Assignment - 3

Python Programming

| | |
|---|---|
| Assignment Date | 4 October 2022 |
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| Student Roll Number | CITC1907041 |
| Maximum Marks | 2 Marks |

# Problem Statement: Abalone Age Prediction

## Importing Modules

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

## 1. Dataset Download

In [ ]:
```
#Name of the dataset: abalone.csv
```

## 2. Loading 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 |

# Shape of data:

In [ ]:
```
data.shape
```
Out[ ]:
```
(4177, 9)
```

# Adding 'Age' into 'Rings' - adding '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': 'Shucked_weight','Viscera weight': 'Viscera_weight',
                            'Shell weight': 'Shell_weight'})
data=data.drop(columns=["Rings"],axis=1)
data.head()
```
Out[ ]:

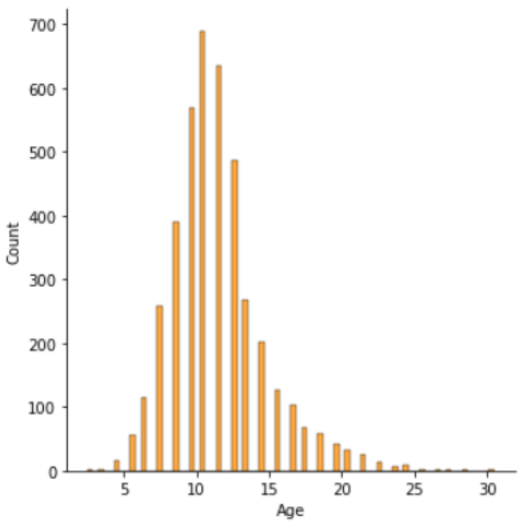
| | Sex | Length | Diameter | Height | Whole_weight | Shucked_weight | Viscera_weight | Shell_weight | Age |
|---|---|---|---|---|---|---|---|---|---|
| 0 | M | 0.455 | 0.365 | 0.095 | 0.5140 | 0.2245 | 0.1010 | 0.150 | 16.5 |
| 1 | M | 0.350 | 0.265 | 0.090 | 0.2255 | 0.0995 | 0.0485 | 0.070 | 8.5 |
| 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 |

## 3. Perform below visualizations:

## (i)Univariate Analysis

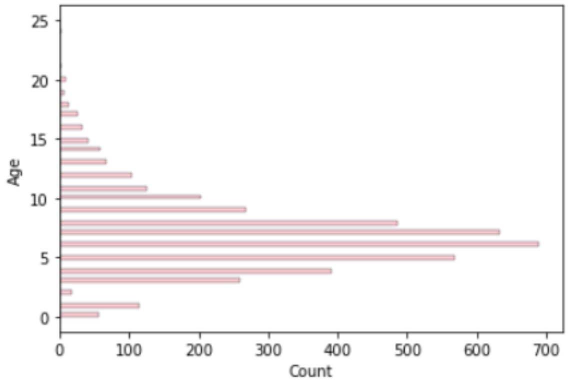
### Histogram

In [ ]:
```
sns.displot(data["Age"], color='darkorange')
```
Out[ ]:
```
<seaborn.axisgrid.FacetGrid at 0x7fd3f837a430>
```



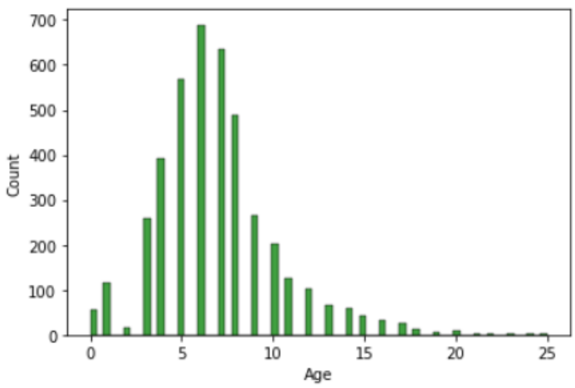
In [ ]:
```python
sns.histplot(y=data.Age,color='pink')
```

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




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

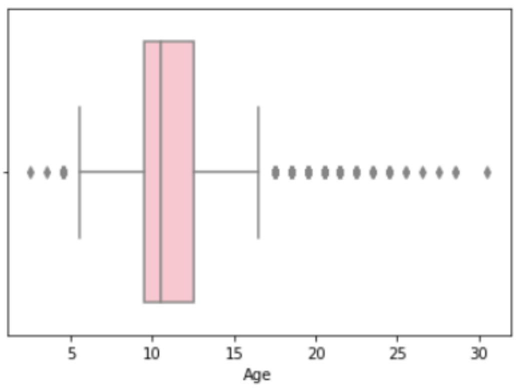
Out[ ]:
```
<AxesSubplot:xlabel='Age', ylabel='Count'>
```




## Boxplot

In [ ]:
```python
sns.boxplot(x=data.Age,color='pink')
```

Out[ ]:
```
<AxesSubplot:xlabel='Age'>
```

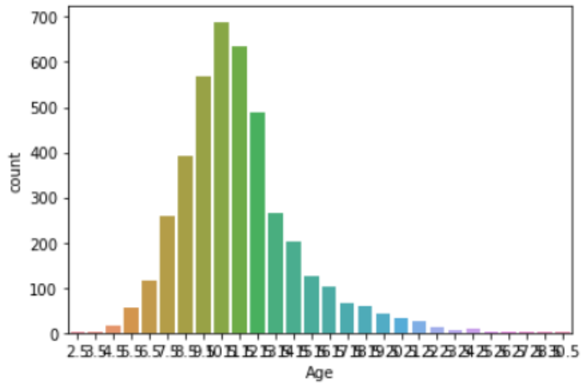


### Countplot

In [ ]:

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

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



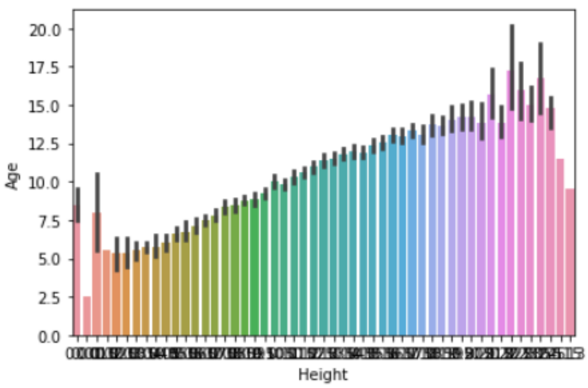

## (ii) Bi-Variate Analysis

### Barplot

In [ ]:

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

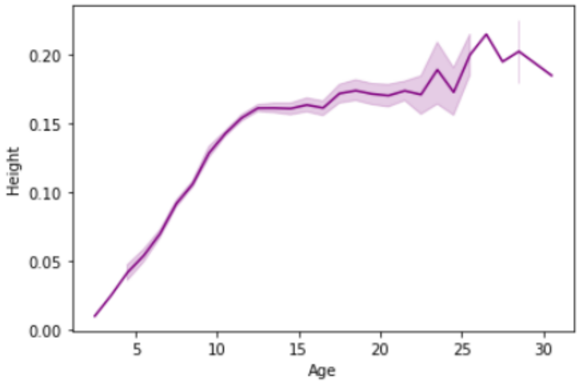
Out[ ]: <AxesSubplot:xlabel='Height', ylabel='Age'>



## Linearplot

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

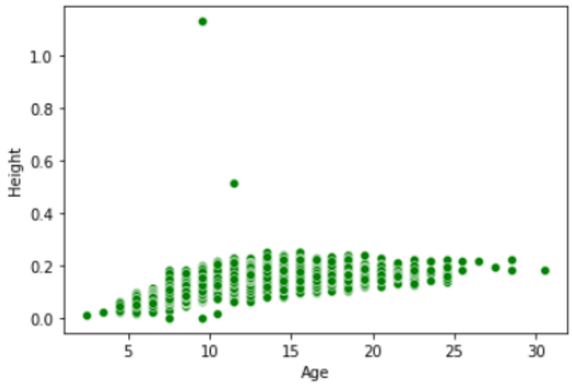
Out[ ]: <AxesSubplot:xlabel='Age', ylabel='Height'>




## Scatterplot

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

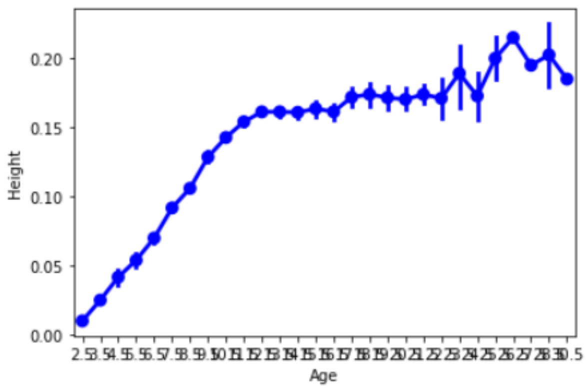
Out[ ]: <AxesSubplot:xlabel='Age', ylabel='Height'>




## Pointplot

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

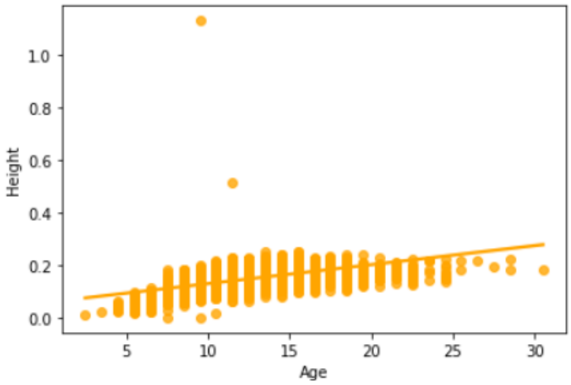
Out[ ]: <AxesSubplot:xlabel='Age', ylabel='Height'>



### Regplot

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

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

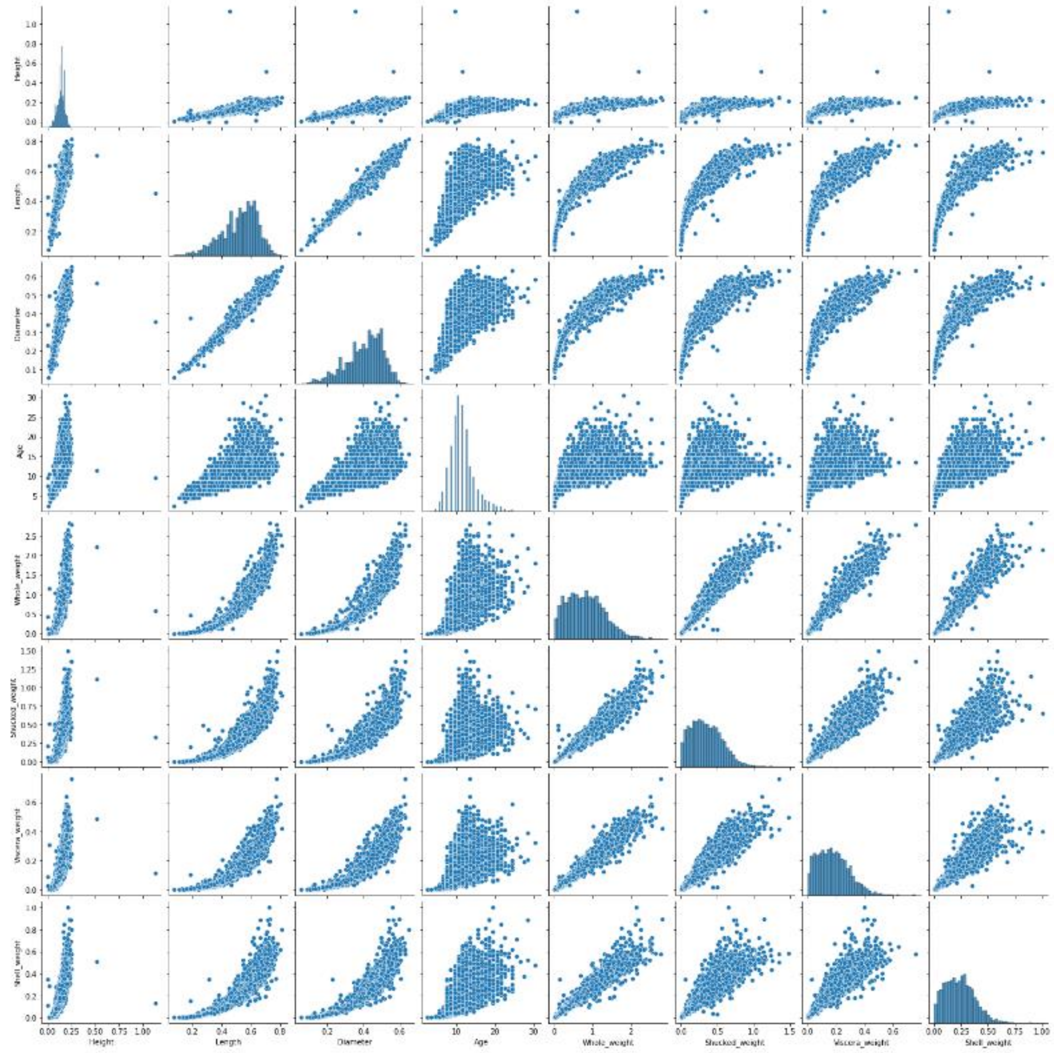



## (iii) Multi-Variate Analysis

### Pairplot

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

Out[ ]: <seaborn.axisgrid.PairGrid at 0x7fd3d93e1040>

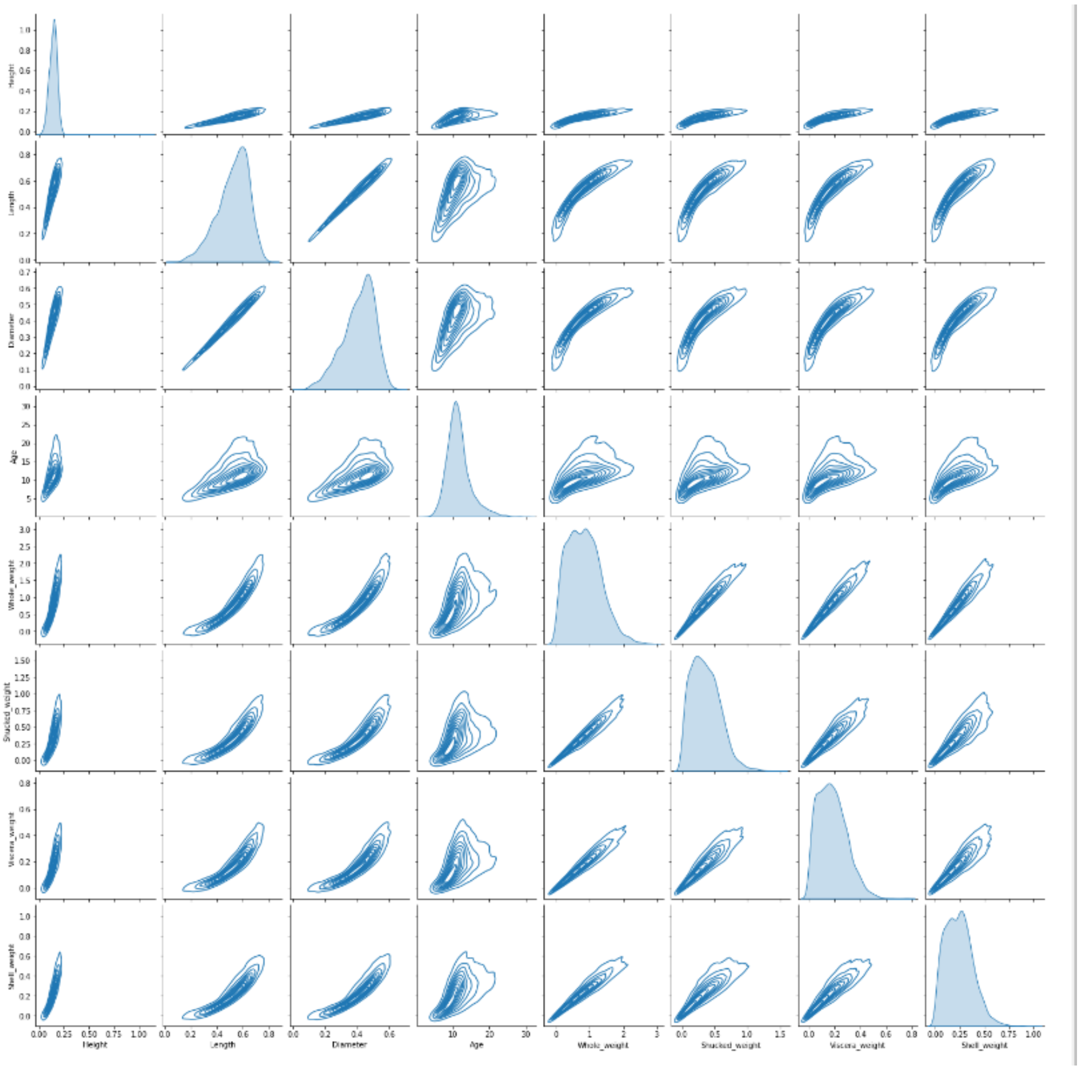



In [ ]:

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

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_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. 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[ ]:

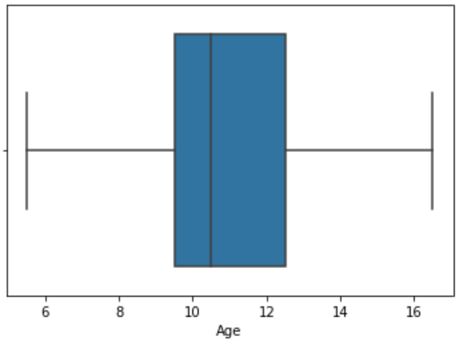
| | Length | Diameter | Height | Whole_weight | Shucked_weight | Viscera_weight | Shell_weight | Age |
|---|---|---|---|---|---|---|---|---|
| **0.25** | 0.450 | 0.35 | 0.115 | 0.4415 | 0.186 | 0.0935 | 0.130 | 9.5 |
| **0.75** | 0.615 | 0.48 | 0.165 | 1.1530 | 0.502 | 0.2530 | 0.329 | 12.5 |

In [ ]:
```
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_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 [ ]:
```
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_weight | Age |
|---|---|---|---|---|---|---|---|---|---|
| 0 | 2 | 0.455 | 0.365 | 0.095 | 0.5140 | 0.2245 | 0.1010 | 0.150 | 12 |
| 1 | 2 | 0.350 | 0.265 | 0.090 | 0.2255 | 0.0995 | 0.0485 | 0.070 | 4 |
| 2 | 0 | 0.530 | 0.420 | 0.135 | 0.6770 | 0.2565 | 0.1415 | 0.210 | 6 |
| 3 | 2 | 0.440 | 0.365 | 0.125 | 0.5160 | 0.2155 | 0.1140 | 0.155 | 7 |
| 4 | 1 | 0.330 | 0.255 | 0.080 | 0.2050 | 0.0895 | 0.0395 | 0.055 | 4 |

## 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 | Age |
|---|---|---|---|---|---|---|---|---|
| 0 | 0.455 | 0.365 | 0.095 | 0.5140 | 0.2245 | 0.1010 | 0.150 | 12 |
| 1 | 0.350 | 0.265 | 0.090 | 0.2255 | 0.0995 | 0.0485 | 0.070 | 4 |
| 2 | 0.530 | 0.420 | 0.135 | 0.6770 | 0.2565 | 0.1415 | 0.210 | 6 |
| 3 | 0.440 | 0.365 | 0.125 | 0.5160 | 0.2155 | 0.1140 | 0.155 | 7 |
| 4 | 0.330 | 0.255 | 0.080 | 0.2050 | 0.0895 | 0.0395 | 0.055 | 4 |

## 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_weight | Age |
|---|---|---|---|---|---|---|---|---|
| 0 | -0.574558 | -0.432149 | -1.064424 | -0.641898 | -0.607685 | -0.726212 | -0.638217 | 1.555152 |
| 1 | -1.448986 | -1.439929 | -1.183978 | -1.230277 | -1.170910 | -1.205221 | -1.212987 | -0.884841 |
| 2 | 0.050033 | 0.122130 | -0.107991 | -0.309469 | -0.463500 | -0.356690 | -0.207139 | -0.274842 |
| 3 | -0.699476 | -0.432149 | -0.347099 | -0.637819 | -0.648238 | -0.607600 | -0.602294 | 0.030157 |
| 4 | -1.615544 | -1.540707 | -1.423087 | -1.272086 | -1.215968 | -1.287337 | -1.320757 | -0.884841 |

## 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, random_state=0)
```

```
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_weight | Age |
|---|---|---|---|---|---|---|---|---|
| **3141** | -2.864726 | -2.750043 | -1.423087 | -1.622870 | -1.553902 | -1.583867 | -1.644065 | -1.799838 |
| **3521** | -2.573250 | -2.598876 | -2.020857 | -1.606554 | -1.551650 | -1.565619 | -1.626104 | -1.494839 |
| **883** | 1.132658 | 1.230689 | 0.728888 | 1.145672 | 1.041436 | 0.286552 | 1.538726 | 1.555152 |
| **3627** | 1.590691 | 1.180300 | 1.446213 | 2.164373 | 2.661269 | 2.330326 | 1.377072 | 0.030157 |
| **2106** | 0.591345 | 0.474853 | 0.370226 | 0.432887 | 0.255175 | 0.272866 | 0.906479 | 1.250153 |

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

Out[ ]:

| | 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 | 0.945154 |
| **1580** | -0.199803 | -0.079426 | -0.466653 | -0.433875 | -0.443224 | -0.343004 | -0.325685 | -0.579842 |
| **3784** | 0.799543 | 0.726798 | 0.370226 | 0.870348 | 0.755318 | 1.764639 | 0.565209 | 0.335156 |
| **463** | -2.531611 | -2.447709 | -2.020857 | -1.579022 | -1.522362 | -1.538247 | -1.572219 | -1.799838 |
| **2615** | 1.007740 | 0.928354 | 0.848442 | 1.390405 | 1.415417 | 1.778325 | 0.996287 | 0.640155 |

```
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_report
```

```
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
```