1. Importing necessary Modules

In [1]:

```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import numpy as np
```

2.Uploading the given Dataset

In [2]:

```
data=pd.read_csv("abalone.csv")
data.head()
```

Out[2]:

	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

In [3]:

```
data.shape
```

Out[3]:

```
(4177, 9)
```

In [4]:

```
#Modifying the given dataset
Age=1.5+data.Rings
data["Age"]=Age
data=data.rename(columns = {'Whole weight':'Whole_weight','Shucked weight': 'Shucked_weight','Viscera weight': 'Viscera_weight',
                            'Shell weight': 'Shell_weight'})
data=data.drop(columns=["Rings"],axis=1)
data.head()
```

Out[4]:

	Sex	Length	Diameter	Height	Whole_weight	Shucked_weight	Viscera_weight	Shell_weight	Age
0	M	0.455	0.365	0.095	0.5140	0.2245	0.1010	0.150	16.5
1	M	0.350	0.265	0.090	0.2255	0.0995	0.0485	0.070	8.5
2	F	0.530	0.420	0.135	0.6770	0.2565	0.1415	0.210	10.5
3	M	0.440	0.365	0.125	0.5160	0.2155	0.1140	0.155	11.5
4	I	0.330	0.255	0.080	0.2050	0.0895	0.0395	0.055	8.5

In [5]:

```
data.info()
```

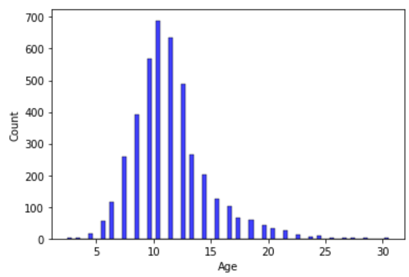
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4177 entries, 0 to 4176
Data columns (total 9 columns):
 #   Column          Non-Null Count  Dtype  
---  ------          --------------  -----  
 0   Sex             4177 non-null   object 
 1   Length          4177 non-null   float64
 2   Diameter        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   Age             4177 non-null   float64
dtypes: float64(8), object(1)
memory usage: 293.8+ KB
```

3.Performing various Visualizations

Univariate Analysis

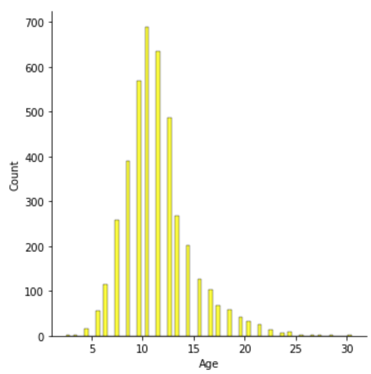
In [6]:
```
sns.histplot(data["Age"],color='blue')
```

Out[6]: <matplotlib.axes._subplots.AxesSubplot at 0x7f5db9fa2690>



In [7]:
```
sns.displot(data["Age"],color='yellow')
```

Out[7]: <seaborn.axisgrid.FacetGrid at 0x7f5db9e01a10>

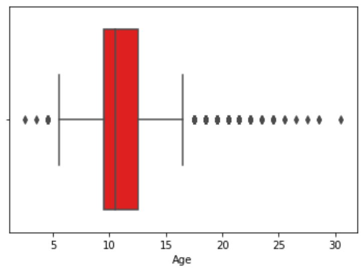


In [8]:

```
sns.boxplot(data["Age"],color='red')
```

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

Out[8]: <matplotlib.axes._subplots.AxesSubplot at 0x7f5db70117d0>



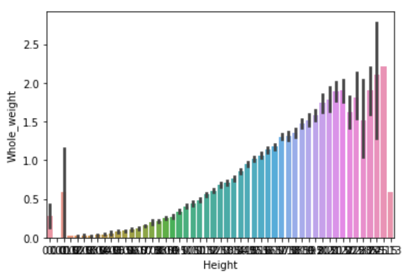
Bivariate Analysis

In [9]:

```
sns.barplot(data["Height"],data["Whole_weight"])
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarning: Pass the following variables as keyword args: x, y. From version 0.1
2, the only valid positional argument will be `data`, and passing other arguments without an explicit keyword will result in an error or misinterpreta
tion.
  FutureWarning
```

Out[9]: <matplotlib.axes._subplots.AxesSubplot at 0x7f5db6f99750>

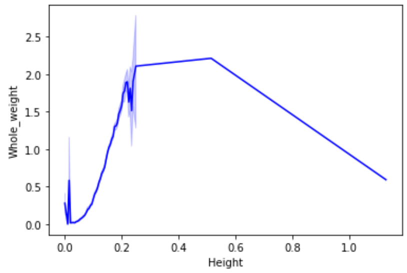


In [10]:

```
sns.lineplot(data["Height"],data["Whole_weight"], color='blue')
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarning: Pass the following variables as keyword args: x, y. From version 0.1
2, the only valid positional argument will be `data`, and passing other arguments without an explicit keyword will result in an error or misinterpreta
tion.
  FutureWarning
```

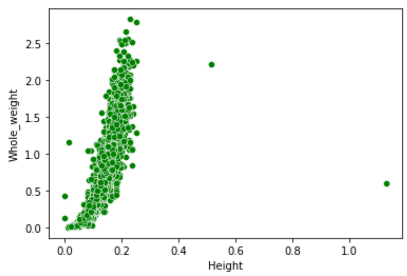
Out[10]: <matplotlib.axes._subplots.AxesSubplot at 0x7f5db6cfcbd0>



In [11]:

```
sns.scatterplot(x=data.Height,y=data.Whole_weight,color='green')
```

Out[11]: <matplotlib.axes._subplots.AxesSubplot at 0x7f5db6d38110>

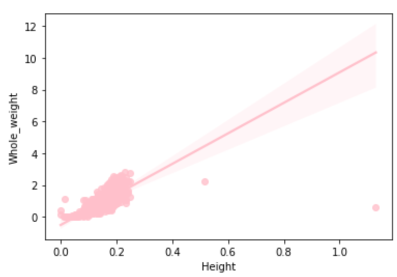


In [12]:

```
sns.regplot(data['Height'],data['Whole_weight'],color='pink')
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarning: Pass the following variables as keyword args: x, y. From version 0.1
2, the only valid positional argument will be `data`, and passing other arguments without an explicit keyword will result in an error or misinterpreta
tion.
  FutureWarning
```

Out[12]: <matplotlib.axes._subplots.AxesSubplot at 0x7f5db6d5f9d0>

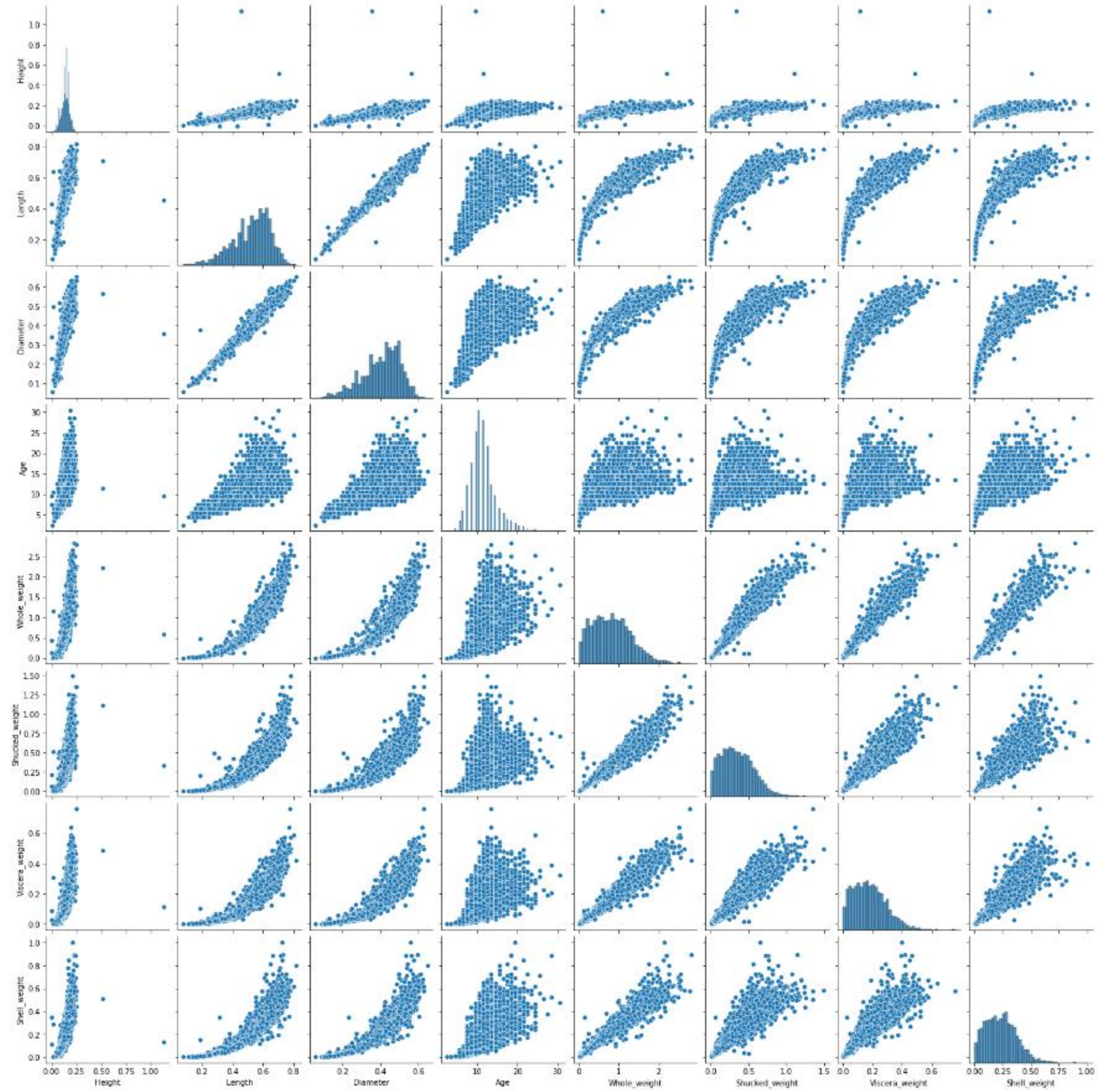


Multivariate Analysis

In [13]:

```
sns.pairplot(data=data[["Height","Length","Diameter","Age","Whole_weight","Shucked_weight","Viscera_weight","Shell_weight"]])
```

Out[13]: <seaborn.axisgrid.PairGrid at 0x7f5db6c59d10>



4. Performing descriptive statistics on the dataset.

In [14]:
```
data.describe(include='all')
```

Out[14]:

	Sex	Length	Diameter	Height	Whole_weight	Shucked_weight	Viscera_weight	Shell_weight	Age
count	4177	4177.000000	4177.000000	4177.000000	4177.000000	4177.000000	4177.000000	4177.000000	4177.000000
unique	3	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
top	M	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
freq	1528	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
mean	NaN	0.523992	0.407881	0.139516	0.828742	0.359367	0.180594	0.238831	11.433684
std	NaN	0.120093	0.099240	0.041827	0.490389	0.221963	0.109614	0.139203	3.224169
min	NaN	0.075000	0.055000	0.000000	0.002000	0.001000	0.000500	0.001500	2.500000
25%	NaN	0.450000	0.350000	0.115000	0.441500	0.186000	0.093500	0.130000	9.500000
50%	NaN	0.545000	0.425000	0.140000	0.799500	0.336000	0.171000	0.234000	10.500000
75%	NaN	0.615000	0.480000	0.165000	1.153000	0.502000	0.253000	0.329000	12.500000
max	NaN	0.815000	0.650000	1.130000	2.825500	1.488000	0.760000	1.005000	30.500000

5. Checking for Missing values

In [15]:
```
data.isnull().sum()
```

Out[15]:
```
Sex               0
Length            0
Diameter          0
Height            0
Whole_weight      0
Shucked_weight    0
Viscera_weight    0
Shell_weight      0
Age               0
dtype: int64
```

6. Finding the outliers and replacing them outliers

In [16]:
```
outliers=data.quantile(q=(0.25,0.75))
outliers
```

Out[16]:

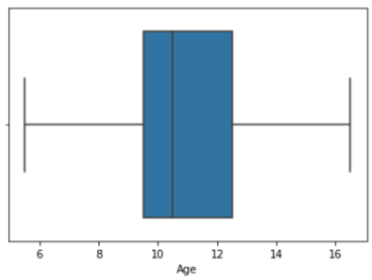
	Length	Diameter	Height	Whole_weight	Shucked_weight	Viscera_weight	Shell_weight	Age
0.25	0.450	0.35	0.115	0.4415	0.186	0.0935	0.130	9.5
0.75	0.615	0.48	0.165	1.1530	0.502	0.2530	0.329	12.5

In [17]:
```
q1 = data.Age.quantile(0.25)
q3 = data.Age.quantile(0.75)
IQR = q3 - q1
lower_limit = q1 - 1.5 * IQR
data.median(numeric_only=True)
```

Out[17]:
```
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
Age               10.5000
dtype: float64
```

In [18]:
```
data['Age'] = np.where(data['Age'] < lower_limit, 7, data['Age'])
sns.boxplot(x=data.Age,showfliers = False)
```

Out[18]: <matplotlib.axes._subplots.AxesSubplot at 0x7f5db4d71950>



7.Checking for Categorical columns and perform Encoding

In [19]:
```
data.head()
```

Out[19]:

	Sex	Length	Diameter	Height	Whole_weight	Shucked_weight	Viscera_weight	Shell_weight	Age
0	M	0.455	0.365	0.095	0.5140	0.2245	0.1010	0.150	16.5
1	M	0.350	0.265	0.090	0.2255	0.0995	0.0485	0.070	8.5
2	F	0.530	0.420	0.135	0.6770	0.2565	0.1415	0.210	10.5
3	M	0.440	0.365	0.125	0.5160	0.2155	0.1140	0.155	11.5
4	I	0.330	0.255	0.080	0.2050	0.0895	0.0395	0.055	8.5

8. Split the data into dependent and independent variables

In [22]:
```
y = data["Sex"]
y.head()
```

Out[22]:
```
0    2
1    2
2    0
3    2
4    1
Name: Sex, dtype: int64
```

In [23]:
```
x=data.drop(columns=["Sex"],axis=1)
x.head()
```

Out[23]:

	Length	Diameter	Height	Whole_weight	Shucked_weight	Viscera_weight	Shell_weight	Age
0	0.455	0.365	0.095	0.5140	0.2245	0.1010	0.150	16.5
1	0.350	0.265	0.090	0.2255	0.0995	0.0485	0.070	8.5
2	0.530	0.420	0.135	0.6770	0.2565	0.1415	0.210	10.5
3	0.440	0.365	0.125	0.5160	0.2155	0.1140	0.155	11.5
4	0.330	0.255	0.080	0.2050	0.0895	0.0395	0.055	8.5

9.Scaling the values

In [24]:
```
from sklearn.preprocessing import scale
X_Scaled = pd.DataFrame(scale(x), columns=x.columns)
X_Scaled.head()
```

Out[24]:

	Length	Diameter	Height	Whole_weight	Shucked_weight	Viscera_weight	Shell_weight	Age
0	-0.574558	-0.432149	-1.064424	-0.641898	-0.607685	-0.726212	-0.638217	1.577830
1	-1.448986	-1.439929	-1.183978	-1.230277	-1.170910	-1.205221	-1.212987	-0.919022
2	0.050033	0.122130	-0.107991	-0.309469	-0.463500	-0.356690	-0.207139	-0.294809
3	-0.699476	-0.432149	-0.347099	-0.637819	-0.648238	-0.607600	-0.602294	0.017298
4	-1.615544	-1.540707	-1.423087	-1.272086	-1.215968	-1.287337	-1.320757	-0.919022

10. Split the data into training and testing

In [25]:
```
from sklearn.model_selection import train_test_split
X_Train, X_Test, Y_Train, Y_Test = train_test_split(X_Scaled, y, test_size=0.2, random_state=0)
```

In [26]:
```
X_Train.shape,X_Test.shape
```

Out[26]:
```
((3341, 8), (836, 8))
```

In [27]:
```
Y_Train.shape,Y_Test.shape
```

Out[27]:
```
((3341,), (836,))
```

In [28]:
```
X_Train.head()
```

Out[28]:

	Length	Diameter	Height	Whole_weight	Shucked_weight	Viscera_weight	Shell_weight	Age
3141	-2.864726	-2.750043	-1.423087	-1.622870	-1.553902	-1.583867	-1.644065	-1.543234
3521	-2.573250	-2.598876	-2.020857	-1.606554	-1.551650	-1.565619	-1.626104	-1.387181
883	1.132658	1.230689	0.728888	1.145672	1.041436	0.286552	1.538726	1.577830
3627	1.590691	1.180300	1.446213	2.164373	2.661269	2.330326	1.377072	0.017298
2106	0.591345	0.474853	0.370226	0.432887	0.255175	0.272866	0.906479	1.265723

In [29]:
```
X_Test.head()
```

Out[29]:

	Length	Diameter	Height	Whole_weight	Shucked_weight	Viscera_weight	Shell_weight	Age
668	0.216591	0.172519	0.370226	0.181016	-0.368878	0.569396	0.690940	0.953617
1580	-0.199803	-0.079426	-0.466653	-0.433875	-0.443224	-0.343004	-0.325685	-0.606915
3784	0.799543	0.726798	0.370226	0.870348	0.755318	1.764639	0.565209	0.329404
463	-2.531611	-2.447709	-2.020857	-1.579022	-1.522362	-1.538247	-1.572219	-1.543234
2615	1.007740	0.928354	0.848442	1.390405	1.415417	1.778325	0.996287	0.641511

In [30]:
```
Y_Train.head()
```

Out[30]:
```
3141    1
3521    1
883     2
3627    2
2106    2
Name: Sex, dtype: int64
```

In [31]:
```
Y_Test.head()
```

Out[31]:
```
668     2
1580    1
3784    2
463     1
2615    2
Name: Sex, dtype: int64
```

11. Build the Model

In [32]:
```
from sklearn.ensemble import RandomForestClassifier
model = RandomForestClassifier(n_estimators=10,criterion='entropy')
```

In [33]:
```
model.fit(X_Train,Y_Train)
```

Out[33]:
```
RandomForestClassifier(criterion='entropy', n_estimators=10)
```

In [34]:
```
y_predict = model.predict(X_Test)
```

In [35]:
```
y_predict_train = model.predict(X_Train)
```

12. Train the Model

In [36]:
```
from sklearn.metrics import accuracy_score,confusion_matrix,classification_report
```

In [37]:
```
print('Training accuracy: ',accuracy_score(Y_Train,y_predict_train))
```

```
Training accuracy:  0.9811433702484286
```

13.Test the Model

In [38]:

```
print('Testing accuracy: ',accuracy_score(Y_Test,y_predict))
```

```
Testing accuracy:  0.5526315789473685
```

14. Measure the performance using Metrics

In [39]:

```
pd.crosstab(Y_Test,y_predict)
```

Out[39]:

col_0	0	1	2
Sex			
0	112	33	104
1	45	211	35
2	100	57	139

In [40]:

```
print(classification_report(Y_Test,y_predict))
```

```
              precision    recall  f1-score   support

           0       0.44      0.45      0.44       249
           1       0.70      0.73      0.71       291
           2       0.50      0.47      0.48       296

    accuracy                           0.55       836
   macro avg       0.55      0.55      0.55       836
weighted avg       0.55      0.55      0.55       836
```