Decision Tree Q1 (Company Data)

Decision Tree

Assignment: **Problem Statement:**
A cloth manufacturing company is interested to know about the segment or attributes causes high sale.
Approach - A decision tree can be built with target variable Sale (we will first convert it in categorical variable) & all other variable will be independent in the analysis.

About the data:
Let's consider a Company dataset with around 10 variables and 400 records.
The attributes are as follows:

Sales -- Unit sales (in thousands) at each location
Competitor Price -- Price charged by competitor at each location
Income -- Community income level (in thousands of dollars)
Advertising -- Local advertising budget for company at each location (in thousands of dollars)
Population -- Population size in region (in thousands)
Price -- Price company charges for car seats at each site
Shelf Location at stores -- A factor with levels Bad, Good and Medium indicating the quality of the shelving location for the car seats at each site
Age -- Average age of the local population
Education -- Education level at each location
Urban -- A factor with levels No and Yes to indicate whether the store is in an urban or rural location
US -- A factor with levels No and Yes to indicate whether the store is in the US or not

The company dataset looks like this:

1. Import Libs

In [1]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn import preprocessing
from io import StringIO
from sklearn import tree
from sklearn.tree import DecisionTreeRegressor
from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder
from sklearn.metrics import classification_report, confusion_matrix
from sklearn import metrics
from sklearn import externals
from sklearn.metrics import accuracy_score
from sklearn.metrics import confusion_matrix
```

2. Import Data

In [2]:

```
companey = pd.read_csv('Company_Data.csv')
companey
```

Out[2]:

	Sales	CompPrice	Income	Advertising	Population	Price	ShelveLoc	Age	Education	U
0	9.50	138	73	11	276	120	Bad	42	17	
1	11.22	111	48	16	260	83	Good	65	10	
2	10.06	113	35	10	269	80	Medium	59	12	
3	7.40	117	100	4	466	97	Medium	55	14	
4	4.15	141	64	3	340	128	Bad	38	13	
...	...	...	...	...	...	...	...	...	...	
395	12.57	138	108	17	203	128	Good	33	14	
396	6.14	139	23	3	37	120	Medium	55	11	
397	7.41	162	26	12	368	159	Medium	40	18	
398	5.94	100	79	7	284	95	Bad	50	12	
399	9.71	134	37	0	27	120	Good	49	16	

400 rows × 11 columns

3. EDA

In [3]:

```
companey.describe()
```

Out[3]:

	Sales	CompPrice	Income	Advertising	Population	Price	Age	E
count	400.000000	400.000000	400.000000	400.000000	400.000000	400.000000	400.000000	40
mean	7.496325	124.975000	68.657500	6.635000	264.840000	115.795000	53.322500	1
std	2.824115	15.334512	27.986037	6.650364	147.376436	23.676664	16.200297	
min	0.000000	77.000000	21.000000	0.000000	10.000000	24.000000	25.000000	1
25%	5.390000	115.000000	42.750000	0.000000	139.000000	100.000000	39.750000	1
50%	7.490000	125.000000	69.000000	5.000000	272.000000	117.000000	54.500000	1
75%	9.320000	135.000000	91.000000	12.000000	398.500000	131.000000	66.000000	1
max	16.270000	175.000000	120.000000	29.000000	509.000000	191.000000	80.000000	1

In [4]:

```
companey.isna().sum()
```

Out[4]:

```
Sales          0
CompPrice      0
Income         0
Advertising    0
Population     0
Price          0
ShelveLoc      0
Age            0
Education      0
Urban          0
US             0
dtype: int64
```

In [5]:

```
companey.dtypes
```

Out[5]:

```
Sales          float64
CompPrice        int64
Income           int64
Advertising      int64
Population       int64
Price            int64
ShelveLoc       object
Age              int64
Education        int64
Urban           object
US              object
dtype: object
```

checking outliers

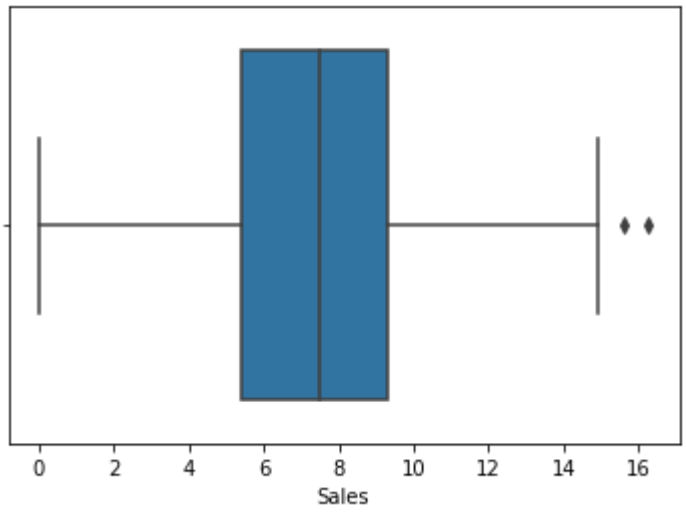
In [6]:

```
sns.boxplot(companey['Sales'])
```

```
C:\Users\shubham\anaconda3\lib\site-packages\seaborn\_decorators.py:36: Futu
reWarning: Pass the following variable as a keyword arg: x. From version 0.1
2, the only valid positional argument will be `data`, and passing other argu
ments without an explicit keyword will result in an error or misinterpretati
on.
  warnings.warn(
```

Out[6]:

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

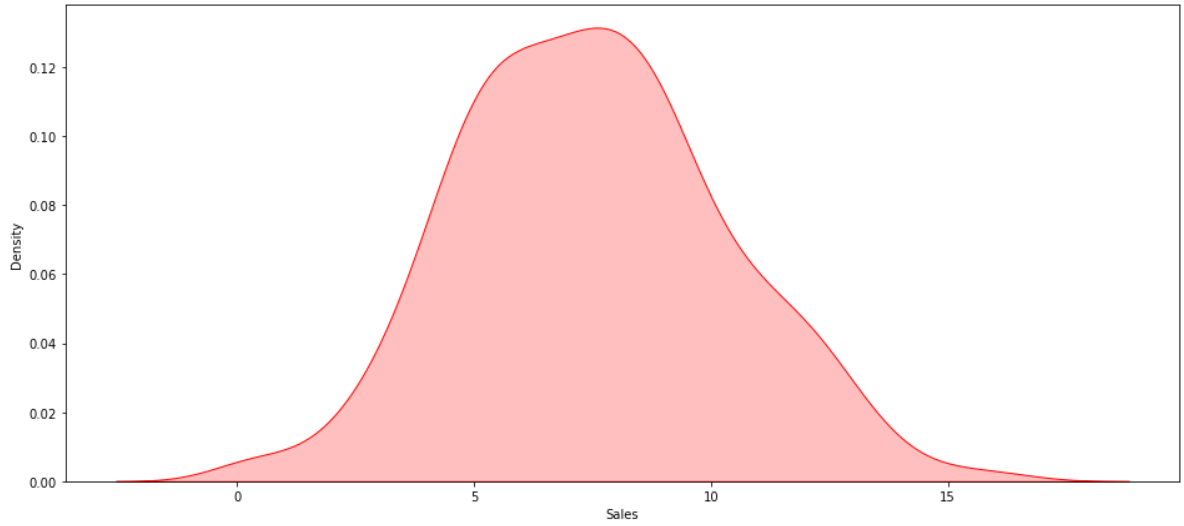


we can see there are 2 outliers present in the data

In [7]:

```
plt.figure(figsize=(16,7))
print("Skewness =",companey['Sales'].skew())
print("Kurtosis =",companey['Sales'].kurtosis())
sns.kdeplot(companey['Sales'],shade=True,color='r')
plt.show()
```

```
Skewness = 0.18556036318721578
Kurtosis = -0.08087736743346197
```



Sales Data is skewed to the right and Data has negative kurtosis

In [8]:

```
obj_colum = companey.select_dtypes(include='object')
obj_colum
```

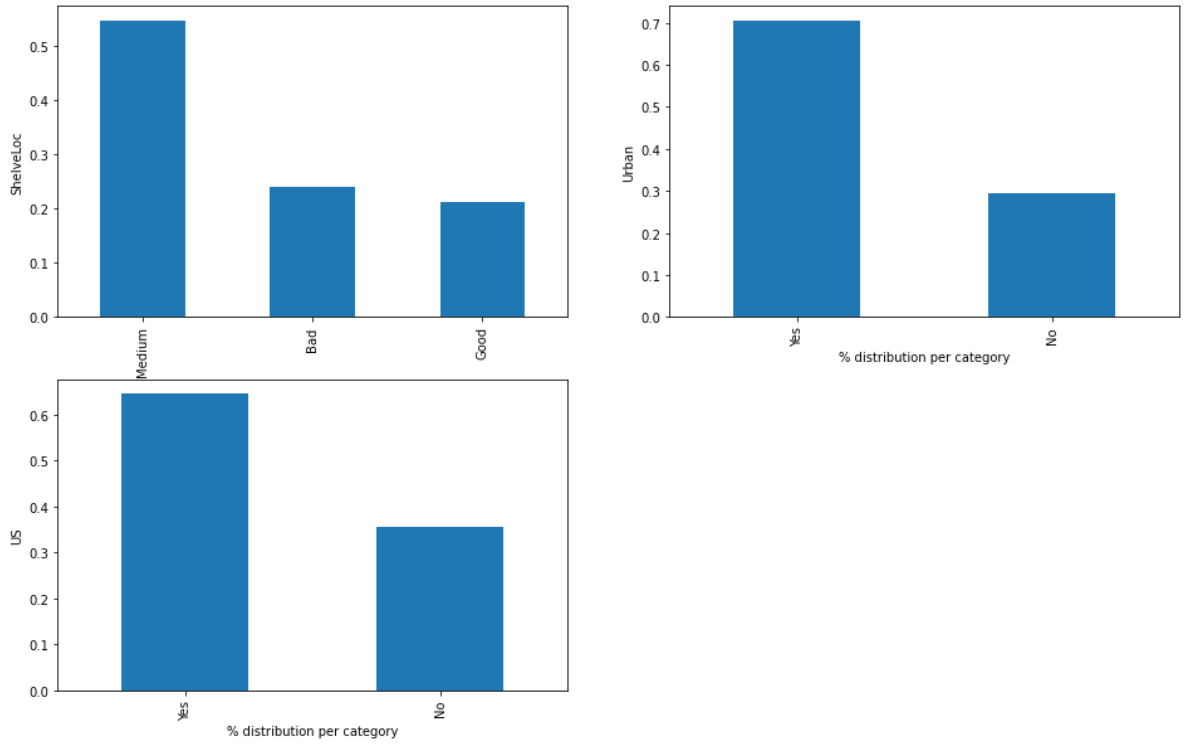
Out[8]:

	ShelveLoc	Urban	US
0	Bad	Yes	Yes
1	Good	Yes	Yes
2	Medium	Yes	Yes
3	Medium	Yes	Yes
4	Bad	Yes	No
...	...	...	...
395	Good	Yes	Yes
396	Medium	No	Yes
397	Medium	Yes	Yes
398	Bad	Yes	Yes
399	Good	Yes	Yes

400 rows × 3 columns

In [9]:

```
plt.figure(figsize=(16,10))
for i,col in enumerate(obj_colum,1):
    plt.subplot(2,2,i)
    companey[col].value_counts(normalize=True).plot.bar()
    plt.ylabel(col)
    plt.xlabel('% distribution per category')
```



In [10]:

```
num_columns = companey.select_dtypes(include=['float64','int64'])
num_columns
```

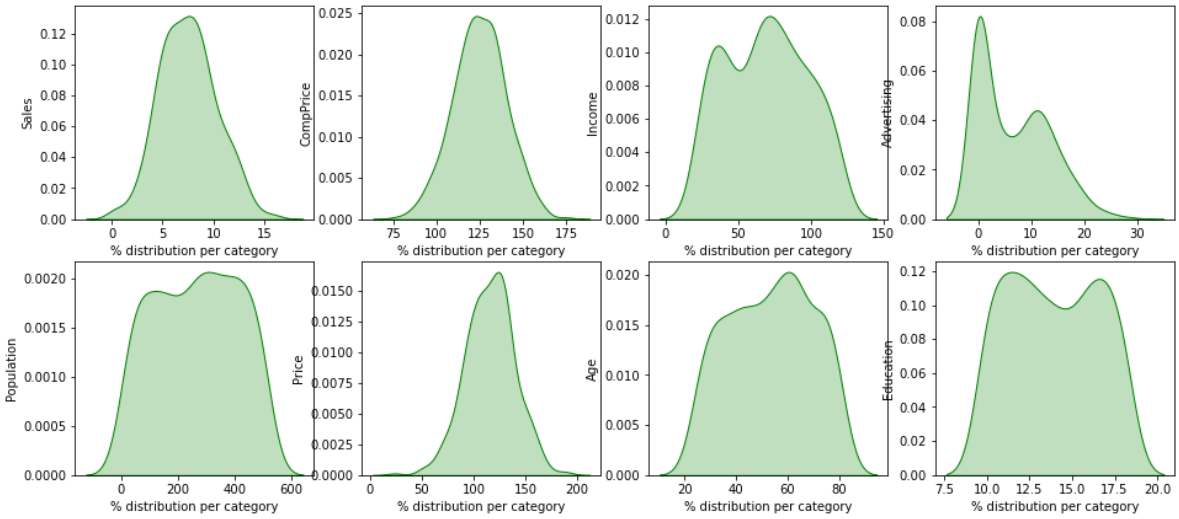
Out[10]:

	Sales	CompPrice	Income	Advertising	Population	Price	Age	Education
0	9.50	138	73	11	276	120	42	17
1	11.22	111	48	16	260	83	65	10
2	10.06	113	35	10	269	80	59	12
3	7.40	117	100	4	466	97	55	14
4	4.15	141	64	3	340	128	38	13
...	...	...	...	...	...	...	...	...
395	12.57	138	108	17	203	128	33	14
396	6.14	139	23	3	37	120	55	11
397	7.41	162	26	12	368	159	40	18
398	5.94	100	79	7	284	95	50	12
399	9.71	134	37	0	27	120	49	16

400 rows × 8 columns

In [11]:

```
plt.figure(figsize=(16,30))
for i,col in enumerate(num_columns,1):
    plt.subplot(8,4,i)
    sns.kdeplot(companey[col],color='g',shade=True)
    plt.ylabel(col)
    plt.xlabel('% distribution per category')
```



In [12]:

```
pd.DataFrame(data=[num_columns.skew(),num_columns.kurtosis()],index=['skewness','kurtosis']
```

Out[12]:

	Sales	CompPrice	Income	Advertising	Population	Price	Age	Edu
skewness	0.185560	-0.042755	0.049444	0.639586	-0.051227	-0.125286	-0.077182	0.0
kurtosis	-0.080877	0.041666	-1.085289	-0.545118	-1.202318	0.451885	-1.134392	-1.2

In [13]:

```
df = pd.get_dummies(companey, columns = ['ShelveLoc','Urban','US'])
```

In [14]:

```
df
```

Out[14]:

	Sales	CompPrice	Income	Advertising	Population	Price	Age	Education	ShelveLoc_Ba
0	9.50	138	73	11	276	120	42	17	
1	11.22	111	48	16	260	83	65	10	
2	10.06	113	35	10	269	80	59	12	
3	7.40	117	100	4	466	97	55	14	
4	4.15	141	64	3	340	128	38	13	
...	...	...	...	...	...	...	...	...	.
395	12.57	138	108	17	203	128	33	14	
396	6.14	139	23	3	37	120	55	11	
397	7.41	162	26	12	368	159	40	18	
398	5.94	100	79	7	284	95	50	12	
399	9.71	134	37	0	27	120	49	16	

400 rows × 15 columns

In [15]:

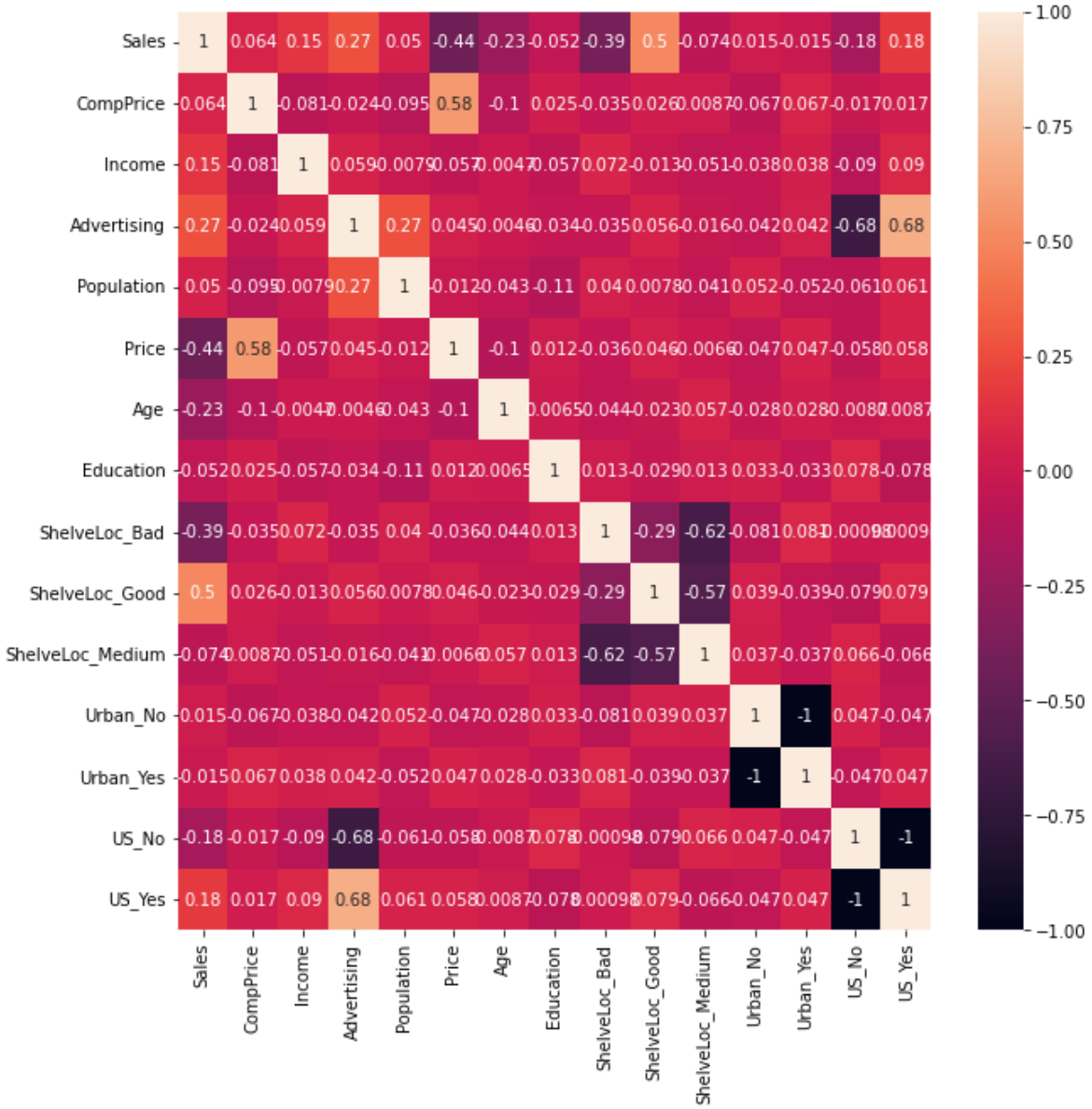
```
corr = df.corr()
```

In [16]:

```
plt.figure(figsize=(10,10))
sns.heatmap(corr,annot=True)
```

Out[16]:

```
<AxesSubplot:>
```



4. Model Building

Since the target variable is continious, we create a class of the value based on the mean

In [17]:

```
df['Sales'].mean()
```

Out[17]:

```
7.496325
```

In [18]:

```
df["Sales"]
```

Out[18]:

```
0       9.50
1      11.22
2      10.06
3       7.40
4       4.15
       ...
395    12.57
396     6.14
397     7.41
398     5.94
399     9.71
Name: Sales, Length: 400, dtype: float64
```

for <= 7.49 = "small" and > 7.49 = "Large"

Creating new column as sales

In [19]:

```
df['sales']="small"
```

replacing the values(small) which are greater than 7.49 with large

In [20]:

```
df.loc[df["Sales"]>7.49,"sales"]="large"
```

Droping the Sales column

In [21]:

```
df.drop(["Sales"],axis=1,inplace=True)
```

In [22]:

```
df
```

Out[22]:

	CompPrice	Income	Advertising	Population	Price	Age	Education	ShelveLoc_Bad	Shel
0	138	73	11	276	120	42	17	1	
1	111	48	16	260	83	65	10	0	
2	113	35	10	269	80	59	12	0	
3	117	100	4	466	97	55	14	0	
4	141	64	3	340	128	38	13	1	
...	...	...	...	...	...	...	...	...	
395	138	108	17	203	128	33	14	0	
396	139	23	3	37	120	55	11	0	
397	162	26	12	368	159	40	18	0	
398	100	79	7	284	95	50	12	1	
399	134	37	0	27	120	49	16	0	

400 rows × 15 columns

In [23]:

```
x = df.iloc[:,0:14]
x
```

Out[23]:

	CompPrice	Income	Advertising	Population	Price	Age	Education	ShelveLoc_Bad	Shel
0	138	73	11	276	120	42	17	1	
1	111	48	16	260	83	65	10	0	
2	113	35	10	269	80	59	12	0	
3	117	100	4	466	97	55	14	0	
4	141	64	3	340	128	38	13	1	
...	...	...	...	...	...	...	...	...	
395	138	108	17	203	128	33	14	0	
396	139	23	3	37	120	55	11	0	
397	162	26	12	368	159	40	18	0	
398	100	79	7	284	95	50	12	1	
399	134	37	0	27	120	49	16	0	

400 rows × 14 columns

In [24]:

```
y =df['sales']

df.sales.value_counts()
```

Out[24]:

```
small    201
large    199
Name: sales, dtype: int64
```

5. Model Traning

Decision Tree - Model using Entropy Criteria and Gini Criteria

Splitting data into training and testing data set

In [25]:

```
x_train,x_test,y_train,y_test = train_test_split(x,y,test_size = 0.2, stratify = y)
```

In [26]:

```
y_train.value_counts()
```

Out[26]:

```
small    161
large    159
Name: sales, dtype: int64
```

Building Decision Tree Classifier using Entropy Criteria

In [27]:

```
model = DecisionTreeClassifier(criterion = 'entropy',max_depth=5)
model.fit(x_train,y_train)
```

Out[27]:

```
DecisionTreeClassifier(criterion='entropy', max_depth=5)
```

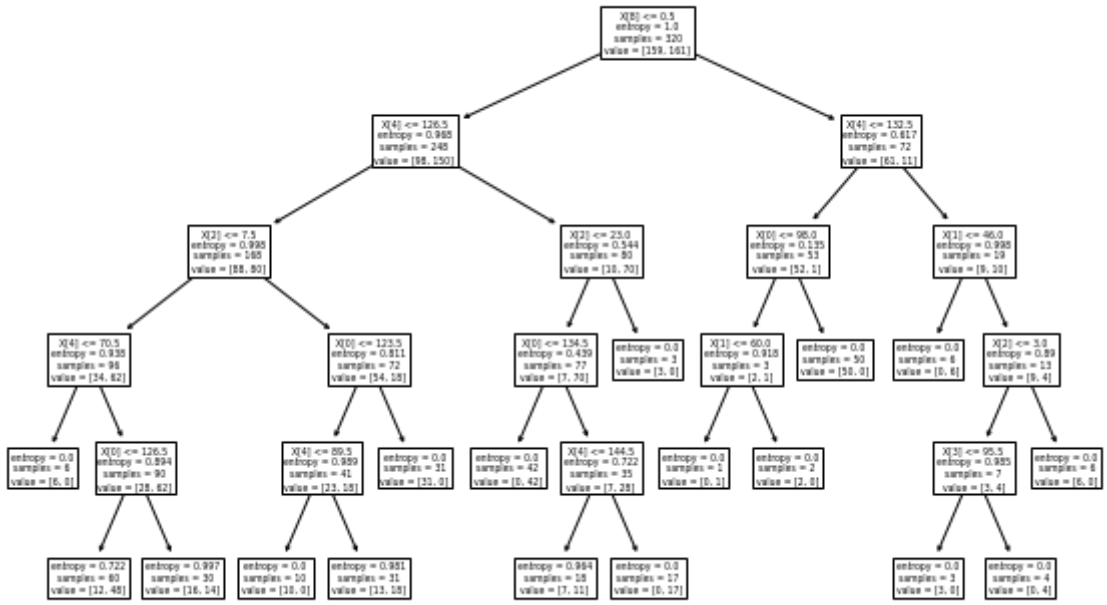
In [28]:

```
#PLot the decision tree
plt.figure(figsize=(10,6))
tree.plot_tree(model)
```

Out[28]:

```
[Text(0.5833333333333334, 0.9166666666666666, 'X[8] <= 0.5\nentropy = 1.0\ns
amples = 320\nvalue = [159, 161]'),
 Text(0.375, 0.75, 'X[4] <= 126.5\nentropy = 0.968\nsamples = 248\nvalue =
[98, 150]'),
 Text(0.20833333333333334, 0.5833333333333334, 'X[2] <= 7.5\nentropy = 0.998
\nsamples = 168\nvalue = [88, 80]'),
 Text(0.08333333333333333, 0.4166666666666667, 'X[4] <= 70.5\nentropy = 0.93
8\nsamples = 96\nvalue = [34, 62]'),
 Text(0.041666666666666664, 0.25, 'entropy = 0.0\nsamples = 6\nvalue = [6,
0]'),
 Text(0.125, 0.25, 'X[0] <= 126.5\nentropy = 0.894\nsamples = 90\nvalue = [2
8, 62]'),
 Text(0.08333333333333333, 0.08333333333333333, 'entropy = 0.722\nsamples =
60\nvalue = [12, 48]'),
 Text(0.16666666666666666, 0.08333333333333333, 'entropy = 0.997\nsamples =
30\nvalue = [16, 14]'),
 Text(0.3333333333333333, 0.4166666666666667, 'X[0] <= 123.5\nentropy = 0.81
1\nsamples = 72\nvalue = [54, 18]'),
 Text(0.2916666666666667, 0.25, 'X[4] <= 89.5\nentropy = 0.989\nsamples = 41
\nvalue = [23, 18]'),
 Text(0.25, 0.08333333333333333, 'entropy = 0.0\nsamples = 10\nvalue = [10,
0]'),
 Text(0.3333333333333333, 0.08333333333333333, 'entropy = 0.981\nsamples = 3
1\nvalue = [13, 18]'),
 Text(0.375, 0.25, 'entropy = 0.0\nsamples = 31\nvalue = [31, 0]'),
 Text(0.5416666666666666, 0.5833333333333334, 'X[2] <= 23.0\nentropy = 0.544
\nsamples = 80\nvalue = [10, 70]'),
 Text(0.5, 0.4166666666666667, 'X[0] <= 134.5\nentropy = 0.439\nsamples = 77
\nvalue = [7, 70]'),
 Text(0.4583333333333333, 0.25, 'entropy = 0.0\nsamples = 42\nvalue = [0, 4
2]'),
 Text(0.5416666666666666, 0.25, 'X[4] <= 144.5\nentropy = 0.722\nsamples = 3
5\nvalue = [7, 28]'),
 Text(0.5, 0.08333333333333333, 'entropy = 0.964\nsamples = 18\nvalue = [7,
11]'),
 Text(0.5833333333333334, 0.08333333333333333, 'entropy = 0.0\nsamples = 17
\nvalue = [0, 17]'),
 Text(0.5833333333333334, 0.4166666666666667, 'entropy = 0.0\nsamples = 3\nv
alue = [3, 0]'),
 Text(0.7916666666666666, 0.75, 'X[4] <= 132.5\nentropy = 0.617\nsamples = 7
2\nvalue = [61, 11]'),
 Text(0.7083333333333334, 0.5833333333333334, 'X[0] <= 98.0\nentropy = 0.135
\nsamples = 53\nvalue = [52, 1]'),
 Text(0.6666666666666666, 0.4166666666666667, 'X[1] <= 60.0\nentropy = 0.918
\nsamples = 3\nvalue = [2, 1]'),
 Text(0.625, 0.25, 'entropy = 0.0\nsamples = 1\nvalue = [0, 1]'),
 Text(0.7083333333333334, 0.25, 'entropy = 0.0\nsamples = 2\nvalue = [2,
0]'),
 Text(0.75, 0.4166666666666667, 'entropy = 0.0\nsamples = 50\nvalue = [50,
0]'),
 Text(0.875, 0.5833333333333334, 'X[1] <= 46.0\nentropy = 0.998\nsamples = 1
9\nvalue = [9, 10]'),
 Text(0.8333333333333334, 0.4166666666666667, 'entropy = 0.0\nsamples = 6\nv
```

```
alue = [0, 6]'),
 Text(0.9166666666666666, 0.4166666666666667, 'X[2] <= 3.0\nentropy = 0.89\n
samples = 13\nvalue = [9, 4]'),
 Text(0.875, 0.25, 'X[3] <= 95.5\nentropy = 0.985\nsamples = 7\nvalue = [3,
4]'),
 Text(0.8333333333333334, 0.08333333333333333, 'entropy = 0.0\nsamples = 3\n
value = [3, 0]'),
 Text(0.9166666666666666, 0.08333333333333333, 'entropy = 0.0\nsamples = 4\n
value = [0, 4]'),
 Text(0.9583333333333334, 0.25, 'entropy = 0.0\nsamples = 6\nvalue = [6,
0]')]
```



In [29]:

```
pred_train = model.predict(x_train)
```

accuracy check

In [30]:

```
accuracy_score(y_train,pred_train)
```

Out[30]:

```
0.85625
```

In [31]:

```
confusion_matrix(y_train,pred_train)
```

Out[31]:

```
array([[127,  32],
       [ 14, 147]], dtype=int64)
```

In [32]:

```
pred_test = model.predict(x_test)
```

accuracy check

In [33]:

```
accuracy_score(y_test,pred_test)
```

Out[33]:

```
0.7625
```

In [34]:

```
confusion_matrix(y_test,pred_test)
```

Out[34]:

```
array([[28, 12],
       [ 7, 33]], dtype=int64)
```

In [35]:

```
df_Entropy=pd.DataFrame({'Actual':y_test, 'Predicted':pred_test})
```

In [36]:

```
df_Entropy
```

Out[36]:

	Actual	Predicted
158	large	large
244	large	large
365	small	small
140	small	small
161	small	small
...	...	...
248	small	small
8	small	large
256	small	small
273	large	large
218	large	large

80 rows × 2 columns

In [37]:

```
model.feature_importances_
```

Out[37]:

```
array([0.19150531, 0.05095673, 0.16891384, 0.03465585, 0.37553429,
       0.        , 0.        , 0.        , 0.17843398, 0.        ,
       0.        , 0.        , 0.        , 0.        ])
```

In [38]:

```
feature_importance = pd.DataFrame({'feature': list(x_train.columns),
                   'importance': model.feature_importances_}).\
                    sort_values('importance', ascending = False)
```

In [39]:

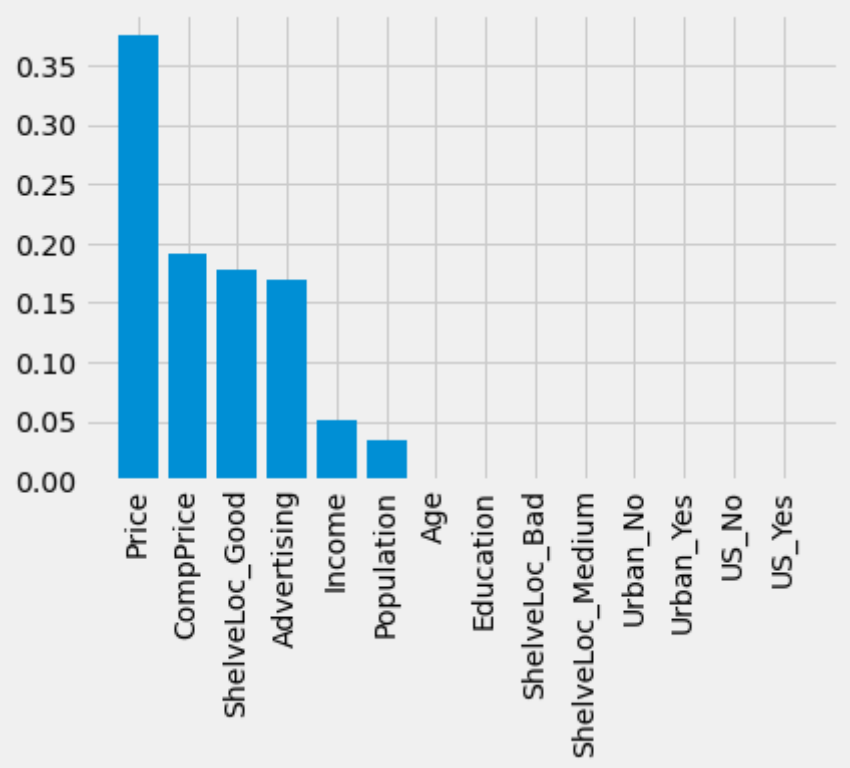
```
feature_importance
```

Out[39]:

	feature	importance
4	Price	0.375534
0	CompPrice	0.191505
8	ShelveLoc_Good	0.178434
2	Advertising	0.168914
1	Income	0.050957
3	Population	0.034656
5	Age	0.000000
6	Education	0.000000
7	ShelveLoc_Bad	0.000000
9	ShelveLoc_Medium	0.000000
10	Urban_No	0.000000
11	Urban_Yes	0.000000
12	US_No	0.000000
13	US_Yes	0.000000

In [40]:

```
plt.style.use('fivethirtyeight')
plt.bar(feature_importance['feature'],feature_importance['importance'], orientation = 'vert
plt.xticks(rotation = 90)
plt.show()
```



As seen in the above chart, Price is most important feature

END

In [ ]: