Assignment -3

Abalone Age Prediction

Assignment Date	10 october 2022
Student Name	Santha Kumar.P
Student Roll Number	820419104058
Maximum Marks	2 Marks

1.Importing necessary packages & Downloading the packages

Solution:

```
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

Solution:

```
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
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

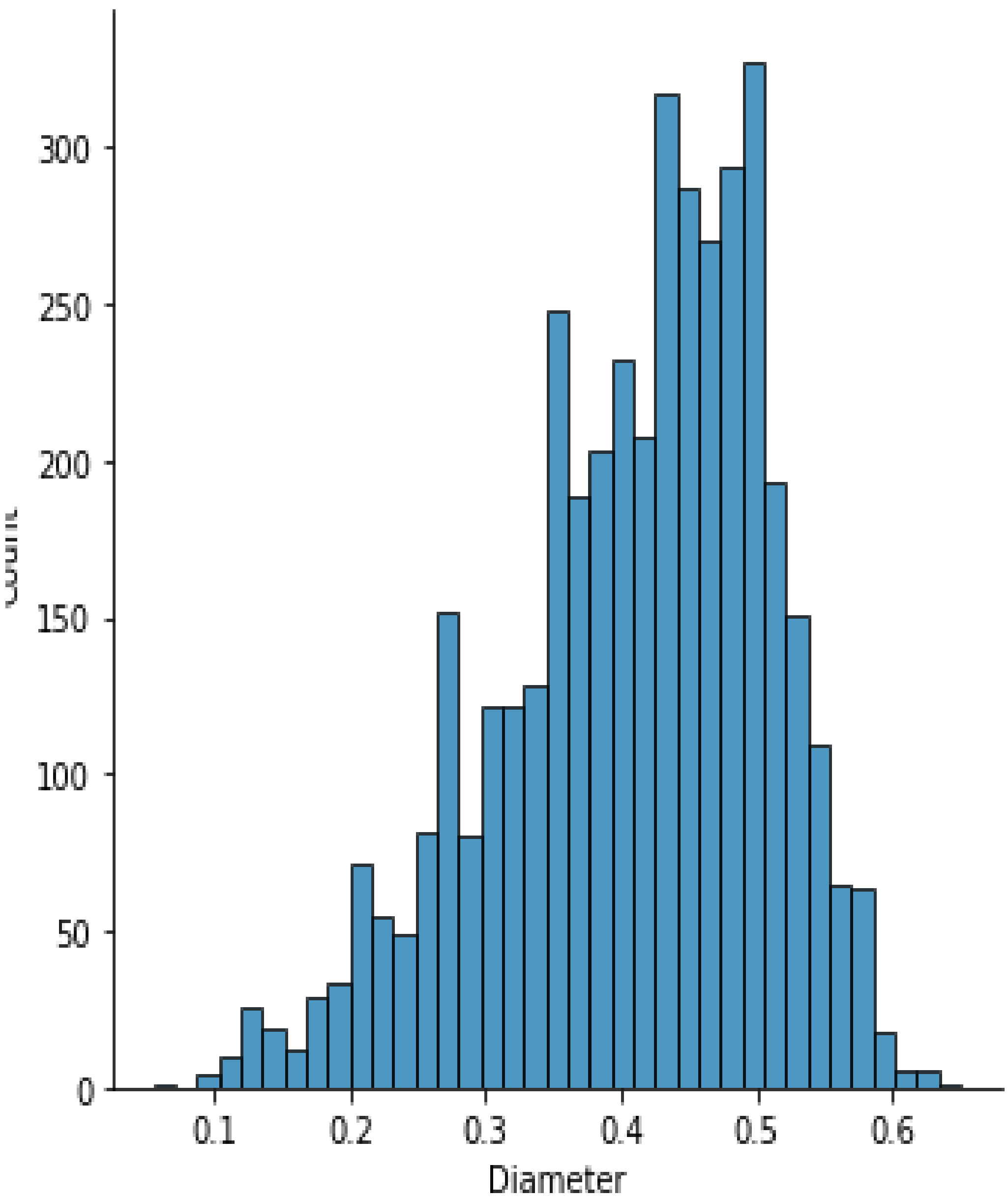
(i) Univariate Analysis

Solution:

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

Output:

```
<seaborn.axisgrid.FacetGrid at 0x1a7c3cc60a0>
```

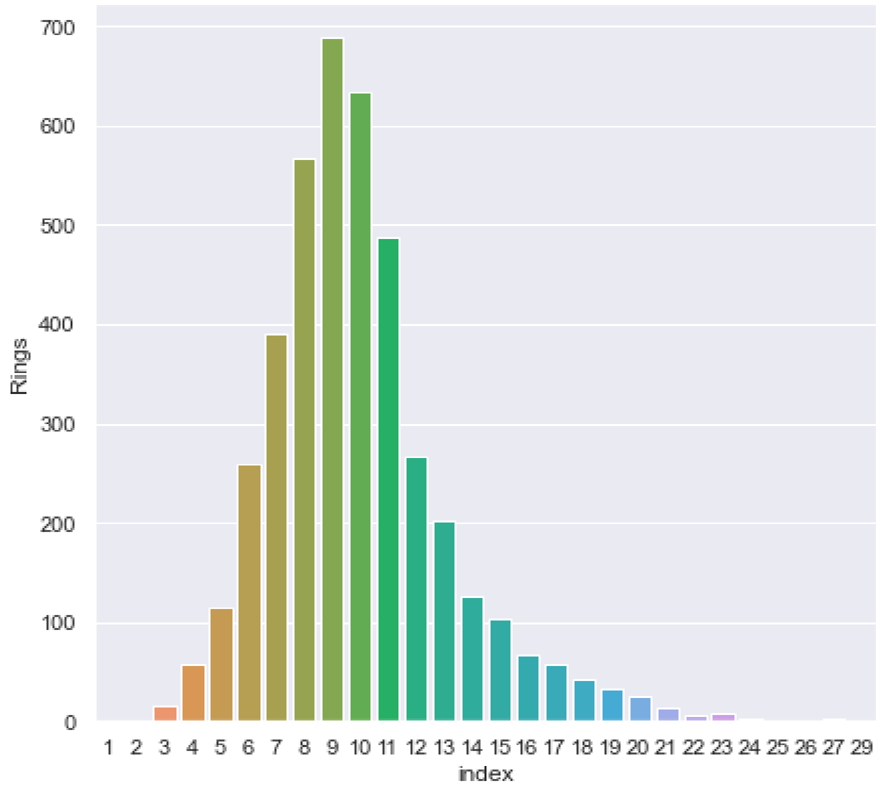


Solution:

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'>

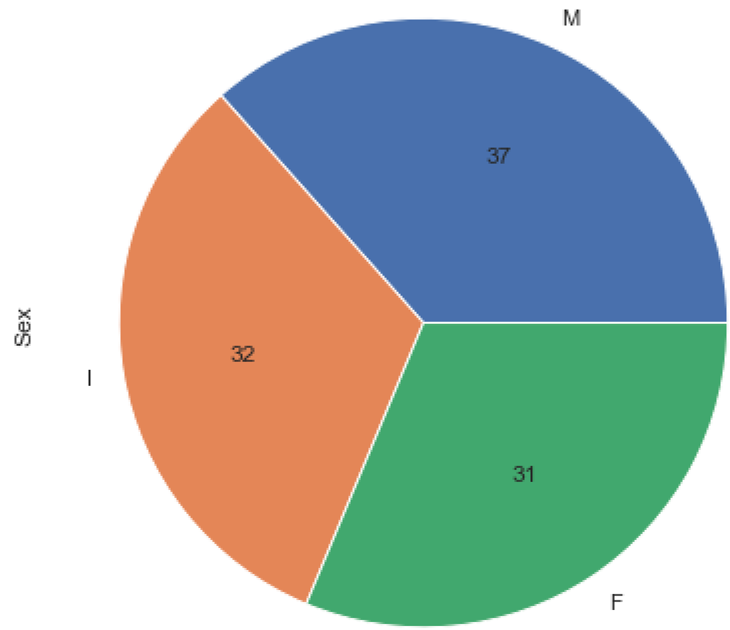


Solution:

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

Output:

<AxesSubplot:ylabel='Sex'>

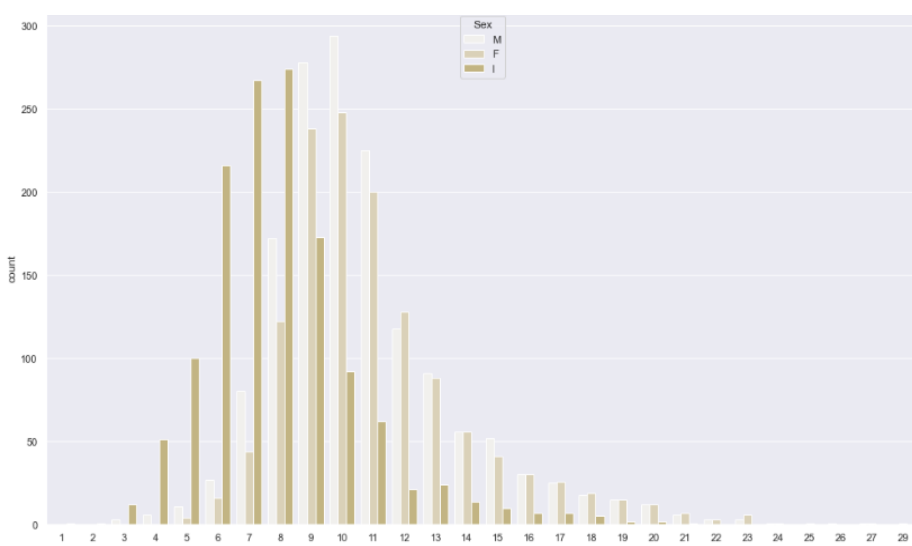


(ii) BiVariate Analysis

Solution:

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

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

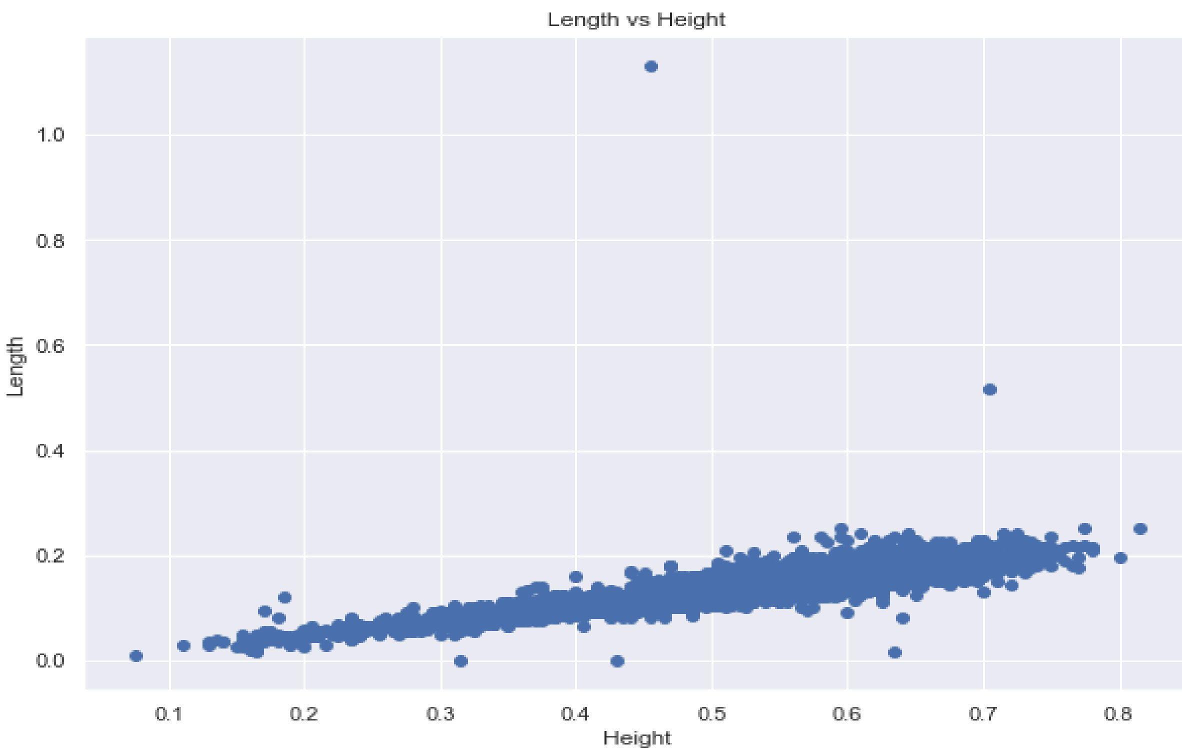


Solution:

```
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

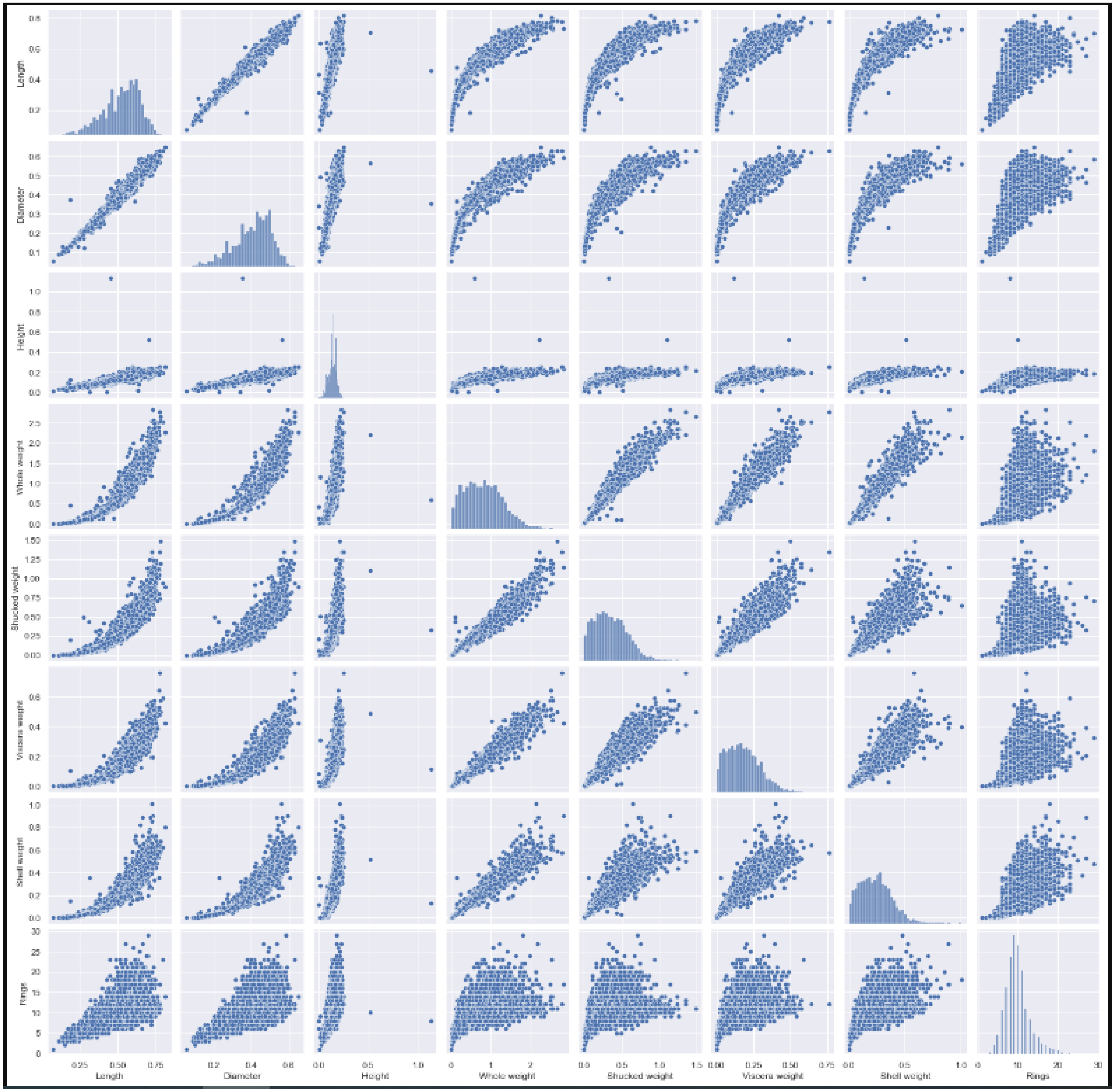
Solution:

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

Output:

<seaborn.axisgrid.PairGrid at 0x1a8005d43a0>

<Figure size 864x720 with 0 Axes>

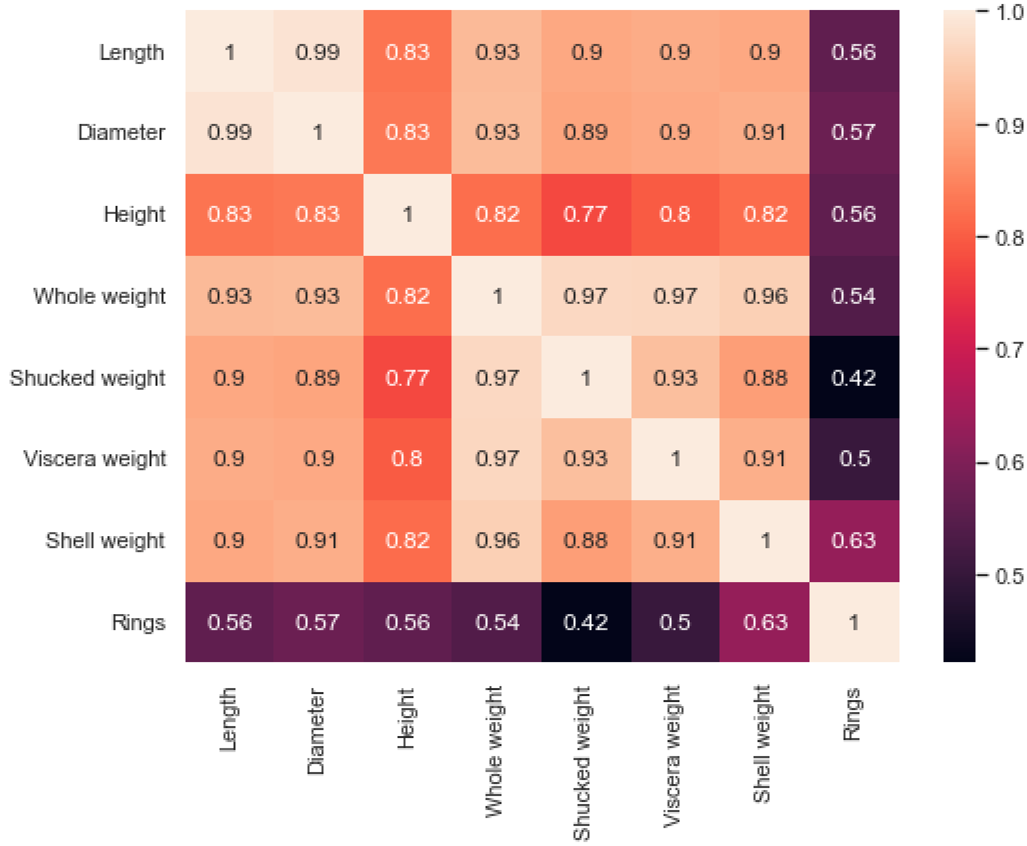


Solution:

```
plt.figure(figsize = (8,6))
corr = df.corr()
sns.heatmap(corr, annot = True)
```

Output:

<AxesSubplot:>



4.Descriptive Statistics

Solution:

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
```

Solution:

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
max	0.815000	0.650000	1.130000	2.825500	1.488000	0.760000	1.005000	29.000000

5.Handle Missing Values

Solution:

```
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

Solution:

```
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

Solution:

```
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'])
```

Solution:

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})
```

Solution:

```
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, 2
114: 1, 2169: 1, 2171: 1, 2381: 1, 2711: 1, 3190: 1, 3837: 1, 3899: 1, 3902: 1, 1428: 1, 1763: 1, 1
65: 1, 891: 1, 1052: 1, 1193: 1, 1206: 1, 1207: 1, 1209: 1, 1427: 1, 1761: 1, 1762: 1, 2623: 1, 262
4: 1, 2811: 1, 2863: 1, 3427: 1, 3715: 1})
```

Solution:

```
df=df.drop(multiple_outlier_indices,axis=0).reset_index(drop = True)
df
```

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

Solution:

df.shape

Output:

(4139, 9)

7. Categorical Attribute Encoding

Solution:

```
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

Solution:

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

9. Scaling the Predictor variables

Solution:

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

10. Perform the train test split

Solution:

```
X_train, X_test, y_train, y_test = train_test_split(feature, label, test_size = 0.2, random_state = 0)
```

Solution:

```
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

Solution:

```
pipelines={
'rf':make_pipeline(RandomForestRegressor(random_state=1234)),
'ridge':make_pipeline(Ridge(random_state=1234)),
'lasso':make_pipeline(Lasso(random_state=1234)),
}
```

Solution:

```
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

Solution:

```
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

Solution:

```
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]})
```

Solution:

```
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]})
```

Solution:

```
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]})
```

Solution:

```
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)))
```

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