In [1]:

```
import pandas as pd
from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score
from sklearn.ensemble import BaggingClassifier
from sklearn.ensemble import AdaBoostClassifier
from sklearn.metrics import classification_report, confusion_matrix
```

In [2]:

```
company=pd.read_csv("Company_Data.csv")
company.head()
```

Out[2]:

	Sales	CompPrice	Income	Advertising	Population	Price	ShelveLoc	Age	Education	Urban	U
0	9.50	138	73	11	276	120	Bad	42	17	Yes	Y
1	11.22	111	48	16	260	83	Good	65	10	Yes	Y
2	10.06	113	35	10	269	80	Medium	59	12	Yes	Y
3	7.40	117	100	4	466	97	Medium	55	14	Yes	Y
4	4.15	141	64	3	340	128	Bad	38	13	Yes	N

In [3]:

```
company.dtypes
```

Out[3]:

```
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 [22]:

```
company.shape
```

Out[22]:

```
(400, 12)
```

In [23]:

```
company.isna().sum()
```

Out[23]:

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

In [24]:

```
company.describe()
```

Out[24]:

	Sales	CompPrice	Income	Advertising	Population	Price	ShelveLoc	A
count	400.000000	400.000000	400.000000	400.000000	400.000000	400.000000	400.000000	400.000
mean	7.496325	124.975000	68.657500	6.635000	264.840000	115.795000	1.307500	53.322
std	2.824115	15.334512	27.986037	6.650364	147.376436	23.676664	0.833475	16.200
min	0.000000	77.000000	21.000000	0.000000	10.000000	24.000000	0.000000	25.000
25%	5.390000	115.000000	42.750000	0.000000	139.000000	100.000000	1.000000	39.750
50%	7.490000	125.000000	69.000000	5.000000	272.000000	117.000000	2.000000	54.500
75%	9.320000	135.000000	91.000000	12.000000	398.500000	131.000000	2.000000	66.000
max	16.270000	175.000000	120.000000	29.000000	509.000000	191.000000	2.000000	80.000

Converting from Categorical data

In [4]:

```
company['High'] = company.Sales.map(lambda x: 1 if x>8 else 0)
company['ShelveLoc']=company['ShelveLoc'].astype('category')
company['Urban']=company['Urban'].astype('category')
company['US']=company['US'].astype('category')
company.dtypes
company.head()
```

Out[4]:

	Sales	CompPrice	Income	Advertising	Population	Price	ShelveLoc	Age	Education	Urban	U
0	9.50	138	73	11	276	120	Bad	42	17	Yes	Y
1	11.22	111	48	16	260	83	Good	65	10	Yes	Y
2	10.06	113	35	10	269	80	Medium	59	12	Yes	Y
3	7.40	117	100	4	466	97	Medium	55	14	Yes	Y
4	4.15	141	64	3	340	128	Bad	38	13	Yes	N

In [5]:

```
#label encoding to convert categorical values into numeric
company['ShelveLoc']=company['ShelveLoc'].cat.codes
company['Urban']=company['Urban'].cat.codes
company['US']=company['US'].cat.codes
company.tail()
```

Out[5]:

	Sales	CompPrice	Income	Advertising	Population	Price	ShelveLoc	Age	Education	Urban
395	12.57	138	108	17	203	128	1	33	14	1
396	6.14	139	23	3	37	120	2	55	11	0
397	7.41	162	26	12	368	159	2	40	18	1
398	5.94	100	79	7	284	95	0	50	12	1
399	9.71	134	37	0	27	120	1	49	16	1

Setting feature and Target variables

In [6]:

```
feature_cols=['CompPrice','Income','Advertising','Population','Price','ShelveLoc','A
x = company[feature_cols]
y = company.High
print(x)
print(y)
```

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

     Education  Urban  US  
0           17      1   1  
1           10      1   1  
2           12      1   1  
3           14      1   1  
4           13      1   0  
..         ...    ...  ..  
395         14      1   1  
396         11      0   1  
397         18      1   1  
398         12      1   1  
399         16      1   1  

[400 rows x 10 columns]
0      1
1      1
2      1
3      0
4      0
      ..
395    1
396    0
397    0
398    0
399    1
Name: High, Length: 400, dtype: int64
```

Splitting into Train and Test data

In [21]:

```
x_train,x_test,y_train,y_test= train_test_split(x,y, test_size=0.2,random_state=0)
x_train,x_test,y_train,y_test
```

Out[21]:

```
(      CompPrice  Income  Advertising  Population  Price  ShelveLoc  Age  \
 336        138      35            6          60    143          0   28   
 64         100      67           12         184    104          2   32   
 55         143      81            5          60    154          2   61   
 106        102      33            0         217    139          2   70   
 300        116      78            1         158     99          2   45   
 ..         ...     ...          ...         ...    ...        ...  ...   
 323        107     105           18         428    103          2   34   
 192        108      26            0         408     93          2   56   
 117        145      53            0         507    119          2   41   
 47         126      98            0         173    108          0   55
 172        104     102           13         123    110          1   35

      Education  Urban  US
 336         18      1   0
 64          16      0   1
 55          18      1   1
 106         18      0   0
 300         11      1   1
 ..         ...    ...  ..
 323         12      1   1
 192         14      0   0
 117         12      1   0
 47          16      1   0
 172         16      1   1

 [320 rows x 10 columns],
      CompPrice  Income  Advertising  Population  Price  ShelveLoc  Age  \
 132        125      87            9         232    136          1   72
 309        131     111           13          33     80          0   68
 341         98     120            0         268     93          2   72
 196        130      28            6         410    133          0   72
 246        120      56           20         266     90          0   78
 ..         ...     ...          ...         ...    ...        ...  ...
 14         107     117           11         148    118          1   52
 363        111      75            1         377    108          1   25
 304        123      98           12         408    134          1   29
 361        131      25           10         183    104          2   56
 329        100      54            9         433     89          1   45

      Education  Urban  US
 132         10      1   1
 309         18      1   1
 341         10      0   0
 196         16      1   1
 246         18      1   1
 ..         ...    ...  ..
 14          18      1   1
 363         12      1   0
 304         10      1   1
 361         15      0   1
 329         12      1   1

 [80 rows x 10 columns],
 336    0
 64     0
 55     0
 106    0
 300    1
       ..
 323    1
 192    0
 117    1
 47     0
 172    1
 Name: High, Length: 320, dtype: int64,
 132    1
 309    1
 341    0
 196    0
 246    0
       ..
 14     1
 363    1
 304    1
 361    1
 329    1
 Name: High, Length: 80, dtype: int64)
```

Building Decision Tree

In [12]:

```
dcmodel =  BaggingClassifier(DecisionTreeClassifier(max_depth = 6), random_state=0)
dcmodel =  AdaBoostClassifier(DecisionTreeClassifier(max_depth = 6), random_state=0)
dcmodel = dcmodel.fit(x_train,y_train)
y_predict = dcmodel.predict(x_test)
```

In [13]:

```
#Accuracy
print("Accuracy : ", accuracy_score(y_test,y_predict)*100 )
```

```
Accuracy :  67.5
```

In [14]:

```
print(confusion_matrix(y_test,y_predict))
print(classification_report(y_test,y_predict))
```

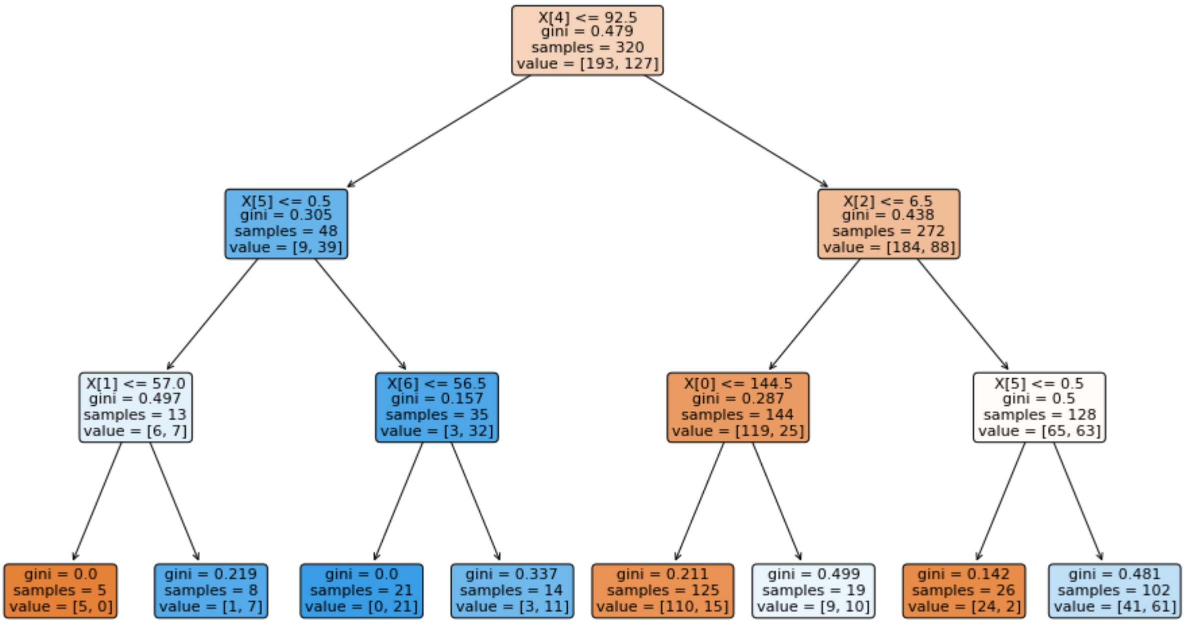
```
[[36  7]
 [19 18]]
              precision    recall  f1-score   support

           0       0.65      0.84      0.73        43
           1       0.72      0.49      0.58        37

    accuracy                           0.68        80
   macro avg       0.69      0.66      0.66        80
weighted avg       0.68      0.68      0.66        80
```

In [19]:

```
dcmodel = DecisionTreeClassifier(criterion='gini',
    max_depth=3)
dcmodel = dcmodel.fit(x_train , y_train)
```

In [20]:

```
# Prepare a plot figure with set size.
from sklearn.tree import plot_tree
from matplotlib import pyplot as plt
plt.figure(figsize = (16,10))
# Plot the decision tree.
plot_tree(dcmodel,rounded = True,filled = True)# Display the tree plot figure.
plt.show()
```


X[4] <= 92.5
gini = 0.479
samples = 320
value = [193, 127]
X[5] <= 0.5
gini = 0.305
samples = 48
value = [9, 39]
X[2] <= 6.5
gini = 0.438
samples = 272
value = [184, 88]
X[1] <= 57.0
gini = 0.497
samples = 13
value = [6, 7]
X[6] <= 56.5
gini = 0.157
samples = 35
value = [3, 32]
X[0] <= 144.5
gini = 0.287
samples = 144
value = [119, 25]
X[5] <= 0.5
gini = 0.5
samples = 128
value = [65, 63]
gini = 0.0
samples = 5
value = [5, 0]
gini = 0.219
samples = 8
value = [1, 7]
gini = 0.0
samples = 21
value = [0, 21]
gini = 0.337
samples = 14
value = [3, 11]
gini = 0.211
samples = 125
value = [110, 15]
gini = 0.499
samples = 19
value = [9, 10]
gini = 0.142
samples = 26
value = [24, 2]
gini = 0.481
samples = 102
value = [41, 61]

```
In [ ]:
```