**Assignment – 3**
Python Programming

| | |
|---|---|
| Assignment Date | |
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| Student Roll Number | 111519104119 |
| 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
```

Out[ ]:

```
(4177, 9)
```

#### 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.

## #

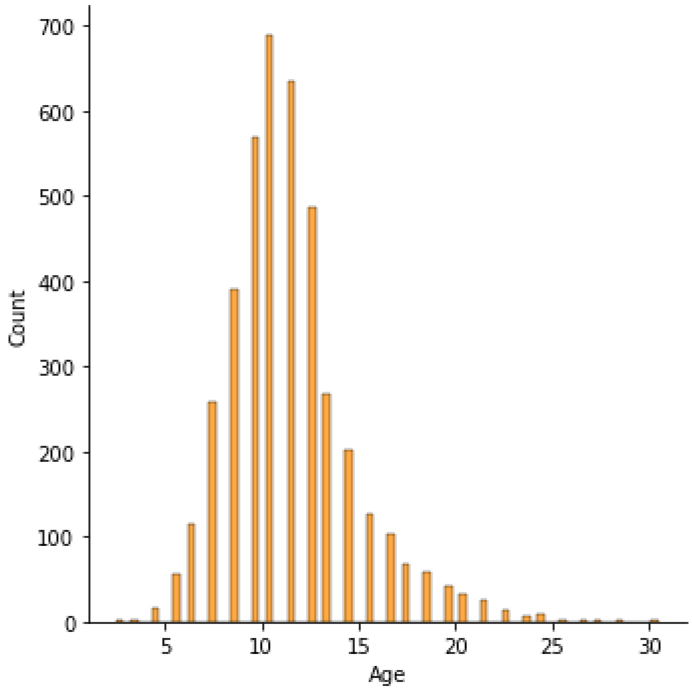
## Histogram

In [ ]:

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

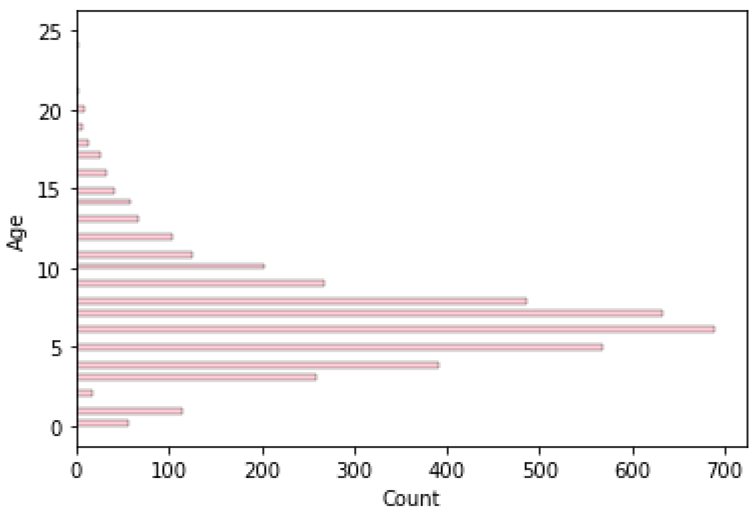
Out[ ]:

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



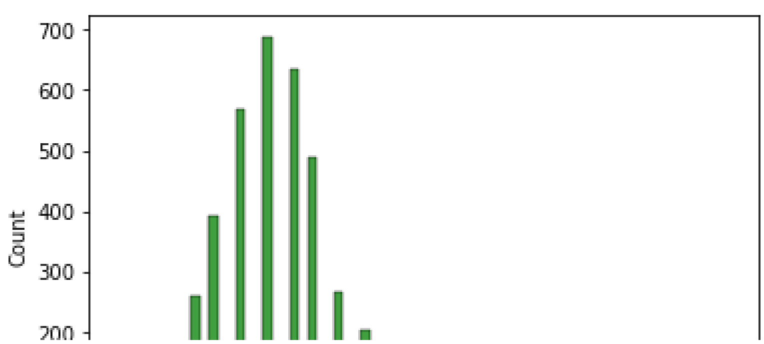

In [ ]:
```
sns.histplot(y=data.Age,color='pink')
```

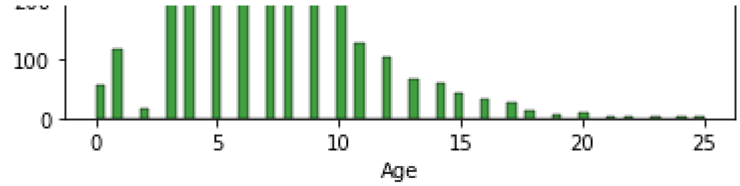
Out[ ]: <AxesSubplot:xlabel='Count', ylabel='Age'>




In [ ]:
```
sns.histplot(x=data.Age,color='green')
```

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





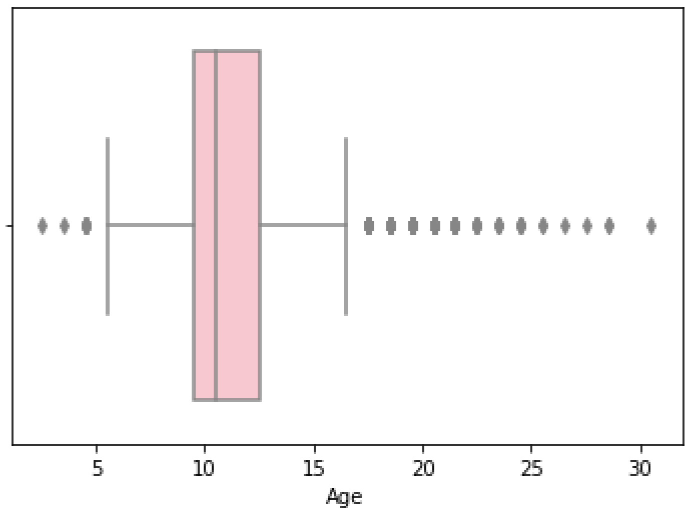

## Boxplot

In [ ]:

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

Out[ ]:

<AxesSubplot:xlabel='Age'>



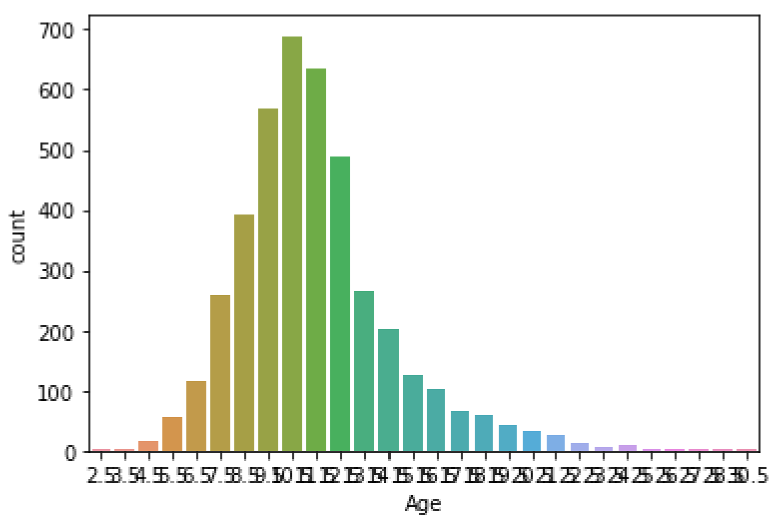

## Countplot

In [ ]:

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

Out[ ]:

<AxesSubplot:xlabel='Age', ylabel='count'>




# (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).

# 

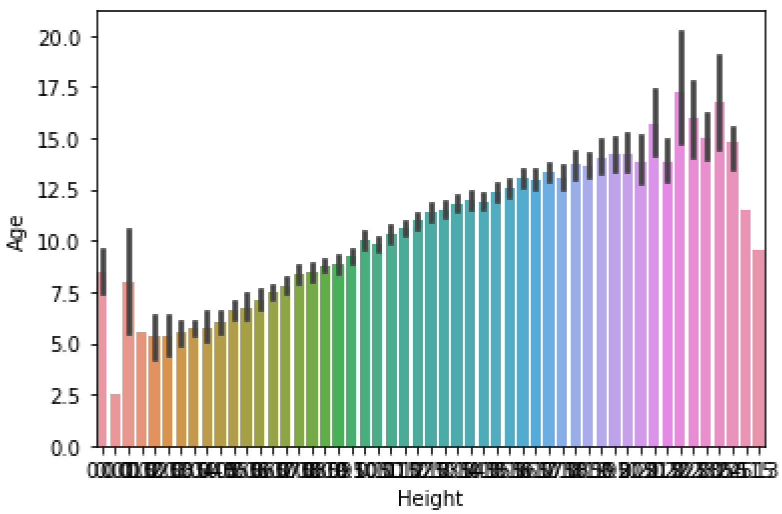
## Barplot

In [ ]:

```
sns.barplot(x=data.Height,y=data.Age)
```

Out[ ]:

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



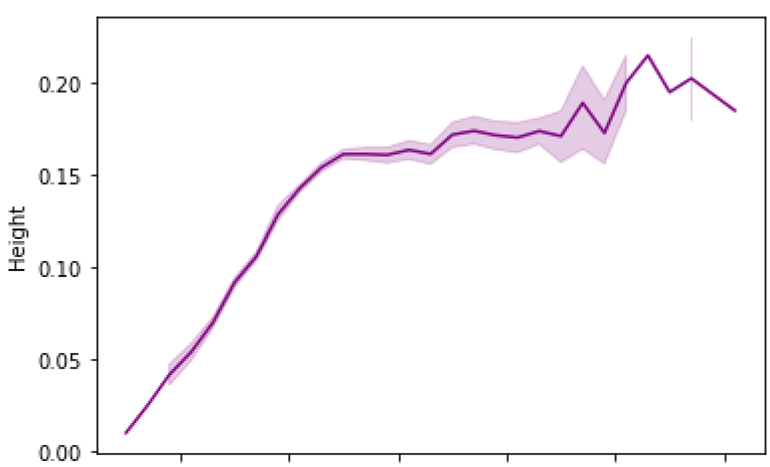

## Linearplot

In [ ]:

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

Out[ ]:

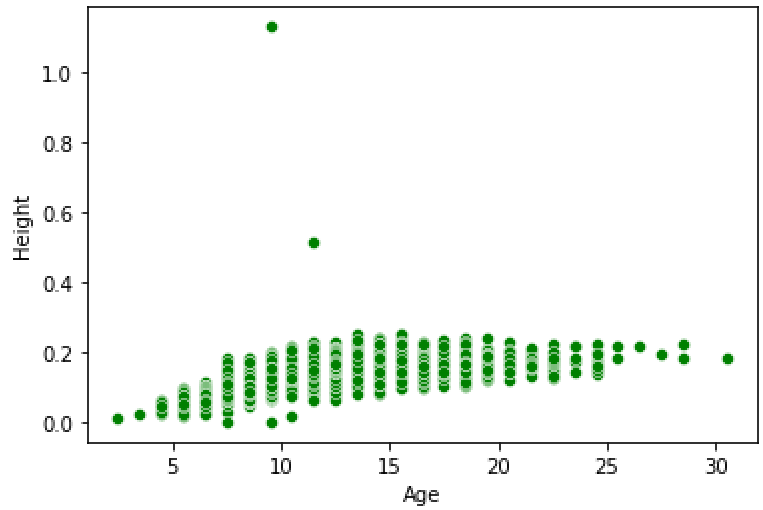
```
<AxesSubplot:xlabel='Age', ylabel='Height'>
```




## Scatterplot

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

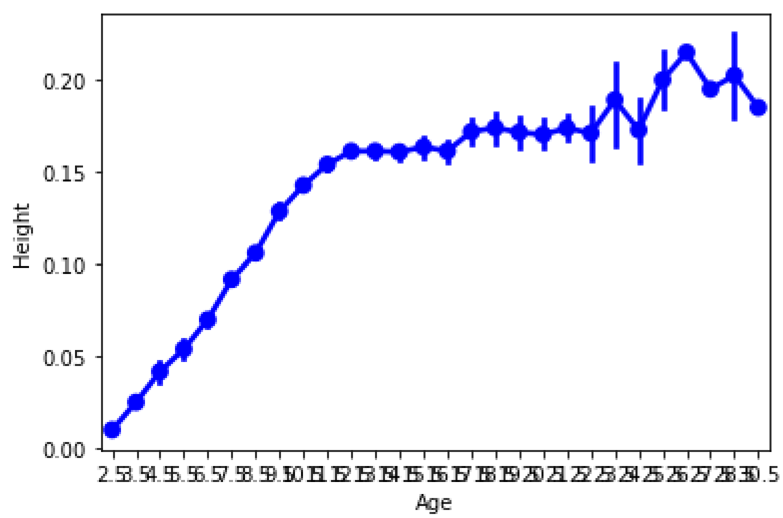
Out[ ]: <AxesSubplot:xlabel='Age', ylabel='Height'>




## Pointplot

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

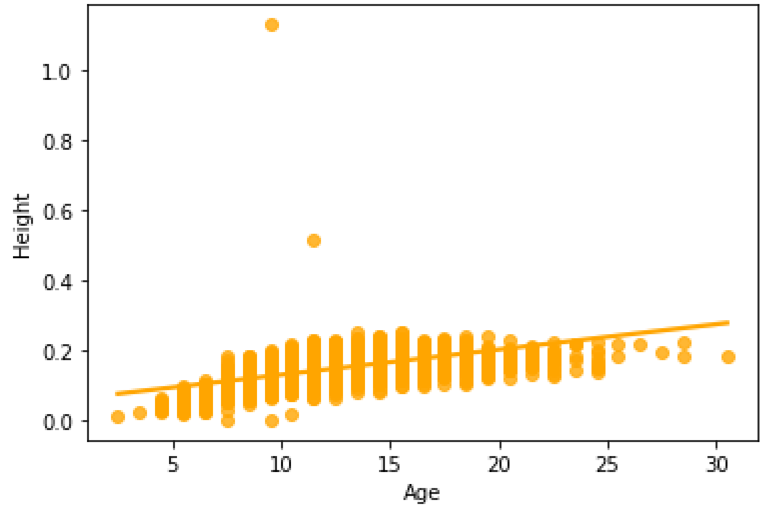
Out[ ]: <AxesSubplot:xlabel='Age', ylabel='Height'>




## Regplot

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

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




# (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.

# #

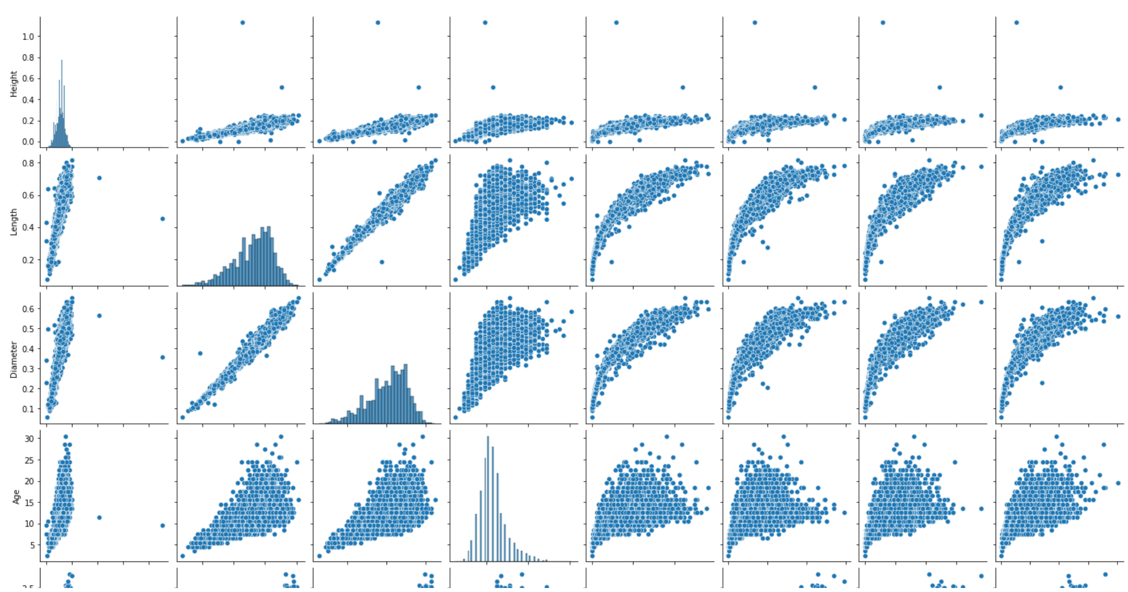
## Pairplot

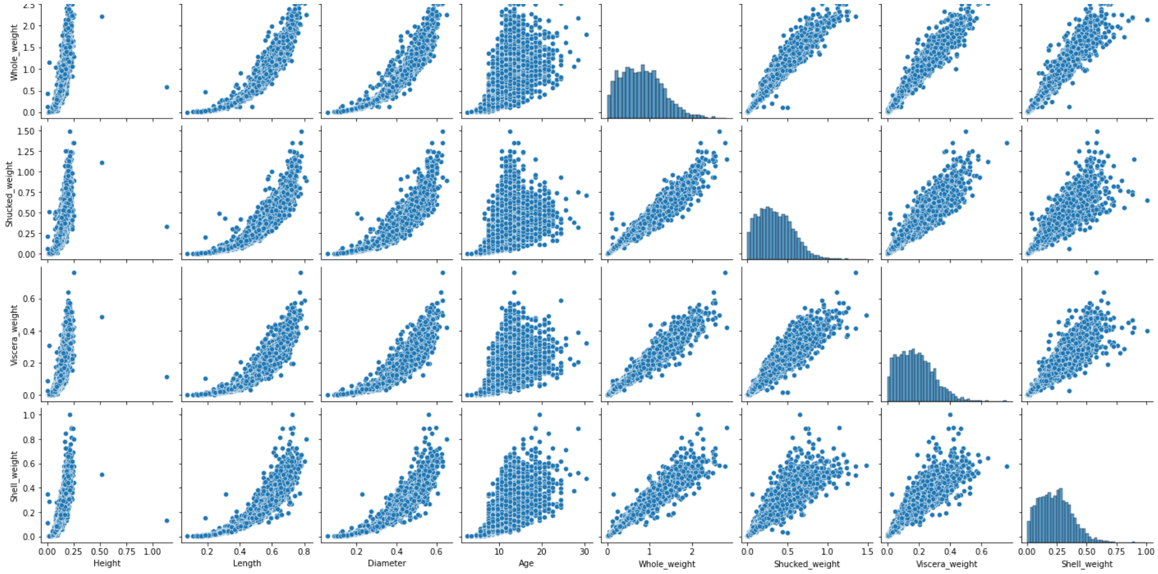
In [ ]:

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

Out[ ]:

```
<seaborn.axisgrid.PairGrid at 0x7fd3d93e1040>
```



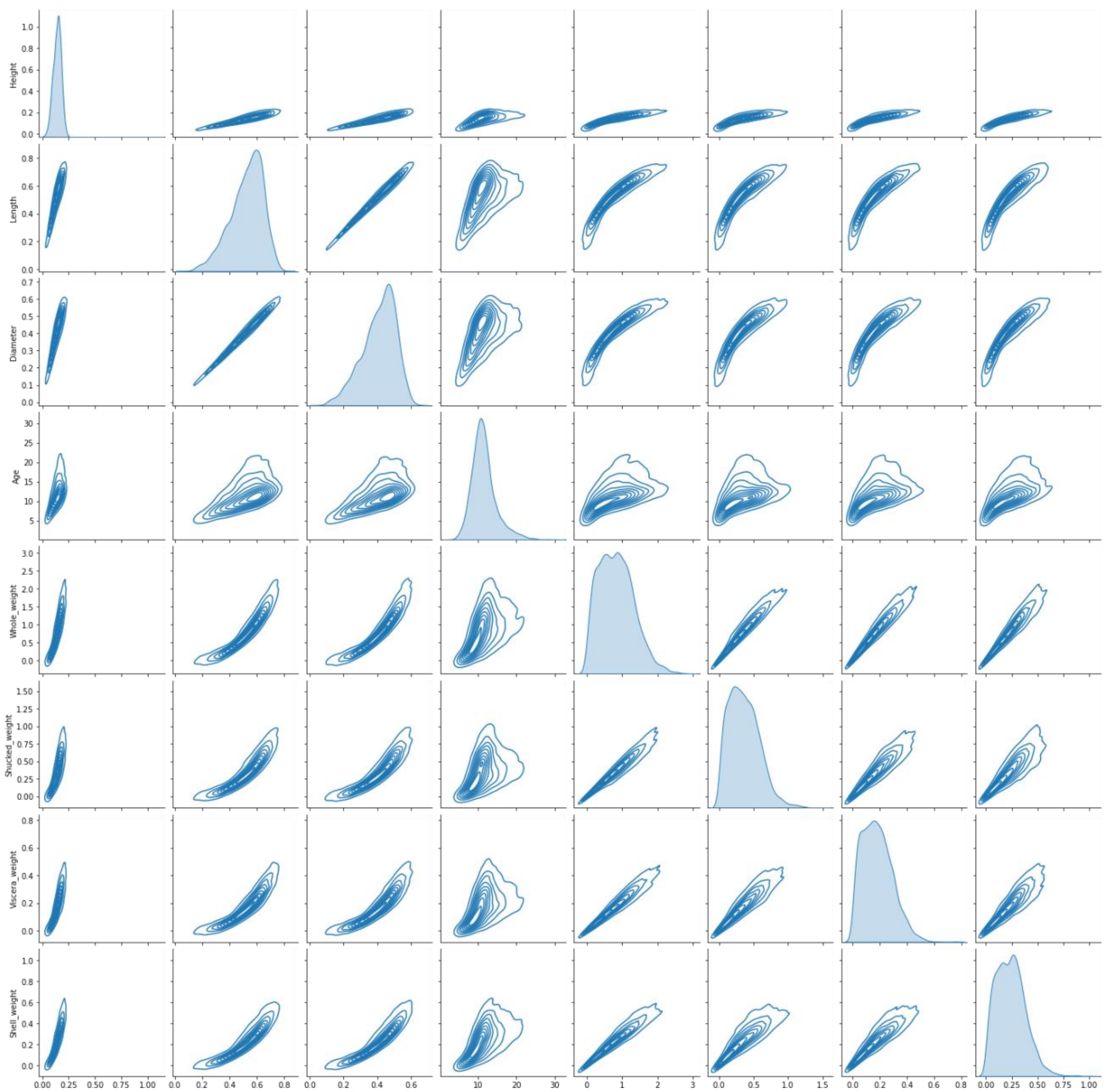


In [ ]:

```
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 [ ]:

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

Out[ ]:

```
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. Find the outliers and replace them outliers

In [ ]:

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

Out[ ]:

| | 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[ ]:

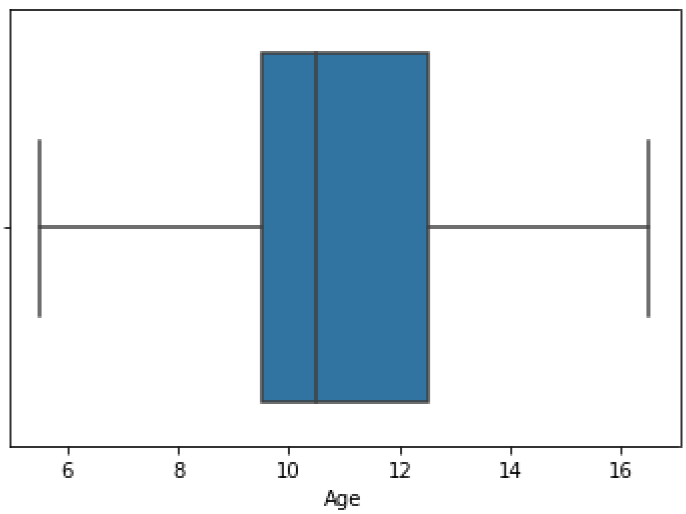
```
Length             0.5450
Diameter           0.4250
Height             0.1400
Whole_weight       0.7995
Shucked_weight     0.3360
Viscera_weight     0.1710
Shell_weight       0.2340
Age               10.5000
dtype: float64
```

In [ ]:

```
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()
```

Out[ ]:

```
0    2
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
```

Out[ ]:

```
((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 |
| 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 | 0.6 |
| 1580 | -0.199803 | -0.079426 | -0.466653 | -0.433875 | -0.443224 | -0.343004 | -0.3 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| **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 |

In [ ]:

```
Y_Train.head()
```

Out[ ]:

```
3141    1
3521    1
883     2
3627    2
2106    2
Name: Sex, dtype: int64
```

In [ ]:

```
Y_Test.head()
```

Out[ ]:

```
668     2
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
```