Objective of the problem statement

- Use decision trees to prepare a model on fraud data treating those who have taxable_income <= 30000 as "Risky" and others are "Good"

1. Import necessary libraries

In [3]:
```
import pandas as pd
```

2. Importing data

In [5]:
```
fc_data = pd.read_csv('Fraud_check.csv')
fc_data
```

Out[5]:

	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 [5]:
```
fc_data.shape
```

Out[5]:
```
(600, 6)
```

In [6]:
```
fc_data.dtypes
```

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

In [7]:
```
fc_data.isna().sum()
```

Out[7]:
```
Undergrad          0
Marital.Status     0
Taxable.Income     0
City.Population    0
Work.Experience    0
Urban              0
dtype: int64
```

4. Data Preparation

In [14]:
```
from sklearn import preprocessing
```

In [15]:
```
# Create numerical variable for categorical data
label_encoder = preprocessing.LabelEncoder()
fc_data['Undergrad'] = label_encoder.fit_transform(fc_data['Undergrad'])
fc_data['Marital.Status'] = label_encoder.fit_transform(fc_data['Marital.Status']
fc_data['Urban'] = label_encoder.fit_transform(fc_data['Urban'])
```

In [16]:
```
fc_data
```

Out[16]:

	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 [17]:
```
fc_data.head(20)
```

Out[17]:

	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
5	0	0	33329	116382	0	0
6	0	0	83357	80890	8	1
7	1	2	62774	131253	3	1
8	0	2	83519	102481	12	1
9	1	0	98152	155482	4	1
10	0	2	29732	102602	19	1
11	0	2	61063	94875	6	1
12	0	0	11794	148033	14	1
13	0	1	61830	86649	16	1
14	0	1	64070	57529	13	1
15	0	0	69869	107764	29	0
16	1	0	24987	34551	29	0
17	1	1	39476	57194	25	0
18	1	0	97957	59269	6	0
19	0	2	10987	126953	30	1

In [18]:
```
fc_data.info
```

Out[18]:
```
<bound method DataFrame.info of      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

     Work.Experience  Urban
0                 10      1
1                 18      1
2                 30      1
3                 15      1
4                 28      0
..               ...    ...
595                7      1
596                2      1
597                0      1
598               17      0
599               16      0

[600 rows x 6 columns]>
```

5. Model Building

5.1 Separate input & output

In [19]:
```
X = fc_data.drop(labels = 'Taxable.Income', axis=1)
y = fc_data[['Taxable.Income']]
```

In [20]:
```
X
```

Out[20]:

	Undergrad	Marital.Status	City.Population	Work.Experience	Urban
0	0	2	50047	10	1
1	1	0	134075	18	1
2	0	1	160205	30	1
3	1	2	193264	15	1
4	0	1	27533	28	0
...	...	...	...	...	...
595	1	0	39492	7	1
596	1	0	55369	2	1
597	0	0	154058	0	1
598	1	1	180083	17	0
599	0	0	158137	16	0

600 rows × 5 columns

In [21]:
```
y
```

Out[21]:

	Taxable.Income
0	68833
1	33700
2	36925
3	50190
4	81002
...	...
595	76340
596	69967
597	47334
598	98592
599	96519

600 rows × 1 columns

5.2 Train test split

In [22]:
```
from sklearn.model_selection import train_test_split
X_train,X_test,y_train,y_test = train_test_split(X,y, test_size = 0.20, random_st
```

In [23]:
```
X_train
```

Out[23]:

	Undergrad	Marital.Status	City.Population	Work.Experience	Urban
82	0	0	111068	26	1
568	0	2	150036	22	1
347	0	1	80991	0	1
544	0	2	133877	21	1
34	1	0	183767	1	1
...	...	...	...	...	...
129	1	2	65469	26	0
144	1	2	156503	29	1
72	1	0	108300	27	1
235	0	0	87541	9	0
37	0	1	66912	5	1

480 rows × 5 columns

In [24]:
```
# for training data
X_train.shape,y_train.shape
```

Out[24]: ((480, 5), (480, 1))

In [25]:
```
# for test data
X_test.shape,y_test.shape
```

Out[25]: ((120, 5), (120, 1))

6. Model training

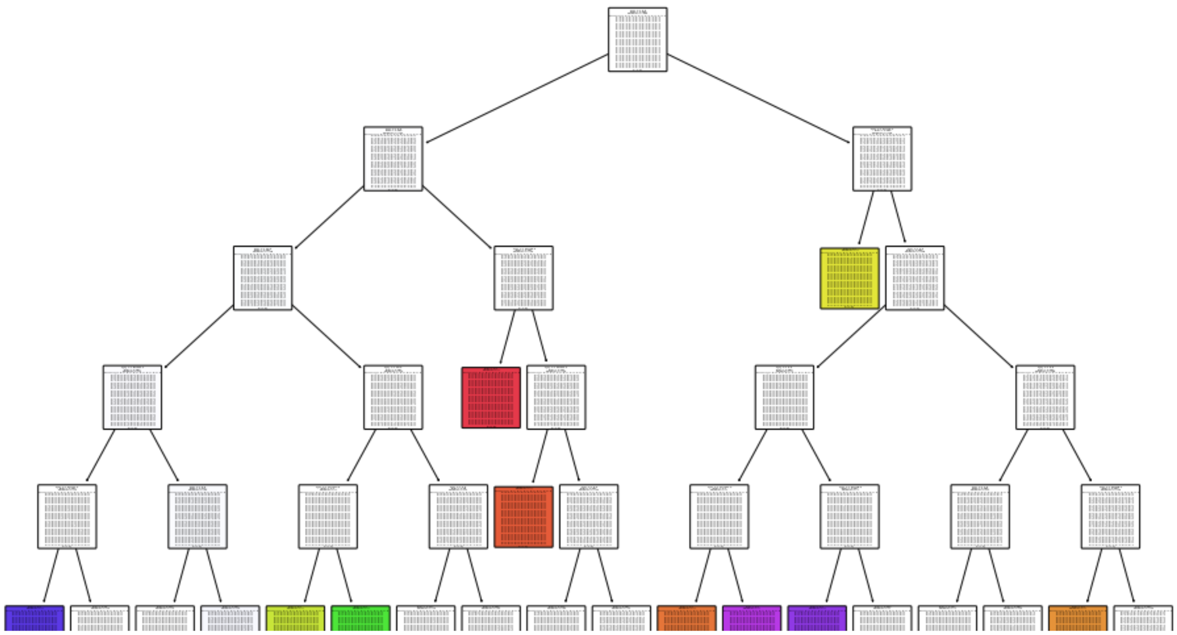
In [26]:
```
from sklearn.tree import DecisionTreeClassifier
dt_model = DecisionTreeClassifier(criterion='gini', max_depth=5)
dt_model.fit(X_train,y_train)
```

Out[26]: DecisionTreeClassifier(max_depth=5)

Plot Tree

In [27]:
```
#Prepare a plot figure with set size
from sklearn.tree import plot_tree
from matplotlib import pyplot as plt
```

In [28]:
```
plt.figure(figsize=(16,10))
plot_tree(dt_model,rounded=True,filled=True)
plt.show()
```



7. Model Testing

In [29]:
```
#Training data
y_train_pred = dt_model.predict(X_train)
```

In [30]:
```
# Test data
y_test_pred = dt_model.predict(X_test)
```

8. Model Evaluation

In [31]:
```
from sklearn.metrics import accuracy_score,precision_score,recall_score,confusion
```

Training data

In [32]:
```
accuracy_score(y_train,y_train_pred)
```

Out[32]:
```
0.04583333333333333
```

In [33]:
```
confusion_matrix(y_train,y_train_pred)
```

Out[33]:
```
array([[0, 0, 0, ..., 0, 0, 0],
       [0, 1, 0, ..., 0, 0, 0],
       [0, 0, 1, ..., 0, 0, 0],
       ...,
       [0, 1, 0, ..., 0, 0, 0],
       [0, 0, 1, ..., 0, 0, 0],
       [0, 1, 0, ..., 0, 0, 0]], dtype=int64)
```

In [49]:
```
print(classification_report(y_train,y_train_pred))
```

```
              precision    recall  f1-score   support

       10150       0.00      0.00      0.00         1
       10163       0.01      1.00      0.01         1
       10329       0.03      1.00      0.05         1
       10348       0.01      1.00      0.03         1
       10379       0.00      0.00      0.00         1
       10735       0.00      0.00      0.00         1
       10870       0.00      0.00      0.00         1
       10900       0.00      0.00      0.00         1
       10933       1.00      1.00      1.00         1
       10987       0.00      0.00      0.00         1
       11794       0.00      0.00      0.00         1
       11804       0.00      0.00      0.00         1
       12011       0.00      0.00      0.00         1
       12072       0.00      0.00      0.00         1
       12453       0.02      1.00      0.03         1
       12514       0.33      1.00      0.50         1
       12659       0.00      0.00      0.00         1
```

9 .Model Deployment

In [35]:
```
from pickle import dump
```

In [45]:
```
dump(dt_model,open('log_model.pkl','wb'))
```

In [46]:
```
from pickle import load
```

In [47]:
```
dt_model_pickle = load(open('log_model.pkl','rb'))
```

In [48]:
```
pickle_pred = dt_model_pickle.predict(X_test)
```

Conclusion:-We can see maximum depth of tree 5 is good as accuracy prospective & classsification is good technique for predict the sale & regression is not usual to good at this dataset