Assignment -3

Abalone Age Prediction

Assignment Date	10 October 2022
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Maximum Marks	2 Marks

1.Importing necessary packages & Downloading the packages

```
import pandas as pd
from sklearn.model_selection import train_test_split
import matplotlib.pyplot as plt import seaborn as sns
from sklearn.preprocessing import StandardScaler from
sklearn.preprocessing import LabelEncoder import numpy
as np from collections import Counter from sklearn.pipeline
import make_pipeline from sklearn.linear_model import
Ridge, Lasso from sklearn.ensemble import
RandomForestRegressor from sklearn.pipeline import
make_pipeline from sklearn.linear_model import Ridge,
Lasso from sklearn.model_selection import GridSearchCV
from sklearn.exceptions import NotFittedError from
sklearn.metrics import r2_score,mean_absolute_error
```

2. Download the dataset:

```
df= pd.read_csv("abalone.csv")

df.head()
```

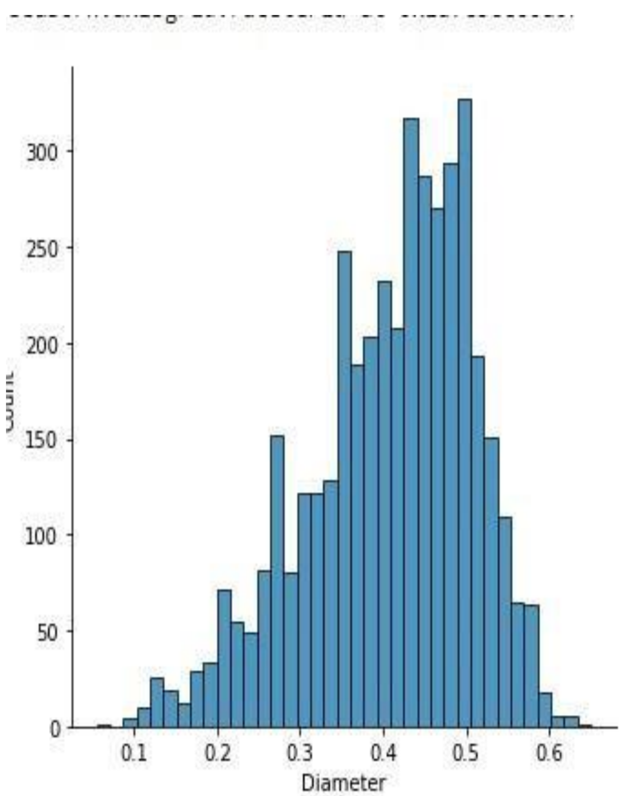
Output:

	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
	Sex	**Length**	**Diameter**	**Height**	**Whole weight**	**Shucked weight**	**Viscera weight**	**Shell weight**	**Rings**
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

3. Visualizations (i) Univariate Analysis

Input: sns.displot(df["Diameter"]) **Output:**
<seaborn.axisgrid.FacetGrid at 0x1a7c3cc60a0>



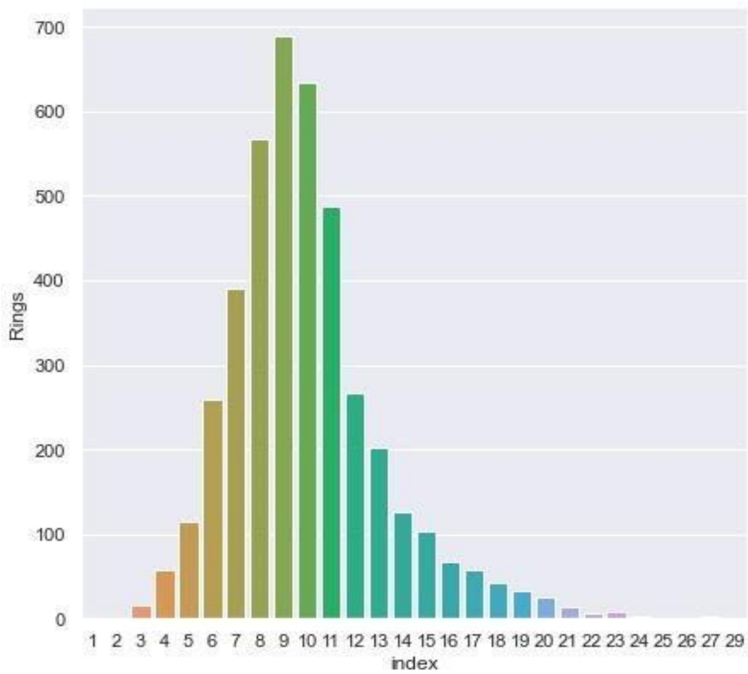
Input:

sns**.**set(rc={'figure.figsize':(7,7)}) depth =

df['Rings']**.**value_counts(normalize**=False**)**.**reset_index()

sns**.**barplot(data=depth,x='index',y='Rings') **Output:**

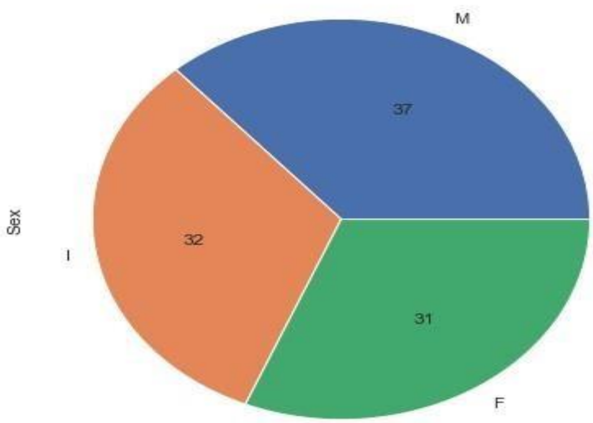
<AxesSubplot:xlabel='index', ylabel='Rings'>



Input: df['Sex'].value_counts().plot(kind='pie',autopct='%.0f')

Output:

<AxesSubplot:ylabel='Sex'>

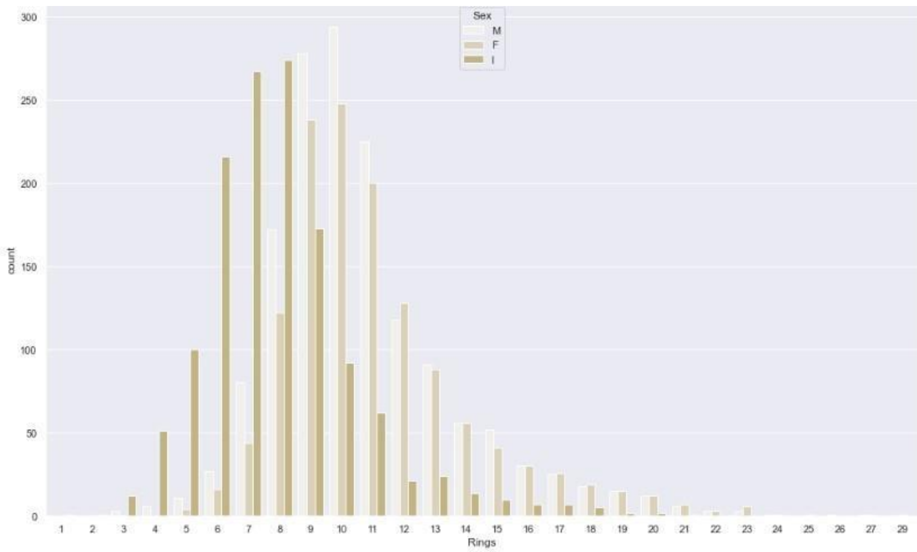


(ii) BiVariate Analysis

Input:

sns.set(rc={'figure.figsize':(17,10)})
sns.countplot(df['Rings'] ,hue = df['Sex'] ,color ='y') **Output:**

<AxesSubplot:xlabel='Rings', ylabel='count'>

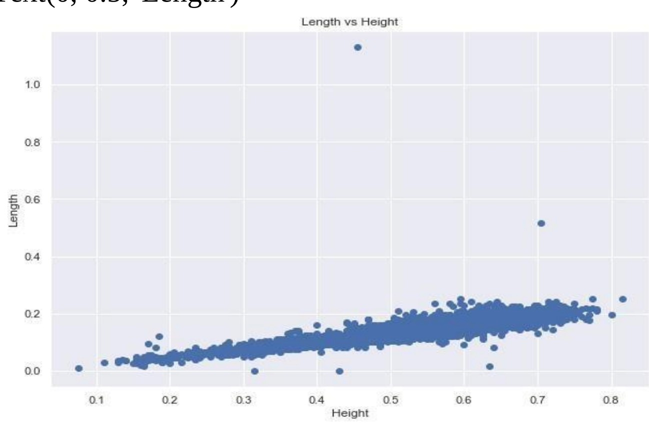


Input:

```
sns.set(rc={'figure.figsize':(10,7)})
plt.scatter(df.Length,      df.Height)
plt.title('Length       vs       Height')
plt.xlabel('Height')
plt.ylabel('Length')
```

Output:

Text(0, 0.5, 'Length')



(iii) MultiVariate Analysis

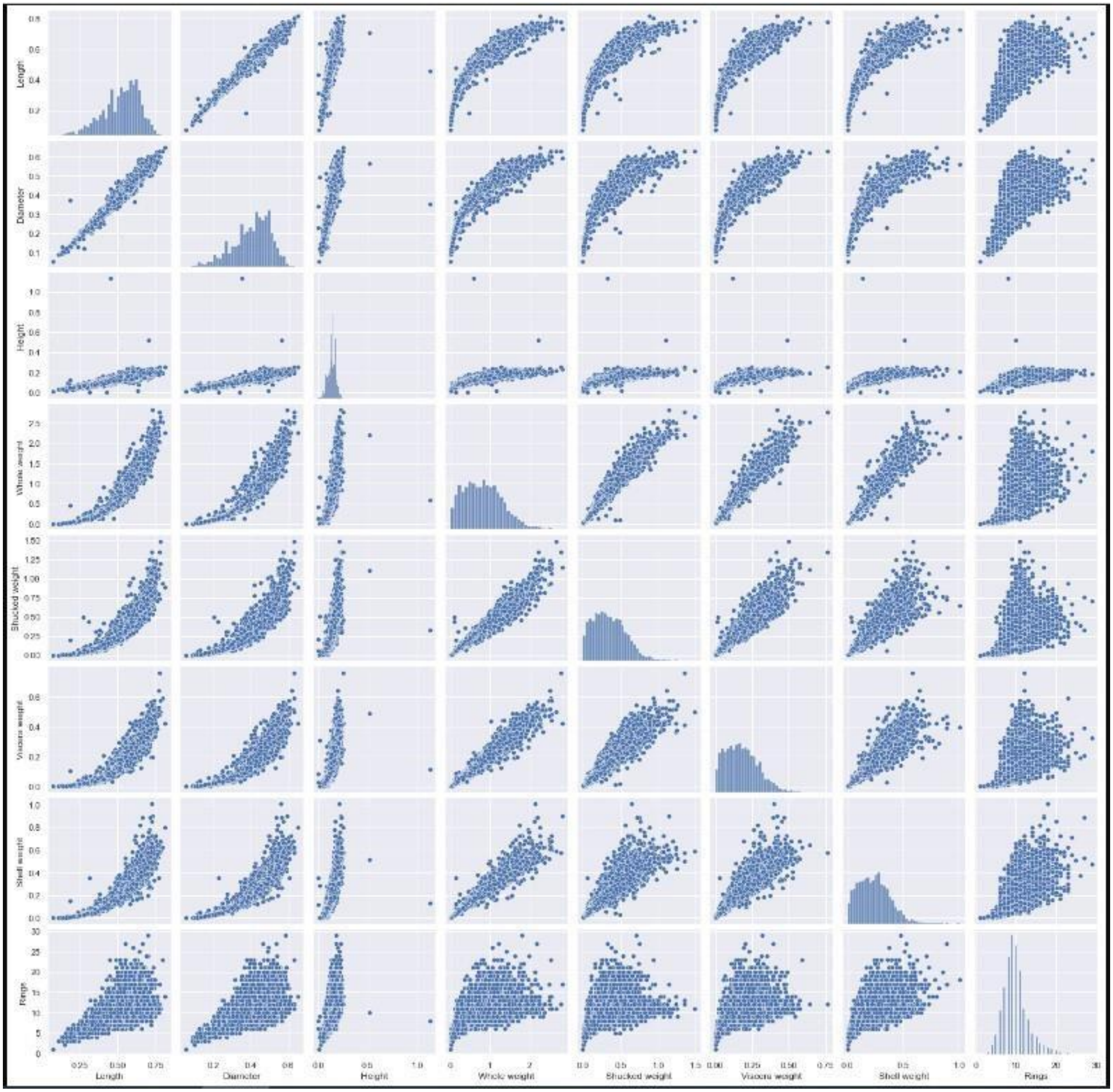
Input:

```
plt.figure(figsize=(12,10))
sns.pairplot(df)
```

Output:

<seaborn.axisgrid.PairGrid at 0x1a8005d43a0>

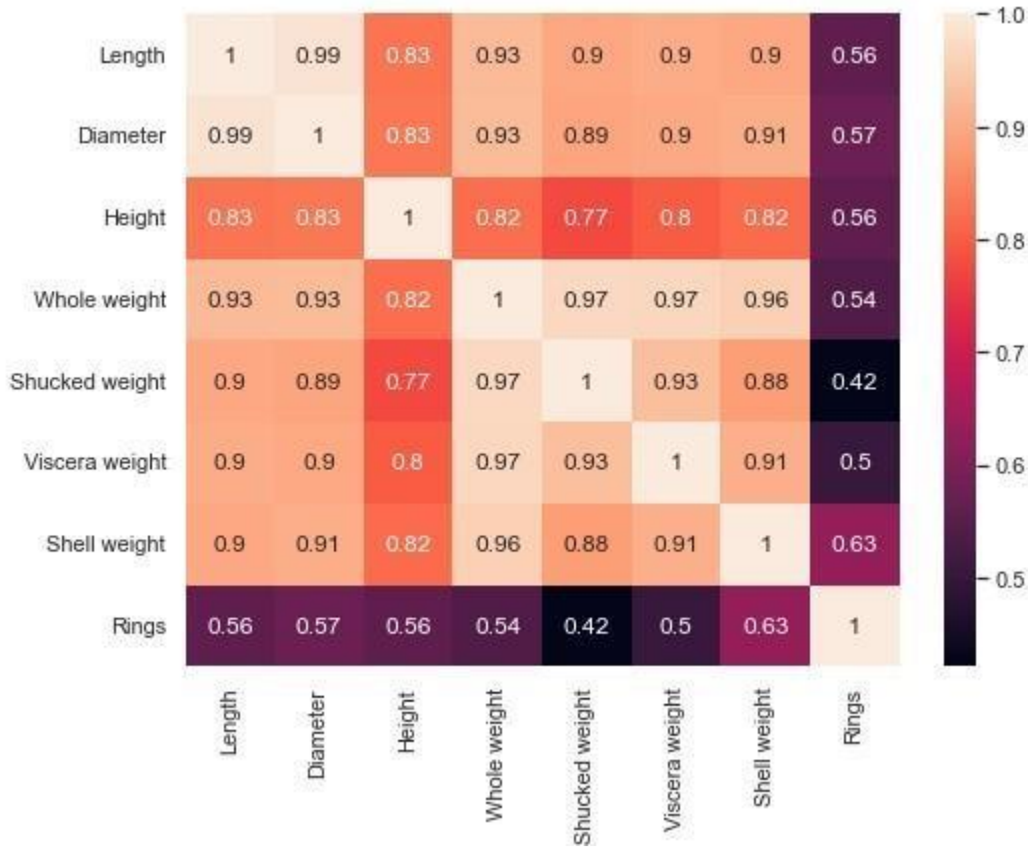
<Figure size 864x720 with 0 Axes>



Input:
plt**.**figure(figsize **=** (8,6)) corr **=**
df**.**corr() sns**.**heatmap(corr,

annot **= True**) **Output:**

<AxesSubplot:>



4.Descriptive Statistics

Input: df.info()

Output:
<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

Input:

df.describe() **Output:**

	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
ma	0.81500	0.65000	1.13000	2.82550	1.48800	0.76000	1.00500	29.0000
	Length	**Diameter**	**Height**	**Whole weight**	**Shucked weight**	**Viscera weight**	**Shell weight**	**Rings**
x	0	0	0	0	0	0	0	00

5.Handle Missing Values

Input:

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

Output:

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

6. Outlier Detection

Input: outlier_correction_df = df.drop(columns=['Sex'],axis=1) outlier_correction_df.head()

Output:

	Length	Diameter	Height	Whole weight	Shucked weight	Viscera weight	Shell weight	Rings
0	0.455	0.365	0.095	0.5140	0.2245	0.1010	0.150	15
1	0.350	0.265	0.090	0.2255	0.0995	0.0485	0.070	7
2	0.530	0.420	0.135	0.6770	0.2565	0.1415	0.210	9
3	0.440	0.365	0.125	0.5160	0.2155	0.1140	0.155	10
4	0.330	0.255	0.080	0.2050	0.0895	0.0395	0.055	7

Input:

```
def detection(df,features):
outlier_indices=[]

  for c in features:
       Q1 = np.percentile(df[c],25)

       Q3 = np.percentile(df[c],75)

       IQR = Q3 - Q1         outlier_step
= IQR * 1.5         lower_range = Q1 -
(outlier_step)          upper_range = Q3
+ (outlier_step)

       outlier_list_col=df[  (df[c] < lower_range) | (df[c] > upper_range)  ].index

       outlier_indices.extend(outlier_list_col)
return outlier_indices

       def multiple_outlier_indices(outlier_indices):          outlier_indices=Counter(outlier_indices)
multiple_outliers = list(i for i, v in outlier_indices.items() if v > 2 )

       return multiple_outliers
```

Solution: outlier_correction_df.columns

Output:

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

Solution:

outliers=detection(df,['Length', 'Diameter', 'Height', 'Whole weight', 'Shucked weight', 'Viscera weight', 'Shell weight']) **Input:** Counter(outliers) **Output:**

```
Counter({148: 2,

   149: 2,
   236: 3,
```

237: 3,
238: 3,
239: 3,
305: 2,
306: 3,
321: 2,
465: 2,
523: 2,
525: 2, 526: 2,
611: 2,
694: 3,
696: 2, 718:
3,
719: 3,
720: 3,
1053: 2,
1054: 2,
1055: 2,
1056: 1,
1210: 1,
1429: 3,
1824: 2,
1986: 2,
1987: 3,
2114: 3,
2115: 2,
2169: 3,
2171: 3,
2343: 2,
2371: 2,
2380: 2, 2381:
3,
2458: 2,
2711: 3,
3141: 2,
3143: 2,
3190: 3,
3318: 2,
3380: 2,
3472: 2,
3600: 2,
3837: 3,
3899: 3,

3902: 3,
3994: 2,
43: 1,
44: 1,
520: 1,
892: 1,
898: 1,
1988: 1,
2172: 2,
2545: 1,
2712: 1,
3473: 1,
3521: 1,
3716: 1,
1174: 1,
1257: 1,
1417: 2,
1428: 3,
1763: 4,
2051: 1,
2179: 1,
3996: 1,
165: 3,
358: 2,
891: 3,
1051: 2,
1052: 3,
1193: 3,
1206: 3, 1207: 4,
1209: 3,
1426: 2, 1427:
3,
1761: 3,
1762: 4,
2265: 1,
2334: 2,
2623: 3,
2624: 3,
2811: 3,
2862: 2,
2863: 3,
3007: 2,
3008: 2,

3188: 2,
3427: 3,
3599: 2,
3715: 4,
3800: 1,
3993: 2,
1048: 2,
1197: 1,
1199: 1,
1202: 1,
1418: 1, 1527:
1,
1528: 1,
1749: 1,
1750: 2,
1754: 1,
1756: 1,
1821: 1,
1982: 1,
2544: 1,
2625: 1,
2675: 1,
2710: 2,
2810: 2,
2970: 1,
2972: 1,
3082: 1,
3713: 1,
3961: 1,
3962: 1,
170: 1, 1204: 1,
1422: 1,
1757: 1,
1759: 1,
2709: 1,
3628: 1,
4148: 1,
81: 1,
129: 1,
157: 1,
163: 1,
164: 1,
166: 1,

167: 1,
168: 1,
277: 1,
334: 1,
1823: 1,
1985: 1,
2090: 1,
2108: 1,
2157: 1,
2161: 1,
2208: 1, 2274:
1,
2368: 1,
3148: 1,
3149: 1,
3151: 1,
3928: 1,
4145: 1})

Input: multiple_outlier_indices =
multiple_outlier_indices(outliers) **Solution:**
print(Counter(multiple_outlier_indices))
Counter({236: 1, 237: 1, 238: 1, 239: 1, 306: 1, 694: 1, 718: 1, 719: 1, 720: 1, 1429: 1, 1987: 1, 2114: 1, 2169: 1, 2171: 1, 2381: 1, 2711: 1, 3190: 1, 3837: 1, 3899: 1, 3902: 1, 1428: 1, 1763: 1, 165: 1, 891: 1, 1052: 1, 1193: 1, 1206: 1, 1207: 1, 1209: 1, 1427: 1, 1761: 1, 1762: 1, 2623: 1, 2624: 1, 2811: 1, 2863: 1, 3427: 1, 3715: 1})

Input: df=df**.**drop(multiple_outlier_indices,axis=0)**.**reset_index(drop =
True) **Output:**

	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
...	...	...	...	...	...	...	...	...	...
4134	F	0.565	0.450	0.165	0.8870	0.3700	0.2390	0.2490	11
4135	M	0.590	0.440	0.135	0.9660	0.4390	0.2145	0.2605	10
4136	M	0.600	0.475	0.205	1.1760	0.5255	0.2875	0.3080	9
4137	F	0.625	0.485	0.150	1.0945	0.5310	0.2610	0.2960	10
4138	M	0.710	0.555	0.195	1.9485	0.9455	0.3765	0.4950	12

4139 rows × 9 columns

Input:
df.shape
Output:
(4139, 9)

7. Categorical Attribute Encoding

Input: le=LabelEncoder()
df['Sex']=le.fit_transform(df['Sex']
) **Solution:** df.head() **Output:**

	Sex	Length	Diameter	Height	Whole weight	Shucked weight	Viscera weight	Shell weight	Rings
0	2	0.455	0.365	0.095	0.5140	0.2245	0.1010	0.150	15
1	2	0.350	0.265	0.090	0.2255	0.0995	0.0485	0.070	7
2	0	0.530	0.420	0.135	0.6770	0.2565	0.1415	0.210	9
3	2	0.440	0.365	0.125	0.5160	0.2155	0.1140	0.155	10
4	1	0.330	0.255	0.080	0.2050	0.0895	0.0395	0.055	7

8. Seperate dataframe into Predictor and Target

Input: feature =pd.DataFrame(df.drop(['Rings'], axis =
1)) label
= pd.DataFrame(df.Rings)

9. Scaling the Predictor variables Input:

convert = StandardScaler() feature =
pd.DataFrame(convert.fit_transform(feature))

10. Perform the train test split

Input:
X_train, X_test, y_train, y_test = train_test_split(feature, label, test_size = 0.2, random_state = 0)
Input:
print('X_train : ') print(X_train)
print(X_train.shape)

print('') print('X_test
: ') print(X_test)
print(X_test.shape)

print('') print('y_train
: ') print(y_train)
print(y_train.shape)

print('')
print('y_test : ')
print(y_test)
print(y_test.shape) X_train
:

```
            0         1         2         3         4         5         6  \
64    1.151942 -0.040971 -0.087769 -0.481759 -0.514480 -0.574405 -0.453057
1521 -0.062807 -1.409929 -1.432469 -1.091508 -1.310493 -1.322352 -1.158735
3436  1.151942  1.670227  1.618965  1.469438  2.013909  1.674082  1.916340
3444 -0.062807 -0.768230 -0.760119 -0.725659 -0.868496 -0.720742 -0.798886
3993 -0.062807 -0.725450 -0.863557 -0.725659 -0.689393 -0.462910 -0.565218
...        ...       ...       ...       ...       ...       ...       ...
1033  1.151942  1.413547  1.205212  0.859689  1.832711  2.173488  1.701365
3264  1.151942  1.028527  0.946616  1.225538  0.845026  0.772829  0.916240
1653 -1.277555  0.729068  0.688019  0.493839  0.607270  0.120118  0.402169
2607 -0.062807 -0.725450 -0.708400 -0.969558 -0.876875 -0.690546 -0.995167
2732 -0.062807  0.215709  0.119108  0.371889  0.180984  0.638106  0.004933

            7
64   -0.390700
1521 -1.300351
3436  2.132846
3444 -1.014251
3993 -0.959232
...        ...
1033  1.223195
3264  1.149837
1653  1.032462
```

2607 -0.992243
2732 -0.243983

[3311 rows x 8 columns]
(3311, 8)

X_test :

```
             0         1         2         3         4         5         6  \
958   1.151942 -0.126531  0.015669  0.127990 -0.062009  0.134054  0.014280
2613 -0.062807 -0.425991 -0.346365 -0.603709 -0.639119 -0.579050 -0.569891
45   -0.062807 -1.153250 -1.173873 -1.091508 -1.304208 -1.254990 -1.261549
3145 -1.277555 -0.169311  0.015669 -0.115910 -0.353182 -0.309604 -0.439037    3994
-0.062807 -0.340431 -0.449804 -1.213458 -0.365751 -0.191140 -0.448384
...        ...       ...       ...       ...       ...       ...       ...
620  -1.277555 -0.853790 -0.760119 -1.091508 -1.054931 -1.101684 -1.112002
1544 -0.062807 -0.597110 -0.501523 -0.603709 -0.772137 -0.692869 -0.883007
2954  1.151942  0.087369 -0.036050  0.859689  0.931959  0.884324  1.369556
177  -0.062807 -2.564988 -2.570292 -2.311006 -1.632040 -1.545343 -1.541951     50
-0.062807 -0.040971  0.015669 -0.481759 -0.483058 -0.553499 -0.644665

             7
958  -0.313674
2613 -0.680468
45   -1.197648
3145 -0.317342
3994 -0.427380
...        ...
620  -0.830854
1544 -0.669464
2954  0.724355
177  -1.637802
50   -0.354021
```

[828 rows x 8 columns]
(828, 8)
y_train
:
Rings
64 8
1521 8
3436 11
3444 7
3993 8

... ...
1033 8
3264 17
1653 10
2607 7
2732 9

[3311 rows x 1 columns]
(3311, 1)
y_test
:
Rings
958 8
2613 7
45 7
3145 15
3994 8
... ...
620 10
1544 10
2954 13
177 4
50 8

[828 rows x 1 columns] (828,
1)

11.Build Model

Input: pipelines={
'rf':make_pipeline(RandomForestRegressor(random_state=1234)),
'ridge':make_pipeline(Ridge(random_state=1234)),
'lasso':make_pipeline(Lasso(random_state=1234)),
} **Input:** hyperparagrid={
'rf':{
'randomforestregressor__min_samples_split':[2,4,6],
'randomforestregressor__min_samples_leaf':[1,2,3]
},

'ridge':{
'ridge__alpha':[0.001,0.005,0.01,0.05,0.1,0.5,0.99]
},

'lasso':{
    'lasso__alpha':[0.001,0.005,0.01,0.05,0.1,0.5,0.99]
}
}

12. Traning the Model

Input: fit_models={} **for**
algo,pipeline **in**
pipelines.items():
    model=GridSearchCV(pipeline,hyperparagrid[algo],cv=10,n_jobs=-1)
try: print('Start training for {}'.format(algo))
model.fit(X_train,y_train)   fit_models[algo]=model
except
NotFittedError **as** e: print(repr(e)) Start training
for rf
Start training for ridge Start
training for lasso

13,14 Testing and Measuring Performance

Input: best_model_rf=fit_models['rf'] best_model_rf
Output:

```
GridSearchCV(cv=10,
 estimator=Pipeline(steps=[('randomforestregressor',
                    RandomForestRegressor(random_state=1234))]),        n_jobs=-
1,
 param_grid={'randomforestregressor__min_samples_leaf': [1, 2, 3],
'randomforestregressor__min_samples_split': [2, 4, 6]})
```

Input:
best_model_ridge=fit_models['ridge']
best_model_ridge **Output:**

```
GridSearchCV(cv=10,
estimator=Pipeline(steps=[('ridge', Ridge(random_state=1234))]),
n_jobs=-1,
 param_grid={'ridge__alpha': [0.001, 0.005, 0.01, 0.05, 0.1, 0.5,
```

0.99]})

Input: best_model_lasso=fit_models['lasso']
best_model_lasso
Output:

```
GridSearchCV(cv=10,
estimator=Pipeline(steps=[('lasso', Lasso(random_state=1234))]),
n_jobs=-1,
param_grid={'lasso__alpha': [0.001, 0.005, 0.01, 0.05, 0.1, 0.5,
0.99]})
```

Input:

```
for algo,model in fit_models.items():     ya=model.predict(X_test)
print('{} scores-R2:{} MAE:{}'.format(algo,r2_score(y_test,ya),
mean_absolute_error(y_test,ya)))
```

Output:

rf scores-R2:0.5255029479701915 MAE:1.570513566816263
ridge scores-R2:0.5189099860811324 MAE:1.6528099660919895 lasso
scores-R2:0.5190720174119673 MAE:1.6525494856846143