

```

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

Mounted at /content/gdrive

from google.colab import files
uploaded = files.upload()

<IPython.core.display.HTML object>

Saving abalone.csv to abalone.csv

```

2. Load the dataset into the tool

```

import pandas as pd
import io
import numpy as np

df = pd.read_csv(io.BytesIO(uploaded['abalone.csv']))
df.head()

```

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

	Shell weight	Rings
0	0.150	15
1	0.070	7
2	0.210	9
3	0.155	10
4	0.055	7

3. Perform Below Visualizations. · Univariate Analysis · Bi-Variate Analysis · Multi-Variate Analysis

Univariate Analysis

```

import seaborn as sns
import matplotlib.pyplot as plt
import sklearn
import matplotlib.pyplot as plt

```

```

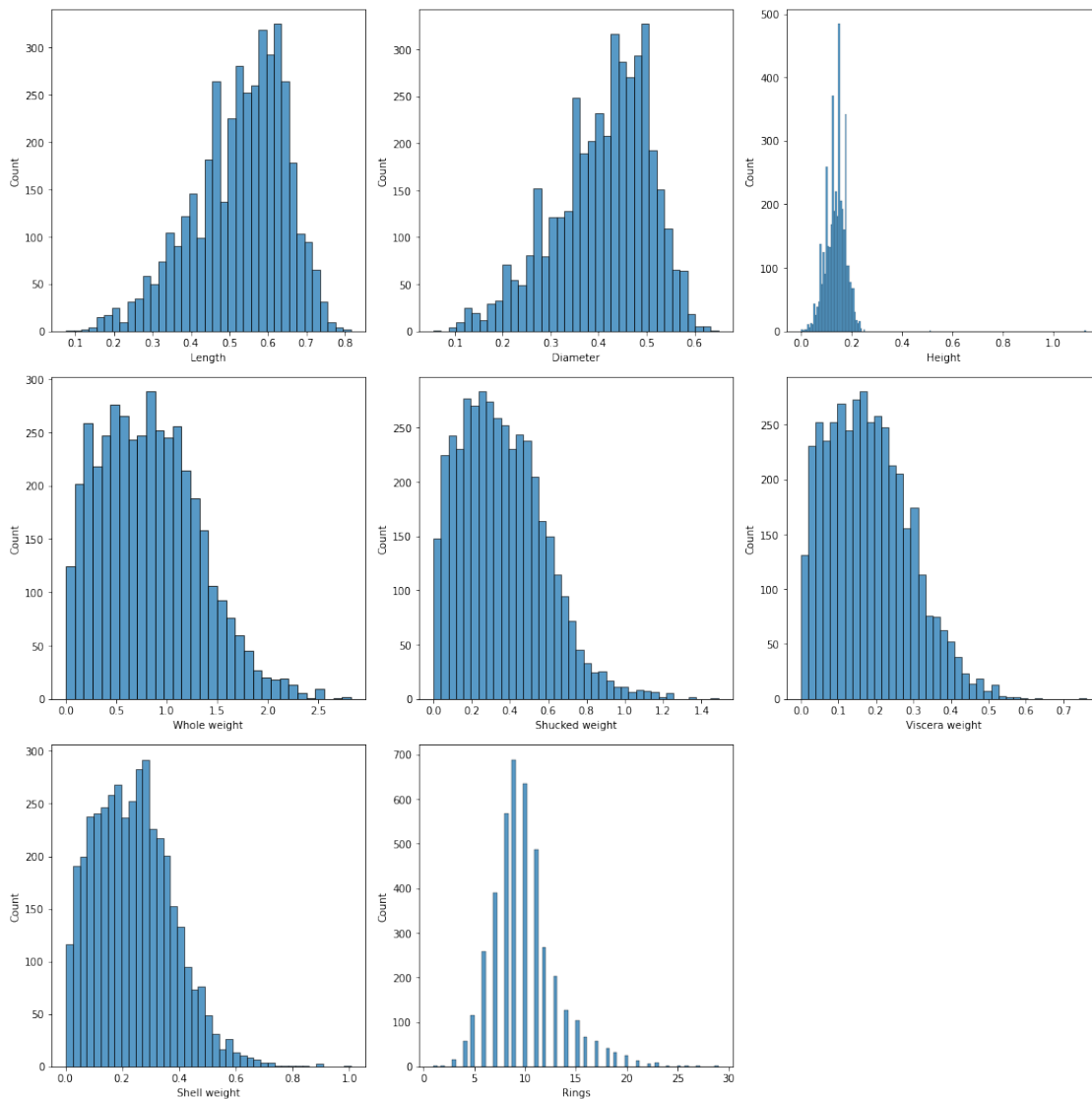
cols = 3
rows = 3
num_cols = df.select_dtypes(exclude='object').columns
fig = plt.figure(figsize=(cols*5, rows*5))
for i, col in enumerate(num_cols):

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

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

fig.tight_layout()
plt.show()

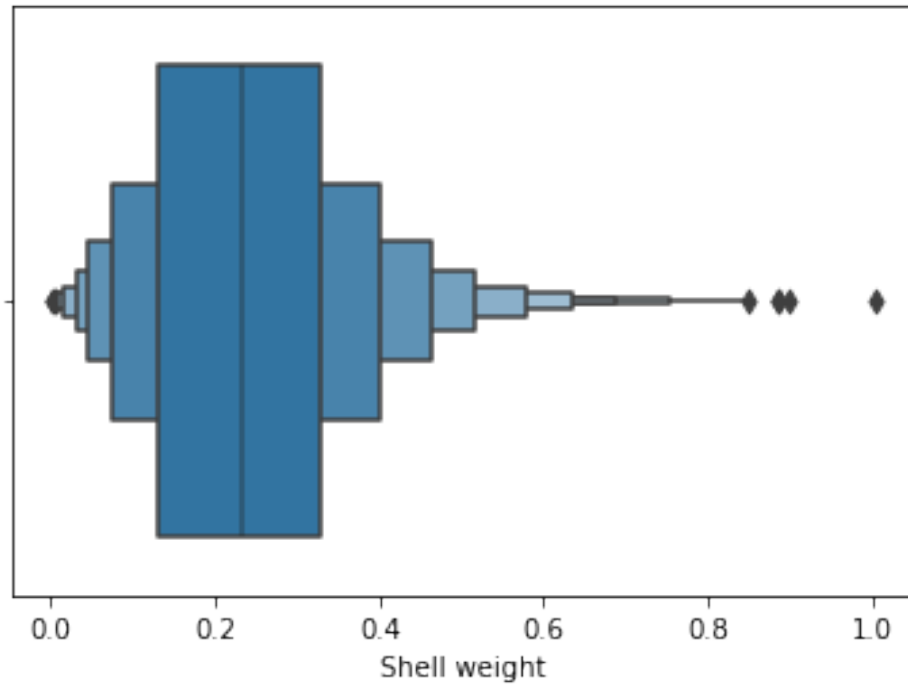
```



```

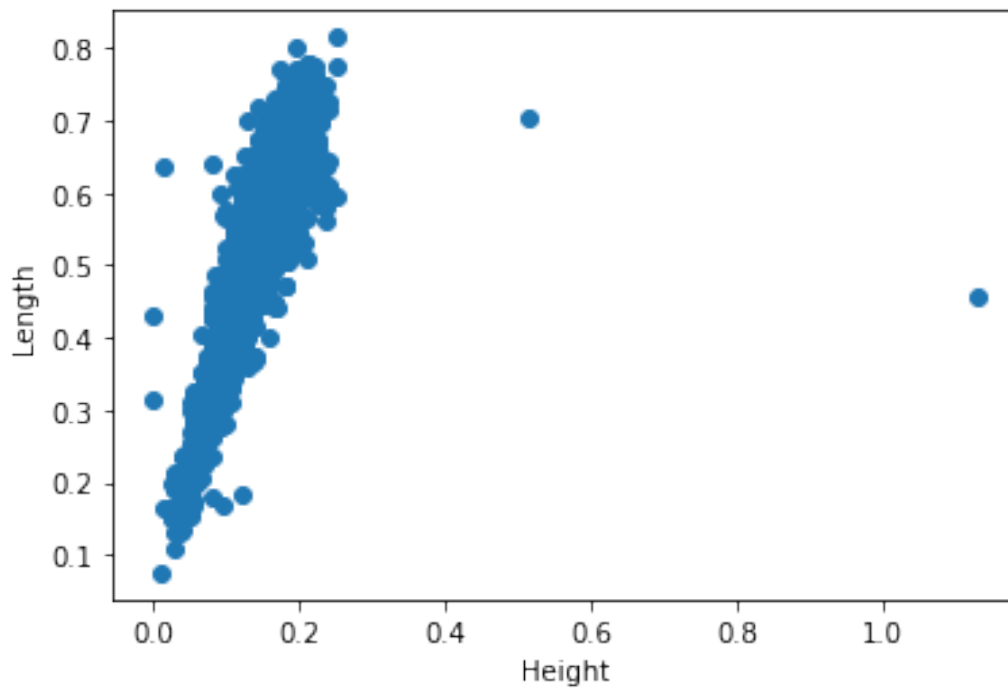
sns.boxenplot(x=df["Shell weight"])
<matplotlib.axes._subplots.AxesSubplot at 0x7fafc8665210>

```



Bi-Variate Analysis

```
plt.scatter(df.Height,df.Length)  
plt.xlabel('Height')  
plt.ylabel('Length')  
Text(0, 0.5, 'Length')
```



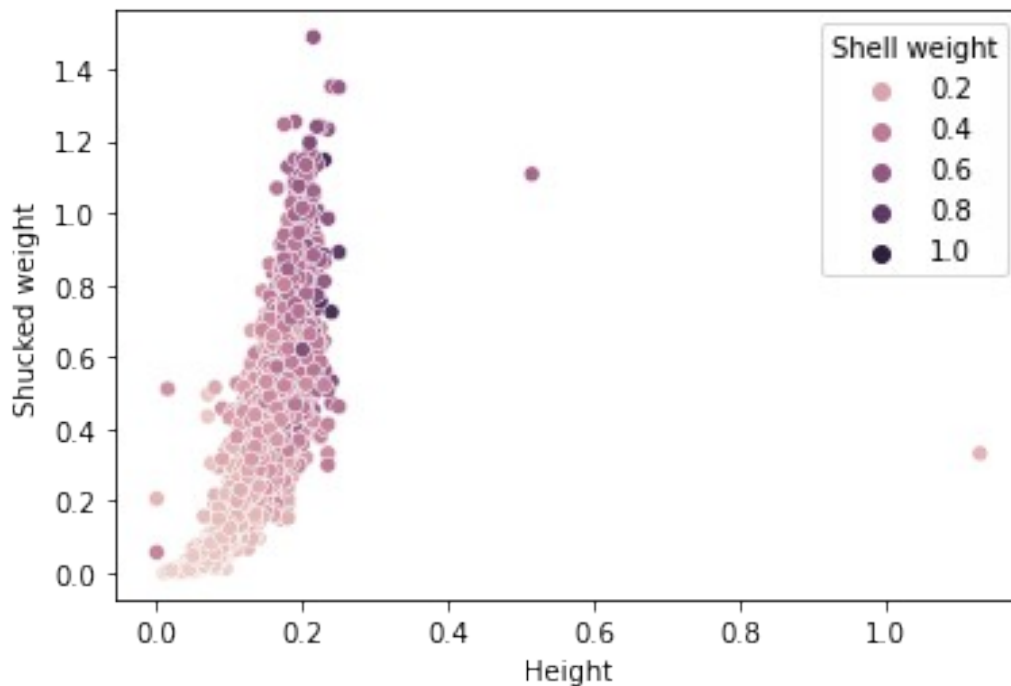
Multi-Variate Analysis

```
sns.scatterplot(df['Height'], df['Shucked weight'], hue = df['Shell weight'])
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43:
FutureWarning: Pass the following variables as keyword args: x, y.
From version 0.12, the only valid positional argument will be `data`,
and passing other arguments without an explicit keyword will result in
an error or misinterpretation.
```

FutureWarning

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fafcabb110>
```



4. Perform descriptive statistics on the dataset.

```
df.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
```

```
df.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
```

```
df.mode()
```

	Sex	Length	Diameter	Height	Whole weight	Shucked weight	\
0	M	0.550	0.45	0.15	0.2225	0.175	
1	NaN	0.625	NaN	NaN	NaN	NaN	

	Viscera weight	Shell weight	Rings
0	0.1715	0.275	9.0
1	NaN	NaN	NaN

5. Check for Missing values and deal with them.

```
df.isnull().sum()
```

```
Sex            0
Length         0
Diameter       0
Height         0
Whole weight   0
Shucked weight 0
Viscera weight 0
Shell weight   0
Rings         0
dtype: int64
```

There is no missing values

6. Find the outliers and replace them outliers

```
df['Shell weight'] = np.where(df['Shell weight'] > 325, 140, df['Shell weight'])
df.describe()
```

	Length	Diameter	Height	Whole weight	Shucked
weight \					
count	4177.000000	4177.000000	4177.000000	4177.000000	4177.000000
mean	0.523992	0.407881	0.139516	0.828742	0.359367
std	0.120093	0.099240	0.041827	0.490389	0.221963
min	0.075000	0.055000	0.000000	0.002000	0.001000
25%	0.450000	0.350000	0.115000	0.441500	0.186000
50%	0.545000	0.425000	0.140000	0.799500	0.336000
75%	0.615000	0.480000	0.165000	1.153000	0.502000
max	0.815000	0.650000	1.130000	2.825500	1.488000

	Viscera weight	Shell weight	Rings
count	4177.000000	4177.000000	4177.000000
mean	0.180594	0.238831	9.933684
std	0.109614	0.139203	3.224169
min	0.000500	0.001500	1.000000
25%	0.093500	0.130000	8.000000
50%	0.171000	0.234000	9.000000
75%	0.253000	0.329000	11.000000
max	0.760000	1.005000	29.000000

1. Check for Categorical columns and perform encoding.

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

```
categorical_columns_selector = selector(dtype_include=object)
categorical_columns = categorical_columns_selector(df)
categorical_columns
```

```
['Sex']
```

```
data_categorical = df[categorical_columns]
data_categorical.head()
```

	Sex
0	M
1	M
2	F
3	M
4	I

```

from sklearn import preprocessing

label_encoder = preprocessing.LabelEncoder()

df['Sex']= label_encoder.fit_transform(df['Sex'])
df['Sex'].unique()

array([2, 0, 1])

```

1. Split the data into dependent and independent variables.

```

x=df.iloc[:, :-1]
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

```

y=df.iloc[:, -1]
y.head()

```

```

0    15
1     7
2     9
3    10
4     7
Name: Rings, dtype: int64

```

.9. Scale the independent variables

```

from sklearn.preprocessing import StandardScaler
scaler=StandardScaler()
x=scaler.fit_transform(x)

```

```

df_scaled =df.copy()
col_names = ['Shucked weight', 'Whole weight']
features = df_scaled[col_names]
from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler()
df_scaled[col_names] = scaler.fit_transform(features.values)
from sklearn.preprocessing import MinMaxScaler

```

```
scaler = MinMaxScaler(feature_range=(5, 10))
```

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

	Sex	Length	Diameter	Height	Whole weight	Shucked weight \
0	2	0.455	0.365	0.095	5.906676	5.751513
1	2	0.350	0.265	0.090	5.395785	5.331204
2	0	0.530	0.420	0.135	6.195325	5.859112
3	2	0.440	0.365	0.125	5.910218	5.721251
4	1	0.330	0.255	0.080	5.359483	5.297579
...
4172	0	0.565	0.450	0.165	6.567204	6.240753
4173	2	0.590	0.440	0.135	6.707101	6.472764
4174	2	0.600	0.475	0.205	7.078980	6.763618
4175	0	0.625	0.485	0.150	6.934656	6.782112
4176	2	0.710	0.555	0.195	8.446963	8.175857

	Viscera weight	Shell weight	Rings
0	0.1010	0.1500	15
1	0.0485	0.0700	7
2	0.1415	0.2100	9
3	0.1140	0.1550	10
4	0.0395	0.0550	7
...
4172	0.2390	0.2490	11
4173	0.2145	0.2605	10
4174	0.2875	0.3080	9
4175	0.2610	0.2960	10
4176	0.3765	0.4950	12

```
[4177 rows x 9 columns]
```

10.Split the data into training 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=0.33)
```

```
x_train.shape
```

```
(2798, 8)
```

```
x_test.shape
```

```
(1379, 8)
```

1. Build the Model

```
from sklearn.ensemble import RandomForestRegressor
reg=RandomForestRegressor()
```


1. Train the Model

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

```
RandomForestRegressor()
```

13. Test the Model

```
y_pred=reg.predict(x_test)
```

```
print(y_pred)
```

```
[ 9.28  7.07 10.19 ...  8.58 11.18  6.61]
```

14. Measure the performance using Metrics.

```
from sklearn.metrics import mean_squared_error
```

```
import math
```

```
print(math.sqrt(mean_squared_error(y_test,y_pred)))
```

```
2.179257695735751
```