!pip install category_encoders
import category_encoders as ce

import pandas as pd

from sklearn import datasets

import numpy as np

from sklearn.model selection import KFold

from sklearn.model_selection import cross_val_score
from sklearn.ensemble import RandomForestClassifier

from sklearn.tree import DecisionTreeClassifier

import warnings

warnings.filterwarnings("ignore")

Requirement already satisfied: scikit-learn>=0.20.0 in c:\users\acer\anaconda3\lib\site-packages (from ca tegory encoders) (0.23.2)

Requirement already satisfied: patsy>=0.5.1 in c:\users\acer\anaconda3\lib\site-packages (from category_e ncoders) (0.5.1)

Requirement already satisfied: pandas>=0.21.1 in c:\users\acer\anaconda3\lib\site-packages (from category $_$ encoders) (1.1.3)

Requirement already satisfied: statsmodels>=0.9.0 in c:\users\acer\anaconda3\lib\site-packages (from cate gory encoders) (0.12.0)

Requirement already satisfied: scipy>=1.0.0 in c:\users\acer\anaconda3\lib\site-packages (from category_e ncoders) (1.5.2)

Requirement already satisfied: numpy>=1.14.0 in c:\users\acer\anaconda3\lib\site-packages (from category_encoders) (1.19.2)

Requirement already satisfied: threadpoolctl>=2.0.0 in c:\users\acer\anaconda3\lib\site-packages (from sc ikit-learn>=0.20.0->category_encoders) (2.1.0)

Requirement already satisfied: joblib>=0.11 in c:\users\acer\anaconda3\lib\site-packages (from scikit-lea rn>=0.20.0->category encoders) (0.17.0)

Requirement already satisfied: six in c:\users\acer\anaconda3\lib\site-packages (from patsy>=0.5.1->categ ory encoders) (1.15.0)

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: pytz>=2017.2 in c:\users\acer\anaconda3\lib\site-packages (from pandas>=0. 21.1->category encoders) (2020.1)

[▲]
In [2]:

import fraud check set

fc = pd.read_csv('/Users/acer/Sandesh Pal/Data Science Assgn/random Forest/Fraud_check.csv')

In [3]:

Out[3]:

fc

	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

158137

16

NO

600 rows × 6 columns

NO

599

In [4]:

checking for null values
fc.info()

Divorced

96519

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 600 entries, 0 to 599
Data columns (total 6 columns):
 # Column
                      Non-Null Count Dtype
                        _____
     ----
     Undergrad
                        600 non-null
                                          object
     Marital.Status 600 non-null
1
                                          object
    Taxable.Income 600 non-null
                                          int64
    City.Population 600 non-null
   Work.Experience 600 non-null
                                         int64
 4
    Urban
                        600 non-null
                                          object
dtypes: int64(3), object(3)
memory usage: 28.2+ KB
                                                                                                                 In [5]:
fc.describe()
                                                                                                                Out[5]:
      Taxable.Income City.Population Work.Experience
count
         600.000000
                      600.000000
                                    600.000000
 mean
       55208.375000 108747.368333
                                     15.558333
       26204.827597
                    49850.075134
                                      8.842147
       10003.000000
                    25779.000000
                                      0.000000
  min
 25%
       32871.500000
                    66966.750000
                                      8.000000
 50%
       55074.500000 106493.500000
                                     15.000000
 75%
       78611.750000 150114.250000
                                     24.000000
       99619.000000 199778.000000
                                     30.000000
                                                                                                                 In [6]:
import category encoders as ce
# encode variables with ordinal encoding
encoder = ce.OrdinalEncoder(cols=['Undergrad', 'Marital.Status', 'Urban'])
fc1 = encoder.fit transform(fc)
                                                                                                                 In [8]:
# Converting the Target column i.e. Taxable Income into Categorical value
tax val = []
for value in fc["Taxable.Income"]:
     if value<=30000:</pre>
         tax_val.append("Risky")
         tax_val.append("Good")
fc1["tax_val"]= tax_val
                                                                                                                 In [9]:
fc1
                                                                                                                Out[9]:
     Undergrad Marital.Status Taxable.Income City.Population Work.Experience Urban tax_val
                                 68833
                                              50047
           1
                        1
                                                               10
                                                                      1
                                                                          Good
                        2
                                 33700
                                             134075
                                                                          Good
                                 36925
  2
            1
                        3
                                             160205
                                                               30
                                                                      1
                                                                          Good
  3
                                 50190
                                             193264
                                                               15
                                                                          Good
  4
            1
                        3
                                 81002
                                              27533
                                                               28
                                                                      2
                                                                          Good
  ...
                       ...
                                                                      ...
595
            2
                        2
                                 76340
                                              39492
                                                                7
                                                                      1
                                                                          Good
                        2
                                 69967
596
                                              55369
                                                                      1
                                                                          Good
597
                        2
                                 47334
                                             154058
                                                                0
                                                                      1
                                                                          Good
                        3
                                 98592
598
                                             180083
                                                               17
                                                                      2
                                                                          Good
599
                        2
                                 96519
                                             158137
                                                               16
                                                                      2
                                                                          Good
```

600 rows × 7 columns

```
x = fc1.drop(['tax val','Taxable.Income'], axis =1)
y = fc1['tax_val']
                                                                                                         In [11]:
x.head()
                                                                                                        Out[11]:
   Undergrad Marital.Status City.Population Work.Experience Urban
                     1
                             50047
0
         2
                     2
                             134075
                                             18
                     3
                             160205
                                             30
         2
                     1
                            193264
                                             15
         1
                     3
                             27533
                                             28
                                                    2
                                                                                                         In [12]:
y.value counts()
                                                                                                        Out[12]:
Good
         476
Risky
         124
Name: tax val, dtype: int64
Random Forest Classification
                                                                                                         In [13]:
num trees = 100
max features = 4
kfold = KFold(n_splits=20)
model = RandomForestClassifier(n estimators=num trees, max features=max features)
results = cross_val_score(model, x, y, cv=kfold)
print(results.mean())
0.7500000000000001
lets use the various ensemble techniques to check the accuracy %
Bagging
                                                                                                         In [15]:
# Bagged Decision Trees for Classification
from sklearn.ensemble import BaggingClassifier
kfold = KFold(n_splits=20, random_state=seed)
cart = DecisionTreeClassifier()
num trees = 100
model = BaggingClassifier(base_estimator=cart, n_estimators=num_trees, random_state=seed)
results = cross val score (model, x, y, cv=kfold)
print(results.mean())
0.73500000000000001
```

Boosting

In [16]:

```
# AdaBoost Classification
from sklearn.ensemble import AdaBoostClassifier
num_trees = 100
seed=7
kfold = KFold(n_splits=20, random_state=seed)
model = AdaBoostClassifier(n_estimators=num_trees, random_state=seed)
results = cross_val_score(model, x, y, cv=kfold)
print(results.mean())
0.7733333333333333335
```

Stacking

```
# Stacking Ensemble for Classification
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.svm import SVC
```

In [17]:

```
# create the sub models
estimators = []
model1 = LogisticRegression(max_iter=500)
estimators.append(('logistic', model1))
model2 = DecisionTreeClassifier()
estimators.append(('cart', model2))
model3 = SVC()
estimators.append(('svm', model3))
# create the ensemble model
ensemble = VotingClassifier(estimators)
results = cross_val_score(ensemble, x, y, cv=kfold)
print(results.mean())
0.79333333333333333334
```

In [18]:

In []: