MICRO CREDIT LOAN PRIDICTION

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PROBLAM STATEMENT

Micro finance plays institutions a major role in economic development in many developing countries. However, many of these microfinance institutions are faced with the problem of default because of the non-formal nature of the business and individuals they lend money to. This study seeks to find the determinants of credit default in microfinance institution

Data Sources and their formats

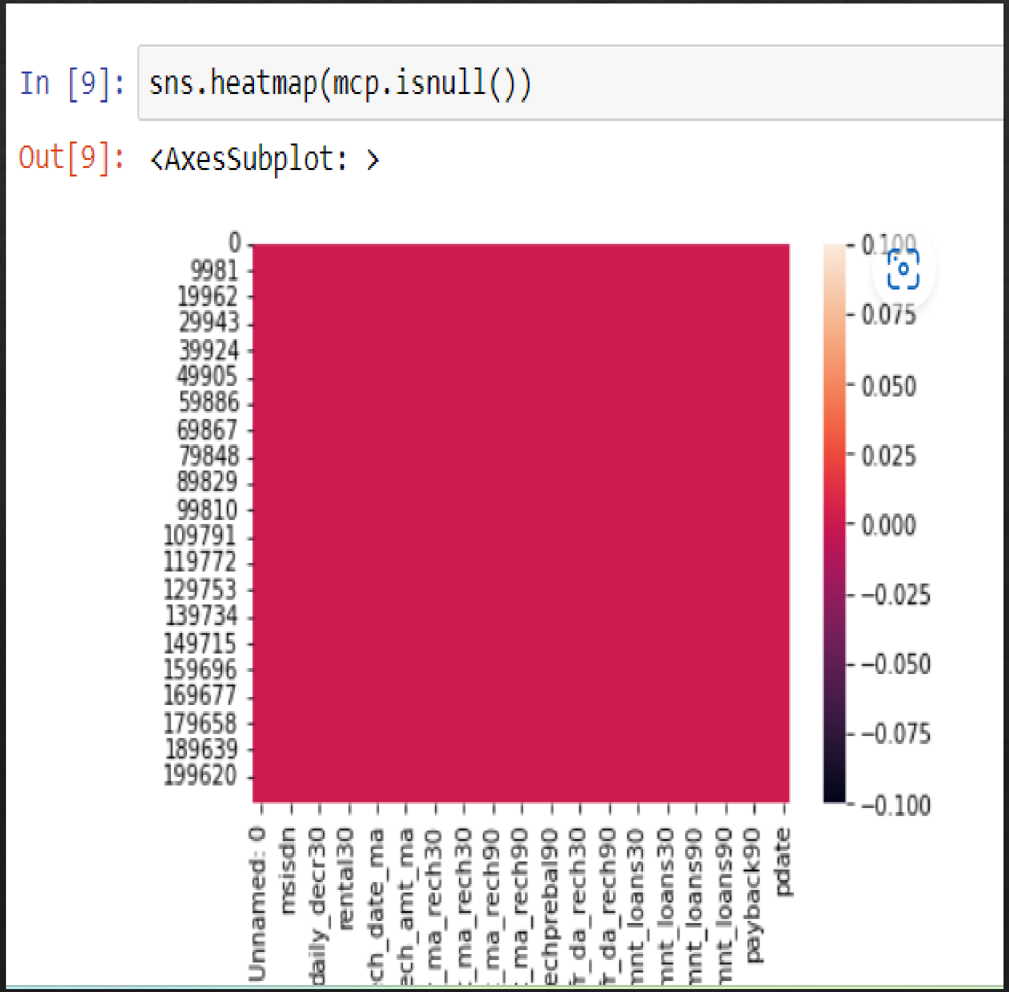
Variable	Definition	Com
label	Flag indicating whether the user paid back the credit amount within 5 days of issuing the loan{1:success, 0:failure}	
msisdn	mobile number of user	
aon	age on cellular network in days	
daily_decr30	Daily amount spent from main account, averaged over last 30 days (in Indonesian Rupiah)	
daily_decr90	Daily amount spent from main account, averaged over last 90 days (in Indonesian Rupiah)	
rental30	Average main account balance over last 30 days	Uns
rental90	Average main account balance over last 90 days	Uns
last_rech_date_ma	Number of days till last recharge of main account	
last_rech_date_da	Number of days till last recharge of data account	
last_rech_amt_ma	Amount of last recharge of main account (in Indonesian Rupiah)	
cnt_ma_rech30	Number of times main account got recharged in last 30 days	
fr_ma_rech30	Frequency of main account recharged in last 30 days	Uns
sumamnt_ma_rech30	Total amount of recharge in main account over last 30 days (in Indonesian Rupiah)	
medianamnt_ma_rech30	Median of amount of recharges done in main account over last 30 days at user level (in Indonesian Rupiah)	
medianmarechprebal30	Median of main account balance just before recharge in last 30 days at user level (in Indonesian Rupiah)	
cnt_ma_rech90	Number of times main account got recharged in last 90 days	
fr_ma_rech90	Frequency of main account recharged in last 90 days	Uns
sumamnt_ma_rech90	Total amount of recharge in main account over last 90 days (in Indonasian Rupiah)	
medianamnt_ma_rech90	Median of amount of recharges done in main account over last 90 days at user level (in Indonasian Rupiah)	
medianmarechprebal90	Median of main account balance just before recharge in last 90 days at user level (in Indonasian Rupiah)	
cnt_da_rech30	Number of times data account got recharged in last 30 days	
fr_da_rech30	Frequency of data account recharged in last 30 days	
cnt_da_rech90	Number of times data account got recharged in last 90 days	
fr_da_rech90	Frequency of data account recharged in last 90 days	
cnt_loans30	Number of loans taken by user in last 30 days	
amnt_loans30	Total amount of loans taken by user in last 30 days	
maxamnt_loans30	maximum amount of loan taken by the user in last 30 days	The
medianamnt_loans30	Median of amounts of loan taken by the user in last 30 days	
cnt_loans90	Number of loans taken by user in last 90 days	
amnt_loans90	Total amount of loans taken by user in last 90 days	
maxamnt_loans90	maximum amount of loan taken by the user in last 90 days	
medianamnt_loans90	Median of amounts of loan taken by the user in last 90 days	
payback30	Average payback time in days over last 30 days	
payback90	Average payback time in days over last 90 days	
pcircle	telecom circle	
pdate	date	

Data Pre-processing Done

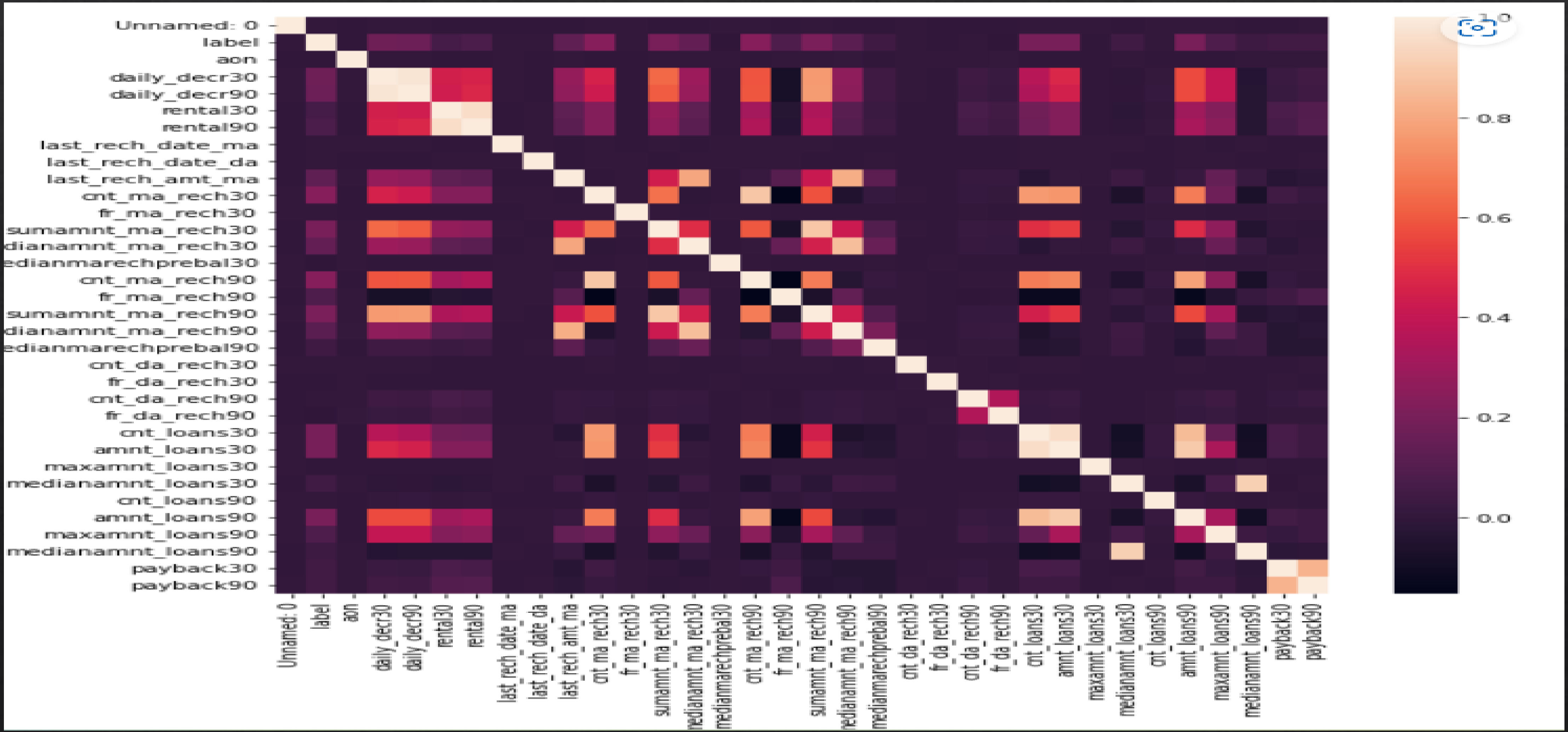
There are no null values in microcredit loan case project.

In microcredit loan case project in many features data are skewed. With the help of sklearn.preprocessing.power_tranform, I had removed the skewness from the dataset.

47335 outliers present in microcredit loan case Dataset, with the help of scipy.states.zscore I had removed the outliers from the Dataset.



Data Inputs- Logic- Output Relationships



Data Inputs- Logic- Output Relationships

We can see by the graph how all features are correlated with the y label. Some features are positively correlated and some features are very less correlated with the y.

daily_decr30(daily amount spent from main account, over last 30 days), daily_decr90(daily amount spent from main account, over last 90 days), rental30(average main account balance over last 30 days) and rental90(average main account balance over last 90 days) features are positively correlated,

Thou we know that if someone take a micro credit loan or any type of loan so it is very important that how much money they are spending and how much money they have in their account respected to pay the loan back,

And another way unnamed, last_rech_date_ma (number of days till last recharge amount), msisdn (mobile number of user) features are negative correlated with y label.

Because mobile number of user and number of days till recharge are not so important respected to pay the loan back,

So those who need the loan and who can pay back the loan, only those people can get micro credit loan. This is how these all positive and negative correlations affect the y label.

Model/s Development and Evaluation

Testing of Identified Approaches (Algorithms)

Micro Credit Loan Case prediction is a classifier problem, where we have to predict that people who had taken the micro credit loan have paid the amount or not.

To predict MicroCreditLoanCase project I had used four algorithms such as RandomForestClassifier, DecisionTreeClassifier, KNeighborsClassifier, and SVC.

Run and evaluate selected models

In [174]:

```
rfc=RandomForestClassifier()
rfc.fit(x_train,y_train)
rfcpred=rfc.predict(x_test)
print(accuracy_score(y_test,rfcpred)*100)
print(classification_report(y_test,rfcpred))
print(confusion_matrix(y_test,rfcpred))
```

```
90.79871810674226
              precision    recall  f1-score   support

           0       0.76      0.48      0.59      6701
           1       0.92      0.98      0.95     41977

    accuracy                           0.91     48678
   macro avg       0.84      0.73      0.77     48678
weighted avg       0.90      0.91      0.90     48678

[[ 3244  3457]
 [ 1022 40955]]
```

In Random Forest classifier accuracy score is 90.798%.

Run and evaluate selected models

```
In [175]: dtc=DecisionTreeClassifier()
          dtc.fit(x_train,y_train)
          dtcpred=dtc.predict(x_test)
          print(accuracy_score(y_test,dtcpred)*100)
          print(classification_report(y_test,dtcpred))
          print(confusion_matrix(y_test,dtcpred))

85.80262130736678
              precision    recall  f1-score   support

           0       0.49      0.53      0.50      6701
           1       0.92      0.91      0.92     41977

    accuracy                           0.86     48678
   macro avg       0.70      0.72      0.71     48678
weighted avg       0.86      0.86      0.86     48678

[[ 3521  3180]
 [ 3731 38246]]
```

In Decision Tree classifier accuracy score is 85.802%.

Run and evaluate selected models

```
In [176]: knn=KNeighborsClassifier()
knn.fit(x_train,y_train)
predknn=knn.predict(x_test)
print(accuracy_score(y_test,predknn)*100)
print(confusion_matrix(y_test,predknn))
print(classification_report(y_test,predknn))

87.46456304696166
[[ 2558  4143]
 [ 1959 40018]]
              precision    recall  f1-score   support

           0       0.57      0.38      0.46      6701
           1       0.91      0.95      0.93     41977

    accuracy                           0.87     48678
   macro avg       0.74      0.67      0.69     48678
weighted avg       0.86      0.87      0.86     48678
```

```
In [177]: svc=SVC()
svc.fit(x_train,y_train)
svcpred=svc.predict(x_test)
print(accuracy_score(y_test,svcpred)*100)
print(classification_report(y_test,svcpred))
print(confusion_matrix(y_test,svcpred))

86.43740498787955
              precision    recall  f1-score   support

           0       0.68      0.03      0.05      6701
           1       0.87      1.00      0.93     41977

    accuracy                           0.86     48678
   macro avg       0.77      0.51      0.49     48678
weighted avg       0.84      0.86      0.81     48678

[[  187  6514]
 [   88 41889]]
```

In KNeighbors classifier accuracy score is 87.464%.

In SVC accuracy score is 86.437%.

Visualizations

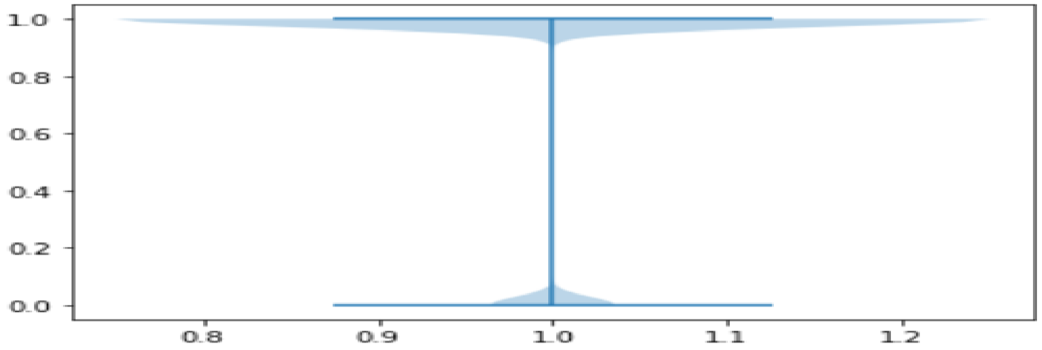
For visualization I had used matplotlib.pyplot and seaborn modules.

```
In [20]: mcp["label"].value_counts()

Out[20]: 1    183431
         0     26162
         Name: label, dtype: int64

In [21]: plt.violinplot(mcp["label"])

Out[21]: {'bodies': [<matplotlib.collections.PolyCollection at 0x213c385b760>],
          'cmaxes': <matplotlib.collections.LineCollection at 0x213c2bda070>,
          'cmins': <matplotlib.collections.LineCollection at 0x213c385bd60>,
          'cbars': <matplotlib.collections.LineCollection at 0x213c3762100>}
```

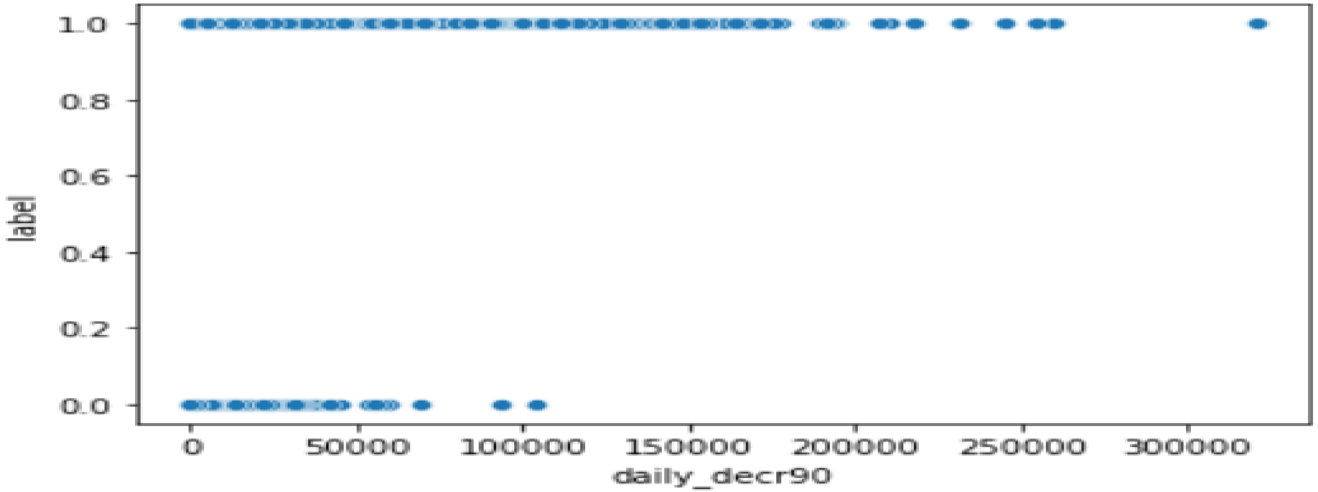


label means (Flag indicating whether the user paid back the credit amount within 5 days of issuing the loan {1: success, 0: failure})

So out of 209593 people, 183431 people have success to take the credit amount and 26162 people have failure to take the credit amount.

Visualizations

```
In [29]: sns.scatterplot(x="daily_decr90",y="label",data=mcp)
Out[29]: <AxesSubplot: xlabel='daily_decr90', ylabel='label'>
```

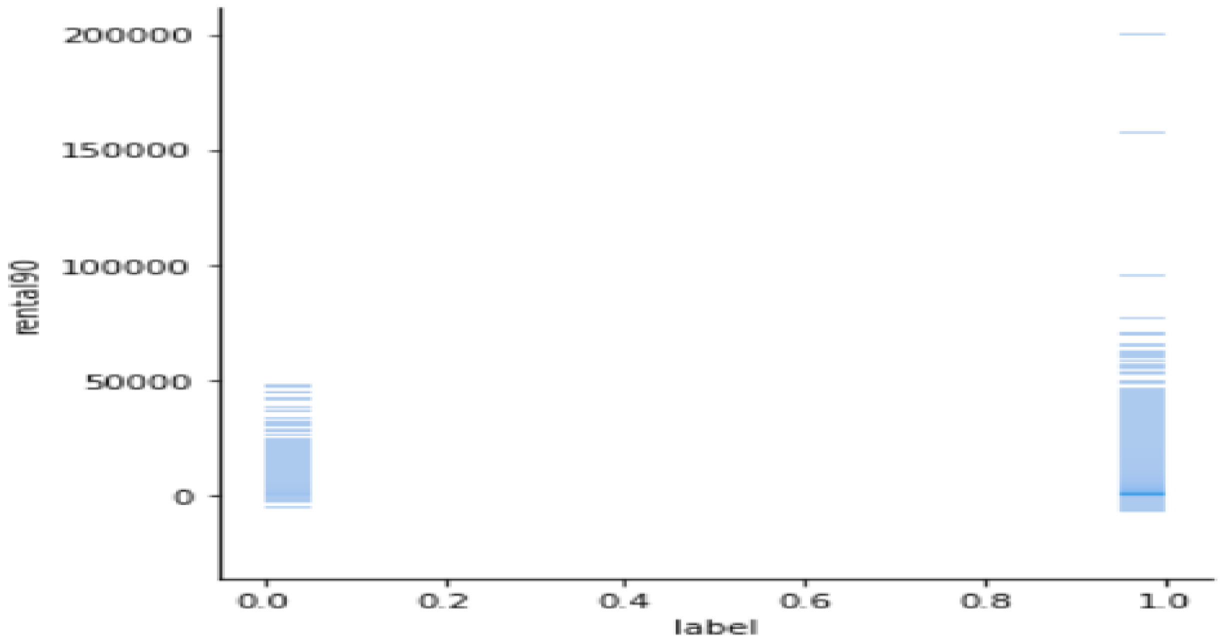


1 type of people have 0 to 250000 daily_decr90(Daily amount spent from main account, averaged over last 90 days (in Indonesian Rupiah))

and 0 type of people have 0 to 80000 daily_decr90(Daily amount spent from main account, averaged over last 90 days (in Indonesian Rupiah).

Visualizations

In [36]:
```
sns.displot(y="rental90",x="label",data=mcp)
```
Out[36]: <seaborn.axisgrid.FacetGrid at 0x213cfab93d0>

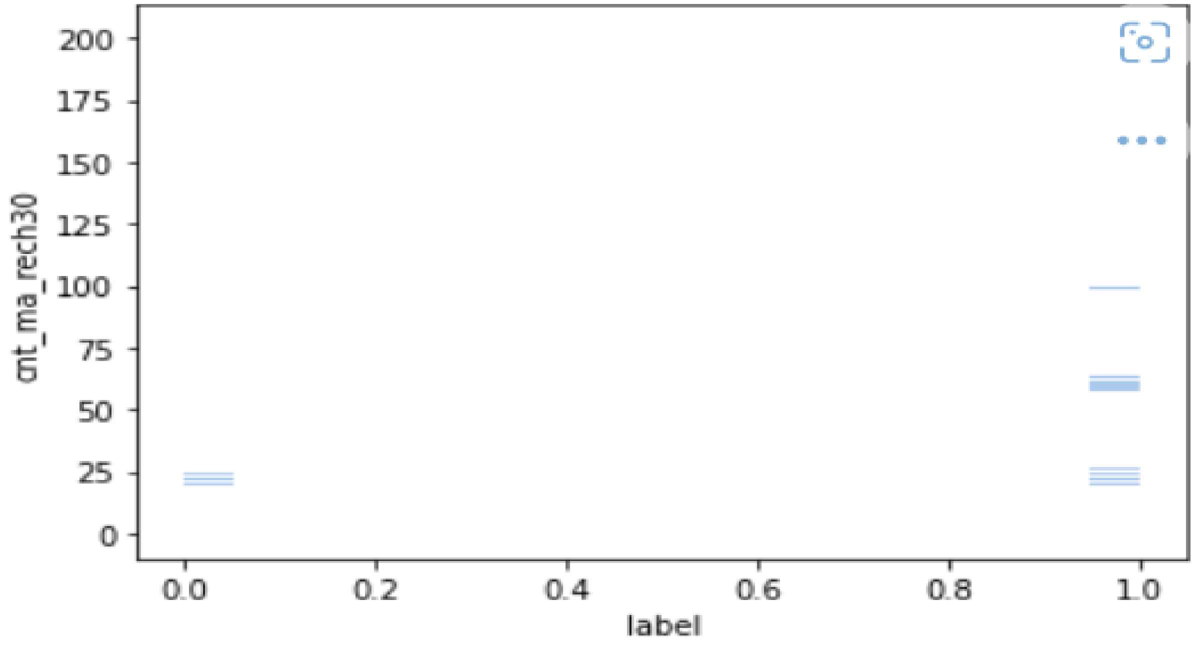


1(success) people have 0 to 80000 rental90(Average main account balance over last 90 days) and 0(failure) people have 0 to 50000 rental90(Average main account balance over last 90 days).

Visualizations

```
n [46]: sns.histplot(x="label",y="cnt_ma_rech30",data=mcp)

ut[46]: <AxesSubplot: xlabel='label', ylabel='cnt_ma_rech30'>
```



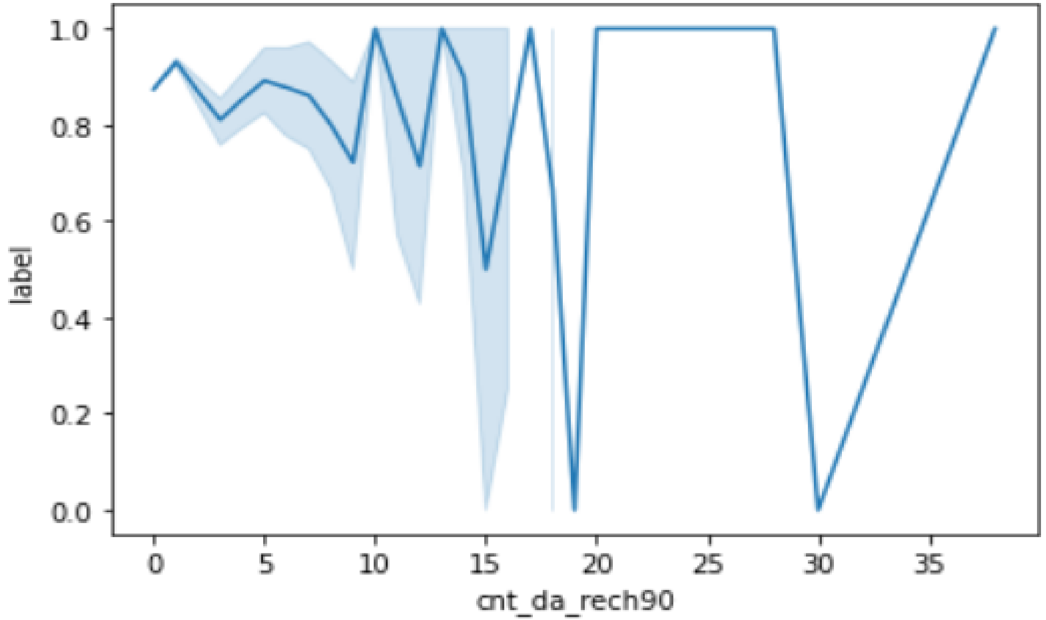
1(success), cnt_ma_rech30(Number of times main account got recharged in last 30 days) data is high in between 0 to 100.

and 0(failure), cnt_ma_rech30(Number of times main account got recharged in last 30 days) data is high in between 0 to 25.

Visualizations

```
In [81]: sns.lineplot(x="cnt_da_rech90",y="label",data=mcp)
```

```
Out[81]: <AxesSubplot: xlabel='cnt_da_rech90', ylabel='label'>
```

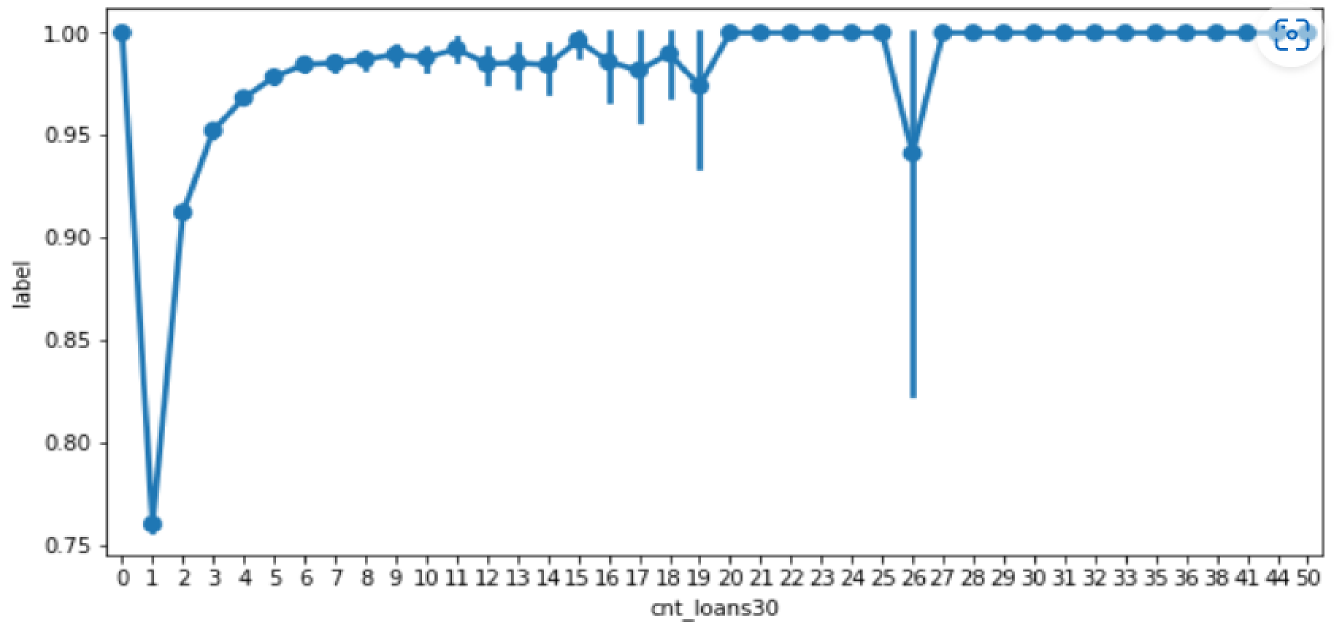


1(success), cnt_da_rech90(Number of times data account got recharged in last 90 days) is higher than 0(failure).

Visualizations

In [86]:
```
plt.figure(figsize=(10,5))
sns.pointplot(x="cnt_loans30",y="label",data=mcp)
```

Out[86]: <AxesSubplot: xlabel='cnt_loans30', ylabel='label'>



cnt_loans30(Number of loans taken by user in last 30 days) data is higher in 1(success) type of label.

CONCLUSION

The importance of microfinance in the developing countries like India cannot be undermined it play a vital role for socio-economic upliftment of poor and low-income peoples. Since 1990, poverty reduction has taken priority at both nation and international developments levels. Within this framework, various initiatives have been taken by government. Microfinance has caught the attention as an effective tool for poverty reduction and socio- economic development.

Hence, Microfinance can play a vital role for improving the standard of living of poor. The economic development of any country is severely influenced by the availability of financial service. Microfinance is the form of a board range of financial service such as deposits, loans, payment service, money transfer, insurance, saving, micro credit etc. to the poor and low-income individuals.