```
from google.colab import files
uploaded = files.upload()
```

```
<IPython.core.display.HTML object>

Saving Carseats.csv to Carseats (3).csv
```

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

```
import pandas as pd
import io
import numpy as np
```

```
carseats_df =
pd.read_csv(io.StringIO(uploaded['Carseats.csv'].decode('utf-8')))
carseats_df
```

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

     Education Urban   US
0           17   Yes  Yes
1           10   Yes  Yes
2           12   Yes  Yes
3           14   Yes  Yes
4           13   Yes   No
..         ...   ...  ...
395         14   Yes  Yes
```

```
396         11    No  Yes
397         18   Yes  Yes
398         12   Yes  Yes
399         16   Yes  Yes

[400 rows x 11 columns]
```

```
carseats_df.describe()
```

```
            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  
```

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
sns.set()
%matplotlib inline

import warnings
warnings.filterwarnings('ignore')

from sklearn import tree
import graphviz
from sklearn import metrics
from sklearn.model_selection import cross_val_score, train_test_split,
GridSearchCV
from sklearn.ensemble import BaggingRegressor, RandomForestRegressor,
AdaBoostRegressor, GradientBoostingRegressor
from xgboost import XGBRegressor
```

```
carseats_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
```

```
carseats_df.isnull().sum()
```

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

```
carseats_df['Education'] = carseats_df['Education'].astype(str)
```

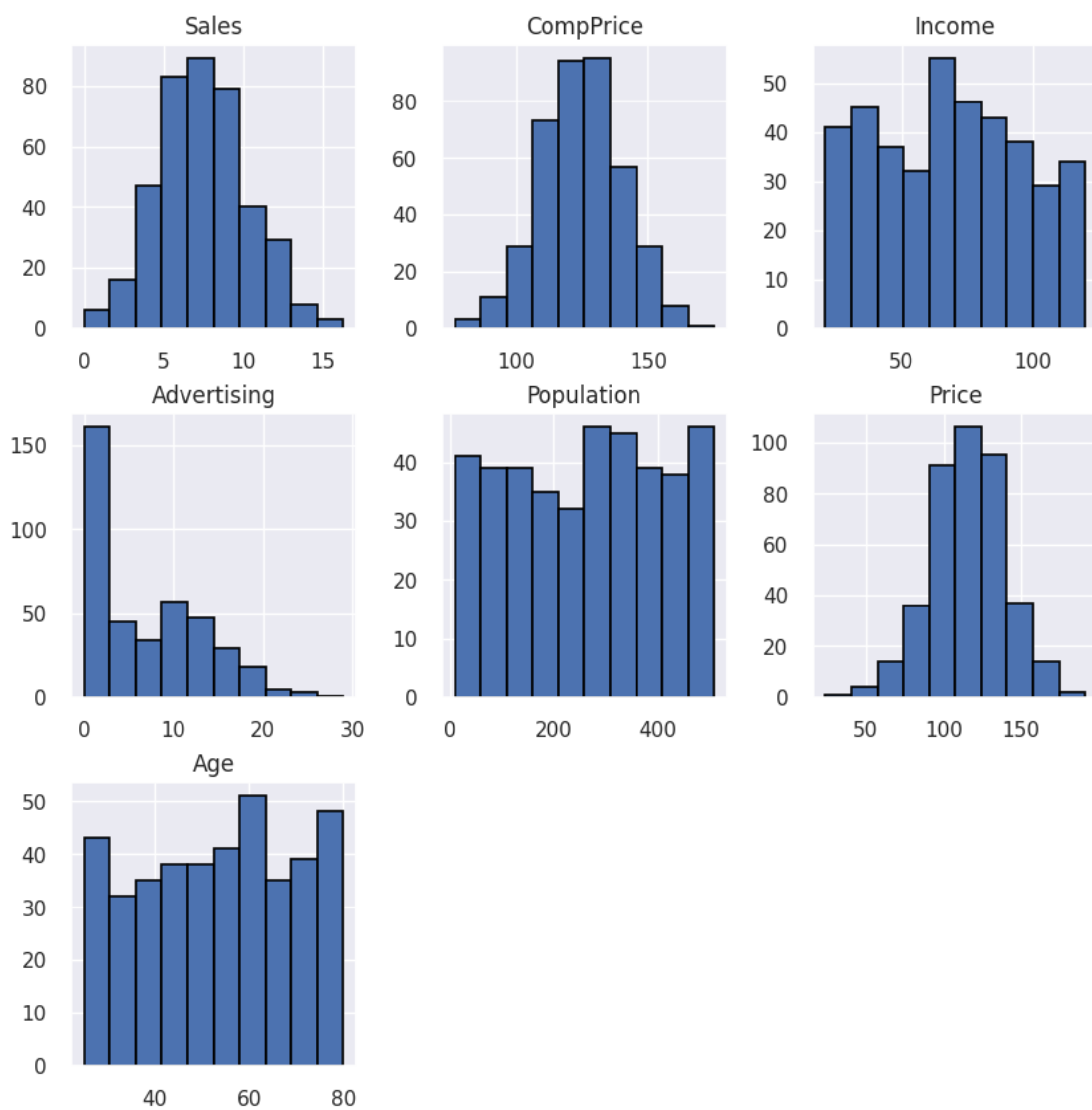
```
carseats_df.info()
```

```
<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    object
 9   Urban        400 non-null    object
 10  US           400 non-null    object
dtypes: float64(1), int64(6), object(4)
memory usage: 34.5+ KB
```

```python
# Visulazing the distibution of the data for every feature
carseats_df.hist(edgecolor='black', linewidth=1.2, figsize=(10, 10))
```

```
array([[<Axes: title={'center': 'Sales'}>,
        <Axes: title={'center': 'CompPrice'}>,
        <Axes: title={'center': 'Income'}>],
       [<Axes: title={'center': 'Advertising'}>,
        <Axes: title={'center': 'Population'}>,
        <Axes: title={'center': 'Price'}>],
       [<Axes: title={'center': 'Age'}>, <Axes: >, <Axes: >]],
      dtype=object)
```



```python
# Target Sales : Skewness check
carseats_df['Sales'].skew()
```

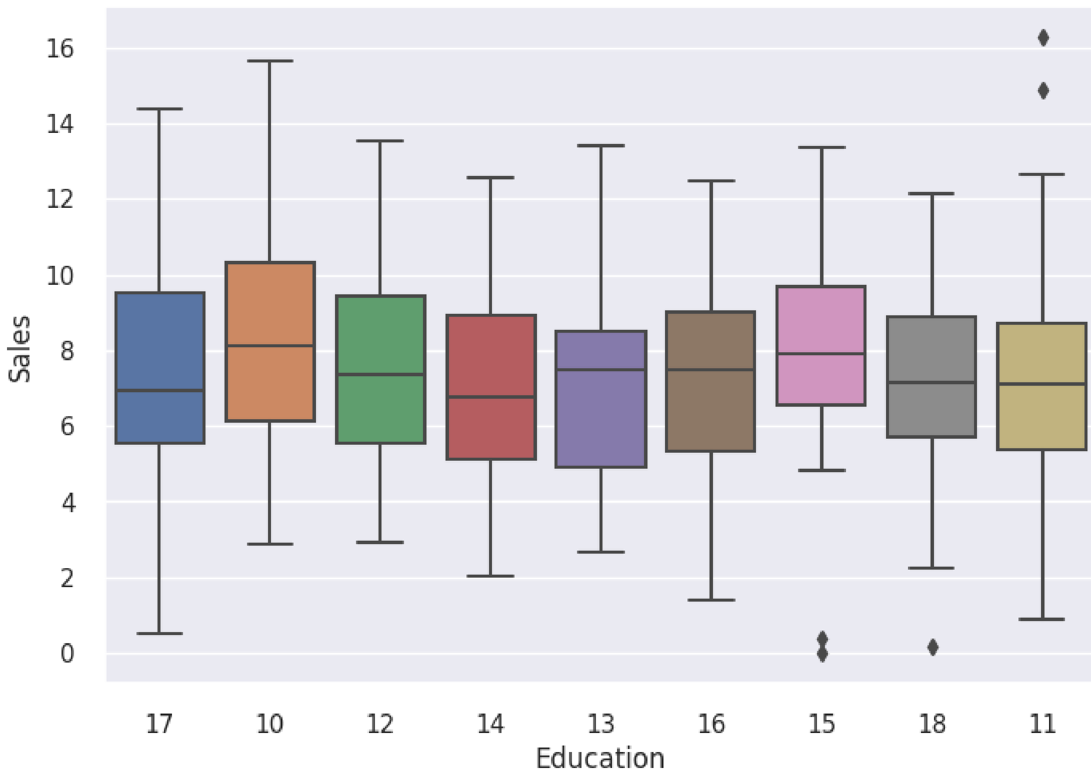
```
0.18556036318721578
```

```python
# Categorical features : Value check
cat_cols = ['Education', 'ShelveLoc', 'Urban', 'US']
for col in cat_cols:
    print(f"Feature Name {col} : \n{carseats_df[col].value_counts()}")
```

```
Feature Name Education :
17    49
12    49
10    48
11    48
16    47
13    43
14    40
18    40
15    36
Name: Education, dtype: int64
Feature Name ShelveLoc :
Medium    219
Bad        96
Good       85
Name: ShelveLoc, dtype: int64
Feature Name Urban :
Yes    282
No     118
Name: Urban, dtype: int64
Feature Name US :
Yes    258
No     142
Name: US, dtype: int64
```

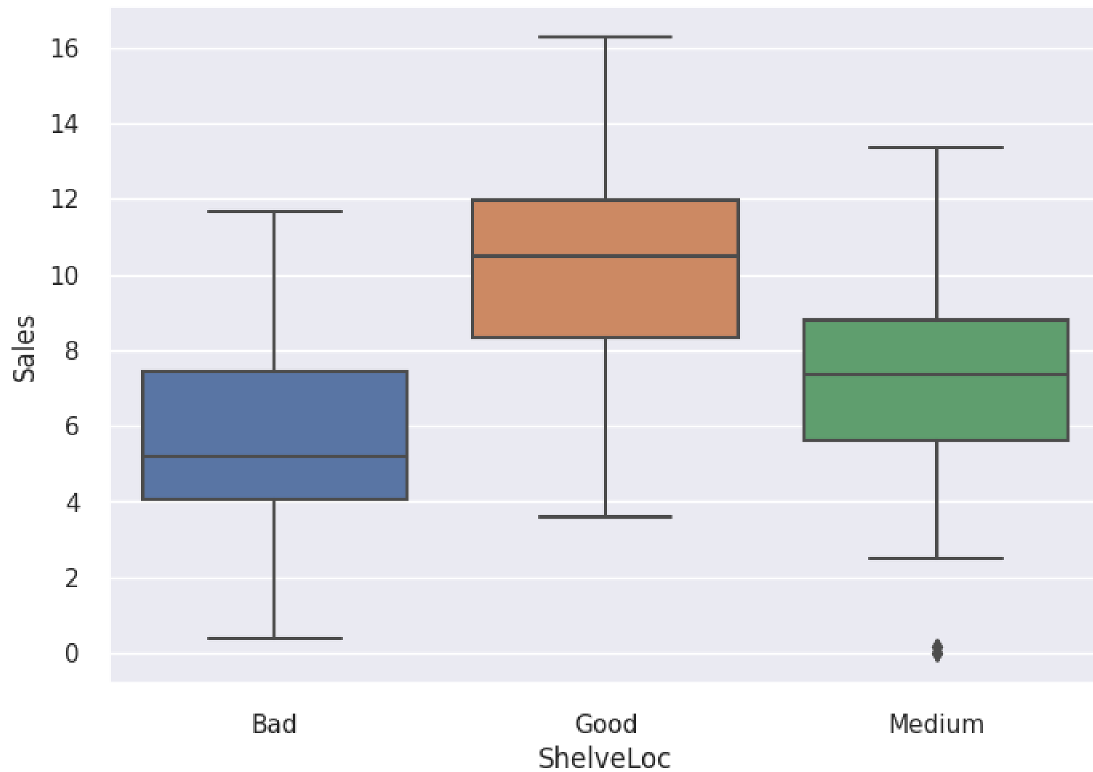
```python
#Education
sns.boxplot(x="Education", y="Sales", data=carseats_df)
```

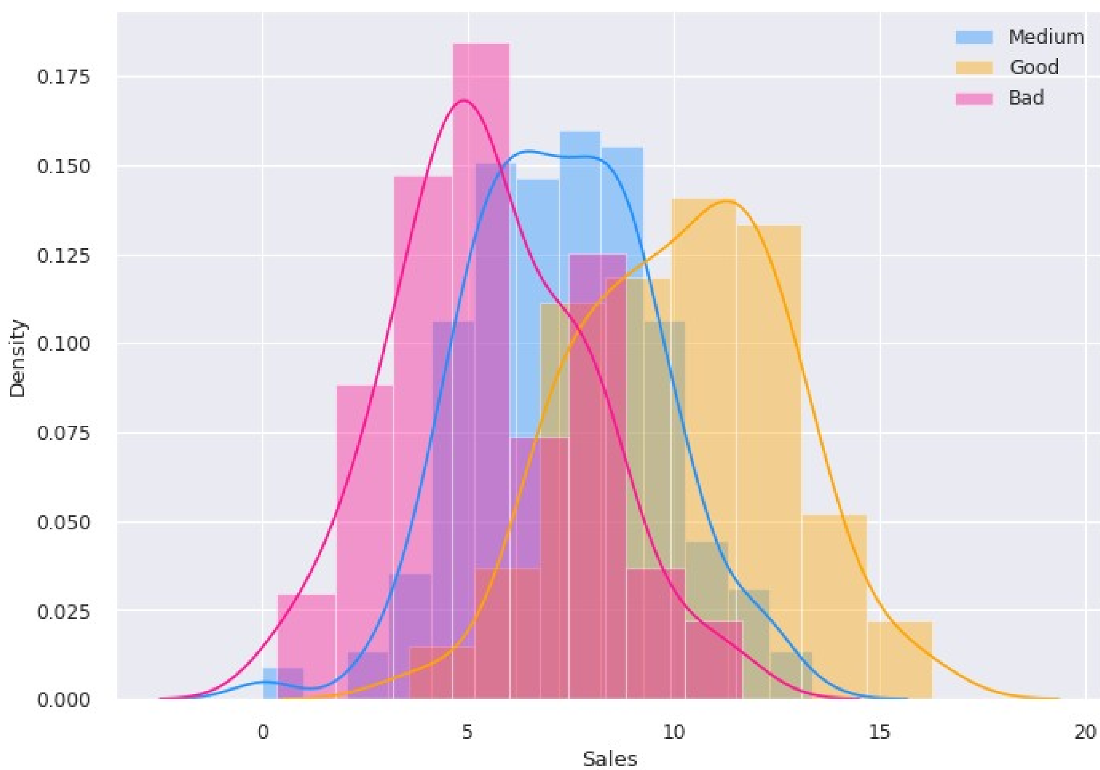
```
<Axes: xlabel='Education', ylabel='Sales'>
```




```
#ShelveLoc
sns.boxplot(x="ShelveLoc", y="Sales", data=carseats_df)
plt.figure(figsize=(10,7), dpi= 80)
sns.distplot(carseats_df['Sales'].loc[carseats_df['ShelveLoc'] ==
'Medium'], color="dodgerblue", label="Medium")
sns.distplot(carseats_df['Sales'].loc[carseats_df['ShelveLoc'] ==
'Good'], color="orange", label="Good")
sns.distplot(carseats_df['Sales'].loc[carseats_df['ShelveLoc'] ==
'Bad'], color="deeppink", label="Bad")
plt.legend()
```

```
<matplotlib.legend.Legend at 0x7f6ad105d4e0>
```

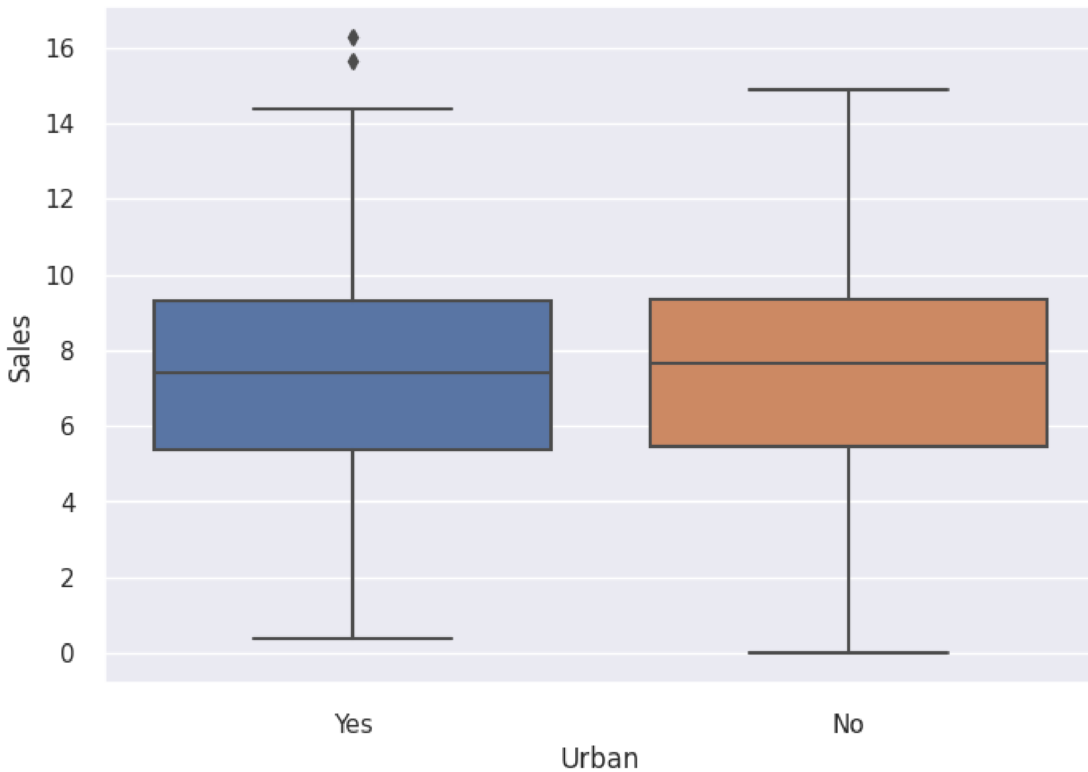


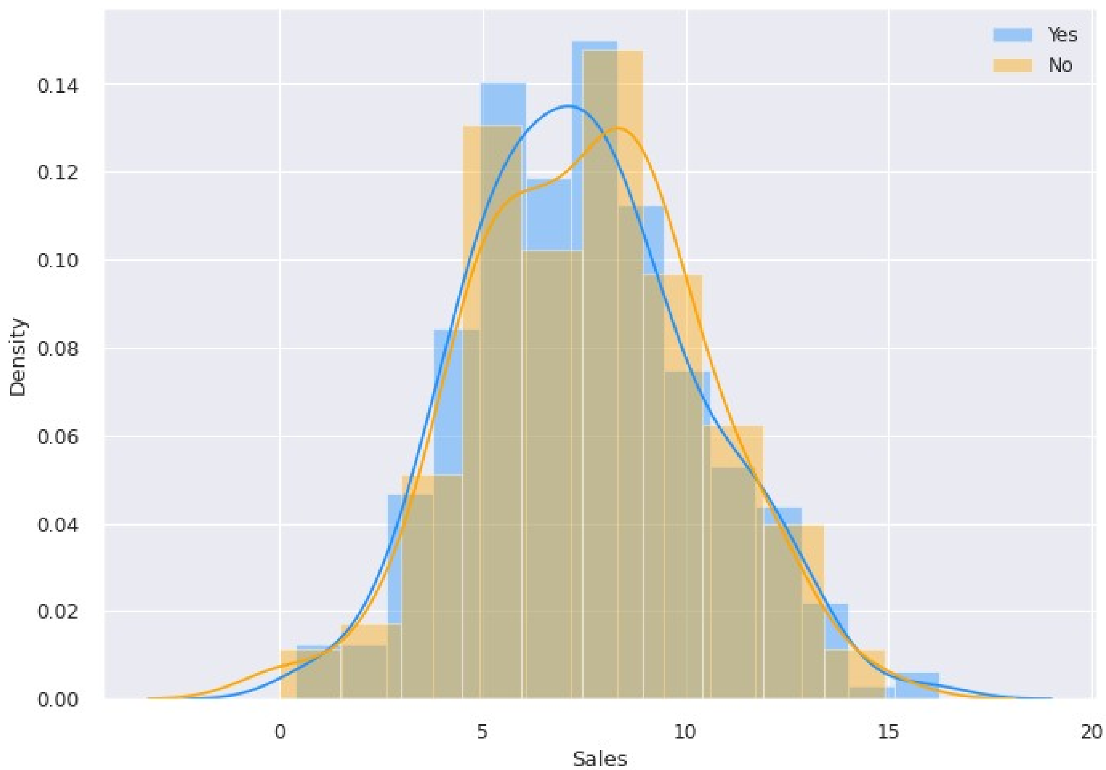



```
#Urban
sns.boxplot(x="Urban", y="Sales", data=carseats_df)
```

```
plt.figure(figsize=(10,7), dpi= 80)
sns.distplot(carseats_df['Sales'].loc[carseats_df['Urban'] == 'Yes'],
color="dodgerblue", label="Yes")
sns.distplot(carseats_df['Sales'].loc[carseats_df['Urban'] == 'No'],
color="orange", label="No")
plt.legend()
```

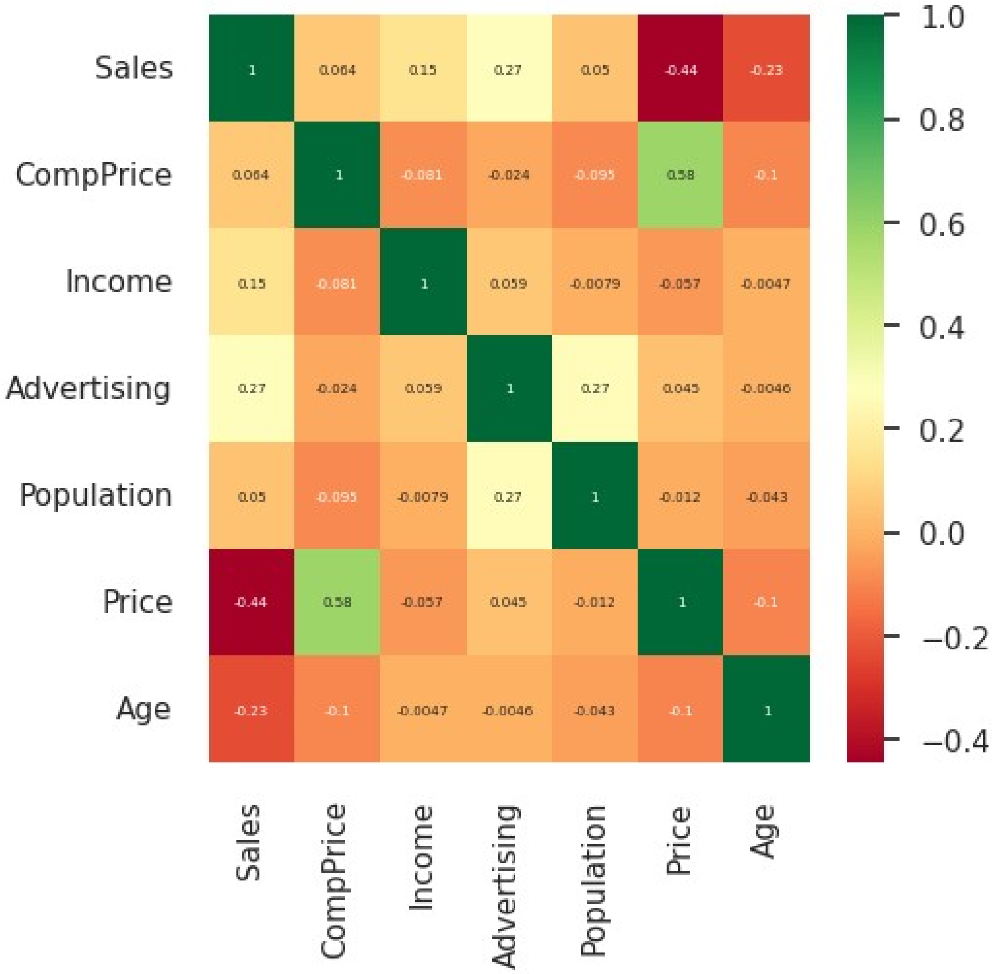
```
<matplotlib.legend.Legend at 0x7f6ad095b700>
```






```
#find correlation between continuous variables and Sales
plt.figure(figsize=(5, 5))
sns.heatmap(carseats_df.corr(), annot=True, cmap="RdYlGn",
annot_kws={"size":5})
```

```
<Axes: >
```




```python
def compute_impurity(feature, impurity_criterion):
    """
    This function calculates impurity of a feature.
    Supported impurity criteria: 'entropy', 'gini'
    input: feature (this needs to be a Pandas series)
    output: feature impurity
    """
    probs = feature.value_counts(normalize=True)

    if impurity_criterion == 'entropy':
        impurity = -1 * np.sum(np.log2(probs) * probs)
    elif impurity_criterion == 'gini':
        impurity = 1 - np.sum(np.square(probs))
    else:
        raise ValueError('Unknown impurity criterion')

    return(round(impurity, 3))

def comp_feature_information_gain(df, target, descriptive_feature,
split_criterion):
```

```
    """
    This function calculates information gain for splitting on
    a particular descriptive feature for a given dataset
    and a given impurity criteria.
    Supported split criterion: 'entropy', 'gini'
    """

    print('target feature:', target)
    print('descriptive_feature:', descriptive_feature)
    print('split criterion:', split_criterion)

    target_entropy = compute_impurity(df[target], split_criterion)

    # we define two lists below:
    # entropy_list to store the entropy of each partition
    # weight_list to store the relative number of observations in each
partition
    entropy_list = list()
    weight_list = list()

    # loop over each level of the descriptive feature
    # to partition the dataset with respect to that level
    # and compute the entropy and the weight of the level's partition
    for level in df[descriptive_feature].unique():
        df_feature_level = df[df[descriptive_feature] == level]
        entropy_level = compute_impurity(df_feature_level[target],
split_criterion)
        entropy_list.append(round(entropy_level, 3))
        weight_level = len(df_feature_level) / len(df)
        weight_list.append(round(weight_level, 3))

    print('impurity of partitions:', entropy_list)
    print('weights of partitions:', weight_list)

    feature_remaining_impurity = np.sum(np.array(entropy_list) *
np.array(weight_list))
    print('remaining impurity:', feature_remaining_impurity)

    information_gain = target_entropy - feature_remaining_impurity
    print('information gain:', information_gain)

    print('====================')

    return(information_gain)

split_criterion = 'entropy'
for feature in carseats_df.drop(columns='Sales').columns:
    feature_info_gain = comp_feature_information_gain(carseats_df,
'Sales', feature, split_criterion)
```

```
target feature: Sales
descriptive_feature: CompPrice
split criterion: entropy
impurity of partitions: [3.17, 3.17, 3.0, 3.17, 2.585, 3.322, 3.585,
3.0, 3.585, 3.875, 3.807, 3.17, 2.0, 3.322, 2.0, 1.585, 2.322, 3.459,
3.459, 3.459, 2.0, 2.807, 2.585, 2.0, 2.322, 2.322, 3.807, 2.322,
3.585, 2.807, 1.0, -0.0, 3.7, -0.0, 2.585, 2.322, 3.459, 1.0, 1.585,
2.0, 3.322, 1.585, -0.0, 1.585, 1.0, 2.0, 2.0, -0.0, 1.0, 1.0, -0.0, -
0.0, 3.17, 2.322, -0.0, 2.585, 1.0, 2.0, 2.0, 2.0, 2.0, 2.322, 2.807,
2.0, -0.0, -0.0, 1.0, -0.0, 1.0, 1.0, -0.0, -0.0, 1.0]
weights of partitions: [0.022, 0.022, 0.02, 0.022, 0.015, 0.025, 0.03,
0.02, 0.03, 0.04, 0.035, 0.022, 0.01, 0.025, 0.01, 0.007, 0.013,
0.028, 0.028, 0.028, 0.01, 0.018, 0.015, 0.01, 0.013, 0.013, 0.035,
0.013, 0.03, 0.018, 0.005, 0.003, 0.033, 0.003, 0.015, 0.013, 0.028,
0.005, 0.007, 0.01, 0.025, 0.007, 0.003, 0.007, 0.005, 0.01, 0.01,
0.003, 0.005, 0.005, 0.003, 0.003, 0.022, 0.013, 0.003, 0.015, 0.005,
0.01, 0.01, 0.01, 0.01, 0.013, 0.018, 0.01, 0.003, 0.003, 0.005,
0.003, 0.005, 0.005, 0.003, 0.003, 0.005]
remaining impurity: 2.8238580000000004
information gain: 5.480142
====================
target feature: Sales
descriptive_feature: Income
split criterion: entropy
impurity of partitions: [2.807, 2.0, 2.585, 3.0, 2.585, 2.322, 2.585,
2.585, 1.585, 2.322, 2.0, 2.322, 2.585, -0.0, 3.0, 2.0, 2.0, 2.322,
2.322, 2.322, 1.585, 2.0, 1.585, 2.0, 1.0, 2.322, 2.0, 2.0, 2.807,
2.0, 2.807, 2.322, 1.0, 3.459, 3.322, 2.0, 2.585, 1.585, 2.807, 2.0,
2.322, 2.322, 1.585, 2.0, 2.0, 2.0, 2.322, 2.807, 2.585, 1.585, 2.0,
1.0, 1.585, 2.322, 2.322, 1.585, 2.0, 2.585, 2.0, 2.585, 1.585, 2.0,
2.322, 1.0, 2.0, 1.0, 1.585, 2.807, 1.585, 2.0, 2.322, 2.0, 2.0, 2.0,
1.0, 2.0, 1.585, 1.585, 2.0, -0.0, 2.0, 2.0, 2.585, 2.322, 1.0, -0.0,
1.585, -0.0, 1.0, 1.0, 1.0, -0.0, -0.0, -0.0, -0.0, -0.0, -0.0, -0.0]
weights of partitions: [0.018, 0.01, 0.015, 0.02, 0.015, 0.013, 0.015,
0.015, 0.007, 0.013, 0.01, 0.013, 0.015, 0.003, 0.02, 0.01, 0.01,
0.013, 0.013, 0.013, 0.007, 0.01, 0.007, 0.01, 0.005, 0.013, 0.01,
0.01, 0.018, 0.01, 0.018, 0.013, 0.005, 0.028, 0.025, 0.01, 0.015,
0.007, 0.018, 0.01, 0.013, 0.013, 0.007, 0.01, 0.01, 0.01, 0.013,
0.018, 0.015, 0.007, 0.01, 0.005, 0.007, 0.013, 0.013, 0.007, 0.01,
0.015, 0.01, 0.015, 0.007, 0.01, 0.013, 0.005, 0.01, 0.005, 0.007,
0.018, 0.007, 0.01, 0.013, 0.01, 0.01, 0.01, 0.005, 0.01, 0.007,
0.007, 0.01, 0.003, 0.01, 0.01, 0.015, 0.013, 0.005, 0.003, 0.007,
0.003, 0.005, 0.005, 0.005, 0.003, 0.003, 0.003, 0.003, 0.003, 0.003,
0.003]
remaining impurity: 2.219114
information gain: 6.084886000000001
====================
target feature: Sales
descriptive_feature: Advertising
split criterion: entropy
```

```
impurity of partitions: [4.459, 3.459, 4.564, 3.585, 3.807, 4.322,
7.067, 3.585, 3.322, 2.948, 4.248, 3.875, 2.807, 3.278, 2.585, 3.0,
2.0, 1.0, 3.0, 4.0, -0.0, 3.459, 2.585, -0.0, -0.0, -0.0, 1.0, -0.0]
weights of partitions: [0.055, 0.028, 0.062, 0.03, 0.035, 0.05, 0.36,
0.03, 0.025, 0.022, 0.048, 0.04, 0.018, 0.028, 0.015, 0.02, 0.01,
0.005, 0.02, 0.04, 0.003, 0.028, 0.015, 0.003, 0.003, 0.003, 0.005,
0.003]
remaining impurity: 4.867151999999999
information gain: 3.4368480000000012
====================
target feature: Sales
descriptive_feature: Population
split criterion: entropy
impurity of partitions: [2.0, -0.0, -0.0, 1.0, -0.0, 1.585, 1.0, 1.0,
1.0, 1.0, 1.0, -0.0, -0.0, 1.0, 2.0, 1.585, 1.585, 1.0, 1.585, 1.0, -
0.0, -0.0, 2.0, -0.0, -0.0, 1.0, 1.585, -0.0, 1.0, -0.0, 1.0, -0.0, -
0.0, 1.0, -0.0, -0.0, 1.585, -0.0, 1.585, -0.0, 1.0, 1.0, 1.0, 1.0, -
0.0, -0.0, 1.0, -0.0, 1.0, 1.0, -0.0, 1.585, 1.0, -0.0, 1.0, -0.0,
1.0, -0.0, 2.0, -0.0, -0.0, 1.0, 1.0, 1.0, -0.0, 2.0, 1.0, 2.0, 1.0, -
0.0, -0.0, 1.0, -0.0, 1.0, -0.0, -0.0, -0.0, 1.0, -0.0, 1.0, -0.0, -
0.0, 1.0, -0.0, 1.0, -0.0, -0.0, 2.0, -0.0, 1.0, -0.0, -0.0, 1.0, -
0.0, 1.0, -0.0, 1.585, 1.0, 1.0, 1.0, 1.0, -0.0, -0.0, 1.0, -0.0, 1.0,
-0.0, 1.0, -0.0, -0.0, 1.0, 1.0, -0.0, 1.0, -0.0, 1.0, -0.0, 1.0, 1.0,
1.0, 1.0, -0.0, 1.0, -0.0, -0.0, 1.585, 1.585, -0.0, 1.0, -0.0, -0.0,
-0.0, -0.0, -0.0, -0.0, -0.0, -0.0, -0.0, -0.0, -0.0, -0.0, -0.0, 1.0,
-0.0, -0.0, 1.0, 1.0, -0.0, -0.0, 1.0, -0.0, -0.0, -0.0, -0.0, -0.0, -
0.0, 1.0, 1.0, -0.0, -0.0, 1.0, -0.0, -0.0, -0.0, 1.0, -0.0, -0.0, -
0.0, -0.0, -0.0, -0.0, 1.0, 1.0, -0.0, -0.0, 1.0, -0.0, -0.0, -0.0, -
0.0, 1.0, -0.0, -0.0, -0.0, 1.0, 1.0, -0.0, -0.0, 1.0, -0.0, 1.0, -
0.0, 1.0, 1.0, -0.0, 1.0, -0.0, -0.0, -0.0, -0.0, -0.0, -0.0, -0.0, -
0.0, -0.0, -0.0, -0.0, -0.0, 1.0, 1.0, -0.0, -0.0, -0.0, 1.0, -0.0, -
0.0, -0.0, -0.0, -0.0, -0.0, -0.0, -0.0, -0.0, -0.0, -0.0, -0.0, -0.0,
-0.0, 1.0, -0.0, -0.0, -0.0, 1.0, -0.0, -0.0, -0.0, -0.0, -0.0, -0.0,
-0.0, -0.0, -0.0, -0.0, -0.0, -0.0, 1.0, -0.0, -0.0, -0.0, -0.0, -0.0,
-0.0, -0.0, -0.0, -0.0, 1.0, -0.0, -0.0, -0.0, 1.0, -0.0, -0.0, -0.0,
-0.0, -0.0, -0.0, 1.0, -0.0, -0.0, -0.0, -0.0, -0.0, -0.0, -0.0, -0.0]
weights of partitions: [0.01, 0.003, 0.003, 0.005, 0.003, 0.007,
0.005, 0.005, 0.005, 0.005, 0.005, 0.003, 0.003, 0.005, 0.01, 0.007,
0.007, 0.005, 0.007, 0.005, 0.003, 0.003, 0.01, 0.003, 0.003, 0.005,
0.007, 0.003, 0.005, 0.003, 0.005, 0.003, 0.003, 0.005, 0.003, 0.003,
0.007, 0.003, 0.007, 0.003, 0.005, 0.005, 0.005, 0.005, 0.003, 0.003,
0.005, 0.003, 0.005, 0.005, 0.003, 0.007, 0.005, 0.003, 0.005, 0.003,
0.005, 0.003, 0.01, 0.003, 0.003, 0.005, 0.005, 0.005, 0.003, 0.01,
0.005, 0.01, 0.005, 0.003, 0.003, 0.005, 0.003, 0.005, 0.003, 0.003,
0.003, 0.005, 0.003, 0.005, 0.003, 0.003, 0.005, 0.003, 0.005, 0.003,
0.003, 0.01, 0.003, 0.005, 0.003, 0.003, 0.005, 0.003, 0.005, 0.003,
0.007, 0.005, 0.005, 0.005, 0.005, 0.003, 0.003, 0.005, 0.003, 0.005,
0.003, 0.005, 0.003, 0.003, 0.005, 0.005, 0.003, 0.005, 0.003, 0.005,
0.003, 0.005, 0.005, 0.005, 0.005, 0.003, 0.005, 0.003, 0.003, 0.007,
0.007, 0.003, 0.005, 0.003, 0.003, 0.003, 0.003, 0.003, 0.003, 0.003,
```

```
0.003, 0.003, 0.003, 0.003, 0.003, 0.003, 0.005, 0.003, 0.003, 0.005,
0.005, 0.003, 0.003, 0.005, 0.003, 0.003, 0.003, 0.003, 0.003, 0.003,
0.005, 0.005, 0.003, 0.003, 0.005, 0.003, 0.003, 0.003, 0.005, 0.003,
0.003, 0.003, 0.003, 0.003, 0.003, 0.005, 0.005, 0.003, 0.003, 0.005,
0.003, 0.003, 0.003, 0.003, 0.005, 0.003, 0.003, 0.003, 0.005, 0.005,
0.003, 0.003, 0.005, 0.003, 0.005, 0.003, 0.005, 0.005, 0.003, 0.005,
0.003, 0.003, 0.003, 0.003, 0.003, 0.003, 0.003, 0.003, 0.003, 0.003,
0.003, 0.003, 0.005, 0.005, 0.003, 0.003, 0.003, 0.005, 0.003, 0.003,
0.003, 0.003, 0.003, 0.003, 0.003, 0.003, 0.003, 0.003, 0.003, 0.003,
0.003, 0.003, 0.005, 0.003, 0.003, 0.003, 0.005, 0.003, 0.003, 0.003,
0.003, 0.003, 0.003, 0.003, 0.003, 0.003, 0.003, 0.003, 0.003, 0.005,
0.003, 0.003, 0.003, 0.003, 0.003, 0.003, 0.003, 0.003, 0.003, 0.005,
0.003, 0.003, 0.003, 0.005, 0.003, 0.003, 0.003, 0.003, 0.003, 0.003,
0.005, 0.003, 0.003, 0.003, 0.003, 0.003, 0.003, 0.003, 0.003]
remaining impurity: 0.6720450000000001
information gain: 7.6319550000000005
====================
target feature: Sales
descriptive_feature: Price
split criterion: entropy
impurity of partitions: [3.585, 1.0, 1.0, 3.17, 3.585, 2.322, 3.0,
2.807, 2.0, 2.585, 2.0, 1.585, 3.17, 2.322, 3.17, 3.322, 1.0, 2.322,
1.585, 2.0, 1.0, 1.0, 3.322, 2.0, 2.807, 1.585, 2.807, 3.0, -0.0,
2.807, 1.0, 2.0, 1.585, 1.585, 2.0, 3.17, 2.807, 1.585, 1.0, 2.585,
2.585, 2.0, 2.0, 2.322, 2.585, 3.322, 2.0, 1.585, 2.585, 1.585, 2.585,
1.585, 2.0, 2.585, 1.0, 2.322, 3.17, 2.322, 2.585, -0.0, 3.17, 1.0,
1.585, 2.0, 1.585, -0.0, -0.0, 1.0, 1.0, 1.585, -0.0, 1.0, 1.585, 1.0,
-0.0, 1.585, -0.0, -0.0, 2.807, 1.585, -0.0, -0.0, 1.0, 2.585, -0.0,
2.322, -0.0, -0.0, 1.0, 1.0, -0.0, -0.0, -0.0, -0.0, -0.0, -0.0, -0.0,
-0.0, -0.0, -0.0, -0.0]
weights of partitions: [0.03, 0.005, 0.005, 0.022, 0.03, 0.013, 0.02,
0.018, 0.01, 0.015, 0.01, 0.007, 0.022, 0.013, 0.022, 0.025, 0.005,
0.013, 0.007, 0.01, 0.005, 0.005, 0.025, 0.01, 0.018, 0.007, 0.018,
0.02, 0.003, 0.018, 0.005, 0.01, 0.007, 0.007, 0.01, 0.022, 0.018,
0.007, 0.005, 0.015, 0.015, 0.01, 0.01, 0.013, 0.015, 0.025, 0.01,
0.007, 0.015, 0.007, 0.015, 0.007, 0.01, 0.015, 0.005, 0.013, 0.022,
0.013, 0.015, 0.003, 0.022, 0.005, 0.007, 0.01, 0.007, 0.003, 0.003,
0.005, 0.005, 0.007, 0.003, 0.005, 0.007, 0.005, 0.003, 0.007, 0.003,
0.003, 0.018, 0.007, 0.003, 0.003, 0.005, 0.015, 0.003, 0.013, 0.003,
0.003, 0.005, 0.005, 0.003, 0.003, 0.003, 0.003, 0.003, 0.003, 0.003,
0.003, 0.003, 0.003, 0.003]
remaining impurity: 2.332548
information gain: 5.971452
====================
target feature: Sales
descriptive_feature: ShelveLoc
split criterion: entropy
impurity of partitions: [6.481, 6.292, 7.558]
weights of partitions: [0.24, 0.212, 0.547]
remaining impurity: 7.023569999999999
```

```
information gain: 1.2804300000000008
====================
target feature: Sales
descriptive_feature: Age
split criterion: entropy
impurity of partitions: [3.17, 3.322, 2.322, 3.322, 2.585, 2.0, 2.322,
2.322, 3.459, 3.0, 3.0, 3.807, 2.585, 2.585, 2.807, 2.0, 2.585, 2.585,
3.0, 3.0, 3.122, 2.322, 2.585, 3.0, 3.0, 3.322, 2.585, 2.585, 3.7,
2.585, 3.17, 3.585, 2.585, 2.807, 2.585, 3.17, 2.585, 3.17, 1.585,
2.807, 2.807, 2.0, 2.0, 2.807, 2.807, 2.0, 3.322, 3.0, 3.17, 3.0,
1.585, 3.0, 3.0, 2.585, 2.585, 1.585]
weights of partitions: [0.022, 0.025, 0.013, 0.025, 0.015, 0.01,
0.013, 0.013, 0.028, 0.02, 0.02, 0.035, 0.015, 0.015, 0.018, 0.01,
0.015, 0.015, 0.02, 0.02, 0.025, 0.013, 0.015, 0.02, 0.02, 0.025,
0.015, 0.015, 0.033, 0.015, 0.022, 0.03, 0.015, 0.018, 0.015, 0.022,
0.015, 0.022, 0.007, 0.018, 0.018, 0.01, 0.01, 0.018, 0.018, 0.01,
0.025, 0.02, 0.022, 0.02, 0.007, 0.02, 0.02, 0.015, 0.015, 0.007]
remaining impurity: 2.918732
information gain: 5.385268
====================
target feature: Sales
descriptive_feature: Education
split criterion: entropy
impurity of partitions: [5.574, 5.543, 5.615, 5.272, 5.38, 5.512,
5.17, 5.272, 5.585]
weights of partitions: [0.122, 0.12, 0.122, 0.1, 0.107, 0.117, 0.09,
0.1, 0.12]
remaining impurity: 5.440682
information gain: 2.8633180000000005
====================
target feature: Sales
descriptive_feature: Urban
split criterion: entropy
impurity of partitions: [7.921, 6.713]
weights of partitions: [0.705, 0.295]
remaining impurity: 7.56464
information gain: 0.7393600000000005
====================
target feature: Sales
descriptive_feature: US
split criterion: entropy
impurity of partitions: [7.827, 7.032]
weights of partitions: [0.645, 0.355]
remaining impurity: 7.544775
information gain: 0.7592250000000007
====================
```

```python
split_criteria = 'gini'
for feature in carseats_df.drop(columns='Sales').columns:
```

```
    feature_info_gain = comp_feature_information_gain(carseats_df,
'Sales', feature, split_criteria)

target feature: Sales
descriptive_feature: CompPrice
split criterion: gini
impurity of partitions: [0.889, 0.889, 0.875, 0.889, 0.833, 0.9,
0.917, 0.875, 0.917, 0.93, 0.929, 0.889, 0.75, 0.9, 0.75, 0.667, 0.8,
0.909, 0.909, 0.909, 0.75, 0.857, 0.833, 0.75, 0.8, 0.8, 0.929, 0.8,
0.917, 0.857, 0.5, 0.0, 0.923, 0.0, 0.833, 0.8, 0.909, 0.5, 0.667,
0.75, 0.9, 0.667, 0.0, 0.667, 0.5, 0.75, 0.75, 0.0, 0.5, 0.5, 0.0,
0.0, 0.889, 0.8, 0.0, 0.833, 0.5, 0.75, 0.75, 0.75, 0.75, 0.8, 0.857,
0.75, 0.0, 0.0, 0.5, 0.0, 0.5, 0.5, 0.0, 0.0, 0.5]
weights of partitions: [0.022, 0.022, 0.02, 0.022, 0.015, 0.025, 0.03,
0.02, 0.03, 0.04, 0.035, 0.022, 0.01, 0.025, 0.01, 0.007, 0.013,
0.028, 0.028, 0.028, 0.01, 0.018, 0.015, 0.01, 0.013, 0.013, 0.035,
0.013, 0.03, 0.018, 0.005, 0.003, 0.033, 0.003, 0.015, 0.013, 0.028,
0.005, 0.007, 0.01, 0.025, 0.007, 0.003, 0.007, 0.005, 0.01, 0.01,
0.003, 0.005, 0.005, 0.003, 0.003, 0.022, 0.013, 0.003, 0.015, 0.005,
0.01, 0.01, 0.01, 0.01, 0.013, 0.018, 0.01, 0.003, 0.003, 0.005,
0.003, 0.005, 0.005, 0.003, 0.003, 0.005]
remaining impurity: 0.820051
information gain: 0.17694900000000002
====================
target feature: Sales
descriptive_feature: Income
split criterion: gini
impurity of partitions: [0.857, 0.75, 0.833, 0.875, 0.833, 0.8, 0.833,
0.833, 0.667, 0.8, 0.75, 0.8, 0.833, 0.0, 0.875, 0.75, 0.75, 0.8, 0.8,
0.8, 0.667, 0.75, 0.667, 0.75, 0.5, 0.8, 0.75, 0.75, 0.857, 0.75,
0.857, 0.8, 0.5, 0.909, 0.9, 0.75, 0.833, 0.667, 0.857, 0.75, 0.8,
0.8, 0.667, 0.75, 0.75, 0.75, 0.8, 0.857, 0.833, 0.667, 0.75, 0.5,
0.667, 0.8, 0.8, 0.667, 0.75, 0.833, 0.75, 0.833, 0.667, 0.75, 0.8,
0.5, 0.75, 0.5, 0.667, 0.857, 0.667, 0.75, 0.8, 0.75, 0.75, 0.75, 0.5,
0.75, 0.667, 0.667, 0.75, 0.0, 0.75, 0.75, 0.833, 0.8, 0.5, 0.0,
0.667, 0.0, 0.5, 0.5, 0.5, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0]
weights of partitions: [0.018, 0.01, 0.015, 0.02, 0.015, 0.013, 0.015,
0.015, 0.007, 0.013, 0.01, 0.013, 0.015, 0.003, 0.02, 0.01, 0.01,
0.013, 0.013, 0.013, 0.007, 0.01, 0.007, 0.01, 0.005, 0.013, 0.01,
0.01, 0.018, 0.01, 0.018, 0.013, 0.005, 0.028, 0.025, 0.01, 0.015,
0.007, 0.018, 0.01, 0.013, 0.013, 0.007, 0.01, 0.01, 0.01, 0.013,
0.018, 0.015, 0.007, 0.01, 0.005, 0.007, 0.013, 0.013, 0.007, 0.01,
0.015, 0.01, 0.015, 0.007, 0.01, 0.013, 0.005, 0.01, 0.005, 0.007,
0.018, 0.007, 0.01, 0.013, 0.01, 0.01, 0.01, 0.005, 0.01, 0.007,
0.007, 0.01, 0.003, 0.01, 0.01, 0.015, 0.013, 0.005, 0.003, 0.007,
0.003, 0.005, 0.005, 0.005, 0.003, 0.003, 0.003, 0.003, 0.003, 0.003,
0.003]
remaining impurity: 0.7597240000000001
information gain: 0.23727599999999993
====================
```

```
target feature: Sales
descriptive_feature: Advertising
split criterion: gini
impurity of partitions: [0.955, 0.909, 0.957, 0.917, 0.929, 0.95,
0.992, 0.917, 0.9, 0.864, 0.947, 0.93, 0.857, 0.893, 0.833, 0.875,
0.75, 0.5, 0.875, 0.938, 0.0, 0.909, 0.833, 0.0, 0.0, 0.0, 0.5, 0.0]
weights of partitions: [0.055, 0.028, 0.062, 0.03, 0.035, 0.05, 0.36,
0.03, 0.025, 0.022, 0.048, 0.04, 0.018, 0.028, 0.015, 0.02, 0.01,
0.005, 0.02, 0.04, 0.003, 0.028, 0.015, 0.003, 0.003, 0.003, 0.005,
0.003]
remaining impurity: 0.9295219999999998
information gain: 0.06747800000000015
====================
target feature: Sales
descriptive_feature: Population
split criterion: gini
impurity of partitions: [0.75, 0.0, 0.0, 0.5, 0.0, 0.667, 0.5, 0.5,
0.5, 0.5, 0.5, 0.0, 0.0, 0.5, 0.75, 0.667, 0.667, 0.5, 0.667, 0.5,
0.0, 0.0, 0.75, 0.0, 0.0, 0.5, 0.667, 0.0, 0.5, 0.0, 0.5, 0.0, 0.0,
0.5, 0.0, 0.0, 0.667, 0.0, 0.667, 0.0, 0.5, 0.5, 0.5, 0.5, 0.0, 0.0,
0.5, 0.0, 0.5, 0.5, 0.0, 0.667, 0.5, 0.0, 0.5, 0.0, 0.5, 0.0, 0.75,
0.0, 0.0, 0.5, 0.5, 0.5, 0.0, 0.75, 0.5, 0.75, 0.5, 0.0, 0.0, 0.5,
0.0, 0.5, 0.0, 0.0, 0.0, 0.5, 0.0, 0.5, 0.0, 0.0, 0.5, 0.0, 0.5, 0.0,
0.0, 0.75, 0.0, 0.5, 0.0, 0.0, 0.5, 0.0, 0.5, 0.0, 0.667, 0.5, 0.5,
0.5, 0.5, 0.0, 0.0, 0.5, 0.0, 0.5, 0.0, 0.5, 0.0, 0.0, 0.5, 0.5, 0.0,
0.5, 0.0, 0.5, 0.0, 0.5, 0.5, 0.5, 0.5, 0.0, 0.5, 0.0, 0.0, 0.667,
0.667, 0.0, 0.5, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0,
0.0, 0.0, 0.0, 0.5, 0.0, 0.0, 0.5, 0.5, 0.0, 0.0, 0.5, 0.0, 0.0, 0.0,
0.0, 0.0, 0.0, 0.5, 0.5, 0.0, 0.0, 0.5, 0.0, 0.0, 0.0, 0.5, 0.0, 0.0,
0.0, 0.0, 0.0, 0.0, 0.5, 0.5, 0.0, 0.0, 0.5, 0.0, 0.0, 0.0, 0.0, 0.5,
0.0, 0.0, 0.0, 0.5, 0.5, 0.0, 0.0, 0.5, 0.0, 0.5, 0.0, 0.5, 0.5, 0.0,
0.5, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.5,
0.5, 0.0, 0.0, 0.0, 0.5, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0,
0.0, 0.0, 0.0, 0.0, 0.0, 0.5, 0.0, 0.0, 0.0, 0.5, 0.0, 0.0, 0.0, 0.0,
0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.5, 0.0, 0.0, 0.0, 0.0, 0.0,
0.0, 0.0, 0.0, 0.0, 0.5, 0.0, 0.0, 0.0, 0.5, 0.0, 0.0, 0.0, 0.0, 0.0,
0.0, 0.5, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0]
weights of partitions: [0.01, 0.003, 0.003, 0.005, 0.003, 0.007,
0.005, 0.005, 0.005, 0.005, 0.005, 0.003, 0.003, 0.005, 0.01, 0.007,
0.007, 0.005, 0.007, 0.005, 0.003, 0.003, 0.01, 0.003, 0.003, 0.005,
0.007, 0.003, 0.005, 0.003, 0.005, 0.003, 0.003, 0.005, 0.003, 0.003,
0.007, 0.003, 0.007, 0.003, 0.005, 0.005, 0.005, 0.005, 0.003, 0.003,
0.005, 0.003, 0.005, 0.005, 0.003, 0.007, 0.005, 0.003, 0.005, 0.003,
0.005, 0.003, 0.01, 0.003, 0.003, 0.005, 0.005, 0.005, 0.003, 0.01,
0.005, 0.01, 0.005, 0.003, 0.003, 0.005, 0.003, 0.005, 0.003, 0.003,
0.003, 0.005, 0.003, 0.005, 0.003, 0.003, 0.005, 0.003, 0.005, 0.003,
0.003, 0.01, 0.003, 0.005, 0.003, 0.003, 0.005, 0.003, 0.005, 0.003,
0.007, 0.005, 0.005, 0.005, 0.005, 0.003, 0.003, 0.005, 0.003, 0.005,
0.003, 0.005, 0.003, 0.003, 0.005, 0.005, 0.003, 0.005, 0.003, 0.005,
0.003, 0.005, 0.005, 0.005, 0.005, 0.003, 0.005, 0.003, 0.003, 0.007,
```

```
0.007, 0.003, 0.005, 0.003, 0.003, 0.003, 0.003, 0.003, 0.003, 0.003,
0.003, 0.003, 0.003, 0.003, 0.003, 0.003, 0.005, 0.003, 0.003, 0.005,
0.005, 0.003, 0.003, 0.005, 0.003, 0.003, 0.003, 0.003, 0.003, 0.003,
0.005, 0.005, 0.003, 0.003, 0.005, 0.003, 0.003, 0.003, 0.005, 0.003,
0.003, 0.003, 0.003, 0.003, 0.003, 0.005, 0.005, 0.003, 0.003, 0.005,
0.003, 0.003, 0.003, 0.003, 0.005, 0.003, 0.003, 0.003, 0.005, 0.005,
0.003, 0.003, 0.005, 0.003, 0.005, 0.003, 0.005, 0.005, 0.003, 0.005,
0.003, 0.003, 0.003, 0.003, 0.003, 0.003, 0.003, 0.003, 0.003, 0.003,
0.003, 0.003, 0.005, 0.005, 0.003, 0.003, 0.003, 0.005, 0.003, 0.003,
0.003, 0.003, 0.003, 0.003, 0.003, 0.003, 0.003, 0.003, 0.003, 0.003,
0.003, 0.003, 0.005, 0.003, 0.003, 0.003, 0.005, 0.003, 0.003, 0.003,
0.003, 0.003, 0.003, 0.003, 0.003, 0.003, 0.003, 0.003, 0.003, 0.005,
0.003, 0.003, 0.003, 0.003, 0.003, 0.003, 0.003, 0.003, 0.003, 0.005,
0.003, 0.003, 0.003, 0.005, 0.003, 0.003, 0.003, 0.003, 0.003, 0.003,
0.005, 0.003, 0.003, 0.003, 0.003, 0.003, 0.003, 0.003, 0.003]
remaining impurity: 0.308859
information gain: 0.688141
====================
target feature: Sales
descriptive_feature: Price
split criterion: gini
impurity of partitions: [0.917, 0.5, 0.5, 0.889, 0.917, 0.8, 0.875,
0.857, 0.75, 0.833, 0.75, 0.667, 0.889, 0.8, 0.889, 0.9, 0.5, 0.8,
0.667, 0.75, 0.5, 0.5, 0.9, 0.75, 0.857, 0.667, 0.857, 0.875, 0.0,
0.857, 0.5, 0.75, 0.667, 0.667, 0.75, 0.889, 0.857, 0.667, 0.5, 0.833,
0.833, 0.75, 0.75, 0.8, 0.833, 0.9, 0.75, 0.667, 0.833, 0.667, 0.833,
0.667, 0.75, 0.833, 0.5, 0.8, 0.889, 0.8, 0.833, 0.0, 0.889, 0.5,
0.667, 0.75, 0.667, 0.0, 0.0, 0.5, 0.5, 0.667, 0.0, 0.5, 0.667, 0.5,
0.0, 0.667, 0.0, 0.0, 0.857, 0.667, 0.0, 0.0, 0.5, 0.833, 0.0, 0.8,
0.0, 0.0, 0.5, 0.5, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0,
0.0]
weights of partitions: [0.03, 0.005, 0.005, 0.022, 0.03, 0.013, 0.02,
0.018, 0.01, 0.015, 0.01, 0.007, 0.022, 0.013, 0.022, 0.025, 0.005,
0.013, 0.007, 0.01, 0.005, 0.005, 0.025, 0.01, 0.018, 0.007, 0.018,
0.02, 0.003, 0.018, 0.005, 0.01, 0.007, 0.007, 0.01, 0.022, 0.018,
0.007, 0.005, 0.015, 0.015, 0.01, 0.01, 0.013, 0.015, 0.025, 0.01,
0.007, 0.015, 0.007, 0.015, 0.007, 0.01, 0.015, 0.005, 0.013, 0.022,
0.013, 0.015, 0.003, 0.022, 0.005, 0.007, 0.01, 0.007, 0.003, 0.003,
0.005, 0.005, 0.007, 0.003, 0.005, 0.007, 0.005, 0.003, 0.007, 0.003,
0.003, 0.018, 0.007, 0.003, 0.003, 0.005, 0.015, 0.003, 0.013, 0.003,
0.003, 0.005, 0.005, 0.003, 0.003, 0.003, 0.003, 0.003, 0.003, 0.003,
0.003, 0.003, 0.003, 0.003]
remaining impurity: 0.745214
information gain: 0.25178599999999995
====================
target feature: Sales
descriptive_feature: ShelveLoc
split criterion: gini
impurity of partitions: [0.988, 0.987, 0.994]
weights of partitions: [0.24, 0.212, 0.547]
```

```
remaining impurity: 0.990082
information gain: 0.006917999999999998
====================
target feature: Sales
descriptive_feature: Age
split criterion: gini
impurity of partitions: [0.889, 0.9, 0.8, 0.9, 0.833, 0.75, 0.8, 0.8,
0.909, 0.875, 0.875, 0.929, 0.833, 0.833, 0.857, 0.75, 0.833, 0.833,
0.875, 0.875, 0.88, 0.8, 0.833, 0.875, 0.875, 0.9, 0.833, 0.833,
0.923, 0.833, 0.889, 0.917, 0.833, 0.857, 0.833, 0.889, 0.833, 0.889,
0.667, 0.857, 0.857, 0.75, 0.75, 0.857, 0.857, 0.75, 0.9, 0.875,
0.889, 0.875, 0.667, 0.875, 0.875, 0.833, 0.833, 0.667]
weights of partitions: [0.022, 0.025, 0.013, 0.025, 0.015, 0.01,
0.013, 0.013, 0.028, 0.02, 0.02, 0.035, 0.015, 0.015, 0.018, 0.01,
0.015, 0.015, 0.02, 0.02, 0.025, 0.013, 0.015, 0.02, 0.02, 0.025,
0.015, 0.015, 0.033, 0.015, 0.022, 0.03, 0.015, 0.018, 0.015, 0.022,
0.015, 0.022, 0.007, 0.018, 0.018, 0.01, 0.01, 0.018, 0.018, 0.01,
0.025, 0.02, 0.022, 0.02, 0.007, 0.02, 0.02, 0.015, 0.015, 0.007]
remaining impurity: 0.861319
information gain: 0.13568100000000005
====================
target feature: Sales
descriptive_feature: Education
split criterion: gini
impurity of partitions: [0.979, 0.978, 0.98, 0.974, 0.976, 0.978,
0.972, 0.974, 0.979]
weights of partitions: [0.122, 0.12, 0.122, 0.1, 0.107, 0.117, 0.09,
0.1, 0.12]
remaining impurity: 0.9749760000000001
information gain: 0.022023999999999933
====================
target feature: Sales
descriptive_feature: Urban
split criterion: gini
impurity of partitions: [0.996, 0.99]
weights of partitions: [0.705, 0.295]
remaining impurity: 0.99423
information gain: 0.0027700000000000005
====================
target feature: Sales
descriptive_feature: US
split criterion: gini
impurity of partitions: [0.995, 0.992]
weights of partitions: [0.645, 0.355]
remaining impurity: 0.993935
information gain: 0.0030649999999999844
====================
```

```python
carseats_df
carseats_df1 = carseats_df[['Population','Price', 'Age', 'Sales']]
```

```
carseats_df2 = carseats_df[['Population','Price', 'Age', 'Sales']]
carseats_df1
```

```
     Population  Price  Age  Sales
0           276    120   42   9.50
1           260     83   65  11.22
2           269     80   59  10.06
3           466     97   55   7.40
4           340    128   38   4.15
..          ...    ...  ...    ...
395         203    128   33  12.57
396          37    120   55   6.14
397         368    159   40   7.41
398         284     95   50   5.94
399          27    120   49   9.71

[400 rows x 4 columns]
```

```
from sklearn.preprocessing import LabelEncoder

# Define the label encoder
label_encoder = LabelEncoder()

# Convert the float column to integer using the label encoder
carseats_df2['Population'] =
label_encoder.fit_transform(carseats_df2['Population'].astype(int))
carseats_df2['Price'] =
label_encoder.fit_transform(carseats_df2['Price'].astype(int))
carseats_df2['Age'] =
label_encoder.fit_transform(carseats_df2['Age'].astype(int))
carseats_df2['Sales'] =
label_encoder.fit_transform(carseats_df2['Sales'].astype(int))



carseats_df2.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 400 entries, 0 to 399
Data columns (total 4 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   Population  400 non-null    int64
 1   Price       400 non-null    int64
 2   Age         400 non-null    int64
 3   Sales       400 non-null    int64
dtypes: int64(4)
memory usage: 12.6 KB
```

```
#Get Dummies
X = carseats_df2.drop(['Population','Price', 'Age'], axis=1)
y = carseats_df2['Sales']

X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.3, random_state=42)

print('Train features shape: {}'.format(X_train.shape))
print('Train labels shape: {}'.format(y_train.shape))
print('Test features shape: {}'.format(X_test.shape))
print('Test labels shape: {}'.format(y_test.shape))
```

```
Train features shape: (280, 1)
Train labels shape: (280,)
Test features shape: (120, 1)
Test labels shape: (120,)
```

```
#USING entropy  Load libraries
from sklearn.metrics import mean_squared_error, r2_score
from sklearn.linear_model import LinearRegression
import pandas as pd
from sklearn.tree import DecisionTreeClassifier # Import Decision Tree
Classifier
from sklearn.model_selection import train_test_split # Import
train_test_split function
from sklearn import metrics #Import scikit-learn metrics module for
accuracy calculation
# Create Decision Tree classifer object
clf = DecisionTreeClassifier(criterion="entropy", min_samples_leaf=2,
min_samples_split=2, max_depth=3, random_state=42)

# Train Decision Tree Classifer
clf = clf.fit(X_train,y_train)

#Predict the response for test dataset
y_pred = clf.predict(X_test)
print('Error', np.sqrt(mean_squared_error(y_test, y_pred)))
```

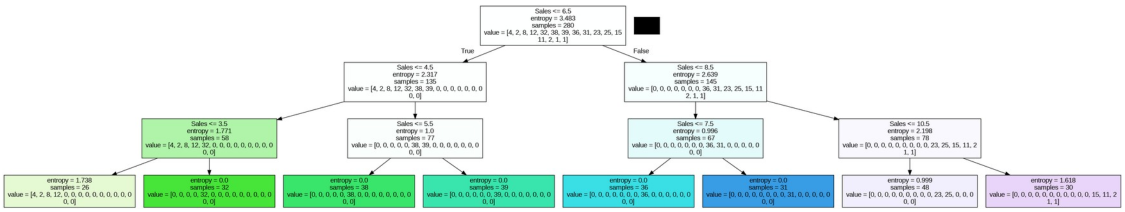
```
Error 0.8266397845091497
```

```
# Model Accuracy, how often is the classifier correct?
print("Accuracy:",metrics.accuracy_score(y_test, y_pred))
```

```
Accuracy: 0.775
```

```
#3.1.3 Tree Visualization
from IPython.display import Image
from six import StringIO
from sklearn.tree import export_graphviz
import pydot
```

```
features = list(X.columns)

dot_data = StringIO()
export_graphviz(clf, out_file=dot_data, feature_names=features,
filled=True)
graph = pydot.graph_from_dot_data(dot_data.getvalue())
Image(graph[0].create_png())
```

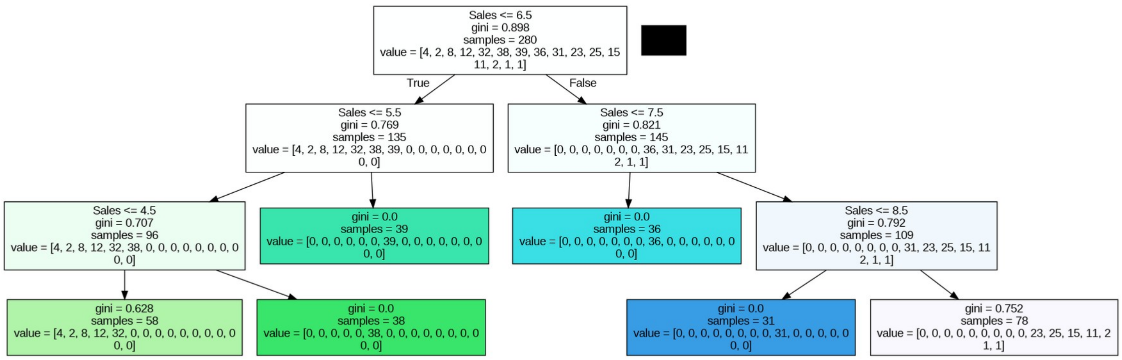


```
# Load libraries USING GINI
from sklearn.metrics import mean_squared_error, r2_score
from sklearn.linear_model import LinearRegression
import pandas as pd
from sklearn.tree import DecisionTreeClassifier # Import Decision Tree
Classifier
from sklearn.model_selection import train_test_split # Import
train_test_split function
from sklearn import metrics #Import scikit-learn metrics module for
accuracy calculation
# Create Decision Tree classifer object
clf1 = DecisionTreeClassifier(criterion="gini", min_samples_leaf=2,
min_samples_split=2, max_depth=3, random_state=42)

# Train Decision Tree Classifer
clf1 = clf1.fit(X_train,y_train)

#Predict the response for test dataset
y_pred = clf1.predict(X_test)
print('Error', np.sqrt(mean_squared_error(y_test, y_pred)))
# Model Accuracy, how often is the classifier correct?
print("Accuracy:",metrics.accuracy_score(y_test, y_pred))
```

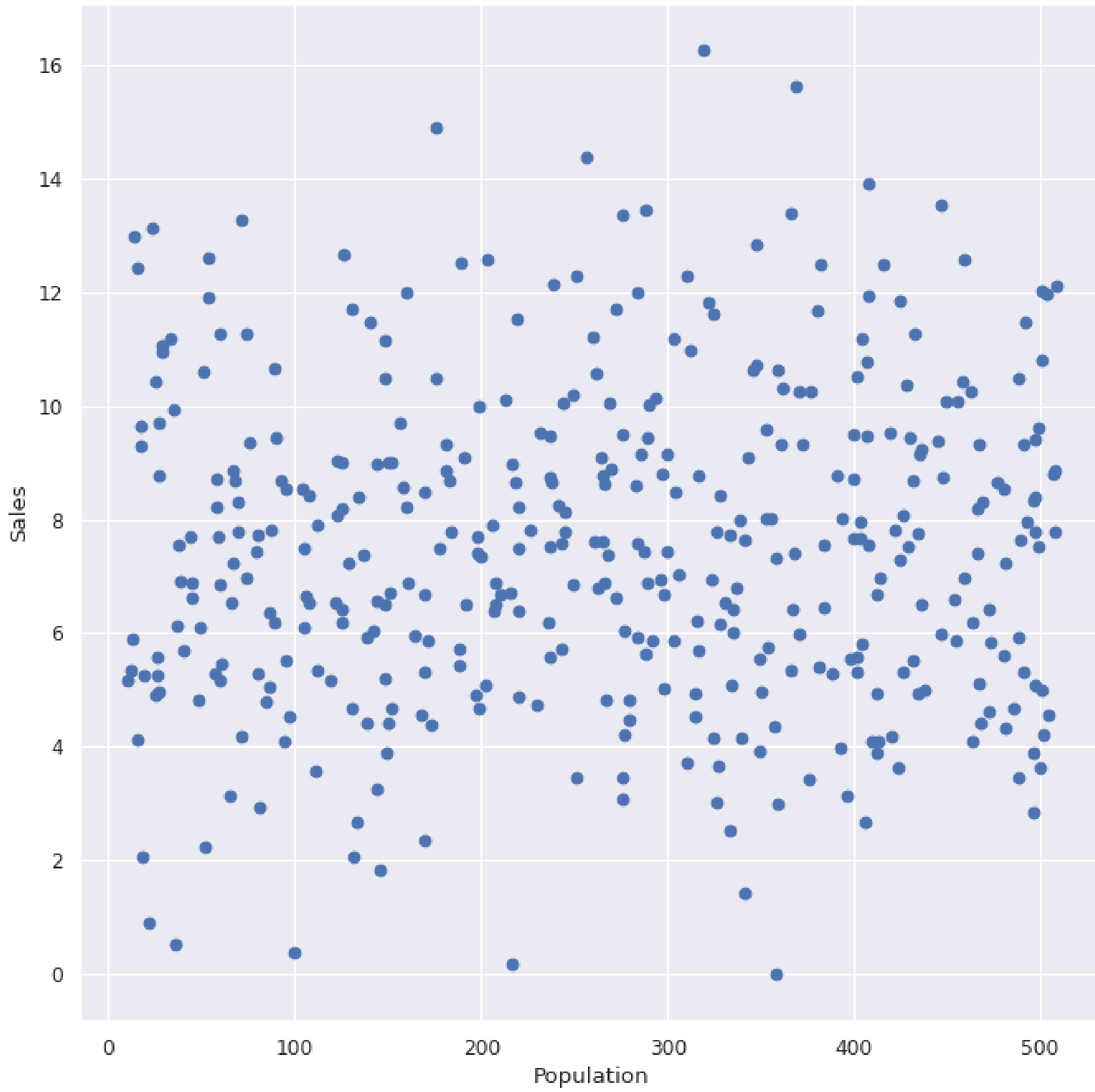
```
Error 1.179689224612426
Accuracy: 0.6583333333333333
```

```
#3.1.3 Tree Visualization
from IPython.display import Image
from six import StringIO
from sklearn.tree import export_graphviz
import pydot

features = list(X.columns)
```

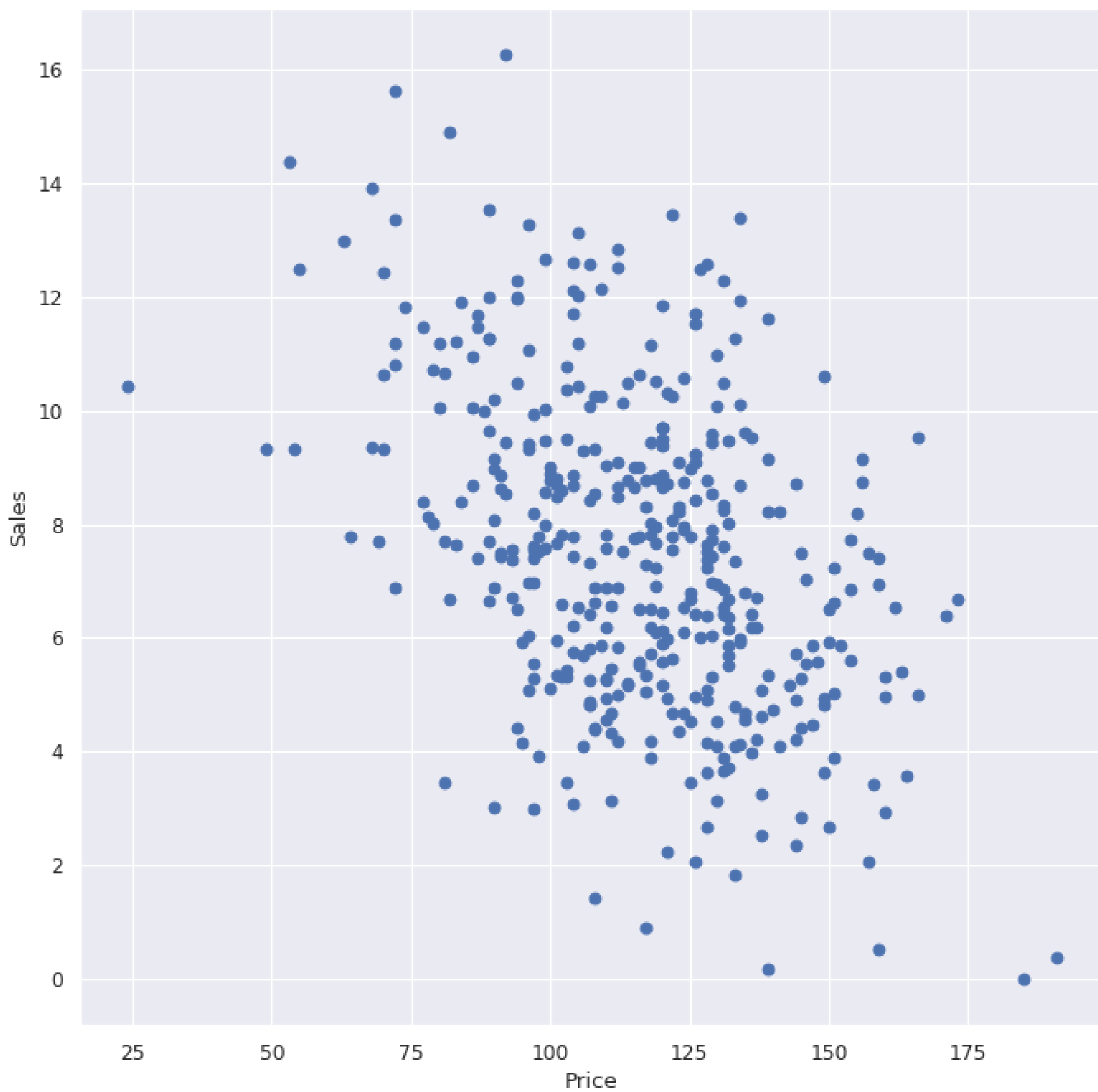
```python
dot_data = StringIO()
export_graphviz(clf1, out_file=dot_data, feature_names=features,
filled=True)
graph = pydot.graph_from_dot_data(dot_data.getvalue())
Image(graph[0].create_png())
```



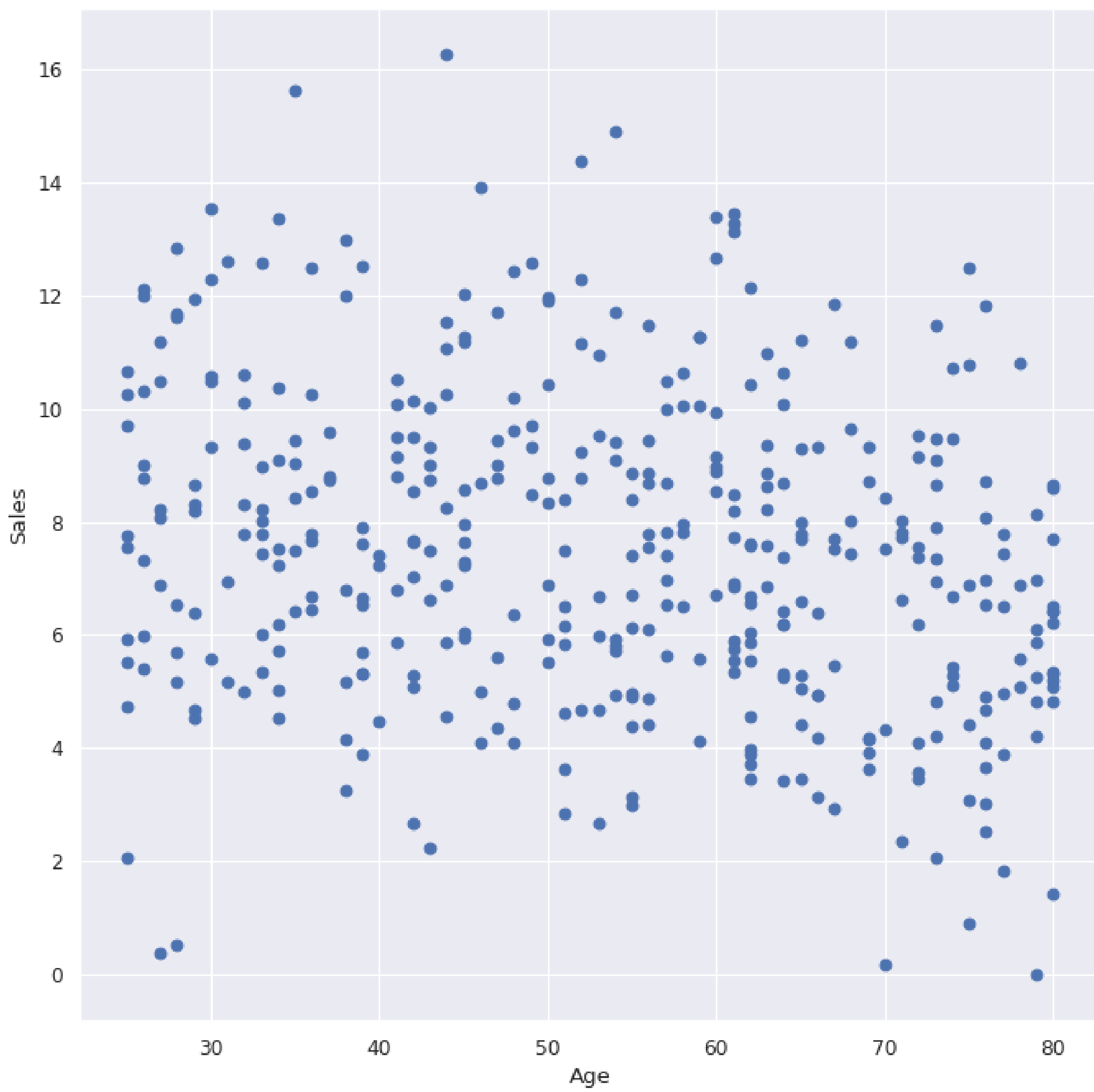

```python
## Visulazing the distibution of the data for every feature with Sales
cont_cols = ['Population','Price', 'Age']
for col in cont_cols:
    plt.figure(figsize=(10,10), dpi= 80)
    plt.scatter(x=col, y='Sales', data=carseats_df1)
    plt.xlabel(f"{col}")
    plt.ylabel('Sales')
    plt.show()
```



Sales
16
14
12
10
8
6
4
2
0
0
100
200
300
400
500
Population

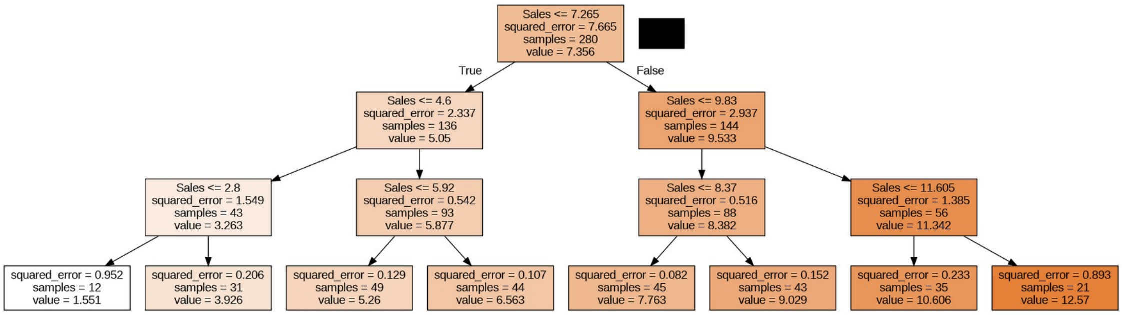


Sales
Price



SIMPLE DECISION TREE REGRESSOR

```
#3.1.3 Tree Visualization
from IPython.display import Image
from six import StringIO
from sklearn.tree import export_graphviz
import pydot

features = list(X1.columns)

dot_data = StringIO()
export_graphviz(reg_dt, out_file=dot_data, feature_names=features,
filled=True)
graph = pydot.graph_from_dot_data(dot_data.getvalue())
Image(graph[0].create_png())
```




```
from google.colab import files
uploaded = files.upload()
```

```
<IPython.core.display.HTML object>

Saving Carseats.csv to Carseats (7).csv
```

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

import pandas as pd
import io
import numpy as np

carseats_dfnn =
pd.read_csv(io.StringIO(uploaded['Carseats.csv'].decode('utf-8')))
carseats_dfnn
```

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

```
Good   49

     Education Urban   US
0           17   Yes  Yes
1           10   Yes  Yes
2           12   Yes  Yes
3           14   Yes  Yes
4           13   Yes   No
..         ...   ...  ...
395         14   Yes  Yes
396         11    No  Yes
397         18   Yes  Yes
398         12   Yes  Yes
399         16   Yes  Yes

[400 rows x 11 columns]
```

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
sns.set()
%matplotlib inline

import warnings
from sklearn import tree
import graphviz
from sklearn import metrics


#carseats_dfnn = carseats_dfnn[['Price','Sales']]
carseats_dfnn = carseats_dfnn[['Population','Price', 'Age', 'Sales']]
carseats_dfnn
```

```
     Population  Price  Age  Sales
0           276    120   42   9.50
1           260     83   65  11.22
2           269     80   59  10.06
3           466     97   55   7.40
4           340    128   38   4.15
..          ...    ...  ...    ...
395         203    128   33  12.57
396          37    120   55   6.14
397         368    159   40   7.41
398         284     95   50   5.94
399          27    120   49   9.71

[400 rows x 4 columns]
```

```
from sklearn.preprocessing import LabelEncoder

# Define the label encoder
label_encoder = LabelEncoder()

# Convert the float column to integer using the label encoder
carseats_dfnn['Population'] =
label_encoder.fit_transform(carseats_dfnn['Population'].astype(int))
carseats_dfnn['Price'] =
label_encoder.fit_transform(carseats_dfnn['Price'].astype(int))
carseats_dfnn['Age'] =
label_encoder.fit_transform(carseats_dfnn['Age'].astype(int))
carseats_dfnn['Sales'] =
label_encoder.fit_transform(carseats_dfnn['Sales'].astype(int))

carseats_dfnn.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 400 entries, 0 to 399
Data columns (total 4 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   Population  400 non-null    int64
 1   Price       400 non-null    int64
 2   Age         400 non-null    int64
 3   Sales       400 non-null    int64
dtypes: int64(4)
memory usage: 12.6 KB
```

```
#Get Dummies
Xnn = carseats_dfnn.drop(['Population','Price', 'Age'], axis=1)
ynn = carseats_dfnn['Sales']

X_trainn, X_testnn, y_trainn, y_testnn = train_test_split(Xnn, ynn,
test_size=0.3, random_state=42)

print('Train features shape: {}'.format(X_trainn.shape))
print('Train labels shape: {}'.format(y_trainn.shape))
print('Test features shape: {}'.format(X_testnn.shape))
print('Test labels shape: {}'.format(y_testnn.shape))
```

```
Train features shape: (280, 1)
Train labels shape: (280,)
Test features shape: (120, 1)
Test labels shape: (120,)
```

```
#USING entropy  Load libraries
from sklearn.metrics import mean_squared_error, r2_score
from sklearn.linear_model import LinearRegression
import pandas as pd
from sklearn.tree import DecisionTreeClassifier # Import Decision Tree
```

```
Classifier
from sklearn.model_selection import train_test_split # Import
train_test_split function
from sklearn import metrics #Import scikit-learn metrics module for
accuracy calculation
# Create Decision Tree classifer object
clfnn = DecisionTreeClassifier()

# Train Decision Tree Classifer
clfnn = clfnn.fit(X_trainnn,y_trainnn)

#Predict the response for test dataset
y_prednn = clfnn.predict(X_testnn)
print('Error', np.sqrt(mean_squared_error(y_testnn, y_prednn)))
```

```
Error 0.09128709291752768
```

```
# Model Accuracy, how often is the classifier correct?
print("Accuracy:",metrics.accuracy_score(y_testnn, y_prednn))
```

```
Accuracy: 0.9916666666666667
```

```
from sklearn.metrics import confusion_matrix
cm = confusion_matrix(y_testnn, y_prednn)
print(cm)
```

```
[[ 1  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0]
 [ 0  2  0  0  0  0  0  0  0  0  0  0  0  0  0  0]
 [ 0  0  7  0  0  0  0  0  0  0  0  0  0  0  0  0]
 [ 0  0  0  9  0  0  0  0  0  0  0  0  0  0  0  0]
 [ 0  0  0  0 15  0  0  0  0  0  0  0  0  0  0  0]
 [ 0  0  0  0  0 15  0  0  0  0  0  0  0  0  0  0]
 [ 0  0  0  0  0  0 16  0  0  0  0  0  0  0  0  0]
 [ 0  0  0  0  0  0  0 19  0  0  0  0  0  0  0  0]
 [ 0  0  0  0  0  0  0  0 12  0  0  0  0  0  0  0]
 [ 0  0  0  0  0  0  0  0  0  5  0  0  0  0  0  0]
 [ 0  0  0  0  0  0  0  0  0  0  7  0  0  0  0  0]
 [ 0  0  0  0  0  0  0  0  0  0  0  5  0  0  0  0]
 [ 0  0  0  0  0  0  0  0  0  0  0  0  5  0  0  0]
 [ 0  0  0  0  0  0  0  0  0  0  0  0  0  1  0  0]
 [ 0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0]
 [ 0  0  0  0  0  0  0  0  0  0  0  0  0  0  1  0]]
```

```
from sklearn.metrics import classification_report

print(classification_report(y_testnn, y_prednn))
```

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00         1
           2       1.00      1.00      1.00         2
```

```
           3       1.00      1.00      1.00         7
           4       1.00      1.00      1.00         9
           5       1.00      1.00      1.00        15
           6       1.00      1.00      1.00        15
           7       1.00      1.00      1.00        16
           8       1.00      1.00      1.00        19
           9       1.00      1.00      1.00        12
          10       1.00      1.00      1.00         5
          11       1.00      1.00      1.00         7
          12       1.00      1.00      1.00         5
          13       1.00      1.00      1.00         5
          14       1.00      1.00      1.00         1
          15       0.00      0.00      0.00         0
          16       0.00      0.00      0.00         1

    accuracy                           0.99       120
   macro avg       0.88      0.88      0.88       120
weighted avg       0.99      0.99      0.99       120
```

KNN APPLICATIO

```
#applying K-nn
import numpy as np
import pandas as pd
from matplotlib import pyplot as plt
from sklearn.datasets import load_breast_cancer
from sklearn.metrics import confusion_matrix
from sklearn.neighbors import KNeighborsClassifier
from sklearn.model_selection import train_test_split
import seaborn as sns
sns.set()

#Get Dummies
Xknn = carseats_dfnn.drop(['Population','Price', 'Age'], axis=1)
yknn = carseats_dfnn['Sales']

X_traiknn, X_testknn, y_traiknn, y_testknn = train_test_split(Xknn,
yknn, test_size=0.3, random_state=42)

print('Train features shape: {}'.format(X_traiknn.shape))
print('Train labels shape: {}'.format(y_traiknn.shape))
print('Test features shape: {}'.format(X_testknn.shape))
print('Test labels shape: {}'.format(y_testknn.shape))
```

```
Train features shape: (280, 1)
Train labels shape: (280,)
Test features shape: (120, 1)
Test labels shape: (120,)
```

```
knn = KNeighborsClassifier(n_neighbors=5, metric='euclidean')
knn.fit(X_traiknn, y_traiknn)
y_pred1nn = knn.predict(X_testknn)
print('Error', np.sqrt(mean_squared_error(y_testknn, y_pred1nn)))
```

```
Error 0.3535533905932738
```

```
# Model Accuracy, how often is the classifier correct?
print("Accuracy  of Nearest
neighbor:",metrics.accuracy_score(y_testknn, y_pred1nn))
```

```
Accuracy  of Nearest neighbor: 0.9416666666666667
```

```
from sklearn.metrics import classification_report
print(classification_report(y_testknn, y_pred1nn))
```

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00         1
           2       1.00      1.00      1.00         2
           3       1.00      1.00      1.00         7
           4       1.00      1.00      1.00         9
           5       1.00      1.00      1.00        15
           6       1.00      1.00      1.00        15
           7       1.00      1.00      1.00        16
           8       1.00      1.00      1.00        19
           9       1.00      1.00      1.00        12
          10       1.00      1.00      1.00         5
          11       1.00      1.00      1.00         7
          12       0.50      1.00      0.67         5
          13       0.00      0.00      0.00         5
          14       0.00      0.00      0.00         1
          16       0.00      0.00      0.00         1

    accuracy                           0.94       120
   macro avg       0.77      0.80      0.78       120
weighted avg       0.92      0.94      0.93       120
```

```
from sklearn.metrics import roc_curve

# roc curve for models
fpr1, tpr1, thresh1 = roc_curve(y_testnn, y_prednn, pos_label=0)
fpr2, tpr2, thresh2 = roc_curve(y_testknn, y_pred1nn, pos_label=0)

# roc curve for tpr = fpr
random_probs = [0 for i in range(len(y_testnn))]
p_fpr, p_tpr, _ = roc_curve(y_testnn, random_probs, pos_label=0)

# matplotlib
import matplotlib.pyplot as plt
```

```python
plt.style.use('seaborn')

# plot roc curves
plt.plot(fpr1, tpr1, linestyle='--',color='red', label='decision tree')
plt.plot(fpr2, tpr2, linestyle='--',color='green', label='KNN')
plt.plot(p_fpr, p_tpr, linestyle='--', color='red')
# title
plt.title('ROC curve')
# x label
plt.xlabel('False Positive Rate')
# y label
plt.ylabel('True Positive rate')

plt.legend(loc='best')
plt.savefig('ROC',dpi=300)
plt.show();
```