In [1]:
```python
import pandas as pd
import matplotlib.pyplot as plt
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
```

In [2]:
```python
fraud= pd.read_csv('/Users/SAURABH/Saurabh patil/DATA SCIENCE/DEsicion TRee/Fraud_check.csv')
```

In [3]:
```python
fraud
```

Out[3]:

	Undergrad	Marital.Status	Taxable.Income	City.Population	Work.Experience	Urban
0	NO	Single	68833	50047	10	YES
1	YES	Divorced	33700	134075	18	YES
2	NO	Married	36925	160205	30	YES
3	YES	Single	50190	193264	15	YES
4	NO	Married	81002	27533	28	NO
...	...	...	...	...	...	...
595	YES	Divorced	76340	39492	7	YES
596	YES	Divorced	69967	55369	2	YES
597	NO	Divorced	47334	154058	0	YES
598	YES	Married	98592	180083	17	NO
599	NO	Divorced	96519	158137	16	NO

600 rows × 6 columns

In [4]:
```python
fraud.describe()
```

Out[4]:

	Taxable.Income	City.Population	Work.Experience
count	600.000000	600.000000	600.000000
mean	55208.375000	108747.368333	15.558333
std	26204.827597	49850.075134	8.842147
min	10003.000000	25779.000000	0.000000
25%	32871.500000	66966.750000	8.000000
50%	55074.500000	106493.500000	15.000000
75%	78611.750000	150114.250000	24.000000
max	99619.000000	199778.000000	30.000000

In [5]:
```python
#Changing the categorical variables into dummies.
df = pd.get_dummies(fraud)

#Converting the Target variable i.e. Taxable Income into Categorical (As mentioned in the problem statement)
df['Category'] = pd.cut(df['Taxable.Income'],
                        bins=[0,30000, np.inf],
                        labels=['Risky','Good'],
                        include_lowest=True)
```

In [6]:
```python
df
```

Out[6]:

	Taxable.Income	City.Population	Work.Experience	Undergrad_NO	Undergrad_YES	Marital.Status_Divorced	Marital.Status_Married	Marital.Status_Single	Urban_NO	Urban_YES	Category
0	68833	50047	10	1	0	0	0	1	0	1	Good
1	33700	134075	18	0	1	1	0	0	0	1	Good
2	36925	160205	30	1	0	0	1	0	0	1	Good
3	50190	193264	15	0	1	0	0	1	0	1	Good
4	81002	27533	28	1	0	0	1	0	1	0	Good
...	...	...	...	...	...	...	...	...	...	...	...
595	76340	39492	7	0	1	1	0	0	0	1	Good
596	69967	55369	2	0	1	1	0	0	0	1	Good
597	47334	154058	0	1	0	1	0	0	0	1	Good
598	98592	180083	17	0	1	0	1	0	1	0	Good
599	96519	158137	16	1	0	1	0	0	1	0	Good

600 rows × 11 columns

In [7]:
```python
x = df.iloc[:,1:10]
y = df.iloc[:,10]
```

In [8]:
```python
x
```

Out[8]:

	City.Population	Work.Experience	Undergrad_NO	Undergrad_YES	Marital.Status_Divorced	Marital.Status_Married	Marital.Status_Single	Urban_NO	Urban_YES
0	50047	10	1	0	0	0	1	0	1
1	134075	18	0	1	1	0	0	0	1
2	160205	30	1	0	0	1	0	0	1
3	193264	15	0	1	0	0	1	0	1
4	27533	28	1	0	0	1	0	1	0
...	...	...	...	...	...	...	...	...	...
595	39492	7	0	1	1	0	0	0	1
596	55369	2	0	1	1	0	0	0	1
597	154058	0	1	0	1	0	0	0	1
598	180083	17	0	1	0	1	0	1	0
599	158137	16	1	0	1	0	0	1	0

600 rows × 9 columns

In [9]:
```python
y
```

Out[9]:
```
0      Good
1      Good
2      Good
3      Good
4      Good
       ...
595    Good
596    Good
597    Good
598    Good
599    Good
Name: Category, Length: 600, dtype: category
Categories (2, object): ['Risky' < 'Good']
```

In [10]:
```python
# Splitting data into training and testing data set
x_train, x_test,y_train,y_test = train_test_split(x,y, test_size=0.3,random_state=40)
```

In [11]:
```python
y_train.value_counts()
```

Out[11]:
```
Good     336
Risky     84
Name: Category, dtype: int64
```

In [12]:
```python
y_test.value_counts()
```

Out[12]:
```
Good     140
Risky     40
Name: Category, dtype: int64
```

Building Decision Tree Classifier using Entropy Criteria

Iteration-1: Max Depth = 2

In [13]:
```python
model1 = DecisionTreeClassifier(criterion = 'entropy',max_depth=2)
model1.fit(x_train,y_train)
preds1 = model1.predict(x_test) # predicting on test data set

print('Model leaves:',model1.get_n_leaves(),'\n','\n',
      pd.Series(preds1).value_counts(),'\n','\n',
      'Model Accuracy is:',np.mean(preds1==y_test))
```

```
Model leaves: 4

 Good    180
dtype: int64

 Model Accuracy is: 0.7777777777777778
```

Iteration-2: Max Depth = 3

In [14]:
```python
model2 = DecisionTreeClassifier(criterion = 'entropy',max_depth=3)
model2.fit(x_train,y_train)
preds2 = model2.predict(x_test) # predicting on test data set

print('Model leaves:',model2.get_n_leaves(),'\n','\n',
      pd.Series(preds2).value_counts(),'\n','\n',
      'Model Accuracy is:',np.mean(preds2==y_test))
```

```
Model leaves: 7

 Good     179
Risky      1
dtype: int64

 Model Accuracy is: 0.7722222222222223
```

Iteration-3: Max Depth = 4

In [15]:
```python
model3 = DecisionTreeClassifier(criterion = 'entropy',max_depth=4)
model3.fit(x_train,y_train)
preds3 = model3.predict(x_test) # predicting on test data set

print('Model leaves:',model3.get_n_leaves(),'\n','\n',
      pd.Series(preds3).value_counts(),'\n','\n',
      'Model Accuracy is:',np.mean(preds3==y_test))
```

```
Model leaves: 10

 Good     177
Risky      3
dtype: int64

 Model Accuracy is: 0.7611111111111111
```

Iteration-4: Max Depth = 5

In [16]:
```python
model4 = DecisionTreeClassifier(criterion = 'entropy',max_depth=5)
model4.fit(x_train,y_train)
preds4 = model4.predict(x_test) # predicting on test data set

print('Model leaves:',model4.get_n_leaves(),'\n','\n',
      pd.Series(preds4).value_counts(),'\n','\n',
      'Model Accuracy is:',np.mean(preds4==y_test))
```

```
Model leaves: 15

 Good     178
Risky      2
dtype: int64

 Model Accuracy is: 0.7666666666666667
```

Iteration-5: Max Depth = 6

In [17]:
```python
model5 = DecisionTreeClassifier(criterion = 'entropy',max_depth=6)
model5.fit(x_train,y_train)
preds5 = model5.predict(x_test) # predicting on test data set

print('Model leaves:',model5.get_n_leaves(),'\n','\n',
      pd.Series(preds5).value_counts(),'\n','\n',
      'Model Accuracy is:',np.mean(preds5==y_test))
```

```
Model leaves: 20

 Good     178
Risky      2
dtype: int64

 Model Accuracy is: 0.7666666666666667
```

Iteration-6: Max Depth = 7

In [18]:
```python
model6 = DecisionTreeClassifier(criterion = 'entropy',max_depth=7)
model6.fit(x_train,y_train)
preds6 = model6.predict(x_test) # predicting on test data set

print('Model leaves:',model6.get_n_leaves(),'\n','\n',
      pd.Series(preds6).value_counts(),'\n','\n',
      'Model Accuracy is:',np.mean(preds6==y_test))
```

```
Model leaves: 27

 Good     167
Risky     13
dtype: int64

 Model Accuracy is: 0.7277777777777777
```

Hence, the classifier model at the end of iteration 1 has the max accuracy i.e. 77.77%

In [19]:
```python
print(classification_report(preds1,y_test))
```

```
              precision    recall  f1-score   support

        Good       1.00      0.78      0.88       180
       Risky       0.00      0.00      0.00         0

    accuracy                           0.78       180
   macro avg       0.50      0.39      0.44       180
weighted avg       1.00      0.78      0.88       180
```

```
C:\Users\SAURABH\anaconda3\lib\site-packages\sklearn\metrics\_classification.py:1221: UndefinedMetricWarning: Recall and F-score are ill-defined and being set to 0.0 in labels with no true samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```

We'll perform EDA to find outlier and see if that can increase the model accuracy

In [20]:
```python
from sklearn.ensemble import IsolationForest
```

In [21]:
```python
newdf= pd.get_dummies(fraud)
```

In [22]:
```python
newdf
```

Out[22]:

	Taxable.Income	City.Population	Work.Experience	Undergrad_NO	Undergrad_YES	Marital.Status_Divorced	Marital.Status_Married	Marital.Status_Single	Urban_NO	Urban_YES
0	68833	50047	10	1	0	0	0	1	0	1
1	33700	134075	18	0	1	1	0	0	0	1
2	36925	160205	30	1	0	0	1	0	0	1
3	50190	193264	15	0	1	0	0	1	0	1
4	81002	27533	28	1	0	0	1	0	1	0
...	...	...	...	...	...	...	...	...	...	...
595	76340	39492	7	0	1	1	0	0	0	1
596	69967	55369	2	0	1	1	0	0	0	1
597	47334	154058	0	1	0	1	0	0	0	1
598	98592	180083	17	0	1	0	1	0	1	0
599	96519	158137	16	1	0	1	0	0	1	0

600 rows × 10 columns

In [23]:
```python
# training the model
clf = IsolationForest(random_state=40,contamination=.01)
clf.fit(newdf)
```

Out[23]:
```
IsolationForest(contamination=0.01, random_state=40)
```

In [24]:
```python
# predictions
y_pred_outliers = clf.predict(newdf)
```

In [25]:
```python
#-1 for outliers and 1 for inliers.
y_pred_outliers
```

Out[25]:
```
array([ 1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,
        1,  1,  1,  1, -1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,
       -1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,
        1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,
        1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,
        1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,
        1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,
        1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,
        1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,
        1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,
        1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,
        1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,
        1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,
        1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,
        1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,
        1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,
        1,  1,  1,  1,  1,  1,  1,  1, -1,  1,  1,  1,  1,  1,  1,  1,  1,
        1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,
        1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,
        1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,
        1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,
        1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,
        1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,
        1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,
        1,  1,  1,  1,  1,  1, -1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,
        1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,
        1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,
        1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1, -1,  1,
        1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,
        1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,
        1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,
        1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1, -1,  1,  1,
        1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,
        1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,
        1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,
        1,  1,  1,  1,  1])
```

In [26]:
```python
newdf['scores']=clf.decision_function(newdf.iloc[:,0:10])
newdf['anomaly']=clf.predict(newdf.iloc[:,0:10])
newdf
```

Out[26]:

	Taxable.Income	City.Population	Work.Experience	Undergrad_NO	Undergrad_YES	Marital.Status_Divorced	Marital.Status_Married	Marital.Status_Single	Urban_NO	Urban_YES	scores	anomaly
0	68833	50047	10	1	0	0	0	1	0	1	0.068081	1
1	33700	134075	18	0	1	1	0	0	0	1	0.068363	1
2	36925	160205	30	1	0	0	1	0	0	1	0.012120	1
3	50190	193264	15	0	1	0	0	1	0	1	0.066546	1
4	81002	27533	28	1	0	0	1	0	1	0	0.030292	1
...	...	...	...	...	...	...	...	...	...	...	...	...
595	76340	39492	7	0	1	1	0	0	0	1	0.050155	1
596	69967	55369	2	0	1	1	0	0	0	1	0.052740	1
597	47334	154058	0	1	0	1	0	0	0	1	0.015952	1
598	98592	180083	17	0	1	0	1	0	1	0	0.005133	1
599	96519	158137	16	1	0	1	0	0	1	0	0.048917	1

600 rows × 12 columns

In [27]:
```python
#Print the outlier data points
newdf[newdf['anomaly']==-1]
```

Out[27]:

	Taxable.Income	City.Population	Work.Experience	Undergrad_NO	Undergrad_YES	Marital.Status_Divorced	Marital.Status_Married	Marital.Status_Single	Urban_NO	Urban_YES	scores	anomaly
21	14310	29106	7	0	1	1	0	0	0	1	-0.000964	-1
34	12514	183767	1	0	1	1	0	0	0	1	-0.003339	-1
280	17783	33184	1	1	0	1	0	0	1	0	-0.011553	-1
414	97980	27300	1	1	0	1	0	0	0	1	-0.003410	-1
474	99128	80729	0	0	1	1	0	0	1	0	-0.005492	-1
541	12453	191874	30	0	1	1	0	0	0	1	-0.009326	-1

In [28]:
```python
df1 = newdf.drop([34,280,409,414,474,541],axis=0).reset_index(drop=True)
df1
```

Out[28]:

	Taxable.Income	City.Population	Work.Experience	Undergrad_NO	Undergrad_YES	Marital.Status_Divorced	Marital.Status_Married	Marital.Status_Single	Urban_NO	Urban_YES	scores	anomaly
0	68833	50047	10	1	0	0	0	1	0	1	0.068081	1
1	33700	134075	18	0	1	1	0	0	0	1	0.068363	1
2	36925	160205	30	1	0	0	1	0	0	1	0.012120	1
3	50190	193264	15	0	1	0	0	1	0	1	0.066546	1
4	81002	27533	28	1	0	0	1	0	1	0	0.030292	1
...	...	...	...	...	...	...	...	...	...	...	...	...
589	76340	39492	7	0	1	1	0	0	0	1	0.050155	1
590	69967	55369	2	0	1	1	0	0	0	1	0.052740	1
591	47334	154058	0	1	0	1	0	0	0	1	0.015952	1
592	98592	180083	17	0	1	0	1	0	1	0	0.005133	1
593	96519	158137	16	1	0	1	0	0	1	0	0.048917	1

594 rows × 12 columns

In [29]:
```python
#Converting the Target variable i.e. Taxable Income into Categorical (As mentioned in the problem statement)
df1['Category'] = pd.cut(df1['Taxable.Income'],
                        bins=[0,30000, np.inf],
                        labels=['Risky','Good'],
                        include_lowest=True)

df1
```

Out[29]:

	Taxable.Income	City.Population	Work.Experience	Undergrad_NO	Undergrad_YES	Marital.Status_Divorced	Marital.Status_Married	Marital.Status_Single	Urban_NO	Urban_YES	scores	anomaly	Category
0	68833	50047	10	1	0	0	0	1	0	1	0.068081	1	Good
1	33700	134075	18	0	1	1	0	0	0	1	0.068363	1	Good
2	36925	160205	30	1	0	0	1	0	0	1	0.012120	1	Good
3	50190	193264	15	0	1	0	0	1	0	1	0.066546	1	Good
4	81002	27533	28	1	0	0	1	0	1	0	0.030292	1	Good
...	...	...	...	...	...	...	...	...	...	...	...	...	...
589	76340	39492	7	0	1	1	0	0	0	1	0.050155	1	Good
590	69967	55369	2	0	1	1	0	0	0	1	0.052740	1	Good
591	47334	154058	0	1	0	1	0	0	0	1	0.015952	1	Good
592	98592	180083	17	0	1	0	1	0	1	0	0.005133	1	Good
593	96519	158137	16	1	0	1	0	0	1	0	0.048917	1	Good

594 rows × 13 columns

In [30]:
```python
x1 = df1.iloc[:,1:10]
y1 = df1.iloc[:,12]
```

In [31]:
```python
x1
```

Out[31]:

	City.Population	Work.Experience	Undergrad_NO	Undergrad_YES	Marital.Status_Divorced	Marital.Status_Married	Marital.Status_Single	Urban_NO	Urban_YES
0	50047	10	1	0	0	0	1	0	1
1	134075	18	0	1	1	0	0	0	1
2	160205	30	1	0	0	1	0	0	1
3	193264	15	0	1	0	0	1	0	1
4	27533	28	1	0	0	1	0	1	0
...	...	...	...	...	...	...	...	...	...
589	39492	7	0	1	1	0	0	0	1
590	55369	2	0	1	1	0	0	0	1
591	154058	0	1	0	1	0	0	0	1
592	180083	17	0	1	0	1	0	1	0
593	158137	16	1	0	1	0	0	1	0

594 rows × 9 columns

In [32]:
```python
y1
```

Out[32]:
```
0      Good
1      Good
2      Good
3      Good
4      Good
       ...
589    Good
590    Good
591    Good
592    Good
593    Good
Name: Category, Length: 594, dtype: category
Categories (2, object): ['Risky' < 'Good']
```

In [33]:
```python
# Splitting data into training and testing data set
x_train1, x_test1,y_train1,y_test1 = train_test_split(x1,y1, test_size=0.25,random_state=40)
```

Building Decision Tree Classifier using Entropy Criteria

Since last time the iteration 1 and 2 had the highest accuracy, so we'll make new models with this new dataframe, i.e. with max depth = 2 & 3

In [34]:
```python
model11 = DecisionTreeClassifier(criterion = 'entropy',max_depth=2)
model11.fit(x_train,y_train)
preds11 = model11.predict(x_test) # predicting on test data set

print('Model leaves:',model11.get_n_leaves(),'\n','\n',
      pd.Series(preds11).value_counts(),'\n','\n',
      'Model Accuracy is:',np.mean(preds11==y_test))
```

```
Model leaves: 4

 Good    180
dtype: int64

 Model Accuracy is: 0.7777777777777778
```

In [35]:
```python
model12 = DecisionTreeClassifier(criterion = 'entropy',max_depth=3)
model12.fit(x_train,y_train)
preds12 = model12.predict(x_test) # predicting on test data set

print('Model leaves:',model12.get_n_leaves(),'\n','\n',
      pd.Series(preds12).value_counts(),'\n','\n',
      'Model Accuracy is:',np.mean(preds12==y_test))
```

```
Model leaves: 7

 Good     179
Risky      1
dtype: int64

 Model Accuracy is: 0.7722222222222223
```

Since the accuracy hasn't improved, we can finalise the model 1 as our final model

Building Decision Tree Classifier (CART) using Gini Criteria

In [36]:
```python
from sklearn.tree import DecisionTreeClassifier
model_gini = DecisionTreeClassifier(criterion='gini', max_depth=2)
```

In [37]:
```python
model_gini.fit(x_train, y_train)
```

Out[37]:
```
DecisionTreeClassifier(max_depth=2)
```

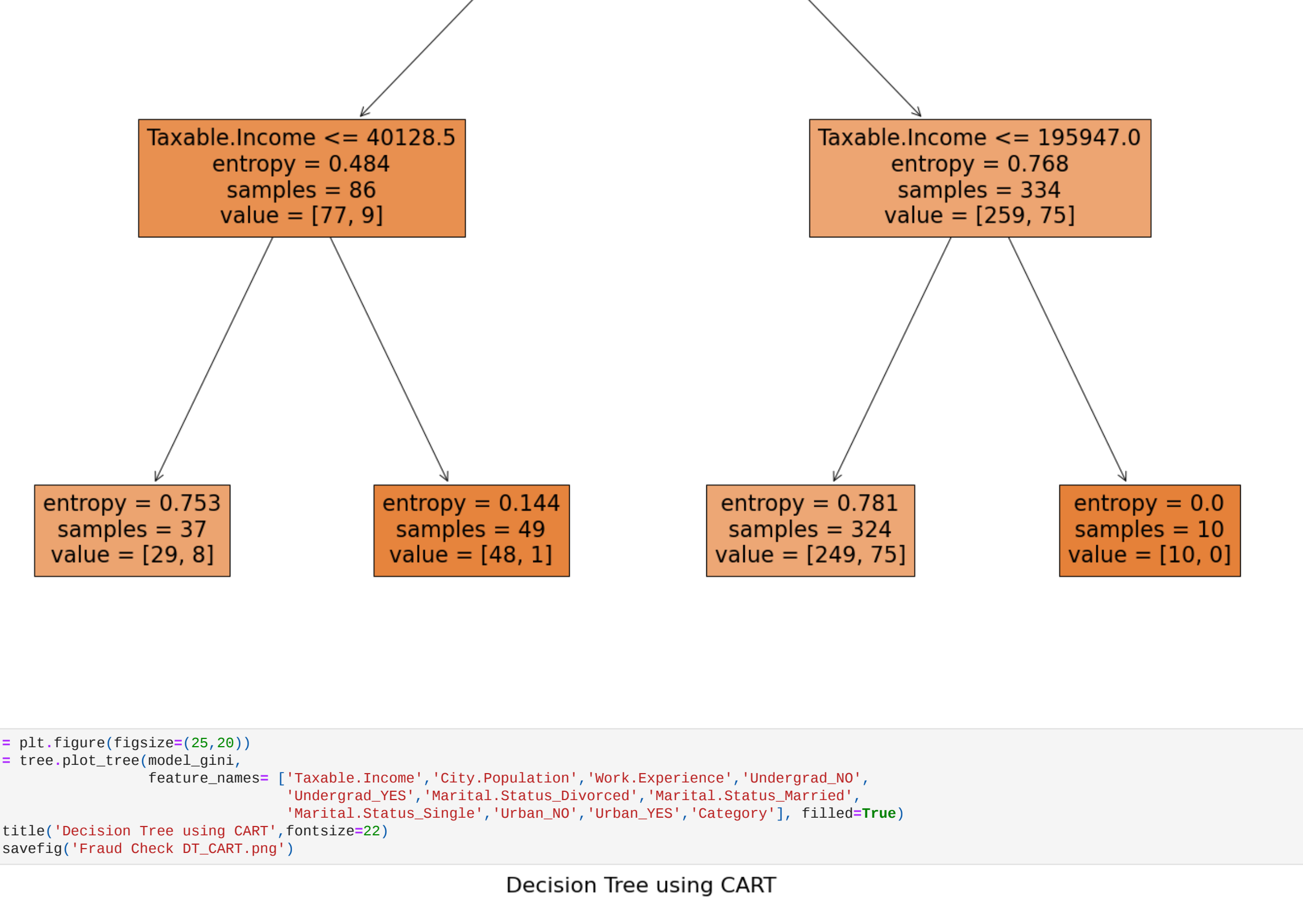
In [38]:
```python
#Prediction and computing the accuracy
predG=model_gini.predict(x_test)
print('Model Accuracy is:',np.mean(predG==y_test))
```

```
Model Accuracy is: 0.7777777777777778
```

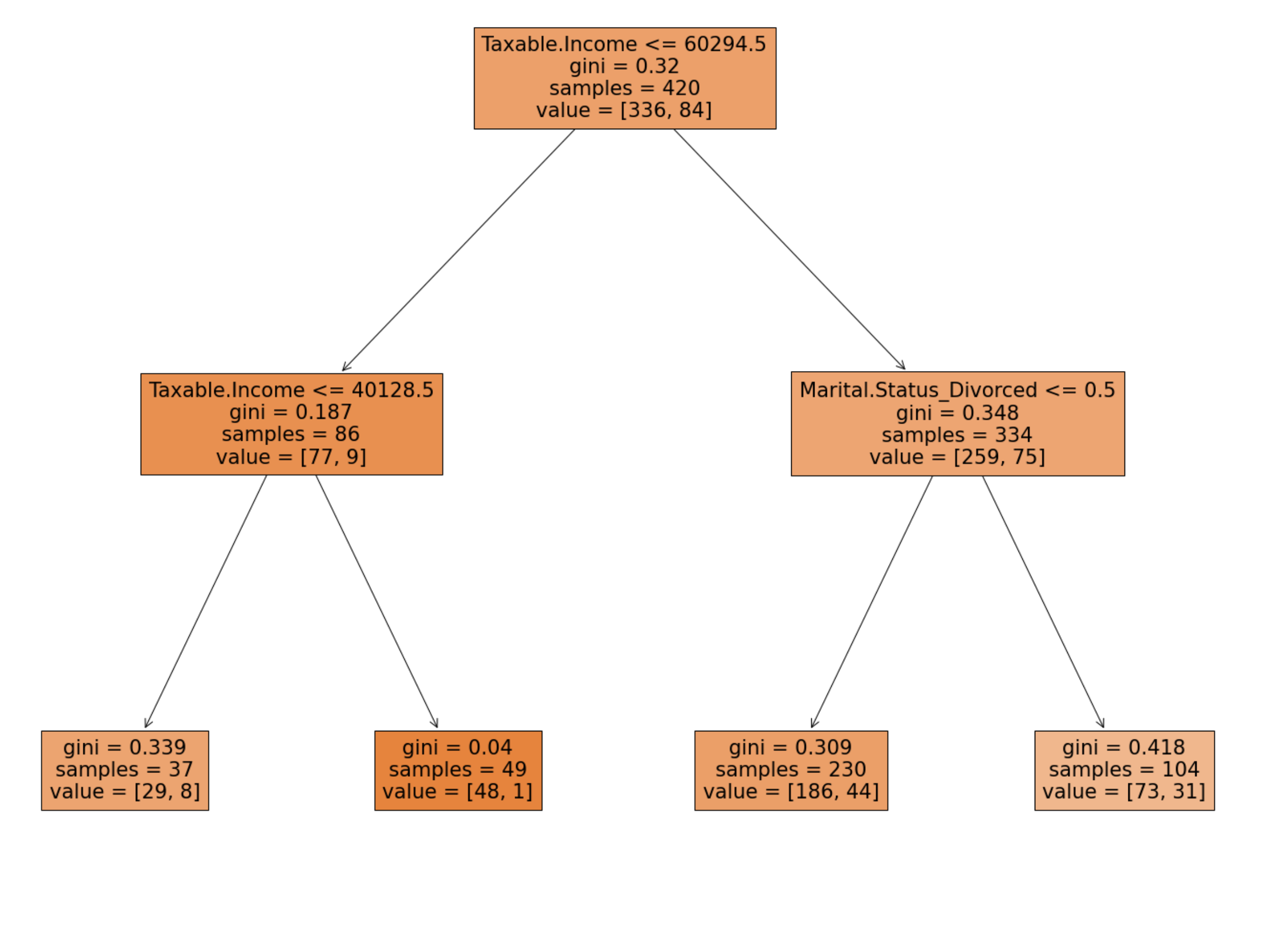
Same Accuracy is achieved using CART as well

Let's Visualize both the Decision Trees

In [39]:
```python
fig = plt.figure(figsize=(25,20))
fig = tree.plot_tree(model1,
                   feature_names= ['Taxable.Income','City.Population','Work.Experience','Undergrad_NO',
                                   'Undergrad_YES','Marital.Status_Divorced','Marital.Status_Married',
                                   'Marital.Status_Single','Urban_NO','Urban_YES','Category'], filled=True)
plt.title('Decision Tree using Entropy',fontsize=22)
plt.savefig('Fraud Check DT_Entropy.png')
```



In [40]:
```python
fig = plt.figure(figsize=(25,20))
fig = tree.plot_tree(model_gini,
                   feature_names= ['Taxable.Income','City.Population','Work.Experience','Undergrad_NO',
                                   'Undergrad_YES','Marital.Status_Divorced','Marital.Status_Married',
                                   'Marital.Status_Single','Urban_NO','Urban_YES','Category'], filled=True)
plt.title('Decision Tree using CART',fontsize=22)
plt.savefig('Fraud Check DT_CART.png')
```



In [ ]: