Problem Statement: Abalone Age Prediction

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.

```
IN[]:import libraries
     import numpy as np
     import pandas as pd
     import matplotlib.pyplot as plt
     import seaborn as sb
     import plotly.express as px
```

Load the dataset into the tool

```
IN[]: = pd.read_csv('/content/drive/My Drive/Machine Learning/abalone.csv')
data
```

OUT[]: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
...	...	...	...	...	...	...	...	...	...

OUT[]:Sex	Length	Diameter	Height	Whole weight	Shucked weight	Viscera weight	Shell weight	Rings	
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

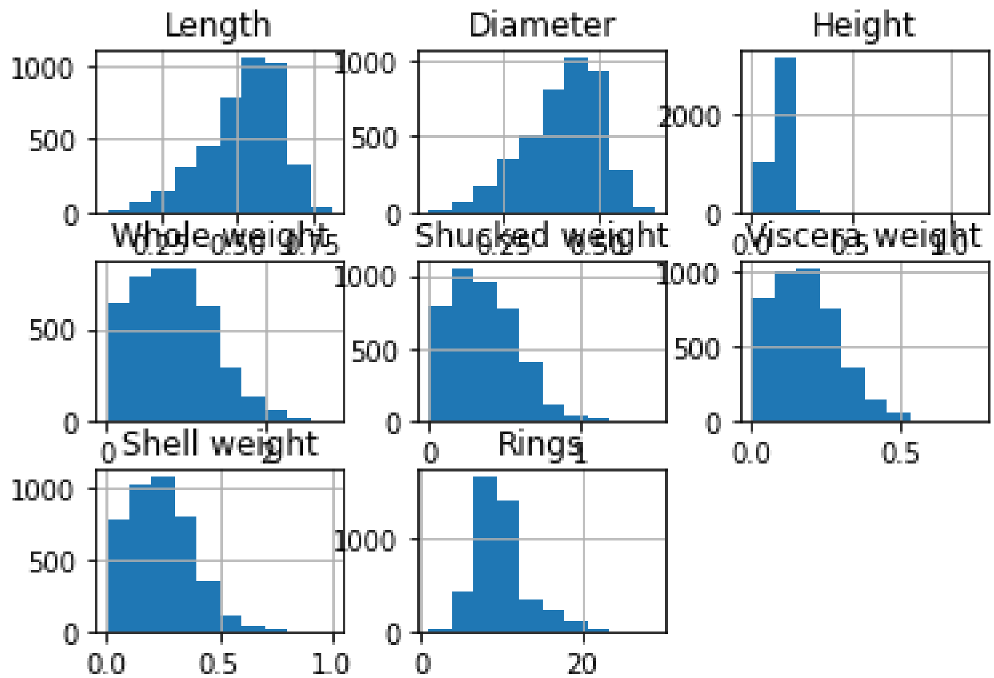
4177 rows × 9 column

3. Perform Below Visualizations.

Univariate Analysis

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

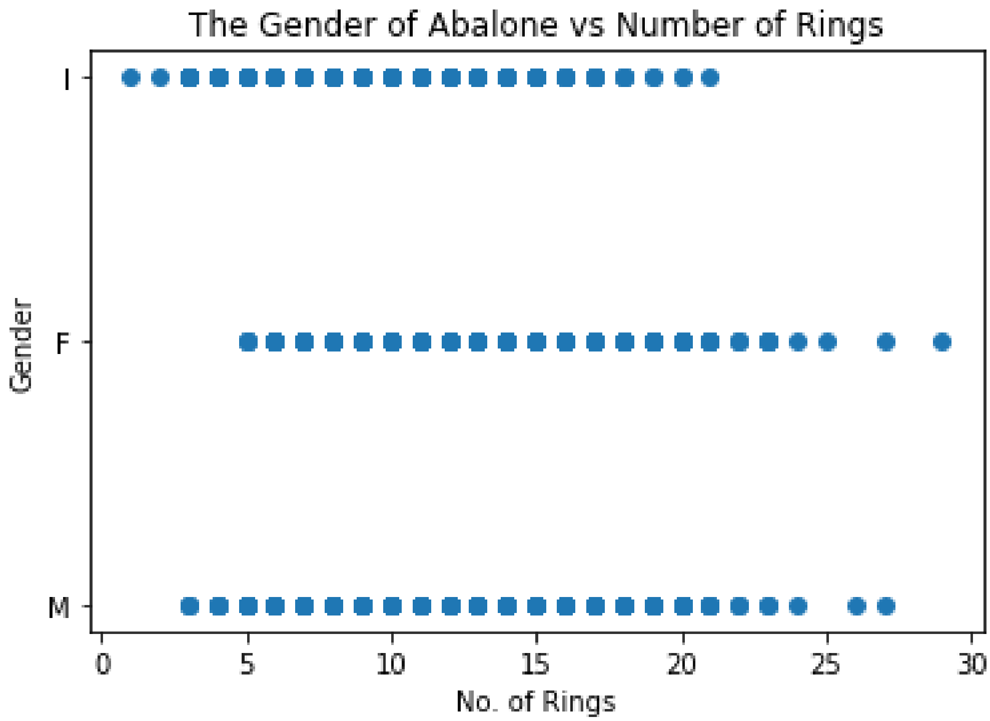
```
OUT[]: array([[,
         ,
         ],
        [,
         ,
         ],
        [,
         ,
         ]],
       dtype=object)
```



· Bi-Variate Analysis

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

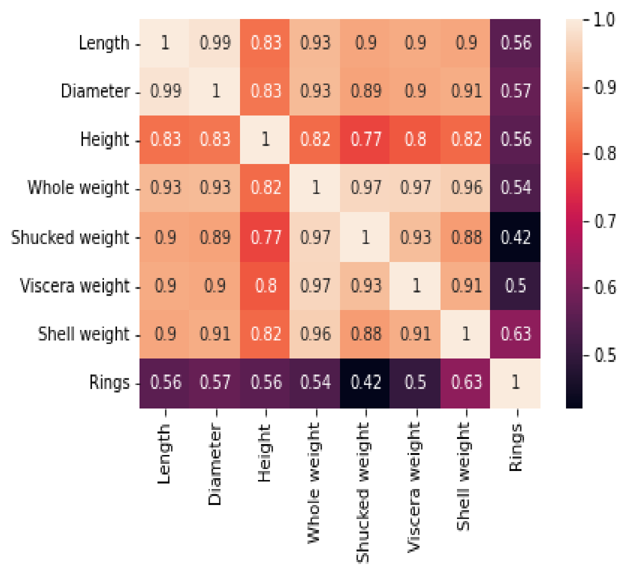
```
OUT[]: Text(0, 0.5, 'Gender')
```



Multi-Variate Analysis

```
IN[]: sb.heatmap(data.corr(),annot=True)
```

OUT[]:



	Length	Diameter	Height	Whole weight	Shucked weight	Viscera weight	Shell weight	Rings
Length	1	0.99	0.83	0.93	0.9	0.9	0.9	0.56
Diameter	0.99	1	0.83	0.93	0.89	0.9	0.91	0.57
Height	0.83	0.83	1	0.82	0.77	0.8	0.82	0.56
Whole weight	0.93	0.93	0.82	1	0.97	0.97	0.96	0.54
Shucked weight	0.9	0.89	0.77	0.97	1	0.93	0.88	0.42
Viscera weight	0.9	0.9	0.8	0.97	0.93	1	0.91	0.5
Shell weight	0.9	0.91	0.82	0.96	0.88	0.91	1	0.63
Rings	0.56	0.57	0.56	0.54	0.42	0.5	0.63	1

4. Perform descriptive statistics on the dataset.

```
IN[]:data.info()


    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()
```

```
IN[]: 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

	Length	Diameter	Height	Whole weight	Shucked weight	Viscera weight	Shell weight	Rings
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. Check for Missing values and deal with them.

There is no missing values

```
IN[]:data.isnull().any()
```

```
OUT[]: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 outliers and replace them outliers

The dataset does not have a outliers

In [ ]:

```
IN[]: fig = px.histogram(data, x='Whole weight')
fig.show()
```

7. Check for Categorical columns and perform encoding.

There is one Categorical column SEX is replaced by an Integer

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

```
OUT[]:
      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.

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

```
 IN[]: x
 OUT[]:

 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 ]])
```

```
 IN[]:   y
OUT[]:array([[15],
           [ 7],
           [ 9],
            ...,
           [ 9],
           [10],
           [12]])
```

9. Scale the independent variables

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

OUT[]:   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 training and testing

```
 from sklearn.model_selection import train_test_split
  x_train,x_test,y_train,y_test =


IN[]:  train_test_split(x,y,test_size=0.3,random_state=0)


IN[]: x_train.shape

OUT[]:(2923, 8)

IN[]:x_test.shape

OUT[]:(836, 8)
```

11. Build the Model

IN[]:
```
from sklearn.linear_model import LinearRegression
lr = LinearRegression()
```

12. Train the Model

IN[]:
```
lr.fit(x_train, y_train)
```
```
LinearRegression()
```

13. Test the Model

IN[]:
```
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)
```

IN[]:
```
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 : 2.26
```

IN[]:
```
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
```