



Micro Credit Loan Use Case

Submitted by:

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Thanks all.

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INTRODUCTION

- A Microfinance Institution (MFI) is an organization that offers financial services to low income populations. MFS becomes very useful when targeting especially the unbanked poor families living in remote areas with not much sources of income.
- the MFI industry is primarily focusing on low income families and are very useful in such areas, the implementation of MFS has been uneven with both significant challenges and successes.
- They understand the importance of communication and how it affects a person's life, thus, focusing on providing their services and products to low income families and poor customers that can help them in the need of hour.
- They are collaborating with an MFI to provide micro-credit on mobile balances to be paid back in 5 days. The Consumer is believed to be defaulter if he deviates from the path of paying back the loaned amount within the time duration of 5 days.
- The sample data is provided to us from our client database. It is hereby given to you for this exercise. In order to improve the selection of customers for the credit, the client wants some predictions that could help them in further investment and improvement in selection of customers

Analytical Problem Framing

- Import library and load the dataset.

```
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

import warnings
warnings.filterwarnings('ignore')
```

```
import pandas as pd
df = pd.read_csv('Data file.csv')
df
```

Unnamed: 0	label	msisdn	aon	daily_decr30	daily_decr90	rental30	rental90	last_rech_date_ma	last_rech_date_da	...	maxamnt_loans30	mec
0	1	0	21408170789	272.0	3055.050000	3055.150000	220.13	260.13	2.0	0.0	...	6.0
1	2	1	76482170374	712.0	12122.000000	12124.750000	3691.26	3691.26	20.0	0.0	...	12.0
2	3	1	17943170372	535.0	1398.000000	1398.000000	900.13	900.13	3.0	0.0	...	6.0
3	4	1	56773170781	241.0	21.228000	21.228000	159.42	159.42	41.0	0.0	...	6.0
4	5	1	03813182730	947.0	150.619333	150.619333	1098.90	1098.90	4.0	0.0	...	6.0
...
209588	209589	1	22758185348	404.0	151.872333	151.872333	1089.19	1089.19	1.0	0.0	...	6.0
209589	209590	1	95583184455	1075.0	36.936000	36.936000	1728.36	1728.36	4.0	0.0	...	6.0
209590	209591	1	28558185350	1013.0	11843.111667	11904.350000	5881.83	5883.20	3.0	0.0	...	12.0
209591	209592	1	59712182733	1732.0	12488.228333	12574.370000	411.83	984.58	2.0	38.0	...	12.0
209592	209593	1	65061185339	1581.0	4489.362000	4534.820000	483.92	631.20	13.0	0.0	...	12.0

209593 rows x 37 columns

```
: #checking data dimension
df.shape
: (209593, 37)
```

```
: #display columns of dataframe
df.columns
: Index(['Unnamed: 0', 'label', 'msisdn', 'aon', 'daily_decr30', 'daily_decr90',
        'rental30', 'rental90', 'last_rech_date_ma', 'last_rech_date_da',
        'last_rech_amt_ma', 'cnt_ma_rech30', 'fr_ma_rech30',
        'sumamnt_ma_rech30', 'medianamnt_ma_rech30', 'medianmarechprebal30',
        'cnt_ma_rech90', 'fr_ma_rech90', 'sumamnt_ma_rech90',
        'medianamnt_ma_rech90', 'medianmarechprebal90', 'cnt_da_rech30',
        'fr_da_rech30', 'cnt_da_rech90', 'fr_da_rech90', 'cnt_loans30',
        'amnt_loans30', 'maxamnt_loans30', 'medianamnt_loans30', 'cnt_loans90',
        'amnt_loans90', 'maxamnt_loans90', 'medianamnt_loans90', 'payback30',
        'payback90', 'pcircle', 'pdate'],
        dtype='object')
```

```
: #drop unnamed column
df.drop('Unnamed: 0',axis=1,inplace=True)
df
```

label	msisdn	aon	daily_decr30	daily_decr90	rental30	rental90	last_rech_date_ma	last_rech_date_da	last_rech_amt_ma	...	maxamnt_loans
0	0	21408170789	272.0	3055.050000	3055.150000	220.13	260.13	2.0	0.0	1539	...
1	1	76482170374	712.0	12122.000000	12124.750000	3691.26	3691.26	20.0	0.0	5787	...
2	1	17943170372	535.0	1398.000000	1398.000000	900.13	900.13	3.0	0.0	1539	...
3	1	56773170781	241.0	21.228000	21.228000	159.42	159.42	41.0	0.0	947	...
4	1	03813182730	947.0	150.619333	150.619333	1098.90	1098.90	4.0	0.0	2309	...
...
209588	1	22758185348	404.0	151.872333	151.872333	1089.19	1089.19	1.0	0.0	4048	...
209589	1	95583184455	1075.0	36.936000	36.936000	1728.36	1728.36	4.0	0.0	773	...

- Display all column name of dataset.

```
#display datatypes of columns
df.dtypes
```

```
label          int64
msisdn         object
aon            float64
daily_decr30   float64
daily_decr90   float64
rental30       float64
rental90       float64
last_rech_date_ma float64
last_rech_date_da float64
last_rech_amt_ma int64
cnt_ma_rech30  int64
fr_ma_rech30   float64
sumamnt_ma_rech30 float64
medianamnt_ma_rech30 float64
medianmarechprebal30 float64
cnt_ma_rech90  int64
fr_ma_rech90   int64
sumamnt_ma_rech90 int64
medianamnt_ma_rech90 float64
medianmarechprebal90 float64
cnt_da_rech30  float64
fr_da_rech30   float64
cnt_da_rech90  int64
fr_da_rech90   int64
cnt_loans30    int64
amnt_loans30    int64
maxamnt_loans30 float64
medianamnt_loans30 float64
cnt_loans90    float64
amnt_loans90    int64
maxamnt_loans90 int64
medianamnt_loans90 float64
payback30      float64
payback90      float64
pcircle         object
pdate          object
dtype: object
```

```
#display information of columns
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 209593 entries, 0 to 209592
Data columns (total 36 columns):
#   Column                                Non-Null Count  Dtype
---  -
0   label                                209593 non-null int64
1   msisdn                              209593 non-null object
2   aon                                  209593 non-null float64
3   daily_decr30                        209593 non-null float64
4   daily_decr90                        209593 non-null float64
5   rental30                            209593 non-null float64
6   rental90                            209593 non-null float64
7   last_rech_date_ma                   209593 non-null float64
8   last_rech_date_da                   209593 non-null float64
9   last_rech_amt_ma                    209593 non-null int64
10  cnt_ma_rech30                       209593 non-null int64
11  fr_ma_rech30                        209593 non-null float64
12  sumamnt_ma_rech30                   209593 non-null float64
13  medianamnt_ma_rech30                 209593 non-null float64
14  medianmarechprebal30                 209593 non-null float64
15  cnt_ma_rech90                       209593 non-null int64
16  fr_ma_rech90                        209593 non-null int64
17  sumamnt_ma_rech90                   209593 non-null int64
18  medianamnt_ma_rech90                 209593 non-null float64
19  medianmarechprebal90                 209593 non-null float64
20  cnt_da_rech30                       209593 non-null float64
21  fr_da_rech30                        209593 non-null float64
22  cnt_da_rech90                       209593 non-null int64
23  fr_da_rech90                        209593 non-null int64
24  cnt_loans30                         209593 non-null int64
25  amnt_loans30                        209593 non-null int64
26  maxamnt_loans30                     209593 non-null float64
27  medianamnt_loans30                   209593 non-null float64
28  cnt_loans90                         209593 non-null float64
29  amnt_loans90                        209593 non-null int64
30  maxamnt_loans90                     209593 non-null int64
31  medianamnt_loans90                   209593 non-null float64
32  payback30                           209593 non-null float64
33  payback90                           209593 non-null float64
34  pcircle                             209593 non-null object
35  pdate                               209593 non-null object
dtypes: float64(21), int64(12), object(3)
memory usage: 57.6+ MB
```

- Display datatypes and sum of null values.

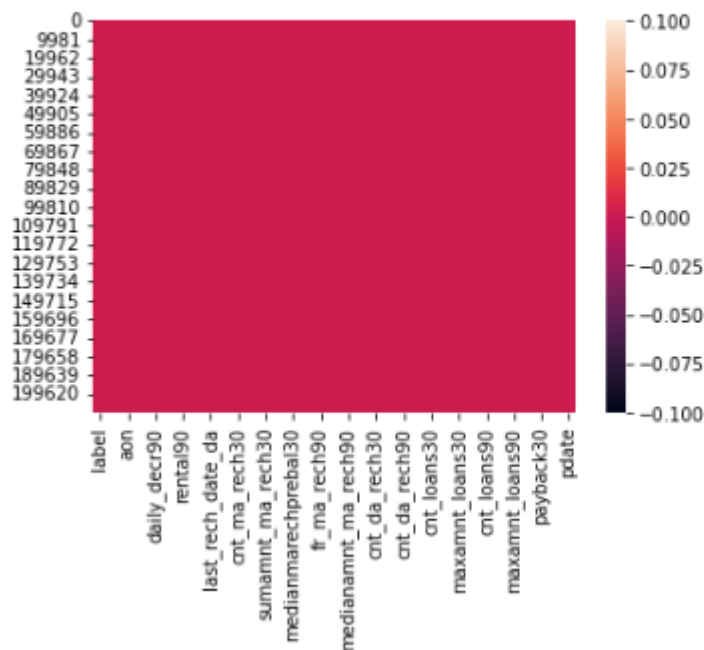
```
#display sum of null values in columns
df.isnull().sum()
```

```
label      0
msisdn     0
aon         0
daily_decr30  0
daily_decr90  0
rental30     0
rental90     0
last_rech_date_ma  0
last_rech_date_da  0
last_rech_amt_ma  0
cnt_ma_rech30  0
fr_ma_rech30  0
sumamnt_ma_rech30  0
medianamnt_ma_rech30  0
medianmarechprebal30  0
cnt_ma_rech90  0
fr_ma_rech90  0
sumamnt_ma_rech90  0
medianamnt_ma_rech90  0
medianmarechprebal90  0
cnt_da_rech30  0
fr_da_rech30  0
cnt_da_rech90  0
fr_da_rech90  0
cnt_loans30  0
amnt_loans30  0
maxamnt_loans30  0
medianamnt_loans30  0
cnt_loans90  0
amnt_loans90  0
maxamnt_loans90  0
medianamnt_loans90  0
payback30    0
payback90    0
pcircle      0
pdate        0
dtype: int64
```

- Display null values of columns using heatmap.

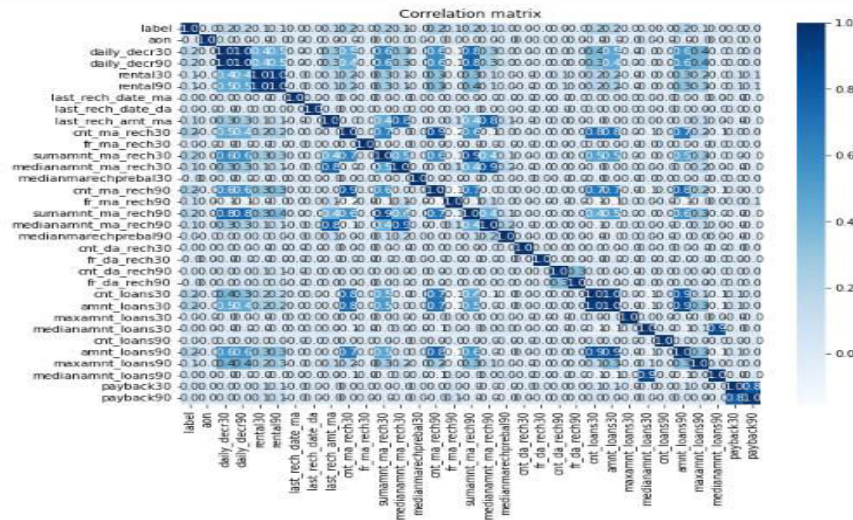
```
: #display heatmap of null values in columns
sns.heatmap(df.isnull())
```

```
: <AxesSubplot:>
```



- Display correlation of columns using heatmap.

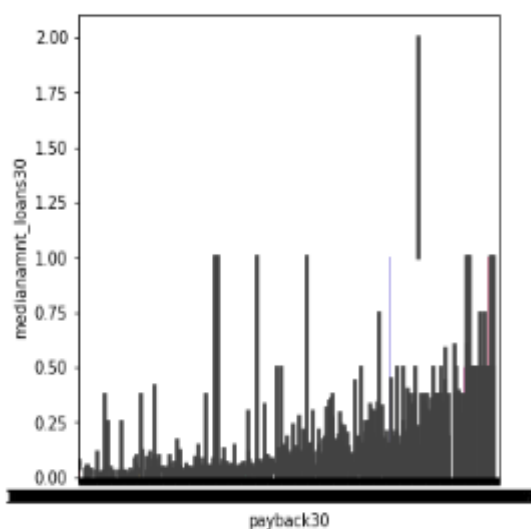
```
corr_mat = df.corr()
plt.figure(figsize=(10,8))
sns.heatmap(corr_mat, annot=True, fmt = '.1f', cmap = 'Blues')
plt.title('Correlation matrix')
plt.show()
```



- Display barplot of all columns.

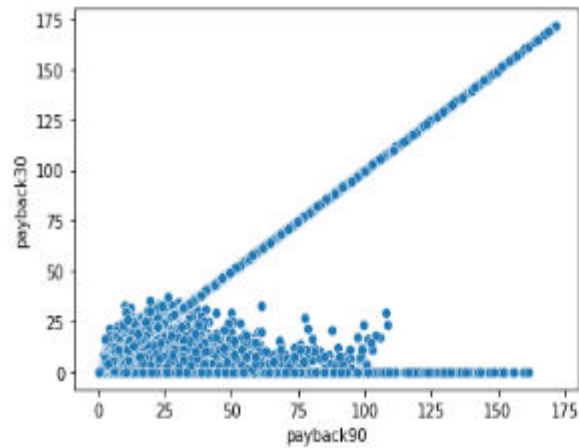
```
: #citric acid vs Quality
plot = plt.figure(figsize=(5,5))
sns.barplot(x='payback30',y='medianamnt_loans30', data=df)

: <AxesSubplot: xlabel='payback30', ylabel='medianamnt_loans30'>
```



- Display Scatterplot of payback30column.

```
: sns.scatterplot(x='payback90',y='payback30',data=df)
plt.show()
```



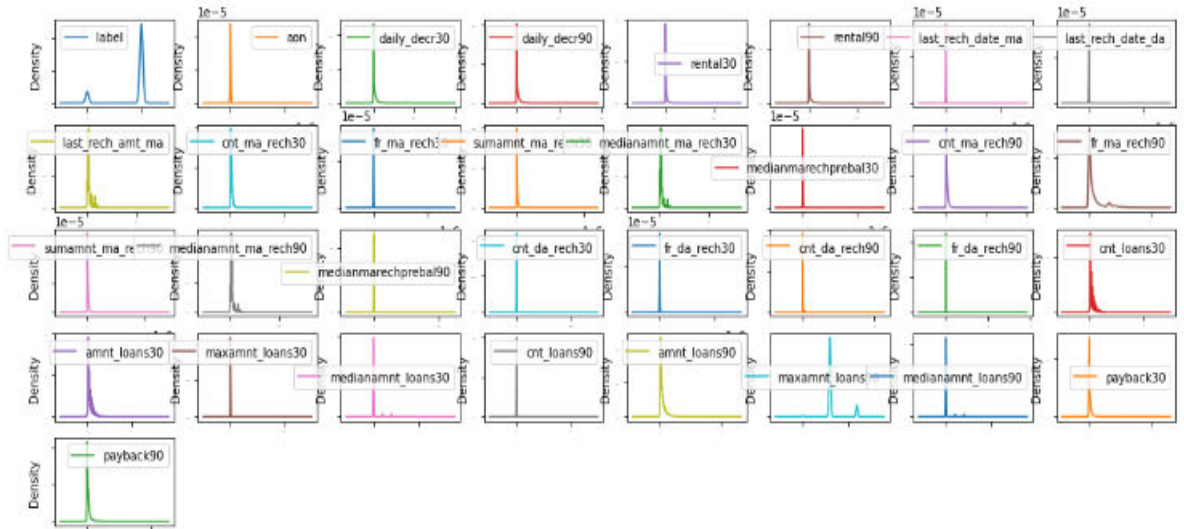
- Display statistical summary.

```
#statistical summary.
df.describe().style.background_gradient()
```

	label	aon	daily_decr30	daily_decr90	rental30	rental90	last_rech_date_ma	last_rech_date_da	last_rech_amt_ma	cr
count	209593.000000	209593.000000	209593.000000	209593.000000	209593.000000	209593.000000	209593.000000	209593.000000	209593.000000	2
mean	0.875177	8112.343445	5381.402289	8082.515068	2892.581910	3483.408534	3755.847800	3712.202921	2064.452797	
std	0.330519	75898.082631	9220.823400	10918.812787	4308.588781	5770.481279	53905.892230	53374.833430	2370.788034	
min	0.000000	-48.000000	-93.012887	-93.012887	-23737.140000	-24720.580000	-29.000000	-29.000000	0.000000	
25%	1.000000	246.000000	42.440000	42.692000	280.420000	300.280000	1.000000	0.000000	770.000000	
50%	1.000000	527.000000	1489.175887	1500.000000	1083.570000	1334.000000	3.000000	0.000000	1539.000000	
75%	1.000000	982.000000	7244.000000	7802.790000	3356.940000	4201.790000	7.000000	0.000000	2309.000000	
max	1.000000	999880.755188	265926.000000	320830.000000	198926.110000	200148.110000	998850.377733	999171.809410	55000.000000	

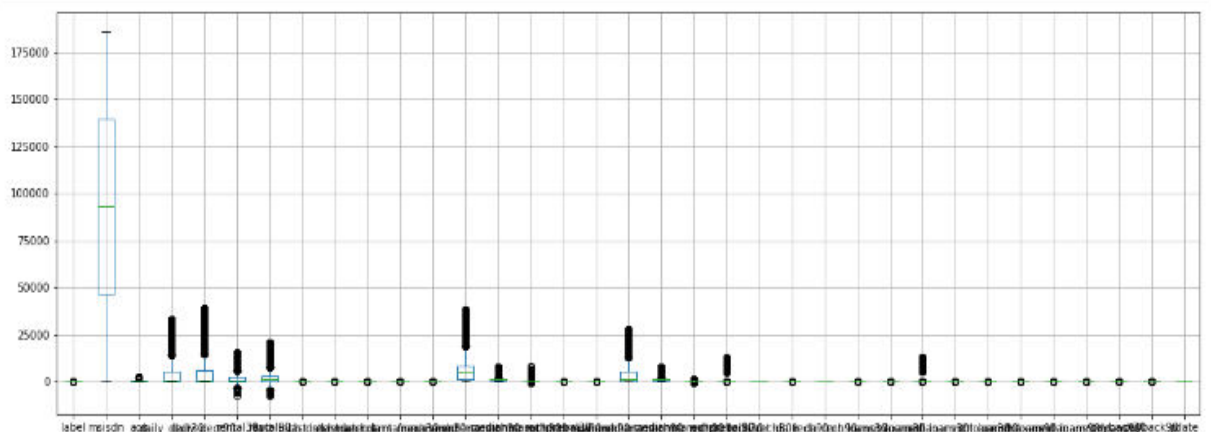
- Check the data distribution among all the columns

```
# Let's check the data distribution among all the columns
df.plot(kind='density', subplots=True, layout=(8,8), sharex=False, legend=True, fontsize=1, figsize=(18,12))
plt.show()
```



- Checking outliers with boxplot.

```
#checking outliers with boxplot
df.iloc[:,:].boxplot(figsize=[20,8])
plt.subplots_adjust(bottom=0.25)
plt.show()
```



- Train test split Here:

```
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=.20, random_state = 58)
```

```
x_train
```

	label	maxwin	win	daily decr20	daily decr30	netba20	netba30	last rech date ms	last rech date ds	last rech wmt ms	...	cnt loans20	wmtnt lo
120600	1	15031	433.0	55.284000	55.284000	1301.76	1301.76	3.0	0.0	6	...	3	
127590	1	41888	1276.0	9329.804000	9357.720000	1808.20	2237.39	4.0	0.0	23	...	5	
162895	1	36907	211.0	40.880000	40.880000	870.58	870.58	1.0	0.0	21	...	2	
157586	0	117791	737.0	2883.896000	2888.040000	2039.55	2708.43	8.0	0.0	14	...	2	
192273	1	170829	1032.0	8905.930000	8936.450000	741.98	829.98	3.0	0.0	14	...	8	
...
33081	1	102200	1780.0	3689.000000	4872.890000	3852.30	4444.19	21.0	0.0	14	...	1	
162607	1	144273	118.0	4148.554000	4215.180000	1387.91	1978.84	2.0	0.0	14	...	2	
54652	0	164931	1725.0	-5.000000	-5.000000	2478.30	2478.30	0.0	0.0	0	...	1	
45124	0	136819	180.0	-0.058887	-0.058887	2142.80	2142.80	0.0	0.0	0	...	1	
83790	1	7571	129.0	8771.810000	8825.220000	2709.92	3154.67	4.0	0.0	14	...	3	

129620 rows x 34 columns

```
y_train
```

```
198600    1
127590    1
162895    1
157586    1
192273    1
..
33081     0
162607     0
54652     0
45124     0
83790     1
Name: payback30, Length: 129620, dtype: int64
```

```
y_test
```

```
114683    0
31301     1
284345    1
158409    0
52324     1
..
76588     1
158481    0
57914     0
111071    1
119424    0
Name: payback30, Length: 32485, dtype: int64
```

```
print(x.shape, x_train.shape, x_test.shape)
```

```
(162025, 34) (129620, 34) (32485, 34)
```

- Display creating model:

```
: # create model:
from sklearn.ensemble import RandomForestClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score
from sklearn.metrics import confusion_matrix, classification_report
from sklearn.model_selection import train_test_split

maxAccu = 0
maxRS = 0

for i in range(1,100):
    x_train, x_test, y_train, y_test = train_test_split(x, y, test_size = .20, random_state = i)
    rfc = RandomForestClassifier()
    rfc.fit(x_train, y_train)
    pred = rfc.predict(x_test)
    acc = accuracy_score(y_test, pred)
    print('accuracy', acc, 'random_state', i)

    if acc > maxAccu:
        maxAccu = acc
        maxRS = i
```

```

: #Random Forest Classifier
from sklearn.ensemble import RandomForestClassifier

rfc = RandomForestClassifier()
rfc.fit(x_train,y_train)
pred = rfc.predict(x_test)
print('accuracy',accuracy_score(y_test, pred)*100)
print(confusion_matrix(y_test,pred))
print(classification_report(y_test,pred))

accuracy 98.17620737540503
[[17013  404]
 [ 187 14801]]
           precision    recall  f1-score   support

      0       0.99       0.98       0.98       17417
      1       0.97       0.99       0.98       14988

 accuracy          0.98
 macro avg          0.98
weighted avg          0.98

```

- Cross Validation Here:

```

: #Cross Validation
from sklearn.model_selection import cross_val_score

scr = cross_val_score(rfc, x, y, cv=5)
print('cross validation score of random forest classifier model :',scr.mean())

cross validation score of random forest classifier model : 0.9823977781206604

: scr2 = cross_val_score(lr, x, y, cv=5)
print('cross validation score of logistic regression model :',scr2.mean())

cross validation score of logistic regression model : 0.7694553309674432

: scr3 = cross_val_score(dtc, x, y, cv=5)
print('cross validation score of decision tree classifier model :',scr3.mean())

cross validation score of decision tree classifier model : 0.9756951087795093

```

- Hyper parameter tuning here:

```

: #Hyper parameter tuning
from sklearn.model_selection import GridSearchCV

parameters = {'max_features': ['auto','sqrt','log2'],
              'max_depth': [4,5,6,7,8],
              'criterion':['gini','entropy']}

: GCV = GridSearchCV(RandomForestClassifier(),parameters,cv=5,scoring='accuracy')
GCV.fit(x_train,y_train)
GCV.best_params_

: {'criterion': 'entropy', 'max_depth': 8, 'max_features': 'auto'}

: type(GCV)

: sklearn.model_selection._search.GridSearchCV

: GCV.best_estimator_

: RandomForestClassifier(criterion='entropy', max_depth=8)

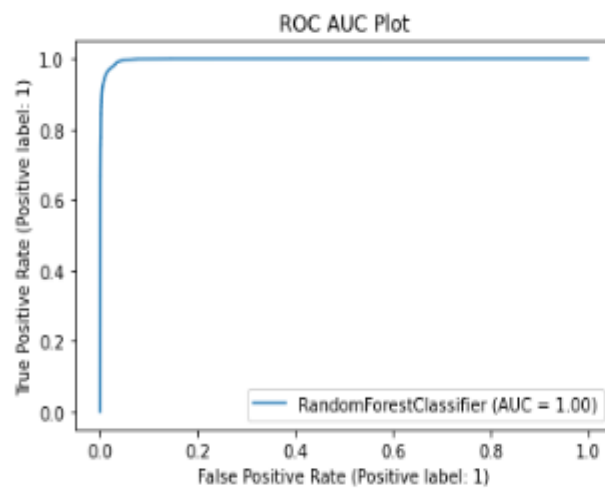
: GCV_pred = GCV.best_estimator_.predict(x_test)
accuracy_score(y_test,GCV_pred)

: 0.9757753433112174

```

- Plot roc curve here:

```
: # Here plot_roc_curve:  
from sklearn.metrics import plot_roc_curve  
plot_roc_curve(GCV.best_estimator_,x_test,y_test)  
plt.title("ROC AUC Plot")  
plt.show()
```



- Save the mode here:

```
import pickle  
filename = 'sales.pkl'  
pickle.dump( rfc,open(filename,'wb'))
```

- **Hardware and Software Requirements and Tools Used**

- **Language :-** Python

- **Tool:-** Jupyter

- **OS:-** Windows 10

- **RAM:-** 8gb

CONCLUSION

- The Random Forest approach is appropriate for classification and regression tasks on datasets with many entries and features that are likely to have missing values when we need a highly accurate result while avoiding overfitting.
- the random forest provides relative feature significance, enabling you to select the most important features. It is more interpretable than neural network models but less interpretable than decision trees.
- Predicting Loan Default is highly dependent on the demographics of the people, people with lower income are more likely to default on loans.

