# Random Forest Q1 (Company Data)

# Random Forest

Assignment: **Problem Statement:**
A cloth manufacturing company is interested to know about the segment or attributes causes high sale.
Approach - A Random Forest can be built with target variable Sales (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 plot_tree
from sklearn.ensemble import RandomForestClassifier
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

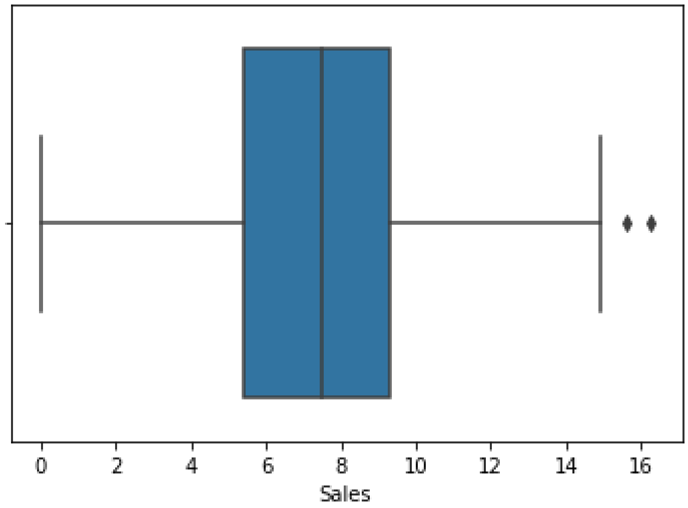
In [6]:

```
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'>
```

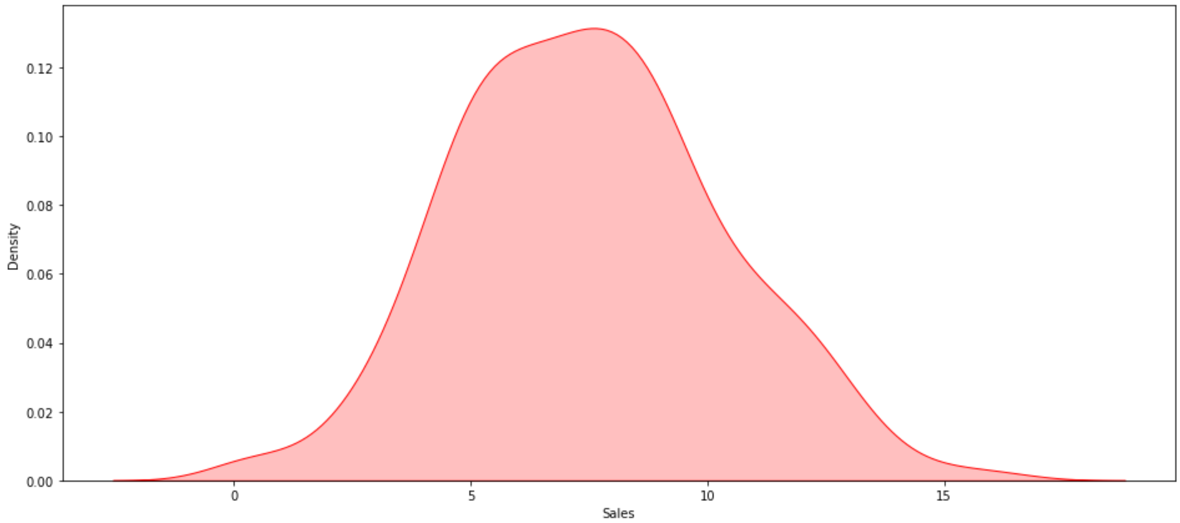



**we can see there are 2 outliers present in the data**

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
```

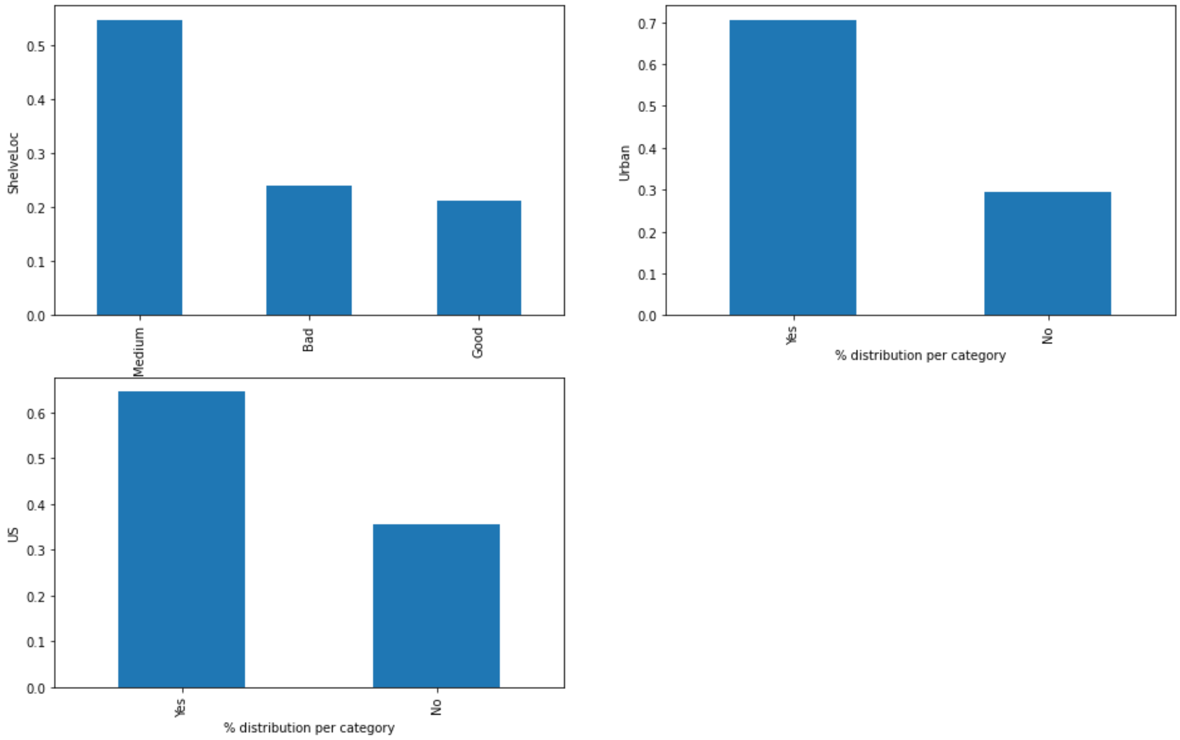
Out[8]:

| | 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
```

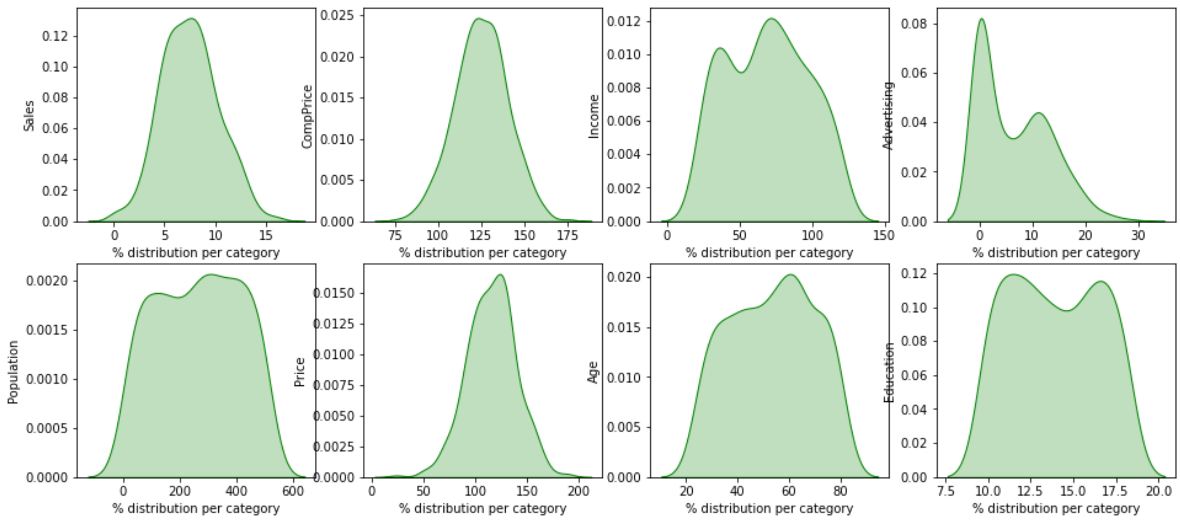
Out[10]:

| | 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]:

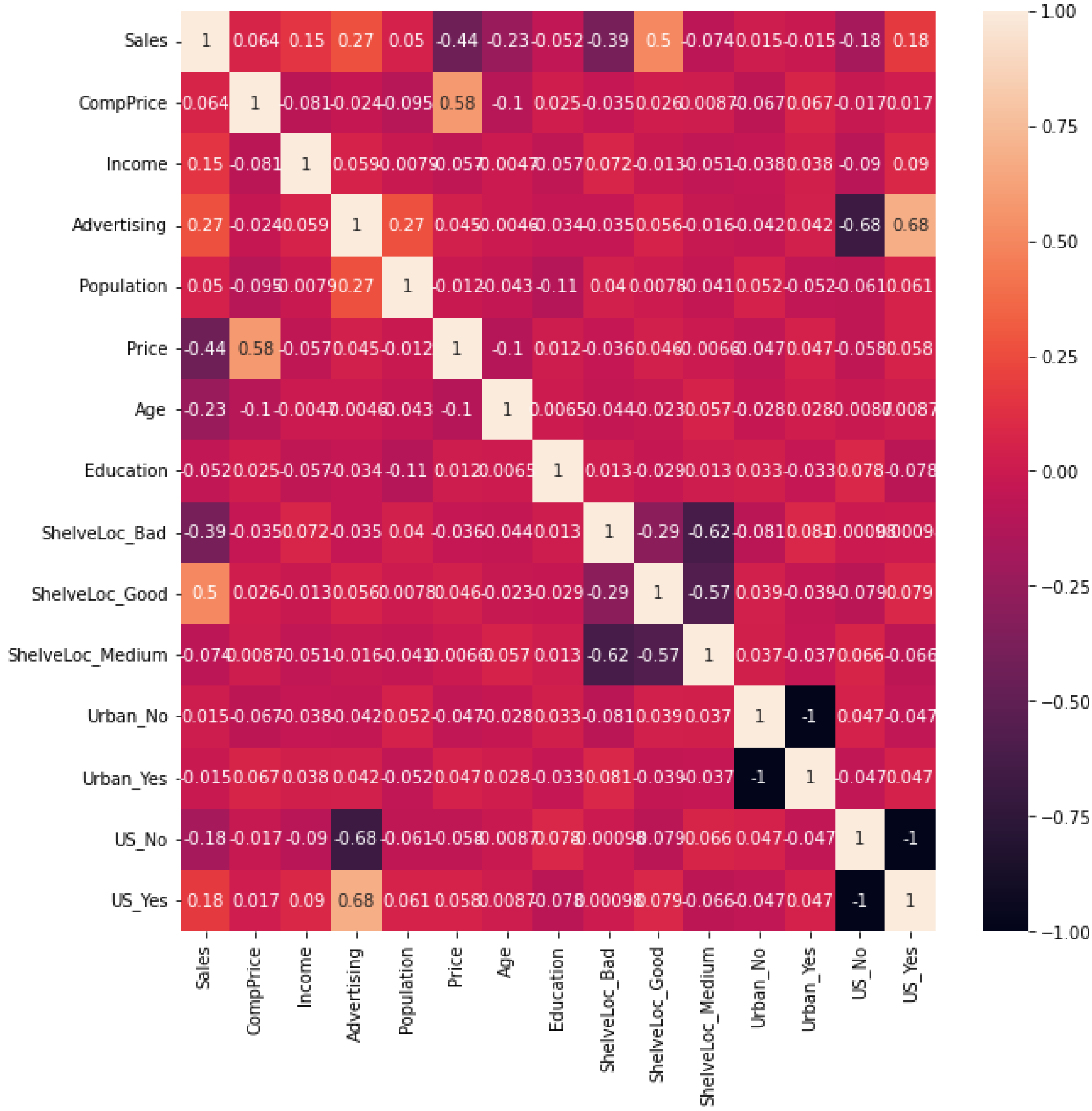
```
corr = df.corr()
```

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

## Random Forest - Model using Entropy 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 Random Forest Classifier

In [27]:

```
model =RandomForestClassifier(n_jobs=4,n_estimators = 150, oob_score =True,criterion ='entr
model.fit(x_train,y_train)
model.oob_score_
```

Out[27]:

```
0.784375
```

In [28]:

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

#### accuracy check

In [29]:

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

Out[29]:

```
1.0
```

In [30]:

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

Out[30]:

```
array([[159,   0],
       [  0, 161]], dtype=int64)
```

In [31]:

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

#### accuracy check

In [32]:

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

Out[32]:

```
0.8
```

In [33]:

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

Out[33]:

```
array([[32,  8],
       [ 8, 32]], dtype=int64)
```

# Visulizaing graph

In [34]:

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

In [35]:

```
df_RF
```

Out[35]:

| | Actual | Predicted |
|---|---|---|
| **386** | small | small |
| **307** | small | small |
| **47** | small | small |
| **242** | small | small |
| **256** | small | small |
| **...** | ... | ... |
| **221** | small | small |
| **362** | small | small |
| **243** | large | large |
| **354** | small | small |
| **189** | large | large |

80 rows × 2 columns

In [36]:

```
model.feature_importances_
```

Out[36]:

```
array([0.1197807 , 0.10051581, 0.07880429, 0.08783112, 0.22826174,
       0.13286984, 0.06431853, 0.04075786, 0.0764499 , 0.02150915,
       0.01153003, 0.01221579, 0.01345363, 0.01170162])
```

In [37]:

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

In [38]:

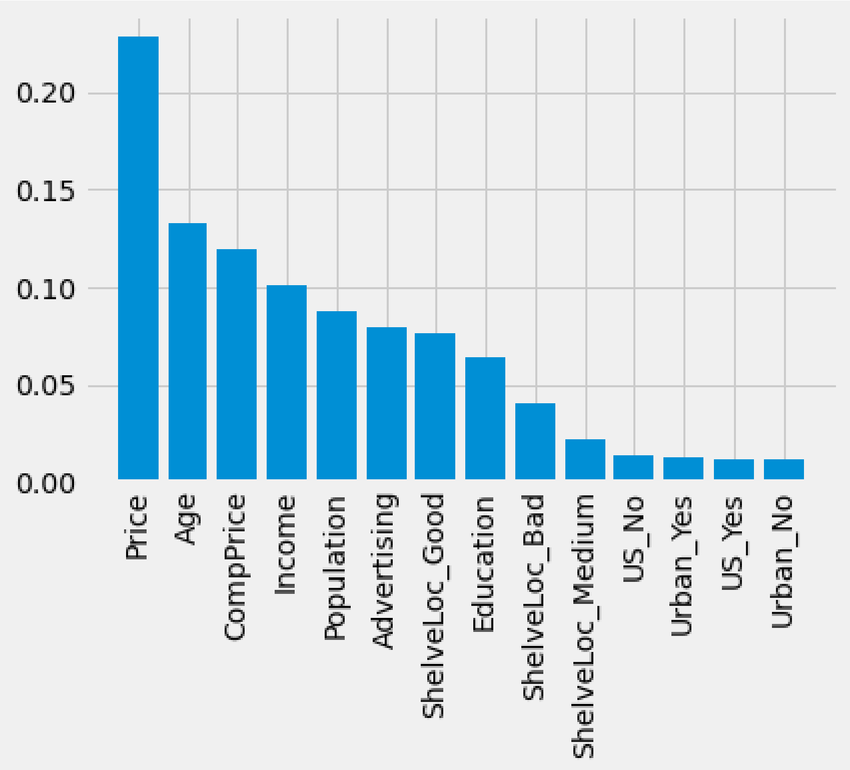
```
feature_importance
```

Out[38]:

| | feature | importance |
|---|---|---|
| 4 | Price | 0.228262 |
| 5 | Age | 0.132870 |
| 0 | CompPrice | 0.119781 |
| 1 | Income | 0.100516 |
| 3 | Population | 0.087831 |
| 2 | Advertising | 0.078804 |
| 8 | ShelveLoc_Good | 0.076450 |
| 6 | Education | 0.064319 |
| 7 | ShelveLoc_Bad | 0.040758 |
| 9 | ShelveLoc_Medium | 0.021509 |
| 12 | US_No | 0.013454 |
| 11 | Urban_Yes | 0.012216 |
| 13 | US_Yes | 0.011702 |
| 10 | Urban_No | 0.011530 |

In [39]:

```
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 most important feature**

# END

In [ ]: