Decision Tree

April 5, 2023

1 Decession Tree Classifier Urban or Not Urban

1.1 Import required libraries

[1]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import warnings
warnings.filterwarnings("ignore")
from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import train_test_split
from sklearn.metrics import confusion_matrix,classification_report
from sklearn import tree
from sklearn.model_selection import GridSearchCV
```

1.2 Import the Dataset

[2]:
```
df=pd.read_csv("Carseats.csv")
df.head()
```

[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

2 Data Exploration

2.1 Summary of Data

[3]:
```
df.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
```

2.2 Descriptive Summary of Data

[4]:
```
df.describe()
```

[4]:

	Sales	CompPrice	Income	Advertising	Population
count	400.000000	400.000000	400.000000	400.000000	400.000000
mean	7.496325	124.975000	68.657500	6.635000	264.840000
std	2.824115	15.334512	27.986037	6.650364	147.376436
min	0.000000	77.000000	21.000000	0.000000	10.000000
25%	5.390000	115.000000	42.750000	0.000000	139.000000
50%	7.490000	125.000000	69.000000	5.000000	272.000000
75%	9.320000	135.000000	91.000000	12.000000	398.500000
max	16.270000	175.000000	120.000000	29.000000	509.000000

	Price	Age	Education
count	400.000000	400.000000	400.000000
mean	115.795000	53.322500	13.900000
std	23.676664	16.200297	2.620528
min	24.000000	25.000000	10.000000
25%	100.000000	39.750000	12.000000
50%	117.000000	54.500000	14.000000
75%	131.000000	66.000000	16.000000
max	191.000000	80.000000	18.000000

2.3 Shape of Dataset

[5]:
```
df.shape
```

[5]:
```
(400, 11)
```

2.4 Check if there were any Null Values

[6]:
```
df.isna().sum()
```

[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
```

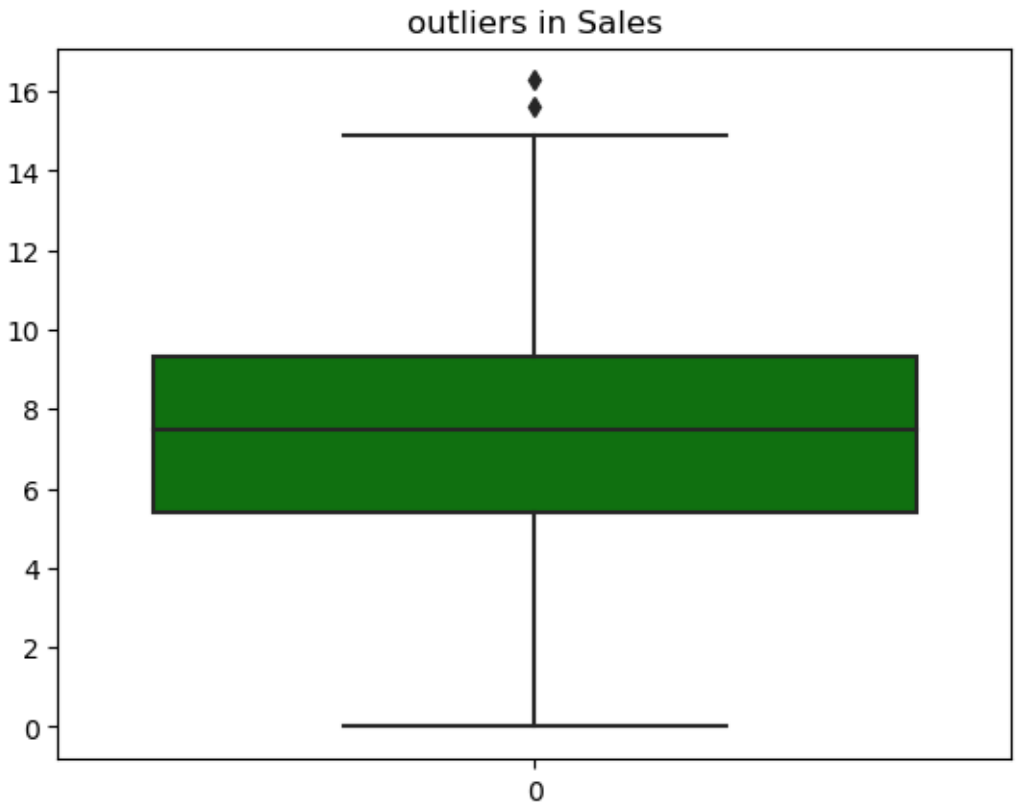
2.5 Check if any duplicate values were Present

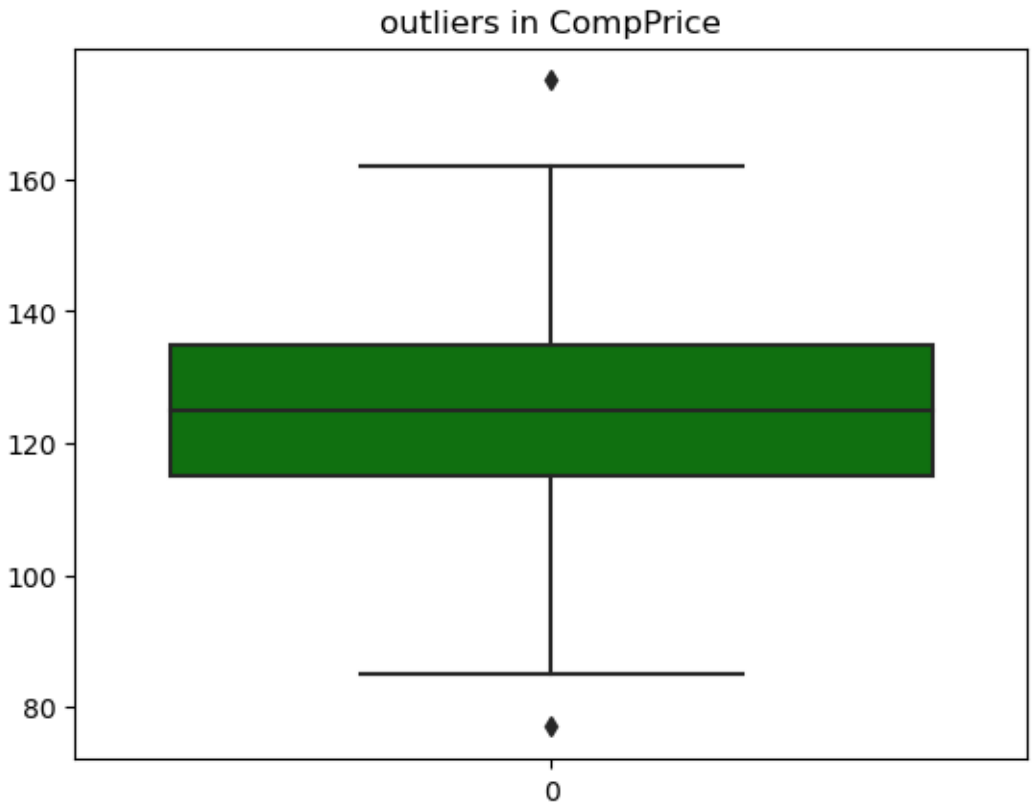
[7]:
```
df.duplicated().sum()
```

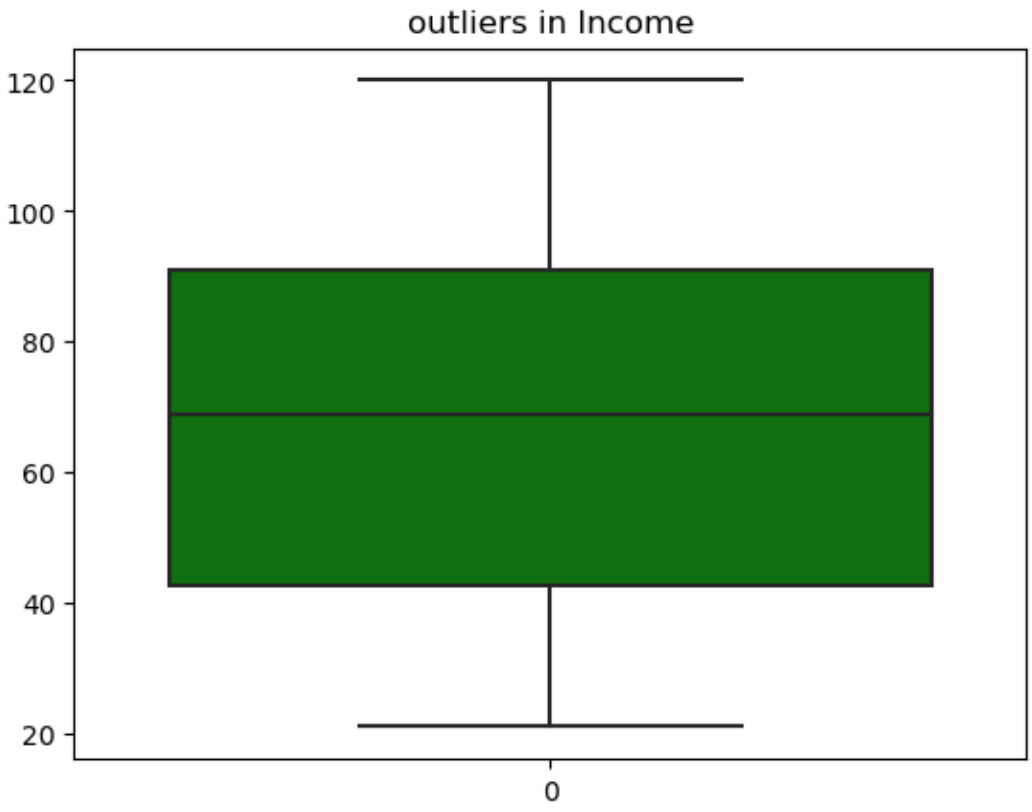
[7]:
```
0
```

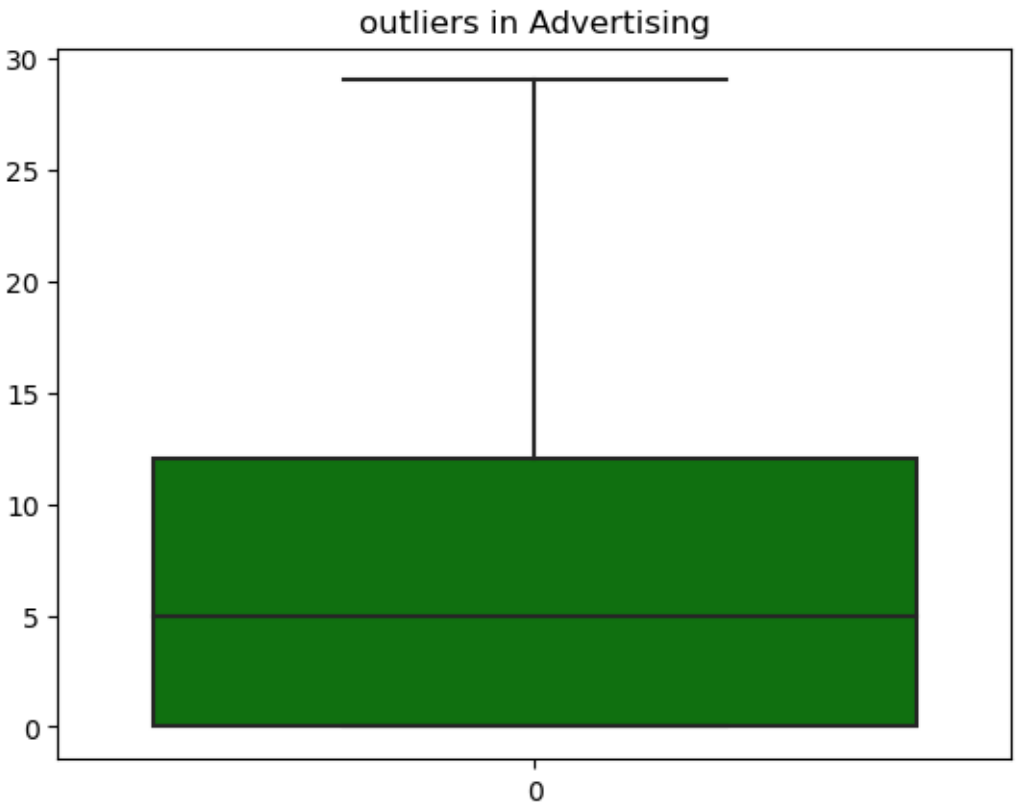
3 Feature Engineering

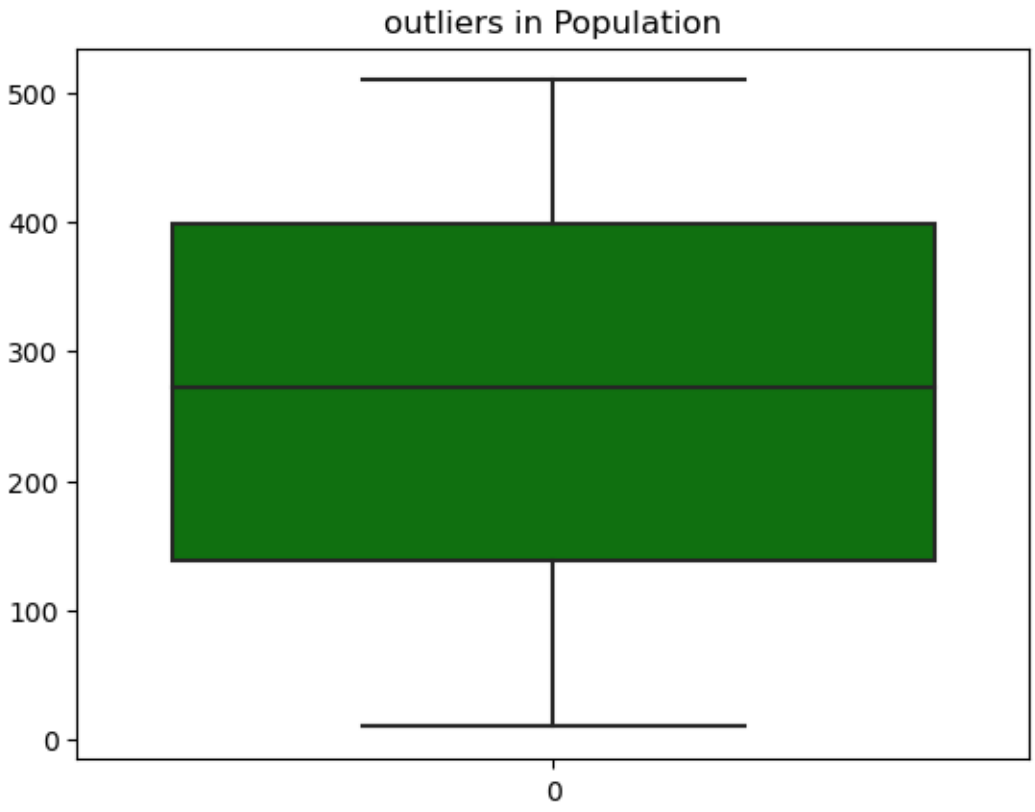
[8]:
```
for i in df.columns:
    if i not in ["ShelveLoc","Urban","US"]:
        sns.boxplot(df[i],color="g")
        plt.title("outliers in "+i)
        plt.show()
```

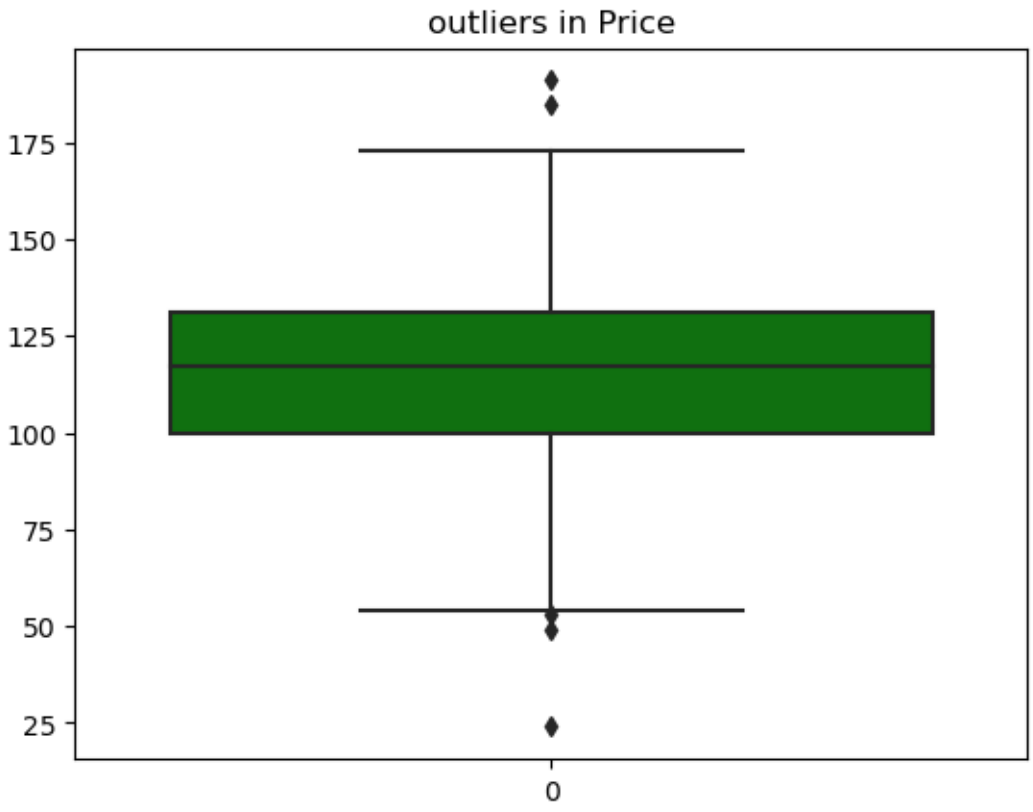

outliers in Sales
16
14
12
10
8
6
4
2
0
0


outliers in CompPrice
160
140
120
100
80
0

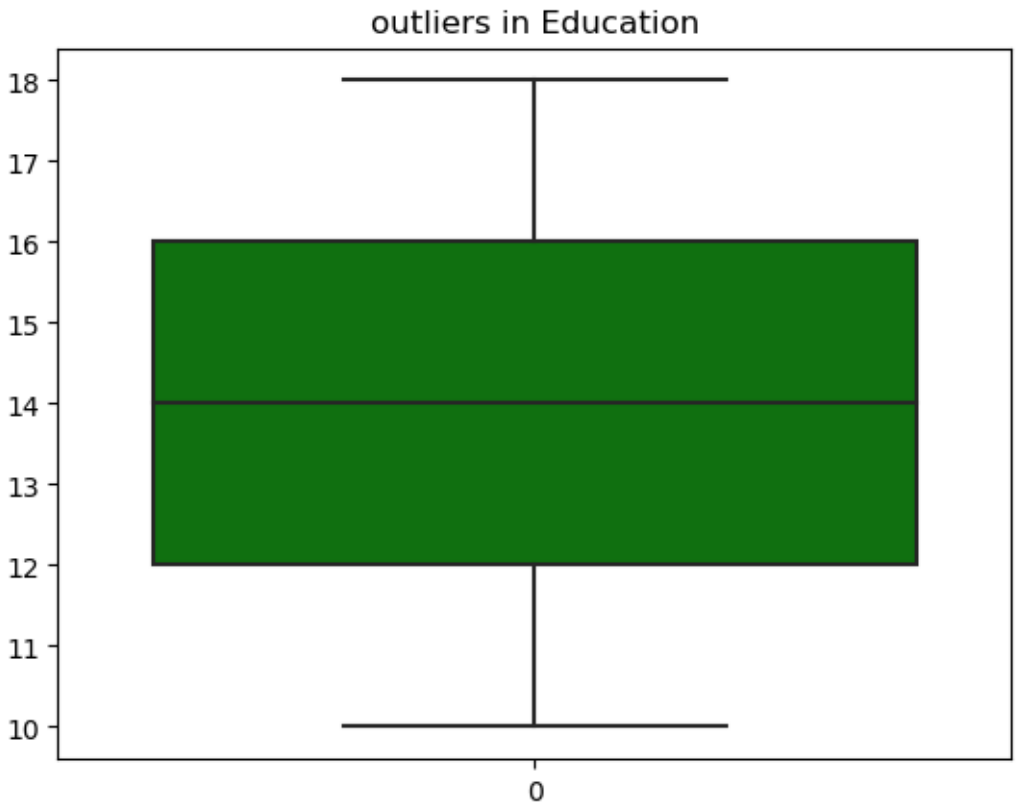

outliers in Income
120
100
80
60
40
20
0


outliers in Advertising
30
25
20
15
10
5
0
0


outliers in Population
500
400
300
200
100
0
0


outliers in Price
175
150
125
100
75
50
25
0


outliers in Age
80
70
60
50
40
30
0



3.0.1 Observations:

- There were few Outliers in Sales, CompPrice and Price

3.1 Remove the outliers

[9]:
```
outliers=["Sales","CompPrice","Price"]
```

[10]:
```
for i in outliers:
    minimum,q1,middle,q3,maximum=np.quantile(df[i],[0,0.25,0.50,0.75,1])
    IQR=q3-q1
    lower_fence=q1-(IQR*1.5)
    higher_fence=q3+(IQR*1.5)
    print("In "+i+" Column any values beyond the Range "+str(lower_fence)+" and␣
 ↪"+str(higher_fence)+" are outliers")
```

```
In Sales Column any values beyond the Range -0.504999999999999 and 15.215 are
outliers
In CompPrice Column any values beyond the Range 85.0 and 165.0 are outliers
In Price Column any values beyond the Range 53.5 and 177.5 are outliers
```

3.1.1 Filter Outliers in Sales column

[11]:
```
df=df[df["Sales"]<=15.215]
```

[12]:
```
df.shape
```

[12]:
```
(398, 11)
```

3.1.2 Filter CompPrice Column

[13]:
```
df=df[(df["CompPrice"]>=85.0) & (df["CompPrice"]<=165.0)]
```

[14]:
```
df.shape
```

[14]:
```
(396, 11)
```

3.1.3 Filter in Price column

[15]:
```
df=df[(df["Price"]>=53.5) & (df["Price"]<=177.5)]
```

[16]:
```
df.shape
```

[16]:
```
(392, 11)
```

[17]:
```
df.head()
```

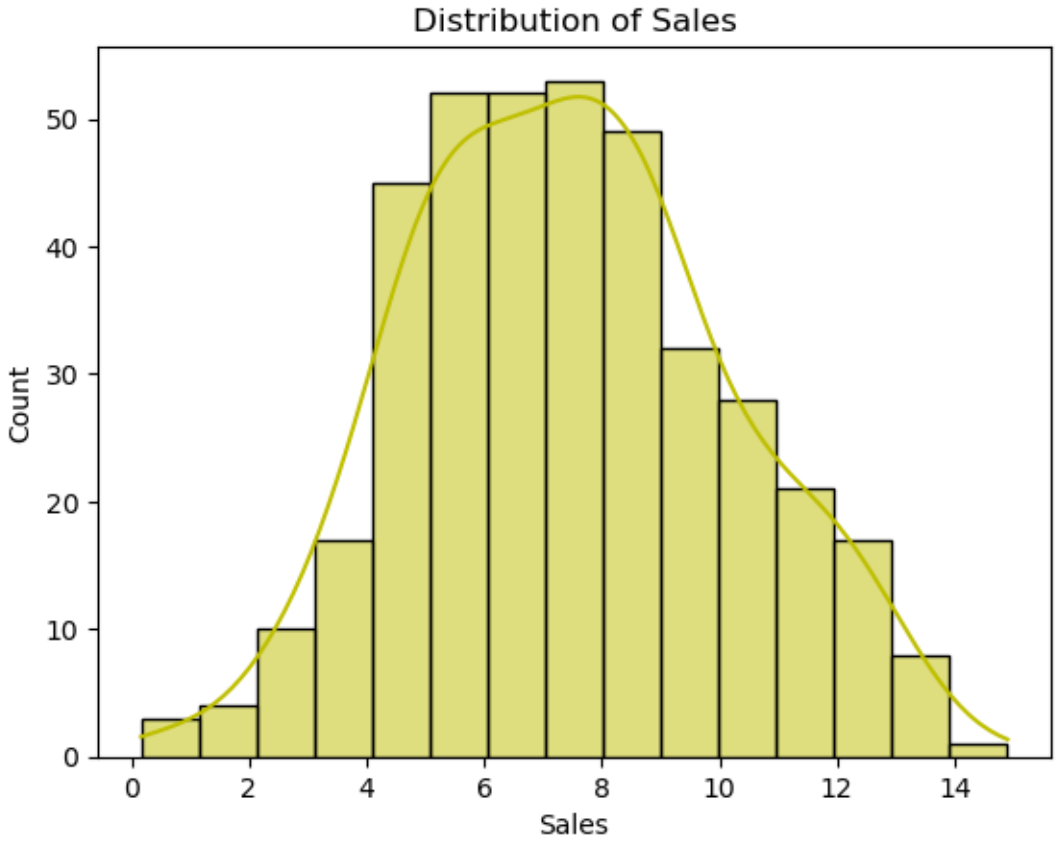
[17]:

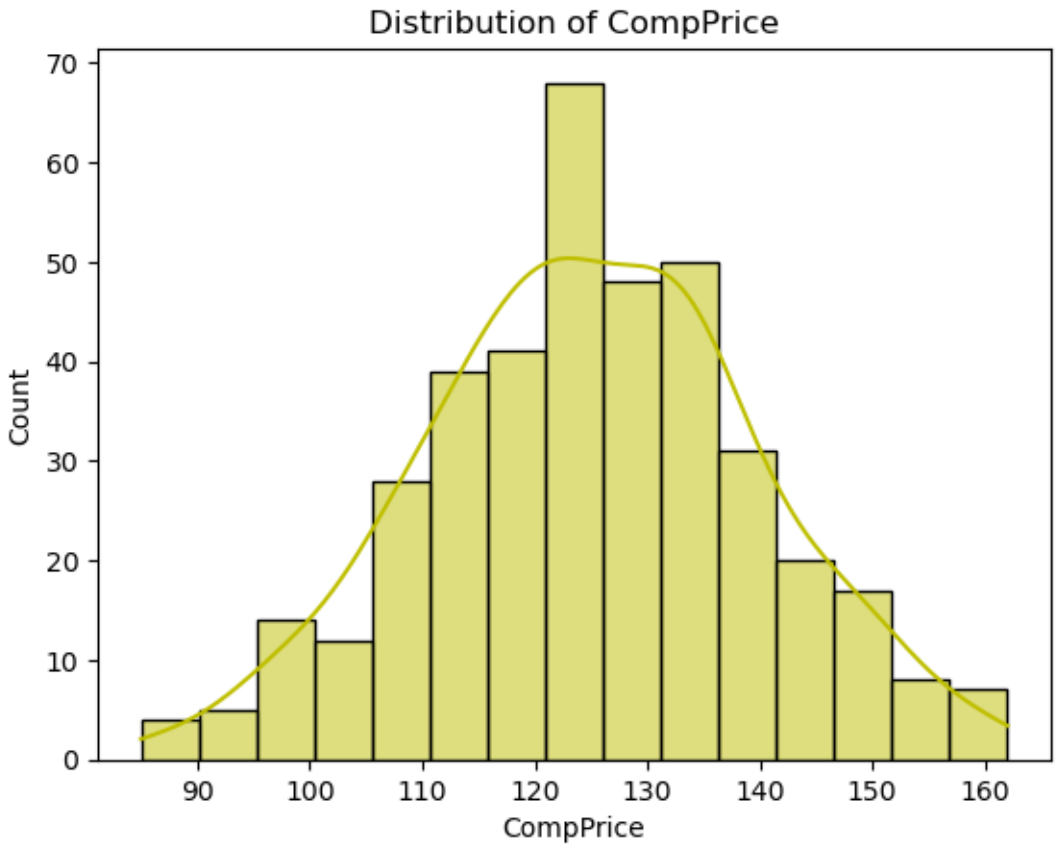
	Sales	CompPrice	Income	Advertising	Population	Price	ShelveLoc	Age	Education	Urban	US
0	9.50	138	73	11	276	120	Bad	42	17	Yes	Yes
1	11.22	111	48	16	260	83	Good	65	10	Yes	Yes
2	10.06	113	35	10	269	80	Medium	59	12	Yes	Yes
3	7.40	117	100	4	466	97	Medium	55	14	Yes	Yes
4	4.15	141	64	3	340	128	Bad	38	13	Yes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

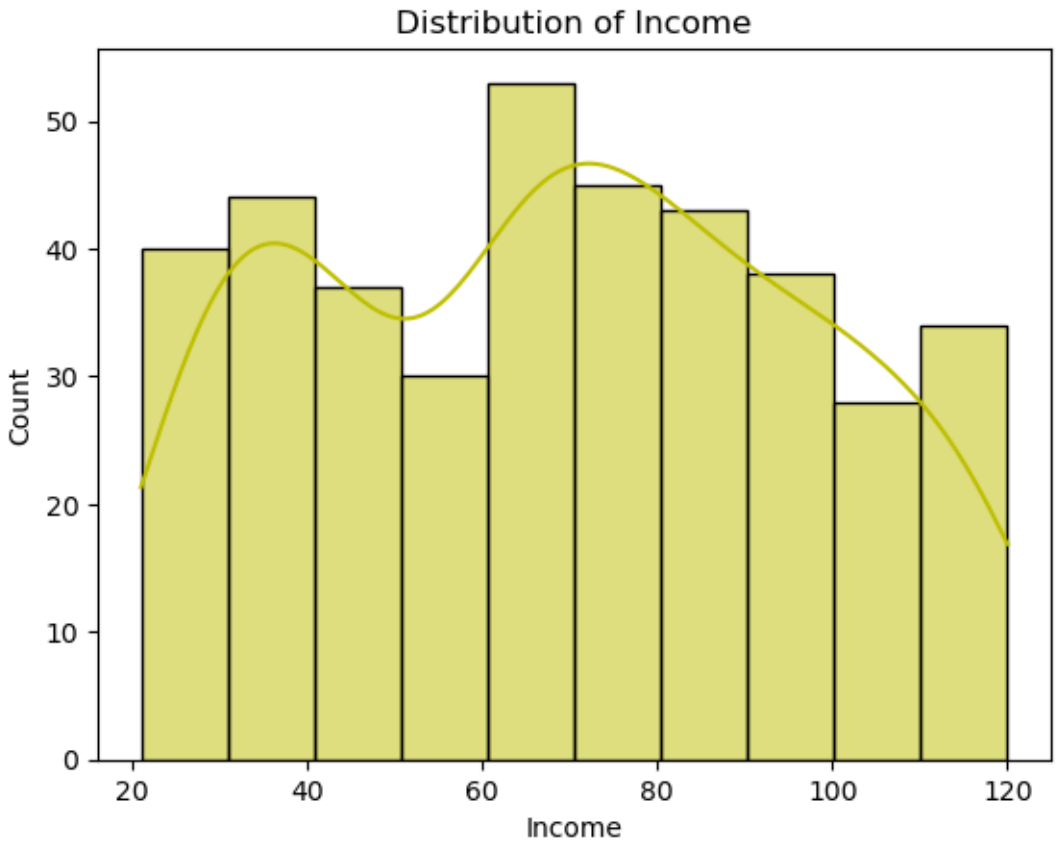
4 EDA

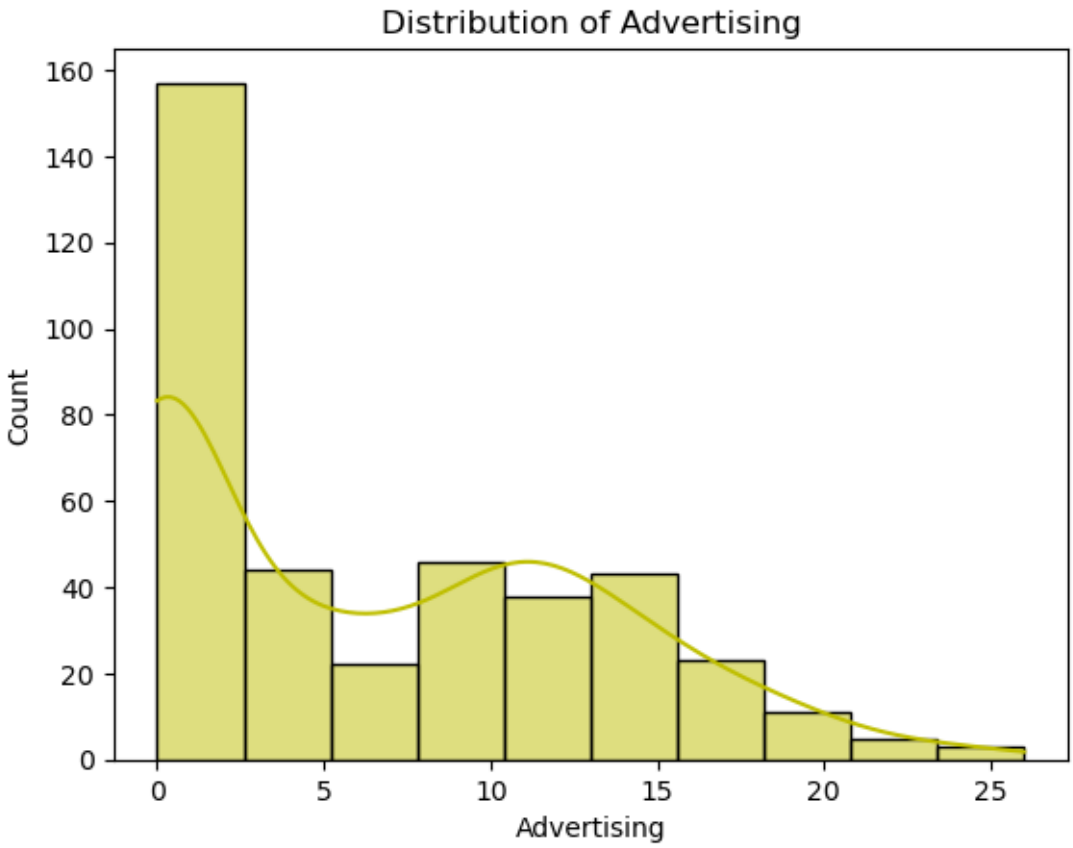
4.1 View Data Distribution of all the features

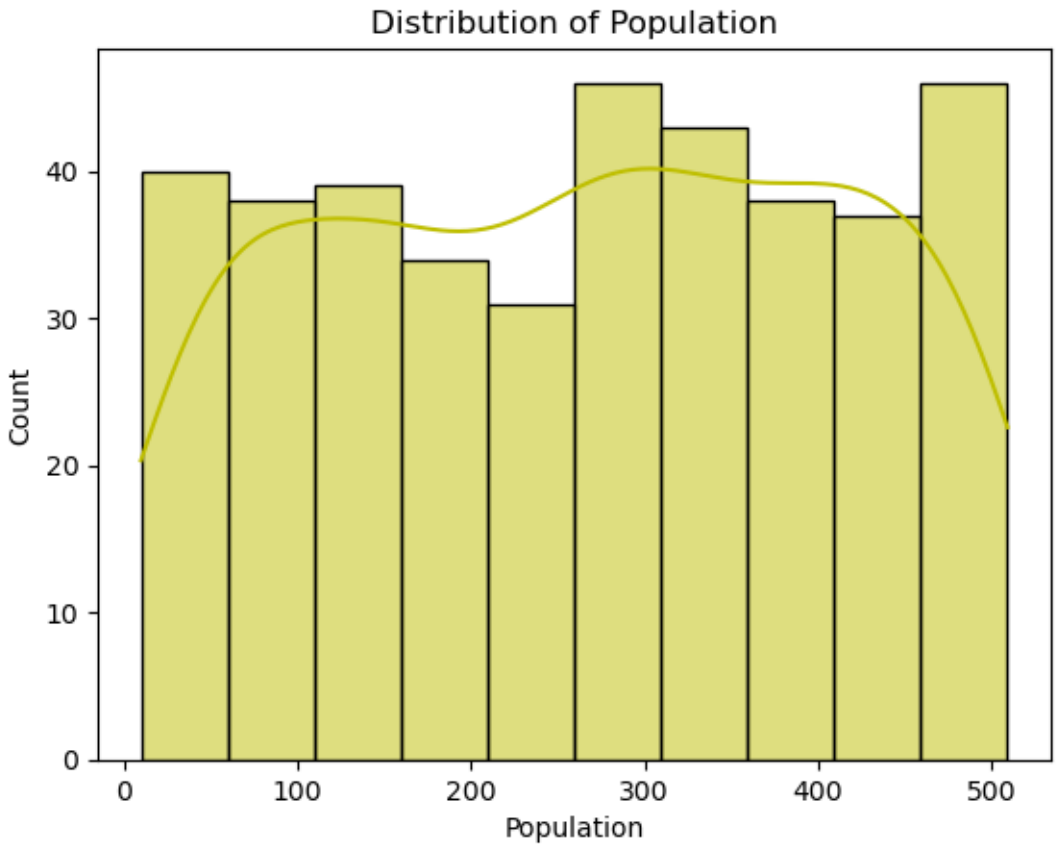
[18]:
```
for i in df.columns:
    sns.histplot(df[i],kde=True,color="y")
    plt.title("Distribution of "+i)
    plt.show()
```



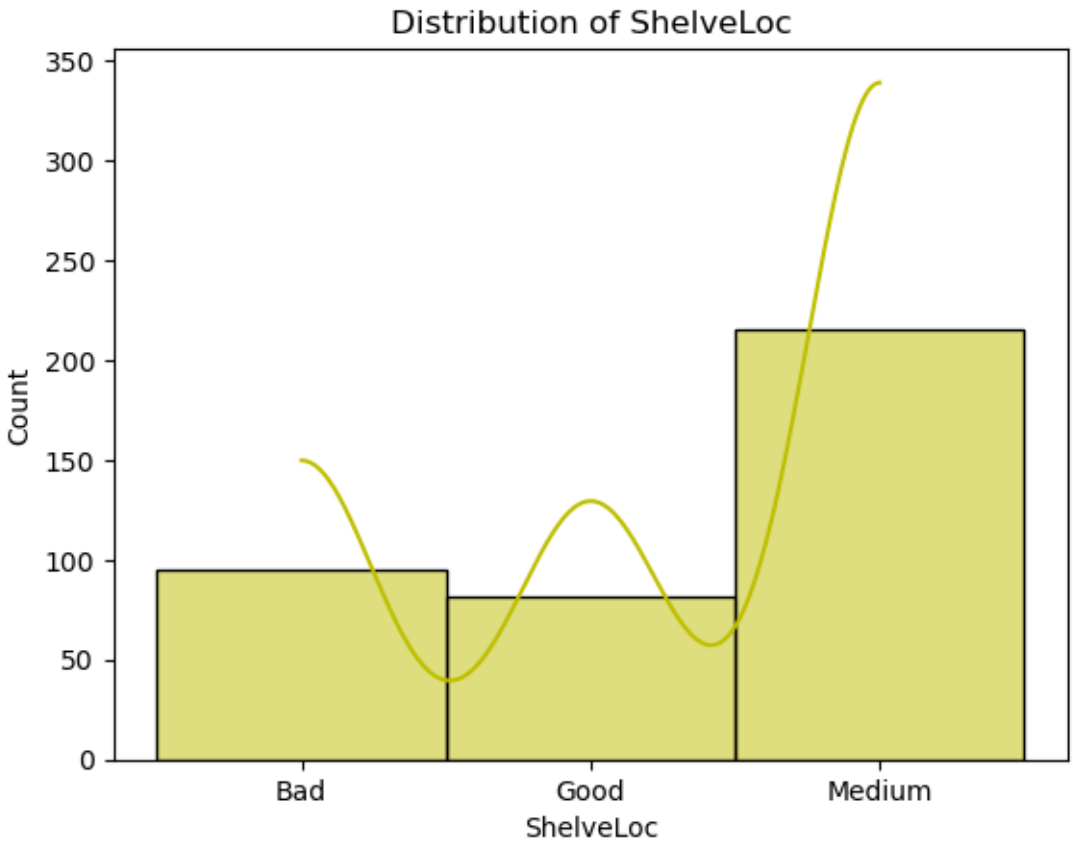

Distribution of CompPrice
Count
CompPrice
0
10
20
30
40
50
60
70
90
100
110
120
130
140
150
160

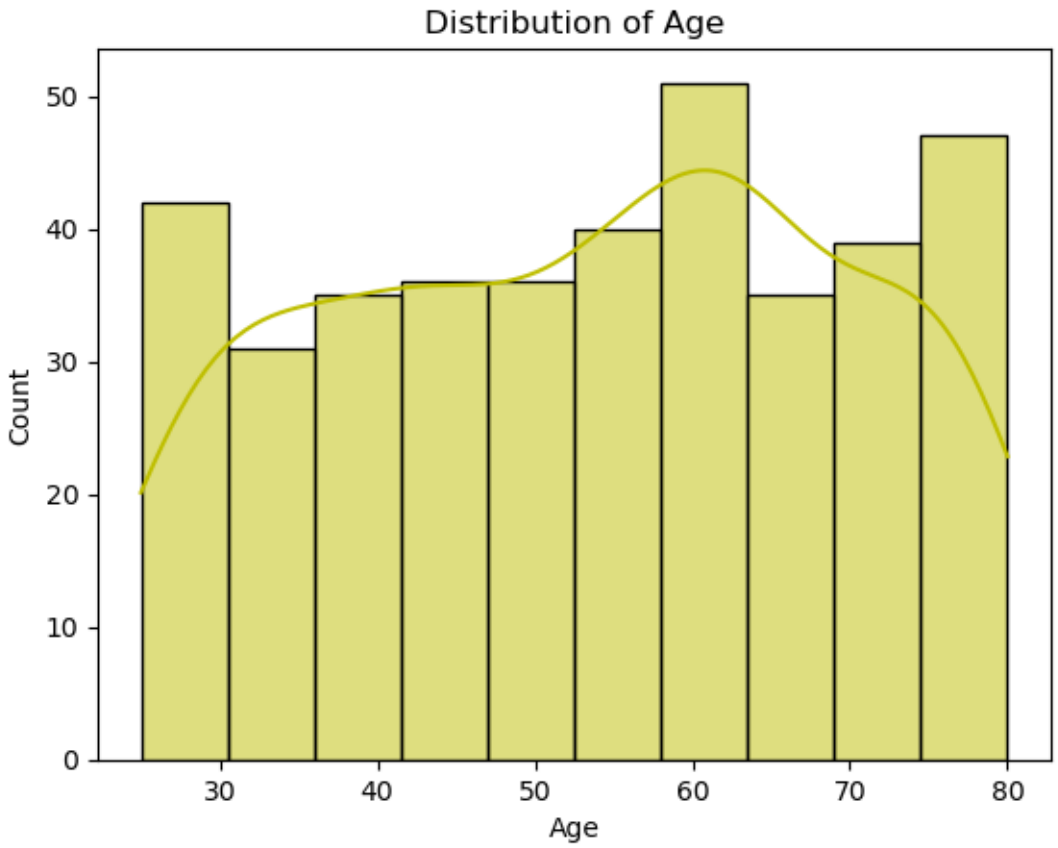

Distribution of Income
Count
Income
0
10
20
30
40
50
20
40
60
80
100
120

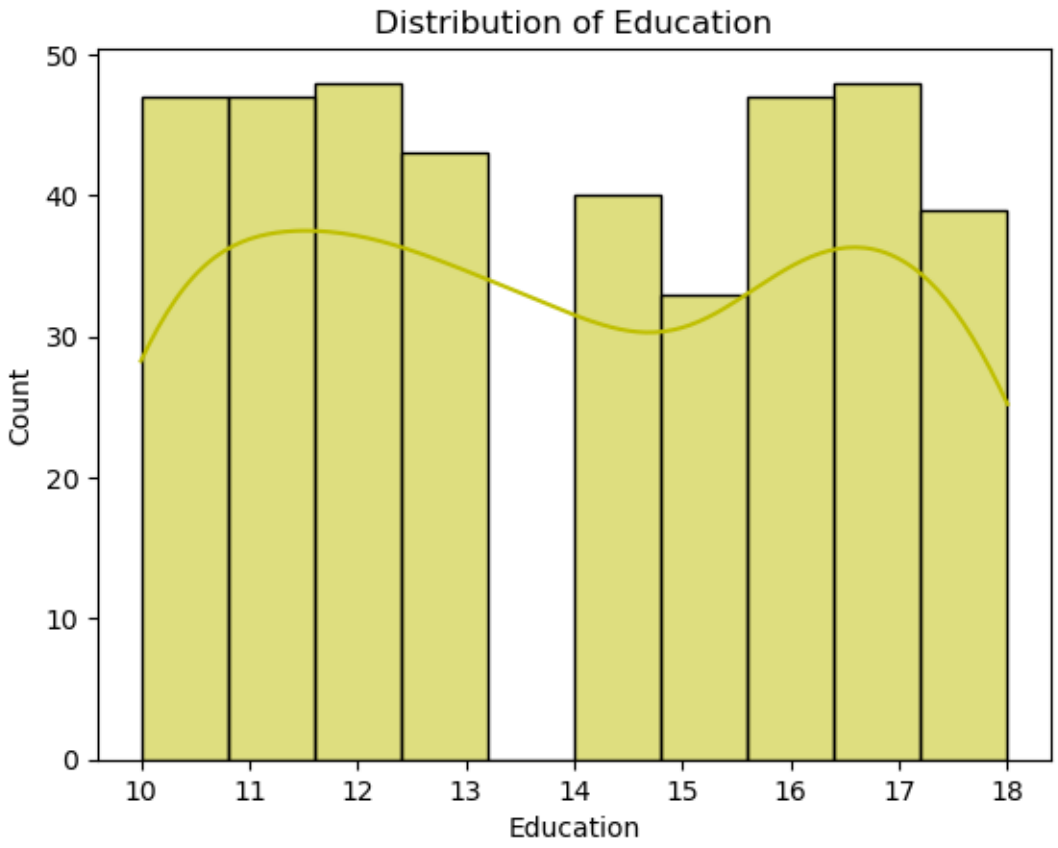

Distribution of Advertising
Count
Advertising
0
20
40
60
80
100
120
140
160
0
5
10
15
20
25

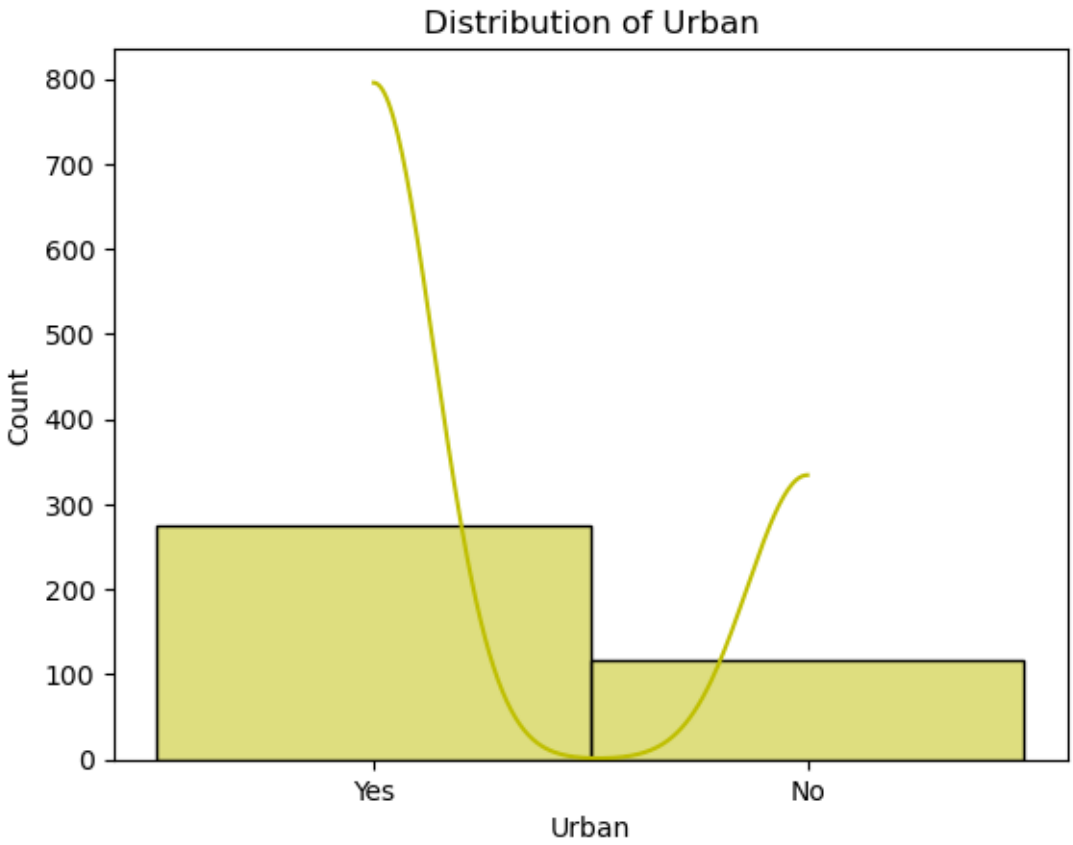

Distribution of Population
Count
Population
0
10
20
30
40
0
100
200
300
400
500

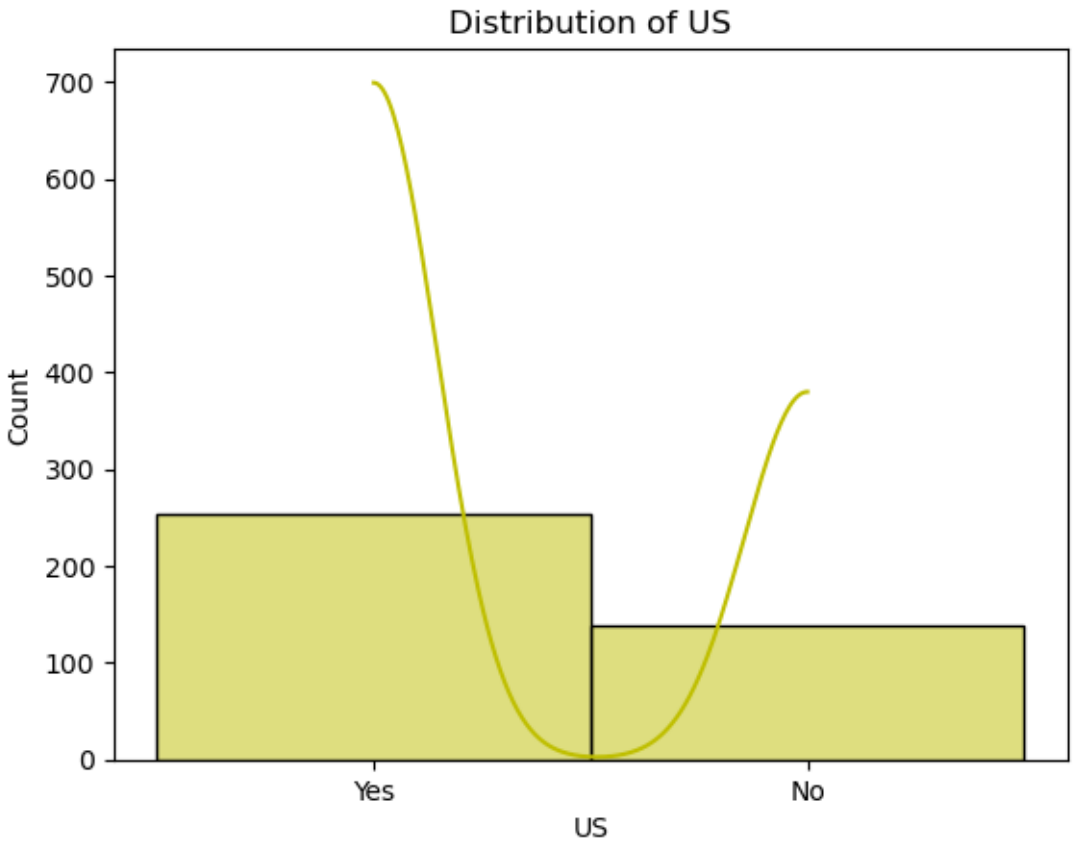

Distribution of Price
Count
Price
0
10
20
30
40
50
60
60
80
100
120
140
160


Distribution of ShelveLoc
350
300
250
200
150
100
50
0
Count
Bad
Good
Medium
ShelveLoc


Distribution of Age
Count
Age
0
10
20
30
40
50
30
40
50
60
70
80


Distribution of Education
Count
Education
0
10
20
30
40
50
10
11
12
13
14
15
16
17
18


Distribution of Urban
800
700
600
500
400
300
200
100
0
Count
Yes
No
Urban



4.1.1 Observations:

- Sales , CompPrice and Price were normally Distributed.
- Advertising is Right Skewed

Decoding Features

[19]:
```
from sklearn.preprocessing import LabelEncoder
```

[20]:
```
encoder=LabelEncoder()
```

[21]:
```
df["ShelveLoc"]=encoder.fit_transform(df["ShelveLoc"])
```

[22]:
```
df["US"]=encoder.fit_transform(df["US"])
```

[23]:
```
df["Urban_c"]=encoder.fit_transform(df["Urban"])
```

[24]:
```
df.head()
```

[24]:

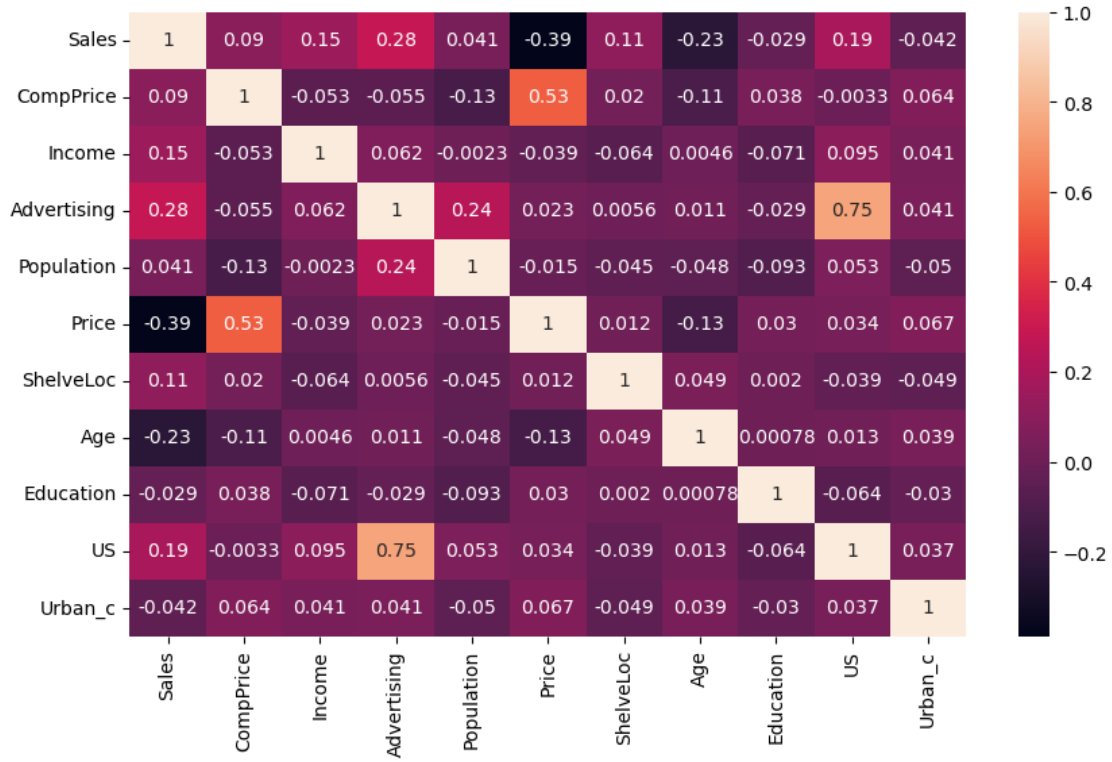
	Sales	CompPrice	Income	Advertising	Population	Price	ShelveLoc	Age	\
0	9.50	138	73	11	276	120	0	42	
1	11.22	111	48	16	260	83	1	65	
2	10.06	113	35	10	269	80	2	59	
3	7.40	117	100	4	466	97	2	55	
4	4.15	141	64	3	340	128	0	38	

	Education	Urban	US	Urban_c
0	17	Yes	1	1
1	10	Yes	1	1
2	12	Yes	1	1
3	14	Yes	1	1
4	13	Yes	0	1

5 Feature Coreleations

[25]:
```
plt.figure(figsize=(10,6))
sns.heatmap(df.corr(method="spearman"),annot=True)
```

[25]: <AxesSubplot: >



6 Checking and Handling Imbalanced Dataset

[26]:
```
from sklearn.utils import resample
```

[27]:
```
major=df[df["Urban"]=="Yes"]
```

[28]:
```
major.shape
```

[28]:
```
(276, 12)
```

[29]:
```
minor=df[df["Urban"]=="No"]
```

[30]:
```
minor.shape
```

[30]:
```
(116, 12)
```

[31]:
```
minor_new=resample(minor,replace=True,n_samples=len(major),random_state=42)
```

[32]:
```
minor_new.shape
```

[32]:
```
(276, 12)
```

[33]:
```
df=pd.concat([minor_new,major])
```

[34]:
```
df.shape
```

[34]:
```
(552, 12)
```

[35]:
```
df.head()
```

[35]:

	Sales	CompPrice	Income	Advertising	Population	Price	ShelveLoc	Age	\
349	9.32	134	27	18	467	96	2	49	
158	12.53	142	90	1	189	112	1	39	
299	9.40	135	40	17	497	96	2	54	
46	12.44	127	90	14	16	70	2	48	
360	8.77	118	86	7	265	114	1	52	

	Education	Urban	US	Urban_c
349	14	No	1	0
158	10	No	1	0
299	17	No	1	0
46	15	No	1	0
360	15	No	1	0

[36]:
```
df=df.sample(frac=1)
```

[37]:
```
df.head()
```

[37]:
```
     Sales  CompPrice  Income  Advertising  Population  Price  ShelveLoc  Age  \
35   11.07        131      84           11          29     96          2   44
281  11.19        122      69            7         303    105          1   45
281  11.19        122      69            7         303    105          1   45
100   4.11        113      69           11          94    106          2   76
224   4.10        134      82            0         464    141          2   48

     Education Urban  US  Urban_c
35          17    No   1        0
281         16    No   1        0
281         16    No   1        0
100         12    No   1        0
224         13    No   0        0
```

[38]:
```
df.reset_index(inplace=True)
```

[39]:
```
df.head()
```

[39]:
```
   index  Sales  CompPrice  Income  Advertising  Population  Price  ShelveLoc  \
0     35  11.07        131      84           11          29     96          2
1    281  11.19        122      69            7         303    105          1
2    281  11.19        122      69            7         303    105          1
3    100   4.11        113      69           11          94    106          2
4    224   4.10        134      82            0         464    141          2

   Age  Education Urban  US  Urban_c
0   44         17    No   1        0
1   45         16    No   1        0
2   45         16    No   1        0
3   76         12    No   1        0
4   48         13    No   0        0
```

[40]:
```
df.drop("index",axis=1,inplace=True)
```

[41]:
```
df.head()
```

[41]:
```
   Sales  CompPrice  Income  Advertising  Population  Price  ShelveLoc  Age  \
0  11.07        131      84           11          29     96          2   44
1  11.19        122      69            7         303    105          1   45
2  11.19        122      69            7         303    105          1   45
3   4.11        113      69           11          94    106          2   76
4   4.10        134      82            0         464    141          2   48

   Education Urban  US  Urban_c
0         17    No   1        0
1         16    No   1        0
2         16    No   1        0
```

```
3          12    No   1          0
4          13    No   0          0
```

[42]:
```
df.shape
```

[42]:
```
(552, 12)
```

7 Spliting Independent and Dependent Features

[43]:
```
x=df.drop(["Urban","Urban_c"],axis=1)
```

[44]:
```
x.head()
```

[44]:
```
    Sales  CompPrice  Income  Advertising  Population  Price  ShelveLoc  Age  \
0  11.07        131      84           11          29     96          2   44
1  11.19        122      69            7         303    105          1   45
2  11.19        122      69            7         303    105          1   45
3   4.11        113      69           11          94    106          2   76
4   4.10        134      82            0         464    141          2   48

   Education  US
0         17   1
1         16   1
2         16   1
3         12   1
4         13   0
```

[45]:
```
y=df["Urban"]
```

[46]:
```
y
```

[46]:
```
0       No
1       No
2       No
3       No
4       No
      ...
547    Yes
548     No
549     No
550     No
551    Yes
Name: Urban, Length: 552, dtype: object
```

7.1 Scaling the Independent Features

[47]:
```
from sklearn.preprocessing import StandardScaler
```

[48]:
```
scaler=StandardScaler()
```

[49]:
```
x_new=scaler.fit_transform(x)
```

[50]:
```
x=pd.DataFrame(x_new,columns=x.columns)
```

[51]:
```
x.head()
```

[51]:
```
      Sales  CompPrice    Income  Advertising  Population     Price  \
0  1.200794   0.420081  0.487168     0.614421   -1.579880 -0.819685
1  1.243861  -0.219895 -0.027801     0.010395    0.203689 -0.410172
2  1.243861  -0.219895 -0.027801     0.010395    0.203689 -0.410172
3 -1.297097  -0.859871 -0.027801     0.614421   -1.156771 -0.364671
4 -1.300686   0.633406  0.418505    -1.046650    1.251699  1.227879

   ShelveLoc       Age  Education        US
0   0.760767 -0.541800   1.175156  0.739066
1  -0.467138 -0.482080   0.789721  0.739066
2  -0.467138 -0.482080   0.789721  0.739066
3   0.760767  1.369212  -0.752016  0.739066
4   0.760767 -0.302923  -0.366582 -1.353059
```

[52]:
```
y=df["Urban"]
```

[53]:
```
y
```

[53]:
```
0       No
1       No
2       No
3       No
4       No
      ...
547    Yes
548     No
549     No
550     No
551    Yes
Name: Urban, Length: 552, dtype: object
```

8 Split the Training and Testing Data

[54]:
```
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.25)
```

[55]:
```
x_train.shape,y_train.shape,x_test.shape,y_test.shape
```

[55]:
```
((414, 10), (414,), (138, 10), (138,))
```

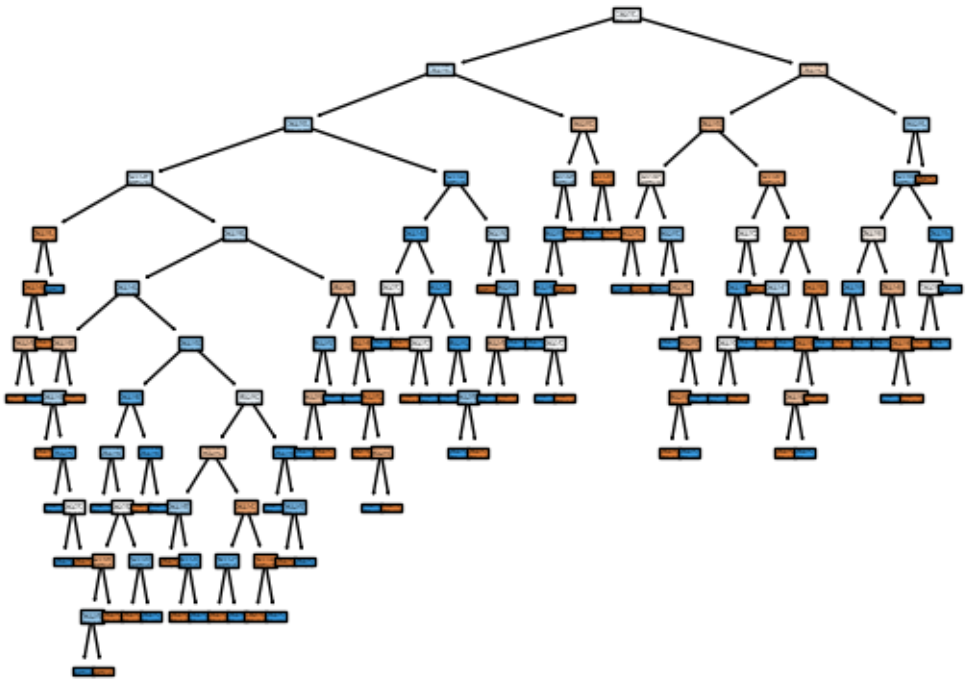
9 Build the Model

[56]:
```
model=DecisionTreeClassifier()
```

[57]:
```
model.fit(x_train,y_train)
```

[57]:
```
DecisionTreeClassifier()
```

[58]:
```
tree.plot_tree(model,filled=True)
plt.show()
```



[59]:
```
y_pred=model.predict(x_test)
```

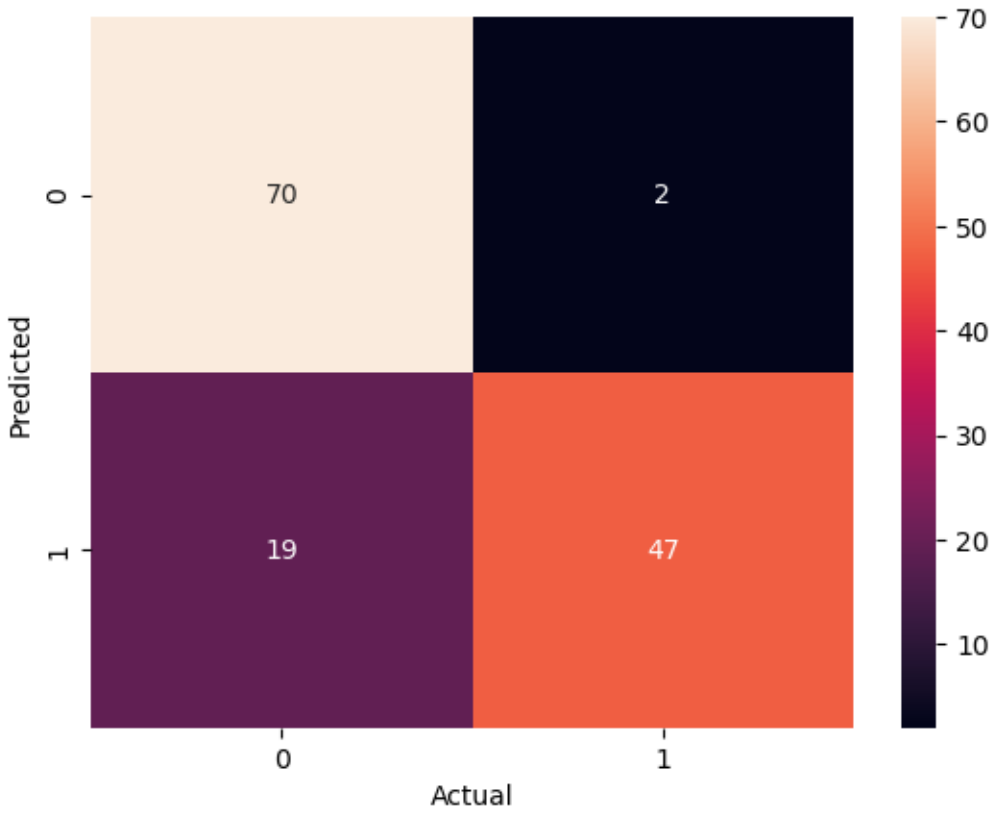
[60]:
```
y_pred
```

[60]:
```
array(['No', 'Yes', 'Yes', 'No', 'No', 'Yes', 'No', 'No', 'No', 'No',
       'Yes', 'Yes', 'No', 'Yes', 'No', 'Yes', 'No', 'Yes', 'No', 'Yes',
       'No', 'Yes', 'Yes', 'No', 'No', 'No', 'No', 'No', 'No', 'Yes',
       'No', 'No', 'No', 'No', 'No', 'Yes', 'No', 'Yes', 'No', 'Yes',
       'No', 'No', 'No', 'No', 'No', 'No', 'No', 'Yes', 'Yes', 'Yes',
       'Yes', 'No', 'No', 'Yes', 'No', 'Yes', 'Yes', 'Yes', 'No', 'No',
       'No', 'No', 'No', 'No', 'No', 'Yes', 'Yes', 'No', 'Yes', 'No',
       'Yes', 'No', 'No', 'No', 'No', 'Yes', 'No', 'No', 'No', 'No', 'No',
       'Yes', 'No', 'No', 'No', 'No', 'Yes', 'No', 'No', 'No', 'No', 'No',
       'No', 'No', 'No', 'No', 'Yes', 'No', 'No', 'Yes', 'No', 'Yes',
       'Yes', 'No', 'No', 'Yes', 'No', 'Yes', 'No', 'Yes', 'Yes', 'Yes',
       'Yes', 'Yes', 'No', 'Yes', 'No', 'Yes', 'No', 'No', 'No', 'Yes',
       'No', 'Yes', 'Yes', 'No', 'Yes', 'No', 'Yes', 'No', 'No', 'No',
       'No', 'No', 'No', 'No', 'No', 'Yes'], dtype=object)
```

9.1 Measure the metrics

[61]:
```
sns.heatmap(confusion_matrix(y_test,y_pred),annot=True)
plt.xlabel("Actual")
plt.ylabel("Predicted")
```

[61]:
```
Text(50.722222222222214, 0.5, 'Predicted')
```



[62]:
```
print(classification_report(y_test,y_pred))
```

```
              precision    recall  f1-score   support

          No       0.79      0.97      0.87        72
         Yes       0.96      0.71      0.82        66

    accuracy                           0.85       138
   macro avg       0.87      0.84      0.84       138
weighted avg       0.87      0.85      0.84       138
```

10 Hyperparameter Tuning

[63]:
```
grid={
 'criterion':['gini','entropy','log_loss'],
  'splitter':['best','random'],
  'max_depth':[11,12,13],
  'max_features':['auto', 'sqrt', 'log2']

}
```

[64]:
```
clf=GridSearchCV(model,param_grid=grid,cv=5)
```

[65]:
```
clf.fit(x_train,y_train)
```

[65]:
```
GridSearchCV(cv=5, estimator=DecisionTreeClassifier(),
             param_grid={'criterion': ['gini', 'entropy', 'log_loss'],
                         'max_depth': [11, 12, 13],
                         'max_features': ['auto', 'sqrt', 'log2'],
                         'splitter': ['best', 'random']})
```

[66]:
```
clf.best_params_
```

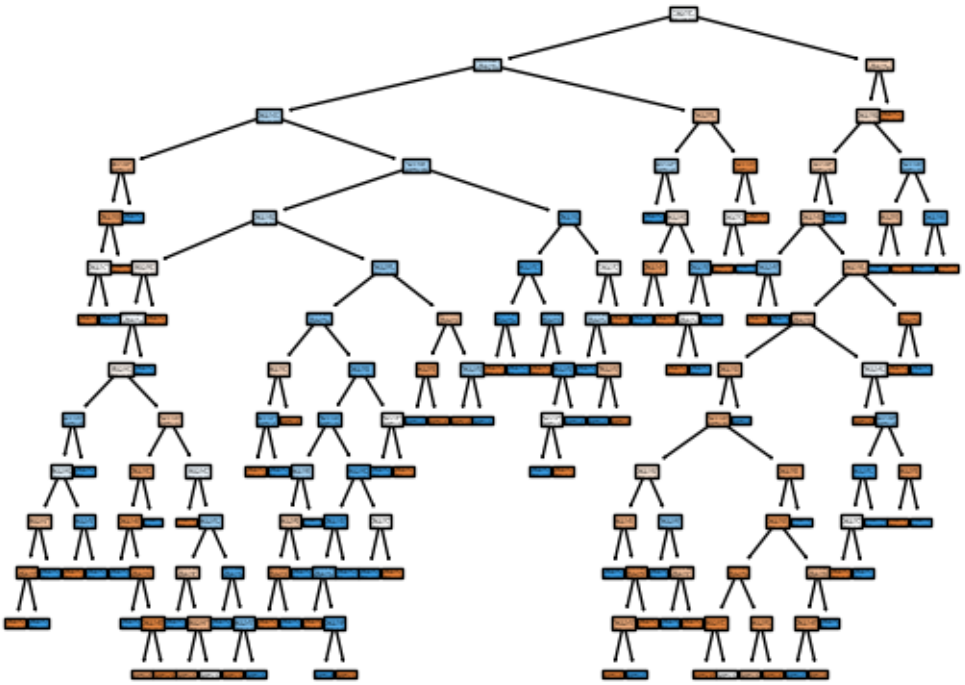
[66]:
```
{'criterion': 'gini',
 'max_depth': 13,
 'max_features': 'auto',
 'splitter': 'best'}
```

[69]:
```
model=DecisionTreeClassifier(criterion="gini",max_depth=13,max_features="auto",splitter="best"
```

[70]:
```
model.fit(x_train,y_train)
```

[70]:
```
DecisionTreeClassifier(max_depth=13, max_features='auto')
```

[71]:
```
tree.plot_tree(model,filled=True)
plt.show()
```



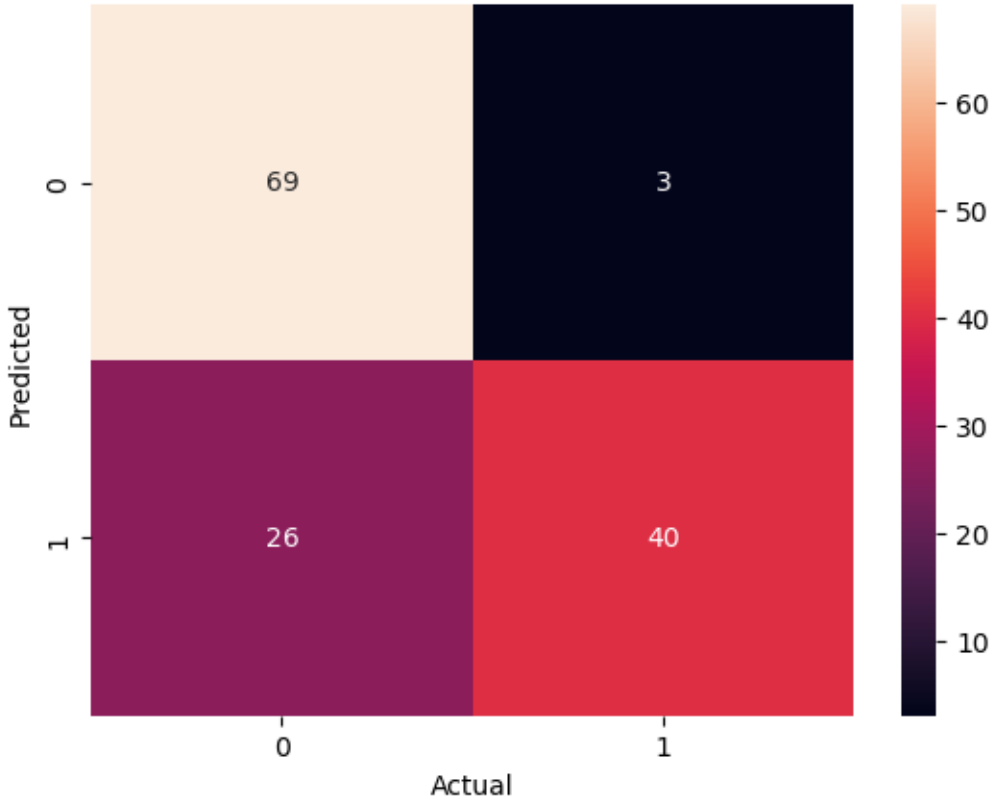
[72]:
```
y_pred=model.predict(x_test)
```

[73]:
```
y_pred
```

[73]:
```
array(['No', 'No', 'Yes', 'No', 'No', 'Yes', 'No', 'No', 'No', 'No',
       'Yes', 'Yes', 'Yes', 'No', 'No', 'Yes', 'No', 'Yes', 'No', 'Yes',
       'No', 'Yes', 'No', 'Yes', 'No', 'No', 'No', 'No', 'No', 'No', 'No',
       'No', 'Yes', 'No', 'No', 'Yes', 'No', 'Yes', 'No', 'Yes', 'No',
       'No', 'No', 'No', 'No', 'No', 'No', 'Yes', 'Yes', 'No', 'No', 'No',
       'Yes', 'Yes', 'No', 'Yes', 'Yes', 'Yes', 'No', 'No', 'No', 'No',
       'Yes', 'No', 'Yes', 'No', 'Yes', 'No', 'Yes', 'No', 'Yes', 'No',
       'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'Yes', 'No',
       'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No',
       'No', 'No', 'No', 'No', 'No', 'Yes', 'Yes', 'Yes', 'Yes', 'No',
       'No', 'No', 'No', 'No', 'Yes', 'Yes', 'Yes', 'No', 'Yes', 'Yes', 'Yes',
       'No', 'No', 'No', 'No', 'No', 'No', 'No', 'Yes', 'No', 'No', 'Yes',
       'Yes', 'No', 'No', 'Yes', 'No', 'No', 'No', 'No', 'No', 'Yes',
       'No', 'Yes', 'No'], dtype=object)
```

[74]:
```
sns.heatmap(confusion_matrix(y_test,y_pred),annot=True)
plt.xlabel("Actual")
plt.ylabel("Predicted")
```

[74]:
```
Text(50.722222222222214, 0.5, 'Predicted')
```



[75]:
```
print(classification_report(y_test,y_pred))
```

```
              precision    recall  f1-score   support

          No       0.73      0.96      0.83        72
         Yes       0.93      0.61      0.73        66

    accuracy                           0.79       138
   macro avg       0.83      0.78      0.78       138
weighted avg       0.82      0.79      0.78       138
```

11 Observation:

- Default model has given us better results than HyperParameter Tuning

[76]:
```
model=DecisionTreeClassifier()
```

[77]:
```
model.fit(x_train,y_train)
```

[77]:
```
DecisionTreeClassifier()
```

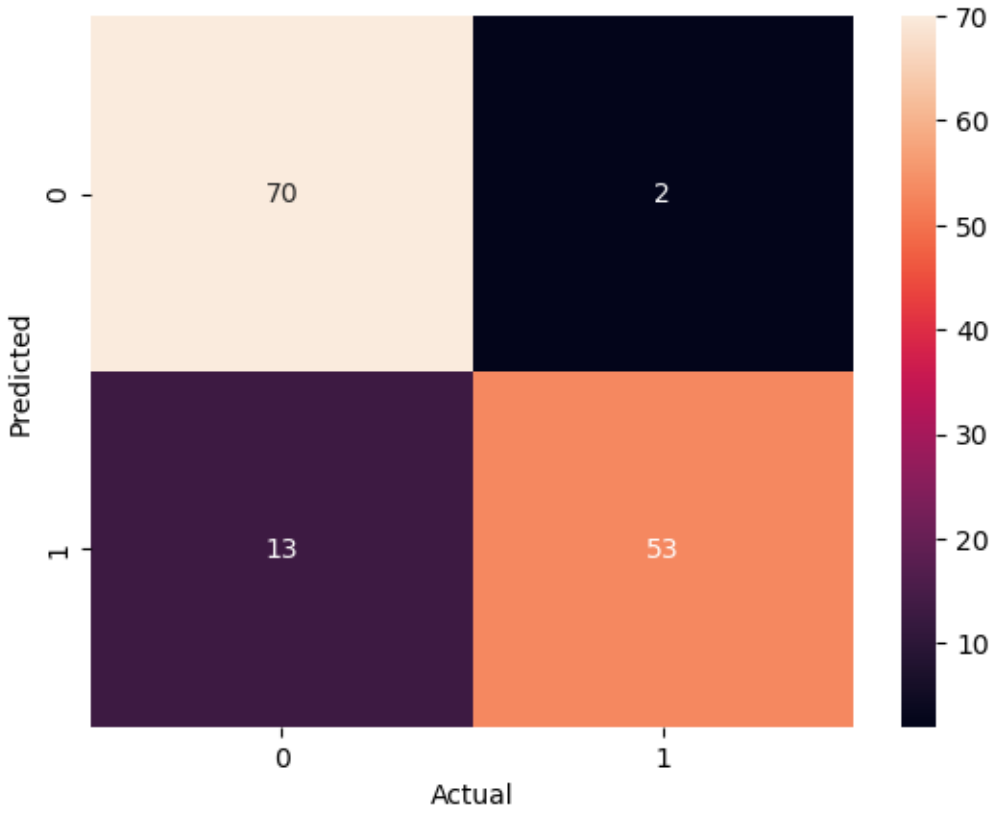
[79]:
```
y_pred=model.predict(x_test)
```

[80]:
```
y_pred
```

[80]:
```
array(['No', 'Yes', 'Yes', 'No', 'Yes', 'Yes', 'No', 'No', 'No', 'Yes',
       'Yes', 'Yes', 'No', 'Yes', 'Yes', 'Yes', 'No', 'No', 'No', 'Yes',
       'No', 'Yes', 'Yes', 'Yes', 'No', 'No', 'No', 'No', 'No', 'Yes',
       'No', 'No', 'Yes', 'No', 'No', 'Yes', 'Yes', 'Yes', 'No', 'Yes',
       'No', 'No', 'No', 'No', 'No', 'No', 'No', 'Yes', 'Yes', 'Yes',
       'Yes', 'No', 'Yes', 'Yes', 'No', 'Yes', 'Yes', 'Yes', 'No', 'No',
       'No', 'No', 'No', 'No', 'No', 'Yes', 'Yes', 'No', 'Yes', 'No',
       'Yes', 'No', 'No', 'No', 'No', 'Yes', 'No', 'No', 'No', 'No', 'No',
       'Yes', 'No', 'No', 'No', 'No', 'Yes', 'No', 'No', 'No', 'No', 'No',
       'No', 'No', 'No', 'No', 'Yes', 'No', 'No', 'Yes', 'No', 'Yes',
       'Yes', 'No', 'No', 'Yes', 'No', 'Yes', 'No', 'Yes', 'No', 'Yes',
       'Yes', 'Yes', 'No', 'Yes', 'No', 'Yes', 'No', 'No', 'No', 'Yes',
       'No', 'Yes', 'Yes', 'Yes', 'Yes', 'No', 'No', 'No', 'No', 'No',
       'No', 'No', 'No', 'No', 'Yes', 'Yes'], dtype=object)
```

[82]:
```
sns.heatmap(confusion_matrix(y_test,y_pred),annot=True)
plt.xlabel("Actual")
plt.ylabel("Predicted")
```

[82]:
```
Text(50.722222222222214, 0.5, 'Predicted')
```


70
2
13
53
0
1
Predicted
0
1
Actual
70
60
50
40
30
20
10