Loan Repayment Prediction

Importing Libraries

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split
import warnings
warnings.filterwarnings('ignore')
from sklearn.model_selection import StratifiedKFold
kFold = StratifiedKFold(n_splits=5)
from sklearn.model_selection import GridSearchCV
from sklearn.preprocessing import StandardScaler
from  sklearn.metrics  import  accuracy_score , precision_score , recall_score,confusion_matrix,classification_
```

Reading file

In [5]:
```
df = pd.read_csv("loan_data.csv")
df.head()
```

Out[5]:

	credit.policy	purpose	int.rate	installment	log.annual.inc	dti	fico	days.with.cr.line	revol.bal	revol.util	inq.last.6mths	delinq.:
0	1	debt_consolidation	0.1189	829.10	11.350407	19.48	737	5639.958333	28854	52.1	0	
1	1	credit_card	0.1071	228.22	11.082143	14.29	707	2760.000000	33623	76.7	0	
2	1	debt_consolidation	0.1357	366.86	10.373491	11.63	682	4710.000000	3511	25.6	1	
3	1	debt_consolidation	0.1008	162.34	11.350407	8.10	712	2699.958333	33667	73.2	1	
4	1	credit_card	0.1426	102.92	11.299732	14.97	667	4066.000000	4740	39.5	0	

In [6]:
```
# Consise Summery

df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9578 entries, 0 to 9577
Data columns (total 14 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   credit.policy      9578 non-null   int64  
 1   purpose            9578 non-null   object 
 2   int.rate           9578 non-null   float64
 3   installment        9578 non-null   float64
 4   log.annual.inc     9578 non-null   float64
 5   dti                9578 non-null   float64
 6   fico               9578 non-null   int64  
 7   days.with.cr.line  9578 non-null   float64
 8   revol.bal          9578 non-null   int64  
 9   revol.util         9578 non-null   float64
 10  inq.last.6mths     9578 non-null   int64  
 11  delinq.2yrs        9578 non-null   int64  
 12  pub.rec            9578 non-null   int64  
 13  not.fully.paid     9578 non-null   int64  
dtypes: float64(6), int64(7), object(1)
memory usage: 1.0+ MB
```

Here we can see that attribute purpose has object datatype. We need to deal with it.

In [7]:
```
# Summery
df.describe()
```

Out[7]:

	credit.policy	int.rate	installment	log.annual.inc	dti	fico	days.with.cr.line	revol.bal	revol.util	inq.last.
count	9578.000000	9578.000000	9578.000000	9578.000000	9578.000000	9578.000000	9578.000000	9.578000e+03	9578.000000	9578.(
mean	0.804970	0.122640	319.089413	10.932117	12.606679	710.846314	4560.767197	1.691396e+04	46.799236	1.5
std	0.396245	0.026847	207.071301	0.614813	6.883970	37.970537	2496.930377	3.375619e+04	29.014417	2.2
min	0.000000	0.060000	15.670000	7.547502	0.000000	612.000000	178.958333	0.000000e+00	0.000000	0.(
25%	1.000000	0.103900	163.770000	10.558414	7.212500	682.000000	2820.000000	3.187000e+03	22.600000	0.(
50%	1.000000	0.122100	268.950000	10.928884	12.665000	707.000000	4139.958333	8.596000e+03	46.300000	1.(
75%	1.000000	0.140700	432.762500	11.291293	17.950000	737.000000	5730.000000	1.824950e+04	70.900000	2.(
max	1.000000	0.216400	940.140000	14.528354	29.960000	827.000000	17639.958330	1.207359e+06	119.000000	33.(

Checking For Null Values

In [8]:
```
df.isnull().sum().sum()
```

Out[8]:
```
0
```

Our DataFrame contain **Zero** Null values.

Now lets solve the problem with **Purpose** Attribute.

In [9]:
```
# unique values in purpose attribute

df.purpose.value_counts()
```

Out[9]:
```
purpose
debt_consolidation    3957
all_other             2331
credit_card           1262
home_improvement       629
small_business         619
major_purchase         437
educational            343
Name: count, dtype: int64
```

It has **6 unique values**. lets convert these labels into numeric form.

Encoding

- We will be using **Label Encoder** to convert labels available in purpose attribute.
- It will Encode purpose labels with value between 0 and n_classes-1(5).

In [10]:
```
df['purpose']=LabelEncoder().fit_transform(df['purpose'])
df.head()
```

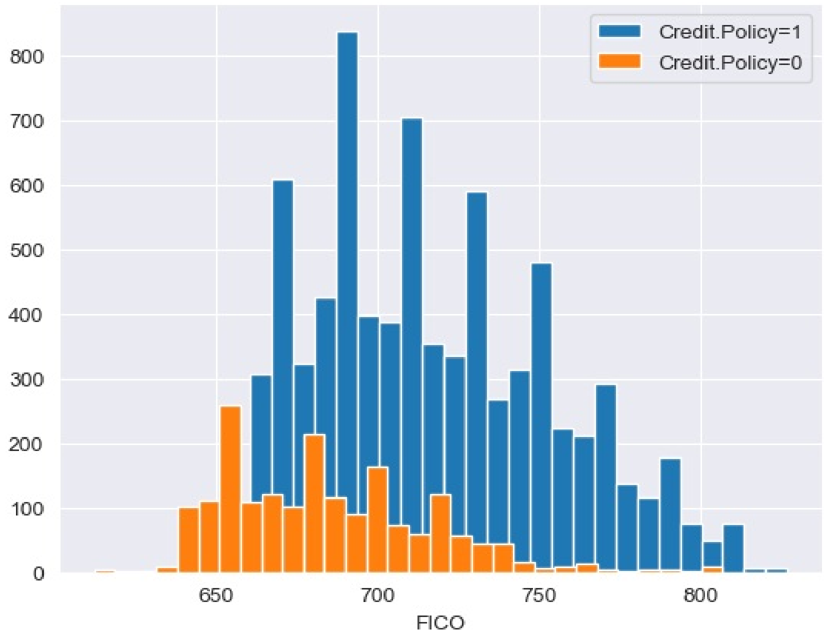
Out[10]:

	credit.policy	purpose	int.rate	installment	log.annual.inc	dti	fico	days.with.cr.line	revol.bal	revol.util	inq.last.6mths	delinq.2yrs	pul
0	1	2	0.1189	829.10	11.350407	19.48	737	5639.958333	28854	52.1	0	0	
1	1	1	0.1071	228.22	11.082143	14.29	707	2760.000000	33623	76.7	0	0	
2	1	2	0.1357	366.86	10.373491	11.63	682	4710.000000	3511	25.6	1	0	
3	1	2	0.1008	162.34	11.350407	8.10	712	2699.958333	33667	73.2	1	0	
4	1	1	0.1426	102.92	11.299732	14.97	667	4066.000000	4740	39.5	0	1	

Data Visualization

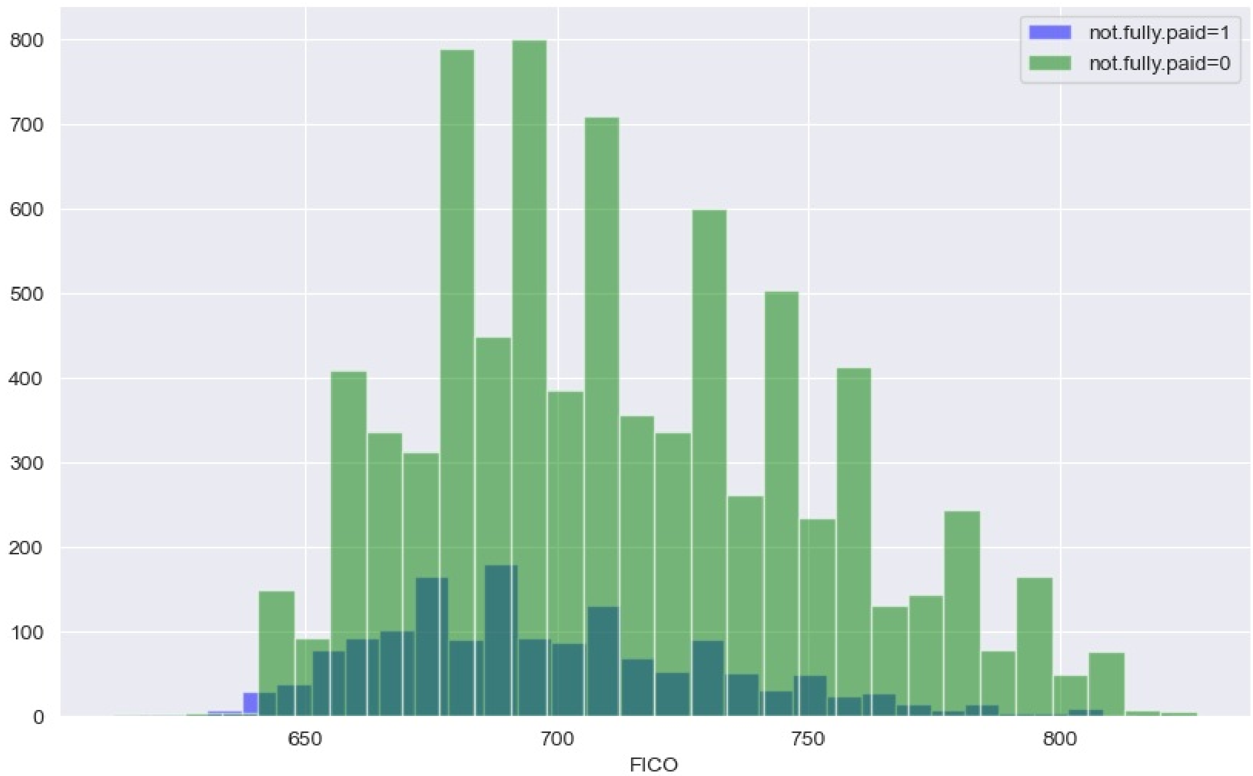
In [11]:
```
sns.set_style('darkgrid')
plt.hist(df['fico'].loc[df['credit.policy']==1], bins=30, label='Credit.Policy=1')
plt.hist(df['fico'].loc[df['credit.policy']==0], bins=30, label='Credit.Policy=0')
plt.legend()
plt.xlabel('FICO')
```

Out[11]:
```
Text(0.5, 0, 'FICO')
```



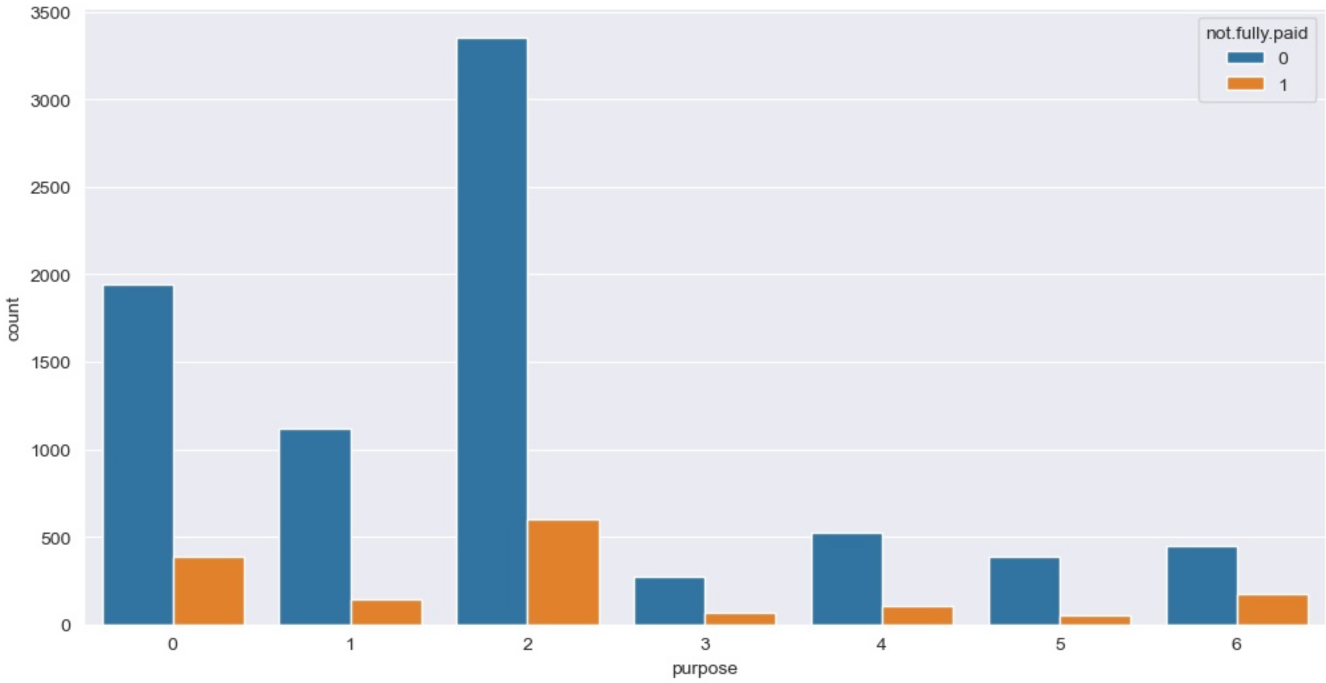
In [12]:
```
plt.figure(figsize=(10,6))
df[df['not.fully.paid']==1]['fico'].hist(bins=30, alpha=0.5, color='blue', label='not.fully.paid=1')
df[df['not.fully.paid']==0]['fico'].hist(bins=30, alpha=0.5, color='green', label='not.fully.paid=0')
plt.legend()
plt.xlabel('FICO')
```

Out[12]:
```
Text(0.5, 0, 'FICO')
```



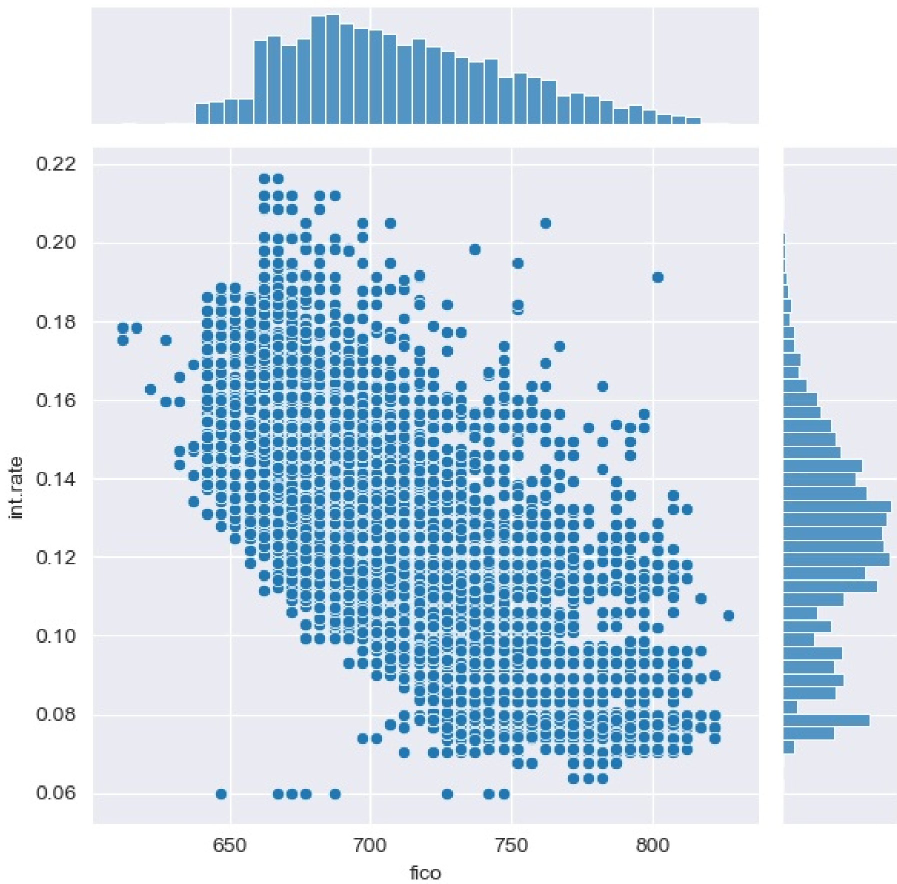
In [13]:
```
#creating a countplot to see the counts of purpose of loans by not.fully.paid
plt.figure(figsize=(12,6))
sns.countplot(data=df, x='purpose', hue='not.fully.paid')
```

Out[13]:
```
<Axes: xlabel='purpose', ylabel='count'>
```



In [14]:
```
#checking the trend between FICO and the interest rate
plt.figure(figsize=(10,6))
sns.jointplot(x='fico', y='int.rate', data=df)
```

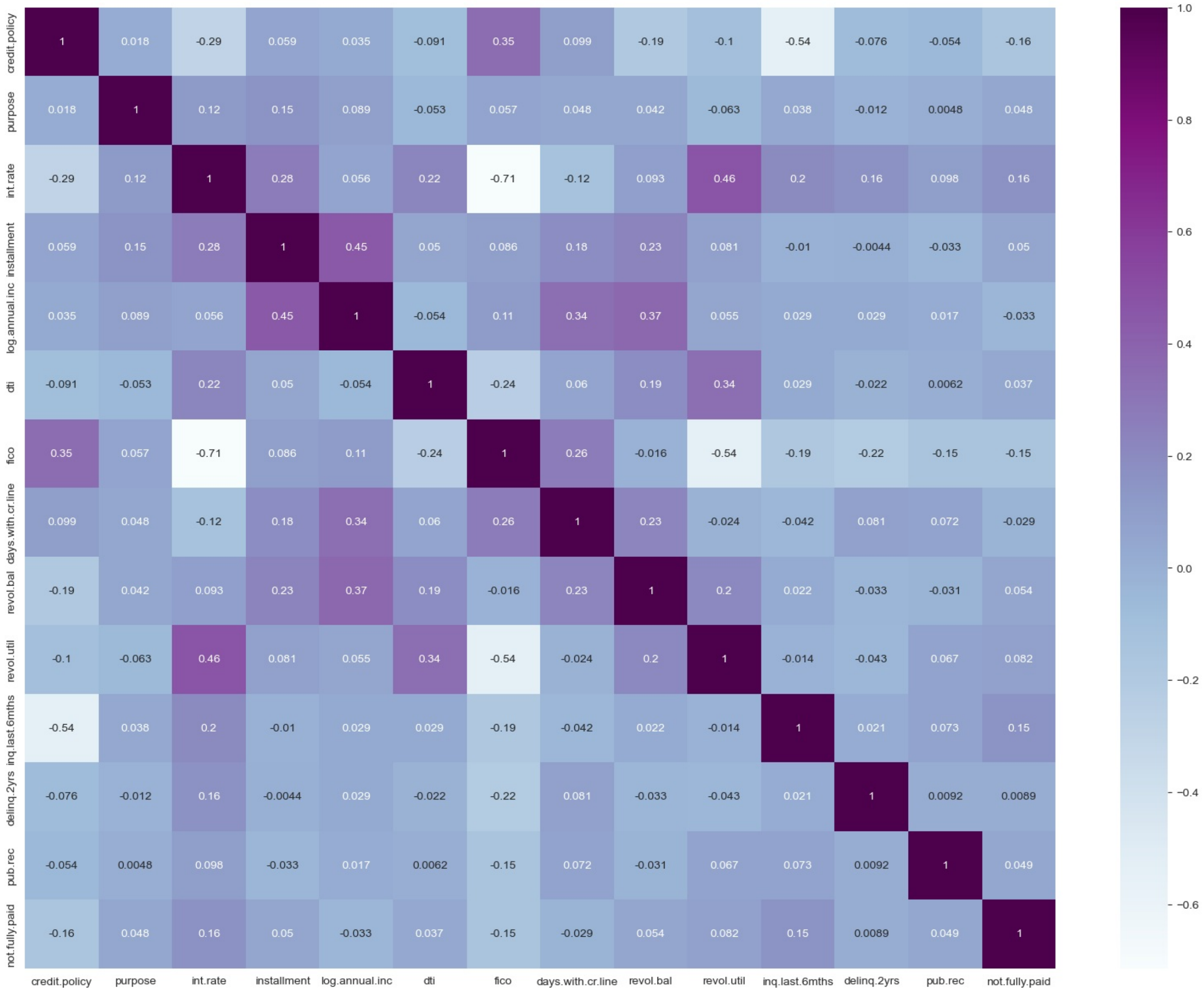
Out[14]:
```
<seaborn.axisgrid.JointGrid at 0x1eca0795410>

<Figure size 1000x600 with 0 Axes>
```



In [15]:
```
#understanding the relationship between credit.policy and not.fully.paid
sns.lmplot(data=df, x='fico', y='int.rate', hue='credit.policy', col='not.fully.paid', palette='Set2')
```

Out[15]: <seaborn.axisgrid.FacetGrid at 0x1eca09a1690>

In [16]:
```
plt.figure(figsize = (20, 15))
sns.heatmap(df.corr(), cmap='BuPu', annot=True)
plt.show()
```



We can see that **init rate, credit policy, fico and inq.last.6mths** has corresponding grater impact on target class(not.gully.paid)

Train-Test Split

Splitting the dataset for training and testing purpose.

In [17]:
```
# Dropping target class

X = df.drop('not.fully.paid',axis=1)
y = df['not.fully.paid']
```

In [18]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3,random_state=101)
```

Modelling

Decision Tree

In [19]:
```
from sklearn.tree import DecisionTreeClassifier

dt_clf = DecisionTreeClassifier()
param_grid = {'max_depth': [2,3, 4,5,6,7,8,9,10,11,13,15,20]}

grid_search = GridSearchCV(dt_clf,
                           param_grid, scoring = 'recall_weighted',
                           cv=kFold,
                           return_train_score=True)
grid_search.fit(X_train,y_train)
```

Out[19]:
```
▸ GridSearchCV
▸ estimator: DecisionTreeClassifier
    ▸ DecisionTreeClassifier
```

In [20]:
```
grid_search.best_params_
```

```
In [20]: grid_search.best_params_
```

```
Out[20]: {'max_depth': 2}
```

```
In [21]: dt_clf = DecisionTreeClassifier(max_depth=2)
dt_clf.fit(X_train, y_train)
y_pred_train = dt_clf.predict(X_train)
y_pred_test = dt_clf.predict(X_test)

train_accuracy = accuracy_score(y_train, y_pred_train)
test_accuracy = accuracy_score(y_test, y_pred_test)
```

```
In [22]: print("Confusion Matrix \n",confusion_matrix(y_test,y_pred_test))
print("\n")
print("<-------------------Classification Report---------------------->\n")
print(classification_report(y_test,y_pred_test))
print("\n")
print("<---------------Accuracy Scores------------------->\n")
print('Train Accuracy score: ',train_accuracy)
print('Test Accuracy score:',test_accuracy)
```

```
Confusion Matrix
 [[2431    0]
 [ 443    0]]


<-------------------Classification Report---------------------->

              precision    recall  f1-score   support

           0       0.85      1.00      0.92      2431
           1       0.00      0.00      0.00       443

    accuracy                           0.85      2874
   macro avg       0.42      0.50      0.46      2874
weighted avg       0.72      0.85      0.78      2874



<---------------Accuracy Scores------------------->

Train Accuracy score:  0.8374105011933174
Test Accuracy score: 0.8458594293667363
```

We got **Accuracy of 84.58%** using Decision Tree Classifier.

Bagging with Decision Tree

```
In [23]: from sklearn.ensemble import BaggingClassifier
from sklearn.model_selection import cross_val_score
scaler=StandardScaler()
X_scaled = scaler.fit_transform(X)
bag_dt = BaggingClassifier(base_estimator=DecisionTreeClassifier(max_depth=2),n_estimators=100,bootstrap=True)
score = cross_val_score(estimator=bag_dt, X=X_scaled, y=y, scoring='recall_weighted', cv=kFold, n_jobs=-1)
print('Mean score:', score.mean())
```

```
Mean score: 0.7310162599410215
```

Bagging is not improving the score of model and giving only **73.10% of mean Score.**

AdaBoosting with Decision Tree

```
In [24]: from sklearn.ensemble import AdaBoostClassifier

adaboost_clf = AdaBoostClassifier(base_estimator = DecisionTreeClassifier(max_depth=2), learning_rate = 0.5)
adaboost_clf.fit(X_train, y_train)
print('Train score: {0:0.2f}'.format(adaboost_clf.score(X_train, y_train)))
print('Test score: {0:0.2f}'.format(adaboost_clf.score(X_test, y_test)))
```

```
Train score: 0.85
Test score: 0.84
```

It giving the same result of **84%** and not improving our Model.

Random Forest Classifier

```
In [25]: from sklearn.ensemble import RandomForestClassifier
rf_clf = RandomForestClassifier(n_estimators=600)
rf_clf.fit(X_train, y_train)
y_pred_train = rf_clf.predict(X_train)
y_pred_test = rf_clf.predict(X_test)

train_accuracy = accuracy_score(y_train, y_pred_train)
test_accuracy = accuracy_score(y_test, y_pred_test)
```

In [26]:
```
print("Confusion Matrix \n",confusion_matrix(y_test,y_pred_test))
print("\n")
print("<-------------------Classification Report--------------------->\n")
print(classification_report(y_test,y_pred_test))
print("\n")
print("<---------------Accuracy Scores------------------->\n")
#print('Train Accuracy score: ',train_accuracy)
print('Test Accuracy score:',test_accuracy)
```

```
Confusion Matrix
 [[2424    7]
 [ 432   11]]


<-------------------Classification Report--------------------->

              precision    recall  f1-score   support

           0       0.85      1.00      0.92      2431
           1       0.61      0.02      0.05       443

    accuracy                           0.85      2874
   macro avg       0.73      0.51      0.48      2874
weighted avg       0.81      0.85      0.78      2874



<---------------Accuracy Scores------------------->

Test Accuracy score: 0.8472512178148921
```

We got the **Accuracy of 84.7%** with random Forest Classifier

AdaBoosting with RandomForest

In [27]:
```
from sklearn.ensemble import AdaBoostClassifier
adaboost_clf = AdaBoostClassifier(base_estimator = rf_clf, learning_rate = 0.5)
adaboost_clf.fit(X_train, y_train)
#print('Train score: {0:0.2f}'.format(adaboost_clf.score(X_train, y_train)))
#print('Test score: {0:0.2f}'.format(adaboost_clf.score(X_test, y_test)))
y_pred_train = adaboost_clf.predict(X_train)
y_pred_test = adaboost_clf.predict(X_test)

train_accuracy = accuracy_score(y_train, y_pred_train)
test_accuracy = accuracy_score(y_test, y_pred_test)
```

In [28]:
```
print("Confusion Matrix \n",confusion_matrix(y_test,y_pred_test))
print("\n")
print("<-------------------Classification Report--------------------->\n")
print(classification_report(y_test,y_pred_test))
print("\n")
print("<---------------Accuracy Scores------------------->\n")
#print('Train Accuracy score: ',train_accuracy)
print('Test Accuracy score:',test_accuracy)
```

```
Confusion Matrix
 [[2423    8]
 [ 433   10]]


<-------------------Classification Report--------------------->

              precision    recall  f1-score   support

           0       0.85      1.00      0.92      2431
           1       0.56      0.02      0.04       443

    accuracy                           0.85      2874
   macro avg       0.70      0.51      0.48      2874
weighted avg       0.80      0.85      0.78      2874



<---------------Accuracy Scores------------------->

Test Accuracy score: 0.8465553235908142
```

Gradient Boosting

In [29]:
```
from sklearn.ensemble import GradientBoostingClassifier
gb_clf = GradientBoostingClassifier(learning_rate = 0.05)
gb_clf.fit(X_train, y_train)
#print('Train score: {0:0.2f}'.format(gb_clf.score(X_train, y_train)))
#print('Test score: {0:0.2f}'.format(gb_clf.score(X_test, y_test)))
y_pred_train = gb_clf.predict(X_train)
```

```
y_pred_test = gb_clf.predict(X_test)

train_accuracy = accuracy_score(y_train, y_pred_train)
test_accuracy = accuracy_score(y_test, y_pred_test)
```

In [30]:

```
print("Confusion Matrix \n",confusion_matrix(y_test,y_pred_test))
print("\n")
print("<-------------------Classification Report---------------------->\n")
print(classification_report(y_test,y_pred_test))
print("\n")
print("<---------------Accuracy Scores------------------->\n")
#print('Train Accuracy score: ',train_accuracy)
print('Test Accuracy score:',test_accuracy)
```

```
Confusion Matrix
 [[2420   11]
 [ 436    7]]


<-------------------Classification Report--------------------->

              precision    recall  f1-score   support

           0       0.85      1.00      0.92      2431
           1       0.39      0.02      0.03       443

    accuracy                           0.84      2874
   macro avg       0.62      0.51      0.47      2874
weighted avg       0.78      0.84      0.78      2874



<---------------Accuracy Scores------------------->

Test Accuracy score: 0.8444676409185804
```

While Computing different **Ensemble Learning Technologies**, We Found that Most of the **Bagging and Boosting** algo are giving similar result with minimum difference in accuracy. Even though in all these Ensembles-

We Found that the **Best Model for this DataSet is Random Forest with Accuracy of 85%.**