Assignment – 3

Python Programming

Assignment Date	
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Maximum Marks	2 Marks

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.

Importing Modules

In [ ]:

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

1. Dataset has been downloaded

In [ ]:

```
#Name of the dataset: abalone.csv
```

2. Load the dataset into the tool

In [ ]:

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

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	0.150	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

Let's know the shape of the data

In [ ]:

```
data.shape
```

(4177, 9) Out[ ]:

One additional task is that, we have to add the "Age" column using "Rings" data. We just have to add '1.5' to the ring data

In [ ]:

```
Age=1.5+data.Rings data["Age"]=Age data=data.rename(columns = {'Whole weight':'Whole_weight','Shucked weight': 'Sh
                              'Shell weight': 'Shell_weight'})
data=data.drop(columns=["Rings"],axis=1) data.head()
```

Out[ ]:

	Sex	Length	Diameter	Height	Whole_weight	Shucked_weight	Viscera_weight	Shell_weig
0	M	0.455	0.365	0.095	0.5140	0.2245	0.1010	0.1
1	M	0.350	0.265	0.090	0.2255	0.0995	0.0485	0.0
2	F	0.530	0.420	0.135	0.6770	0.2565	0.1415	0.2
3	M	0.440	0.365	0.125	0.5160	0.2155	0.1140	0.1
4	I	0.330	0.255	0.080	0.2050	0.0895	0.0395	0.0

3. Perform Below Visualizations.

(i) Univariate Analysis

#

The term univariate analysis refers to the analysis of one variable. You can remember this because the prefix “uni” means “one.” There are three common ways to perform univariate analysis on one variable: 1. Summary statistics – Measures the center and spread of values.

#

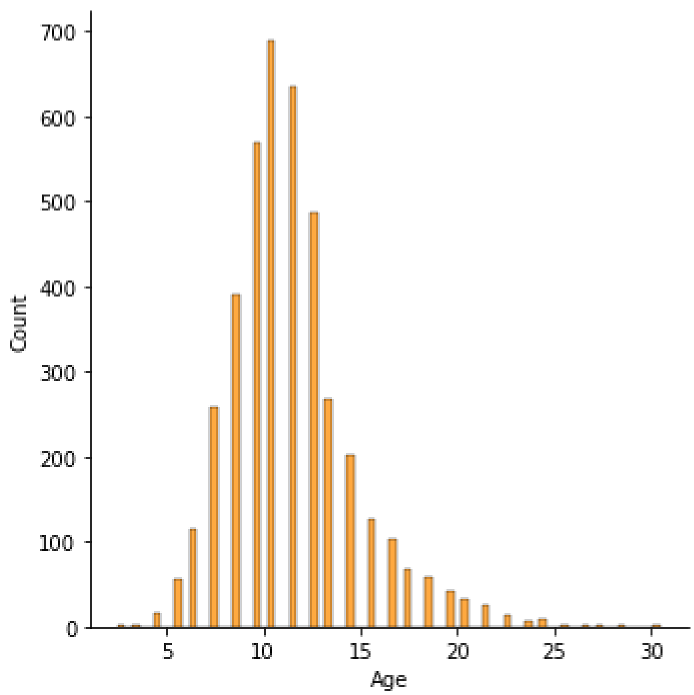
Histogram

In [ ]:

```
sns.displot(data["Age"], color='darkorange')
```

Out[ ]:

```
<seaborn.axisgrid.FacetGrid at 0x7fd3f837a430>
```

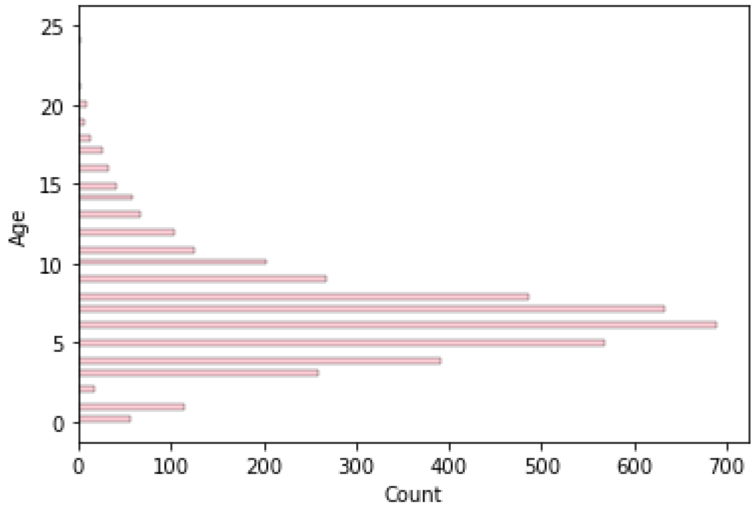


In [ ]:

```
sns.histplot(y=data.Age,color='pink')
```

Out[ ]:

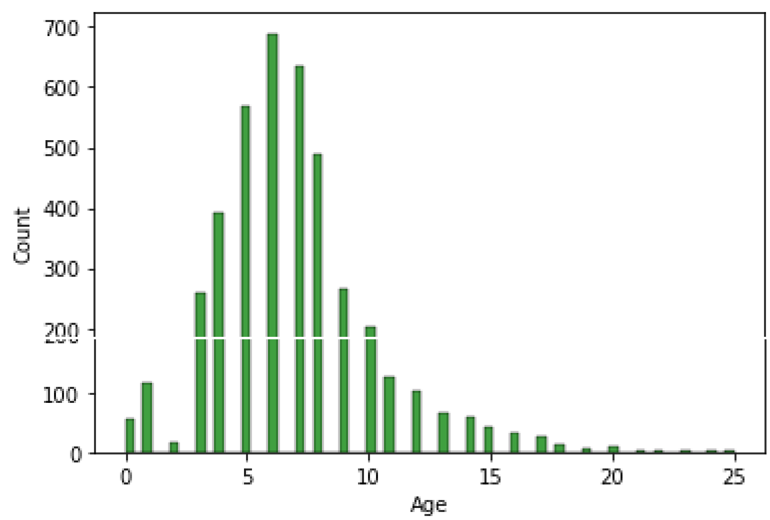
```
<AxesSubplot:xlabel='Count', ylabel='Age'>
```



In [ ]:

```
sns.histplot(x=data.Age,color='green')
```

Out[ ]: < AxesSubplot:xlabel='Age', ylabel='Count'>



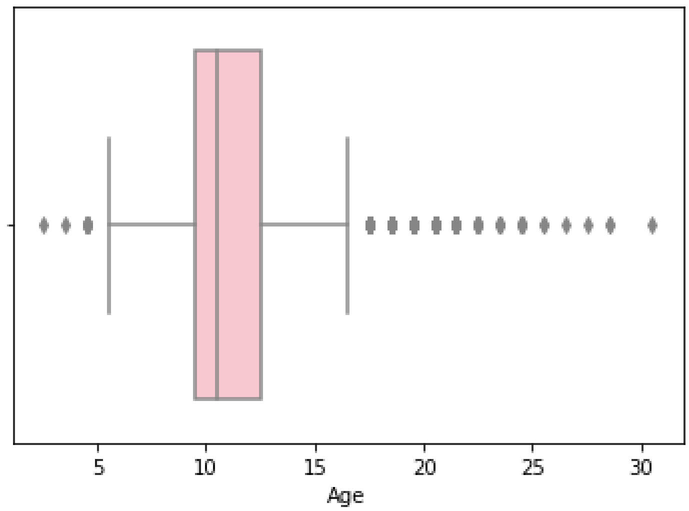
Boxplot

In [ ]:

```
sns.boxplot(x=data.Age,color='pink')
```

<AxesSubplot:xlabel='Age'> Out[

]:

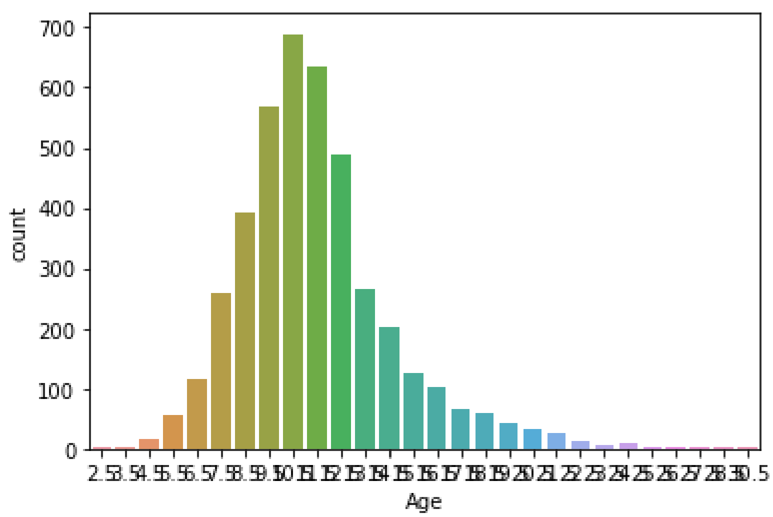


Countplot

In [ ]:

```
sns.countplot(x=data.Age)
```

<AxesSubplot:xlabel='Age', ylabel='count'> Out[
 ]:



(ii) Bi-Variate Analysis

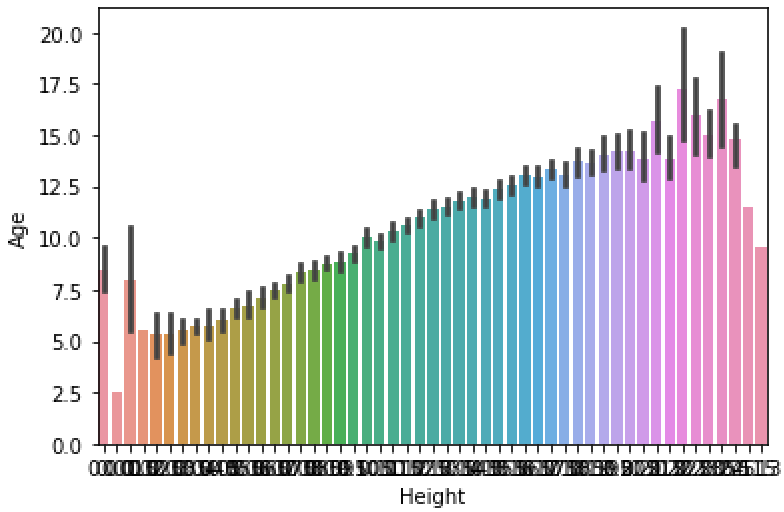
#

Image result for bivariate analysis in python It is a methodical statistical technique applied to a pair of variables (features/ attributes) of data to determine the empirical relationship between them. In order words, it is meant to determine any concurrent relations (usually over and above a simple correlation analysis).

Barplot

In [ ]:
```
sns.barplot(x=data.Height,y=data.Age)
```

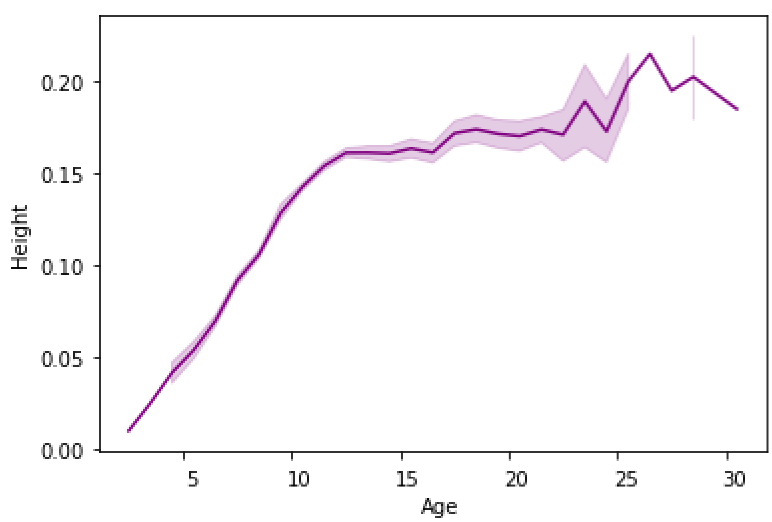
<AxesSubplot:xlabel='Height', ylabel='Age'> Out[
]:



Linearplot

In [ ]:
```
sns.lineplot(x=data.Age,y=data.Height, color='purple')
```

<AxesSubplot:xlabel='Age', ylabel='Height'> Out[
]:

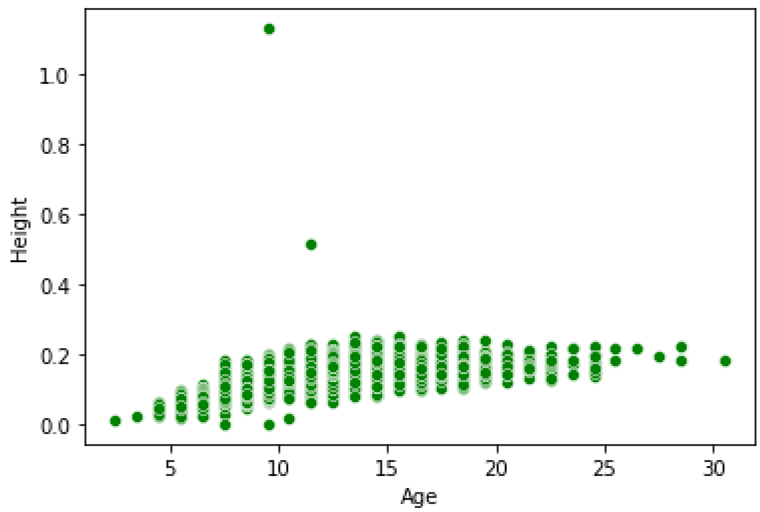


Scatterplot

In [ ]:

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

Out[ ]: <AxesSubplot:xlabel='Age', ylabel='Height'>

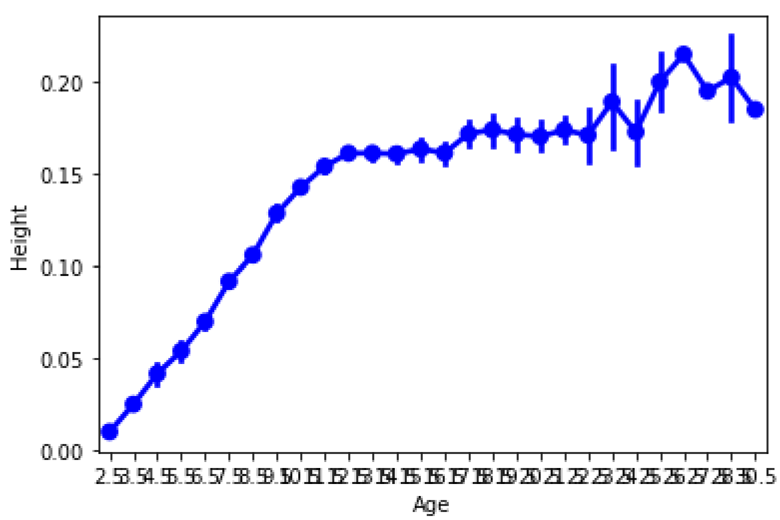


Pointplot

In [ ]:

```
sns.pointplot(x=data.Age, y=data.Height, color="blue")
```

Out[ ]: <AxesSubplot:xlabel='Age', ylabel='Height'>

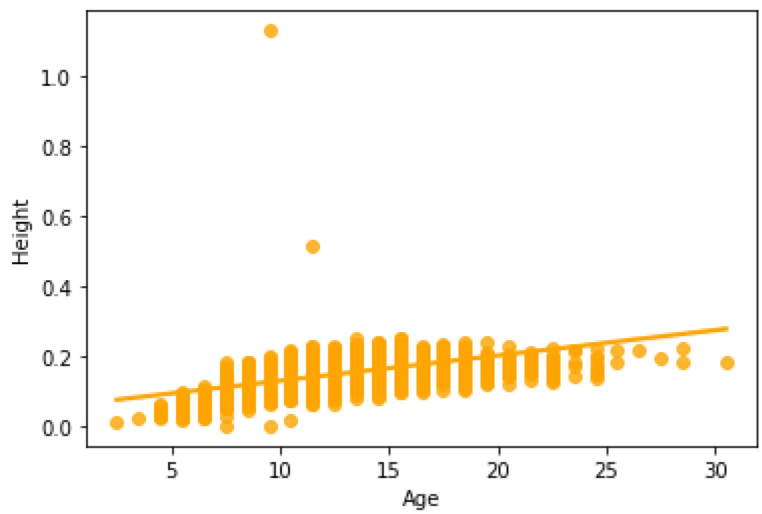


Regplot

In [ ]:

```
sns.regplot(x=data.Age,y=data.Height,color='orange')
```

<AxesSubplot:xlabel='Age', ylabel='Height'> Out[ ]:



(iii) Multi-Variate Analysis

# #

Multivariate analysis is based in observation and analysis of more than one statistical outcome variable at a time. In design and analysis, the technique is used to perform trade studies across multiple dimensions while taking into account the effects of all variables on the responses of interest.

# #

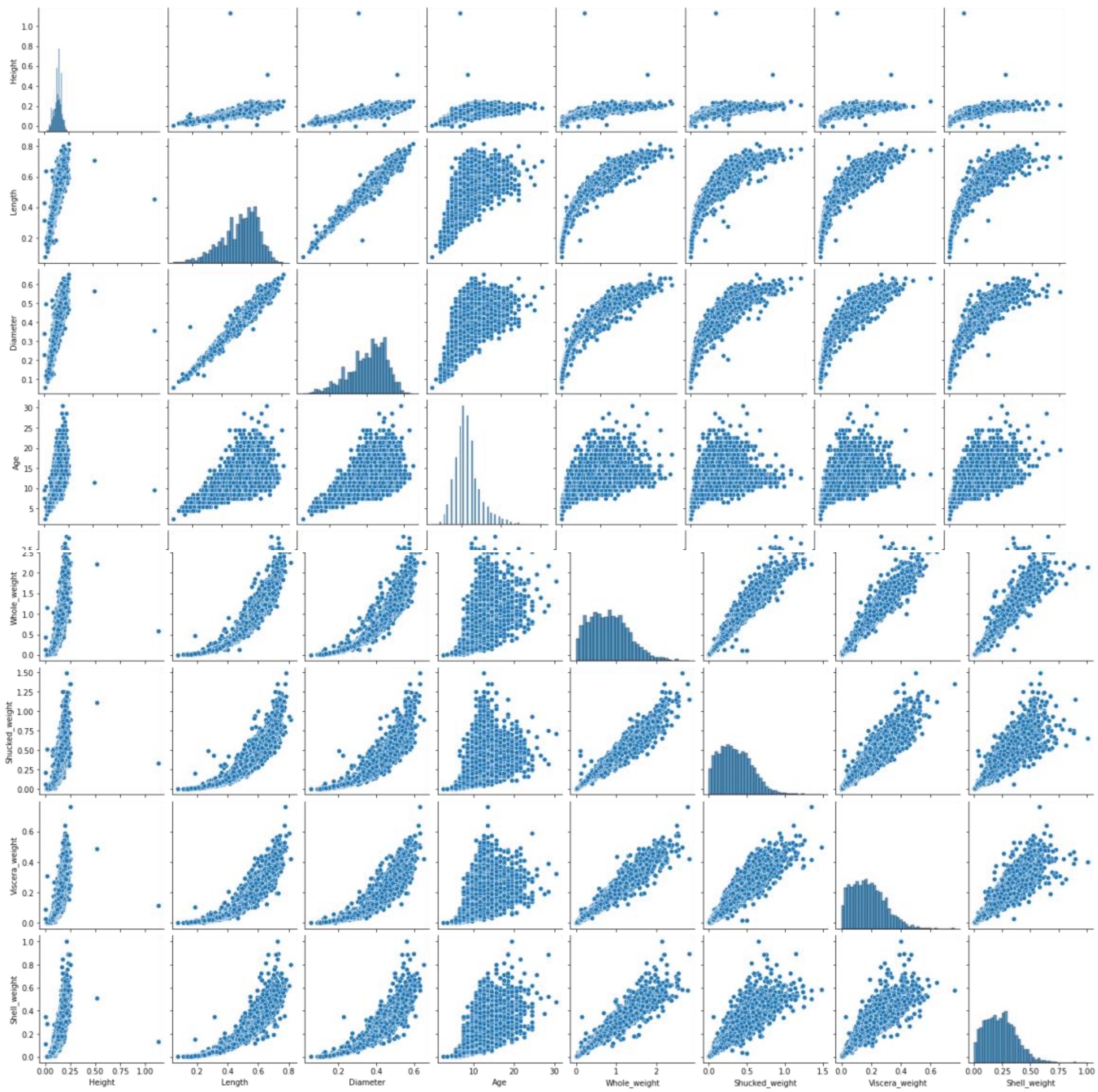
Pairplot

In [ ]:

```
sns.pairplot(data=data[["Height","Length","Diameter","Age","Whole_weight","Shuc
```

<seaborn.axisgrid.PairGrid at 0x7fd3d93e1040>

Out[ ]:

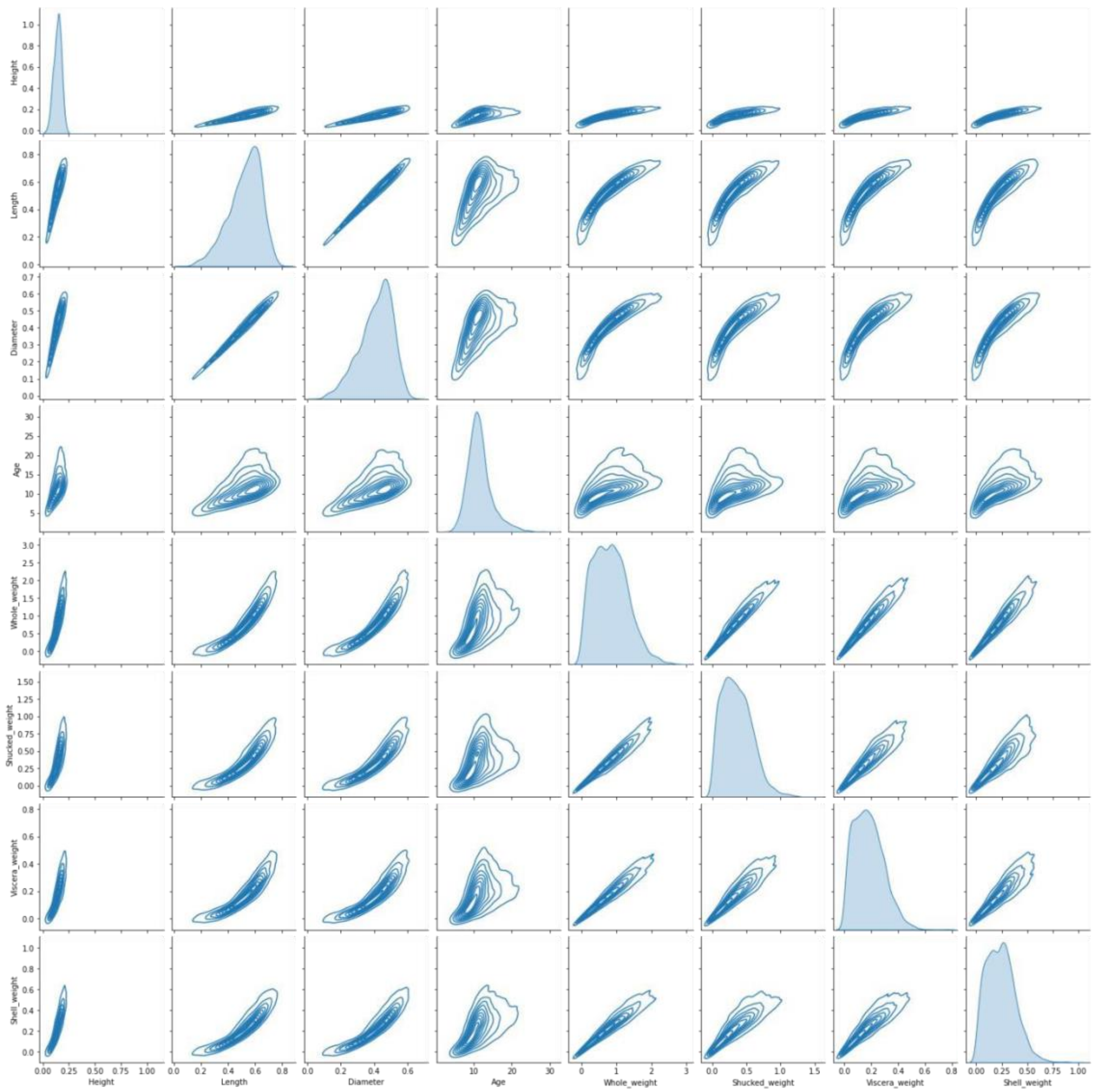


In [ ]:

```
sns.pairplot(data=data[["Height","Length","Diameter","Age","Whole_weight","Shuc
```

Out[ ]:

```
<seaborn.axisgrid.PairGrid at 0x7fd39840c790>
```



4. Perform descriptive statistics on the dataset

In [ ]:

```
data.describe(include='all')
```

Out[ ]:

	Sex	Length	Diameter	Height	Whole_weight	Shucked_weight	Viscera_
count	4177	4177.000000	4177.000000	4177.000000	4177.000000	4177.000000	4177.
unique	3	NaN	NaN	NaN	NaN	NaN	
top	M	NaN	NaN	NaN	NaN	NaN	
freq	1528	NaN	NaN	NaN	NaN	NaN	
mean	NaN	0.523992	0.407881	0.139516	0.828742	0.359367	0.

std	NaN	0.120093	0.099240	0.041827	0.490389	0.221963	0.
min	NaN	0.075000	0.055000	0.000000	0.002000	0.001000	0.
25%	NaN	0.450000	0.350000	0.115000	0.441500	0.186000	0.
50%	NaN	0.545000	0.425000	0.140000	0.799500	0.336000	0.
75%	NaN	0.615000	0.480000	0.165000	1.153000	0.502000	0.
max	NaN	0.815000	0.650000	1.130000	2.825500	1.488000	0.

5. Check for Missing values and deal with them

In [ ]:
Out[ ]:

```
data.isnull().sum()
```

```
Sex               0
Length            0
Diameter          0
Height            0
Whole_weight      0
Shucked_weight    0
Viscera_weight    0
Shell_weight      0
Age dtype:        0
int64
```

In [ ]:

6. Find the outliers and replace them outliers

Out[ ]:

```
outliers=data.quantile(q=(0.25,0.75)) outliers
```

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

In [ ]:

```
a = data.Age.quantile(0.25) b
= data.Age.quantile(0.75)
c = b - a
lower_limit = a - 1.5 * c data.median(numeric_only=True)
```

Out[ ]:

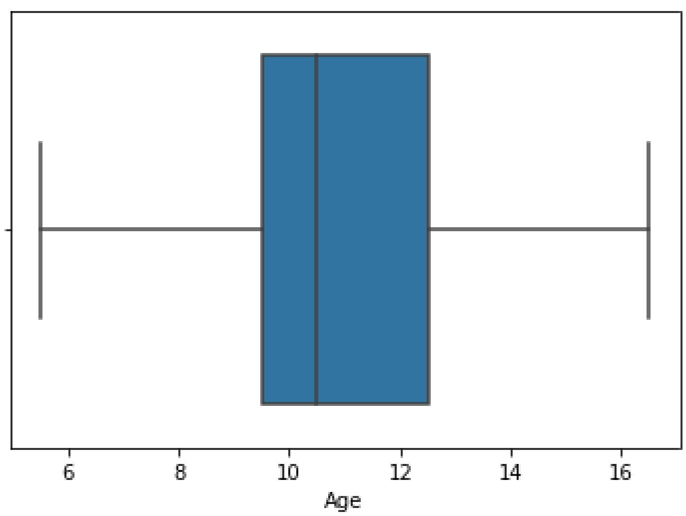
```
Length            0.5450
                  0.4250
Diameter          0.1400
Height            0.7995
Whole_weight      0.3360
Shucked_weight    0.1710
Viscera_weight    0.2340
Shell_weight     10.5000
Age
dtype: float64
```

In [ ]:

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

Out[ ]:

```
<AxesSubplot:xlabel='Age'>
```



7. Check for Categorical columns and perform encoding

In [ ]:

```
data.head()
```

Out[ ]:

	Sex	Length	Diameter	Height	Whole_weight	Shucked_weight	Viscera_weight	Shell_weig
0	M	0.455	0.365	0.095	0.5140	0.2245	0.1010	0.1
1	M	0.350	0.265	0.090	0.2255	0.0995	0.0485	0.0
2	F	0.530	0.420	0.135	0.6770	0.2565	0.1415	0.2
3	M	0.440	0.365	0.125	0.5160	0.2155	0.1140	0.1
4	I	0.330	0.255	0.080	0.2050	0.0895	0.0395	0.0

In [ ]:

```
from sklearn.preprocessing import LabelEncoder
lab = LabelEncoder()
data.Sex = lab.fit_transform(data.Sex)
data.head()
```

Out[ ]:

	Sex	Length	Diameter	Height	Whole_weight	Shucked_weight	Viscera_weight	Shell_weig
0	2	0.455	0.365	0.095	0.5140	0.2245	0.1010	0.1
1	2	0.350	0.265	0.090	0.2255	0.0995	0.0485	0.0
2	0	0.530	0.420	0.135	0.6770	0.2565	0.1415	0.2
3	2	0.440	0.365	0.125	0.5160	0.2155	0.1140	0.1
4	1	0.330	0.255	0.080	0.2050	0.0895	0.0395	0.0

8. Split the data into dependent and independent variables

In [ ]:

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

```
0    2
```

Out[ ]:

```
1    2

2    0

3    2
4    1

Name: Sex, dtype: int64
```

In [ ]:

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

Out[ ]:

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

9. Scale the independent variables

In [ ]:

```
from sklearn.preprocessing import scale
X_Scaled = pd.DataFrame(scale(x), columns=x.columns) X_Scaled.head()
```

Out[ ]: **Length Diameter Height Whole_weight Shucked_weight Viscera_weight Shell_weigh**

0	-0.574558	-0.432149	-1.064424	-0.641898	-0.607685	-0.726212	-0.63821
1	-1.448986	-1.439929	-1.183978	-1.230277	-1.170910	-1.205221	-1.21298
2	0.050033	0.122130	-0.107991	-0.309469	-0.463500	-0.356690	-0.20713
3	-0.699476	-0.432149	-0.347099	-0.637819	-0.648238	-0.607600	-0.60229
4	-1.615544	-1.540707	-1.423087	-1.272086	-1.215968	-1.287337	-1.32075

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_Scaled, y, test_size=0.2,
```

In [ ]:

```
X_Train.shape,X_Test.shape
```

Out[ ]:

```
((3341, 8), (836, 8))
```

In [ ]:

```
Y_Train.shape,Y_Test.shape
```

```
((3341,), (836,))
```

In [ ]:

```
X_Train.head()
```

Out[ ]:

	Length	Diameter	Height	Whole_weight	Shucked_weight	Viscera_weight	Shell_w
3141	-2.864726	-2.750043	-1.423087	-1.622870	-1.553902	-1.583867	-1.64

Out[ ]:

3521	-2.573250	-2.598876	-2.020857	-1.606554	-1.551650	-1.565619	-1.62
883	1.132658	1.230689	0.728888	1.145672	1.041436	0.286552	1.53
3627	1.590691	1.180300	1.446213	2.164373	2.661269	2.330326	1.37
2106	0.591345	0.474853	0.370226	0.432887	0.255175	0.272866	0.90

In [ ]:

```
X_Test.head()
```

Out[ ]:

	Length	Diameter	Height	Whole_weight	Shucked_weight	Viscera_weight	Shell_w
668	0.216591	0.172519	0.370226	0.181016	-0.368878	0.569396	0.69
1580	-0.199803	-0.079426	-0.466653	-0.433875	-0.443224	-0.343004	-0.32
3784	0.799543	0.726798	0.370226	0.870348	0.755318	1.764639	0.56
463	-2.531611	-2.447709	-2.020857	-1.579022	-1.522362	-1.538247	-1.57
2615	1.007740	0.928354	0.848442	1.390405	1.415417	1.778325	0.99

```
Y_Train.head()
```

In [ ]:

```
3141  1
```

Out[ ]:

```
3521  1
883     2
3627  2
2106  2
Name: Sex, dtype: int64
```

```
Y_Test.head()
```

In [ ]:
```
668      2
```

Out[ ]:

```
  1580 1
  3784 2
463      1
  2615 2
Name: Sex, dtype: int64
```

11. Build the Model

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

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

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

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

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

12. Train the Model

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

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

```
Training accuracy: 0.9787488775815624
```

13. Test the Model

In [ ]:

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

```
Testing accuracy: 0.5526315789473685
```

14. Measure the performance using Metrics

In [ ]:

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

Out[ ]:

col_0	0	1	2
Sex			
0	122	29	98
1	37 217	37	
2	120	53 123	

In [ ]:

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

```
              precision    recall  f1-score   support
           0       0.44      0.49      0.46       249
           1       0.73      0.75      0.74       291
           2       0.48      0.42      0.44       296

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