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.

Building a Regression Model

1. Download the 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.

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
```

2. Load the dataset into the tool

In [ ]:

```
data = 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
...	...	...	...	...	...	...	...	...	...
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. Perform Below Visualizations.

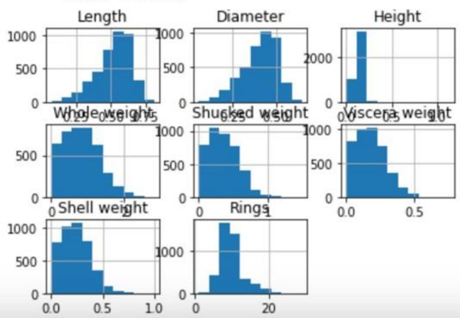
- Univariate Analysis

In [ ]:

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

Out[ ]:

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



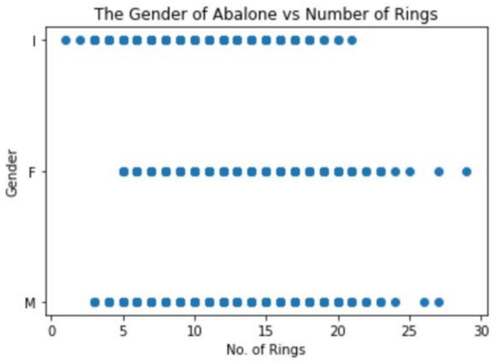
- Bi-Variate Analysis

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')
```

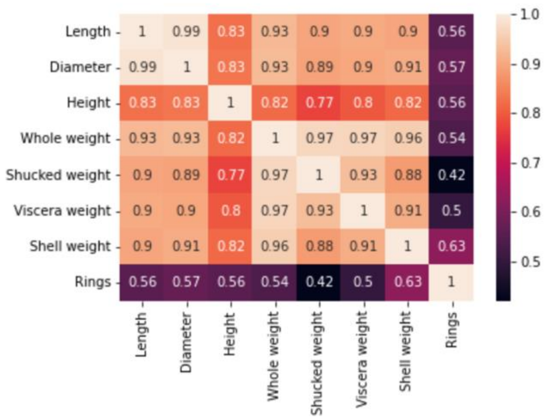


- Multi-Variate Analysis

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
```

In [ ]:

```
data.describe()
```

Out[ ]:

	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. 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 [ ]:

```
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())
```

```
   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

In [ ]:
```
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)
```

In [ ]:
```
x_train.shape
```

Out[ ]:
```
(2923, 8)
```

In [ ]:
```
x_test.shape
```

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

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)
```

Out[ ]: 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.

In [ ]:

```
# 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 : 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
```