In [1]:
```
!pip install category_encoders
import category_encoders as ce
import pandas as pd
import matplotlib.pyplot as plt
from sklearn import datasets
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeClassifier
from sklearn import tree
from sklearn.metrics import classification_report
from sklearn import preprocessing
```

```
Requirement already satisfied: category_encoders in c:\users\acer\anaconda3\lib\site-packages (2.2.2)
Requirement already satisfied: numpy>=1.14.0 in c:\users\acer\anaconda3\lib\site-packages (from category_encoders) (1.19.2)
Requirement already satisfied: scipy>=1.0.0 in c:\users\acer\anaconda3\lib\site-packages (from category_encoders) (1.5.2)
Requirement already satisfied: pandas>=0.21.1 in c:\users\acer\anaconda3\lib\site-packages (from category_encoders) (1.1.3)
Requirement already satisfied: patsy>=0.5.1 in c:\users\acer\anaconda3\lib\site-packages (from category_encoders) (0.5.1)
Requirement already satisfied: statsmodels>=0.9.0 in c:\users\acer\anaconda3\lib\site-packages (from category_encoders) (0.12.0)
Requirement already satisfied: scikit-learn>=0.20.0 in c:\users\acer\anaconda3\lib\site-packages (from category_encoders) (0.23.2)
Requirement already satisfied: pytz>=2017.2 in c:\users\acer\anaconda3\lib\site-packages (from pandas>=0.21.1->category_encoders) (2020.1)
Requirement already satisfied: python-dateutil>=2.7.3 in c:\users\acer\anaconda3\lib\site-packages (from pandas>=0.21.1->category_encoders) (2.8.1)
Requirement already satisfied: six in c:\users\acer\anaconda3\lib\site-packages (from patsy>=0.5.1->category_encoders) (1.15.0)
Requirement already satisfied: joblib>=0.11 in c:\users\acer\anaconda3\lib\site-packages (from scikit-learn>=0.20.0->category_encoders) (0.17.0)
Requirement already satisfied: threadpoolctl>=2.0.0 in c:\users\acer\anaconda3\lib\site-packages (from scikit-learn>=0.20.0->category_encoders) (2.1.0)
```

In [2]:
```
# import company data set
sales = pd.read_csv('/Users/acer/Sandesh Pal/Data Science Assgn/DEsicion TRee/Company_Data.csv')
```

In [3]:
```
sales
```

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
...	...	...	...	...	...	...	...	...	...	...	...
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

In [4]:
```
# checking for null values
sales.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 [5]:
```
sales.describe()
```

Out[5]:

	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 [6]:
```
import category_encoders as ce
# encode variables with ordinal encoding
encoder = ce.OrdinalEncoder(cols=['ShelveLoc', 'Urban', 'US'])
sales1 = encoder.fit_transform(sales)
```

```
C:\Users\acer\anaconda3\lib\site-packages\category_encoders\utils.py:21: FutureWarning: is_categorical is deprecated and will be removed in a future version.  Use is_categorical_dt
ype instead
  elif pd.api.types.is_categorical(cols):
```

In [7]:
```
# Converting the Target column i.e. Sales into Categorical value using mean of the column i.e. 7.49
sales_val = []
for value in sales["Sales"]:
     if value<=7.49:
        sales_val.append("low")
     else:
        sales_val.append("high")

sales1["sales_val"]= sales_val
```

In [8]:
```
sales1.head()
```

Out[8]:

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

In [9]:
```
x = sales1.drop(['sales_val','Sales'], axis =1)
y = sales1['sales_val']
```

In [10]:
```
X
```

```
---------------------------------------------------------------------------
NameError                                 Traceback (most recent call last)
<ipython-input-10-b5fec669aca1> in <module>
----> 1 X

NameError: name 'X' is not defined
```

In [11]:
```
x
```

Out[11]:

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

400 rows × 10 columns

In [12]:
```
y.head(10)
```

Out[12]:
```
0    high
1    high
2    high
3     low
4     low
5    high
6     low
7    high
8     low
9     low
Name: sales_val, dtype: object
```

In [13]:
```
# Splitting data into training and testing data set
x_train, x_test,y_train,y_test = train_test_split(x,y, test_size=0.2,random_state=40)
```

Building Decision Tree Classifier using Entropy Criteria Iteration-1: Max Depth = 4

In [14]:
```
model1 = DecisionTreeClassifier(criterion = 'entropy',max_depth=4)
model1.fit(x_train,y_train)
```

Out[14]:
```
DecisionTreeClassifier(criterion='entropy', max_depth=4)
```

In [15]:
```
#Predicting on test data
pred_test1 = model1.predict(x_test)
#Accuracy on test data
print('Test data Accuracy is:',np.mean(pred_test1==y_test))
#Predicting on train data
pred_train1 = model1.predict(x_train)
#Accuracy on train data
print('Train data Accuracy is:',np.mean(pred_train1==y_train))
```

```
Test data Accuracy is: 0.675
Train data Accuracy is: 0.784375
```

Iteration-2: Max Depth = 5

In [16]:
```
model2 = DecisionTreeClassifier(criterion = 'entropy',max_depth=5)
model2.fit(x_train,y_train)
```

Out[16]:
```
DecisionTreeClassifier(criterion='entropy', max_depth=5)
```

In [17]:
```
#Predicting on test data
pred_test2 = model2.predict(x_test)
#Accuracy on test data
print('Test data Accuracy is:',np.mean(pred_test2==y_test))
#Predicting on train data
pred_train2 = model2.predict(x_train)
#Accuracy on train data
print('Train data Accuracy is:',np.mean(pred_train2==y_train))
```

```
Test data Accuracy is: 0.675
Train data Accuracy is: 0.821875
```

Iteration-3: Max Depth = 6

In [18]:
```
model3 = DecisionTreeClassifier(criterion = 'entropy',max_depth=6)
model3.fit(x_train,y_train)
```

Out[18]:
```
DecisionTreeClassifier(criterion='entropy', max_depth=6)
```

In [19]:
```
#Predicting on test data
pred_test3 = model3.predict(x_test)
#Accuracy on test data
print('Test data Accuracy is:',np.mean(pred_test3==y_test))
#Predicting on train data
pred_train3 = model3.predict(x_train)
#Accuracy on train data
print('Train data Accuracy is:',np.mean(pred_train3==y_train))
```

```
Test data Accuracy is: 0.6625
Train data Accuracy is: 0.90625
```

Iteration-4: Max Depth = 7

In [20]:
```
model4 = DecisionTreeClassifier(criterion = 'entropy',max_depth=7)
model4.fit(x_train,y_train)
```

Out[20]:
```
DecisionTreeClassifier(criterion='entropy', max_depth=7)
```

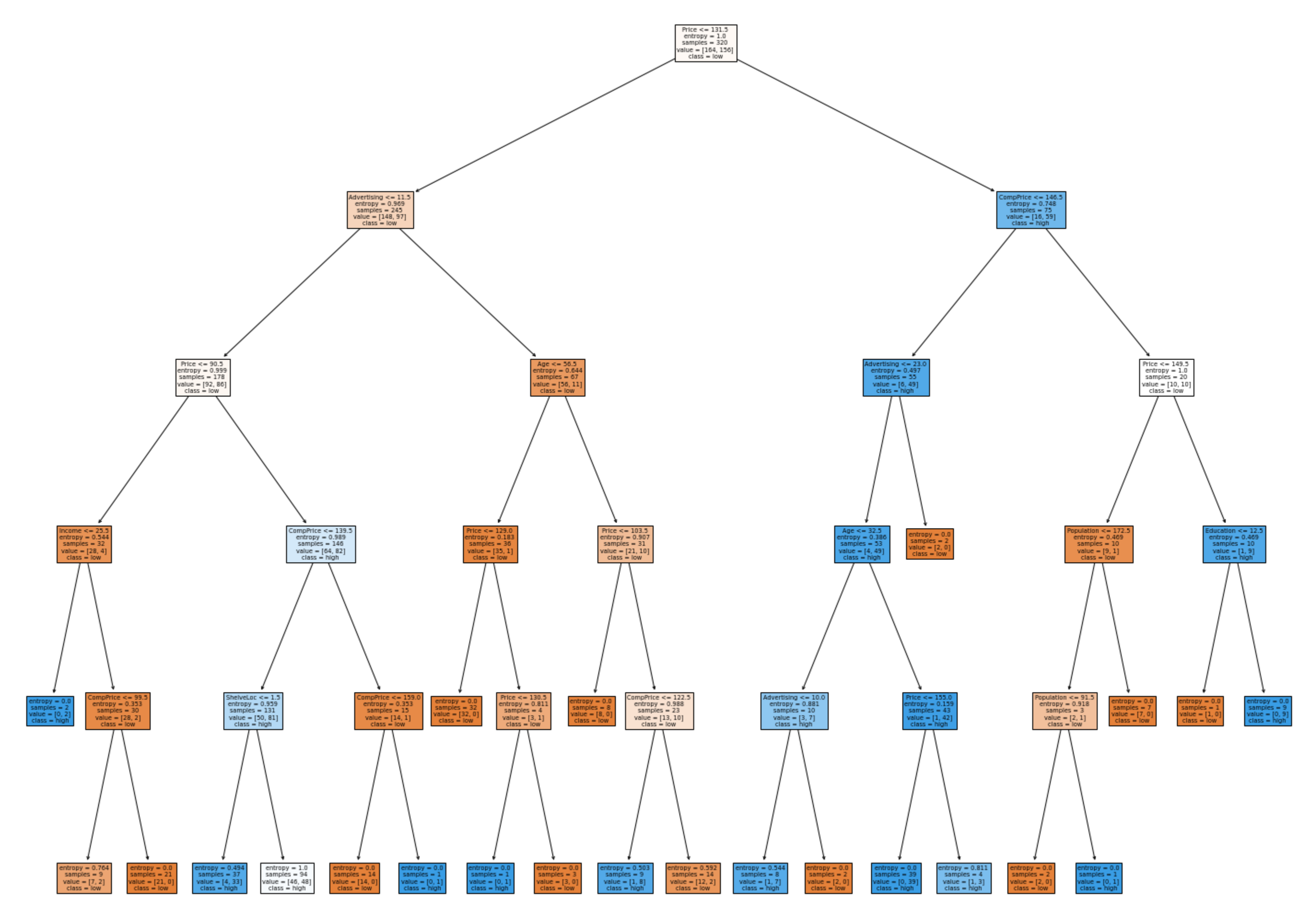
In [21]:
```
#Predicting on test data
pred_test4 = model4.predict(x_test)
#Accuracy on test data
print('Test data Accuracy is:',np.mean(pred_test4==y_test))
#Predicting on train data
pred_train4 = model4.predict(x_train)
#Accuracy on train data
print('Train data Accuracy is:',np.mean(pred_train4==y_train))
```

```
Test data Accuracy is: 0.65
Train data Accuracy is: 0.91875
```

We get the best test results at Iteration-2 max depth = 5. so we will consider that final

In [22]:
```
# let's plot the decision tree
fig = plt.figure(figsize=(25,20))
fig = tree.plot_tree(model2,
 feature_names= ['CompPrice','Income','Advertising','Population','Price', 'ShelveLoc', 'Age', 'Education',
 'Urban', 'US'], class_names= ['low', 'high'], filled=True)
plt.title('Decision tree using Entropy',fontsize=22)
plt.savefig('DT_Entropy.pdf')
```

Decision tree using Entropy



From the above decision tree 3 most important features affecting the sales are - 1) Price 2) Advertising 3) Comp Price Building Decision Tree Classifier (CART) using Gini Criteria Iteration-1: Max Depth = 5

In [23]:
```
from sklearn.tree import DecisionTreeClassifier
model_gini1 = DecisionTreeClassifier(criterion='gini', max_depth=5)
model_gini1.fit(x_train,y_train)
```

Out[23]:
```
DecisionTreeClassifier(max_depth=5)
```

In [24]:
```
#Predicting on test data
pred_testg1 = model_gini1.predict(x_test)
#Accuracy on test data
print('Test data Accuracy is:',np.mean(pred_testg1==y_test))
#Predicting on train data
pred_traing1 = model_gini1.predict(x_train)
#Accuracy on train data
print('Train data Accuracy is:',np.mean(pred_traing1==y_train))
```

```
Test data Accuracy is: 0.7625
Train data Accuracy is: 0.8875
```

Iteration-2: Max Depth = 6

In [25]:
```
model_gini2 = DecisionTreeClassifier(criterion='gini', max_depth=6)
model_gini2.fit(x_train,y_train)
```

Out[25]:
```
DecisionTreeClassifier(max_depth=6)
```

In [26]:
```
#Predicting on test data
pred_testg2 = model_gini2.predict(x_test)
#Accuracy on test data
print('Test data Accuracy is:',np.mean(pred_testg2==y_test))
#Predicting on train data
pred_traing2 = model_gini2.predict(x_train)
#Accuracy on train data
print('Train data Accuracy is:',np.mean(pred_traing2==y_train))
```

```
Test data Accuracy is: 0.7125
Train data Accuracy is: 0.925
```

Iteration-3: Max Depth = 7

In [27]:
```
model_gini3 = DecisionTreeClassifier(criterion='gini', max_depth=7)
model_gini3.fit(x_train,y_train)
```

Out[27]:
```
DecisionTreeClassifier(max_depth=7)
```

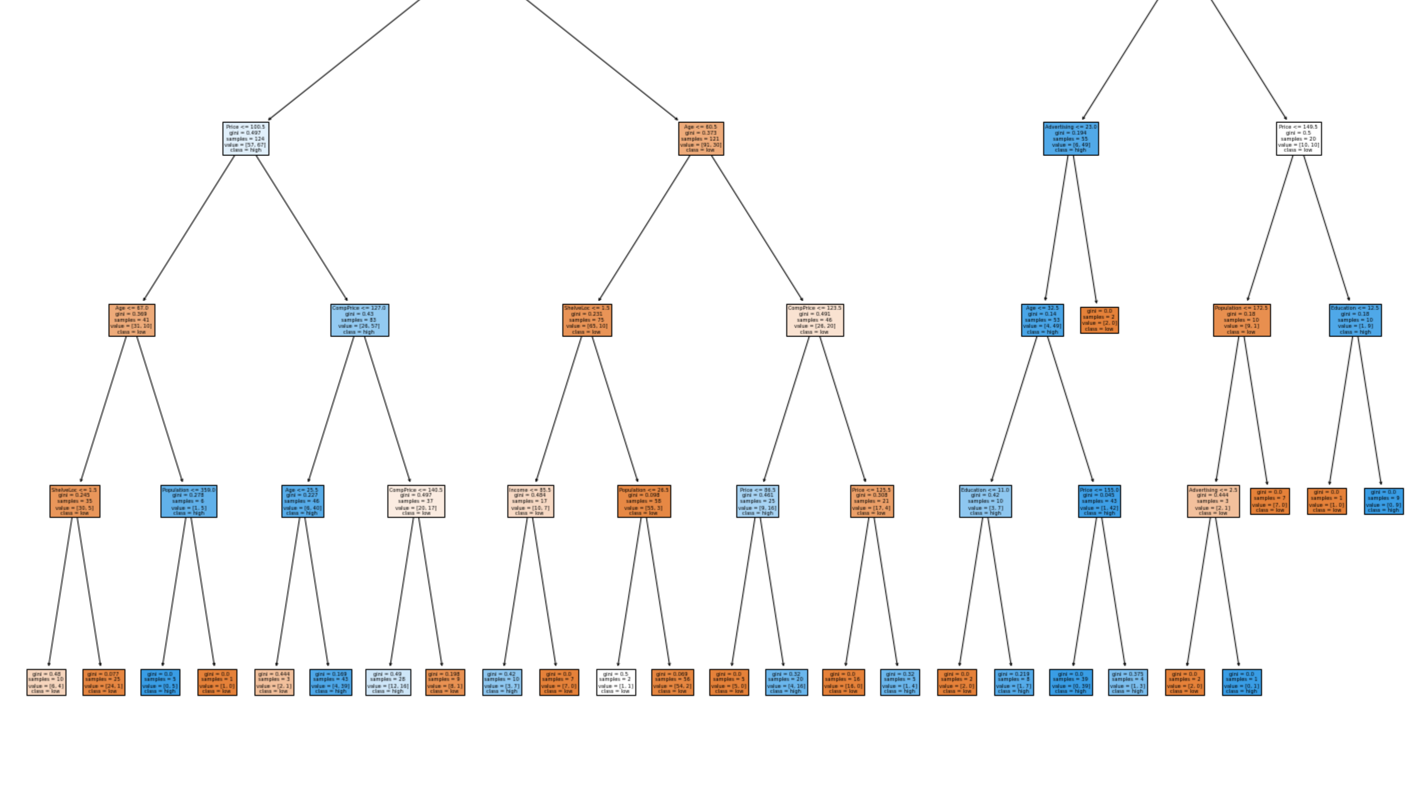
In [28]:
```
#Predicting on test data
pred_testg3 = model_gini3.predict(x_test)
#Accuracy on test data
print('Test data Accuracy is:',np.mean(pred_testg3==y_test))
#Predicting on train data
pred_traing3 = model_gini3.predict(x_train)
#Accuracy on train data
print('Train data Accuracy is:',np.mean(pred_traing3==y_train))
```

```
Test data Accuracy is: 0.6875
Train data Accuracy is: 0.96875
```

We get the best test results at Iteration-1 max depth = 5. so we will consider that final

In [29]:
```
# let's plot the decision tree
fig = plt.figure(figsize=(25,20))
fig = tree.plot_tree(model_gini1,
 feature_names= ['CompPrice','Income','Advertising','Population','Price', 'ShelveLoc', 'Age', 'Education',
 'Urban', 'US'], class_names= ['low', 'high'], filled=True)
plt.title('Decision tree using Gini',fontsize=22)
plt.savefig('DT_Gini.pdf')
```

Decision tree using Gini



From the above decision tree 3 most important features affecting the sales are 1) Price 2) Advertising 3) Comp Price Hence it is concluded that both Entropy and Gini criteria gives us best result at max depth = 5 and 3 most importand features for both is same