ASSIGNMENT - 4

Description:- Predicting the age of abalone from physical measurements. The age of abalone is determined by cutting the shell through the cone, staining it, and counting the number of rings through a microscope -- a boring and time-consuming task. Other measurements, which are easier to obtain, are used to predict age. Further information, such as weather patterns and location (hence food availability) may be required to solve the problem.

Attribute Information:

Given is the attribute name, attribute type, measurement unit, and a brief description. The number of rings is the value to predict: either as a continuous value or as a classification problem.

Name / Data Type / Measurement Unit / Description
1- Sex / nominal / -- / M, F, and I (infant)
2- Length / continuous / mm / Longest shell measurement
3- Diameter / continuous / mm / perpendicular to length
4- Height / continuous / mm / with meat in shell
5- Whole weight / continuous / grams / whole abalone
6- Shucked weight / continuous / grams / weight of meat
7- Viscera weight / continuous / grams / gut weight (after bleeding)
8- Shell weight / continuous / grams / after being dried
9- Rings / integer / -- / +1.5 gives the age in years

Building a Regression Model

1. Download the dataset: Dataset
2. Load the dataset into the tool.
3. Perform Below Visualizations.

- Univariate Analysis
- Bi-Variate Analysis
- Multi-Variate Analysis

4. Perform descriptive statistics on the dataset.
5. Check for Missing values and deal with them.
6. Find the outliers and replace them outliers
7. Check for Categorical columns and perform encoding. 8. Split the data into dependent and independent variables. 9. Scale the independent variables
10. Split the data into training and testing
11. Build the Model
12. Train the Model
13. Test the Model

14. Measure the performance using Metrics.

```
#import libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sb
import plotly.express as px
```

2. Load the dataset into the tool

```
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

```
import os
os.chdir("/content/drive/My Drive")
!ls
```

```
data = pd.read_csv('/content/drive/My Drive/Colab Notebooks/abalone.csv')
data
```

	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

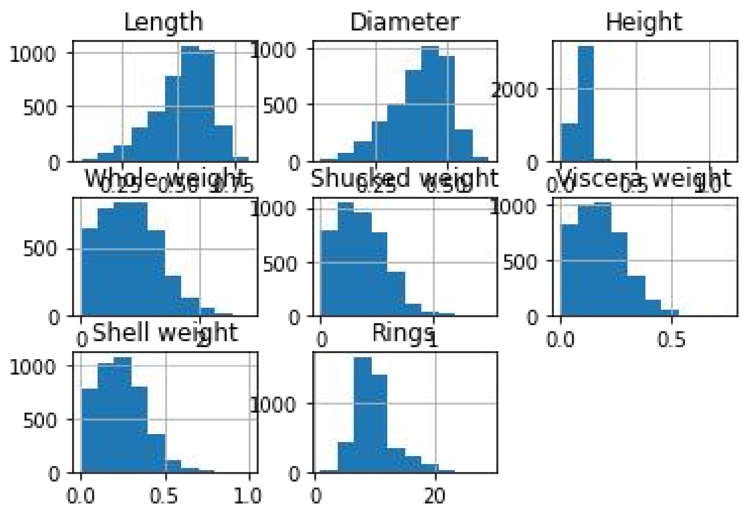
4177 rows × 9 columns

3. Peífoím Below Visualizations.

- **Univaíiate Analysis**

```
data['Rings'].value_counts()
data.hist()
```

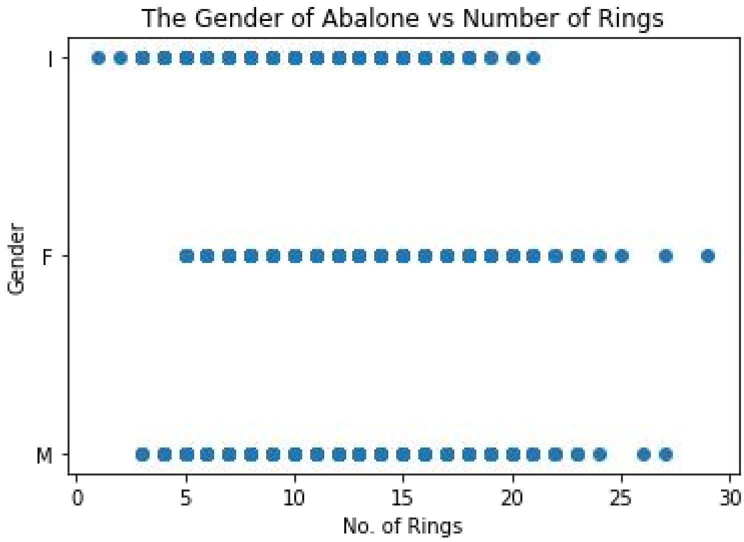
```
array([[<matplotlib.axes._subplots.AxesSubplot object at 0x7fa4a73e35d0>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7fa4a6255990>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7fa4a620df90>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x7fa4a61c3bd0>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7fa4a6188210>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7fa4a6140810>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x7fa4a6173e90>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7fa4a6138410>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7fa4a6138450>]],
      dtype=object)
```



Bi-Vaíiate Analysis

```
plt.scatter(data.Rings, data.Sex)
plt.title('The Gender of Abalone vs Number of Rings')
plt.xlabel('No. of Rings')
plt.ylabel('Gender')
```

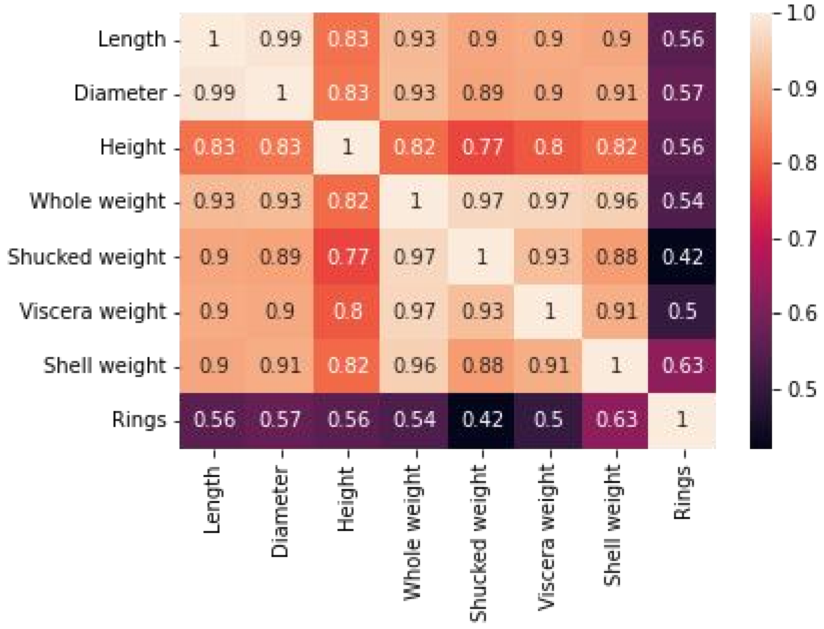
```
Text(0, 0.5, 'Gender')
```



· Multi-Vaíiate Analysis

```
sb.heatmap(data.corr(),annot=True)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fa4a59c4350>
```



4. Perform descriptive statistics on the dataset.

```
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
```

```
data.describe()
```

	Length	Diameter	Height	Whole weight	Shucked weight	Viscera weight	
count	4177.000000	4177.000000	4177.000000	4177.000000	4177.000000	4177.000000	41
mean	0.523992	0.407881	0.139516	0.828742	0.359367	0.180594	
std	0.120093	0.099240	0.041827	0.490389	0.221963	0.109614	
min	0.075000	0.055000	0.000000	0.002000	0.001000	0.000500	
25%	0.450000	0.350000	0.115000	0.441500	0.186000	0.093500	
50%	0.545000	0.425000	0.140000	0.799500	0.336000	0.171000	

5. Check foí Missing values and deal with them.

Theíe is no missing values

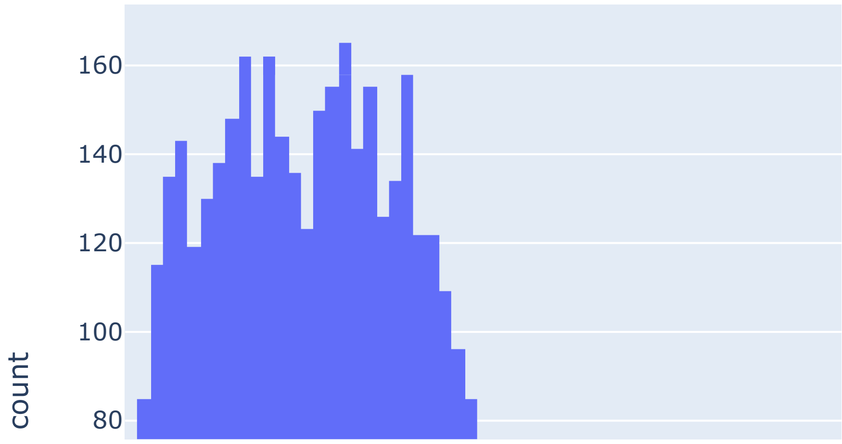
```
data.isnull().any()
```

```
Sex               False
Length            False
Diameter          False
Height            False
Whole   weight    False
Shucked  weight   False
Viscera  weight   False
Shell weight      False
Rings             False
dtype: bool
```

6. Find the outlieís and íeplace them outlieís

The dataset does not have a outlieís

```
fig = px.histogram(data, x='Whole weight')
fig.show()
```



7. Check foí Categoíical columns and peífoím encoding

```
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
data["Sex"] = le.fit_transform(data["Sex"])
data["Sex"]
```

```
0       2
1       2
2       0
3       2
4       1
       ..
4172    0
4173    2
4174    2
4175    0
4176    2
Name: Sex, Length: 4177, dtype: int64
```

8.Split the data into dependent and independent

variables.

```
x=data.iloc[:,0:8].values
y=data.iloc[:,8:9].values
```

```
x
```

```
array([[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 ]])
```

```
y
```

```
array([[15],
       [ 7],
       [ 9],
       ...,
       [ 9],
       [10],
       [12]])
```

9.Scale the independent vaíiables

```
x=data.iloc[:,0:8]
print(x.head())
```

```
   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
0          0.1010         0.150
1          0.0485         0.070
2          0.1415         0.210
3          0.1140         0.155
4          0.0395         0.055
```

10. Split the data into tíaining and testing

```
from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test = train_test_split(x,y,test_size=0.3,random_state=0)
```

```
x_train.shape
```

```
(2923, 8)
```

```
x_test.shape
```

```
(1254, 8)
```

11. Build the Model

```
from sklearn.linear_model import LinearRegression
lr = LinearRegression()
```

12. Train the Model

```
lr.fit(x_train, y_train)
```

```
LinearRegression()
```

13. Test the Model

```
y_pred = lr.predict(x_test)
print((y_test)[0:6])
print((y_pred)[0:6])
```

```
[[13]
 [ 8]
 [11]
 [ 5]
 [12]
 [11]]
[[13.11640829]
 [ 9.65691091]
 [10.35350972]
 [ 5.63648715]
 [10.67436485]
 [11.95341338]]
```

14. Measure the performance using Metrics.

```
# RMSE(Root Mean Square Error)

from sklearn.metrics import mean_squared_error
mse = mean_squared_error(y_test, y_pred)
rmse = np.sqrt(mse)
print("RMSE value : {:.2f}".format(rmse))
```

```
RMSE value : 4.26
```

```
from sklearn.model_selection import cross_val_score
cv_scores = cross_val_score(lr, x, y, cv=5)
sco=cv_scores.round(4)
print(cv_scores.round(4))
print("Average",sco.sum()/5)
```

```
[0.4113 0.1574 0.4807 0.5046 0.4362] -----  Average 0.39803999999999995
```