Loan Repayment Prediction Using Ensemble Learning Methods

Objective:

- Predicts whether the bank should approves the loan of an applicant based on his profit using Ensemble Learning Methods.

Submission by:-

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Importing Libraries

```
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_report
```

Reading file

```
df = pd.read_csv("/content/loan_data.csv")
df.head()
```

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

```
# 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.

```
# Summery
df.describe()
```

	credit.policy	int.rate	installment	log.annual.inc	dti	fico	days.with.cr.line	revol.bal	revol.util
count	9578.000000	9578.000000	9578.000000	9578.000000	9578.000000	9578.000000	9578.000000	9.578000e+03	9578.00000(
mean	0.804970	0.122640	319.089413	10.932117	12.606679	710.846314	4560.767197	1.691396e+04	46.79923(
std	0.396245	0.026847	207.071301	0.614813	6.883970	37.970537	2496.930377	3.375619e+04	29.01441(
min	0.000000	0.060000	15.670000	7.547502	0.000000	612.000000	178.958333	0.000000e+00	0.00000(
25%	1.000000	0.103900	163.770000	10.558414	7.212500	682.000000	2820.000000	3.187000e+03	22.60000(
50%	1.000000	0.122100	268.950000	10.928884	12.665000	707.000000	4139.958333	8.596000e+03	46.30000(
75%	1.000000	0.140700	432.762500	11.291293	17.950000	737.000000	5730.000000	1.824950e+04	70.90000(
max	1.000000	0.216400	940.140000	14.528354	29.960000	827.000000	17639.958330	1.207359e+06	119.00000(

Checking For Null Values

```
df.isnull().sum().sum()
```

```
0
```

Our DataFrame contain **Zero** Null values.

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

```
# unique values in purpose attribute

df.purpose.value_counts()
```

```
debt_consolidation    3957
all_other             2331
credit_card           1262
home_improvement       629
small_business         619
major_purchase         437
educational            343
Name: purpose, 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).

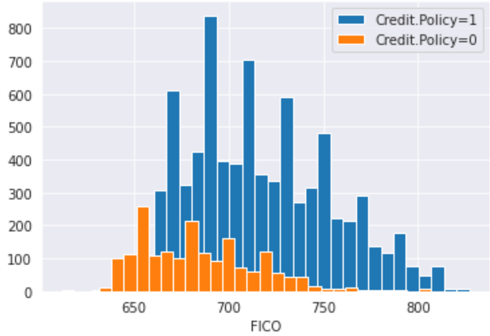
```
df['purpose']=LabelEncoder().fit_transform(df['purpose'])
df.head()
```

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

Data Visualization

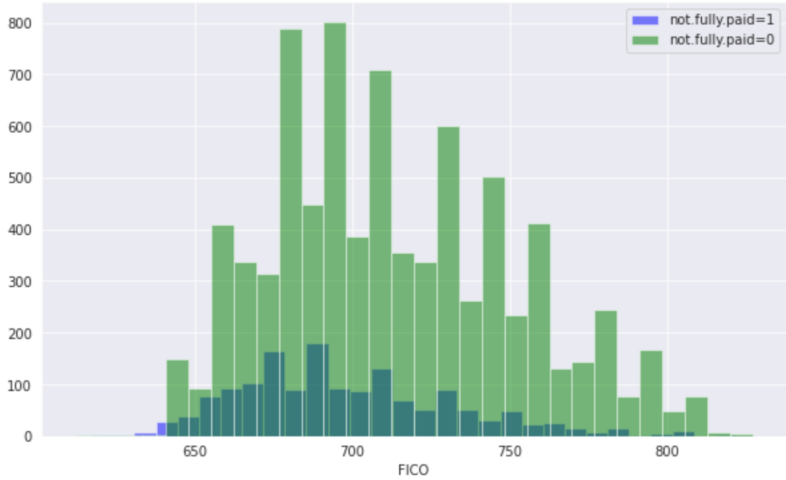
```
sns.set_style('darkgrid')
plt.hist(df['fico'].loc[df['credit.policy']==1], bins=30, label='Credit.Policy=1')
plt.hist(df['fico'].loc[df['credit.policy']==0], bins=30, label='Credit.Policy=0')
plt.legend()
plt.xlabel('FICO')
```

```
Text(0.5, 0, 'FICO')
```



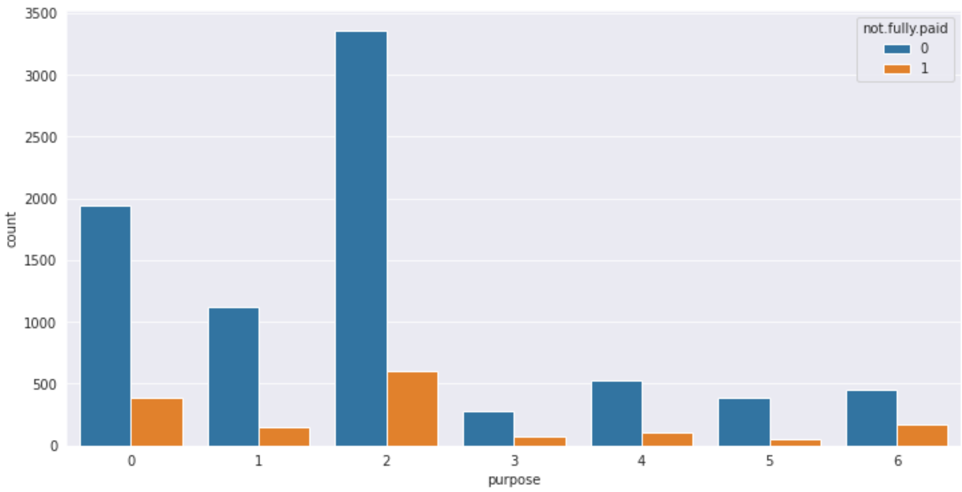

```
plt.figure(figsize=(10,6))
df[df['not.fully.paid']==1]['fico'].hist(bins=30, alpha=0.5, color='blue', label='not.fully.paid=1')
df[df['not.fully.paid']==0]['fico'].hist(bins=30, alpha=0.5, color='green', label='not.fully.paid=0')
plt.legend()
plt.xlabel('FICO')
```

```
Text(0.5, 0, 'FICO')
```



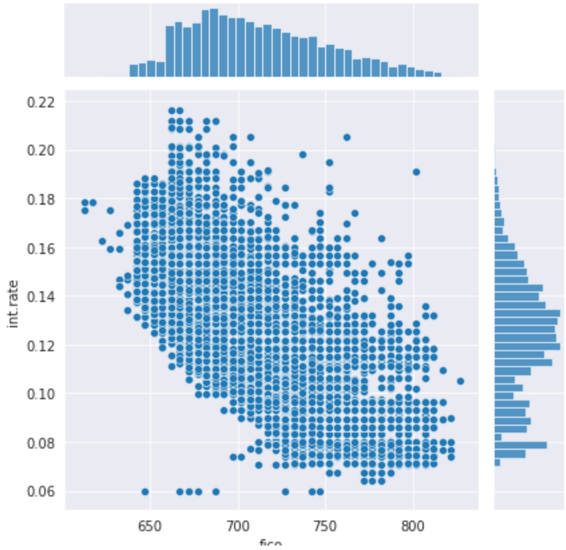

```
#creating a countplot to see the counts of purpose of loans by not.fully.paid
plt.figure(figsize=(12,6))
sns.countplot(data=df, x='purpose', hue='not.fully.paid')
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f52eb32f7f0>
```



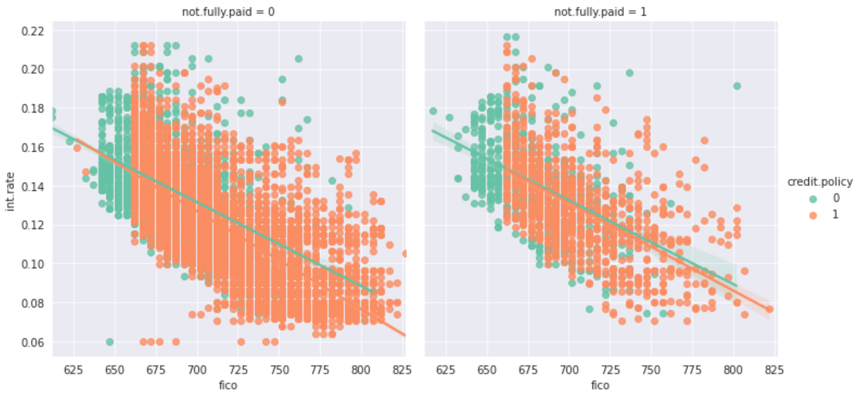

```
#checking the trend between FICO and the interest rate
plt.figure(figsize=(10,6))
sns.jointplot(x='fico', y='int.rate', data=df)
```

```
<seaborn.axisgrid.JointGrid at 0x7f52e9918e48>
<Figure size 720x432 with 0 Axes>
```

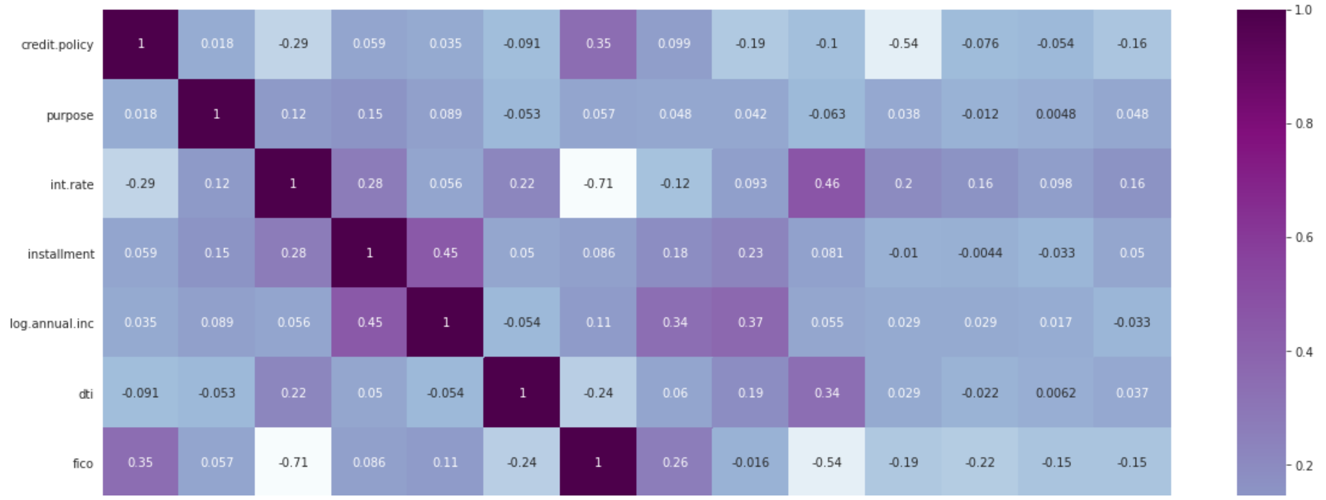



```
#understanding the relationship between credit.policy and not.fully.paid
sns.lmplot(data=df, x='fico', y='int.rate', hue='credit.policy', col='not.fully.paid', palette='Set2')
```

```
<seaborn.axisgrid.FacetGrid at 0x7f52e6eb8278>
```




```
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.

```
# Dropping target class

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

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3,random_state=101)
```

Modellng

Decision Tree

```
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)
```

```
    GridSearchCV(cv=StratifiedKFold(n_splits=5, random_state=None, shuffle=False),
                 error_score=nan,
                 estimator=DecisionTreeClassifier(ccp_alpha=0.0, class_weight=None,
                                                  criterion='gini', max_depth=None,
                                                  max_features=None,
                                                  max_leaf_nodes=None,
                                                  min_impurity_decrease=0.0,
                                                  min_impurity_split=None,
                                                  min_samples_leaf=1,
                                                  min_samples_split=2,
                                                  min_weight_fraction_leaf=0.0,
                                                  presort='deprecated',
                                                  random_state=None,
                                                  splitter='best'),
                 iid='deprecated', n_jobs=None,
                 param_grid={'max_depth': [2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 13, 15,
                                           20]},
                 pre_dispatch='2*n_jobs', refit=True, return_train_score=True,
                 scoring='recall_weighted', verbose=0)
```

```
grid_search.best_params_
```

```
    {'max_depth': 2}
```

```
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)


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

```
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

```
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

```
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)


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
 [[2427    4]
 [ 434    9]]


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

              precision    recall  f1-score   support

           0       0.85      1.00      0.92      2431
           1       0.69      0.02      0.04       443

    accuracy                           0.85      2874
   macro avg       0.77      0.51      0.48      2874
weighted avg       0.82      0.85      0.78      2874



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

Test Accuracy score: 0.8475991649269311
```

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

AdaBoosting with RandomForest

```
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)


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]
 [ 433   10]]


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

              precision    recall  f1-score   support

           0       0.85      1.00      0.92      2431
           1       0.59      0.02      0.04       443

    accuracy                           0.85      2874
   macro avg       0.72      0.51      0.48      2874
weighted avg       0.81      0.85      0.78      2874



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

```
Test Accuracy score: 0.8469032707028532
```

Gradient Boosting

```
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)


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
```

Upon analyzing several ensemble learning technologies, we discovered that the majority of bagging and boosting algorithms yield comparable results with negligible variations in accuracy. While in each of these Ensembles—

We discovered that Random Forest, with an accuracy of 85%, is the best model for this dataset.