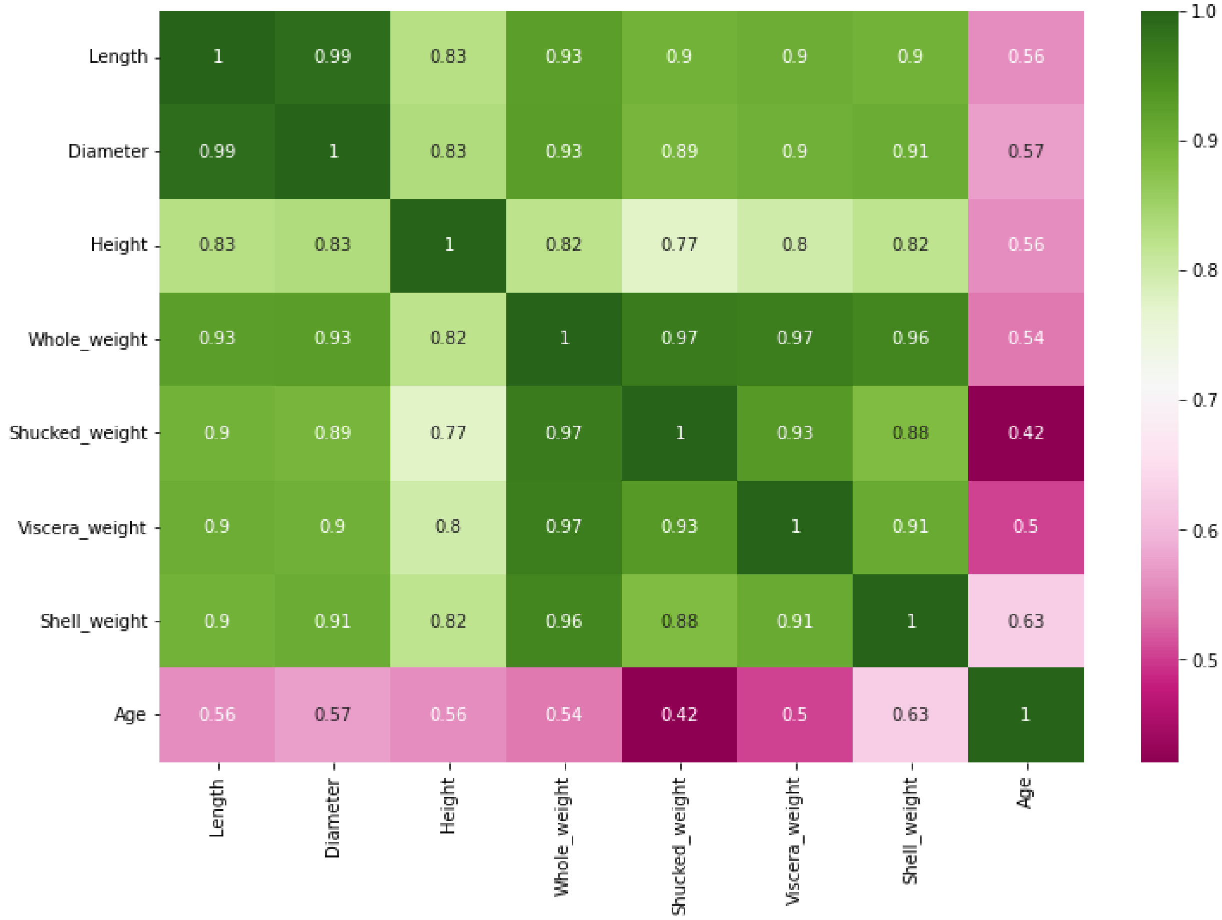
Out[24]:

```
<seaborn.axisgrid.PairGrid at 0x2d752e146d0>
```



In [25]:

```
plt.figure(figsize=(12,8));
sns.heatmap(df.corr(), cmap="PiYG",annot=True);
```



4.Descriptive statistics

In [27]:

```
df.describe(include='all')
```

Out[27]:

	Sex	Length	Diameter	Height	Whole_weight	Shucked_weight	Viscera_weight	Shell_weig
count	4177	4177.000000	4177.000000	4177.000000	4177.000000	4177.000000	4177.000000	4177.0000
unique	3	NaN	NaN	NaN	NaN	NaN	NaN	NaN
top	M	NaN	NaN	NaN	NaN	NaN	NaN	NaN
freq	1528	NaN	NaN	NaN	NaN	NaN	NaN	NaN
mean	NaN	0.523992	0.407881	0.139516	0.828742	0.359367	0.180594	0.238831
std	NaN	0.120093	0.099240	0.041827	0.490389	0.221963	0.109614	0.139203
min	NaN	0.075000	0.055000	0.000000	0.002000	0.001000	0.000500	0.001500
25%	NaN	0.450000	0.350000	0.115000	0.441500	0.186000	0.093500	0.130000
50%	NaN	0.545000	0.425000	0.140000	0.799500	0.336000	0.171000	0.234000
75%	NaN	0.615000	0.480000	0.165000	1.153000	0.502000	0.253000	0.329000
max	NaN	0.815000	0.650000	1.130000	2.825500	1.488000	0.760000	1.005000

5. Check for Missing values and deal with them

In [29]:

```
df.isnull().sum()
```

Out[29]:

```
Sex               0
Length            0
Diameter          0
Height            0
Whole_weight      0
Shucked_weight    0
Viscera_weight    0
Shell_weight      0
Age               0
dtype: int64
```

6. Find the outliers and replacing them outliers

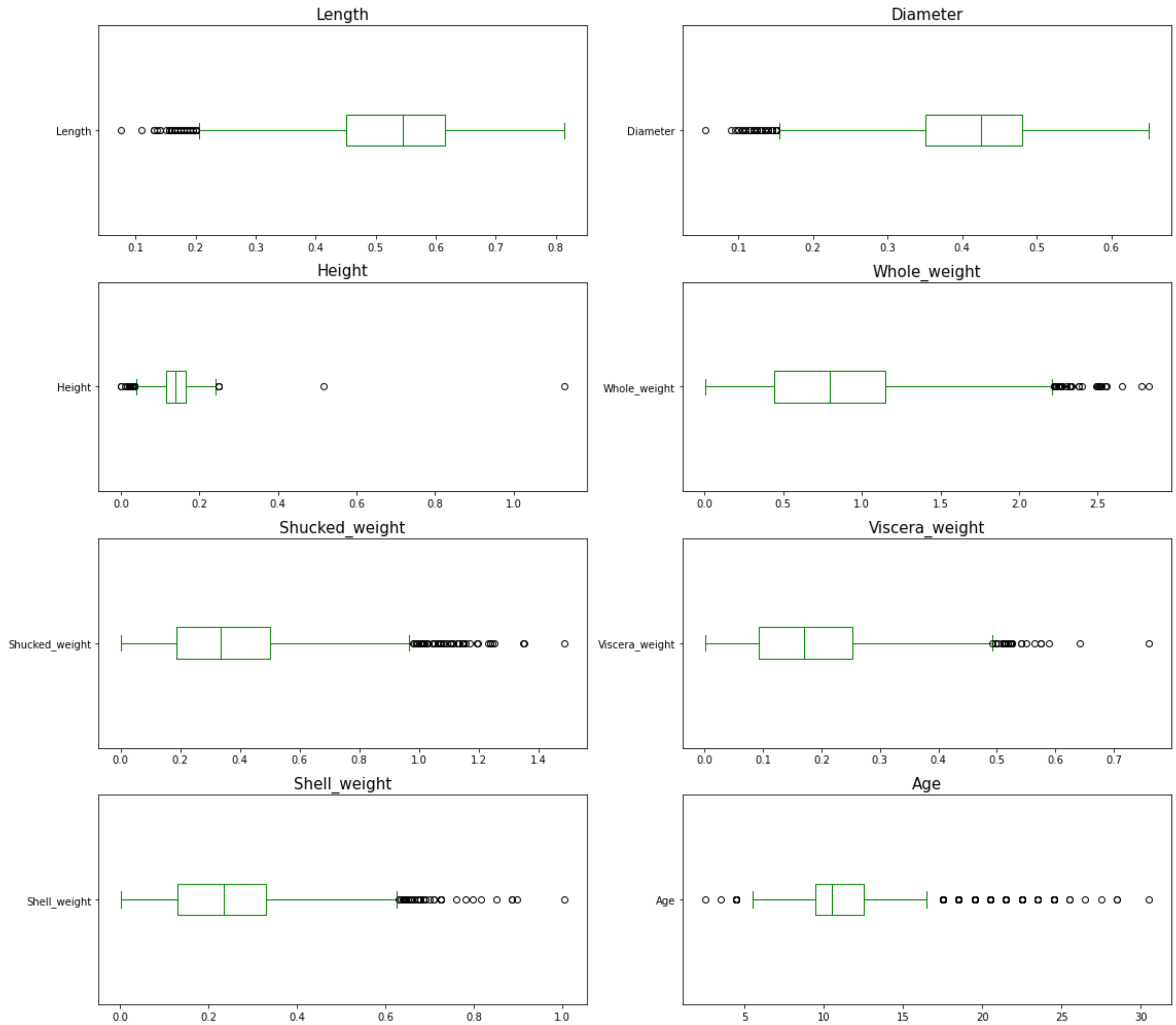
In [30]:

```
col =['Length', 'Diameter', 'Height', 'Whole_weight', 'Shucked_weight',
       'Viscera_weight', 'Shell_weight', 'Age']
```

In [31]:

```
figfig, axes = plt.subplots(4,2,figsize=(16, 14))
axes = np.ravel(axes)
for i, c in enumerate(col):
    hist = df[c].plot(kind = 'box', ax=axes[i],color='green', vert=False)
    axes[i].set_title(c, fontsize=15)

plt.tight_layout()
plt.show()
```



In [32]:

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

Out[32]:

	Length	Diameter	Height	Whole_weight	Shucked_weight	Viscera_weight	Shell_weight	Age
0.75	0.615	0.48	0.165	1.1530	0.502	0.2530	0.329	12.5
0.25	0.450	0.35	0.115	0.4415	0.186	0.0935	0.130	9.5

In [34]:

```
IQR = qnt.loc[0.75] - qnt.loc[0.25]
IQR
```

Out[34]:

```
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
```

```
Age                3.0000
dtype: float64
```

In [35]:

```
lower = qnt.loc[0.25] - 1.5 * IQR
lower
```

Out[35]:

```
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
Age               5.00000
dtype: float64
```

In [36]:

```
upper = qnt.loc[0.75] + 1.5 * IQR
upper
```

Out[36]:

```
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
Age               17.00000
dtype: float64
```

In [37]:

```
df.mean()
```

Out[37]:

```
Length             0.523992
Diameter           0.407881
Height             0.139516
Whole_weight       0.828742
Shucked_weight     0.359367
Viscera_weight     0.180594
Shell_weight       0.238831
Age               11.433684
dtype: float64
```

In [38]:

```
df['Length']=np.where(df['Length']<0.22,0.52,df['Length'])
df['Diameter']=np.where(df['Diameter']<0.155,0.407,df['Diameter'])
df['Height']=np.where(df['Height']<0.04,0.13,df['Height'])
```

In [39]:

```
df['Height']=np.where(df['Height']>0.24,0.13,df['Height'])
df['Whole_weight']=np.where(df['Whole_weight']>2.18,0.83,df['Whole_weight'])
```

```
df['Shucked_weight']=np.where(df['Shucked_weight']>0.958,0.359367,df['Shucked
_weight'])
df['Viscera_weight']=np.where(df['Viscera_weight']>0.478,0.18,df['Viscera_wei
ght'])
```

In [40]:

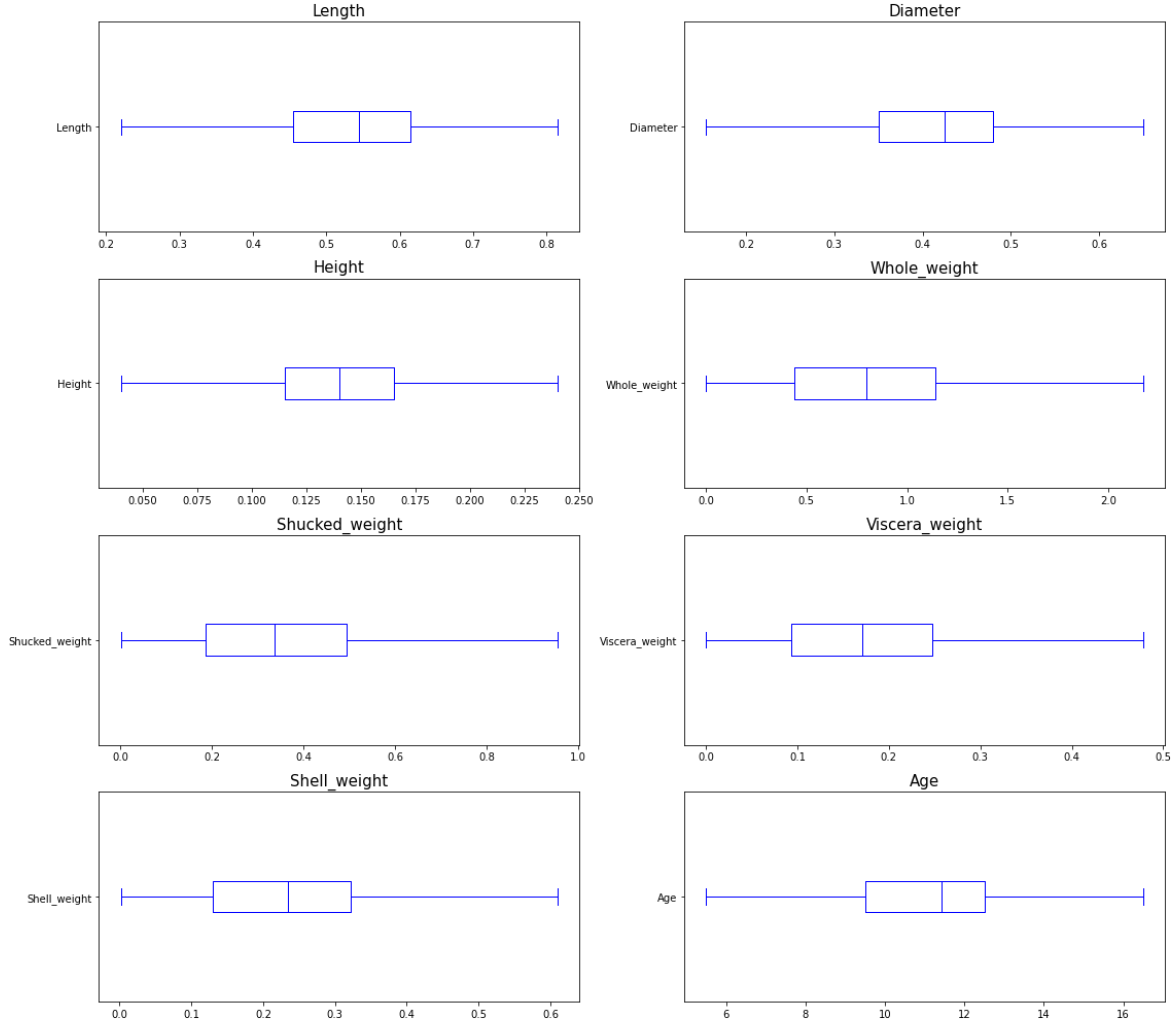
```
df['Shell_weight']=np.where(df['Shell_weight']>0.61,0.238831,df['Shell_weight
'])
df['Age']=np.where(df['Age']<5.0,11.43,df['Age'])
df['Age']=np.where(df['Age']>17.0,11.43,df['Age'])
```

In [41]:

```
figfig, axes = plt.subplots(4,2,figsize=(16, 14))
axes = np.ravel(axes)

for i, c in enumerate(col):
    hist = df[c].plot(kind = 'box', ax=axes[i],color='blue', vert=False)
    axes[i].set_title(c, fontsize=15)

plt.tight_layout()
plt.show()
```



In [42]:

```
df.shape
```

Out[42]:

```
(4177, 9)
```

7. Check for Categorical columns and perform encoding

In [43]:

```
df['Sex'].unique()
```

Out[43]:

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

In [44]:

```
x = pd.get_dummies(df)
```

In [45]:

```
x.head()
```

Out[45]:

	Length	Diameter	Height	Whole_weight	Shucked_weight	Viscera_weight	Shell_weight	Age	Sex_F	Sex_I	Sex_M
0	0.455	0.365	0.095	0.5140	0.2245	0.1010	0.150	16.5	0	0	1

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

8. Split the data into dependent and independent variables

In [46]:

```
x.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4177 entries, 0 to 4176
Data columns (total 11 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   Length          4177 non-null   float64
 1   Diameter        4177 non-null   float64
 2   Height          4177 non-null   float64
 3   Whole_weight    4177 non-null   float64
 4   Shucked_weight  4177 non-null   float64
 5   Viscera_weight  4177 non-null   float64
 6   Shell_weight    4177 non-null   float64
 7   Age             4177 non-null   float64
 8   Sex_F           4177 non-null   uint8
 9   Sex_I           4177 non-null   uint8
 10  Sex_M           4177 non-null   uint8
dtypes: float64(8), uint8(3)
memory usage: 273.4 KB
```

In [47]:

```
X = x.drop(['Age'], axis = 1)
```

In [48]:

```
X.head()
```

Out[48]:

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

In [49]:

```
y = x['Age']
```

In [50]:

```
y.head()
```

Out[50]:

```
0    16.5
1     8.5
2    10.5
3    11.5
4     8.5
Name: Age, dtype: float64
```

9. Scale the independent variables

In [51]:

```
from sklearn.preprocessing import StandardScaler
```

In [52]:

```
X_columns = X.select_dtypes(include=np.number).columns.tolist()
X_columns
```

Out[52]:

```
['Length',
 'Diameter',
 'Height',
 'Whole_weight',
 'Shucked_weight',
 'Viscera_weight',
 'Shell_weight',
 'Sex_F',
 'Sex_I',
 'Sex_M']
```

In [53]:

```
scaler = StandardScaler()
```

In [54]:

```
X[X_columns] = scaler.fit_transform(X[X_columns])
X.head()
```

Out[54]:

	Length	Diameter	Height	Whole_weight	Shucked_weight	Viscera_weight	Shell_weight	Sex_F	Sex_I
0	-0.663474	-0.501673	-1.196422	-0.643390	-0.611770	-0.732343	-0.643590	-0.674834	-0.688018
1	-1.601273	-1.572915	-1.330241	-1.259765	-1.219694	-1.236126	-1.257424	-0.674834	-0.688018
2	0.006383	0.087510	-0.125873	-0.295144	-0.456142	-0.343709	-0.183214	1.481846	-0.688018
3	-0.797445	-0.501673	-0.393511	-0.639118	-0.655541	-0.607596	-0.605225	-0.674834	-0.688018
4	-1.779901	-1.680039	-1.597878	-1.303563	-1.268328	-1.322489	-1.372518	-0.674834	1.453451

10. Split the data into training and testing

In [55]:

```
X.shape, y.shape
```

Out[55]:

```
((4177, 10), (4177,))
```

In [56]:

```
from sklearn.model_selection import train_test_split
x_train, x_test, y_train, y_test = train_test_split(X,y, test_size=0.2,
random_state=42)
```

In [57]:

```
print(' x_train.shape : ',x_train.shape)
print(' y_train.shape : ',y_train.shape)
print(' x_test.shape : ',x_test.shape)
print(' y_test.shape : ',y_test.shape)
 x_train.shape :  (3341, 10)
 y_train.shape :  (3341,)
 x_test.shape :  (836, 10)
 y_test.shape :  (836,)
```

Build the Model, Train the Model and Test the Model

In [58]:

```
#Linear Regression
from sklearn.linear_model import LinearRegression

lr = LinearRegression()
lr.fit(x_train, y_train)

lr_pred = lr.predict(x_test)
```

In [59]:

```
#Random Forest
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_squared_error,make_scorer
from sklearn.model_selection import RandomizedSearchCV

rf = RandomForestRegressor()

param = {
    'max_depth':[3,6,9,12,15],
    'n_estimators' : [10,50,100,150,200]
}

rf_search =
RandomizedSearchCV(rf,param_distributions=param,n_iter=5,scoring=make_scorer(
mean_squared_error),
                               n_jobs=-1,cv=5,verbose=3)
```

```
rf_search.fit(x_train, y_train)
Fitting 5 folds for each of 5 candidates, totalling 25 fits
```

Out[59]:

```
RandomizedSearchCV(cv=5, estimator=RandomForestRegressor(), n_iter=5,
n_jobs=-1,
                   param_distributions={'max_depth': [3, 6, 9, 12, 15],
                                        'n_estimators': [10, 50, 100, 150,
                                                         200]},
                   scoring=make_scorer(mean_squared_error), verbose=3)
```

In [60]:

```
#In a Jupyter environment, please rerun this cell to show the HTML
representation or trust the notebook.
#On GitHub, the HTML representation is unable to render, please try loading
this page with nbviewer.org.
```

In [61]:

```
means = rf_search.cv_results_['mean_test_score']
params = rf_search.cv_results_['params']
for mean, param in zip(means, params):
    print("%f with: %r" % (mean, param))
    if mean == min(means):
        print('Best parameters with the minimum Mean Square Error
are:',param)
2.753132 with: {'n_estimators': 50, 'max_depth': 12}
2.644186 with: {'n_estimators': 200, 'max_depth': 6}
2.640827 with: {'n_estimators': 50, 'max_depth': 6}
Best parameters with the minimum Mean Square Error are: {'n_estimators': 50,
'max_depth': 6}
2.762468 with: {'n_estimators': 50, 'max_depth': 15}
2.739511 with: {'n_estimators': 200, 'max_depth': 15}
```

In [62]:

```
rf = RandomForestRegressor(n_estimators=50, max_depth=6)
rf.fit(x_train,y_train)

rf_pred =  rf.predict(x_test)
```

14. Measure the performance using Metrics

In [64]:

```
from sklearn import metrics
RMSE1 = np.sqrt(metrics.mean_squared_error(y_test, lr_pred))
MAE = metrics.mean_absolute_error(y_test, lr_pred)
MSE = metrics.mean_squared_error(y_test, lr_pred)
R2 = metrics.r2_score(y_test,lr_pred)
print('Linear Regression :')
print('-------------------')
print('MAE:', MAE)
```

```
print('MSE:', MSE)
print('RMSE:', RMSE1)
print('R2 Score :',R2)
print('\n\n')
Linear Regression :
-------------------
MAE: 1.326777442258078
MSE: 2.9868483619389266
RMSE: 1.7282500866306725
R2 Score : 0.4466536519118789
```

In [65]:

```
from sklearn import metrics
RMSE2 = np.sqrt(metrics.mean_squared_error(y_test, rf_pred))
MAE = metrics.mean_absolute_error(y_test, rf_pred)
MSE = metrics.mean_squared_error(y_test, rf_pred)
R2 = metrics.r2_score(y_test,rf_pred)
print('Random Forest Contains:')
print('-------------------')
print('MAE:', MAE)
print('MSE:', MSE)
print('RMSE:', RMSE2)
print('R2 Score :',R2)
Random Forest Contains:
-------------------
MAE: 1.2369731265164512
MSE: 2.5047280907807443
RMSE: 1.5826332774148104
R2 Score : 0.5359717086248263
```

Compare Linear Regression and Random Forest

Random Forest got low rmse value than Linear Regression

In [66]:

```
RMSE = RMSE1-RMSE2
print(RMSE)
0.14561680921586206
```

In [ ]: