Assignment-3

[1]
from google.colab **import** drive
[2]
drive.mount('/content/drive')
Mounted at /content/drive

[5]
import pandas **as** pd
[9]
data =pd.read_csv('/content/drive/MyDrive/abalone.csv')
[11]
data.head()

	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

[12]
import pandas **as** pd
import seaborn **as** sns
import matplotlib.pyplot **as** plt
import numpy **as** np
sns.set_style('darkgrid')
sns.set(font_scale=1.3)
data=pd.read_csv('/content/drive/MyDrive/abalone.csv')
[13]

data.head()

	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

[14]
data.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

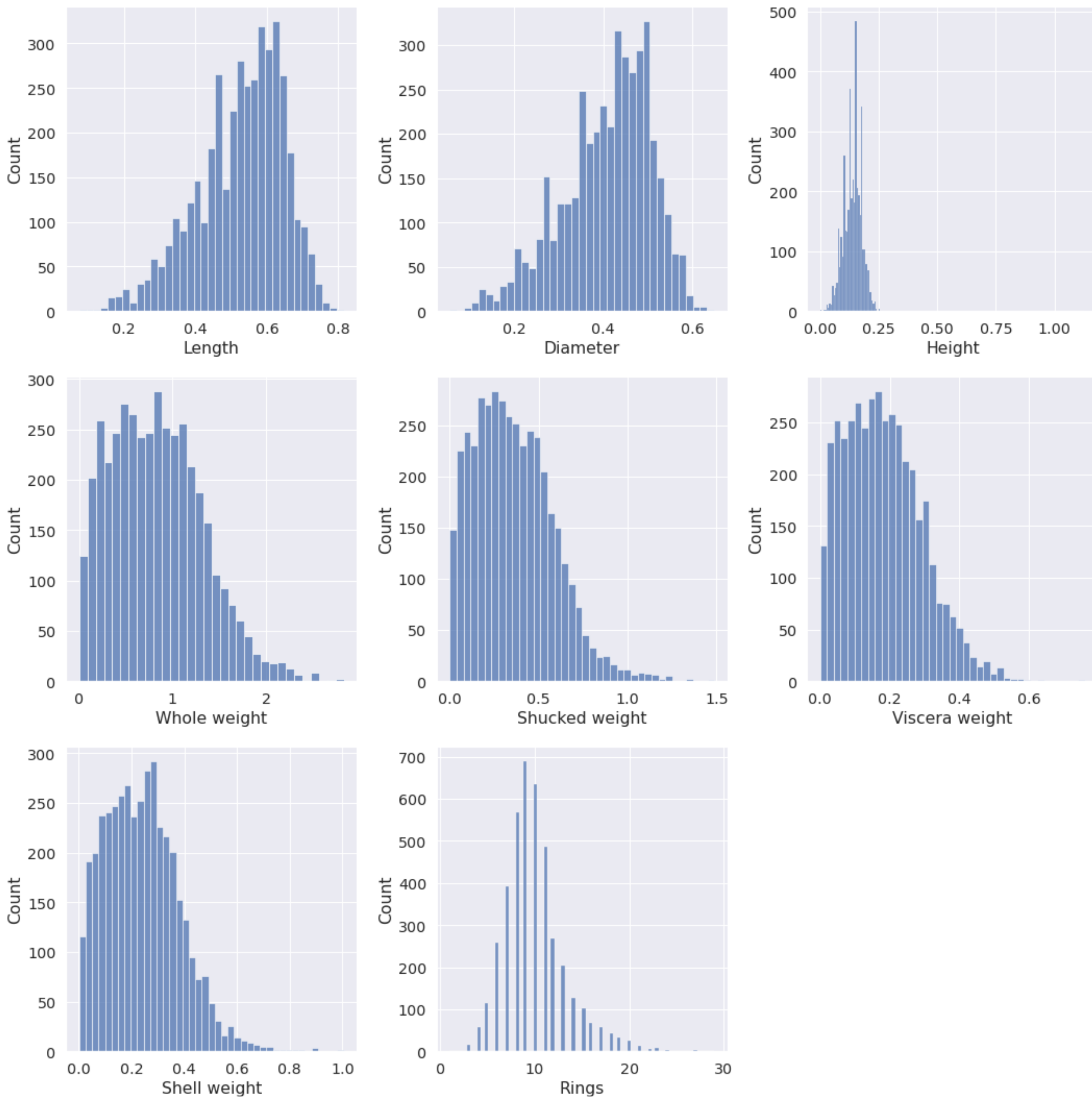
[15]

data.describe()

	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

[16]

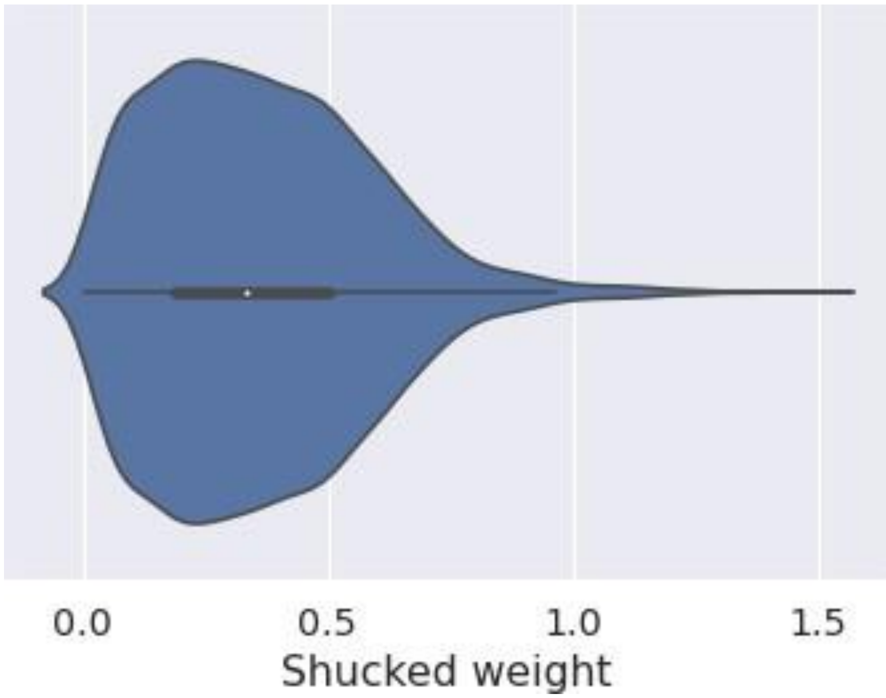
```
#univariate analysis
cols = 3
rows = 3
num_cols = data.select_dtypes(exclude='object').columns
fig = plt.figure( figsize=(cols*5, rows*5))
for i, col in enumerate(num_cols):

    ax=fig.add_subplot(rows,cols,i+1)

    sns.histplot(x = data[col], ax = ax)

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



[17]

```
sns.violinplot(x=data["Shucked weight"])
```

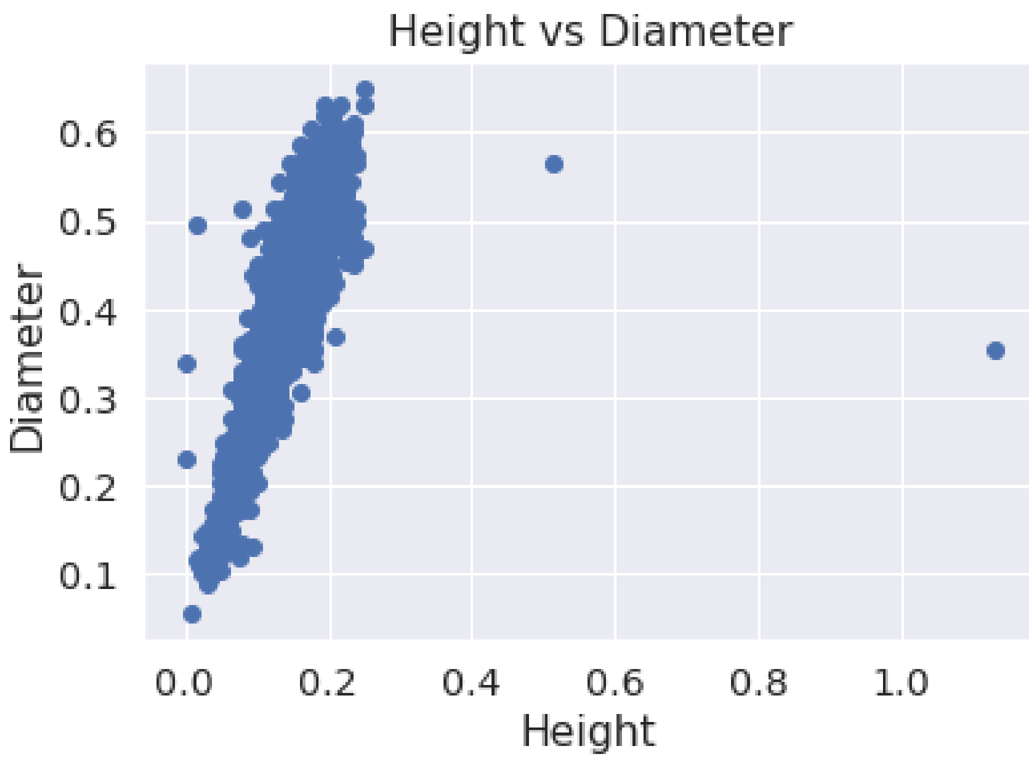
<matplotlib.axes._subplots.AxesSubplot at 0x7f5593102910>



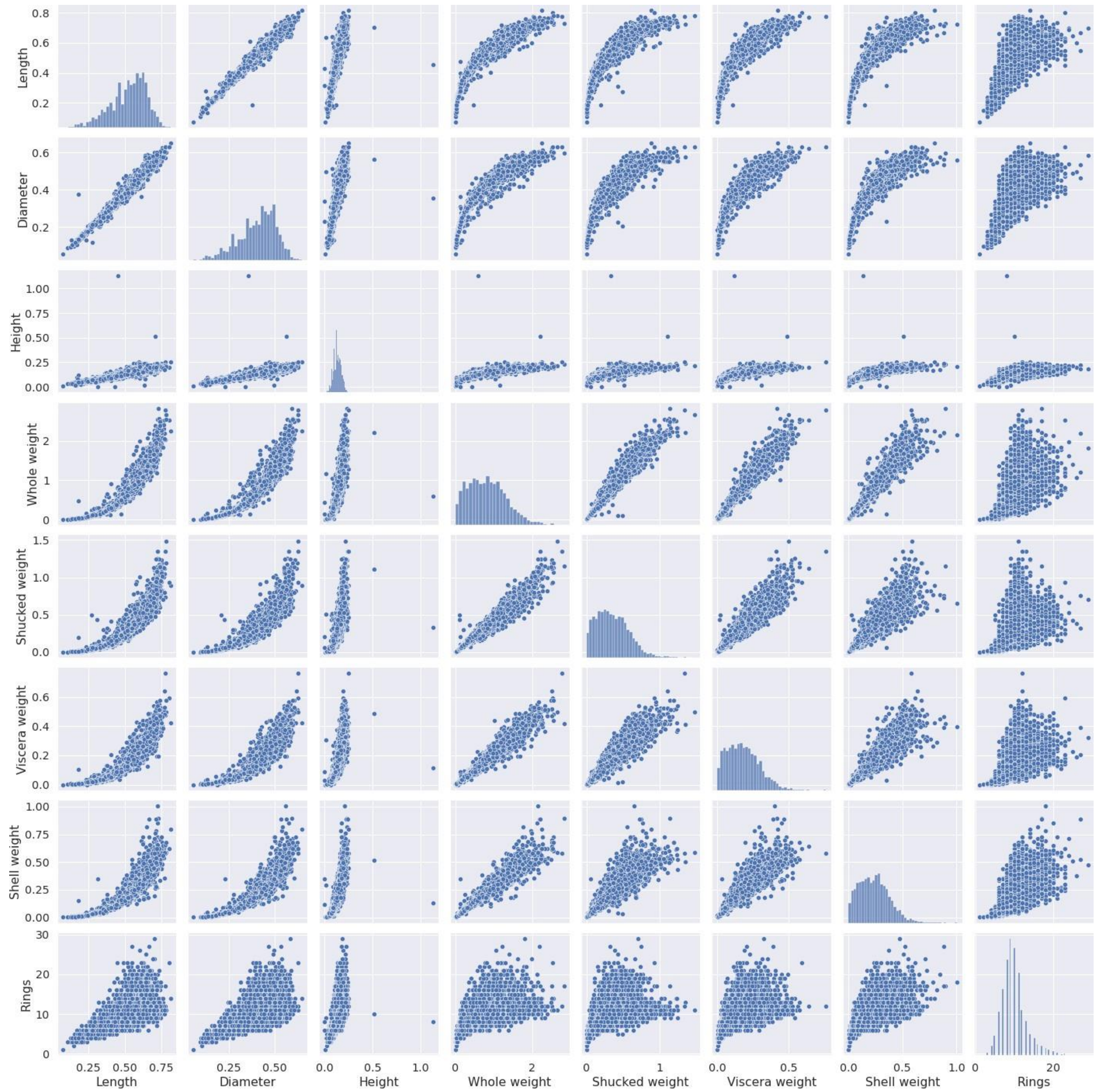
[18]

```
#Bivariate analysis
import matplotlib.pyplot as plt

#create scatterplot of hours vs. score
plt.scatter(data.Height, data.Diameter)
plt.title('Height vs Diameter')
plt.xlabel('Height')
plt.ylabel('Diameter')
```

Text(0, 0.5, 'Diameter')



[19]
#multivariate analysis
sns.pairplot(data);



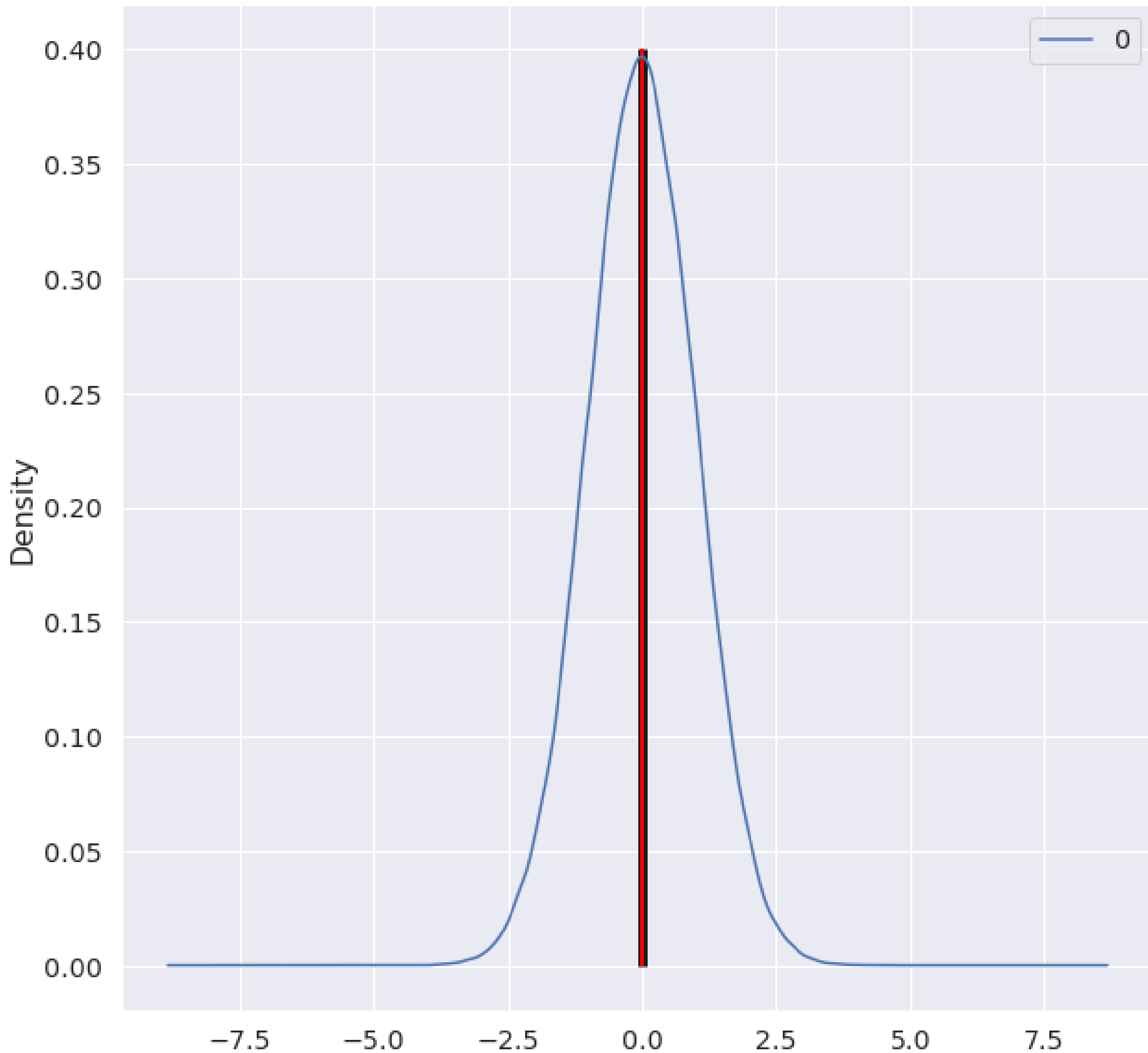
[20]
data.mean()
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:1: FutureWarning: Dropping of nuisance columns in DataFrame reductions (with 'numeric_only=None') is deprecated; in a future version this will raise TypeError. Select only valid columns before calling the reduction.
"""Entry point for launching an IPython kernel.

```
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
Rings   9.933684
dtype: float64
[21]
data.median()
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:1: FutureWarning: Dropping of nuisance columns in DataFrame reductions (with 'numeric_only=None') is deprecated; in a future version this will raise TypeError. Select only valid columns before calling the reduction.
  """Entry point for launching an IPython kernel.

Length   0.5450
Diameter   0.4250
Height   0.1400
Whole weight   0.7995
Shucked weight   0.3360
Viscera weight   0.1710
Shell weight   0.2340
Rings   9.0000
dtype: float64
[22]

```
norm_data = pd.DataFrame(np.random.normal(size=100000))

norm_data.plot(kind="density",
              figsize=(10,10));



plt.vlines(norm_data.mean(),     # Plot black line at mean
           ymin=0,
           ymax=0.4,
           linewidth=5.0);

plt.vlines(norm_data.median(),   # Plot red line at median
           ymin=0,
           ymax=0.4,
           linewidth=2.0,
           color="red");
```



Identifying the Outliers

[23]

```
print(data['Shell weight'].skew())
data['Shell weight'].describe()
```

0.6209268251392077

```
count    4177.000000
mean        0.238831
std         0.139203
min         0.001500
25%         0.130000
50%         0.234000
75%         0.329000
```

max   1.005000
Name: Shell weight, dtype: float64

Replacing the Outliers

[24]

print(data['Shell weight'].quantile(0.50))
print(data['Shell weight'].quantile(0.95))
data['Shell weight'] = np.where(data['Shell weight'] > 325, 140, data['Shell weight']
)
data.describe()

0.234
0.48

	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

Perform Encoding

[25]

from sklearn.compose **import** make_column_selector **as** selector

categorical_columns_selector = selector(dtype_include=object)
categorical_columns = categorical_columns_selector(data)
categorical_columns

['Sex']

[26]

data_categorical = data[categorical_columns]
data_categorical.head()

[27]

from sklearn **import** preprocessing

Label_encoder object knows how to understand word labels.
[28]
```
label_encoder = preprocessing.LabelEncoder()
```

Encode labels in column 'Species'.
[29]
```
data['Sex']= label_encoder.fit_transform(data['Sex'])
data['Sex'].unique()
```
```
array([2, 0, 1])
```
[30]
```
X= data.iloc[ : , :-1].values

y= data.iloc[ : , 4].values
print(X,y)
```
```
[[2.     0.455 0.365 ... 0.2245 0.101 0.15  ]
 [2.     0.35   0.265 ... 0.0995 0.0485 0.07  ]
 [0.     0.53   0.42   ... 0.2565 0.1415 0.21  ]
 ...
 [2.     0.6    0.475 ... 0.5255 0.2875 0.308 ]
 [0.     0.625 0.485 ... 0.531 0.261 0.296 ]
 [2.     0.71   0.555 ... 0.9455 0.3765 0.495 ]] [0.514   0.2255 0.677  ... 1.176
1.0945 1.9485]
```

Import Packages
[31]
```
import numpy as np
import pandas as pd
from sklearn.model_selection import train_test_split
```

Importing Data
[32]
```
print(data.shape)
```
```
(4177, 9)
```

Head of the Data
[33]
```
print('Head of the dataframe : ')
print(data.head())

print(data.columns)
```

X= data['Whole weight']
y=data['Shucked weight']
Head of the dataframe :

	Sex	Length	Diameter	Height	Whole weight	Shucked weight \
0	2	0.455	0.365	0.095	0.5140	0.2245
1	2	0.350	0.265	0.090	0.2255	0.0995
2	0	0.530	0.420	0.135	0.6770	0.2565
3	2	0.440	0.365	0.125	0.5160	0.2155
4	1	0.330	0.255	0.080	0.2050	0.0895

	Viscera weight	Shell weight	Rings
0	0.1010	0.150	15
1	0.0485	0.070	7
2	0.1415	0.210	9
3	0.1140	0.155	10
4	0.0395	0.055	7

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

Using the train test split function

[34]

```
X_train, X_test, y_train, y_test = train_test_split(
X,y , random_state=104,test_size=0.25, shuffle=True)
```

Printing out train and test sets

[35]

```
print('X_train : ')
print(X_train.head())
print(X_train.shape)

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

print('')
print('y_train : ')
print(y_train.head())
```

```
print(y_train.shape)

print('')
print('y_test : ')
print(y_test.head())
print(y_test.shape)
```

```
X_train :
437     0.2520
1331    0.8730
1611    0.7625
1394    1.5210
396     0.7155
Name: Whole weight, dtype: float64
(3132,)

X_test :
4087    0.9840
1699    1.4890
1868    0.6965
2984    1.2240
5       0.3515
Name: Whole weight, dtype: float64
(1045,)

y_train :
437     0.0915
1331    0.3820
1611    0.3270
1394    0.6440
396     0.3165
Name: Shucked weight, dtype: float64
(3132,)

y_test :
4087    0.4865
1699    0.7150
1868    0.3045
2984    0.6180
5       0.1410
```

Name: Shucked weight, dtype: float64
(1045,)

Scaling

[36]

```
data_scaled = data.copy()
col_names = ['Shucked weight', 'Whole weight']
features = data_scaled[col_names]
from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler()
data_scaled[col_names] = scaler.fit_transform(features.values)
from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler(feature_range=(5, 10))

data_scaled[col_names] = scaler.fit_transform(features.values)
data_scaled
```

	Sex	Length	Diameter	Height	Whole weight	Shucked weight	Viscera weight	Shell weight	Rings
0	2	0.455	0.365	0.095	5.906676	5.751513	0.1010	0.1500	15
1	2	0.350	0.265	0.090	5.395785	5.331204	0.0485	0.0700	7
2	0	0.530	0.420	0.135	6.195325	5.859112	0.1415	0.2100	9
3	2	0.440	0.365	0.125	5.910218	5.721251	0.1140	0.1550	10
4	1	0.330	0.255	0.080	5.359483	5.297579	0.0395	0.0550	7
...	...	...	...	...	...	...	...	...	...
4172	0	0.565	0.450	0.165	6.567204	6.240753	0.2390	0.2490	11
4173	2	0.590	0.440	0.135	6.707101	6.472764	0.2145	0.2605	10
4174	2	0.600	0.475	0.205	7.078980	6.763618	0.2875	0.3080	9
4175	0	0.625	0.485	0.150	6.934656	6.782112	0.2610	0.2960	10
4176	2	0.710	0.555	0.195	8.446963	8.175857	0.3765	0.4950	12

4177 rows × 9 columns

Testing and Training

[37]

```
X = data.iloc[:, :-1]
y = data.iloc[:, -1]
```

Split the Dataset

[38]

```
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.05, random_state=0)
print(X_train, X_test, y_train, y_test)
```

```
      Sex Length Diameter Height Whole weight Shucked weight \
678     0   0.450     0.380   0.165        0.8165          0.2500
3009    1   0.255     0.185   0.065        0.0740          0.0305
1906    1   0.575     0.450   0.135        0.8245          0.3375
768     0   0.550     0.430   0.155        0.7850          0.2890
2781    2   0.595     0.475   0.140        1.0305          0.4925
...   ...     ...       ...     ...           ...             ...
1033    2   0.650     0.525   0.185        1.6220          0.6645
3264    0   0.655     0.500   0.140        1.1705          0.5405
1653    2   0.595     0.450   0.145        0.9590          0.4630
2607    0   0.625     0.490   0.165        1.1270          0.4770
2732    1   0.410     0.325   0.110        0.3260          0.1325

      Viscera weight Shell weight
678           0.1915       0.2650
3009          0.0165       0.0200
1906          0.2115       0.2390
768           0.2270       0.2330
2781          0.2170       0.2780
...              ...          ...
1033          0.3225       0.4770
3264          0.3175       0.2850
1653          0.2065       0.2535
2607          0.2365       0.3185
2732          0.0750       0.1010

[3968 rows x 8 columns]       Sex Length Diameter Height Whole weight
Shucked weight \
668     2   0.550     0.425   0.155        0.9175          0.2775
1580    1   0.500     0.400   0.120        0.6160          0.2610
3784    2   0.620     0.480   0.155        1.2555          0.5270
463     1   0.220     0.165   0.055        0.0545          0.0215
2615    2   0.645     0.500   0.175        1.5105          0.6735
...   ...     ...       ...     ...           ...             ...
```

```
1670    0   0.610     0.485   0.150       1.2405          0.6025
3055    0   0.610     0.495   0.160       1.0890          0.4690
3366    2   0.280     0.210   0.065       0.0905          0.0350
1410    0   0.665     0.530   0.180       1.4910          0.6345
4035    1   0.520     0.410   0.140       0.5995          0.2420

      Viscera weight Shell weight
668           0.2430       0.3350
1580          0.1430       0.1935
3784          0.3740       0.3175
463           0.0120       0.0200
2615          0.3755       0.3775
...           ...          ...
1670          0.2915       0.3085
3055          0.1980       0.3840
3366          0.0200       0.0300
1410          0.3420       0.4350
4035          0.1375       0.1820

[209 rows x 8 columns] 678     23
3009     4
1906    11
768     11
2781    10
        ..
1033    10
3264    12
1653    10
2607     9
2732     8
Name: Rings, Length: 3968, dtype: int64 668     13
1580     8
3784    11
463      5
2615    12
        ..
1670    12
3055    11
3366     5
1410    10
```

```
4035    11
Name: Rings, Length: 209, dtype: int64
```

[39]

```
from sklearn.linear_model import LogisticRegression
logreg= LogisticRegression()
logreg.fit(X_train,y_train)
y_pred=logreg.predict(X_test)
print (X_test) #test dataset
print (y_pred) #predicted values
```

```
      Sex  Length  Diameter  Height  Whole weight  Shucked weight  \
668     2   0.550     0.425   0.155        0.9175          0.2775
1580    1   0.500     0.400   0.120        0.6160          0.2610
3784    2   0.620     0.480   0.155        1.2555          0.5270
463     1   0.220     0.165   0.055        0.0545          0.0215
2615    2   0.645     0.500   0.175        1.5105          0.6735
...   ...     ...       ...     ...           ...             ...
1670    0   0.610     0.485   0.150        1.2405          0.6025
3055    0   0.610     0.495   0.160        1.0890          0.4690
3366    2   0.280     0.210   0.065        0.0905          0.0350
1410    0   0.665     0.530   0.180        1.4910          0.6345
4035    1   0.520     0.410   0.140        0.5995          0.2420

      Viscera weight  Shell weight
668           0.2430        0.3350
1580          0.1430        0.1935
3784          0.3740        0.3175
463           0.0120        0.0200
2615          0.3755        0.3775
...              ...           ...
1670          0.2915        0.3085
3055          0.1980        0.3840
3366          0.0200        0.0300
1410          0.3420        0.4350
4035          0.1375        0.1820

[209 rows x 8 columns]
[10 9 10 6 10 10 8 8 7 10 8  6        8 9 6 9 7 10 10 8 7 7 8  6
  9 10 5 10 9 10 7 5 10 11 8  9       8 9 8 10 10 8 9 10 10 8 9 10
  9 7 9 7 8 10 8 8 6 7 7 7 10         9 10 8 7 10 11 10 9 11 8 11
```

```
 10 9 9 9 9 9 10 8 9 6 7 10 9 8 9 11 5 7 9 9 8 8 10 6
  8 7 10 11 10 8 10 9 6 10 8 7 7 10 11 11 9 9 10 11 10 10 6 9
  7 9 7 8 10 10 10 11 7 10 10 8 9 10 11 10 9 9 7 10 9 8 7  9
 10 9 8 8 8 6 8 11 7 10 7 7 9 7 10 7 9 7 9 10 6 10 7 6
  9 9 9 6 8 10 10 10 6 8 7 10 9 9 9 9 10 9 9 8 6 8 9 8
  8 9 10 8 7 9 5 11 8 9 11 9 10 10 6 11 8]
```

```
/usr/local/lib/python3.7/dist-packages/sklearn/linear_model/_logistic.py:818: ConvergenceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
  https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
  extra_warning_msg=_LOGISTIC_SOLVER_CONVERGENCE_MSG,
```

[40]

```
X_train
```

	Sex	Length	Diameter	Height	Whole weight	Shucked weight	Viscera weight	Shell weight
678	0	0.450	0.380	0.165	0.8165	0.2500	0.1915	0.2650
3009	1	0.255	0.185	0.065	0.0740	0.0305	0.0165	0.0200
1906	1	0.575	0.450	0.135	0.8245	0.3375	0.2115	0.2390
768	0	0.550	0.430	0.155	0.7850	0.2890	0.2270	0.2330
2781	2	0.595	0.475	0.140	1.0305	0.4925	0.2170	0.2780
...	...	...	...	...	...	...	...	...
1033	2	0.650	0.525	0.185	1.6220	0.6645	0.3225	0.4770
3264	0	0.655	0.500	0.140	1.1705	0.5405	0.3175	0.2850
1653	2	0.595	0.450	0.145	0.9590	0.4630	0.2065	0.2535
2607	0	0.625	0.490	0.165	1.1270	0.4770	0.2365	0.3185
2732	1	0.410	0.325	0.110	0.3260	0.1325	0.0750	0.1010

3968 rows × 8 columns

[41]
X_test

	Sex	Length	Diameter	Height	Whole weight	Shucked weight	Viscera weight	Shell weight
668	2	0.550	0.425	0.155	0.9175	0.2775	0.2430	0.3350
1580	1	0.500	0.400	0.120	0.6160	0.2610	0.1430	0.1935
3784	2	0.620	0.480	0.155	1.2555	0.5270	0.3740	0.3175
463	1	0.220	0.165	0.055	0.0545	0.0215	0.0120	0.0200
2615	2	0.645	0.500	0.175	1.5105	0.6735	0.3755	0.3775
...	...	...	...	...	...	...	...	...
1670	0	0.610	0.485	0.150	1.2405	0.6025	0.2915	0.3085
3055	0	0.610	0.495	0.160	1.0890	0.4690	0.1980	0.3840
3366	2	0.280	0.210	0.065	0.0905	0.0350	0.0200	0.0300
1410	0	0.665	0.530	0.180	1.4910	0.6345	0.3420	0.4350
4035	1	0.520	0.410	0.140	0.5995	0.2420	0.1375	0.1820

209 rows × 8 columns

[42]
y_train
```
678     23
3009     4
1906    11
768     11
2781    10
        ..
1033    10
3264    12
1653    10
2607     9
2732     8
Name: Rings, Length: 3968, dtype: int64
```
[43]
y_test
```
668     13
1580     8
3784    11
463      5
```

```
2615    12
        ..
1670    12
3055    11
3366     5
1410    10
4035    11
Name: Rings, Length: 209, dtype: int64
```

[44]

```
# Select algorithm
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score
model = DecisionTreeClassifier()
# Fit model to the data
model.fit(X_train, y_train)
# Check model performance on training data
predictions = model.predict(X_train)
print(accuracy_score(y_train, predictions))
```

```
1.0
```

[45]

```
# Evaluate the model on the test data
predictions = model.predict(X_test)
predictions
```

```
array([19, 12, 14, 5, 10, 13, 8, 8, 8, 9, 8, 5, 8, 9, 6, 13, 10,
       15, 9, 8, 6, 7, 9, 6, 11, 11, 4, 17, 14, 11, 9, 4, 11, 18,
        6, 8, 9, 9, 7, 11, 12, 8, 15, 11, 13, 8, 9, 10, 17, 7, 9,
        6, 9, 17, 10, 6, 7, 7, 6, 6, 9, 8, 9, 7, 7, 13, 10, 13,
       12, 10, 10, 14, 10, 9, 10, 9, 10, 8, 9, 8, 9, 6, 6, 10, 12,
        9, 8, 15, 6, 10, 8, 8, 8, 6, 17, 5, 9, 9, 10, 10, 11, 13,
       10, 12, 5, 11, 8, 6, 10, 20, 10, 11, 9, 9, 16, 9, 9, 12, 5,
        9, 7, 14, 8, 11, 13, 9, 13, 13, 6, 9, 9, 8, 9, 11, 10, 10,
       10,  8,  6, 18, 14, 12,  6,  8, 12,  8,  9,  7,  7,  6,  8, 13,  8,
        8,  9,  8, 15,  7, 10,  7,  9, 10,  9,  9,  6, 20,  7,  6, 10, 11,
       10, 3, 6, 10, 21, 11, 6, 8, 6, 13, 11, 9, 8, 10, 17, 10, 10,
        8, 7, 9, 8, 9, 12, 10, 13, 8, 8, 7, 4, 15, 10, 11, 12, 9,
        8, 8, 5, 10, 10])
```

[46]

```
print(accuracy_score(y_test, predictions))
```

```
0.20095693779904306
```

[47]

```
df = X_test.copy()
df['Actual'] = y_test
df['Prediction'] = predictions
df
```

	Sex	Length	Diameter	Height	Whole weight	Shucked weight	Viscera weight	Shell weight	Actual	Prediction
668	2	0.550	0.425	0.155	0.9175	0.2775	0.2430	0.3350	13	19
1580	1	0.500	0.400	0.120	0.6160	0.2610	0.1430	0.1935	8	12
3784	2	0.620	0.480	0.155	1.2555	0.5270	0.3740	0.3175	11	14
463	1	0.220	0.165	0.055	0.0545	0.0215	0.0120	0.0200	5	5
2615	2	0.645	0.500	0.175	1.5105	0.6735	0.3755	0.3775	12	10
...	...	...	...	...	...	...	...	...	...	...
1670	0	0.610	0.485	0.150	1.2405	0.6025	0.2915	0.3085	12	8
3055	0	0.610	0.495	0.160	1.0890	0.4690	0.1980	0.3840	11	8
3366	2	0.280	0.210	0.065	0.0905	0.0350	0.0200	0.0300	5	5
1410	0	0.665	0.530	0.180	1.4910	0.6345	0.3420	0.4350	10	10
4035	1	0.520	0.410	0.140	0.5995	0.2420	0.1375	0.1820	11	10

209 rows × 10 columns

[48]

```
import os
os.environ["PATH"] += os.pathsep + 'C:/Program Files (x86)/Graphviz2.38/bin'
```

[49]

```
from sklearn.metrics import confusion_matrix
from sklearn.metrics import accuracy_score
from sklearn.metrics import classification_report
from sklearn.metrics import roc_auc_score
from sklearn.metrics import log_loss
X_actual = [1, 1, 0, 1, 0, 0, 1, 0, 0, 0]
Y_predic = [1, 0, 1, 1, 1, 0, 1, 1, 0, 0]
results = confusion_matrix(X_actual, Y_predic)
print ('Confusion Matrix :')
print(results)
print ('Accuracy Score is',accuracy_score(X_actual, Y_predic))
print ('Classification Report : ')
print (classification_report(X_actual, Y_predic))
print('AUC-ROC:',roc_auc_score(X_actual, Y_predic))
print('LOGLOSS Value is',log_loss(X_actual, Y_predic))
```

```
Confusion Matrix :
[[3 3]
 [1 3]]
Accuracy Score is 0.6
Classification Report :
              precision    recall  f1-score   support

           0       0.75      0.50      0.60         6
           1       0.50      0.75      0.60         4

    accuracy                           0.60        10
   macro avg       0.62      0.62      0.60        10
weighted avg       0.65      0.60      0.60        10

AUC-ROC: 0.625
LOGLOSS Value is 13.815750437193334
```