Decision Trees Assignment

Data Set - Company_Data

1. Import Necessary libraries

In [1]:
```
import pandas as pd
import numpy as np

from matplotlib import pyplot as plt
import seaborn as sns

from sklearn import datasets
from sklearn.metrics import classification_report

import warnings
warnings.filterwarnings('ignore')
```

2. Import Data

In [2]:
```
company_details = pd.read_csv('Company_Data.csv')
company_details
```

Out[2]:

	Sales	CompPrice	Income	Advertising	Population	Price	ShelveLoc	Age	Education	Urban	US
0	9.50	138	73	11	276	120	Bad	42	17	Yes	Yes
1	11.22	111	48	16	260	83	Good	65	10	Yes	Yes
2	10.06	113	35	10	269	80	Medium	59	12	Yes	Yes
3	7.40	117	100	4	466	97	Medium	55	14	Yes	Yes
4	4.15	141	64	3	340	128	Bad	38	13	Yes	No
...	...	...	...	...	...	...	...	...	...	...	...
395	12.57	138	108	17	203	128	Good	33	14	Yes	Yes
396	6.14	139	23	3	37	120	Medium	55	11	No	Yes
397	7.41	162	26	12	368	159	Medium	40	18	Yes	Yes
398	5.94	100	79	7	284	95	Bad	50	12	Yes	Yes
399	9.71	134	37	0	27	120	Good	49	16	Yes	Yes

400 rows × 11 columns

3. Data Understanding

3.1 Initial Analysis :

In [3]:
```
company_details.head()
```

Out[3]:

	Sales	CompPrice	Income	Advertising	Population	Price	ShelveLoc	Age	Education	Urban	US
0	9.50	138	73	11	276	120	Bad	42	17	Yes	Yes
1	11.22	111	48	16	260	83	Good	65	10	Yes	Yes
2	10.06	113	35	10	269	80	Medium	59	12	Yes	Yes
3	7.40	117	100	4	466	97	Medium	55	14	Yes	Yes
4	4.15	141	64	3	340	128	Bad	38	13	Yes	No

In [4]:
```
company_details.shape
```

Out[4]:
```
(400, 11)
```

In [5]:
```
company_details.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 400 entries, 0 to 399
Data columns (total 11 columns):
 #   Column       Non-Null Count  Dtype  
---  ------       --------------  -----  
 0   Sales        400 non-null    float64
 1   CompPrice    400 non-null    int64  
 2   Income       400 non-null    int64  
 3   Advertising  400 non-null    int64  
 4   Population   400 non-null    int64  
 5   Price        400 non-null    int64  
 6   ShelveLoc    400 non-null    object 
 7   Age          400 non-null    int64  
 8   Education    400 non-null    int64  
 9   Urban        400 non-null    object 
 10  US           400 non-null    object 
dtypes: float64(1), int64(7), object(3)
memory usage: 34.5+ KB
```

In [6]:
```
company_details.isna().sum()
```

Out[6]:
```
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 [7]:
```
company_details.describe()
```

Out[7]:

	Sales	CompPrice	Income	Advertising	Population	Price	Age	Education
count	400.000000	400.000000	400.000000	400.000000	400.000000	400.000000	400.000000	400.000000
mean	7.496325	124.975000	68.657500	6.635000	264.840000	115.795000	53.322500	13.900000
std	2.824115	15.334512	27.986037	6.650364	147.376436	23.676664	16.200297	2.620528
min	0.000000	77.000000	21.000000	0.000000	10.000000	24.000000	25.000000	10.000000
25%	5.390000	115.000000	42.750000	0.000000	139.000000	100.000000	39.750000	12.000000
50%	7.490000	125.000000	69.000000	5.000000	272.000000	117.000000	54.500000	14.000000
75%	9.320000	135.000000	91.000000	12.000000	398.500000	131.000000	66.000000	16.000000
max	16.270000	175.000000	120.000000	29.000000	509.000000	191.000000	80.000000	18.000000

In [8]:
```
company_details.dtypes
```

Out[8]:
```
Sales          float64
CompPrice        int64
Income           int64
Advertising      int64
Population       int64
Price            int64
ShelveLoc       object
Age              int64
Education        int64
Urban           object
US              object
dtype: object
```

In [9]:
```
company_details.columns
```

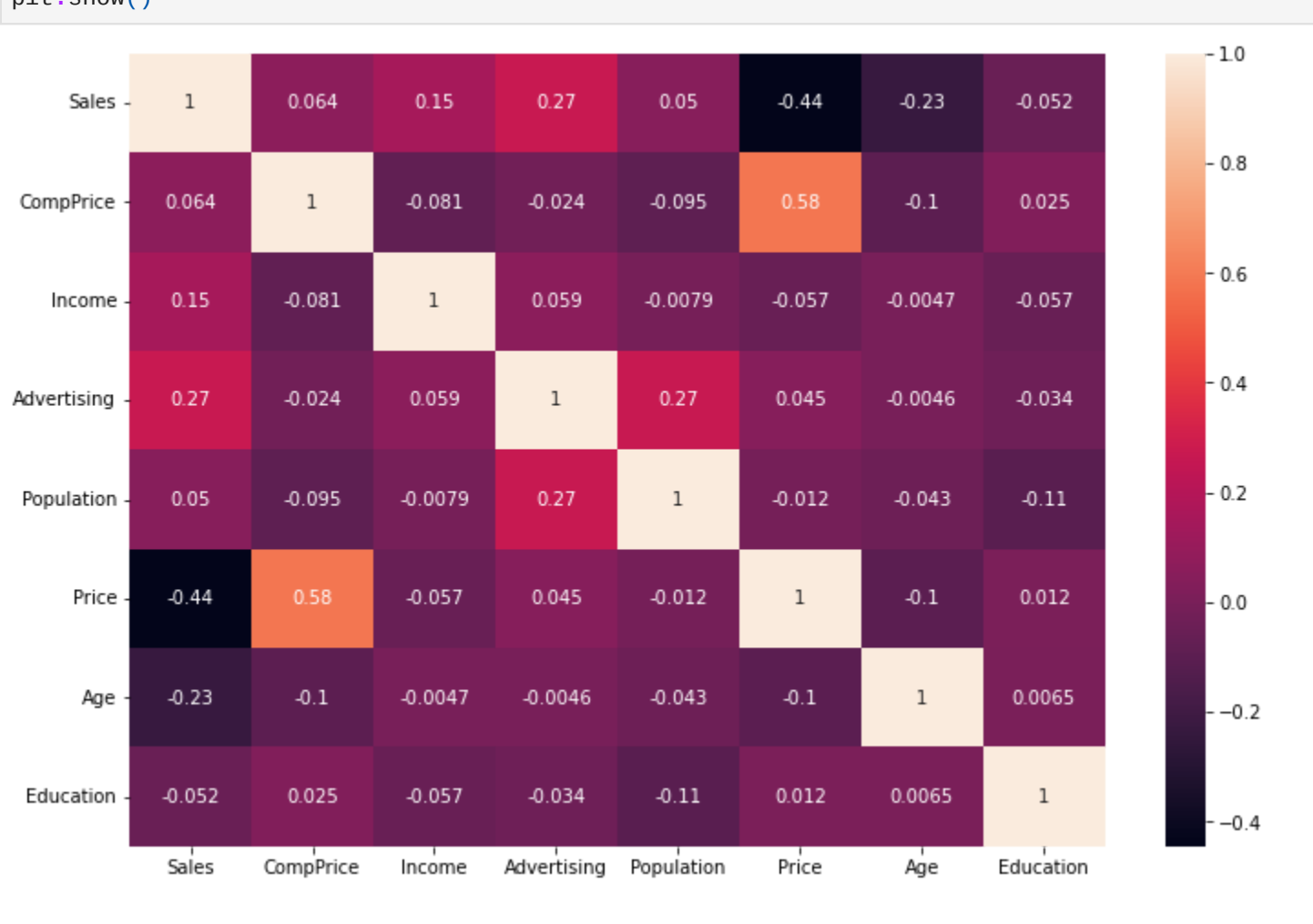
Out[9]:
```
Index(['Sales', 'CompPrice', 'Income', 'Advertising', 'Population', 'Price',
       'ShelveLoc', 'Age', 'Education', 'Urban', 'US'],
      dtype='object')
```

In [10]:
```
company_details.ShelveLoc.value_counts()
```

Out[10]:
```
Medium    219
Bad        96
Good       85
Name: ShelveLoc, dtype: int64
```

3.2 Correlation Matrix :

In [11]:
```
plt.figure(figsize = (12,8))
sns.heatmap(company_details.corr(),annot = True)
plt.show()
```



3.3 Label Encoder :

In [12]:
```
from sklearn import preprocessing
```

In [13]:
```
label_encoder = preprocessing.LabelEncoder()
label_encoder
```

Out[13]:
```
LabelEncoder()
```

In [14]:
```
company_details['ShelveLoc'] = label_encoder.fit_transform(company_details['ShelveLoc'])
company_details['Urban'] = label_encoder.fit_transform(company_details['Urban'])
company_details['US'] = label_encoder.fit_transform(company_details['US'])
```

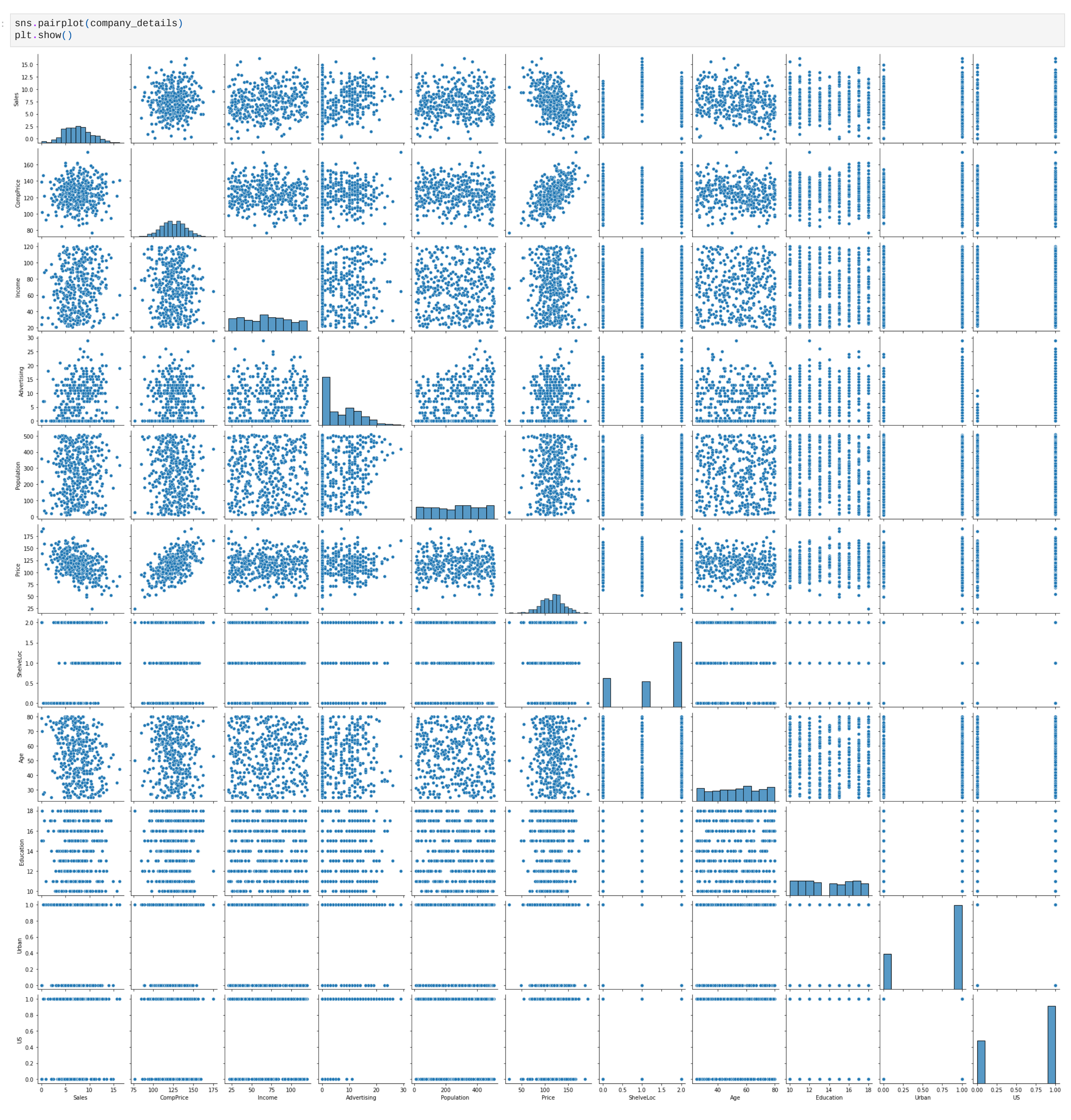
In [15]:
```
company_details
```

Out[15]:

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

400 rows × 11 columns

In [16]:
```
sns.pairplot(company_details)
plt.show()
```



4. Train Test Split

In [17]:
```
from sklearn.model_selection import train_test_split
```

In [18]:
```
x = company_details.iloc[:,0:6]
y = company_details['ShelveLoc']
```

In [19]:
```
x
```

Out[19]:

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

400 rows × 6 columns

In [20]:
```
y
```

Out[20]:
```
0      0
1      1
2      2
3      2
4      0
      ..
395    1
396    2
397    2
398    0
399    1
Name: ShelveLoc, Length: 400, dtype: int32
```

In [21]:
```
company_details['ShelveLoc'].unique()
```

Out[21]:
```
array([0, 1, 2])
```

In [22]:
```
company_details.ShelveLoc.value_counts()
```

Out[22]:
```
2    219
0     96
1     85
Name: ShelveLoc, dtype: int64
```

In [23]:
```
list(company_details.columns)
```

Out[23]:
```
['Sales',
 'CompPrice',
 'Income',
 'Advertising',
 'Population',
 'Price',
 'ShelveLoc',
 'Age',
 'Education',
 'Urban',
 'US']
```

In [24]:
```
x_train, x_test,y_train,y_test = train_test_split(x,y, test_size = 0.2 , random_state = 40)
```

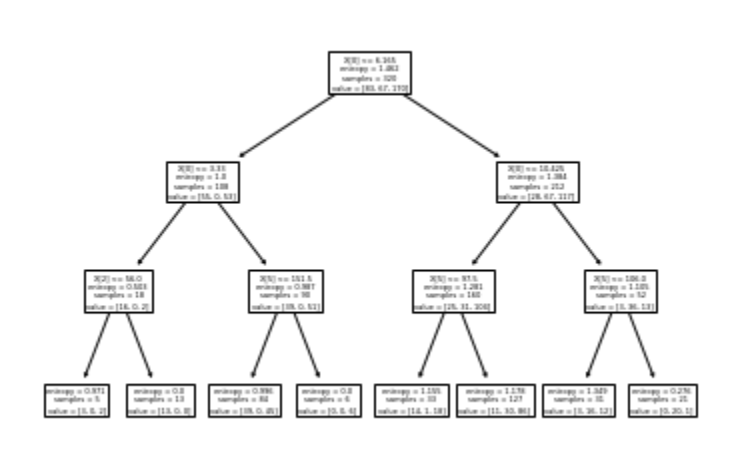
5. Building Model for Decision Tree Classifier using Entropy Criteria

In [25]:
```
from sklearn.tree import  DecisionTreeClassifier
from sklearn import tree
```

In [26]:
```
model = DecisionTreeClassifier(criterion = 'entropy',max_depth = 3)
model.fit(x_train,y_train)
```

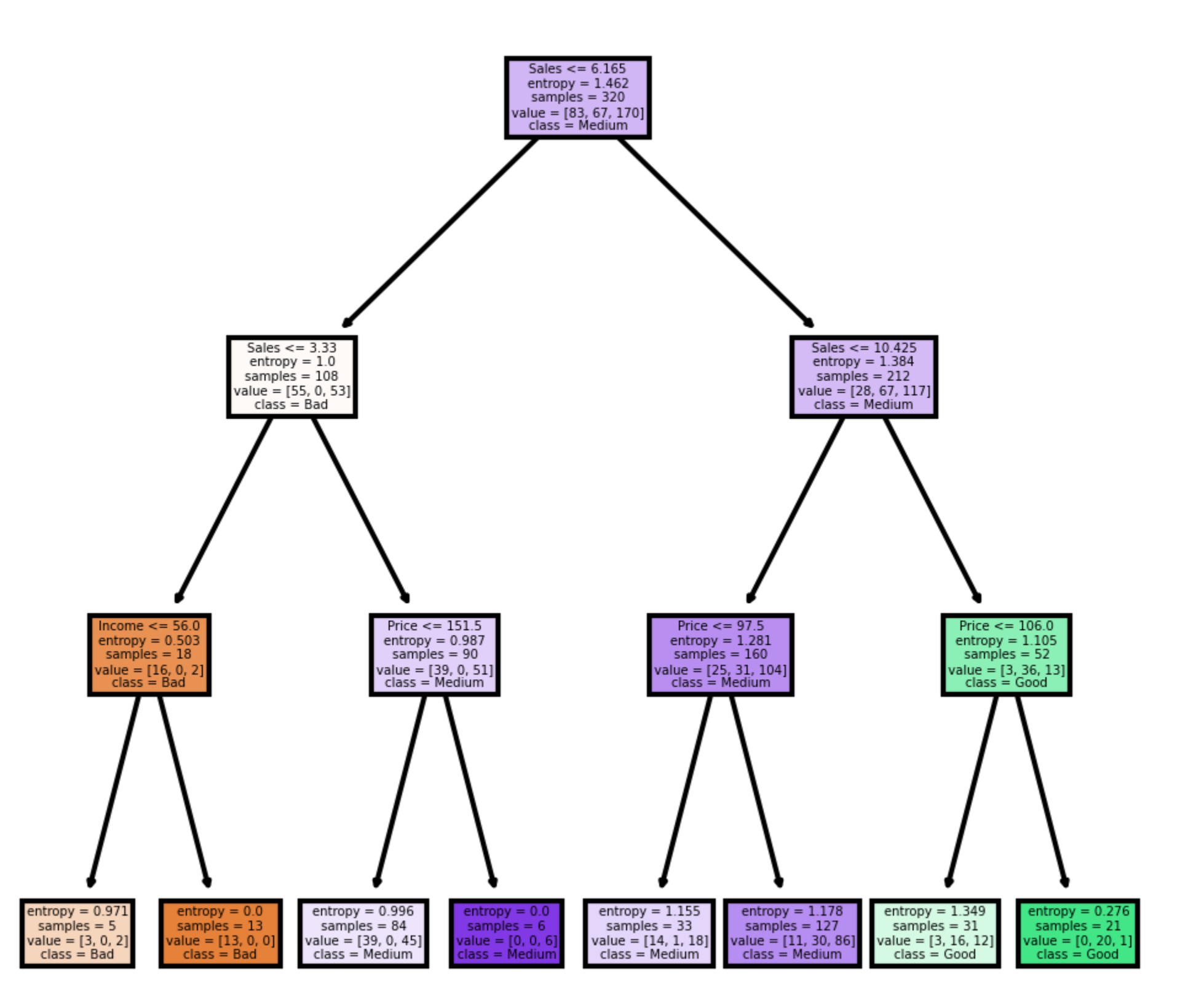
Out[26]:
```
DecisionTreeClassifier(criterion='entropy', max_depth=3)
```

In [27]:
```
tree.plot_tree(model);
```



In [28]:
```
f_n = ['Sales','CompPrice','Income','Advertising','Population','Price']
c_n = ['Bad', 'Good', 'Medium']
```

In [29]:
```
fig, axes = plt.subplots(nrows = 1,ncols = 1,figsize = (4,4), dpi = 300)
tree.plot_tree(model,feature_names = f_n,class_names = c_n,filled = True);
```



5.1 Predicting on Test Data

In [30]:
```
pred = model.predict(x_test)
pd.Series(pred).value_counts()
```

Out[30]:
```
2    63
1    13
0     4
dtype: int64
```

In [31]:
```
pred
```

Out[31]:
```
array([2, 2, 2, 2, 2, 2, 2, 1, 2, 1, 2, 2, 2, 2, 1, 2, 2, 2, 2, 2, 2, 1,
       2, 2, 2, 2, 2, 2, 1, 1, 1, 2, 1, 2, 2, 1, 2, 2, 2, 2, 2, 2, 0, 2,
       2, 2, 2, 2, 2, 2, 0, 2, 2, 2, 2, 1, 1, 2, 2, 0, 2, 2, 1, 2, 2, 2,
       2, 2, 2, 1, 2, 2, 2, 2, 2, 2, 0, 2, 2, 2])
```

In [32]:
```
pd.crosstab(y_test,pred)
```

Out[32]:

ShelveLoc \ col_0	0	1	2
0	1	0	12
1	0	8	10
2	3	5	41

In [33]:
```
np.mean(pred == y_test)
```

Out[33]:
```
0.625
```

5.2 Feature Importance

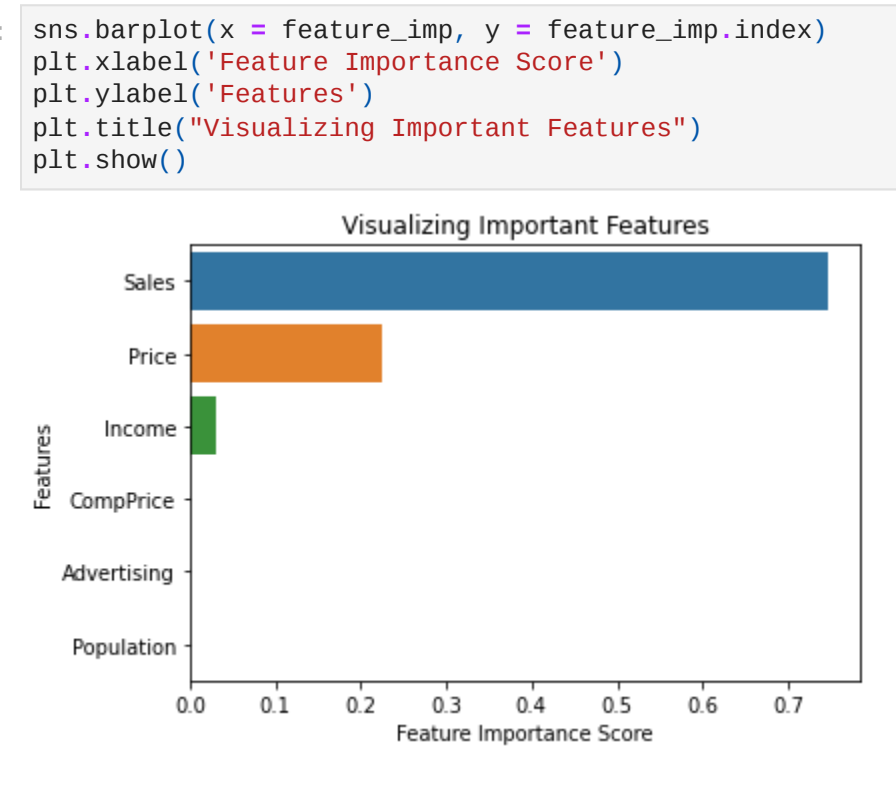
In [34]:
```
model.feature_importances_
```

Out[34]:
```
array([0.74692591, 0.        , 0.02920061, 0.        , 0.        ,
       0.22387348])
```

In [35]:
```
feature_imp = pd.Series(model.feature_importances_,index = f_n).sort_values(ascending = False)
feature_imp
```

Out[35]:
```
Sales          0.746926
Price          0.223873
Income         0.029201
CompPrice      0.000000
Advertising    0.000000
Population     0.000000
dtype: float64
```

In [36]:
```
sns.barplot(x = feature_imp, y = feature_imp.index)
plt.xlabel('Feature Importance Score')
plt.ylabel('Features')
plt.title("Visualizing Important Features")
plt.show()
```

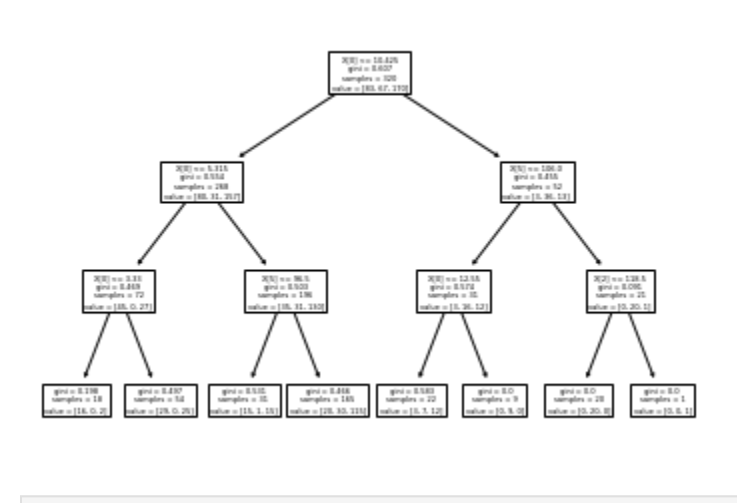


6. Building Model For Decision Tree Classifier (CART) using Gini Criteria

In [37]:
```
model_1 = DecisionTreeClassifier(criterion = 'gini', max_depth = 3)
model_1.fit(x_train, y_train)
```

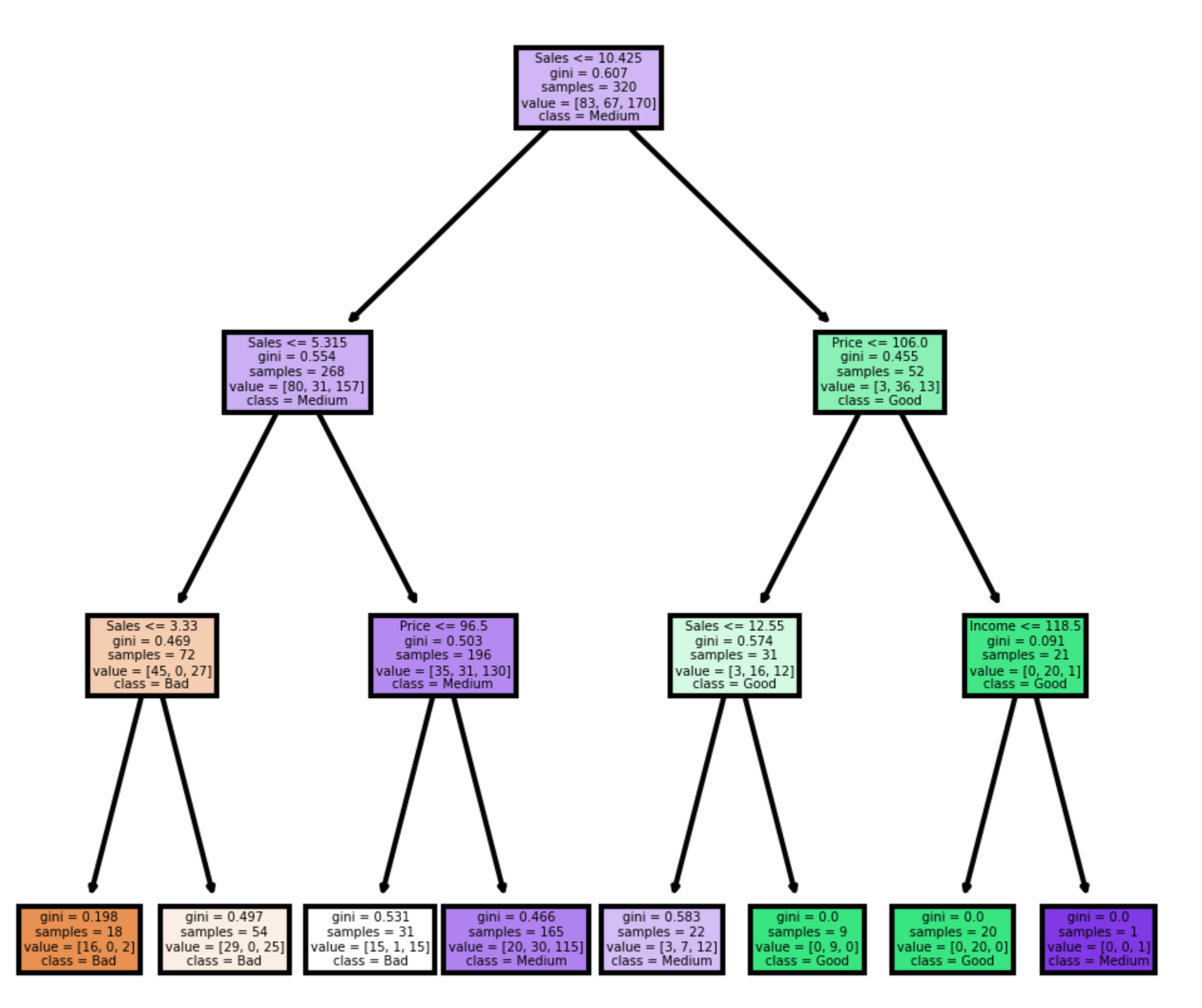
Out[37]:
```
DecisionTreeClassifier(max_depth=3)
```

In [38]:
```
tree.plot_tree(model_1);
```



In [39]:
```
f_n = ['Sales','CompPrice','Income','Advertising','Population','Price']
c_n = ['Bad', 'Good', 'Medium']
```

In [40]:
```
fig, axes = plt.subplots(nrows = 1,ncols = 1,figsize = (4,4), dpi = 300)
tree.plot_tree(model_1,feature_names = f_n,class_names = c_n,filled = True);
```



6.1 Predicting on Test Data

In [41]:
```
pred_1 = model_1.predict(x_test)
pd.Series(pred_1).value_counts()
```

Out[41]:
```
2    42
0    33
1     5
dtype: int64
```

In [42]:
```
pred_1
```

Out[42]:
```
array([2, 2, 2, 2, 2, 0, 2, 2, 2, 2, 0, 0, 2, 0, 1, 0, 2, 2, 0, 0, 0, 2,
       2, 2, 0, 0, 2, 0, 1, 1, 1, 2, 2, 2, 0, 2, 2, 2, 2, 2, 2, 0, 0, 0,
       0, 0, 2, 2, 2, 2, 0, 2, 0, 0, 2, 2, 2, 0, 0, 0, 0, 1, 2, 0, 2,
       2, 0, 2, 2, 0, 0, 0, 2, 0, 2, 0, 2, 0, 2])
```

In [43]:
```
pd.crosstab(y_test,pred_1)
```

Out[43]:

ShelveLoc \ col_0	0	1	2
0	8	0	5
1	2	4	12
2	23	1	25

In [44]:
```
np.mean(pred_1 == y_test)
```

Out[44]:
```
0.4625
```

6.2 Feature Importance

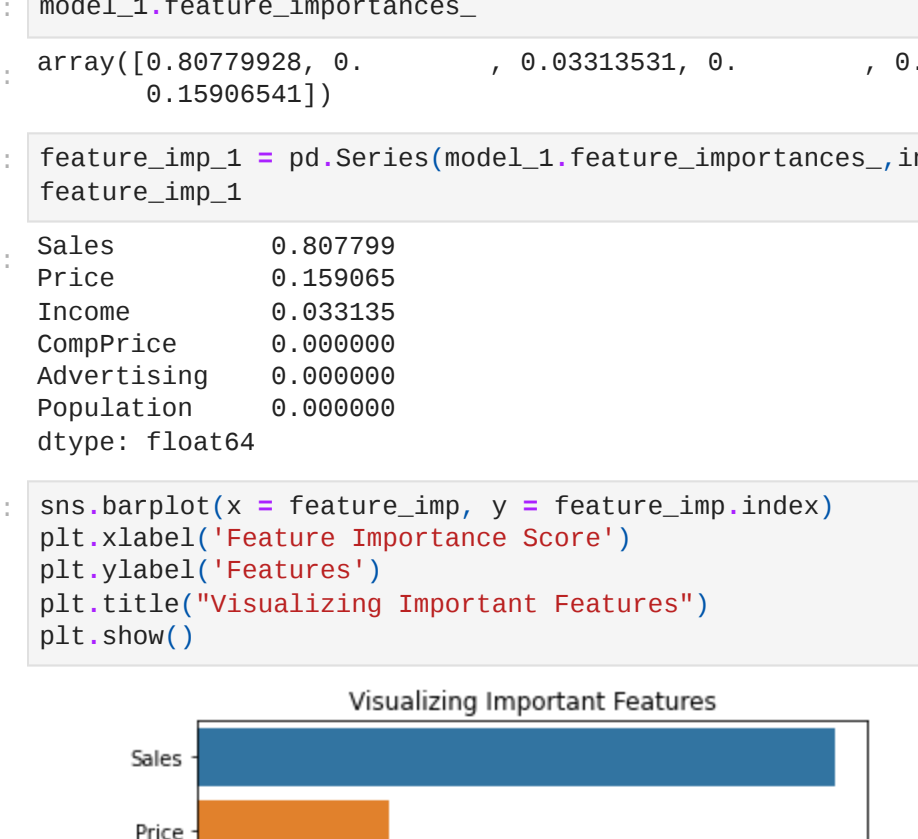
In [45]:
```
model_1.feature_importances_
```

Out[45]:
```
array([0.80779928, 0.        , 0.03313531, 0.        , 0.        ,
       0.15906541])
```

In [46]:
```
feature_imp_1 = pd.Series(model_1.feature_importances_,index = f_n).sort_values(ascending = False)
feature_imp_1
```

Out[46]:
```
Sales          0.807799
Price          0.159065
Income         0.033135
CompPrice      0.000000
Advertising    0.000000
Population     0.000000
dtype: float64
```

In [47]:
```
sns.barplot(x = feature_imp, y = feature_imp.index)
plt.xlabel('Feature Importance Score')
plt.ylabel('Features')
plt.title("Visualizing Important Features")
plt.show()
```



7. Decision Tree Regression

In [48]:
```
from sklearn.tree import DecisionTreeRegressor
```

In [49]:
```
array = company_details.values
X = array[:,0:6]
y = array[:,3]
```

In [50]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.33, random_state = 1)
```

In [51]:
```
model_3 = DecisionTreeRegressor()
model_3.fit(X_train, y_train)
```

Out[51]:
```
DecisionTreeRegressor()
```

In [52]:
```
model_3.score(X_test,y_test)
```

Out[52]:
```
0.9929398820257342
```

Conclusion :

```
Model Accuracy for Entropy Criteria :  0.625
Model Accuracy for Gini Criteria    :  0.4625
Model Accuracy for Decision Tree Regression : 0.9979
```