In [1]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import pickle
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split
from statsmodels.stats.outliers_influence import variance_inflation_factor
from sklearn.metrics import accuracy_score, confusion_matrix,roc_curve,roc_auc_score
from scipy.stats import zscore
from sklearn.preprocessing import StandardScaler
import statsmodels.api as sm
from sklearn.metrics import mean_squared_error,mean_absolute_error
from sklearn.linear_model import Ridge,Lasso,RidgeCV,LassoCV
import warnings
warnings.filterwarnings('ignore')
from sklearn.preprocessing import PowerTransformer
from sklearn.preprocessing import LabelEncoder
from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import GridSearchCV
```

In [2]:

```
df=pd.read_csv(r'https://raw.githubusercontent.com/dsrscientist/dataset1/master/abalone.csv')
```

In [3]:

```
df
```

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

In [4]:

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

Out[4]:

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

In [5]:

```
df.describe()
```

Out[5]:

	Length	Diameter	Height	Whole weight	Shucked weight	Viscera weight	Shell weight	Rings
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	9.933684
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	1.000000
25%	0.450000	0.350000	0.115000	0.441500	0.186000	0.093500	0.130000	8.000000
50%	0.545000	0.425000	0.140000	0.799500	0.336000	0.171000	0.234000	9.000000

75%	0.615000	0.480000	0.165000	1.153000	0.502000	0.253000	0.329000	11.000000
max	0.815000	0.650000	1.130000	2.825500	1.488000	0.760000	1.005000	29.000000

In [6]:

```
df.columns
```

Out[6]:

```
Index(['Sex', 'Length', 'Diameter', 'Height', 'Whole weight', 'Shucked weight',
       'Viscera weight', 'Shell weight', 'Rings'],
      dtype='object')
```

In [7]:

```
from sklearn.preprocessing import OrdinalEncoder
```

In [8]:

```
ord_enc=OrdinalEncoder(categories=[['I','M','F']])
```

In [9]:

```
df1=ord_enc.fit_transform(df[['Sex']])
```

In [10]:

```
df1
```

Out[10]:

```
array([[1.],
       [1.],
       [2.],
       ...,
       [1.],
       [2.],
       [1.]])
```

In [11]:

```
df['Sex']=df1
```

In [12]:

```
df
```

Out[12]:

	Sex	Length	Diameter	Height	Whole weight	Shucked weight	Viscera weight	Shell weight	Rings
0	1.0	0.455	0.365	0.095	0.5140	0.2245	0.1010	0.1500	15
1	1.0	0.350	0.265	0.090	0.2255	0.0995	0.0485	0.0700	7
2	2.0	0.530	0.420	0.135	0.6770	0.2565	0.1415	0.2100	9
3	1.0	0.440	0.365	0.125	0.5160	0.2155	0.1140	0.1550	10
4	0.0	0.330	0.255	0.080	0.2050	0.0895	0.0395	0.0550	7
...	...	...	...	...	...	...	...	...	...
4172	2.0	0.565	0.450	0.165	0.8870	0.3700	0.2390	0.2490	11
4173	1.0	0.590	0.440	0.135	0.9660	0.4390	0.2145	0.2605	10
4174	1.0	0.600	0.475	0.205	1.1760	0.5255	0.2875	0.3080	9
4175	2.0	0.625	0.485	0.150	1.0945	0.5310	0.2610	0.2960	10
4176	1.0	0.710	0.555	0.195	1.9485	0.9455	0.3765	0.4950	12

4177 rows × 9 columns

In [13]:

```
from scipy.stats import skew
```

In [14]:

```
df.skew()
```

Out[14]:

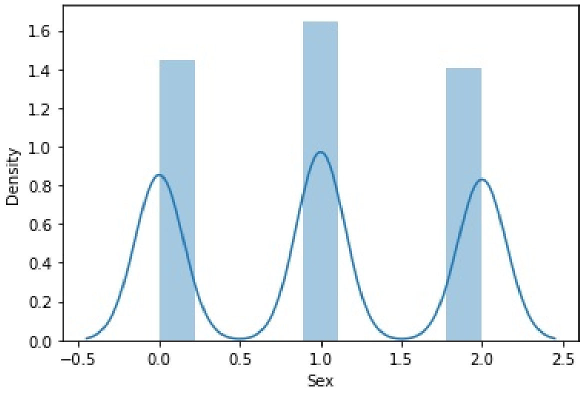
```
Sex               0.014980
Length           -0.639873
Diameter         -0.609198
Height            3.128817
Whole weight      0.530959
Shucked weight    0.719098
Viscera weight    0.591852
Shell weight      0.620927
Rings             1.114102
```

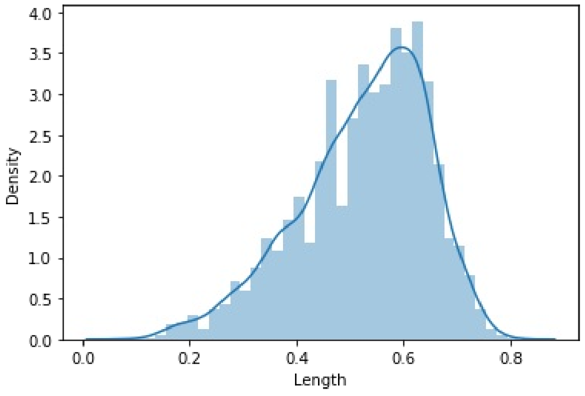
```
dtype: float64
```

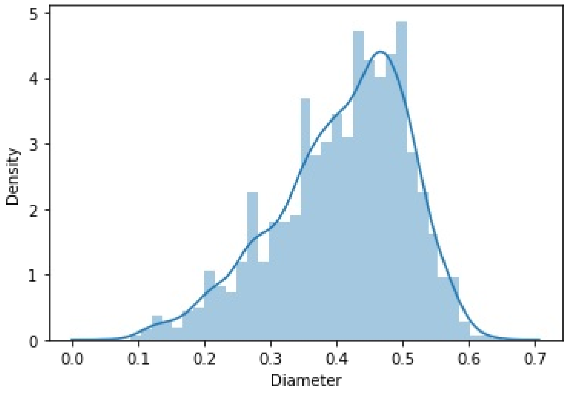
In [15]:

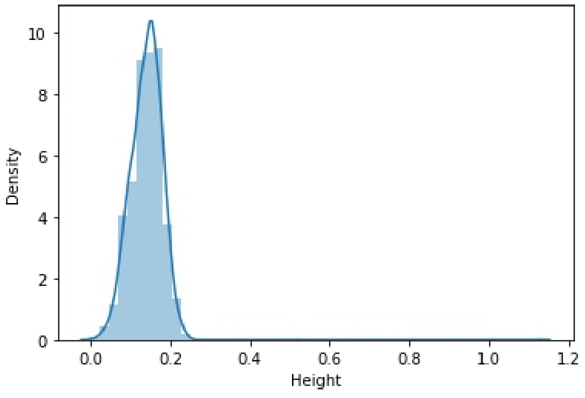
```python
for col in df:
    print(skew(df[col]))
    plt.figure()
    sns.distplot(df[col])
    plt.show
```

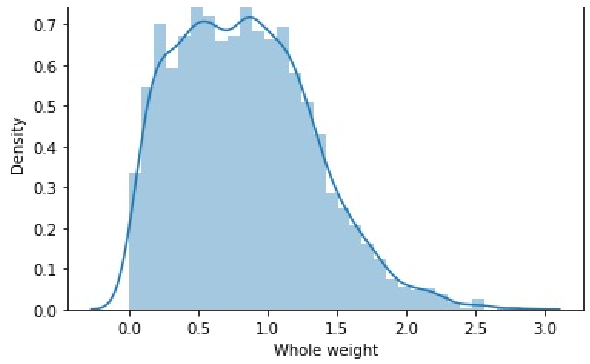
```
0.014974722090408536
-0.6396434615451078
-0.6089793517180232
3.127693679207538
0.5307678720133928
0.7188396611678955
0.5916395905344537
0.6207038222275745
1.1137017739656028
```

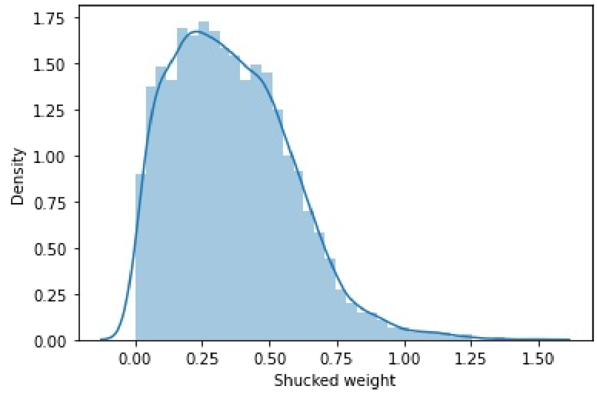


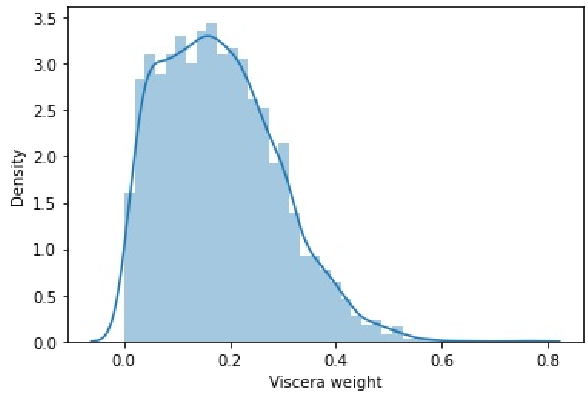


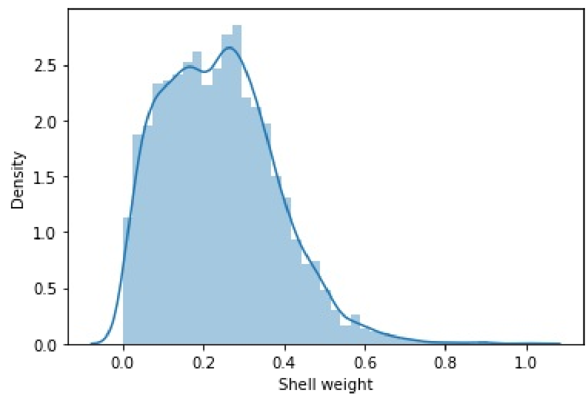


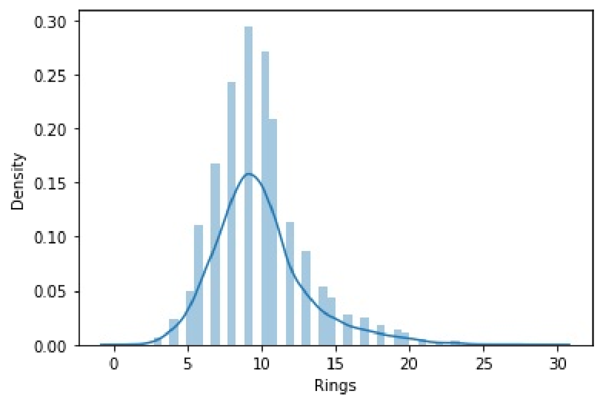



Density
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.0 0.5 1.0 1.5 2.0 2.5 3.0
Whole weight


Density
0.00
0.25
0.50
0.75
1.00
1.25
1.50
1.75
0.00 0.25 0.50 0.75 1.00 1.25 1.50
Shucked weight


Density
0.0
0.5
1.0
1.5
2.0
2.5
3.0
3.5
0.0 0.2 0.4 0.6 0.8
Viscera weight


Density
0.0
0.5
1.0
1.5
2.0
2.5
0.0 0.2 0.4 0.6 0.8 1.0
Shell weight


Density
0.00
0.05
0.10
0.15
0.20
0.25
0.30
0 5 10 15 20 25 30
Rings

In [16]:

```
z_score=zscore(df[['Length','Diameter','Height', 'Whole weight', 'Shucked weight','Viscera weight', 'Shell weight
abs_z_score=np.abs(z_score)
filtering_entry=(abs_z_score<3).all(axis=1)
```

In [17]:

```
df=df[filtering_entry]
df
```

Out[17]:

	Sex	Length	Diameter	Height	Whole weight	Shucked weight	Viscera weight	Shell weight	Rings
0	1.0	0.455	0.365	0.095	0.5140	0.2245	0.1010	0.1500	15
1	1.0	0.350	0.265	0.090	0.2255	0.0995	0.0485	0.0700	7
2	2.0	0.530	0.420	0.135	0.6770	0.2565	0.1415	0.2100	9
3	1.0	0.440	0.365	0.125	0.5160	0.2155	0.1140	0.1550	10
4	0.0	0.330	0.255	0.080	0.2050	0.0895	0.0395	0.0550	7
...	...	...	...	...	...	...	...	...	...
4172	2.0	0.565	0.450	0.165	0.8870	0.3700	0.2390	0.2490	11
4173	1.0	0.590	0.440	0.135	0.9660	0.4390	0.2145	0.2605	10
4174	1.0	0.600	0.475	0.205	1.1760	0.5255	0.2875	0.3080	9
4175	2.0	0.625	0.485	0.150	1.0945	0.5310	0.2610	0.2960	10
4176	1.0	0.710	0.555	0.195	1.9485	0.9455	0.3765	0.4950	12

4084 rows × 9 columns

In [18]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 4084 entries, 0 to 4176
Data columns (total 9 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   Sex             4084 non-null   float64
 1   Length          4084 non-null   float64
 2   Diameter        4084 non-null   float64
 3   Height          4084 non-null   float64
 4   Whole weight    4084 non-null   float64
 5   Shucked weight  4084 non-null   float64
 6   Viscera weight  4084 non-null   float64
 7   Shell weight    4084 non-null   float64
 8   Rings           4084 non-null   int64
dtypes: float64(8), int64(1)
memory usage: 319.1 KB
```

In [19]:

```
df.skew()
```

Out[19]:

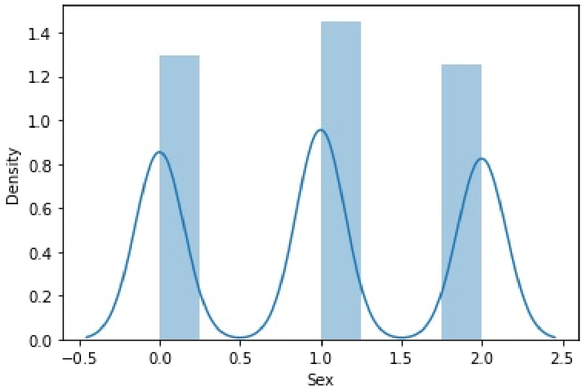
```
Sex               0.021071
Length           -0.633786
Diameter         -0.605450
Height           -0.247192
Whole weight      0.323886
Shucked weight    0.449573
Viscera weight    0.429932
Shell weight      0.358512
Rings             1.136367
dtype: float64
```

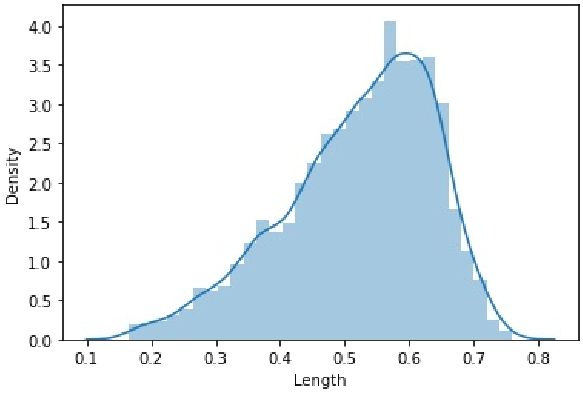
In [20]:

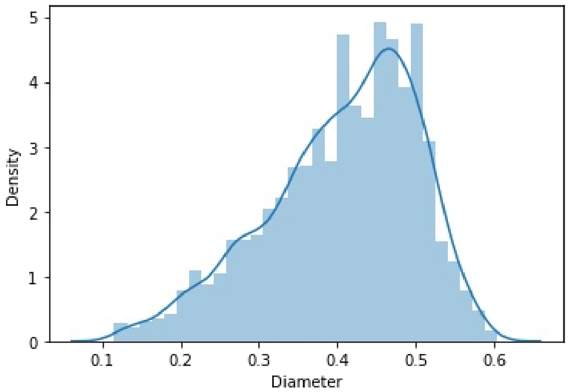
```
for col in df:
    print(skew(df[col]))
    plt.figure()
    sns.distplot(df[col])
    plt.show
```

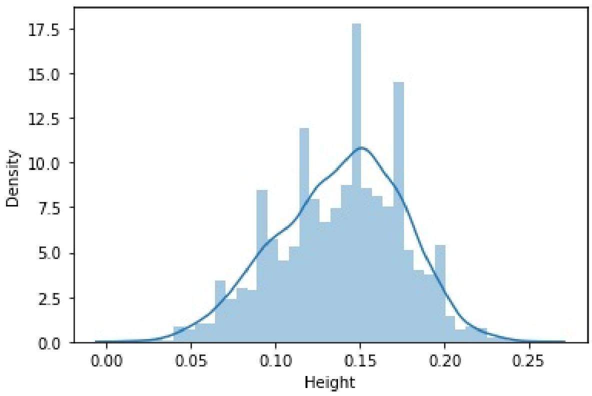
```
0.021063153108848605
-0.6335530357553206
-0.6052273525549002
```

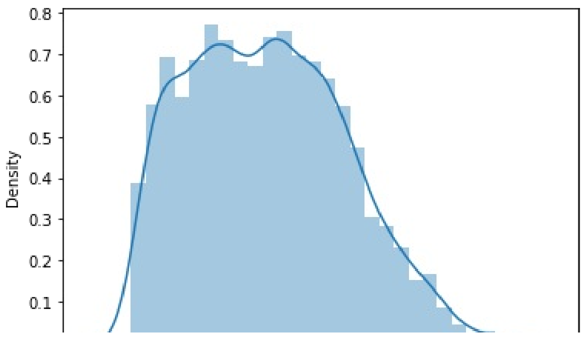
```
-0.2471012361244269
0.32376697427686923
0.44940831970770595
0.42977456978835943
0.35838000704463574
1.135949696170358
```

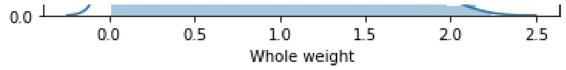


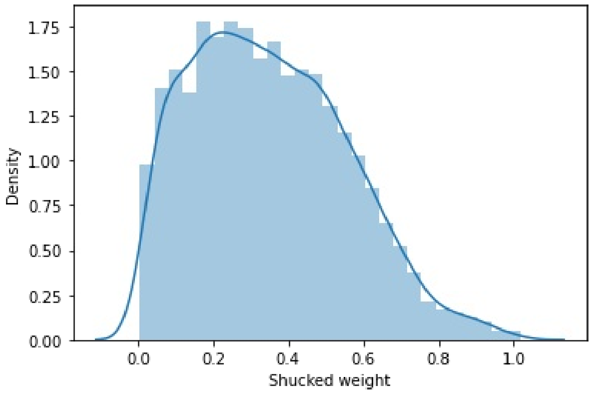


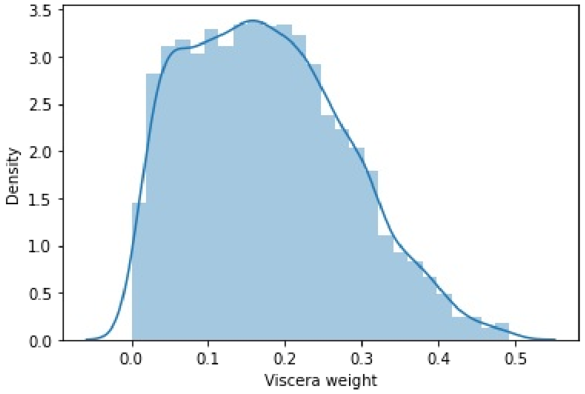


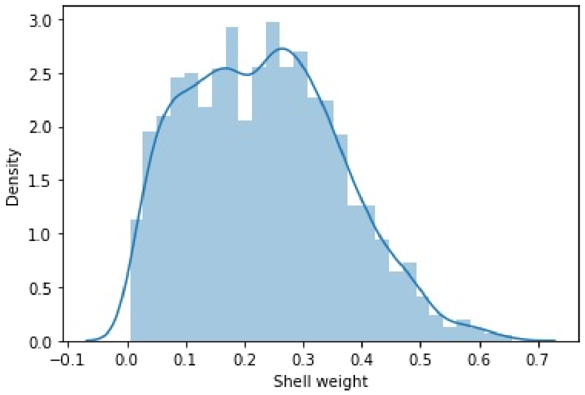


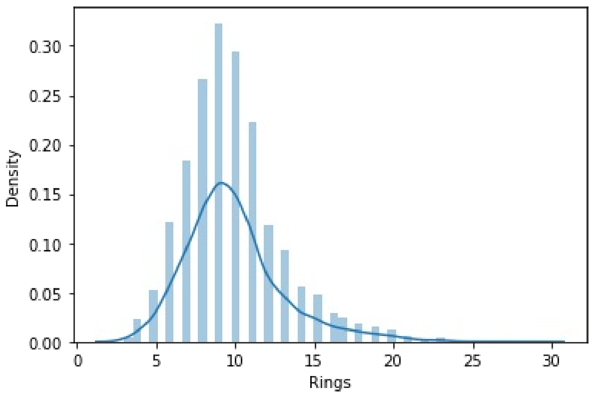












In [21]:

```
data_loss=(4177-4088)/4177*100
data_loss
```

Out[21]: 2.1307158247546085

In [22]:

```
df_corr=df.corr().abs()
```

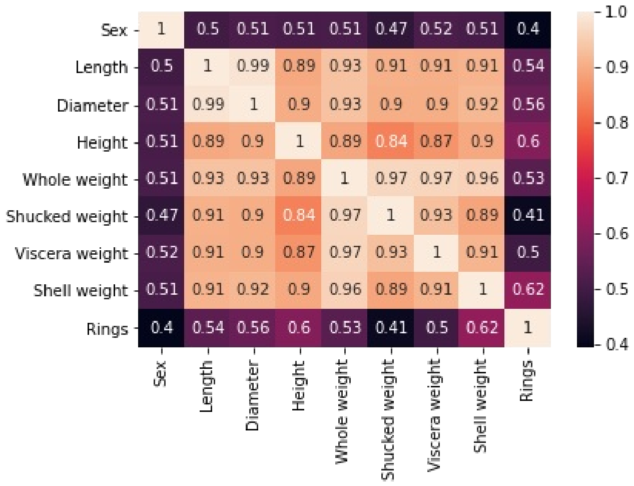
```
df_corr
```

Out[22]:

	Sex	Length	Diameter	Height	Whole weight	Shucked weight	Viscera weight	Shell weight	Rings
Sex	1.000000	0.501745	0.514629	0.510198	0.513865	0.473057	0.515797	0.510892	0.396293
Length	0.501745	1.000000	0.985902	0.894374	0.934127	0.908711	0.907570	0.911001	0.541905
Diameter	0.514629	0.985902	1.000000	0.901033	0.934226	0.903699	0.904090	0.918870	0.561048
Height	0.510198	0.894374	0.901033	1.000000	0.891581	0.839927	0.867448	0.898113	0.597622
Whole weight	0.513865	0.934127	0.934226	0.891581	1.000000	0.969115	0.965893	0.959393	0.533165
Shucked weight	0.473057	0.908711	0.903699	0.839927	0.969115	1.000000	0.929491	0.889464	0.413036
Viscera weight	0.515797	0.907570	0.904090	0.867448	0.965893	0.929491	1.000000	0.914894	0.497026
Shell weight	0.510892	0.911001	0.918870	0.898113	0.959393	0.889464	0.914894	1.000000	0.618991
Rings	0.396293	0.541905	0.561048	0.597622	0.533165	0.413036	0.497026	0.618991	1.000000

In [23]:

```
sns.heatmap(df_corr,annot=True)
plt.show()
```



In [24]:

```
X=df.drop(columns="Rings")
Y=df["Rings"]
```

In [25]:

```
scalar=StandardScaler()
X_scaled=scalar.fit_transform(X)

vif=pd.DataFrame()
vif["vif"]=[variance_inflation_factor(X_scaled,i) for i in range(X_scaled.shape[1])]
vif["Features"]=X.columns
vif
```

Out[25]:

	vif	Features
0	1.416016	Sex
1	38.766761	Length
2	40.513206	Diameter
3	6.547268	Height
4	104.950042	Whole weight
5	27.493110	Shucked weight
6	16.750428	Viscera weight
7	22.991953	Shell weight

In [26]:

```
df=df.drop(["Whole weight"],axis=1)
```

In [27]:

```
X=df.drop(columns="Rings")
Y=df["Rings"]
```

In [28]:

```
scalar=StandardScaler()
```

```
X_scaled=scalar.fit_transform(X)

vif=pd.DataFrame()
vif["vif"]=[variance_inflation_factor(X_scaled,i) for i in range(X_scaled.shape[1])]
vif["Features"]=X.columns
vif
```

Out[28]:

	vif	Features
0	1.413189	Sex
1	38.766281	Length
2	40.509379	Diameter
3	6.542953	Height
4	9.088160	Shucked weight
5	10.764923	Viscera weight
6	9.660229	Shell weight

In [29]:

```
df=df.drop(["Length"],axis=1)
```

In [30]:

```
X=df.drop(columns="Rings")
Y=df["Rings"]
```

In [31]:

```
scalar=StandardScaler()
X_scaled=scalar.fit_transform(X)

vif=pd.DataFrame()
vif["vif"]=[variance_inflation_factor(X_scaled,i) for i in range(X_scaled.shape[1])]
vif["Features"]=X.columns
vif
```

Out[31]:

	vif	Features
0	1.407502	Sex
1	9.995839	Diameter
2	6.525648	Height
3	8.904380	Shucked weight
4	10.633625	Viscera weight
5	9.621787	Shell weight

In [32]:

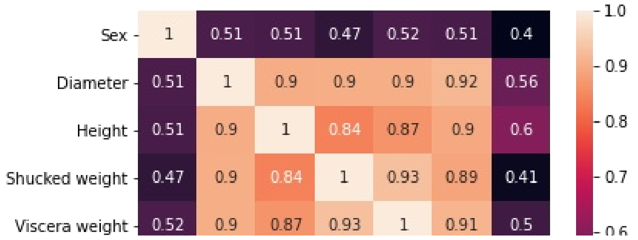
```
df_corr=df.corr().abs()
df_corr
```

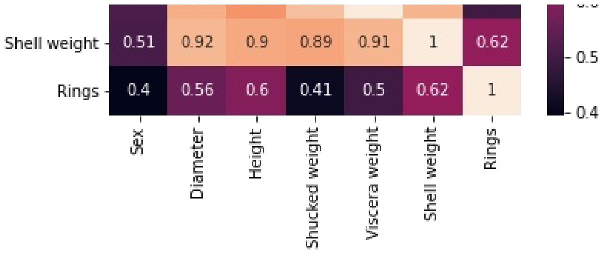
Out[32]:

	Sex	Diameter	Height	Shucked weight	Viscera weight	Shell weight	Rings
Sex	1.000000	0.514629	0.510198	0.473057	0.515797	0.510892	0.396293
Diameter	0.514629	1.000000	0.901033	0.903699	0.904090	0.918870	0.561048
Height	0.510198	0.901033	1.000000	0.839927	0.867448	0.898113	0.597622
Shucked weight	0.473057	0.903699	0.839927	1.000000	0.929491	0.889464	0.413036
Viscera weight	0.515797	0.904090	0.867448	0.929491	1.000000	0.914894	0.497026
Shell weight	0.510892	0.918870	0.898113	0.889464	0.914894	1.000000	0.618991
Rings	0.396293	0.561048	0.597622	0.413036	0.497026	0.618991	1.000000

In [33]:

```
sns.heatmap(df_corr,annot=True)
plt.show()
```





In [34]:
```
df
```

Out[34]:

	Sex	Diameter	Height	Shucked weight	Viscera weight	Shell weight	Rings
0	1.0	0.365	0.095	0.2245	0.1010	0.1500	15
1	1.0	0.265	0.090	0.0995	0.0485	0.0700	7
2	2.0	0.420	0.135	0.2565	0.1415	0.2100	9
3	1.0	0.365	0.125	0.2155	0.1140	0.1550	10
4	0.0	0.255	0.080	0.0895	0.0395	0.0550	7
...	...	...	...	...	...	...	...
4172	2.0	0.450	0.165	0.3700	0.2390	0.2490	11
4173	1.0	0.440	0.135	0.4390	0.2145	0.2605	10
4174	1.0	0.475	0.205	0.5255	0.2875	0.3080	9
4175	2.0	0.485	0.150	0.5310	0.2610	0.2960	10
4176	1.0	0.555	0.195	0.9455	0.3765	0.4950	12

4084 rows × 7 columns

In [35]:
```
df=df.drop(["Viscera weight"],axis=1)
```

In [36]:
```
X=df.drop(columns="Rings")
Y=df["Rings"]
```

In [37]:
```
scalar=StandardScaler()
X_scaled=scalar.fit_transform(X)

vif=pd.DataFrame()
vif["vif"]=[variance_inflation_factor(X_scaled,i) for i in range(X_scaled.shape[1])]
vif["Features"]=X.columns
vif
```

Out[37]:

	vif	Features
0	1.388654	Sex
1	9.940450	Diameter
2	6.438739	Height
3	6.217173	Shucked weight
4	8.672787	Shell weight

In [38]:
```
df
```

Out[38]:

	Sex	Diameter	Height	Shucked weight	Shell weight	Rings
0	1.0	0.365	0.095	0.2245	0.1500	15
1	1.0	0.265	0.090	0.0995	0.0700	7
2	2.0	0.420	0.135	0.2565	0.2100	9
3	1.0	0.365	0.125	0.2155	0.1550	10
4	0.0	0.255	0.080	0.0895	0.0550	7
...	...	...	...	...	...	...
4172	2.0	0.450	0.165	0.3700	0.2490	11
4173	1.0	0.440	0.135	0.4390	0.2605	10

4174	1.0	0.475	0.205	0.5255	0.3080	9
4175	2.0	0.485	0.150	0.5310	0.2960	10
4176	1.0	0.555	0.195	0.9455	0.4950	12

4084 rows × 6 columns

In [39]:
```
X=df.drop(columns="Rings")
Y=df["Rings"]
```

In [40]:
```
lm=LinearRegression()
```

In [41]:
```
lm.fit(X,Y)
```

Out[41]:
```
LinearRegression()
```

In [42]:
```
print(lm.intercept_)
```

```
2.7005351142692557
```

In [43]:
```
print(lm.coef_)
```

```
[  0.37766571   8.22427771  22.87755106 -12.64888911  20.35793802]
```

In [44]:
```
import statsmodels.formula.api as smf
```

In [45]:
```
lm=smf.ols(formula='Y~X',data=df).fit()
```

In [46]:
```
lm.pvalues
```

Out[46]:
```
Intercept     2.022418e-22
X[0]          1.665432e-13
X[1]          5.708108e-13
X[2]          8.571595e-22
X[3]         5.813110e-181
X[4]         6.282038e-137
dtype: float64
```

In [47]:
```
lm.summary()
```

Out[47]:

OLS Regression Results

Dep. Variable:	Y	**R-squared:**	0.513
Model:	OLS	**Adj. R-squared:**	0.513
Method:	Least Squares	**F-statistic:**	859.7
Date:	Thu, 17 Feb 2022	**Prob (F-statistic):**	0.00
Time:	15:30:39	**Log-Likelihood:**	-9029.5
No. Observations:	4084	**AIC:**	1.807e+04
Df Residuals:	4078	**BIC:**	1.811e+04
Df Model:	5		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	2.7005	0.276	9.798	0.000	2.160	3.241
X[0]	0.3777	0.051	7.398	0.000	0.278	0.478
X[1]	8.2243	1.137	7.231	0.000	5.994	10.454
X[2]	22.8776	2.371	9.648	0.000	18.229	27.527

X[3]	-12.6489	0.419	-30.197	0.000	-13.470	-11.828
X[4]	20.3579	0.786	25.886	0.000	18.816	21.900

Omnibus:	996.489	**Durbin-Watson:**	1.424
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	2936.953
Skew:	1.258	**Prob(JB):**	0.00
Kurtosis:	6.306	**Cond. No.**	116.

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

In [48]:
```
scaler=StandardScaler()
X_scaled=scaler.fit_transform(X)
```

In [49]:
```
X_train,X_test,Y_train,Y_test=train_test_split(X_scaled,Y,test_size=0.25,random_state=21)
```

In [50]:
```
regression=LinearRegression()
```

In [51]:
```
regression.fit(X_train,Y_train)
```

Out[51]:
```
LinearRegression()
```

In [52]:
```
lasscv=LassoCV(alphas=None,max_iter=1000,normalize=True)
lasscv.fit(X_train,Y_train)
alpha=lasscv.alpha_
alpha
```

Out[52]:
```
3.534547923217798e-05
```

In [53]:
```
lasso_reg=Lasso(alpha)
lasso_reg.fit(X_train,Y_train)
lasso_reg.score(X_test,Y_test)
```

Out[53]:
```
0.49821006777822874
```

In [54]:
```
Y_pred=regression.predict(X_test)
mean_absolute_error(Y_test,Y_pred)
```

Out[54]:
```
1.6083223717112087
```

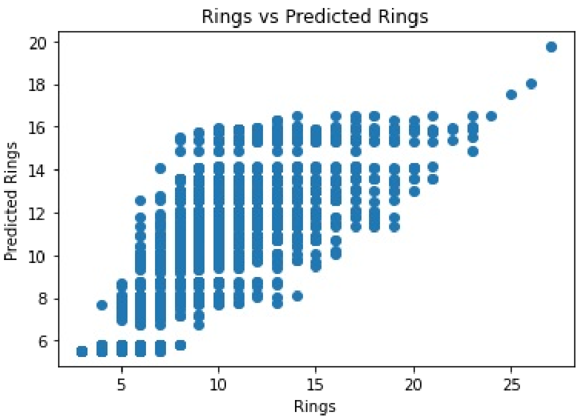
In [55]:
```
from sklearn.ensemble import AdaBoostRegressor
ada=AdaBoostRegressor()
```

In [56]:
```
ada.fit(X_train,Y_train)
```

Out[56]:
```
AdaBoostRegressor()
```

In [57]:
```
y_pred=ada.predict(X_train)
```

In [66]:
```
plt.scatter(Y_train,y_pred)
plt.xlabel("Rings")
plt.ylabel('Predicted Rings')
plt.title("Rings vs Predicted Rings")
plt.show()
```



In [71]:
```
import pickle
filename="abalone.pkl"
pickle.dump(lm,open(filename,"wb"))
```

In [61]:

In [ ]:

Loading [MathJax]/jax/output/CommonHTML/fonts/TeX/fontdata.js