1. Import Libraries

In [1]:

```
import pandas as pd
import numpy as np
import seaborn as sns
```

In [2]:

```
fraud_check = pd.read_csv('Fraud_check.csv')
fraud_check
```

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

In [3]:

fraud_check

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]:

fraud_check.shape

Out[4]:

(600, 6)

In [5]:

fraud_check.info()

RangeIndex: 600 entries, 0 to 599 Data columns (total 6 columns):

<class 'pandas.core.frame.DataFrame'>

| # | 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_check.dtypes
```

Out[6]:

Undergrad object
Marital.Status object
Taxable.Income int64
City.Population int64
Work.Experience int64
Urban object

dtype: object

In [7]:

```
fraud_check.isna().sum()
```

Out[7]:

Undergrad 0
Marital.Status 0
Taxable.Income 0
City.Population 0
Work.Experience 0
Urban 0

dtype: int64

In [8]:

```
fraud_check['Taxable.Income'].max()
```

Out[8]:

99619

In [9]:

```
fraud_check['Taxable.Income'].min()
```

Out[9]:

10003

In [10]:

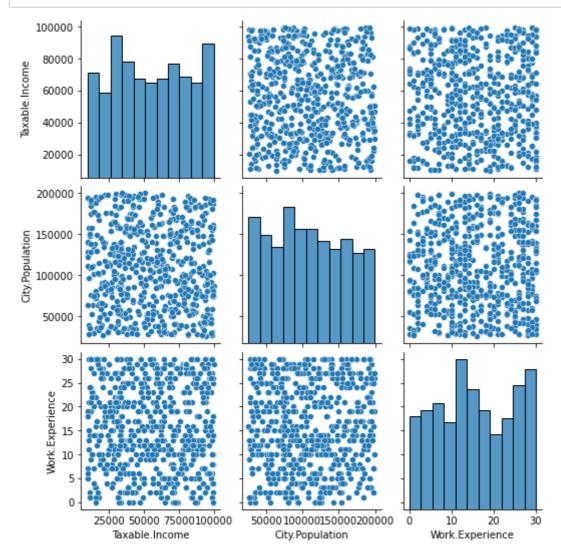
fraud_check.describe(include='all')

Out[10]:

| | Undergrad | Marital.Status | Taxable.Income | City.Population | Work.Experience | Urban |
|--------|-----------|----------------|----------------|-----------------|-----------------|-------|
| count | 600 | 600 | 600.000000 | 600.000000 | 600.000000 | 600 |
| unique | 2 | 3 | NaN | NaN | NaN | 2 |
| top | YES | Single | NaN | NaN | NaN | YES |
| freq | 312 | 217 | NaN | NaN | NaN | 302 |
| mean | NaN | NaN | 55208.375000 | 108747.368333 | 15.558333 | NaN |
| std | NaN | NaN | 26204.827597 | 49850.075134 | 8.842147 | NaN |
| min | NaN | NaN | 10003.000000 | 25779.000000 | 0.000000 | NaN |
| 25% | NaN | NaN | 32871.500000 | 66966.750000 | 8.000000 | NaN |
| 50% | NaN | NaN | 55074.500000 | 106493.500000 | 15.000000 | NaN |
| 75% | NaN | NaN | 78611.750000 | 150114.250000 | 24.000000 | NaN |
| max | NaN | NaN | 99619.000000 | 199778.000000 | 30.000000 | NaN |

In [11]:

```
sns.pairplot(fraud_check)
fraud_check["TaxInc"] = pd.cut(fraud_check["Taxable.Income"],bins = [10003, 30000, 99620],l
fraud_check_2 = fraud_check.drop(columns=["Taxable.Income"])
```



In [12]:

```
fraud_check_2 = pd.get_dummies(fraud_check_2.drop(columns=["TaxInc"]))
fraud_check_2
```

Out[12]:

| | City.Population | Work.Experience | Undergrad_NO | Undergrad_YES | Marital.Status_Divorced | |
|-------|----------------------|-----------------|--------------|---------------|-------------------------|--|
| 0 | 50047 | 10 | 1 | 0 | 0 | |
| 1 | 134075 | 18 | 0 | 1 | 1 | |
| 2 | 160205 | 30 | 1 | 0 | 0 | |
| 3 | 193264 | 15 | 0 | 1 | 0 | |
| 4 | 27533 | 28 | 1 | 0 | 0 | |
| | | | | | | |
| 595 | 39492 | 7 | 0 | 1 | 1 | |
| 596 | 55369 | 2 | 0 | 1 | 1 | |
| 597 | 154058 | 0 | 1 | 0 | 1 | |
| 598 | 180083 | 17 | 0 | 1 | 0 | |
| 599 | 158137 | 16 | 1 | 0 | 1 | |
| 600 r | 600 rows × 9 columns | | | | | |
| 4 | | | | | • | |

In [13]:

fraud_check_final = pd.concat([fraud_check_2, fraud_check["TaxInc"]],axis=1)
fraud_check_final.dtypes

Out[13]:

| City.Population | int64 |
|-------------------------|---------|
| Work.Experience | int64 |
| Undergrad_NO | uint8 |
| Undergrad_YES | uint8 |
| Marital.Status_Divorced | uint8 |
| Marital.Status_Married | uint8 |
| Marital.Status_Single | uint8 |
| Urban_NO | uint8 |
| Urban_YES | uint8 |
| TaxInc | float64 |
| | |

dtype: object

In [14]:

fraud_check_final

Out[14]:

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

600 rows × 10 columns

In [15]:

fraud_check_final.isnull().sum()

Out[15]:

| City.Population | 0 |
|-------------------------|---|
| Work.Experience | 0 |
| Undergrad_NO | 0 |
| Undergrad_YES | 0 |
| Marital.Status_Divorced | 0 |
| Marital.Status_Married | 0 |
| Marital.Status_Single | 0 |
| Urban_NO | 0 |
| Urban_YES | 0 |
| TaxInc | 1 |
| dtype: int64 | |
| | |

In [16]:

```
# Create a DataFrame from dictionary
kl = pd.DataFrame(fraud_check_final)
kl
```

Out[16]:

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

600 rows × 10 columns

→

In [17]:

```
#Finding the mean of the column having NaN
mean_value=kl['TaxInc'].median()
mean_value
```

Out[17]:

1.0

In [18]:

```
# Replace NaNs in column TaxInc with the
# mean of values in the same column
kl['TaxInc'].fillna(value=mean_value, inplace=True)
print('Updated Dataframe:')
print(kl)
Updated Dataframe:
     City.Population Work.Experience Undergrad_NO Undergrad_YES
0
                50047
1
               134075
                                       18
                                                        0
                                                                         1
2
                                       30
                                                        1
                                                                         0
                160205
3
               193264
                                       15
                                                        0
                                                                         1
4
                 27533
                                       28
                                                        1
                                                                         0
. .
                                      . . .
595
                39492
                                        7
                                                        0
                                                                         1
                                        2
596
                55369
                                                        0
                                                                         1
597
               154058
                                        0
                                                        1
                                                                         0
               180083
                                       17
                                                        0
                                                                         1
598
599
               158137
                                       16
                                                        1
                                                                         0
     Marital.Status_Divorced Marital.Status_Married Marital.Status_Single
١
0
                              0
                                                         0
                                                                                   1
                              1
                                                         0
1
                                                                                   0
2
                              0
                                                         1
                                                                                   0
3
                              0
                                                         0
                                                                                   1
4
                              0
                                                         1
                                                                                   0
                                                        . . .
595
                                                         0
                                                                                   0
                              1
596
                              1
                                                         0
                                                                                   0
                              1
                                                         0
                                                                                   0
597
598
                              0
                                                         1
                                                                                   0
599
                              1
                                                         0
                                                                                   0
     Urban NO
                Urban_YES
                             TaxInc
0
             0
                          1
                                1.0
                          1
1
             0
                                1.0
2
             0
                          1
                                1.0
3
             0
                          1
                                1.0
4
             1
                          0
                                1.0
           . . .
                        . . .
                                 . . .
595
             0
                         1
                                1.0
596
             0
                          1
                                1.0
             0
                          1
                                1.0
597
598
             1
                          0
                                1.0
             1
599
                                1.0
```

[600 rows x 10 columns]

In [19]:

```
kl.dtypes
```

Out[19]:

City.Population int64 Work.Experience int64 Undergrad_NO uint8 Undergrad_YES uint8 Marital.Status_Divorced uint8 Marital.Status_Married uint8 Marital.Status_Single uint8 Urban NO uint8 Urban_YES uint8 float64 TaxInc

dtype: object

In [20]:

```
# converting 'Weight' from float to int
kl['TaxInc'] = kl['TaxInc'].astype(int)
```

In [21]:

```
# displaying the datatypes
display(kl.dtypes)
```

City.Population int64 int64 Work.Experience Undergrad_NO uint8 Undergrad_YES uint8 Marital.Status Divorced uint8 uint8 Marital.Status_Married Marital.Status_Single uint8 Urban_NO uint8 Urban_YES uint8 int32 TaxInc

dtype: object

In [22]:

```
kl.isnull().sum()
```

Out[22]:

City.Population 0 Work.Experience 0 0 Undergrad_NO 0 Undergrad_YES Marital.Status Divorced 0 Marital.Status_Married 0 Marital.Status_Single 0 Urban_NO 0 **Urban YES** 0 0 TaxInc dtype: int64

```
In [23]:
colnames =list(kl.columns)
In [24]:
colnames
Out[24]:
['City.Population',
 'Work.Experience',
 'Undergrad_NO',
 'Undergrad_YES',
 'Marital.Status_Divorced',
 'Marital.Status_Married',
 'Marital.Status_Single',
 'Urban_NO',
 'Urban_YES',
 'TaxInc']
In [25]:
predictors = colnames[:9]
predictors
target = colnames[9]
target
Out[25]:
'TaxInc'
In [26]:
# Separating independent and dependent Veriables
x = kl[predictors]
```

```
# Separating independent and dependent Veriables
x = kl[predictors]
x.shape
y = kl[target]
```

```
In [27]:
```

Х

Out[27]:

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

600 rows × 9 columns

```
In [28]:

y

Out[28]:

0    1
1    1
2    1
```

598 1 599 1

Name: TaxInc, Length: 600, dtype: int32

2.Decision Tree Building

```
In [29]:
```

```
from sklearn.model_selection import train_test_split
train , test =train_test_split(kl ,test_size=0.3)
kl ['TaxInc'].unique()
```

Out[29]:

array([1, 0])

In [30]:

```
from sklearn.tree import DecisionTreeClassifier
dc_model = DecisionTreeClassifier(criterion = "entropy")
dc_model.fit(train[predictors], train[[target]])
```

Out[30]:

DecisionTreeClassifier(criterion='entropy')

In [31]:

```
#prediction
pred = dc_model.predict(test[predictors])
pred
type(pred)
```

Out[31]:

numpy.ndarray

In [32]:

```
pd.Series(pred).value_counts()
141/(141+39)
pd.crosstab(test[target],pred)
pd.Series(dc_model.predict(train[predictors])).reset_index(drop=True)
np.mean(pd.Series(train.TaxInc).reset_index(drop=True)==pd.Series(dc_model.predict(train[pr
np.mean(pred==test.TaxInc)
```

Out[32]:

0.66666666666666

In [33]:

```
pd.crosstab(test[target],pred) #64%
temp = pd.Series(dc_model.predict(train[predictors])).reset_index(drop=True)
np.mean(pd.Series(train.TaxInc).reset_index(drop=True)==pd.Series(dc_model.predict(train[pr
np.mean(pred==test.TaxInc)
```

Out[33]:

0.66666666666666

```
In [34]:
```

```
from sklearn.ensemble import RandomForestClassifier
rf = RandomForestClassifier(n_jobs=3, oob_score=True, n_estimators=15,criterion=('gini'))
```

```
In [35]:
```

```
np.shape(kl)
```

Out[35]:

(600, 10)

In [36]:

```
np.shape(kl) # 600,100 => Shape
len(x)
```

Out[36]:

600

In [37]:

```
len(y)
```

Out[37]:

600

In [38]:

```
kl.describe()
```

Out[38]:

| | City.Population | Work.Experience | Undergrad_NO | Undergrad_YES | Marital.Status_Divorced |
|-------|-----------------|-----------------|--------------|---------------|-------------------------|
| count | 600.000000 | 600.000000 | 600.000000 | 600.000000 | 600.000000 |
| mean | 108747.368333 | 15.558333 | 0.480000 | 0.520000 | 0.315000 |
| std | 49850.075134 | 8.842147 | 0.500017 | 0.500017 | 0.464903 |
| min | 25779.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 |
| 25% | 66966.750000 | 8.000000 | 0.000000 | 0.000000 | 0.000000 |
| 50% | 106493.500000 | 15.000000 | 0.000000 | 1.000000 | 0.000000 |
| 75% | 150114.250000 | 24.000000 | 1.000000 | 1.000000 | 1.000000 |
| max | 199778.000000 | 30.000000 | 1.000000 | 1.000000 | 1.000000 |
| 4 | | | | | • |

In [39]:

```
kl.info()
```

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 600 entries, 0 to 599
Data columns (total 10 columns):

| # | Column | Non-Null Count | Dtype |
|---|-------------------------|----------------|-------|
| | | | |
| 0 | City.Population | 600 non-null | int64 |
| 1 | Work.Experience | 600 non-null | int64 |
| 2 | Undergrad_NO | 600 non-null | uint8 |
| 3 | Undergrad_YES | 600 non-null | uint8 |
| 4 | Marital.Status_Divorced | 600 non-null | uint8 |
| 5 | Marital.Status_Married | 600 non-null | uint8 |
| 6 | Marital.Status_Single | 600 non-null | uint8 |
| 7 | Urban_NO | 600 non-null | uint8 |
| 8 | Urban_YES | 600 non-null | uint8 |
| 9 | TaxInc | 600 non-null | int32 |
| | | | |

dtypes: int32(1), int64(2), uint8(7)

memory usage: 15.9 KB

In [40]:

```
type([x])
type([y])
y1 = pd.DataFrame(y)
type(y1)
import warnings
warnings.filterwarnings('ignore')
```

In [41]:

```
rf.fit(x,y1)
rf.predict(x)
```

Out[41]:

```
array([1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 0, 1, 1, 1, 0, 1, 1, 0, 1, 0,
      1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 0, 1, 0, 1, 1, 1, 1, 1,
      1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 0, 1, 1, 0, 1, 1, 0, 1, 1, 1, 1,
      1, 1, 0, 1, 1, 1,
                      1,
                         1,
                            1,
                              1, 1, 1, 1, 0, 1, 1, 1,
                                                    1, 1,
                1, 0,
                      0, 1, 0, 1, 0, 1, 1, 1, 1, 1, 1, 1, 0, 1,
      0, 1, 1, 1, 0, 1, 1, 1, 0, 1, 1, 0, 0, 0, 1, 1, 0, 1, 1, 1, 1, 1,
        1, 1, 0, 1, 0, 1, 1, 0, 1, 1, 0, 1, 1, 1, 1, 1,
                                                    1, 1, 1,
                            1, 0, 1, 1, 1, 1,
      0, 1, 1,
              1, 0, 1,
                      1,
                         1,
                                            0, 1, 1,
                                                    0, 0,
                                                          1,
        1, 1, 0, 1, 0, 0, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 0, 1, 0, 1,
      1, 0, 1, 1, 1, 1, 0, 0, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0,
                      1,
      1, 1, 1, 1, 1, 1,
                         1, 0, 1, 0, 1, 0, 1, 1, 1, 1,
                                                    0, 1,
              1, 1, 1,
                         1,
                            1,
                              1, 1, 1, 1, 1, 1, 1,
                                                 1,
      1, 0, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1,
      1, 1, 1,
              1, 1, 1,
                      1, 0, 1,
                              1, 1, 1, 1, 1, 1, 1, 1,
                                                    1, 0, 0,
      1, 1, 1, 0, 1, 1,
                      1,
                        0, 0, 0, 1, 1,
                                      1, 1, 1, 1, 0, 0, 1, 0,
      0, 1, 0, 1, 0, 0, 1, 1, 1, 1, 0, 0, 1, 1, 1, 0, 1, 1, 1, 1, 1,
      1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1,
              1, 1,
                   1,
                      1,
                         1,
                            1,
                              1, 1, 1, 1, 1,
                                            1, 1,
                                                 1,
                                                    1,
                                                       1,
      1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 0, 0, 1, 1,
      1, 1, 1, 0, 0, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 1, 1,
      0, 1, 1, 1, 1, 1,
                      1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1,
      1, 1, 1, 1, 1, 1,
                      1, 0, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1,
      0, 1, 1, 0, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 0, 1, 0, 1,
      1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 0, 0, 1, 1, 0, 1, 1, 1, 1, 1,
      1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
      1, 1, 1, 1, 1, 1])
```

In [44]:

```
kl['rf_pred']=rf.predict(x)
```

```
In [45]:
```

k1

Out[45]:

| c.Experience | Undergrad_NO | Undergrad_YES | Marital.Status_Divorced | Marital.Status_Married | Marit |
|--------------|--------------|---------------|-------------------------|------------------------|-------|
| 10 | 1 | 0 | 0 | 0 | |
| 18 | 0 | 1 | 1 | 0 | |
| 30 | 1 | 0 | 0 | 1 | |
| 15 | 0 | 1 | 0 | 0 | |
| 28 | 1 | 0 | 0 | 1 | |
| | | | | | |
| 7 | 0 | 1 | 1 | 0 | |
| 2 | 0 | 1 | 1 | 0 | |
| 0 | 1 | 0 | 1 | 0 | |
| 17 | 0 | 1 | 0 | 1 | |
| 16 | 1 | 0 | 1 | 0 | |
| | | | | | |
| 4 | | | | | |

In [47]:

```
cols=['rf_pred','TaxInc']
cols
```

Out[47]:

['rf_pred', 'TaxInc']

In [48]:

```
kl[cols].head()
```

Out[48]:

| | rf_pred | TaxInc |
|---|---------|--------|
| 0 | 1 | 1 |
| 1 | 1 | 1 |
| 2 | 1 | 1 |
| 3 | 1 | 1 |
| 4 | 1 | 1 |

```
In [49]:
kl['TaxInc']
Out[49]:
       1
1
       1
2
       1
3
       1
4
       1
595
       1
596
       1
597
       1
       1
598
599
Name: TaxInc, Length: 600, dtype: int32
In [50]:
from sklearn.metrics import confusion_matrix
In [51]:
confusion_matrix(kl['TaxInc'],kl['rf_pred'])
Out[51]:
array([[117, 6], [ 0, 477]], dtype=int64)
In [52]:
pd.crosstab(kl['TaxInc'],kl['rf_pred'])
Out[52]:
rf_pred
              1
 TaxInc
     0 117
          0 477
```

In [53]:

```
kl['rf_pred']
```

Out[53]:

0 1
1 1
2 1
3 1
4 1
 ...
595 1
596 1
597 1
598 1
599 1

Name: rf_pred, Length: 600, dtype: int32

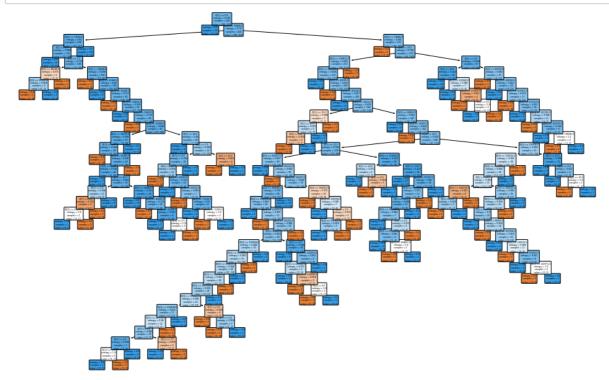
In [54]:

```
print('Accuracy',(477+117)/(477+117+6+0)*100)
```

Accuracy 99.0

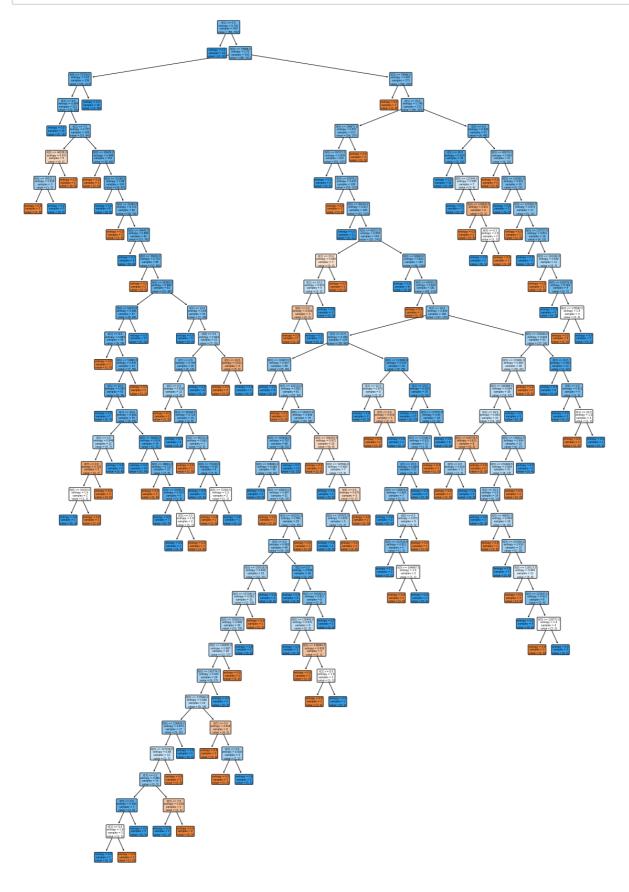
In [55]:

```
# prepare a plot figure with set size
from sklearn.tree import plot_tree
from matplotlib import pyplot as plt
plt.figure(figsize=(16,10))
plot_tree(dc_model,rounded=True,filled=True)
plt.show()
```



In [56]:

```
plt.figure(figsize=(20,30))
plot_tree(dc_model,rounded=True,filled=True)
plt.show()
```



| In []: | | | |
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