Assignment - 3

Python Programming

Assignment Date	4 October 2022
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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[ ]:

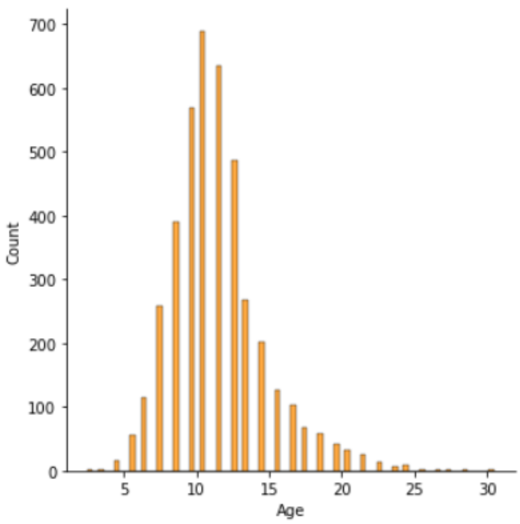
	Sex	Length	Diameter	Height	Whole_weight	Shucked_weight	Viscera_weight	Shell_weight	Age
0	M	0.455	0.365	0.095	0.5140	0.2245	0.1010	0.150	16.5
1	M	0.350	0.265	0.090	0.2255	0.0995	0.0485	0.070	8.5
2	F	0.530	0.420	0.135	0.6770	0.2565	0.1415	0.210	10.5
3	M	0.440	0.365	0.125	0.5160	0.2155	0.1140	0.155	11.5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

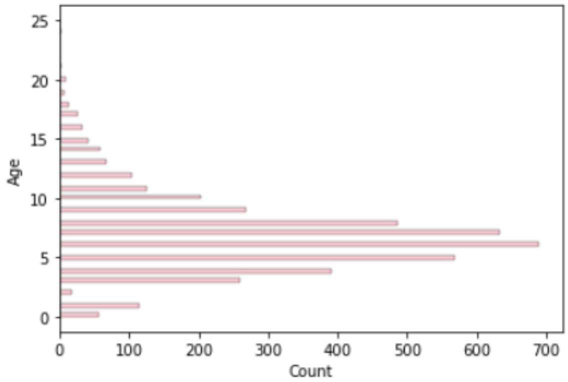
Histogram

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



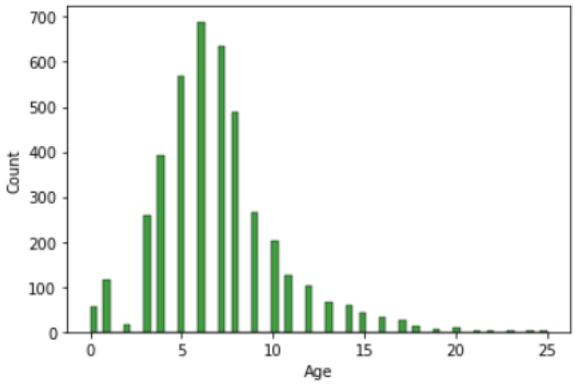
```
In [ ]: sns.histplot(y=data.Age,color='pink')
```

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




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

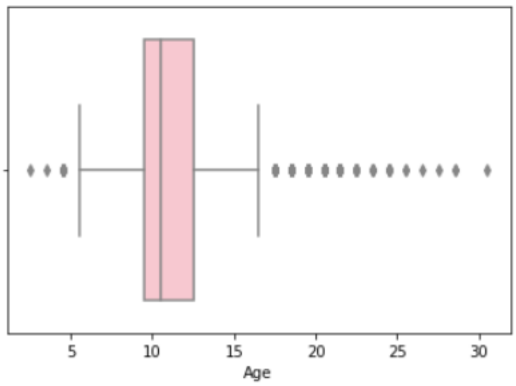
```
Out[ ]: <AxesSubplot:xlabel='Age', ylabel='Count'>
```



Boxplot

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

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



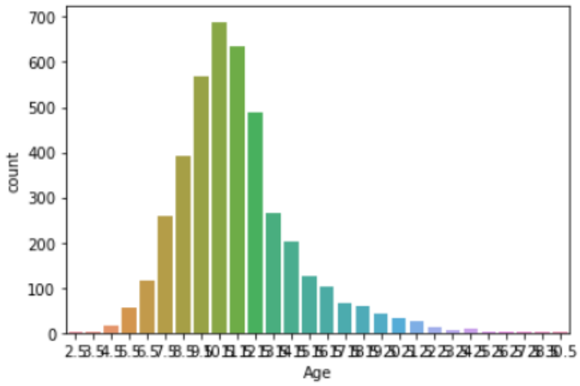
Countplot

In [ ]:

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

Out[ ]:

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



(ii) Bi-Variate Analysis

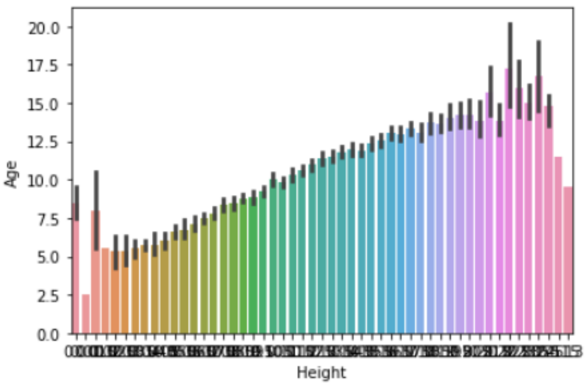
Barplot

In [ ]:

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

Out[ ]:

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

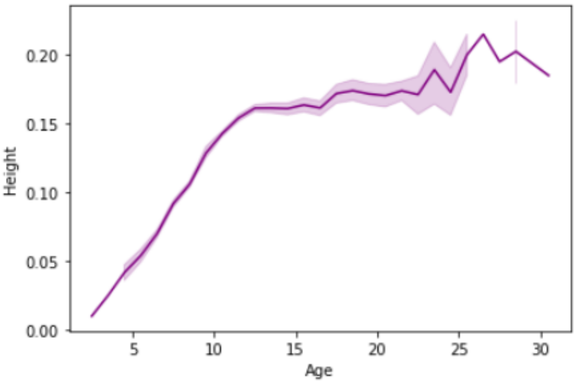


Linearplot

In [ ]:

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

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

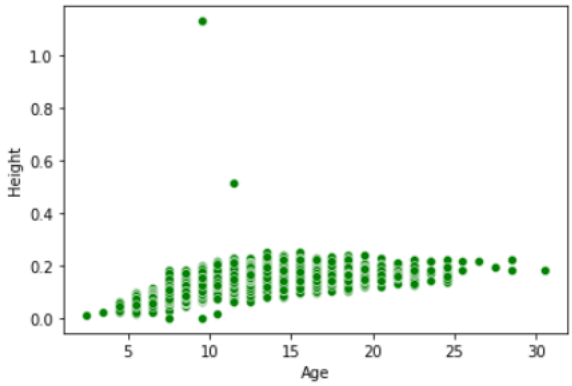


Scatterplot

In [ ]:

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

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

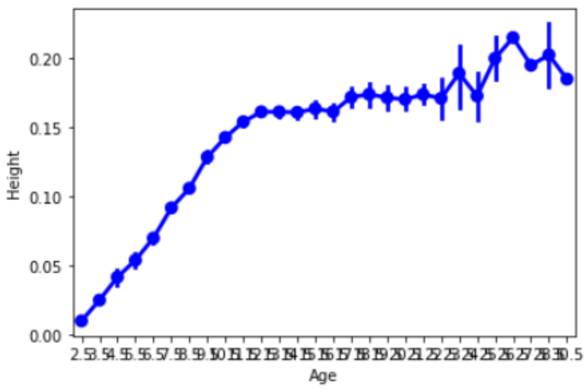


Pointplot

In [ ]:

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

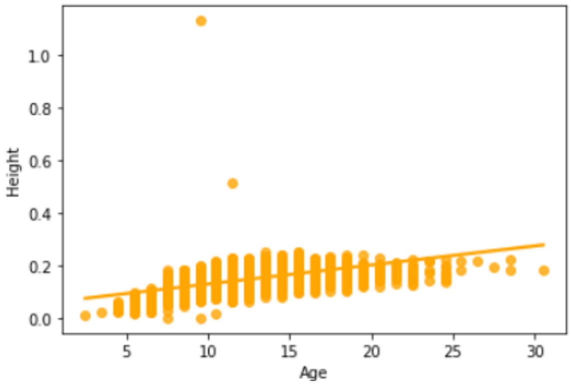
Out[ ]: <AxesSubplot:xlabel='Age', ylabel='Height'>



Regplot

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

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

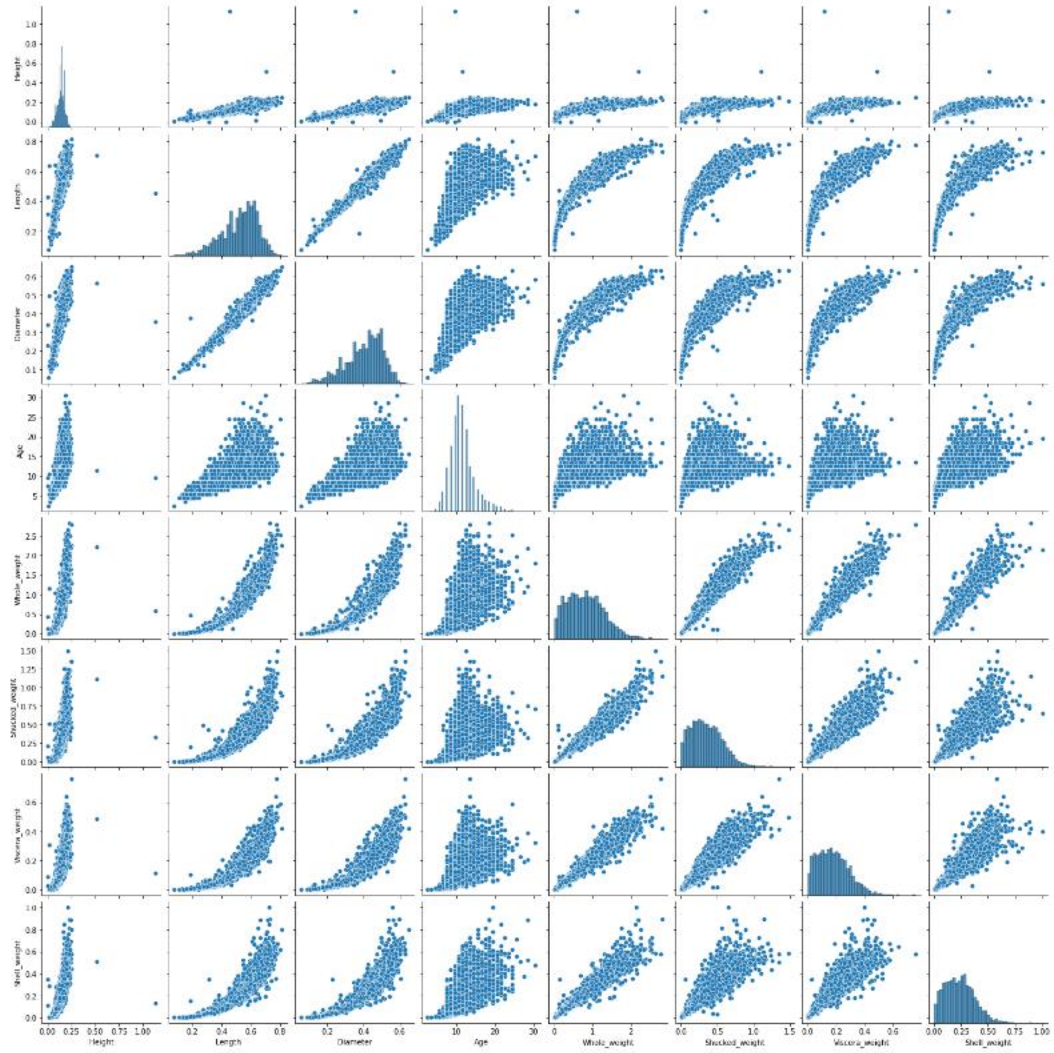


(iii) Multi-Variate Analysis

Pairplot

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

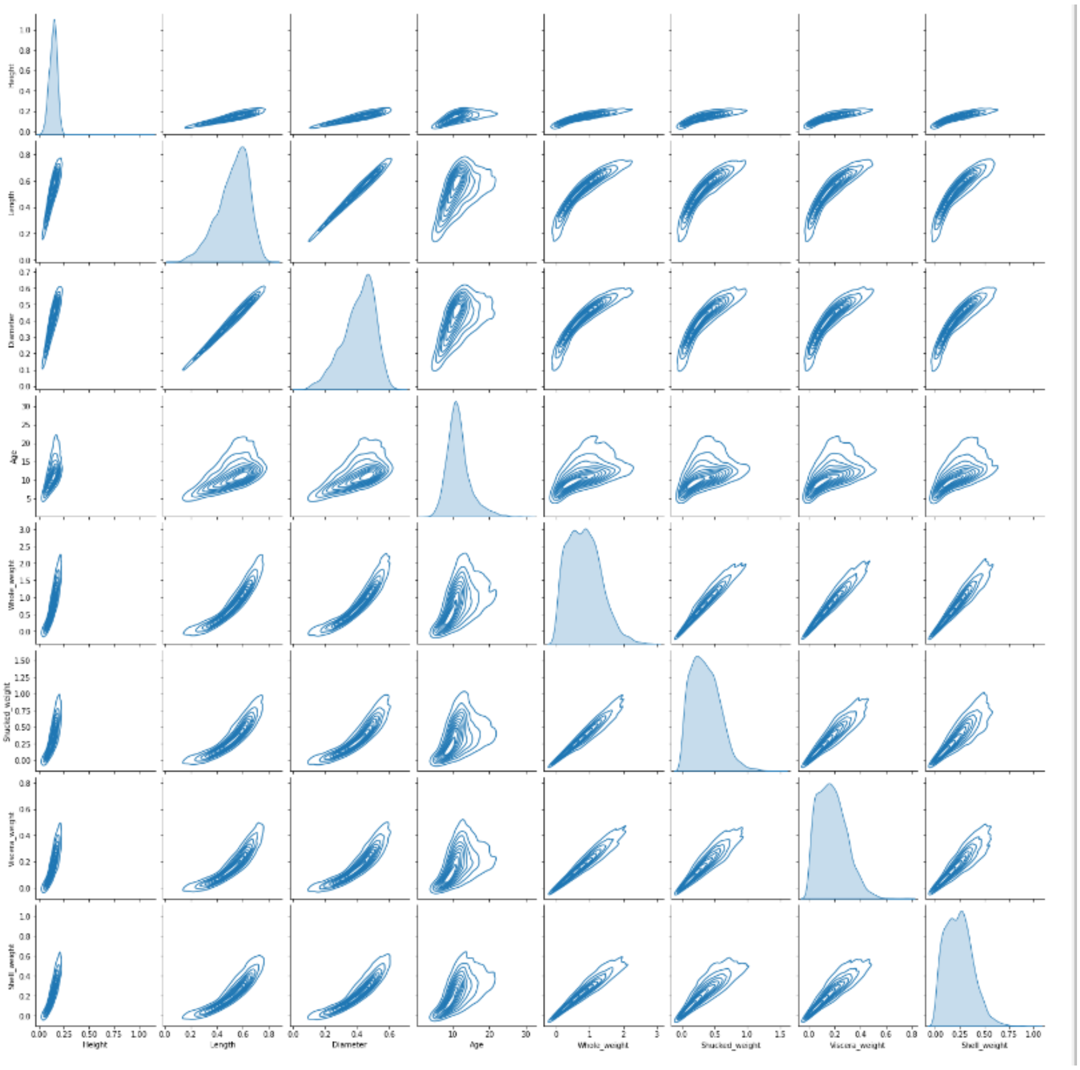
Out[ ]: <seaborn.axisgrid.PairGrid at 0x7fd3d93e1040>



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[ ]:

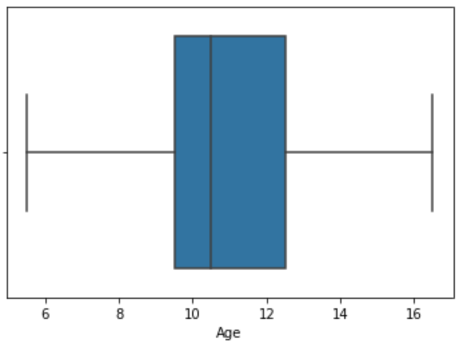
	Length	Diameter	Height	Whole_weight	Shucked_weight	Viscera_weight	Shell_weight	Age
0.25	0.450	0.35	0.115	0.4415	0.186	0.0935	0.130	9.5
0.75	0.615	0.48	0.165	1.1530	0.502	0.2530	0.329	12.5

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
```