LoanTap is an online platform committed to delivering customized loan products to millennials. They innovate in an otherwise dull loan segment, to deliver instant, flexible loans on consumer friendly terms to salaried professionals.

The data science team at LoanTap is building an underwriting layer to determine the creditworthiness of individuals.

Problem Statement:

Given a set of attributes for an Individual, determine if a credit line should be extended to them. If so, what should the repayment terms be in business recommendations?

Data dictionary:

loan_amnt : The listed amount of the loan applied for by the borrower. If at some point in time, the credit department reduces the loan amount, then it will be reflected in this value.

term : The number of payments on the loan. Values are in months and can be either 36 or 60.

int_rate : Interest Rate on the loan

installment : The monthly payment owed by the borrower if the loan originates.

grade : LoanTap assigned loan grade

sub_grade : LoanTap assigned loan subgrade

emp_title :The job title supplied by the Borrower when applying for the loan.

emp_length : Employment length in years. Possible values are between 0 and 10 where 0 means less than one year and 10 means ten or more years.

home_ownership : The home ownership status provided by the borrower during registration or obtained from the credit report.

annual_inc : The self-reported annual income provided by the borrower during registration.

verification_status : Indicates if income was verified by LoanTap, not verified, or if the income source was verified

issue_d : The month which the loan was funded

loan_status : Current status of the loan - **Target Variable**

purpose : A category provided by the borrower for the loan request.

title : The loan title provided by the borrower

dti : A ratio calculated using the borrower’s total monthly debt payments on the total debt obligations, excluding mortgage and the requested LoanTap loan, divided by the borrower’s self-reported monthly income.

earliest_cr_line :The month the borrower's earliest reported credit line was opened

open_acc : The number of open credit lines in the borrower's credit file.

pub_rec : Number of derogatory public records

revol_bal : Total credit revolving balance

revol_util : Revolving line utilization rate, or the amount of credit the borrower is using relative to all available revolving credit.

total_acc : The total number of credit lines currently in the borrower's credit file

initial_list_status : The initial listing status of the loan. Possible values are – W, F

application_type : Indicates whether the loan is an individual application or a joint application with two co-borrowers

mort_acc : Number of mortgage accounts.

pub_rec_bankruptcies : Number of public record bankruptcies

Address: Address of the individual

Concept Used:

Exploratory Data Analysis Feature Engineering Logistic Regression Precision Vs Recall Tradeoff

Import the dataset and do usual exploratory data analysis steps like checking the structure & characteristics of the dataset

Check how much target variable (Loan_Status) depends on different predictor variables (Use count plots, box plots, heat maps etc)

Check correlation among independent variables and how they interact with each other

Simple Feature Engineering steps:

E.g.: Creation of Flags- If value greater than 1.0 then 1 else 0. This can be done on:

1. Pub_rec
2. Mort_acc
3. Pub_rec_bankruptcies

Missing values and Outlier Treatment

Scaling - Using MinMaxScaler or StandardScaler

Use Logistic Regression Model from Sklearn/Statsmodel library and explain the results

Results Evaluation:

Classification Report

ROC AUC curve

Precision recall curve

Tradeoff Questions:

How can we make sure that our model can detect real defaulters and there are less false positives?

This is important as we can lose out on an opportunity to finance more individuals and earn interest on it.

Since NPA (non-performing asset) is a real problem in this industry, it’s important we play safe and shouldn’t disburse loans to anyone

Provide actionable Insights & Recommendations

Questionnaire (Answers should present in the text editor along with insights):

What percentage of customers have fully paid their Loan Amount?

Comment about the correlation between Loan Amount and Installment features.

The majority of people have home ownership as **___**.

People with grades ‘A’ are more likely to fully pay their loan. (T/F)

Name the top 2 afforded job titles.

Thinking from a bank's perspective, which metric should our primary focus be on..

1.ROC AUC 2.Precision 3.Recall 4.F1 Score

How does the gap in precision and recall affect the bank?

Which were the features that heavily affected the outcome?

Will the results be affected by geographical location? (Yes/No)

Problem definition

Given the information about the customer, Predict whether loan should be given to them

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

```
data=pd.read_csv('loantap_logistic_regression.csv')
```

```
data.head()
```

	loan_amnt	term	int_rate	installment	grade	sub_grade	emp_title	emp_length
0	10000.0	36 months	11.44	329.48	B	B4	Marketing	10+ years
1	8000.0	36 months	11.99	265.68	B	B5	Credit analyst	4 years
2	15600.0	36 months	10.49	506.97	B	B3	Statistician	< 1 year
3	7200.0	36 months	6.49	220.65	A	A2	Client Advocate	6 years
4	24375.0	60 months	17.27	609.33	C	C5	Destiny Management Inc.	9 years

5 rows × 27 columns

```
data['application_type'].value_counts()
```

```
INDIVIDUAL    395319
JOINT            425
DIRECT_PAY       286
Name: application_type, dtype: int64
```

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 396030 entries, 0 to 396029
Data columns (total 27 columns):
 #   Column                Non-Null Count   Dtype  
---  ------                --------------   -----  
 0   loan_amnt             396030 non-null  float64
 1   term                  396030 non-null  object 
 2   int_rate              396030 non-null  float64
 3   installment           396030 non-null  float64
 4   grade                 396030 non-null  object 
 5   sub_grade             396030 non-null  object 
 6   emp_title             373103 non-null  object 
 7   emp_length            377729 non-null  object 
 8   home_ownership        396030 non-null  object 
 9   annual_inc            396030 non-null  float64
 10  verification_status   396030 non-null  object 
 11  issue_d               396030 non-null  object 
 12  loan_status           396030 non-null  object 
```

```
 13  purpose               396030 non-null  object 
 14  title                 394275 non-null  object 
 15  dti                   396030 non-null  float64
 16  earliest_cr_line      396030 non-null  object 
 17  open_acc              396030 non-null  float64
 18  pub_rec               396030 non-null  float64
 19  revol_bal             396030 non-null  float64
 20  revol_util            395754 non-null  float64
 21  total_acc             396030 non-null  float64
 22  initial_list_status   396030 non-null  object 
 23  application_type      396030 non-null  object 
 24  mort_acc              358235 non-null  float64
 25  pub_rec_bankruptcies  395495 non-null  float64
 26  address               396030 non-null  object 
dtypes: float64(12), object(15)
memory usage: 81.6+ MB
```

```
data.describe(include=object)
```

	term	grade	sub_grade	emp_title	emp_length	home_ownership	verification_
count	396030	396030	396030	373103	377729	396030	
unique	2	7	35	173105	11	6	
top	36 months	B	B3	Teacher	10+ years	MORTGAGE	
freq	302005	116018	26655	4389	126041	198348	

Null Value Treatment

```
data.isnull().sum()
```

```
loan_amnt                   0
term                        0
int_rate                    0
installment                 0
grade                       0
sub_grade                   0
emp_title               22927
emp_length              18301
home_ownership              0
annual_inc                  0
verification_status         0
issue_d                     0
```

```
loan_status                0
purpose                    0
title                   1755
dti                        0
earliest_cr_line           0
open_acc                   0
pub_rec                    0
revol_bal                  0
revol_util               276
total_acc                  0
initial_list_status        0
application_type           0
mort_acc               37795
pub_rec_bankruptcies     535
address                    0
dtype: int64
```

```
data.isnull().sum()/len(data.index)*100
```

```
loan_amnt               0.000000
term                    0.000000
int_rate                0.000000
installment             0.000000
grade                   0.000000
sub_grade               0.000000
emp_title               5.789208
emp_length              4.621115
home_ownership          0.000000
annual_inc              0.000000
verification_status     0.000000
issue_d                 0.000000
loan_status             0.000000
purpose                 0.000000
title                   0.443148
dti                     0.000000
earliest_cr_line        0.000000
open_acc                0.000000
pub_rec                 0.000000
revol_bal               0.000000
revol_util              0.069692
total_acc               0.000000
initial_list_status     0.000000
application_type        0.000000
mort_acc                9.543469
pub_rec_bankruptcies    0.135091
address                 0.000000
dtype: float64
```

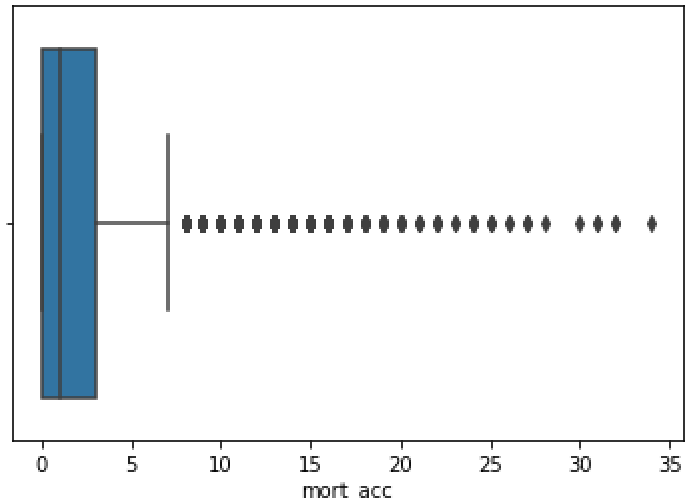
Here, we can see That 'emp_title','emp_length','mort_acc' has significant NULLs in them. Rest all features are having very no of Nulls. we can drop them.

emp_title ---- it is a categorical variable emp_length ---- it is a categorical variable

mort_acc ----- it is numerical variable

```
sns.boxplot(data['mort_acc'])
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarning: Pass t
  FutureWarning
<matplotlib.axes._subplots.AxesSubplot at 0x7fe8520820d0>
```



Since mort_acc is a numerical column. we can impute it with-

1. 0 ---- it would be wrong to assume that mortgage account are 0 when where we have Null values.
2. mean ---- Data has nulls. so we can't impute mean

so we will impute medians

```
data['mort_acc'].fillna(data['mort_acc'].median(), inplace = True)
```

```
data.isnull().sum()/len(data.index)*100
```

```
loan_amnt               0.000000
term                    0.000000
int_rate                0.000000
installment             0.000000
grade                   0.000000
sub_grade               0.000000
emp_title               5.789208
emp_length              4.621115
home_ownership          0.000000
annual_inc              0.000000
verification_status     0.000000
issue_d                 0.000000
```

```
loan_status             0.000000
purpose                 0.000000
title                   0.443148
dti                     0.000000
earliest_cr_line        0.000000
open_acc                0.000000
pub_rec                 0.000000
revol_bal               0.000000
revol_util              0.069692
total_acc               0.000000
initial_list_status     0.000000
application_type        0.000000
mort_acc                0.000000
pub_rec_bankruptcies    0.135091
address                 0.000000
dtype: float64
```

Now work on emp_title column. Instead of Imputing it, let us make it a seperate class

```
data['emp_title'].fillna('unkown_title', inplace = True)
```

```
data.isnull().sum()/len(data.index)*100
```

```
loan_amnt               0.000000
term                    0.000000
int_rate                0.000000
installment             0.000000
grade                   0.000000
sub_grade               0.000000
emp_title               0.000000
emp_length              4.621115
home_ownership          0.000000
annual_inc              0.000000
verification_status     0.000000
issue_d                 0.000000
loan_status             0.000000
purpose                 0.000000
title                   0.443148
dti                     0.000000
earliest_cr_line        0.000000
open_acc                0.000000
pub_rec                 0.000000
revol_bal               0.000000
revol_util              0.069692
total_acc               0.000000
initial_list_status     0.000000
application_type        0.000000
mort_acc                0.000000
pub_rec_bankruptcies    0.135091
address                 0.000000
dtype: float64
```

In emp_length, we can replace it with means. Here years are varying from 0-10. so, replace it with 5

```
data['emp_length'].fillna('5 years', inplace = True)
```

```
data.isnull().sum()/len(data.index)*100
```

```
loan_amnt               0.000000
term                    0.000000
int_rate                0.000000
installment             0.000000
grade                   0.000000
sub_grade               0.000000
emp_title               0.000000
emp_length              0.000000
home_ownership          0.000000
annual_inc              0.000000
verification_status     0.000000
issue_d                 0.000000
loan_status             0.000000
purpose                 0.000000
title                   0.443148
dti                     0.000000
earliest_cr_line        0.000000
open_acc                0.000000
pub_rec                 0.000000
revol_bal               0.000000
revol_util              0.069692
total_acc               0.000000
initial_list_status     0.000000
application_type        0.000000
mort_acc                0.000000
pub_rec_bankruptcies    0.135091
address                 0.000000
dtype: float64
```

```
data=data.dropna()
```

```
data.isnull().sum()
```

```
loan_amnt               0
term                    0
int_rate                0
installment             0
grade                   0
sub_grade               0
emp_title               0
emp_length              0
home_ownership          0
annual_inc              0
verification_status     0
issue_d                 0
loan_status             0
```

```
purpose                 0
title                   0
dti                     0
earliest_cr_line        0
open_acc                0
pub_rec                 0
revol_bal               0
revol_util              0
total_acc               0
initial_list_status     0
application_type        0
mort_acc                0
pub_rec_bankruptcies    0
address                 0
dtype: int64
```

Data Cleaning

```
data['emp_length'].value_counts()
```

```
10+ years    125270
5 years       44429
2 years       35597
< 1 year      31489
3 years       31469
1 year        25637
4 years       23811
6 years       20750
7 years       20727
8 years       19071
9 years       15215
Name: emp_length, dtype: int64
```

We can convert this to Numerical column.Let's make '<1 year' to '0 year' and '10+ year' to '10 year'

```
data['emp_length'] = data ['emp_length'].replace ( ['< 1 year'],'0 year')
```

```
data['emp_length'] = data ['emp_length'].replace ( ['10+ years'],'10 years')
```

```
data['emp_length'].value_counts()
```

```
10 years    125270
5 years      44429
2 years      35597
0 year       31489
3 years      31469
1 year       25637
4 years      23811
```

```
6 years      20750
7 years      20727
8 years      19071
9 years      15215
Name: emp_length, dtype: int64
```

```
data[['employment_age','redundent_data']] = data['emp_length'].str.split(' ',expand=True)
```

```
data.drop(['emp_length','redundent_data'],axis='columns',inplace=True)
```

```
data['employment_age'].value_counts()
```

```
10    125270
5      44429
2      35597
0      31489
3      31469
1      25637
4      23811
6      20750
7      20727
8      19071
9      15215
Name: employment_age, dtype: int64
```

```
data['employment_age']=data['employment_age'].astype(int)
```

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 393465 entries, 0 to 396029
Data columns (total 27 columns):
 #   Column                Non-Null Count   Dtype
---  ------                --------------   -----
 0   loan_amnt             393465 non-null  float64
 1   term                  393465 non-null  object
 2   int_rate              393465 non-null  float64
 3   installment           393465 non-null  float64
 4   grade                 393465 non-null  object
 5   sub_grade             393465 non-null  object
 6   emp_title             393465 non-null  object
 7   home_ownership        393465 non-null  object
 8   annual_inc            393465 non-null  float64
 9   verification_status   393465 non-null  object
 10  issue_d               393465 non-null  object
 11  loan_status           393465 non-null  object
 12  purpose               393465 non-null  object
 13  title                 393465 non-null  object
 14  dti                   393465 non-null  float64
 15  earliest_cr_line      393465 non-null  object
 16  open_acc              393465 non-null  float64
```

```
 17  pub_rec               393465 non-null  float64
 18  revol_bal             393465 non-null  float64
 19  revol_util            393465 non-null  float64
 20  total_acc             393465 non-null  float64
 21  initial_list_status   393465 non-null  object
 22  application_type      393465 non-null  object
 23  mort_acc              393465 non-null  float64
 24  pub_rec_bankruptcies  393465 non-null  float64
 25  address               393465 non-null  object
 26  employment_age        393465 non-null  int64
dtypes: float64(12), int64(1), object(14)
memory usage: 84.1+ MB
```

Term also has months as subscript, let's examine it.

```
data['term'].value_counts()
```

```
 36 months    300024
 60 months     93441
Name: term, dtype: int64
```

so it came out to be categorical column

```
data.describe(include=object)
```

	term	grade	sub_grade	emp_title	home_ownership	verification_status	iss
count	393465	393465	393465	393465	393465	393465	39
unique	2	7	35	172227	6	3	
top	36 months	B	B3	unkown_title	MORTGAGE	Verified	
freq	300024	115395	26518	22668	197110	138867	1

'issued date' and 'earliest_cr_line' are dates. so to make it useful for our analysis we will try to find length which may be useful for our analysis.

Dealing with date columns

```
data['issue_d']=data['issue_d'].astype('datetime64[ns]')
```

```
data['earliest_cr_line']=data['earliest_cr_line'].astype('datetime64[ns]')
```

```
data['issue_d'].head()
```

```
0   2015-01-01
1   2015-01-01
2   2015-01-01
3   2014-11-01
4   2013-04-01
Name: issue_d, dtype: datetime64[ns]
```

```
data['earliest_cr_line'].head()
```

```
0   1990-06-01
1   2004-07-01
2   2007-08-01
3   2006-09-01
4   1999-03-01
Name: earliest_cr_line, dtype: datetime64[ns]
```

```
import datetime
now=datetime.datetime.now()
data['current_date'] = pd.Series([now.date() for x in range(len(data.index))])
data['current_date']=data['current_date'].astype('datetime64[ns]')
data["credit_line_Age"] = (data['current_date'] - data['earliest_cr_line']) / np.timedelta64(
data["loan_Age"] = (data['current_date'] - data['issue_d']) / np.timedelta64(1, 'D')
data.head()
```

	loan_amnt	term	int_rate	installment	grade	sub_grade	emp_title	home_ownersl

```
data.drop(['current_date','earliest_cr_line','issue_d'],inplace=True,axis='columns')
```

Address doesn't seem to be of any use for our analysis.so drop it

months analyst

```
data.drop(['address'],inplace=True,axis='columns')
```

2 15600.0 months 10.49 506.97 B B3 Statistician RE

```
data.head()
```

	loan_amnt	term	int_rate	installment	grade	sub_grade	emp_title	home_ownersl
0	10000.0	36 months	11.44	329.48	B	B4	Marketing	RE
1	8000.0	36 months	11.99	265.68	B	B5	Credit analyst	MORTGA
2	15600.0	36 months	10.49	506.97	B	B3	Statistician	RE
3	7200.0	36 months	6.49	220.65	A	A2	Client Advocate	RE
4	24375.0	60 months	17.27	609.33	C	C5	Destiny Management Inc.	MORTGA

5 rows × 26 columns

```
data.describe(include=object).T
```

	count	unique	top	freq
term	393465	2	36 months	300024
grade	393465	7	B	115395
sub_grade	393465	35	B3	26518

Here we came to know that,emp_title & title are of no use to us as there are large no of unique values in it. We can either drop it or we can do target encoding. Here we will go with Target encoding of one column and dropping the other column.

```
data.drop(['title'],axis='columns',inplace=True)
```

```
categorical_features=list(data.select_dtypes('object').columns)
for i in categorical_features:
  print('unique values in {0} are {1}'.format(i,data[i].unique()))
```

```
unique values in term are [' 36 months' ' 60 months']
unique values in grade are ['B' 'A' 'C' 'E' 'D' 'F' 'G']
unique values in sub_grade are ['B4' 'B5' 'B3' 'A2' 'C5' 'C3' 'A1' 'B2' 'C1' 'A5' 'E4'
 'C2' 'B1' 'D3' 'D5' 'D2' 'E1' 'E2' 'E5' 'F4' 'E3' 'D4' 'G1' 'F5' 'G2'
 'C4' 'F1' 'F3' 'G5' 'G4' 'F2' 'G3']
unique values in emp_title are ['Marketing' 'Credit analyst ' 'Statistician' ...
 "Michael's Arts & Crafts" 'licensed bankere' 'Gracon Services, Inc']
unique values in home_ownership are ['RENT' 'MORTGAGE' 'OWN' 'OTHER' 'ANY' 'NONE']
unique values in verification_status are ['Not Verified' 'Source Verified' 'Verified']
unique values in loan_status are ['Fully Paid' 'Charged Off']
unique values in purpose are ['vacation' 'debt_consolidation' 'credit_card' 'home_impro
 'small_business' 'major_purchase' 'other' 'medical' 'wedding' 'car'
 'moving' 'house' 'educational' 'renewable_energy']
unique values in initial_list_status are ['w' 'f']
unique values in application_type are ['INDIVIDUAL' 'JOINT' 'DIRECT_PAY']
```

subgrade is next level categorization of grade.so we can ignore the first part, it will reduce to 5 categories.

```
data['sub_grade'] = data['sub_grade'].str[1:]
```

```
data['sub_grade'].nunique()
```

```
5
```

```
data['sub_grade']=data['sub_grade'].astype(int)
```

```
data.describe(include=object).T
```

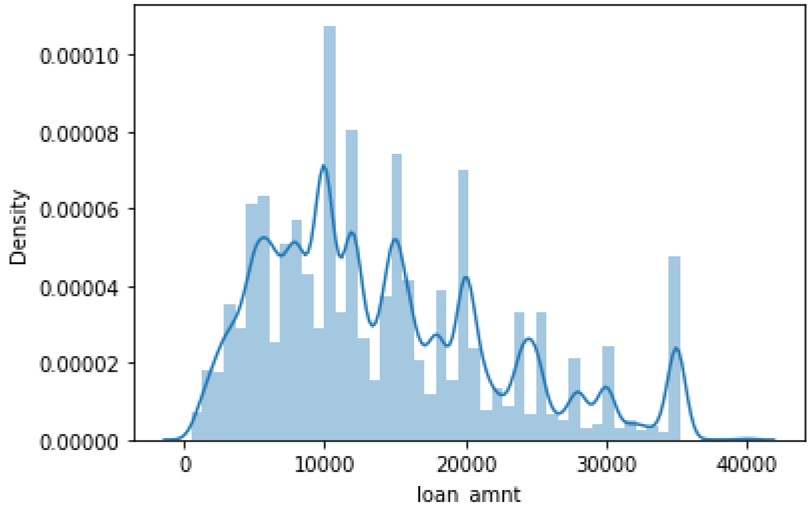
	count	unique	top	freq
term	393465	2	36 months	300024
grade	393465	7	B	115395
emp_title	393465	172227	unkown_title	22668
home_ownership	393465	6	MORTGAGE	197110
verification_status	393465	3	Verified	138867
loan_status	393465	2	Fully Paid	316271
purpose	393465	14	debt_consolidation	233108
initial_list_status	393465	2	f	236947
application_type	393465	3	INDIVIDUAL	392844

```
data.describe().T
```

	count	mean	std	min	25%	50%
loan_amnt	393465.0	14117.269960	8353.190693	500.00	8000.00	12000.00
int_rate	393465.0	13.638728	4.468866	5.32	10.49	13.33
installment	393465.0	431.946979	250.582348	16.08	250.33	375.43
sub_grade	393465.0	2.972028	1.406815	1.00	2.00	3.00
annual_inc	393465.0	74212.294265	61628.502516	0.00	45000.00	64000.00
dti	393465.0	17.383396	18.061993	0.00	11.29	16.91
open_acc	393465.0	11.317601	5.133143	1.00	8.00	10.00
pub_rec	393465.0	0.178189	0.530628	0.00	0.00	0.00
revol_bal	393465.0	15849.758057	20552.685648	0.00	6042.00	11194.00
revol_util	393465.0	53.828586	24.434544	0.00	35.90	54.90
total_acc	393465.0	25.425893	11.883416	2.00	17.00	24.00
mort_acc	393465.0	1.737064	2.058347	0.00	0.00	1.00
pub_rec_bankruptcies	393465.0	0.121597	0.356108	0.00	0.00	0.00
employment_age	393465.0	5.897396	3.565170	0.00	3.00	6.00
credit_line_Age	390920.0	8843.645475	2628.481210	3214.00	7050.00	8358.00
loan_Age	390920.0	3089.639087	522.848005	2057.00	2698.00	3032.00

```
sns.distplot(data['loan_amnt'])
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/distributions.py:2619: FutureWarning: `d
  warnings.warn(msg, FutureWarning)
<matplotlib.axes._subplots.AxesSubplot at 0x7fe855152c50>
```



Normality is not important in logistic regression,so continue

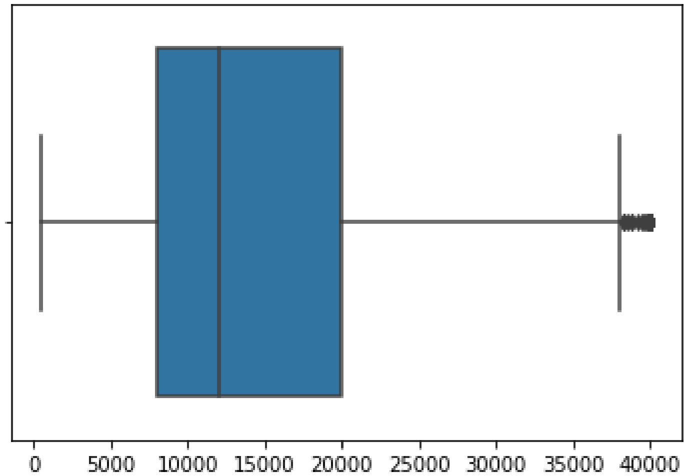
outliers

```
numerical_features=list(data.select_dtypes('number').columns)
numerical_features
```

```
['loan_amnt',
 'int_rate',
 'installment',
 'sub_grade',
 'annual_inc',
 'dti',
 'open_acc',
 'pub_rec',
 'revol_bal',
 'revol_util',
 'total_acc',
 'mort_acc',
 'pub_rec_bankruptcies',
 'employment_age',
 'credit_line_Age',
 'loan_Age']
```

```
sns.boxplot(data['loan_amnt'])
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarning: Pass t
  FutureWarning
<matplotlib.axes._subplots.AxesSubplot at 0x7fe855152490>
```




```
#Handling outliers through Capping method. We will store suspected columns in a list.

#Then we will cap all data to 99.9th percentile and 0.1th percentile.

outlier_columns=['loan_amnt',
 'installment',
 'annual_inc',
 'dti',
 'revol_bal',
 'credit_line_Age',
 'loan_Age']

for col in outlier_columns:
    percentiles = data[col].quantile([0.01, 0.99]).values
    data[col] = np.clip(data[col], percentiles[0], percentiles[1])
```

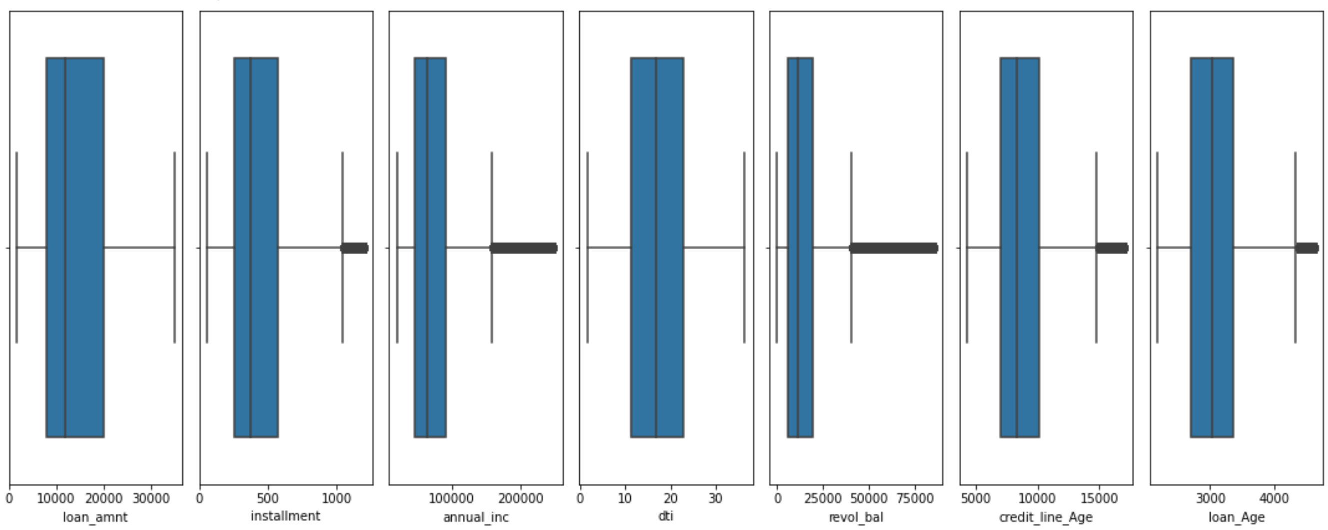
```
sns.boxplot(data['loan_amnt'])
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarning: Pass t
  FutureWarning
```

```
plt.figure(figsize=(15,6))

for i,j in enumerate(outlier_columns):
 plt.subplot(1,len(outlier_columns),i+1)
 plt.subplots_adjust(hspace = 0.8)
 sns.boxplot(data[j])
 plt.tight_layout(pad=1)
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarning: Pass t
  FutureWarning
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarning: Pass t
  FutureWarning
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarning: Pass t
  FutureWarning
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarning: Pass t
  FutureWarning
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarning: Pass t
  FutureWarning
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarning: Pass t
  FutureWarning
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarning: Pass t
  FutureWarning
```



We still have outliers in Data . So, Use IQR Methos to remove them

```
for i,j in enumerate(outlier_columns):
 q1=data[j].quantile(0.25)
 q3=data[j].quantile(0.75)
```

```
q3=data[j].quantile(0.75)
iqr=q3-q1
data=data[(data[j]>=q1-1.5*iqr)&(data[j]<=q3+1.5*iqr)]
```

Encoding Categorical Variables

Categories must not have order in them. we use one-hot encoding where categories don't have order. where categories have order then we can go for label encoding.

when no of categories are large we go for Target encoding.

```
from sklearn.preprocessing import LabelEncoder

le = LabelEncoder()
data['loan_status'] = le.fit_transform(data.loan_status)
data['grade'] = le.fit_transform(data.grade)
data['home_ownership'] = le.fit_transform(data.home_ownership)
data['verification_status'] = le.fit_transform(data.verification_status)
```

```
data['loan_status']
```

```
0         1
1         1
2         1
3         1
4         0
         ..
393459    1
393461    1
393462    1
393463    1
393464    0
Name: loan_status, Length: 325715, dtype: int64
```

```
!pip install category_encoders
```

```
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-wheels/pub
Requirement already satisfied: category_encoders in /usr/local/lib/python3.7/dist-packa
Requirement already satisfied: statsmodels>=0.9.0 in /usr/local/lib/python3.7/dist-pack
Requirement already satisfied: numpy>=1.14.0 in /usr/local/lib/python3.7/dist-packages
Requirement already satisfied: pandas>=1.0.5 in /usr/local/lib/python3.7/dist-packages
Requirement already satisfied: scipy>=1.0.0 in /usr/local/lib/python3.7/dist-packages (
Requirement already satisfied: patsy>=0.5.1 in /usr/local/lib/python3.7/dist-packages (
Requirement already satisfied: scikit-learn>=0.20.0 in /usr/local/lib/python3.7/dist-pa
Requirement already satisfied: python-dateutil>=2.7.3 in /usr/local/lib/python3.7/dist-
Requirement already satisfied: pytz>=2017.3 in /usr/local/lib/python3.7/dist-packages (
Requirement already satisfied: six in /usr/local/lib/python3.7/dist-packages (from pats
```

```
Requirement already satisfied: threadpoolctl>=2.0.0 in /usr/local/lib/python3.7/dist-pa
Requirement already satisfied: joblib>=0.11 in /usr/local/lib/python3.7/dist-packages (
```

```
from category_encoders import TargetEncoder
encoder = TargetEncoder()
data['emp_title'] = encoder.fit_transform(data['emp_title'],data['loan_status'])
data['purpose'] = encoder.fit_transform(data['purpose'],data['loan_status'])
```

```
/usr/local/lib/python3.7/dist-packages/category_encoders/target_encoder.py:94: FutureWa
  category=FutureWarning)
/usr/local/lib/python3.7/dist-packages/category_encoders/target_encoder.py:99: FutureWa
  category=FutureWarning)
```

```
 #data with no order between categories
temp1=pd.get_dummies(data, columns=['application_type','initial_list_status','term'], drop_fi
data=pd.concat([data,temp1],axis=1)

data.drop(['term','initial_list_status','application_type'],axis='columns',inplace=True)
```

```
data['loan_status']
```

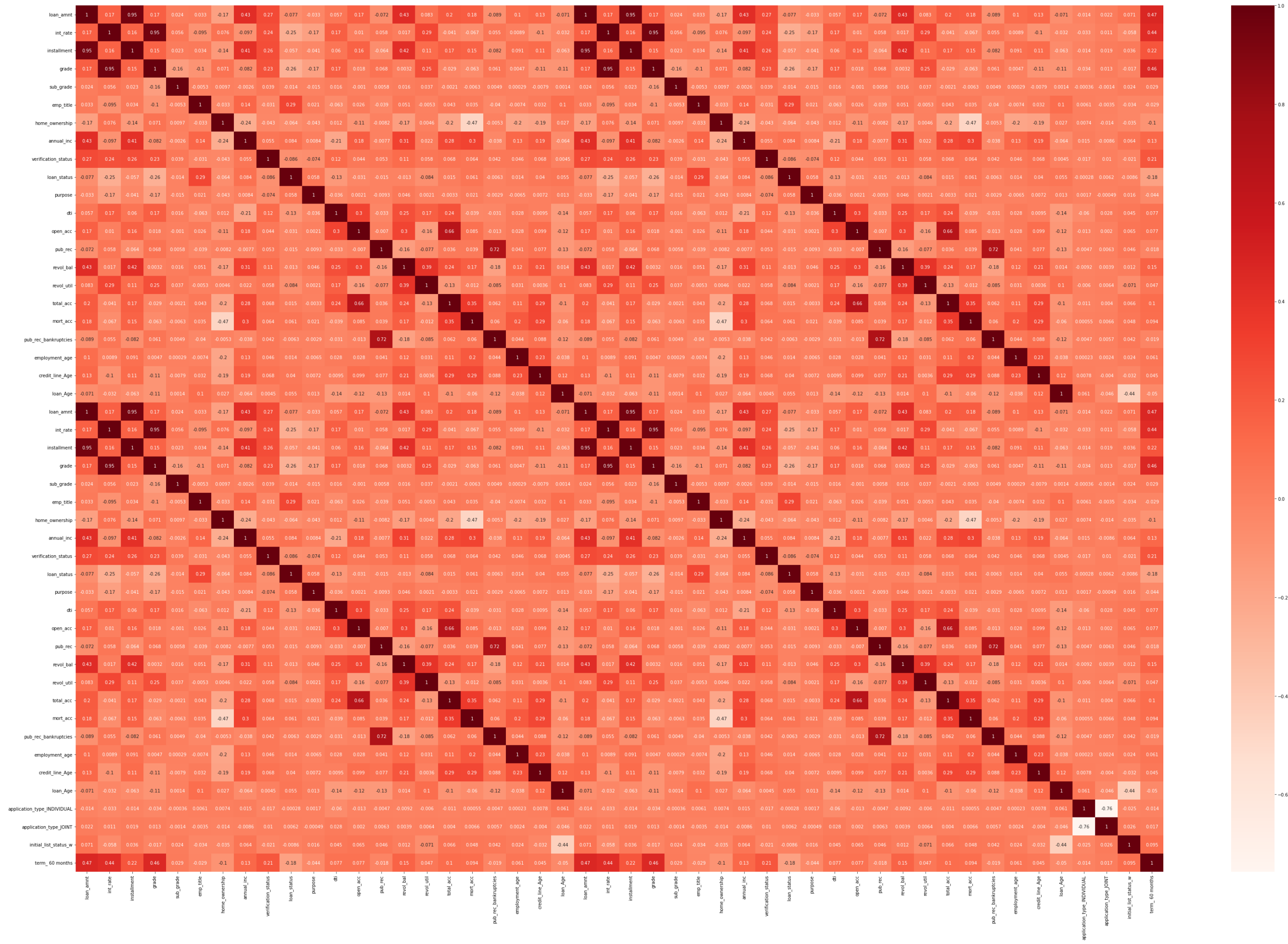
	loan_status	loan_status
0	1	1
1	1	1
2	1	1
3	1	1
4	0	0
...	...	...
393459	1	1
393461	1	1
393462	1	1
393463	1	1
393464	0	0

325715 rows × 2 columns

Model building

```
plt.figure(figsize=(55,36))
sns.heatmap(data.corr(),annot=True,cmap='Reds')
```

<matplotlib.axes._subplots.AxesSubplot at 0x7fe84d2727d0>



```
#split dependent & Independent Variables.
X = data.drop(['loan_status'],axis=1)
y = data['loan_status']
y = y.iloc[:, 1].values
```

```
y
```

```
array([1, 1, 1, ..., 1, 1, 0])
```

```
# Splitting the dataset into the Training set and Test set
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, random_state = 0)
```

```
#Scale the Data
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)
```

```
y_train
```

```
array([0, 1, 1, ..., 0, 1, 0])
```

```
from sklearn.linear_model import LogisticRegression
classifier = LogisticRegression(random_state = 0)
classifier.fit(X_train, y_train)
```

```
LogisticRegression(random_state=0)
```

```
classifier.get_params(deep=True)
```

```
{'C': 1.0,
 'class_weight': None,
 'dual': False,
 'fit_intercept': True,
 'intercept_scaling': 1,
 'l1_ratio': None,
 'max_iter': 100,
 'multi_class': 'auto',
 'n_jobs': None,
 'penalty': 'l2',
 'random_state': 0,
 'solver': 'lbfgs',
 'tol': 0.0001,
 'verbose': 0,
 'warm_start': False}
```

```
weight = classifier.coef_
weight
```

```
array([[-0.02470051,  0.1172764 , -0.03516401, -0.32448086, -0.07126307,
         0.35649176, -0.05391491,  0.07232629, -0.01937667,  0.02113182,
        -0.08504462, -0.07620091, -0.01887878,  0.03607745, -0.07285164,
         0.04641788,  0.02242338,  0.01786648,  0.01247659, -0.0088899 ,
         0.00227975, -0.02470051,  0.1172764 , -0.03516401, -0.32448086,
        -0.07126307,  0.35649176, -0.05391491,  0.07232629, -0.01937667,
         0.02113182, -0.08504462, -0.07620091, -0.01887878,  0.03607745,
```

```
       -0.07285164,  0.04641788,  0.02242338,  0.01786648,  0.01247659,
       -0.0088899 ,  0.00227975, -0.02102622,  0.02290948,  0.0256239 ,
       -0.2153804 ]])
```

```
def logreg_to_dict(clf, feature_names):
    coefs = np.concatenate([clf.intercept_, clf.coef_.squeeze()])
    return dict(zip(["intercept"] + feature_names, coefs))

print(logreg_to_dict(classifier,X.columns.tolist()))
```

```
{'intercept': 1.6602292173675042, 'loan_amnt': -0.024700510184082456, 'int_rate': 0.117
```

Grade and employee title are most Important features here as they are largest in Magnitude.

coeff of employee_title is positive. so it effects the probability of x belonging to class 1 positively.

high Grade means lower probablity of X belonging to class 1.as it has -ve coeff.

```
# Predicting the Test set results
y_pred = classifier.predict(X_test)
```

```
from sklearn.metrics import confusion_matrix,precision_score,recall_score,f1_score
cm = confusion_matrix(y_test, y_pred)
```

```
cm
```

```
array([[ 2704, 10503],
       [ 1588, 50348]])
```

```
precision_score(y_test,y_pred)
```

```
0.827398070697277
```

precision here is 0.83 which is good. Bad precision means we will get False positives.

This will lead to giving loan to people who couldnot pay.This will lead to NPA. so precision help us lower down Bank NPA

```
recall_score(y_test,y_pred)
```

```
0.9694239063462723
```

Recall is also good. Bad recall means more false negatives. This will lead to losing Important customers.

good recall will ensure that we will not lose any important customers.

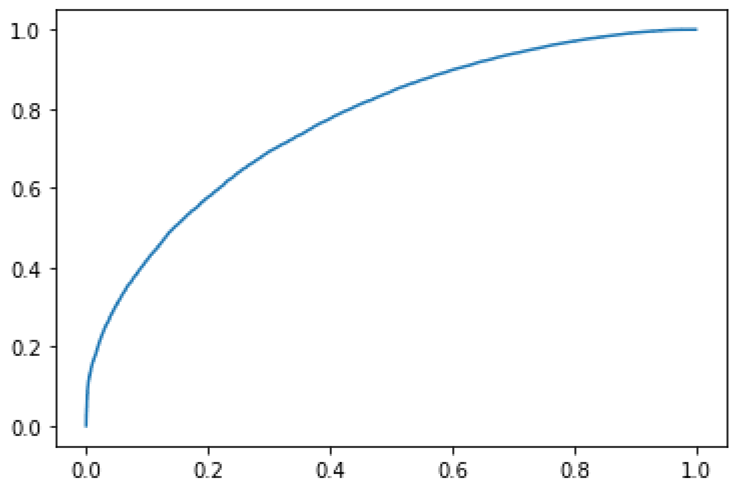
```
f1_score(y_test,y_pred)
```

```
0.8927979288393167
```

```
#Estimate the probability of belonging to class 1
probs=classifier.predict_proba(X_test)[:,1]
```

```
from sklearn.metrics import roc_auc_score,roc_curve
fpr,tpr,thres=roc_curve(y_test,probs)
plt.plot(fpr,tpr)
roc_auc_score(y_test,probs)
```

```
0.7699012287682725
```



Here, AUC score is greater than 0.50. it means our model can predict the positive & Negative class well. Max score can be 1 but we got 0.758.

This can help us compare two models. we make many models for classification and choose the one with max AUC.

Actionable Insights

1.Here Grade and job_title are most Important columns. So we must look for these beore giving loan to someone.

2.we must look for probablity before we sanction loan to someone. and not just the prediction.

looking for probability will give us more confidence about loan_status

0s completed at 7:54 PM