Decision Trees Assignment

Data Set - Fraud_check

1. Import Necessary libraries

In [1]:
```
import pandas as pd
import numpy as np

from matplotlib import pyplot as plt
import seaborn as sns

from sklearn import datasets
from sklearn.metrics import classification_report

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

2. Import Data

In [2]:
```
fraud_details = pd.read_csv('Fraud_check.csv')
fraud_details
```

Out[2]:

	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

3. Data Understanding

3.1 Initial Analysis :

In [3]:
```
fraud_details.head()
```

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

In [4]:
```
fraud_details.shape
```

Out[4]:
```
(600, 6)
```

In [5]:
```
fraud_details.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 600 entries, 0 to 599
Data columns (total 6 columns):
 #   Column           Non-Null Count  Dtype 
---  ------           --------------  ----- 
 0   Undergrad        600 non-null    object
 1   Marital.Status   600 non-null    object
 2   Taxable.Income   600 non-null    int64 
 3   City.Population  600 non-null    int64 
 4   Work.Experience  600 non-null    int64 
 5   Urban            600 non-null    object
dtypes: int64(3), object(3)
memory usage: 28.2+ KB
```

In [6]:
```
fraud_details.isna().sum()
```

Out[6]:
```
Undergrad          0
Marital.Status     0
Taxable.Income     0
City.Population    0
Work.Experience    0
Urban              0
dtype: int64
```

In [7]:
```
fraud_details.describe()
```

Out[7]:

	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 [8]:
```
fraud_details.dtypes
```

Out[8]:
```
Undergrad          object
Marital.Status     object
Taxable.Income      int64
City.Population     int64
Work.Experience     int64
Urban              object
dtype: object
```

In [9]:
```
fraud_details.columns
```

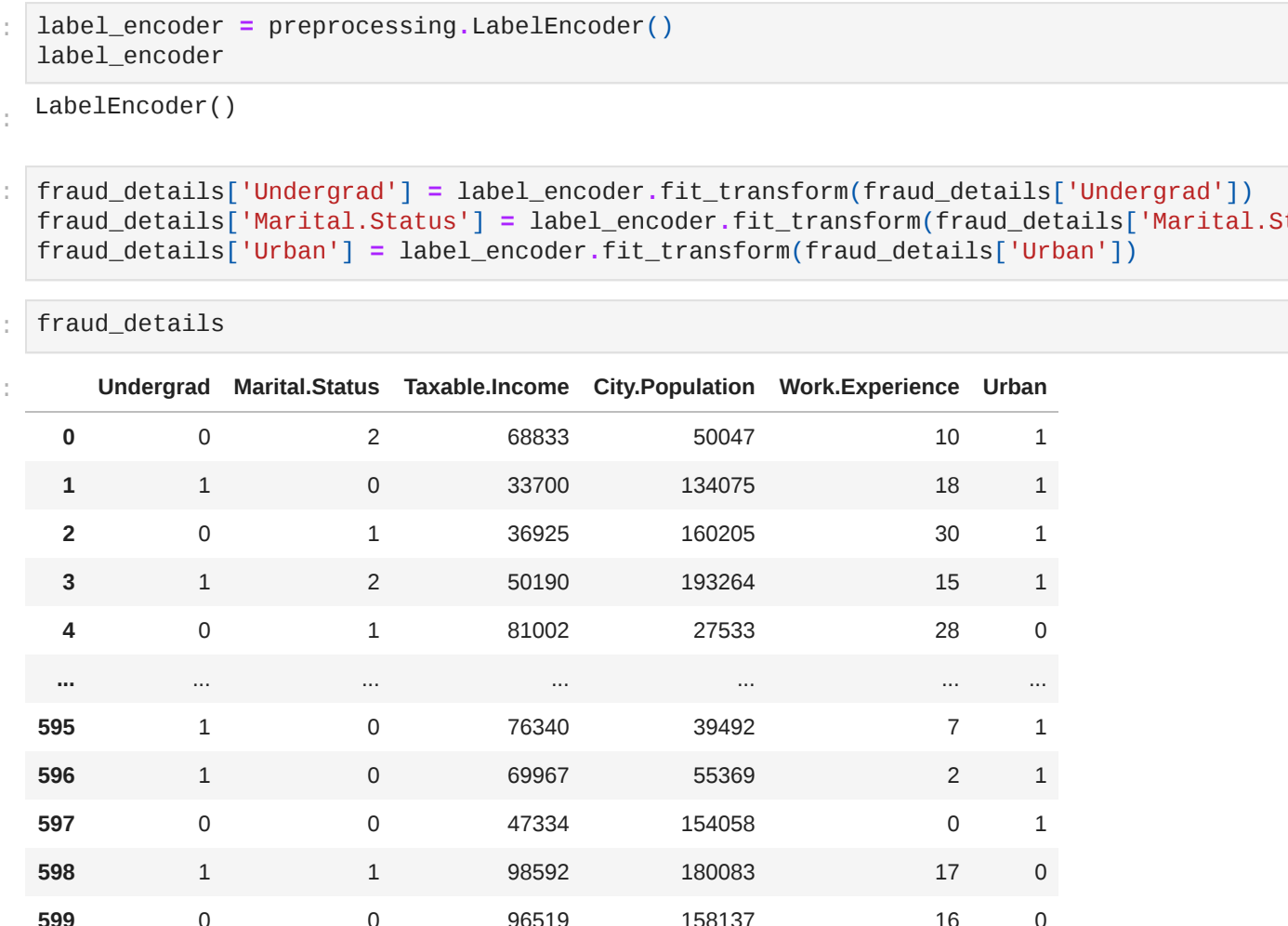
Out[9]:
```
Index(['Undergrad', 'Marital.Status', 'Taxable.Income', 'City.Population',
       'Work.Experience', 'Urban'],
      dtype='object')
```

In [10]:
```
fraud_details['Marital.Status'].value_counts()
```

Out[10]:
```
Single      217
Married     194
Divorced    189
Name: Marital.Status, dtype: int64
```

3.2 Correlation Matrix :

In [11]:
```
plt.figure(figsize = (12,8))
sns.heatmap(fraud_details.corr(),annot = True)
plt.show()
```



3.3 Label Encoder :

In [12]:
```
from sklearn import preprocessing
```

In [13]:
```
label_encoder = preprocessing.LabelEncoder()
label_encoder
```

Out[13]:
```
LabelEncoder()
```

In [14]:
```
fraud_details['Undergrad'] = label_encoder.fit_transform(fraud_details['Undergrad'])
fraud_details['Marital.Status'] = label_encoder.fit_transform(fraud_details['Marital.Status'])
fraud_details['Urban'] = label_encoder.fit_transform(fraud_details['Urban'])
```

In [15]:
```
fraud_details
```

Out[15]:

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

600 rows × 6 columns

In [16]:
```
sns.pairplot(fraud_details)
plt.show()
```

3.4 Adding New Column :

In [17]:
```
fraud_details['Status'] = fraud_details['Taxable.Income'].apply(lambda Income: 'Risky' if Income <= 30000 else 'Good')
fraud_details
```

Out[17]:

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

600 rows × 7 columns

In [18]:
```
fraud_details['Status'].unique()
```

Out[18]:
```
array(['Good', 'Risky'], dtype=object)
```

In [19]:
```
fraud_details['Status'] = label_encoder.fit_transform(fraud_details['Status'])
fraud_details
```

Out[19]:

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

600 rows × 7 columns

4. Train Test Split

In [20]:
```
from sklearn.model_selection import train_test_split
```

In [21]:
```
x = fraud_details.iloc[:,0:4]
y = fraud_details['Status']
```

In [22]:
```
x
```

Out[22]:

	Undergrad	Marital.Status	Taxable.Income	City.Population
0	0	2	68833	50047
1	1	0	33700	134075
2	0	1	36925	160205
3	1	2	50190	193264
4	0	1	81002	27533
...	...	...	...	...
595	1	0	76340	39492
596	1	0	69967	55369
597	0	0	47334	154058
598	1	1	98592	180083
599	0	0	96519	158137

600 rows × 4 columns

In [23]:
```
y
```

Out[23]:
```
0      0
1      0
2      0
3      0
4      0
      ..
595    0
596    0
597    0
598    0
599    0
Name: Status, Length: 600, dtype: int32
```

In [24]:
```
fraud_details['Status'].unique()
```

Out[24]:
```
array([0, 1])
```

In [25]:
```
fraud_details.Status.value_counts()
```

Out[25]:
```
0    476
1    124
Name: Status, dtype: int64
```

In [26]:
```
list(fraud_details.columns)
```

Out[26]:
```
['Undergrad',
 'Marital.Status',
 'Taxable.Income',
 'City.Population',
 'Work.Experience',
 'Urban',
 'Status']
```

In [27]:
```
x_train, x_test,y_train,y_test = train_test_split(x,y, test_size = 0.2 , random_state = 40)
```

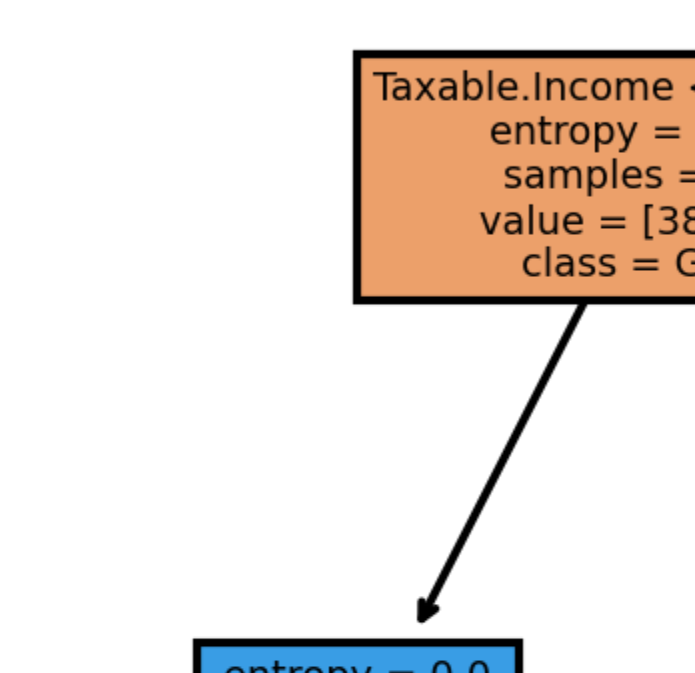
5. Building Model for Decision Tree Classifier using Entropy Criteria

In [28]:
```
from sklearn.tree import  DecisionTreeClassifier
from sklearn import tree
```

In [29]:
```
model = DecisionTreeClassifier(criterion = 'entropy',max_depth = 3)
model.fit(x_train,y_train)
```

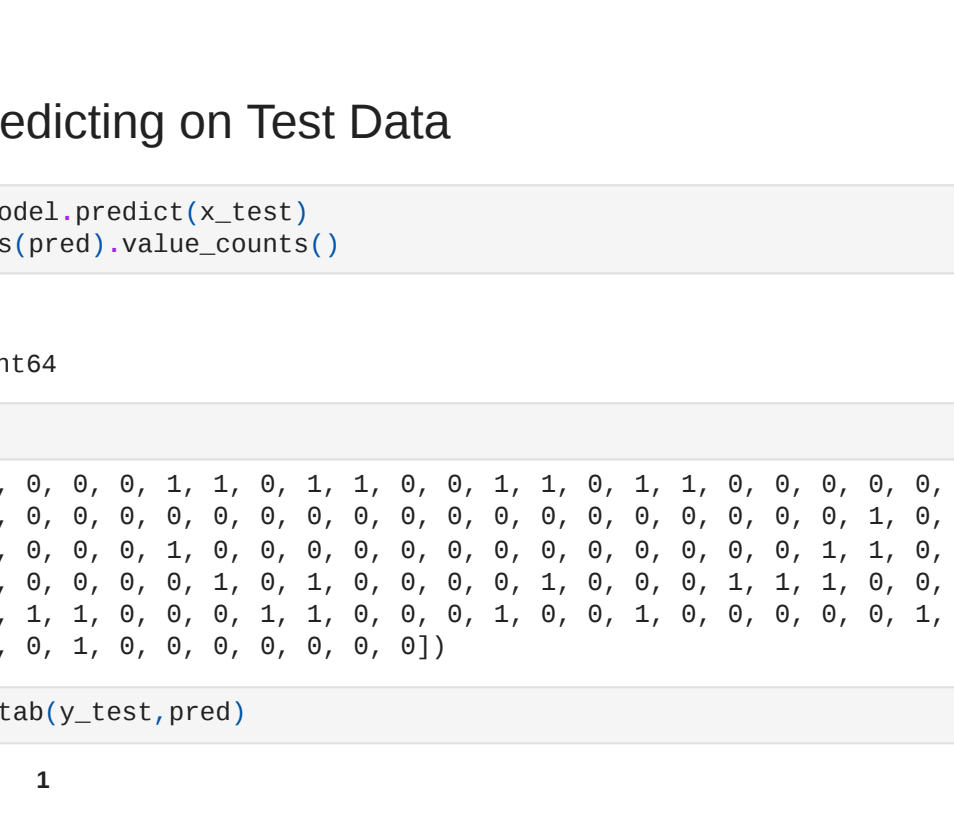
Out[29]:
```
DecisionTreeClassifier(criterion='entropy', max_depth=3)
```

In [30]:
```
tree.plot_tree(model);
```



In [31]:
```
f_n = ['Undergrad','Marital.Status','Taxable.Income','City.Population']
c_n = ['Good', 'Risky']
```

In [32]:
```
fig, axes = plt.subplots(nrows = 1,ncols = 1,figsize = (2.5,2.5), dpi = 300)
tree.plot_tree(model,feature_names = f_n,class_names = c_n,filled = True);
```



5.1 Predicting on Test Data

In [33]:
```
pred = model.predict(x_test)
pd.Series(pred).value_counts()
```

Out[33]:
```
0    92
1    28
dtype: int64
```

In [34]:
```
pred
```

Out[34]:
```
array([0, 0, 0, 0, 1, 1, 0, 1, 1, 0, 0, 1, 1, 0, 1, 1, 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, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0,
       0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 1, 0, 0, 0, 1, 1, 1, 0, 0, 0,
       0, 1, 1, 0, 0, 0, 1, 1, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 1, 1,
       0, 0, 1, 0, 0, 0, 0, 0, 0, 0])
```

In [35]:
```
pd.crosstab(y_test,pred)
```

Out[35]:

col_0	0	1
Status		
0	92	0
1	0	28

In [36]:
```
np.mean(pred == y_test)
```

Out[36]:
```
1.0
```

5.2 Feature Importance

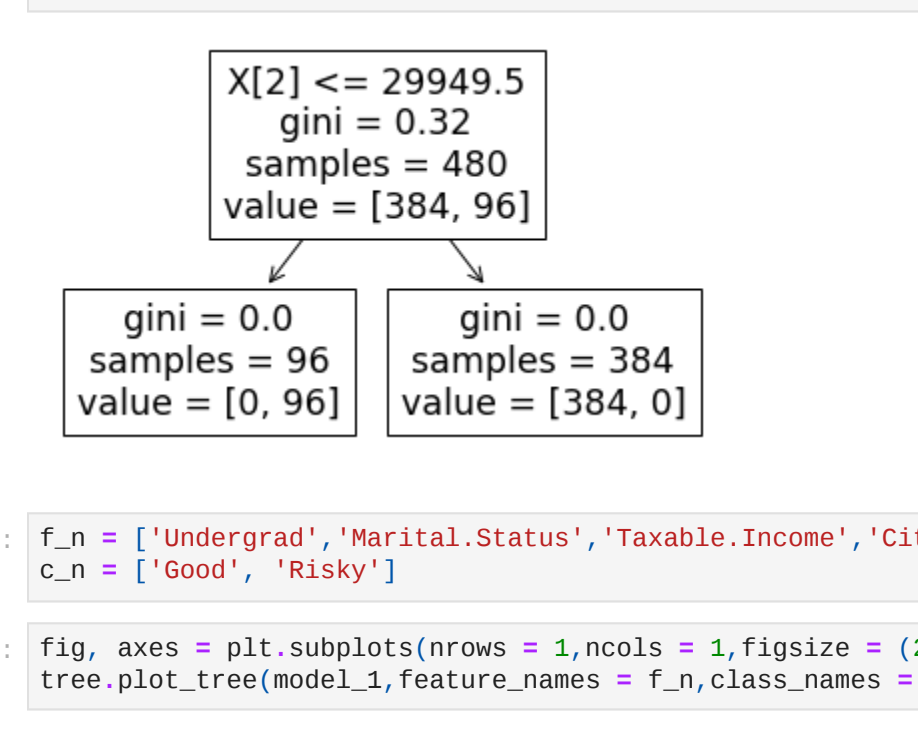
In [37]:
```
model.feature_importances_
```

Out[37]:
```
array([0., 0., 1., 0.])
```

In [38]:
```
feature_imp = pd.Series(model.feature_importances_,index = f_n).sort_values(ascending = False)
feature_imp
```

Out[38]:
```
Taxable.Income     1.0
Undergrad          0.0
Marital.Status     0.0
City.Population    0.0
dtype: float64
```

In [39]:
```
sns.barplot(x = feature_imp, y = feature_imp.index)
plt.xlabel('Feature Importance Score')
plt.ylabel('Features')
plt.title("Visualizing Important Features")
plt.show()
```

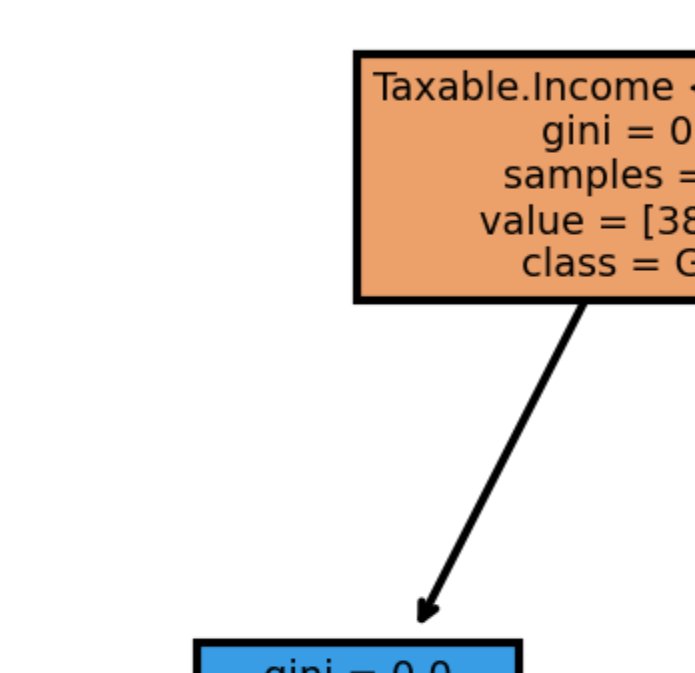


6. Building Model For Decision Tree Classifier (CART) using Gini Criteria

In [40]:
```
model_1 = DecisionTreeClassifier(criterion = 'gini', max_depth = 3)
model_1.fit(x_train, y_train)
```

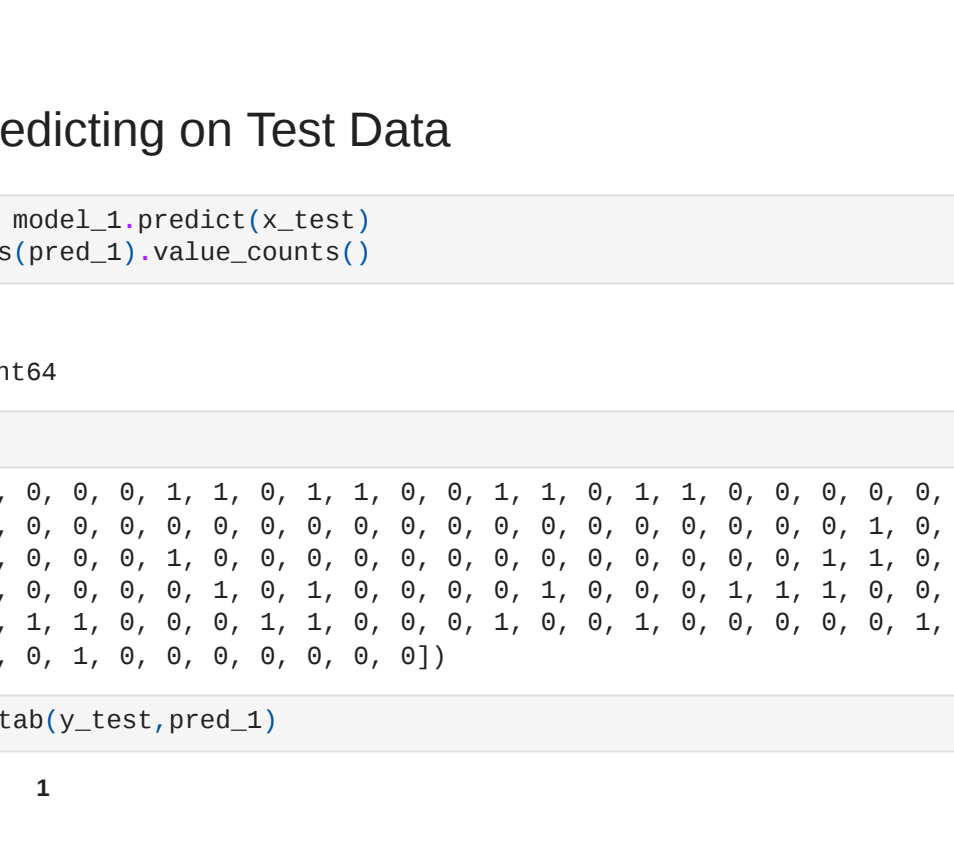
Out[40]:
```
DecisionTreeClassifier(max_depth=3)
```

In [41]:
```
tree.plot_tree(model_1);
```



In [42]:
```
f_n = ['Undergrad','Marital.Status','Taxable.Income','City.Population']
c_n = ['Good', 'Risky']
```

In [43]:
```
fig, axes = plt.subplots(nrows = 1,ncols = 1,figsize = (2.5,2.5), dpi = 300)
tree.plot_tree(model_1,feature_names = f_n,class_names = c_n,filled = True);
```



6.1 Predicting on Test Data

In [44]:
```
pred_1 = model_1.predict(x_test)
pd.Series(pred_1).value_counts()
```

Out[44]:
```
0    92
1    28
dtype: int64
```

In [45]:
```
pred_1
```

Out[45]:
```
array([0, 0, 0, 0, 1, 1, 0, 1, 1, 0, 0, 1, 1, 0, 1, 1, 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, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0,
       0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 1, 0, 0, 0, 1, 1, 1, 0, 0, 0,
       0, 1, 1, 0, 0, 0, 1, 1, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 1, 1,
       0, 0, 1, 0, 0, 0, 0, 0, 0, 0])
```

In [46]:
```
pd.crosstab(y_test,pred_1)
```

Out[46]:

col_0	0	1
Status		
0	92	0
1	0	28

In [47]:
```
np.mean(pred_1 == y_test)
```

Out[47]:
```
1.0
```

6.2 Feature Importance

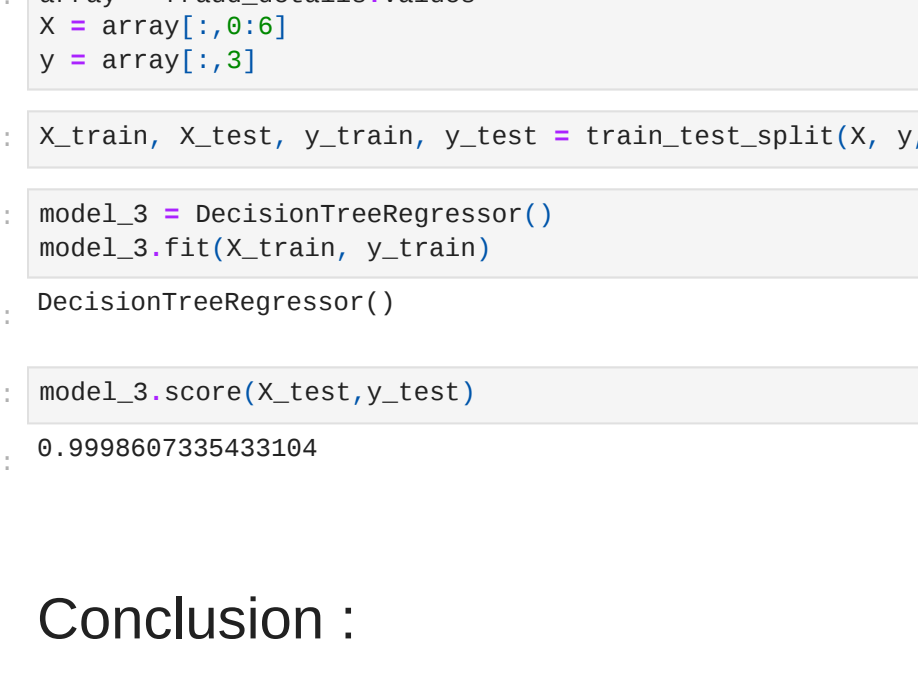
In [48]:
```
model_1.feature_importances_
```

Out[48]:
```
array([0., 0., 1., 0.])
```

In [49]:
```
feature_imp_1 = pd.Series(model_1.feature_importances_,index = f_n).sort_values(ascending = False)
feature_imp_1
```

Out[49]:
```
Taxable.Income     1.0
Undergrad          0.0
Marital.Status     0.0
City.Population    0.0
dtype: float64
```

In [50]:
```
sns.barplot(x = feature_imp, y = feature_imp.index)
plt.xlabel('Feature Importance Score')
plt.ylabel('Features')
plt.title("Visualizing Important Features")
plt.show()
```



7. Decision Tree Regression

In [51]:
```
from sklearn.tree import DecisionTreeRegressor
```

In [52]:
```
array = fraud_details.values
X = array[:,0:6]
y = array[:,3]
```

In [53]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.33, random_state = 1)
```

In [54]:
```
model_3 = DecisionTreeRegressor()
model_3.fit(X_train, y_train)
```

Out[54]:
```
DecisionTreeRegressor()
```

In [55]:
```
model_3.score(X_test,y_test)
```

Out[55]:
```
0.9998607335433104
```

Conclusion :

```
Model Accuracy for Entropy Criteria :  1.0
Model Accuracy for Gini Criteria    :  1.0
Model Accuracy for Decision Tree Regression : 0.999
```