Problem Statement

- A bank had collected data about historical loan default along with respective information for each member.
- You need to build a model that will help this bank by predicting the probability that a member will default.

1. import all the libraries

In [1]:
```
#for importing the datasets
import os
#for exploratory Analysis
import pandas as pd
import numpy as np
#for visulaisation
import matplotlib.pyplot as plt
import seaborn as sns
#for preprocessing
from sklearn.preprocessing import StandardScaler,LabelEncoder
from sklearn.decomposition import PCA
from collections import OrderedDict
import scipy.stats as sci

#for traintest split
from sklearn.model_selection import train_test_split,GridSearchCV,KFold,StratifiedKFold,Randomiz

#Logistic Regression model
from sklearn.linear_model import LogisticRegression

#visualise the logistic regression output summary
import statsmodels.api as sm

#KNN
from sklearn.neighbors import KNeighborsClassifier

#for modelevaluation: metrics
from sklearn.metrics import confusion_matrix,ConfusionMatrixDisplay,roc_auc_score,roc_curve,clas

#supress warnings
import warnings
warnings.filterwarnings("ignore")

from collections import Counter

#feature selection
from sklearn.feature_selection import chi2,RFE,RFECV,f_classif,SelectKBest

#Decission Tree
from sklearn.tree import DecisionTreeClassifier

#Random Forest
from sklearn.ensemble import RandomForestClassifier,AdaBoostClassifier,GradientBoostingClassifie

#SVM
from sklearn.svm import SVC
```

```
#Deal with the minority class
from imblearn.over_sampling import SMOTE
from imblearn.under_sampling import RandomUnderSampler
from imblearn.pipeline import Pipeline
from imblearn.combine import SMOTEENN

#Calculate VIF
from statsmodels.stats.outliers_influence import variance_inflation_factor
```

In [2]:
```
train_df=pd.read_csv('train_data_1.csv')
test_df=pd.read_csv('train_data_2.csv')
```

In [3]:
```
def data_checks(df):
    """ Does basic checks on the input dataframe

    Args:
        (df): Dataframe

    """
    print('=============INFO====================')
    print(df.info())
    print('\n=============SHAPE====================')
    print(df.shape)
```

In [4]:
```
def find_missing_values(df):
#findout percentage of missing values in the categorical data
    missing_cols_list=[]
    for each in df.columns:
        missing_values=(df[each].isnull().sum()/df.shape[0])*100
        if(missing_values>0):
            missing_cols_list.append((each,(str(missing_values)+'%')))

    temp_dict = dict((x,y) for x, y in enumerate(missing_cols_list))
    missing_value_df=pd.DataFrame.from_dict(temp_dict)
    return missing_cols_list,missing_value_df
```

In [5]:
```
def treat_missing_values(df,cols_list_with_missing_values):
    for index, tup in enumerate(cols_list_with_missing_values):
        if(df[tup[0]].dtype=='O'):
            df[tup[0]]=df[tup[0]].fillna(df[tup[0]].mode()[0])
        else:
            df[tup[0]]=df[tup[0]].fillna(df[tup[0]].median())
```

In [6]:
```
def extract_numeric_value(df,col_list):
    for each in cols_to_numeric_list:
        df[each]= df[each].str.extract('(\d*\.?\d+)',expand=True)
        df[each]=pd.to_numeric(df[each])
```

In [7]:
```
def select_cat_features_chi2(x,y):
    f_score=chi2(x,y)   #returns f score and p value
    chi2_summary_dict={
        'features':list(x.columns),
        'chi2':f_score[0],
        'p-value':f_score[1]
                    }
    chi2_summary_df=pd.DataFrame.from_dict(data=chi2_summary_dict)
    selected_cols_df=chi2_summary_df[chi2_summary_df['p-value']<0.05]
    selected_features_list=list(selected_cols_df['features'])
    return chi2_summary_df,selected_features_list
```

In [8]:
```
def select_features_rfe(X_train, y_train):
    log_reg = LogisticRegression()
    rfe_model = RFECV(log_reg,cv=2,scoring='accuracy')
    rfe_values=rfe_model.fit(X_train,y_train)
    rfe_output_dict={
                    'Features':list(X_train.columns),
                    'support':rfe_values.support_,
                    'Ranking':rfe_values.ranking_
                    }
    rfe_output_df=pd.DataFrame.from_dict(rfe_output_dict)
    rfe_output_df.sort_values('Ranking',ascending=True,inplace=True)
    rfe_output_df.reset_index(inplace=True)
    feature_list= rfe_output_df[rfe_output_df['Ranking']==1]['Features']
    return rfe_output_df,feature_list
```

In [9]:
```
def fn_summary(df):
    summary=[]
    for col in df.columns:

        if(df[col].dtypes!='object'):

            result_dict=OrderedDict({
            'Feature_Name':col,
            'Count':df[col].count(),
            'Q1':df[col].quantile(0.25),
            'Q2':df[col].quantile(0.50),
            'Q3':df[col].quantile(0.75),
            'mean':df[col].mean(),
            'min':df[col].min(),
            'max':df[col].max(),
            'variance':np.round(df[col].var(),2),
            'std_dev':df[col].std(),
            'skewness': df[col].skew(),
            'kurtosis': df[col].kurt()})

            summary.append(result_dict)
        summary_df=pd.DataFrame(summary)

        #skewness
        skewness_label=[]
        for i in summary_df['skewness']:
            if i<= -1:
                skewness_label.append('Highly negatively skewed')
            elif -1 <=i <= -0.5:
                skewness_label.append('Moderately Negatively skewed')
            elif -0.5 <= i <= 0:
                skewness_label.append('Fairly negatively skewed')
            elif 0 <= i <= 0.5:
                skewness_label.append('Fairly positively skewed')
            elif 0.5 <= i <= 1:
                skewness_label.append('Moderately positively skewed')
            elif i >= 1:
                skewness_label.append('Highly positively skewed')
        summary_df['skewness_comment']=skewness_label

        #kurtusis
        kurtosis_label=[]
        for i in summary_df['kurtosis']:
            if i >=1 :
                kurtosis_label.append('Leptokurtic')
            elif i <= -1:
```

```
                kurtosis_label.append('Platykurtic')
            else:
                kurtosis_label.append('Mesokurtic')
        summary_df['kurtosis_comment']=kurtosis_label

        #Outliers
        outliers_label=[]
        for col in df.columns:
            if(df[col].dtypes!='object'):
                q1=df[col].quantile(0.25)
                q2=df[col].quantile(0.50)
                q3=df[col].quantile(0.75)
                iqr=q3-q1
                lower_whisker = q1-1.5*iqr
                upper_whisker = q3+1.5*iqr
                if len( df[ (df[col]<lower_whisker) | (df[col]>upper_whisker) ]) > 0:
                    outliers_label.append('Has Outliers')
                else:
                    outliers_label.append('No Outliers')

    summary_df['outlier_comment']= outliers_label
    return summary_df;
```

In [10]:
```
def visualise_features(df,col_name,plot_type):
    """
    Visualize a variable with and without faceting on the loan status.
    - col_name is the variable name in the dataframe
    - plot_type conveys if the plot has to be for continous variable or categorical variable
    """
    # plots for continuous features

    if (plot_type=='continous') :
        f,(axes) = plt.subplots(1,2 ,figsize=(12,4))

        # Plot without loan status
        # DistPlot of feature
        graph1=sns.distplot(df[col_name],ax=axes[0],fit=sci.norm)
        graph1.axvline(df[col_name].mean(),linewidth=2, color='r',ls= '--',label='mean')
        graph1.axvline(df[col_name].median(),linewidth=2, color='b',ls= '--',label='median')
        graph1.set_title(col_name+"- "+'Histogram')
        graph1.set_xlabel("values", fontsize = 10)
        graph1.set_ylabel("Density", fontsize = 10)
        axes[0].legend()

        # Plot with loan status
        # BoxPlot of feature with loan_status
        graph2=sns.boxplot(x='loan_status', y=col_name,data=train_df, ax=axes[1])
        graph2.set_title(col_name+"- "+'Histogram')
        graph2.set_xlabel('loan_status', fontsize = 10)
        graph2.set_ylabel(col_name, fontsize = 10)
        graph2.set_title(col_name +"- "+ 'with Loan Status')

    # plots for discrete features
    elif(plot_type=='discrete'):

        f,(axes2) = plt.subplots(1,3 ,figsize=(18,4))
        # Plot without loan status
        # CountPlot of feature
        graph3=sns.countplot(df[col_name],order=df[col_name].value_counts().index, ax=axes2[0])
        graph3.set_xlabel(col_name)
        graph3.set_ylabel('Count')
```

```
        graph3.set_title(col_name+"- "+"Countplot")
        plt.setp(axes2[0].get_xticklabels(), rotation=90)


        # Plot with loan status
        # BarPlot of feature with loan_status
        proportion_def_ndef_df = df[[col_name,'loan_status']].groupby(col_name, as_index=False).v
        graph4=sns.barplot(x=col_name, y='proportion',hue='loan_status',ax=axes2[1],data=proporti
        graph4.set_xlabel(col_name)
        graph4.set_ylabel('proportion')
        graph4.set_title(col_name+"- "+'Defaulted and Non defaulted Loans proportion')
        plt.setp(axes2[1].get_xticklabels(), rotation=90)

        # Plot with loan status
        # BarPlot of feature with loan_status=1
        proportions_def_df=proportion_def_ndef_df[proportion_def_ndef_df['loan_status']==1].sort_
        graph5=sns.barplot(x=proportions_def_df[col_name],y=proportions_def_df['proportion'],ax=a
        graph5.set_xlabel(col_name)
        graph5.set_ylabel('proportion')
        graph5.set_title(col_name+"- "+'Defaulted Loans proportion')
        plt.setp(axes2[2].get_xticklabels(), rotation=90)

    else:
        print('enter correct plot type')
    plt.tight_layout()
```

In [11]:
```
def label_encode(df,encode_col_list):
    le=LabelEncoder()
    for each in encode_col_list:
        df[each]=le.fit_transform(df[each])
```

In [12]:
```
def ohe_encode(df,ohe_encode_col_list):
    ohe=pd.get_dummies(df,columns=ohe_encode_col_list,prefix_sep='_',drop_first=True)
    return ohe
```

In [13]:
```
def plot_AUC(truth, pred, lab):
    fpr, tpr, _ = roc_curve(truth,pred)
    roc_auc = auc(fpr, tpr)
    lw = 2
    c = (np.random.rand(), np.random.rand(), np.random.rand())
    plt.plot(fpr, tpr, color= 'b',lw=lw, label= lab +'(AUC = %0.2f)' % roc_auc)
    plt.plot([0, 1], [0, 1], color='navy', lw=lw, linestyle='--')
    plt.xlim([0.0, 1.0])
    plt.ylim([0.0, 1.0])
    plt.xlabel('False Positive Rate')
    plt.ylabel('True Positive Rate')
    plt.title('ROC curve') #Receiver Operating Characteristic
    plt.legend(loc="lower right")
```

In [14]:
```
def plot_PR_Curve(y_true, y_pred_prob,lab,f1_score):
    precision, recall, thresholds = precision_recall_curve(y_true, y_pred_prob)
    #create precision recall curve
    c = (np.random.rand(), np.random.rand(), np.random.rand())
    plt.plot(recall, precision, color= 'g',lw=2, label= lab +'(F1-score = %0.2f)' % f1_score)
    plt.xlim([0.0, 1])
    plt.ylim([0.0, 1])
    plt.xlabel('Recall')
    plt.ylabel('Precision')
    plt.title(' #Precision Recall curve') #Precission Recall Curve
    plt.legend(loc="lower right")
```

```
    #display plot
    plt.show()
```

In [15]:
```
def plot_confusion_matrix(y_test,y_pred):
    cm = confusion_matrix(y_test, y_pred, labels=[0, 1])
    disp=ConfusionMatrixDisplay(cm,display_labels=["Will Pay", "Will Default"])
    disp.plot()
```

In [16]:
```
def corr_F_P_scores(X,y):
    feature_sel_df=pd.DataFrame(columns=['Correlation','Fscore','Pvalue'])
    corr_scores=X.corrwith(y)
    best_features=SelectKBest(score_func=f_classif,k='all')
    fit=best_features.fit(X,y)
    feature_sel_df['Correlation']=corr_scores
    feature_sel_df['Fscore']=np.round(fit.scores_,3)
    feature_sel_df['Pvalue']=np.round(fit.pvalues_,3)
    return feature_sel_df
```

In [17]:
```
def calculate_vif(X):
    '''
    lets try analysisng VIF
    '''
    vif = pd.DataFrame()
    vif['Features'] = X.columns
    vif['VIF'] = [variance_inflation_factor(X.values, i) for i in range(X.shape[1])]
    vif['VIF'] = round(vif['VIF'], 2)
    vif = vif.sort_values(by = "VIF", ascending = False)
    return vif
```

In [18]:
```
def to_labels(pos_probs, threshold):
        return (pos_probs >= threshold).astype('int')
```

In [19]:
```
def z_score_standardization(series):
    return (series - series.mean()) / series.std()
```

In [20]:
```
def build_logistic_model(X,y):
    lm = sm.Logit(y,X).fit() # fitting the model
    print(lm.summary()) # model summary
    return X
```

2. Check the train and test data information

In [21]:
```
data_checks(train_df)
data_checks(test_df)
```

```
=============INFO====================
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 270000 entries, 0 to 269999
Data columns (total 45 columns):
 #   Column                        Non-Null Count   Dtype
---  ------                        --------------   -----
 0   member_id                     270000 non-null  int64
 1   loan_amnt                     270000 non-null  int64
 2   funded_amnt                   270000 non-null  int64
 3   funded_amnt_inv               270000 non-null  float64
 4   term                          270000 non-null  object
 5   batch_enrolled                173125 non-null  object
 6   int_rate                      270000 non-null  float64
 7   grade                         270000 non-null  object
 8   sub_grade                     270000 non-null  object
 9   emp_title                     254375 non-null  object
 10  emp_length                    256370 non-null  object
 11  home_ownership                270000 non-null  object
 12  annual_inc                    269998 non-null  float64
 13  verification_status           270000 non-null  object
 14  pymnt_plan                    270000 non-null  object
 15  desc                          38379 non-null   object
 16  purpose                       270000 non-null  object
 17  title                         269957 non-null  object
 18  zip_code                      270000 non-null  object
 19  addr_state                    270000 non-null  object
 20  dti                           270000 non-null  float64
 21  delinq_2yrs                   269994 non-null  float64
 22  inq_last_6mths                269994 non-null  float64
 23  mths_since_last_delinq        131498 non-null  float64
 24  mths_since_last_record        41289 non-null   float64
 25  open_acc                      269994 non-null  float64
 26  pub_rec                       269994 non-null  float64
 27  revol_bal                     270000 non-null  int64
 28  revol_util                    269852 non-null  float64
 29  total_acc                     269994 non-null  float64
 30  initial_list_status           270000 non-null  object
 31  total_rec_int                 270000 non-null  float64
 32  total_rec_late_fee            270000 non-null  float64
 33  recoveries                    270000 non-null  float64
 34  collection_recovery_fee       270000 non-null  float64
 35  collections_12_mths_ex_med    269958 non-null  float64
 36  mths_since_last_major_derog   67505 non-null   float64
 37  application_type              270000 non-null  object
 38  verification_status_joint     141 non-null     object
 39  last_week_pay                 270000 non-null  object
 40  acc_now_delinq                269994 non-null  float64
 41  tot_coll_amt                  248617 non-null  float64
 42  tot_cur_bal                   248617 non-null  float64
 43  total_rev_hi_lim              248617 non-null  float64
 44  loan_status                   270000 non-null  int64
dtypes: float64(22), int64(5), object(18)
memory usage: 92.7+ MB
None

=============SHAPE====================
(270000, 45)
=============INFO====================
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 262428 entries, 0 to 262427
Data columns (total 45 columns):
 #   Column                        Non-Null Count   Dtype
```

```
---  ------                      --------------  -----
 0   member_id                   262428 non-null  int64
 1   loan_amnt                   262428 non-null  int64
 2   funded_amnt                 262428 non-null  int64
 3   funded_amnt_inv             262428 non-null  float64
 4   term                        262428 non-null  object
 5   batch_enrolled              168075 non-null  object
 6   int_rate                    262428 non-null  float64
 7   grade                       262428 non-null  object
 8   sub_grade                   262428 non-null  object
 9   emp_title                   247220 non-null  object
 10  emp_length                  249167 non-null  object
 11  home_ownership              262428 non-null  object
 12  annual_inc                  262427 non-null  float64
 13  verification_status         262428 non-null  object
 14  pymnt_plan                  262428 non-null  object
 15  desc                        37220 non-null   object
 16  purpose                     262428 non-null  object
 17  title                       262381 non-null  object
 18  zip_code                    262428 non-null  object
 19  addr_state                  262428 non-null  object
 20  dti                         262428 non-null  float64
 21  delinq_2yrs                 262418 non-null  float64
 22  inq_last_6mths              262418 non-null  float64
 23  mths_since_last_delinq      128376 non-null  float64
 24  mths_since_last_record      40834 non-null   float64
 25  open_acc                    262418 non-null  float64
 26  pub_rec                     262418 non-null  float64
 27  revol_bal                   262428 non-null  float64
 28  revol_util                  262289 non-null  float64
 29  total_acc                   262418 non-null  float64
 30  initial_list_status         262428 non-null  object
 31  total_rec_int               262428 non-null  float64
 32  total_rec_late_fee          262428 non-null  float64
 33  recoveries                  262428 non-null  float64
 34  collection_recovery_fee     262428 non-null  float64
 35  collections_12_mths_ex_med  262375 non-null  float64
 36  mths_since_last_major_derog 65475 non-null   float64
 37  application_type            262428 non-null  object
 38  verification_status_joint   164 non-null     object
 39  last_week_pay               262428 non-null  object
 40  acc_now_delinq              262418 non-null  float64
 41  tot_coll_amt                241807 non-null  float64
 42  tot_cur_bal                 241807 non-null  float64
 43  total_rev_hi_lim            241807 non-null  float64
 44  loan_status                 262428 non-null  int64
dtypes: float64(23), int64(4), object(18)
memory usage: 90.1+ MB
None

=============SHAPE====================
(262428, 45)
```

3.Data cleaning

> some columns contain the numerics and alphabets, numeric value can be extracted from them.

In [22]:
```
#list of columns which can be converted to numeric
```

```
cols_to_numeric_list=['term','emp_length','zip_code','last_week_pay']
extract_numeric_value(train_df,cols_to_numeric_list)
extract_numeric_value(test_df,cols_to_numeric_list)
```

> in the title column there are many occurances with debt consolidation, Credit Card Debt Consolidation,Loan to payoff credit card debt,Debt Consolidation Loan,Debt Loan, The purpose ws to pay off debts. we can categorise all such occurances under the name "Debt consolidation"

> title contains many entries. it can be categorised into bins(which contribute to almost 70% of the title entries)

In [23]:
```
condition1=train_df['title'].str.contains(r'\b(D|d)ebt[a-zA-Z]*\b', regex=True)
train_df['title']=np.where(condition1==True, 'Debt consolidation', train_df['title'])
```

In [24]:
```
condition2=test_df['title'].str.contains(r'\b(D|d)ebt[a-zA-Z]*\b', regex=True)
test_df['title']=np.where(condition2==True, 'Debt consolidation', test_df['title'])
```

> employee title contains many entries. it can be categorised into 10 types(select top 10 emplyee professions)

In [25]:
```
emp_title_top10_list=list(train_df['emp_title'].value_counts().index)[0:10]
```

In [26]:
```
# titles we can categorise them into bins using np.where
train_df['emp_title'] = np.where(train_df['emp_title'].isin(emp_title_top10_list),train_df['emp_
```

In [27]:
```
# titles we can categorise them into bins using np.where
test_df['emp_title'] = np.where(test_df['emp_title'].isin(emp_title_top10_list),test_df['emp_tit
```

4.Remove unwanted features.

In [28]:
```
#unwanted features can remove them as they dont contribute to predict Y.
unwanted_cols=['member_id','batch_enrolled','desc','verification_status_joint']
```

In [29]:
```
train_df.drop(unwanted_cols,axis=1,inplace=True)
```

In [30]:
```
test_df.drop(unwanted_cols,axis=1,inplace=True)
```

- The batch_enrolled - approximatly 36%,
- description - 86%,
- verification_status_joint 99.9% missing values
- these columns cant be treeated hence drop them.
- The rest of the columns can be treated.

5.Find and treat missing values

In [31]:
```
missing_cols_list,missing_col_df=find_missing_values(train_df)
missing_col_df
```

Out[31]:

	0	1	2	3	
0	emp_length	annual_inc	title	delinq_2yrs	inq_
1	5.048148148148148%	0.0007407407407407407%	0.015925925925925927%	0.0022222222222222222%	0.002222222222

In [32]:
```
treat_missing_values(train_df,missing_cols_list)
```

In [33]:
```
missing_cols_list_after,missing_col_df_after=find_missing_values(train_df)
missing_col_df_after
```

Out[33]: —

In [34]:
```
missing_cols_list_test,missing_col_df_test=find_missing_values(test_df)
missing_col_df_test
```

Out[34]:

	0	1	2	3	
0	emp_length	annual_inc	title	delinq_2yrs	inc
1	5.0531955431585045%	0.00038105689941622087%	0.01790967427256238%	0.0038105689941622086%	0.00381056899

In [35]:
```
treat_missing_values(test_df,missing_cols_list)
```

In [36]:
```
missing_cols_list_test_after,missing_col_df_test_after=find_missing_values(test_df)
missing_col_df_test_after
```

Out[36]: —

7. Pre-processing and Exploratory Analysis

1.Inspect each and every feature. 2.Analyse the summary 3.Check if it is helpful in predicting the target variable.

In [37]:
```
summary_df=fn_summary(train_df)
```

7.1 Loan_amnt:

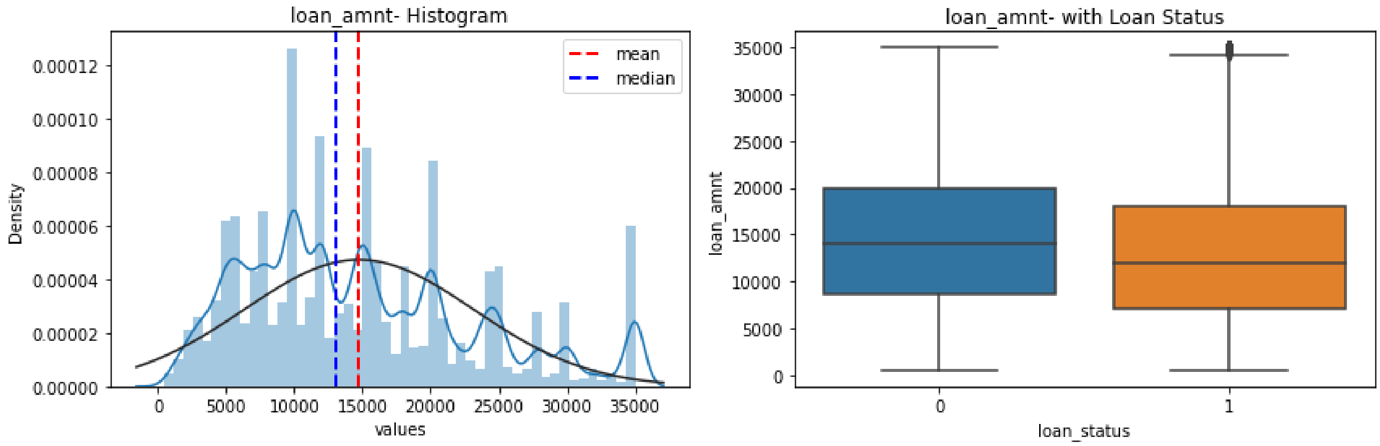
> loan_amnt loan amount ($) applied by the member

In [38]:
```
summary_df[summary_df['Feature_Name']=='loan_amnt']
```

Out[38]:

	Feature_Name	Count	Q1	Q2	Q3	mean	min	max	variance	std_dev	skew
0	loan_amnt	270000	8000.0	13000.0	20000.0	14749.904167	500.0	35000.0	71024000.51	8427.573821	0.67

In [39]:
```
visualise_features(train_df,'loan_amnt','continous')
```



7.1 Inferences:

```
1.The defaulters and non-defaulters applied for apprx. same range of amount 10k
to 20k dollars($)
```

7.2 funded_amnt:

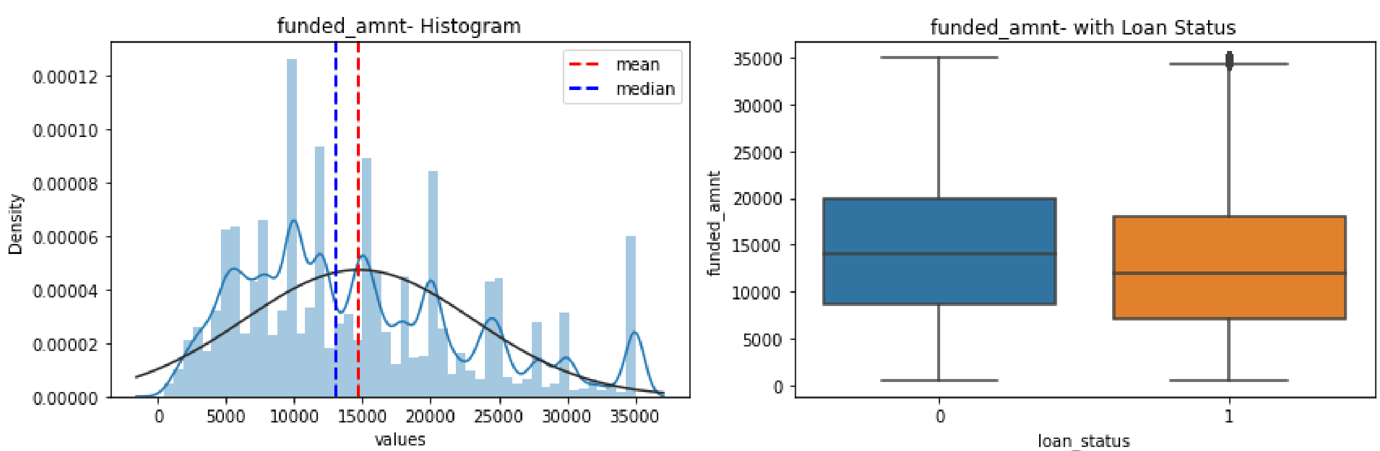
> loan_amnt loan amount ($) sanctioned by the bank

In [40]:
```
summary_df[summary_df['Feature_Name']=='funded_amnt']
```

Out[40]:

	Feature_Name	Count	Q1	Q2	Q3	mean	min	max	variance	std_dev	skew
1	funded_amnt	270000	8000.0	13000.0	20000.0	14736.266296	500.0	35000.0	70928515.73	8421.906894	0.68

In [41]:
```
visualise_features(train_df,'funded_amnt','continous')
```



7.2 Inferences:

```
1.The defaulters and non-defaulters were sanctioned apprx. same range of amount
10k to 20k dollars($)
```

7.3 funded_amnt_inv:

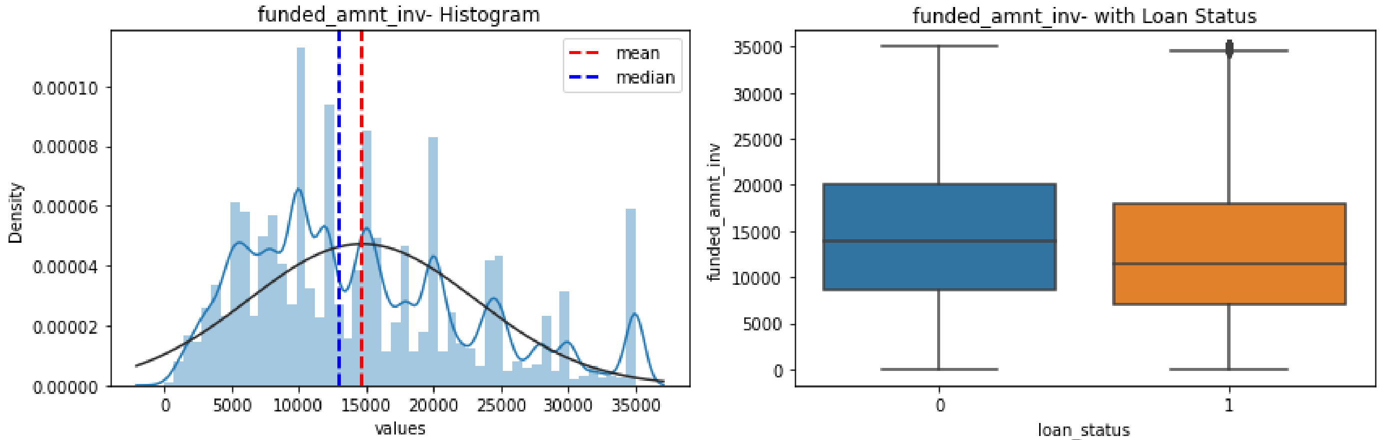
> loan amount ($) sanctioned by the investors

In [42]:
```
summary_df[summary_df['Feature_Name']=='funded_amnt_inv']
```

Out[42]:

	Feature_Name	Count	Q1	Q2	Q3	mean	min	max	variance	std_dev	skewne
2	funded_amnt_inv	270000	8000.0	13000.0	20000.0	14696.20653	0.0	35000.0	71142784.6	8434.618225	0.6786

In [43]:
```
visualise_features(train_df,'funded_amnt_inv','continous')
```



7.3 Inferences:

```
1.The defaulters and non-defaulters were sanctioned apprx. same range of amount
10k to 20k dollars($)
2.The 'Loan_amount', 'funded_amnt','funded_amnt_inv' all these cols look
similar and convey the same information/
3.Propbaby they are highly correlated.
```

7.4 term:

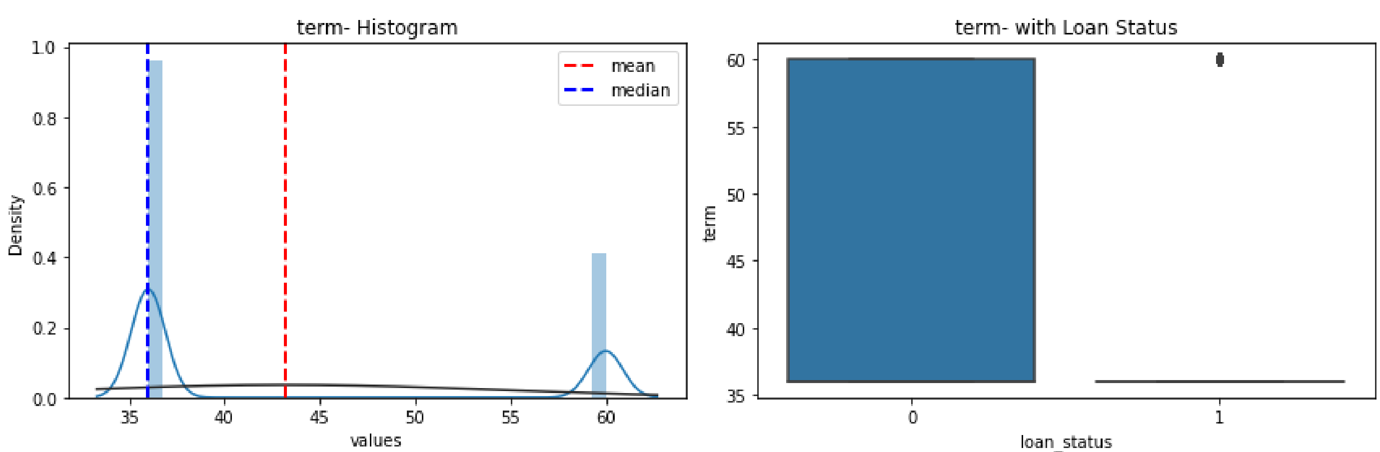
> term term of loan (in months)

In [44]:
```
summary_df[summary_df['Feature_Name']=='term']
```

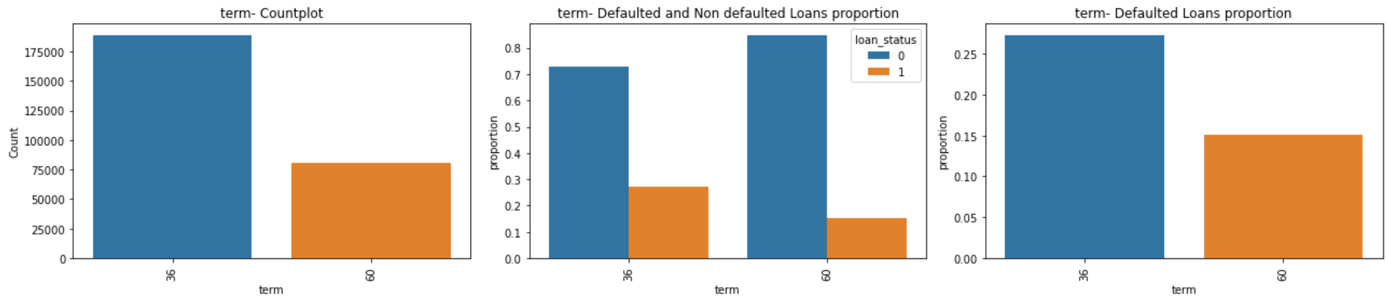
Out[44]:

	Feature_Name	Count	Q1	Q2	Q3	mean	min	max	variance	std_dev	skewness	kurtosis	skew
3	term	270000	36.0	36.0	60.0	43.203378	36.0	60.0	120.99	10.999676	0.872145	-1.239372	p

In [45]:
```
visualise_features(train_df,'term','continous')
```



In [46]:
```
visualise_features(train_df,'term','discrete')
```



In [47]:
```
train_df['term'].value_counts(normalize=True)
```

Out[47]:
```
36    0.699859
60    0.300141
Name: term, dtype: float64
```

In [48]:
```
train_df[['term','loan_status']].groupby('term').value_counts(normalize=True)
```

Out[48]:
```
term  loan_status
36    0              0.726908
      1              0.273092
60    0              0.849231
      1              0.150769
dtype: float64
```

7.4 Inferences:

```
1.The min term is 3 years and max term is 5 years.
2.The loans opted for 5 years have les % of defaulters as compared to loans
opted for 3 years.
```

7.5 term:

> Batch_enrolled

batch numbers allotted to members.

> **Batch number is irrelevant to the loan status**

7.6 int_rate:

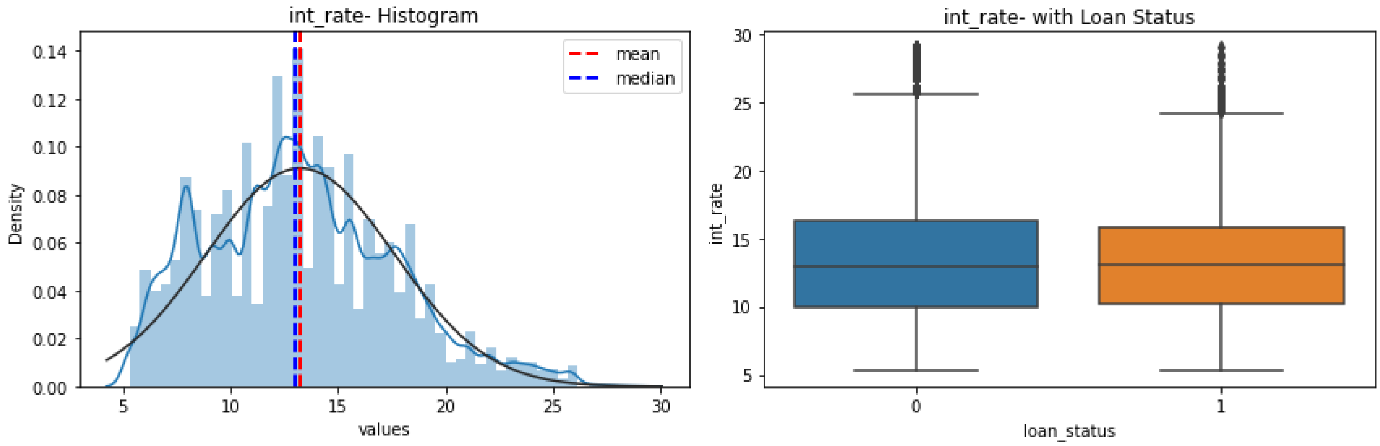
> interest rate (%) on loan

In [49]:
```
summary_df[summary_df['Feature_Name']=='int_rate']
```

Out[49]:

	Feature_Name	Count	Q1	Q2	Q3	mean	min	max	variance	std_dev	skewness	kurtosis	skew
4	int_rate	270000	9.99	12.99	16.2	13.243335	5.32	28.99	19.18	4.379194	0.431118	-0.151731	

In [50]:
```
visualise_features(train_df,'int_rate','continous')
```



In [51]:
```
train_df.groupby('loan_status')['int_rate'].describe()
```

Out[51]:

loan_status	count	mean	std	min	25%	50%	75%	max
0	206178.0	13.239757	4.418093	5.32	9.99	12.99	16.29	28.99
1	63822.0	13.254895	4.251114	5.32	10.16	13.11	15.80	28.99

7.6 inference:

> interest rate (%) for defaulted and non defaluted loans is similar. very less diff between the mean, median of defaulter

and non defaulters

loan_status	count	mean	std	min	25%	50%	75%	max
0	206178.0	13.239757	4.418093	5.32	9.99	12.99	16.29	28.99
1	63822.0	13.254895	4.251114	5.32	10.16	13.11	15.80	28.99

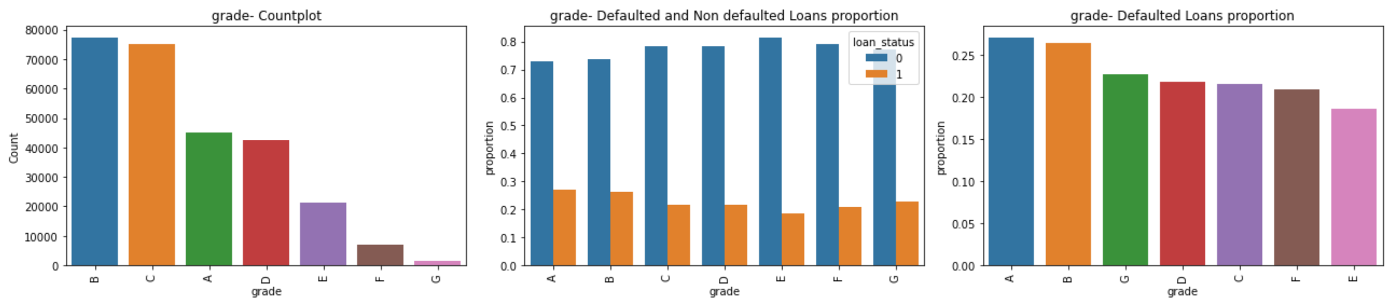
7.7 grade:

> grade assigned by the bank

In [52]:
```
train_df[['grade','loan_status']].groupby('grade').value_counts(normalize=True)
```

```
Out[52]: grade  loan_status
         A      0              0.729312
                1              0.270688
         B      0              0.736161
                1              0.263839
         C      0              0.784693
                1              0.215307
         D      0              0.782508
                1              0.217492
         E      0              0.814399
                1              0.185601
         F      0              0.790813
                1              0.209187
         G      0              0.772616
                1              0.227384
         dtype: float64
```

```
In [53]: # plot_var(train_df,'grade')
         visualise_features(train_df,'grade','discrete')
```



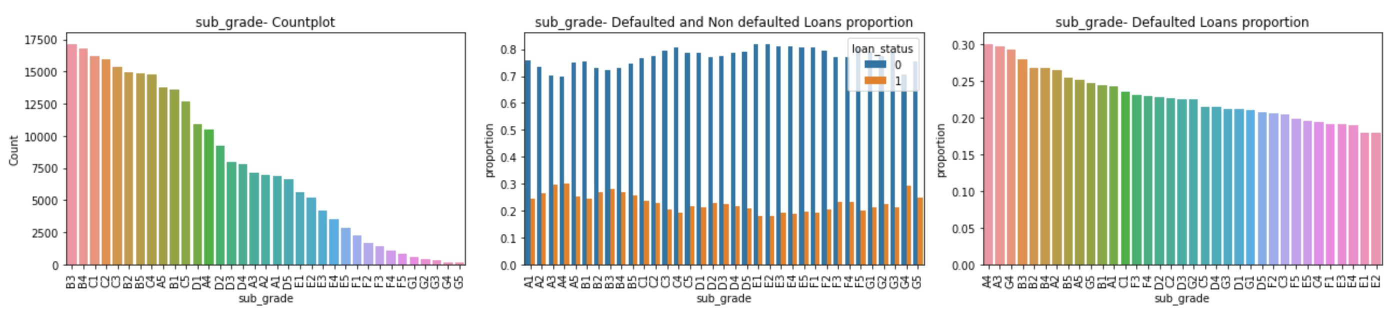
7.7 inference:

> The columns A,B,G account for most of the defulters

7.8 sub_grade:

> grade assigned by the bank

```
In [54]: visualise_features(train_df,'sub_grade','discrete')
```



7.8 inference:

> The subgrades with A,B,G account for most of the defulters

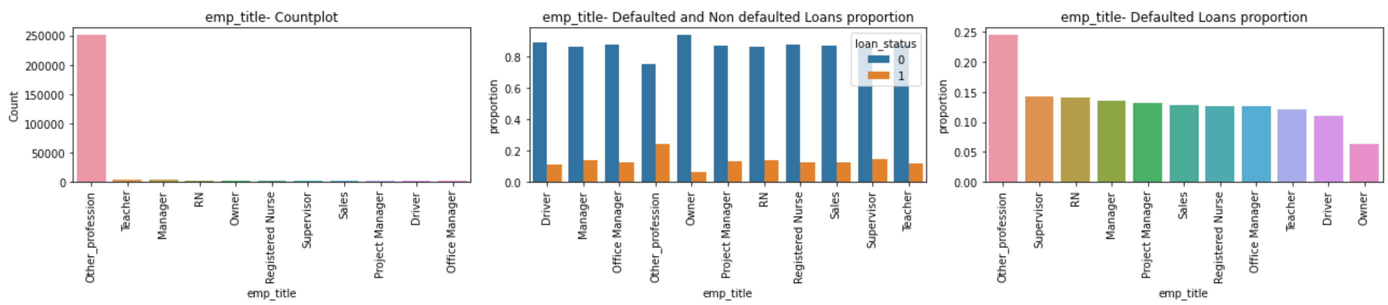
7.9 emp_title:

> emp_title job / Employer title of member

In [55]:
```python
train_df[['emp_title','loan_status']].groupby('emp_title').value_counts(normalize=True).loc[:,1]
```

Out[55]:
```
emp_title
Other_profession     0.245022
Supervisor           0.142857
RN                   0.139988
Manager              0.135733
Project Manager      0.131225
Sales                0.127581
Registered Nurse     0.126888
Office Manager       0.125668
Teacher              0.120567
Driver               0.109735
Owner                0.062722
dtype: float64
```

In [56]:
```python
visualise_features(train_df,'emp_title','discrete')
```



7.9 inference:

> in the supervisor,RN,Manager the defaulters are approx 13% to 14%

7.10 emp_length:

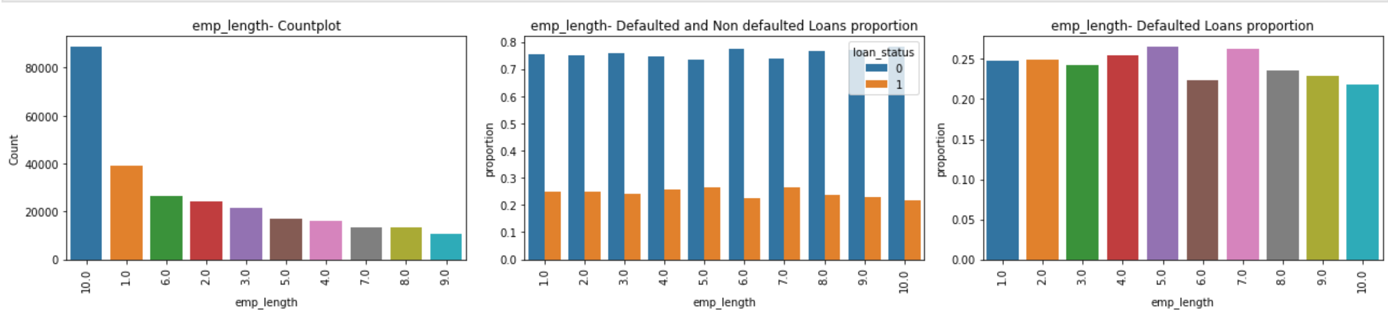
> emp_length employment length, where 0 means less than one year and 10 means ten or more years

In [57]:
```python
summary_df[summary_df['Feature_Name']=='emp_length']
```

Out[57]:

	Feature_Name	Count	Q1	Q2	Q3	mean	min	max	variance	std_dev	skewness	kurtosis	skewness
5	emp_length	270000	3.0	6.0	10.0	6.083544	1.0	10.0	11.89	3.448048	-0.167241	-1.513038	Fairly

In [58]:
```python
visualise_features(train_df,'emp_length','discrete')
```



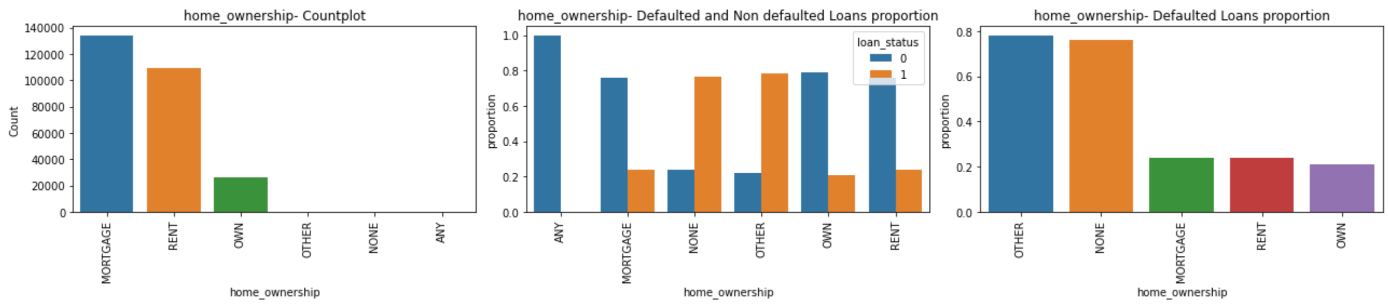
7.10 Inferences:

> There are more number of employees who worked for ~ 10 years The deaulters status is not affected by the employment length. In almost all the employee work duration length the defaulters are present and the proportions are more or less the same

7.11 home_ownership

> status of home ownership

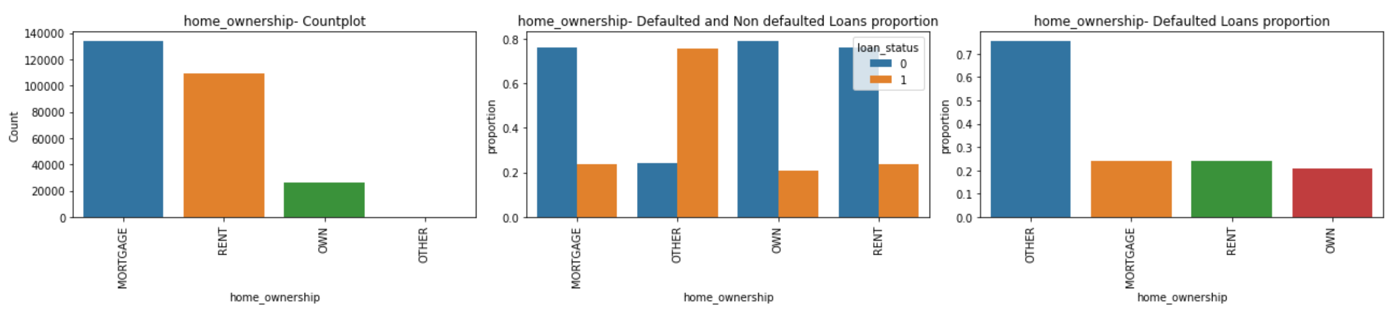
In [59]:
```
visualise_features(train_df,'home_ownership','discrete')
```



replace the none and any category to other. They are also unknown categories

In [60]:
```
train_df['home_ownership'].replace(['NONE', 'ANY'], 'OTHER', inplace=True)
```

In [61]:
```
visualise_features(train_df,'home_ownership','discrete')
```



7.10 Inferences:

> defaulters are more in the other category, followed by mortgage, rent.

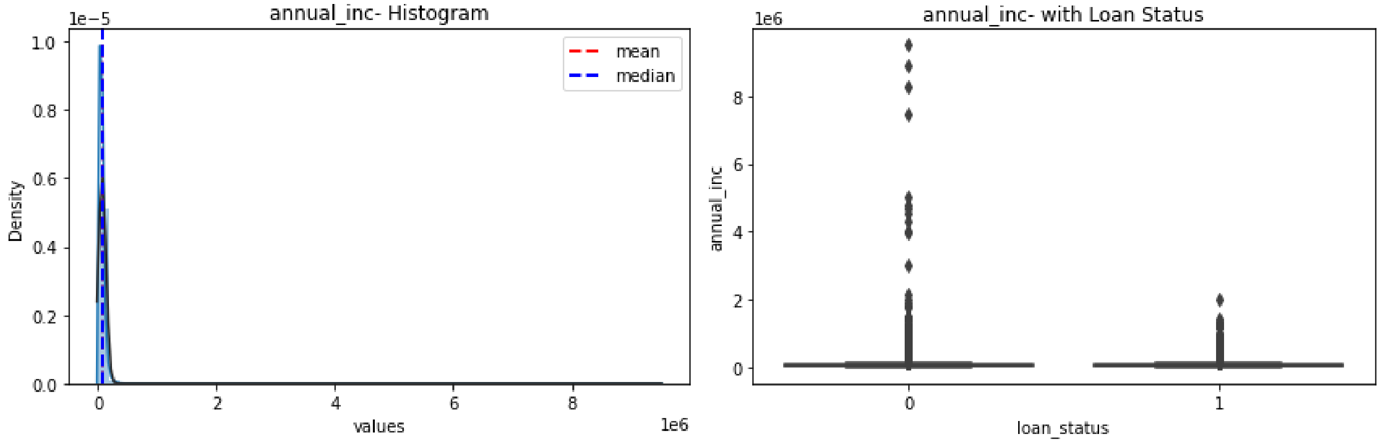
7.11 annual_inc: annual_inc annual income ($) reported by the member

In [62]:
```
summary_df[summary_df['Feature_Name']=='annual_inc']
```

Out[62]:

	Feature_Name	Count	Q1	Q2	Q3	mean	min	max	variance	std_dev
6	annual_inc	270000	45000.0	64857.5	90000.0	75062.075324	1896.0	9500000.0	4.205805e+09	64852.177187

In [63]:
```
visualise_features(train_df,'annual_inc','continous')
```

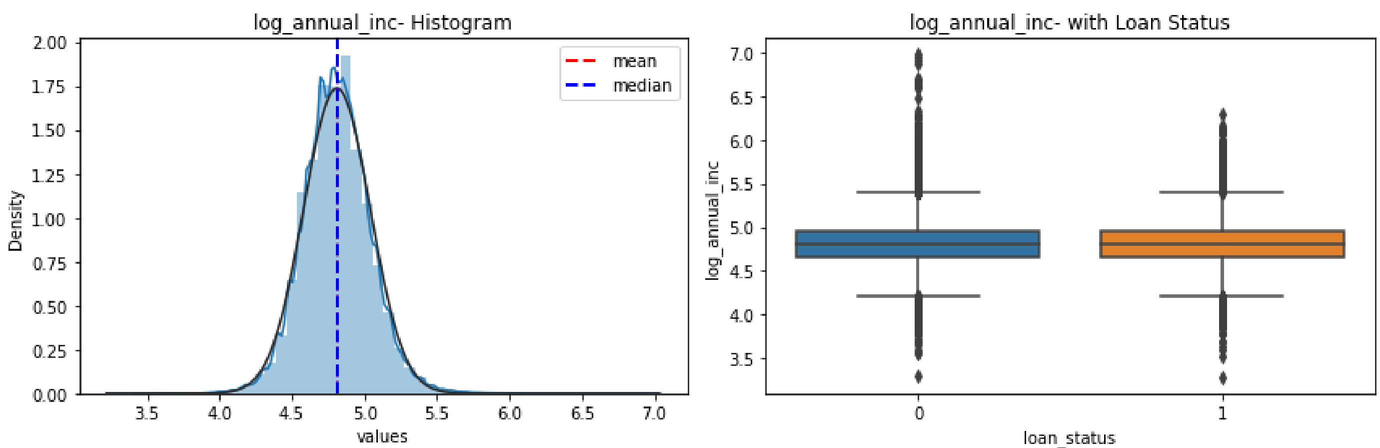


> The annual income ranges from 1896.0()to9500000.0()

```
1.lets apply log transformation as the data looks right skewed.
2.adding 1 to x there may be values of 0 and log10(0) would be infinity
```

In [64]:
```
train_df['log_annual_inc']=train_df['annual_inc'].apply(lambda x: np.log10(x+1))
```

In [65]:
```
visualise_features(train_df,'log_annual_inc','continous')
```



In [66]:
```
train_df.groupby('loan_status')['log_annual_inc'].describe()
```

Out[66]:

loan_status	count	mean	std	min	25%	50%	75%	max
0	206178.0	4.810746	0.230719	3.301247	4.653222	4.812920	4.954247	6.977724
1	63822.0	4.806970	0.226116	3.278067	4.653222	4.806187	4.954247	6.301030

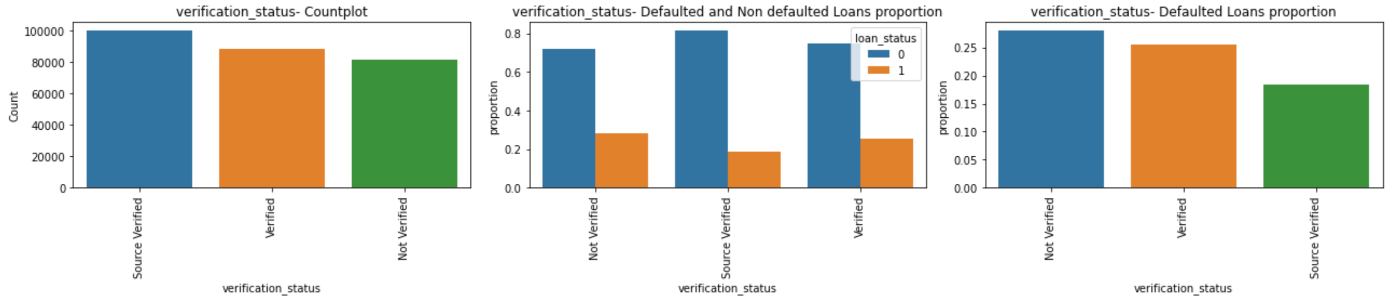
7.11 pending inferences

> There are huge number of outliers in the data. after aplying the log transform there is no diff between the 0 and 1 class in loan status. the mean and median of both the classes is similar.

7.12 verification_status:

verification status of income verified by the bank

In [67]:
```python
visualise_features(train_df,'verification_status','discrete')
```



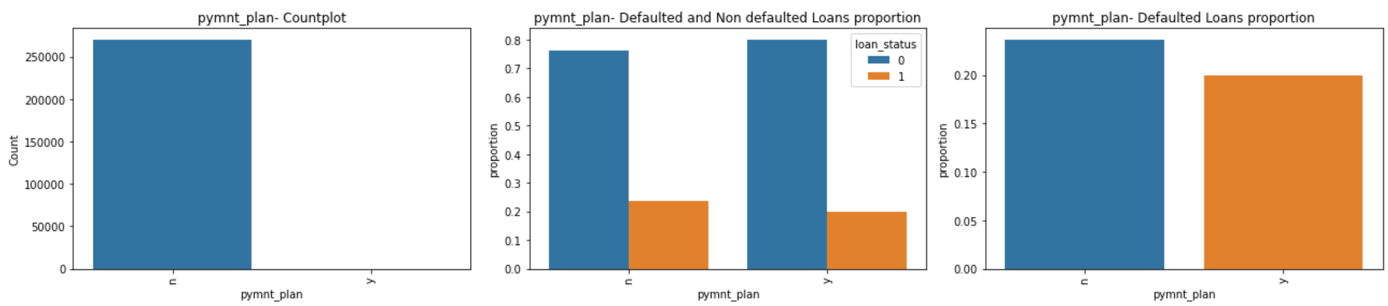
7.12 Inferences:

> wherever the status is not verified there are more chances of default

7.13 pymnt_plan:

> indicates if any payment plan has started against loan

In [68]:
```python
visualise_features(train_df,'pymnt_plan','discrete')
```



7.13 inferences:

> This feature doesnt look useful to predict loan status.

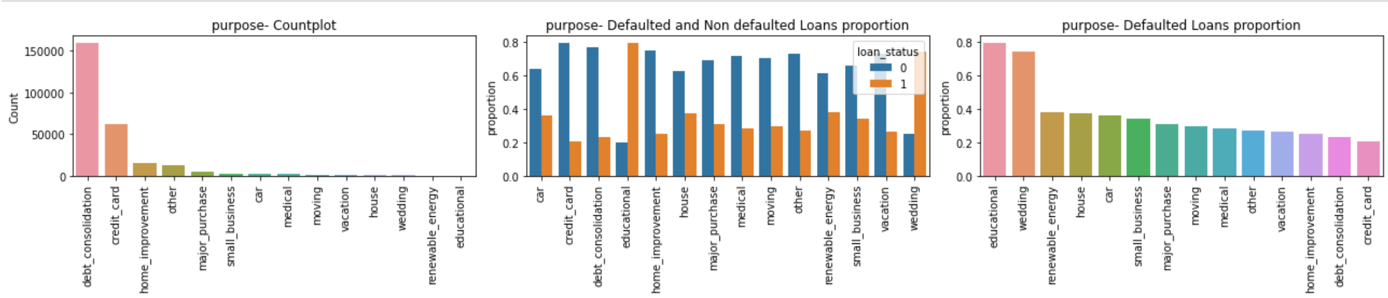
7.14 desc:

```
1.loan description provided by member
2. Not useful feature
```

7.15: purpose

purpose of loan

In [69]:
```python
visualise_features(train_df,'purpose','discrete')
```



In [70]:
```python
train_df[['purpose','loan_status']].groupby('purpose').value_counts(normalize=True)
```

Out[70]:
```
purpose             loan_status
car                 0              0.638899
                    1              0.361101
credit_card         0              0.794038
                    1              0.205962
debt_consolidation  0              0.768054
                    1              0.231946
educational         1              0.798387
                    0              0.201613
home_improvement    0              0.747987
                    1              0.252013
house               0              0.624422
                    1              0.375578
major_purchase      0              0.691112
                    1              0.308888
medical             0              0.718289
                    1              0.281711
moving              0              0.702077
                    1              0.297923
other               0              0.729482
                    1              0.270518
renewable_energy    0              0.617647
                    1              0.382353
small_business      0              0.659302
                    1              0.340698
vacation            0              0.733380
                    1              0.266620
wedding             1              0.746309
                    0              0.253691
dtype: float64
```

7.15 inference:

The reason provided by the customer to take the loan. The loans taken for educational purpose,wedding have high chances of default.

7.16: title

```
1.loan title provided by member
```

In [71]:
```
train_df[['title']].value_counts()
```

Out[71]:
```
title
Debt consolidation                 142342
Credit card refinancing             49834
Home improvement                    12086
Other                                9615
Major purchase                       3682
                                    ...
Home Improvement & Pay Bills            1
Home Improvement & Storage              1
Home Improvement (room add-on)          1
Home Improvement - After Sandy          1
zonball Loan                            1
Length: 18455, dtype: int64
```

In [72]:
```
train_df[['title']].describe()
```

Out[72]:

	title
count	270000
unique	18455
top	Debt consolidation
freq	142342

7.16 Inferences:

The purpose column is a super set of this column. redundant info there are 18455 uinique entries in it and as it is like a subset of pupose it can bo dropped.

7.17 zip_code:

zip_code first three digits of area zipcode of member

In [73]:
```
train_df['zip_code'].nunique()
```

Out[73]: 895

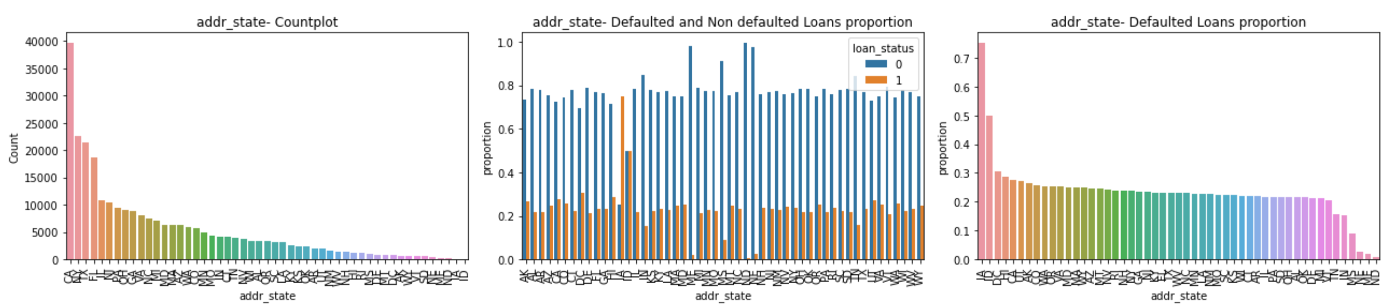
7.18 addr_state

living state of member

In [74]:
```
train_df['addr_state'].nunique()
```

Out[74]: 51

In [75]:
```
visualise_features(train_df,'addr_state','discrete')
```



In [76]:
```
add_df=train_df[['addr_state','loan_status']].groupby('addr_state',as_index=False).value_counts(
```

In [77]:
```
add_df[add_df['loan_status']==1].sort_values(by='proportion',ascending=False)
```

Out[77]:

	addr_state	loan_status	proportion
24	IA	1	0.750000
26	ID	1	0.500000
15	DC	1	0.305292
23	HI	1	0.287471
9	CA	1	0.277515
89	UT	1	0.271865
1	AK	1	0.266176
11	CO	1	0.256926
95	WA	1	0.255080
75	OR	1	0.253309
91	VA	1	0.252946
41	MD	1	0.250664
39	MA	1	0.249165
101	WY	1	0.248748
7	AZ	1	0.247547
53	MT	1	0.246684
67	NV	1	0.242210
79	RI	1	0.239379
61	NH	1	0.238851
69	NY	1	0.237220
21	GA	1	0.234288
63	NJ	1	0.233562
35	KY	1	0.232019
19	FL	1	0.231596
87	TX	1	0.230221
99	WV	1	0.230200
55	NC	1	0.230189
47	MN	1	0.228290
37	LA	1	0.227373
65	NM	1	0.226763
49	MO	1	0.224035
81	SC	1	0.222464
33	KS	1	0.221995
97	WI	1	0.220994
13	CT	1	0.220439
5	AR	1	0.219000

	addr_state	loan_status	proportion
29	IL	1	0.217687
77	PA	1	0.217259
83	SD	1	0.217143
71	OH	1	0.216363
3	AL	1	0.215732
73	OK	1	0.215327
17	DE	1	0.213542
45	MI	1	0.212678
93	VT	1	0.205776
85	TN	1	0.155933
31	IN	1	0.154876
51	MS	1	0.090416
59	NE	1	0.026239
43	ME	1	0.019355
57	ND	1	0.007143

7.18 Inference

```
1. The state and zip code both are similar info but the unique values in zip
code are huge.
2. we can use state and drop zip
```

7.19: dti

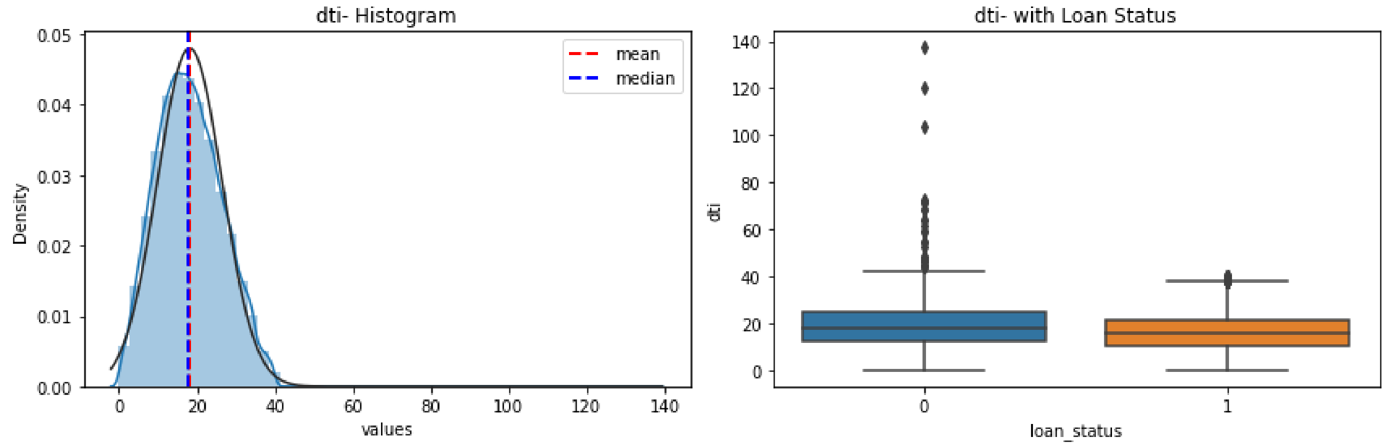
```
1.The debt-to-income (DTI) ratio reflects an individual's monthly loan payment
to their monthly gross income. Your gross earnings is the amount you earn
without taxes and additional deductions. The debt-to-income ratio is the
proportion of your monthly gross income that goes toward debt payments.
2.The debt-to-income ratio formula is:
3.DTI ratio = Total monthly debt payments/Gross monthly income X 100
where: Total monthly debt payments are the aggregate of the monthly EMIs,
including credit card payments. The gross monthly income is the sum of your
monthly earnings.
```

In [78]:
```
summary_df[summary_df['Feature_Name']=='dti']
```

Out[78]:

	Feature_Name	Count	Q1	Q2	Q3	mean	min	max	variance	std_dev	skewness	kurtosis	sk
8	dti	270000	11.91	17.63	23.94	18.128041	0.0	137.4	69.01	8.307225	0.260178	-0.224051	

In [79]:
```
visualise_features(train_df,'dti','continous')
```



In [80]:
```python
train_df.groupby('loan_status')['dti'].describe()
```

Out[80]:

loan_status	count	mean	std	min	25%	50%	75%	max
0	206178.0	18.751314	8.387706	0.0	12.44	18.27	24.71	137.40
1	63822.0	16.114549	7.704621	0.0	10.39	15.71	21.45	39.96

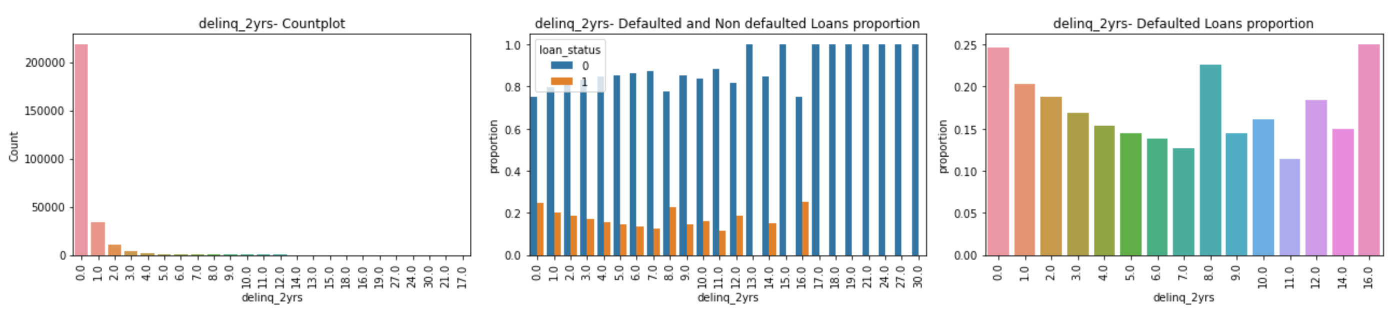
7.19 Inference:

There are many outliers. Need to treat the column. The mean and median for the defaulter and non defaulter are close by.

7.20 delinq_2yrs: number of 30+ days delinquency in past 2 years

```
1.Delinquency occurs as soon as a borrower misses a payment on a loan, which
can affect their credit score.
2.Delinquency rates are used to show how many accounts in a financial
institution's portfolio are delinquent.
3.Consistently delinquent borrowers end up in default.
```

In [81]:
```python
visualise_features(train_df,'delinq_2yrs','discrete')
```



In [82]:
```python
delinq=train_df[['delinq_2yrs','loan_status']].groupby('delinq_2yrs',as_index=False).value_count
```

In [83]:
```python
delinq[delinq['loan_status']==1].sort_values(by='proportion',ascending=False)
```

Out[83]:

	delinq_2yrs	loan_status	proportion
31	16.0	1	0.250000
1	0.0	1	0.246513
17	8.0	1	0.225564
3	1.0	1	0.202713
5	2.0	1	0.188246
25	12.0	1	0.184211
7	3.0	1	0.168740
21	10.0	1	0.161290
9	4.0	1	0.154086
28	14.0	1	0.150000
19	9.0	1	0.144444
11	5.0	1	0.144089
13	6.0	1	0.137634
15	7.0	1	0.127119
23	11.0	1	0.113636

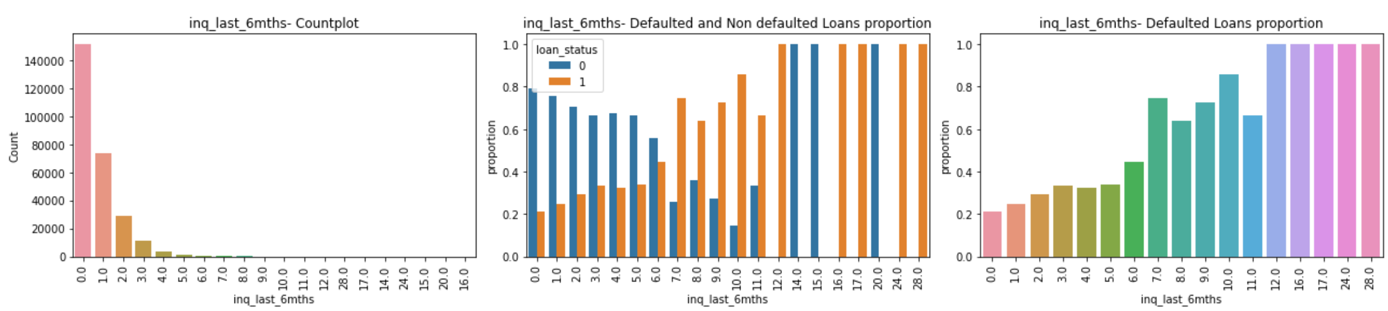
7.20 delinq_2yrs:

There is no specific pattern of loan_status with delinq_2yrs. as the no of delinquecy increase we cant exactly say that the person defaults

7.21 inq_last_6mths

number of inquiries in last 6 months multiple credit inquiries do have an adverse impact on consumer credit scores and thus they represent significant credit risk, often prompting rejection.

In [84]:
```
visualise_features(train_df,'inq_last_6mths','discrete')
```



7.21 Inference:

```
As the number of inqueries increase the defaulter proprtion also increases
```

7.22 mths_since_last_delinq

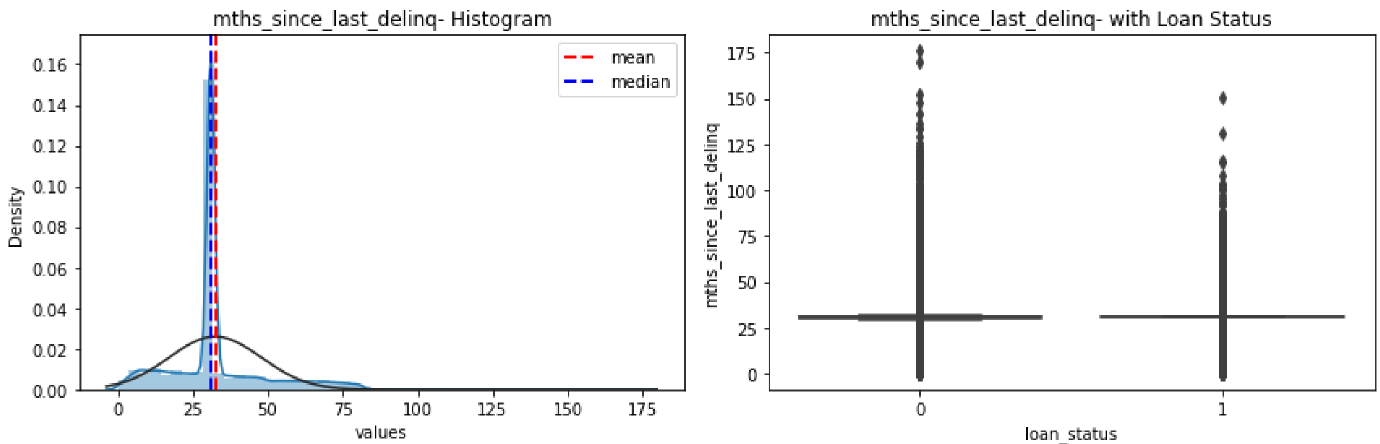
```
number of months since last delinq
```

In [85]:
```
summary_df[summary_df['Feature_Name']=='mths_since_last_delinq']
```

Out[85]:

	Feature_Name	Count	Q1	Q2	Q3	mean	min	max	variance	std_dev	skewness	kurtosi
11	mths_since_last_delinq	270000	31.0	31.0	31.0	32.462915	0.0	176.0	234.81	15.323568	0.941266	1.79252

In [86]:
```
visualise_features(train_df,'mths_since_last_delinq','continous')
```

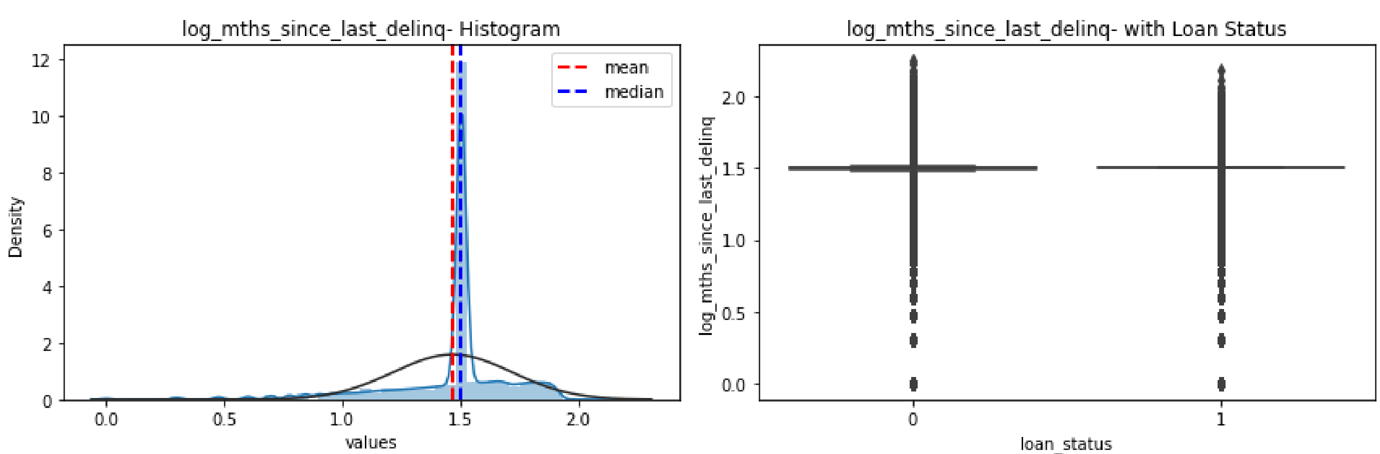


In [87]:
```
train_df[['mths_since_last_delinq','loan_status']].groupby('mths_since_last_delinq').value_count:
```

Out[87]:
```
mths_since_last_delinq  loan_status
0.0                     0               292
                        1               212
1.0                     0               820
                        1               157
2.0                     0              1018
                                       ...
148.0                   0                 1
151.0                   1                 1
152.0                   0                 1
170.0                   0                 1
176.0                   0                 1
Length: 231, dtype: int64
```

In [88]:
```
train_df['log_mths_since_last_delinq']=train_df['mths_since_last_delinq'].apply(lambda x: np.log:
```

In [89]:
```
visualise_features(train_df,'log_mths_since_last_delinq','continous')
```



7.22 Inferences

```
1.There are many number of outliers
2.The visual plot doesnt give clear idea of the loan_status vs mnths since last
```

deling

7.23 mths_since_last_record

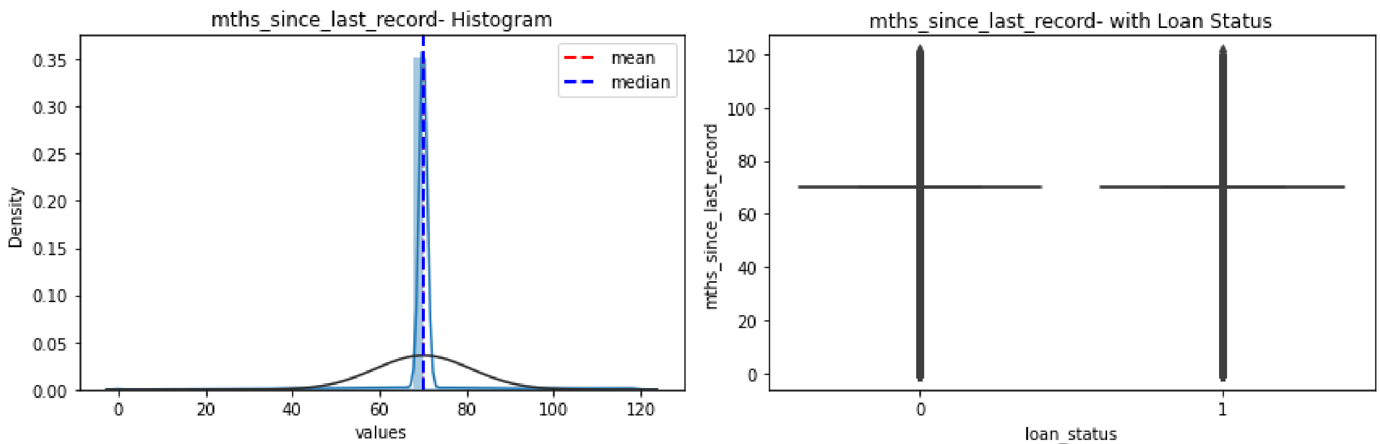
number of months since last public record

In [90]:
```
summary_df[summary_df['Feature_Name']=='mths_since_last_record']
```

Out[90]:

	Feature_Name	Count	Q1	Q2	Q3	mean	min	max	variance	std_dev	skewness	kurto
12	mths_since_last_record	270000	70.0	70.0	70.0	70.000915	0.0	121.0	121.51	11.023297	-0.514263	12.7514

In [91]:
```
visualise_features(train_df,'mths_since_last_record','continous')
```



In [92]:
```
train_df['mths_since_last_record'].nunique()
```

Out[92]: 122

In [93]:
```
train_df['mths_since_last_record'].value_counts()
```

Out[93]:
```
70.0     229264
62.0        599
61.0        599
69.0        595
75.0        588
          ...
3.0          41
1.0          25
2.0          16
120.0         5
121.0         2
Name: mths_since_last_record, Length: 122, dtype: int64
```

7.23 Inferences

1.There are many number of outliers 2.The visual plot doesnt give clear idea of the loan_status vs mths_since_last_record 3.mths_since_last_record doesnt look useful to predict loan status

7.24 open_acc

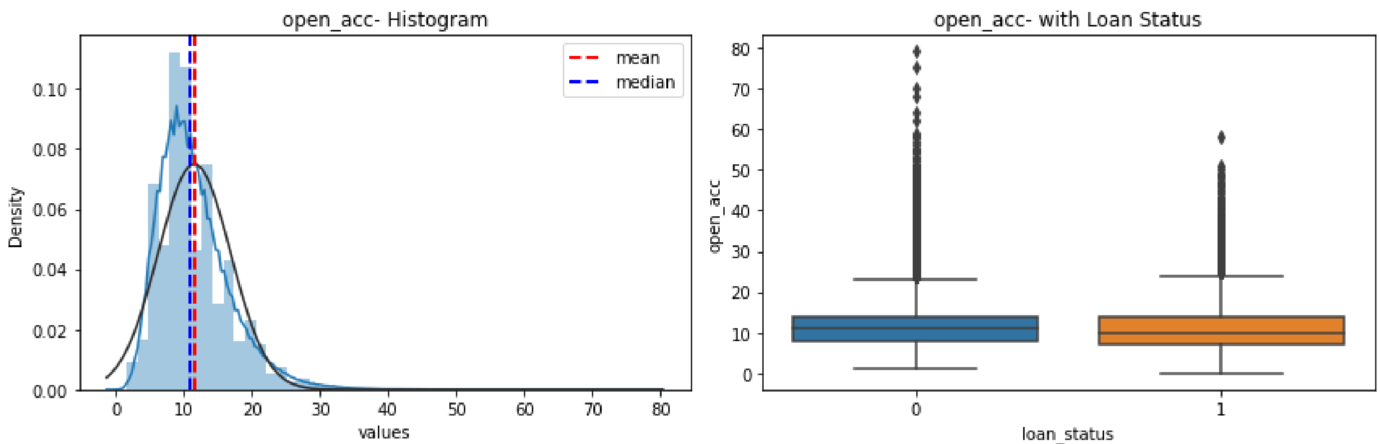
number of open credit line in member's credit line

In [94]:
```
summary_df[summary_df['Feature_Name']=='open_acc']
```

Out[94]:

	Feature_Name	Count	Q1	Q2	Q3	mean	min	max	variance	std_dev	skewness	kurtosis	skewness_c
13	open_acc	270000	8.0	11.0	14.0	11.55	0.0	79.0	28.34	5.323457	1.256553	3.128307	Highly

In [95]:
```
visualise_features(train_df,'open_acc','continous')
```



In [96]:
```
train_df.groupby('loan_status')['open_acc'].describe()
```

Out[96]:

loan_status	count	mean	std	min	25%	50%	75%	max
0	206178.0	11.739943	5.437548	1.0	8.0	11.0	14.0	79.0
1	63822.0	10.936386	4.886746	0.0	7.0	10.0	14.0	58.0

7.24 Inference

1.There is no significant difference between the loan status 0 and 1 wrt to open_acc feature.

7.25 pub_rec

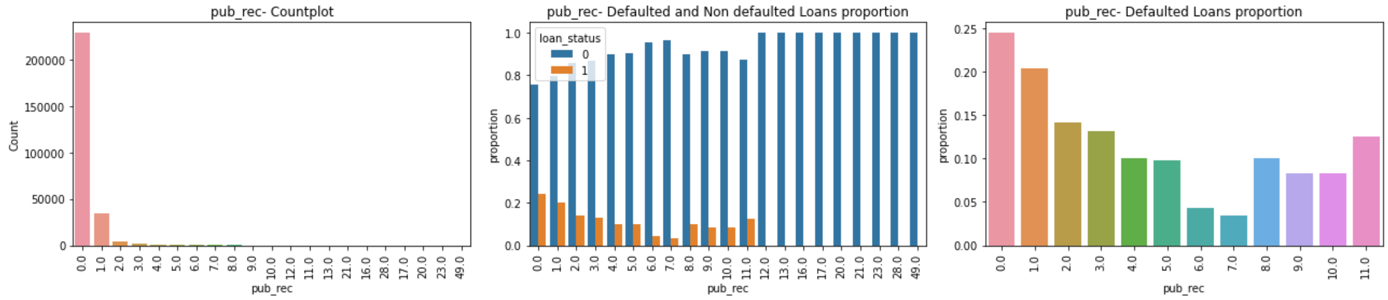
number of derogatory public records
Public records come from government documents. A public record with adverse information could indicate you stopped paying your debt, which could crush your credit.

In [97]:
```
summary_df[summary_df['Feature_Name']=='pub_rec']
```

Out[97]:

	Feature_Name	Count	Q1	Q2	Q3	mean	min	max	variance	std_dev	skewness	kurtosis	skewne
14	pub_rec	270000	0.0	0.0	0.0	0.193281	0.0	49.0	0.32	0.569066	8.596114	306.588134	Hig

In [98]:
```
visualise_features(train_df,'pub_rec','discrete')
```



In [99]:
```
train_df.groupby('loan_status')['pub_rec'].describe()
```

Out[99]:

loan_status	count	mean	std	min	25%	50%	75%	max
0	206178.0	0.208839	0.604703	0.0	0.0	0.0	0.0	49.0
1	63822.0	0.143023	0.430582	0.0	0.0	0.0	0.0	11.0

7.25 Inferences:

```
1.The variance in this col is very less.
2.There is diff between the avg pub_rec and loan status.
3.The loan status cant be judged as the number of public records increases.
```

7.26 revol_bal

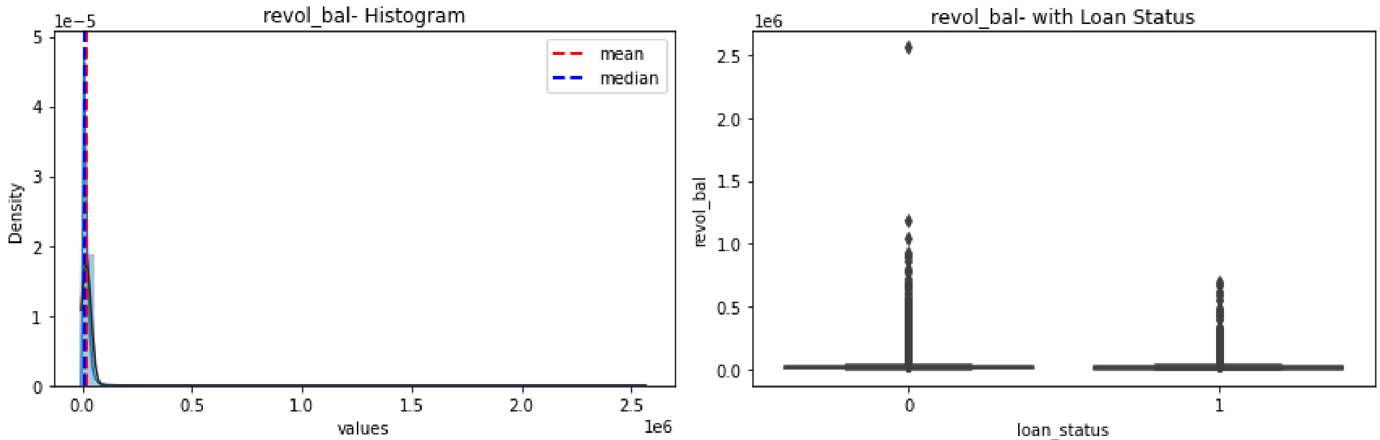
```
total credit revolving balance

If you’re approved for a revolving credit account, like a credit card, the
lender will set a credit limit. The credit limit is the maximum amount you can
charge to that account. When you make a purchase, you’ll have less available
credit. And every time you make a payment, your available credit goes back up.

Revolving credit accounts are open ended, meaning they don’t have an end date.
As long as the account remains open and in good standing, you can continue to
use it. Keep in mind that your minimum payment might vary from month to month
because it’s often calculated based on how much you owe at that time.

What Is a Revolving Balance?
If you don’t pay the balance on your revolving credit account in full every
month, the unpaid portion carries over to the next month. That’s called a
revolving balance.

You might apply for credit assuming you’ll always pay your balance in full
every month. But real life can get in the way. Cars break down. Doctors’
appointments come up. And if you can’t pay your full balance, you’ll find
yourself carrying a revolving balance to the following month.
```

In [100…
```
summary_df[summary_df['Feature_Name']=='revol_bal']
```

Out[100]:

	Feature_Name	Count	Q1	Q2	Q3	mean	min	max	variance	std_dev
15	revol_bal	270000	6451.0	11900.0	20861.0	16912.038519	0.0	2560703.0	4.824580e+08	21964.927297

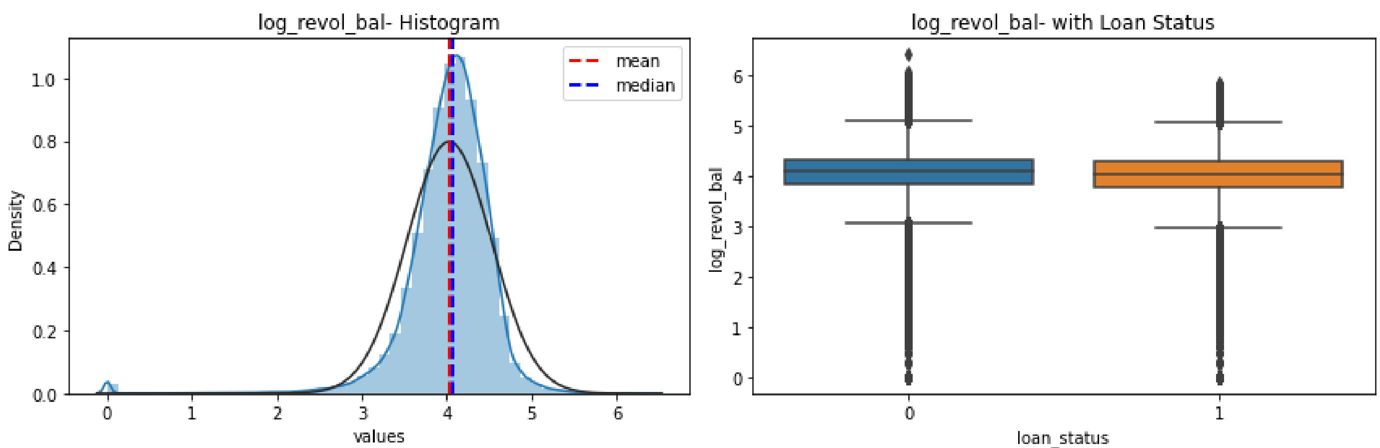
In [101…
```
visualise_features(train_df,'revol_bal','continous')
```



In [102…
```
#lets check the plot after applying log transformation
#since the data is highly right skewed chosed to apply log transform
```

In [103…
```
train_df['log_revol_bal']=train_df['revol_bal'].apply(lambda x: np.log10(x+1))
#adding 1 to x since there are many revol_bal with 0 as input and log 0 would be infinity
```

In [104…
```
visualise_features(train_df,'log_revol_bal','continous')
```



In [105…
```
# By the visual it looks like the log revol bal doesnt differentiate the loan status 0 and 1
```

In [106…
```
train_df.groupby('loan_status')['log_revol_bal'].describe()
```

Out[106]:

loan_status	count	mean	std	min	25%	50%	75%	max
0	206178.0	4.049140	0.473053	0.0	3.825491	4.087994	4.331199	6.408359
1	63822.0	3.961022	0.572606	0.0	3.759743	4.033866	4.278656	5.841745

7.26 Inferences:

```
1. The revol_bal is having many outliers.
2. The min balance is 0.0 and max is 2560703.0 ($)
3. After working with the log transform there seems to be hardly any diff
between the means of both the classes 0 and 1
```

7.27 revol_util:

```
1.amount of credit a member is using relative to revol_bal
2.Your credit utilization ratio—sometimes called revolving utilization—is how
```

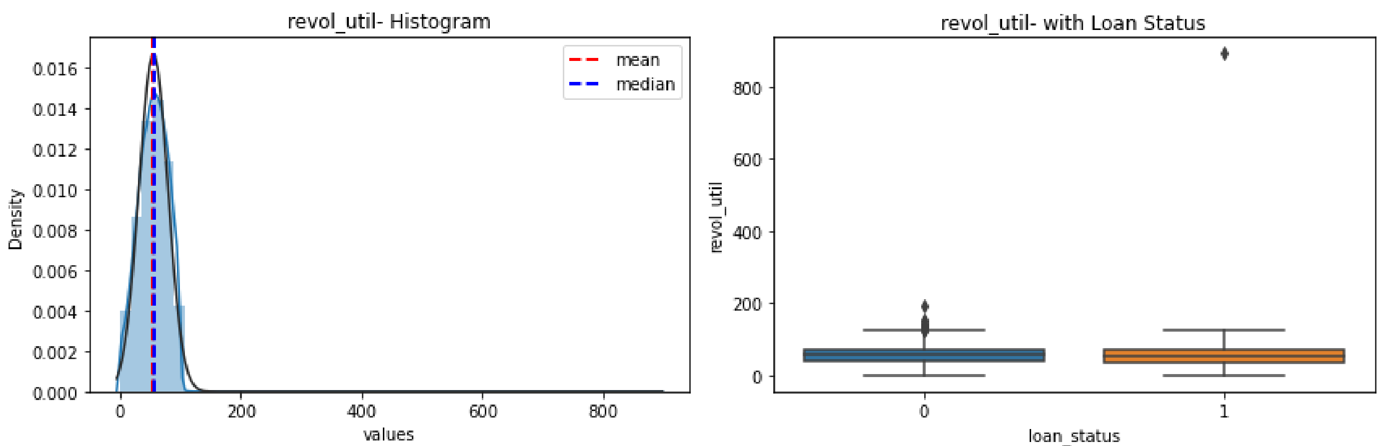
```
much available credit you have
compared with the amount of credit you're using.
3.According to the CFPB, you can calculate your credit utilization ratio by
dividing your total balances across all of your accounts by your total credit
limit.
```

In [107...
```
summary_df[summary_df['Feature_Name']=='revol_util']
```

Out[107]:

	Feature_Name	Count	Q1	Q2	Q3	mean	min	max	variance	std_dev	skewness	kurtosis	ske
16	revol_util	270000	37.7	56.0	73.6	55.068662	0.0	892.3	570.1	23.876852	-0.017092	4.865157	

In [108...
```
visualise_features(train_df,'revol_util','continous')
```



In [109...
```
train_df.groupby('loan_status')['revol_util'].describe()
```

Out[109]:

	count	mean	std	min	25%	50%	75%	max
loan_status								
0	206178.0	55.706531	23.456373	0.0	38.5	56.5	73.9	193.0
1	63822.0	53.008014	25.076857	0.0	34.7	54.3	72.6	892.3

7.27 Inference:

1.The difference between means of both the classes is less. This feature doesnt differentiate both the classes.

7.28: total_acc

```
1.total number of credit lines available in members credit line.
2.A line of credit (LOC) is a preset borrowing limit that can be tapped into at
any time. The borrower can take money out as needed until the limit is reached.
As money is repaid, it can be borrowed again in the case of an open line of
credit.
3.An LOC is an arrangement between a financial institution—usually a bank—and a
customer that establishes the maximum loan amount that the customer can borrow.
The borrower can access funds from the LOC at any time as long as they do not
exceed the maximum amount (or credit limit) set in the agreement.
```

In [110...
```
summary_df[summary_df['Feature_Name']=='total_acc']
```

Out[110]:

	Feature_Name	Count	Q1	Q2	Q3	mean	min	max	variance	std_dev	skewness	kurtosis	ske
17	total_acc	270000	17.0	24.0	32.0	25.254933	1.0	138.0	140.45	11.851032	0.893654	1.315517	

In [111...
```
train_df['total_acc'].nunique()
```

Out[111]: 114

many unique credit line difficult to plot

In [112...
```
train_df.groupby('loan_status')['total_acc'].describe()
```

Out[112]:

	count	mean	std	min	25%	50%	75%	max
loan_status								
0	206178.0	25.268055	11.871131	1.0	17.0	24.0	32.0	138.0
1	63822.0	25.212544	11.785862	1.0	17.0	24.0	32.0	104.0

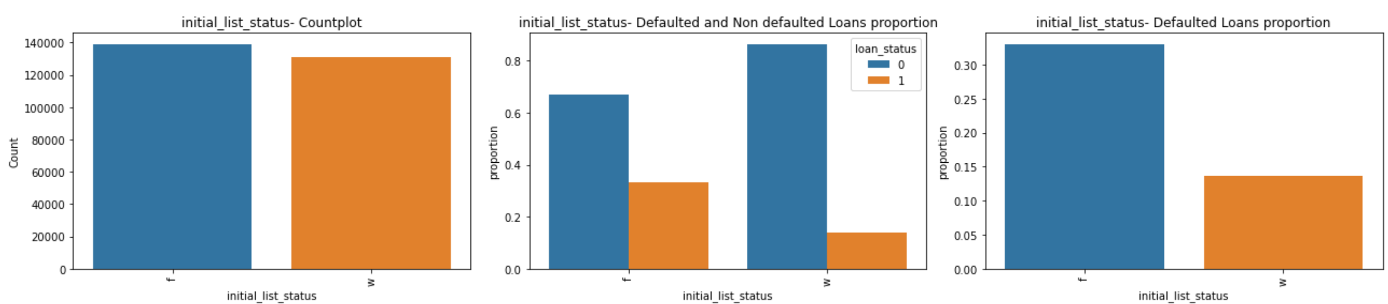
7.28 Inference:

```
1.There is no difference between the means of both the classes
```

7.29 initial_list_status:

unique listing status of the loan - W(Waiting), F(Forwarded)

In [113...
```
visualise_features(train_df,'initial_list_status','discrete')
```



7.29 Inference:

```
1. The forwarded list have more defaulters as compared to waiting list
```

7.30 total_rec_int:

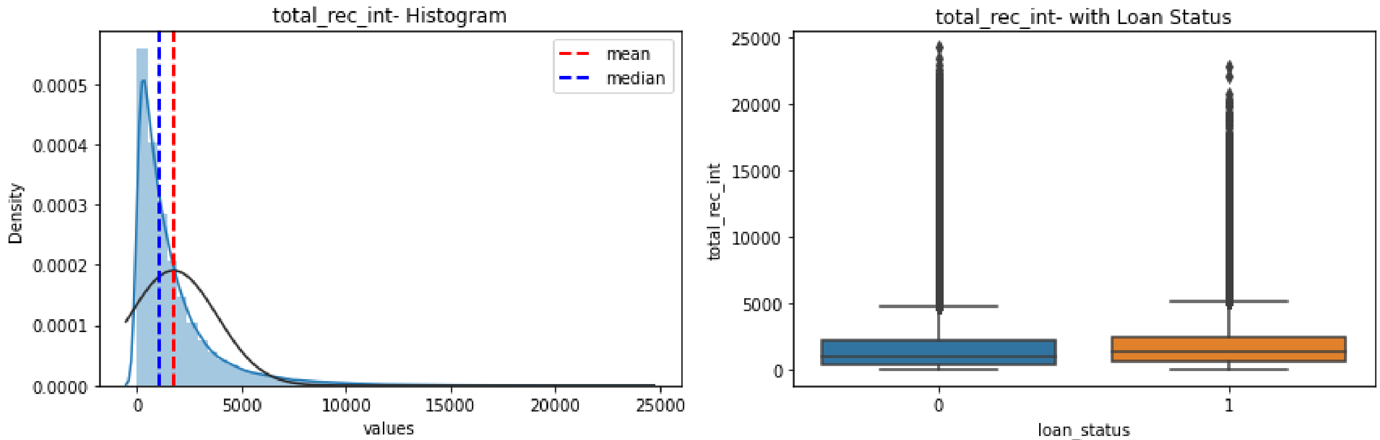
interest received till date

In [114...
```
summary_df[summary_df['Feature_Name']=='total_rec_int']
```

Out[114]:

	Feature_Name	Count	Q1	Q2	Q3	mean	min	max	variance	std_dev	skew
18	total_rec_int	270000	441.38	1072.615	2229.7225	1751.244025	0.0	24205.62	4379309.16	2092.6799	2.85

In [115...
```
visualise_features(train_df,'total_rec_int','continous')
```



In [116…

```
train_df.groupby('loan_status')['total_rec_int'].describe()
```

Out[116]:

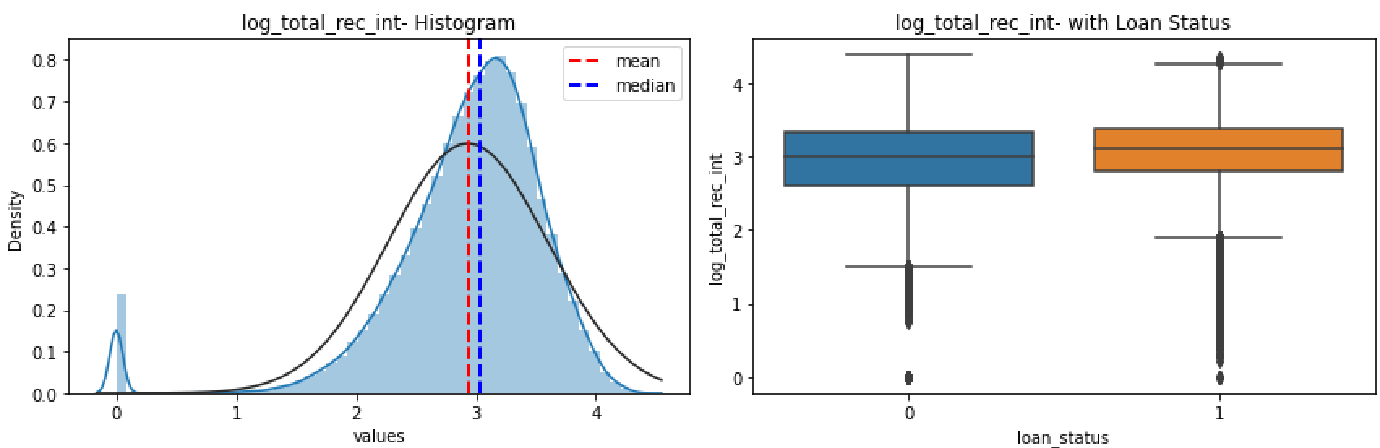
loan_status	count	mean	std	min	25%	50%	75%	max
0	206178.0	1707.425737	2118.690138	0.0	395.165	1000.72	2157.8300	24205.62
1	63822.0	1892.799709	1999.816528	0.0	619.585	1289.26	2418.3225	22777.58

In [117…

```
train_df['log_total_rec_int']=train_df['total_rec_int'].apply(lambda x : np.log10(x+1))
```

In [118…

```
visualise_features(train_df,'log_total_rec_int','continous')
```



In [119…

```
train_df.groupby('loan_status')['log_total_rec_int'].describe()
```

Out[119]:

loan_status	count	mean	std	min	25%	50%	75%	max
0	206178.0	2.894766	0.706578	0.0	2.597876	3.000746	3.334218	4.383934
1	63822.0	3.055748	0.493680	0.0	2.792801	3.110677	3.383694	4.357527

7.30 inference:

1. There is no substantial difference between the classes with this feature

7.31 total_rec_late_fee:

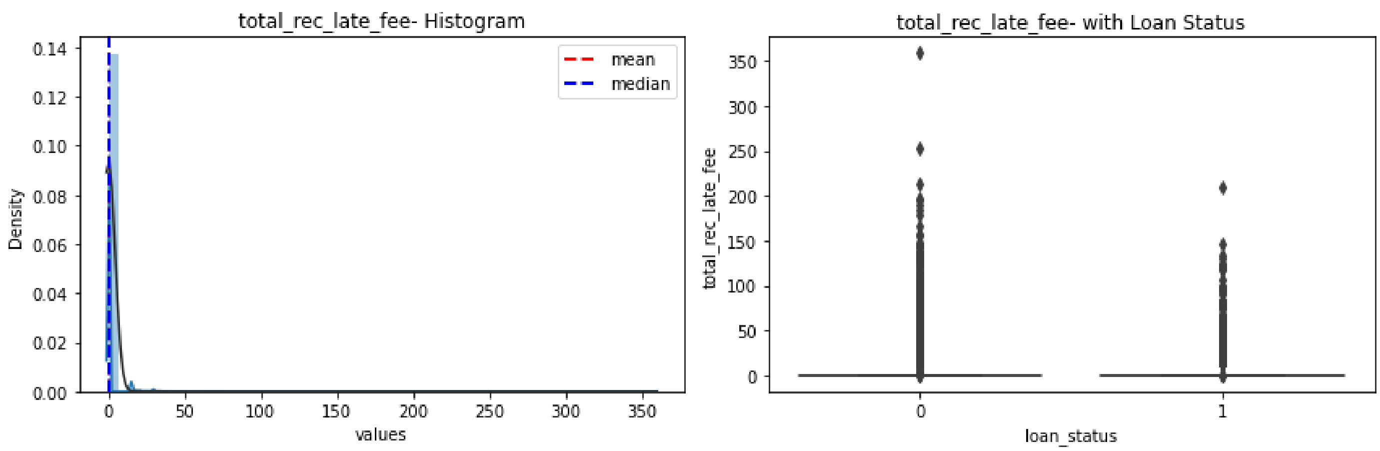
Late fee received till date

In [120…
```
summary_df[summary_df['Feature_Name']=='total_rec_late_fee']
```

Out[120]:

	Feature_Name	Count	Q1	Q2	Q3	mean	min	max	variance	std_dev	skewness	kurtosis	ske
19	total_rec_late_fee	270000	0.0	0.0	0.0	0.402963	0.0	358.68	17.82	4.220959	18.739246	622.052145	

In [121…
```
visualise_features(train_df,'total_rec_late_fee','continous')
```



In [122…
```
train_df.groupby('loan_status')['total_rec_late_fee'].describe()
```

Out[122]:

	count	mean	std	min	25%	50%	75%	max
loan_status								
0	206178.0	0.412139	4.314994	0.0	0.0	0.0	0.0	358.68000
1	63822.0	0.373319	3.901607	0.0	0.0	0.0	0.0	208.81953

7.31 Inference:

```
1.There is no substantial difference between the classes with this feature
```

7.32 recoveries:

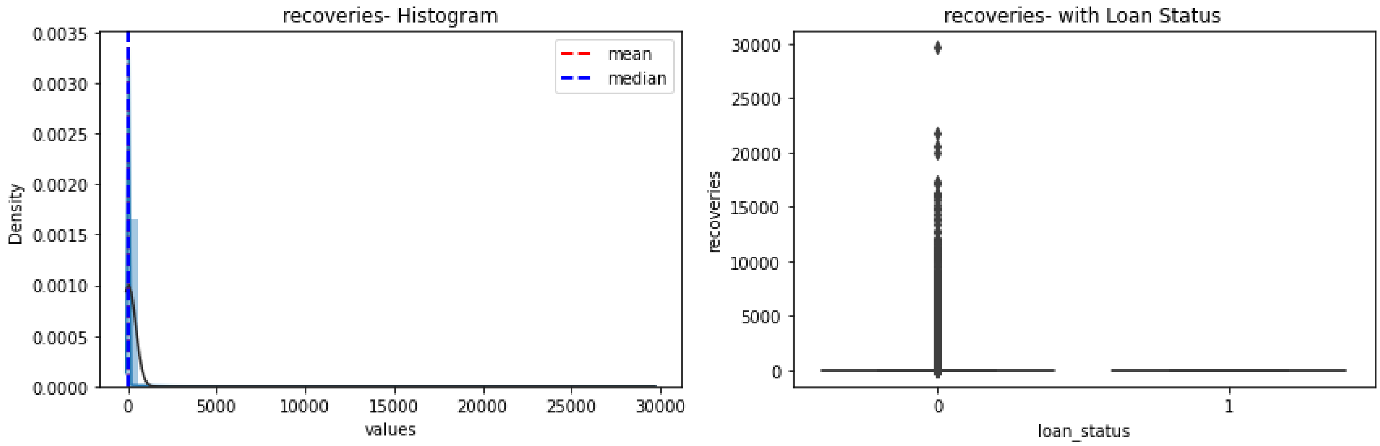
post charge off gross recovery

In [123…
```
summary_df[summary_df['Feature_Name']=='recoveries']
```

Out[123]:

	Feature_Name	Count	Q1	Q2	Q3	mean	min	max	variance	std_dev	skewness	kurtosis
20	recoveries	270000	0.0	0.0	0.0	45.419585	0.0	29623.35	158026.79	397.52584	16.020333	459.405876

In [124…
```
visualise_features(train_df,'recoveries','continous')
```



In [125...
```
train_df.groupby('loan_status')['recoveries'].describe()
```

Out[125]:

loan_status	count	mean	std	min	25%	50%	75%	max
0	206178.0	59.47913	453.99082	0.0	0.0	0.0	0.0	29623.35
1	63822.0	0.00000	0.00000	0.0	0.0	0.0	0.0	0.00

7.32 Inference:

```
1. Almost all the values are centered near zero.
2. This feature dosnt differentiate both the classes.
```

7.33 collection_recovery_fee:

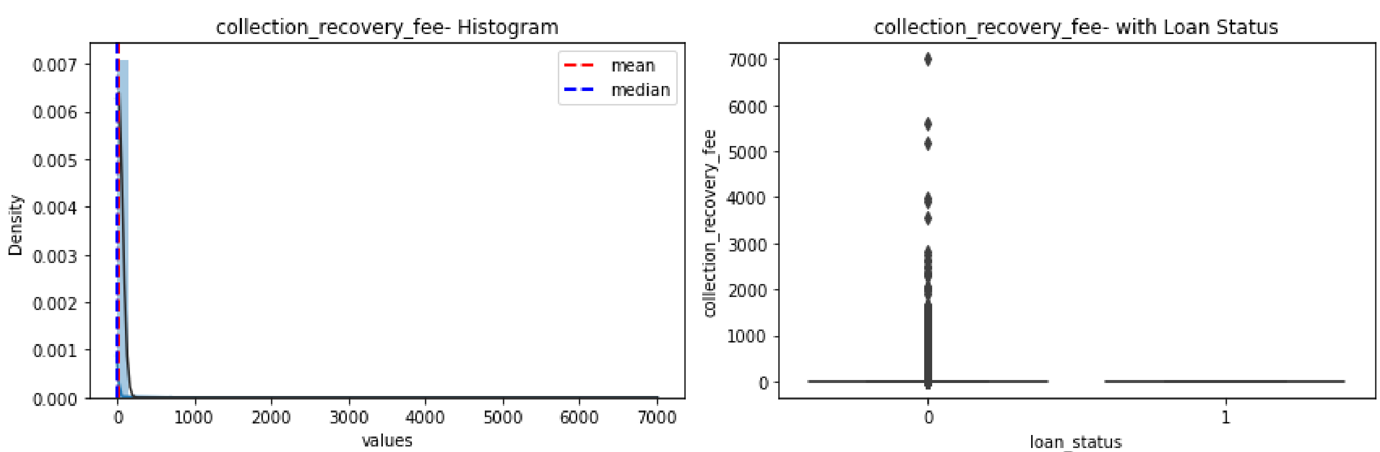
```
1.post charge off collection fee
```

In [126...
```
summary_df[summary_df['Feature_Name']=='collection_recovery_fee']
```

Out[126]:

	Feature_Name	Count	Q1	Q2	Q3	mean	min	max	variance	std_dev	skewness	kurt
21	collection_recovery_fee	270000	0.0	0.0	0.0	4.805591	0.0	7002.19	3645.88	60.381161	27.585743	1622.315

In [127...
```
visualise_features(train_df,'collection_recovery_fee','continous')
```



In [128...
```
train_df.groupby('loan_status')['collection_recovery_fee'].describe()
```

Out[128]:

loan_status	count	mean	std	min	25%	50%	75%	max
0	206178.0	6.293152	69.02974	0.0	0.0	0.0	0.0	7002.19
1	63822.0	0.000000	0.00000	0.0	0.0	0.0	0.0	0.00

7.33 Inference:

```
1. most data is centereda round zero
not useful for classifying
```

7.34 collections_12_mths_ex_med:

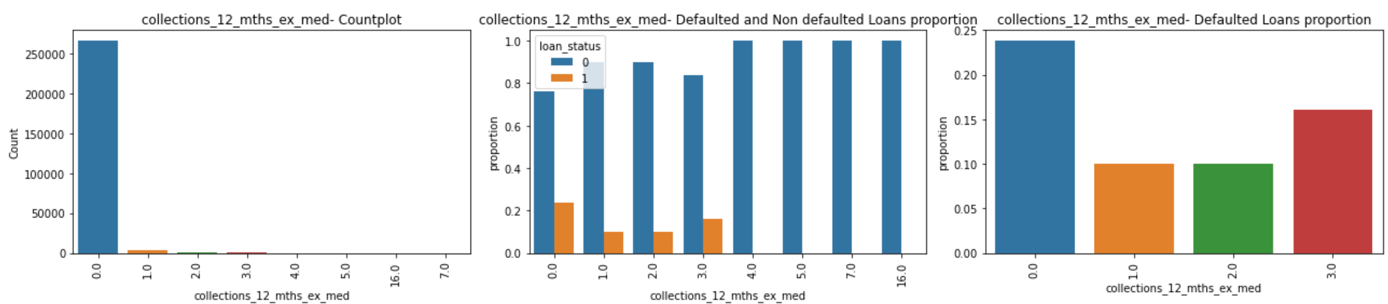
```
1.number of collections in last 12 months excluding medical collections
```

In [129…
```
summary_df[summary_df['Feature_Name']=='collections_12_mths_ex_med']
```

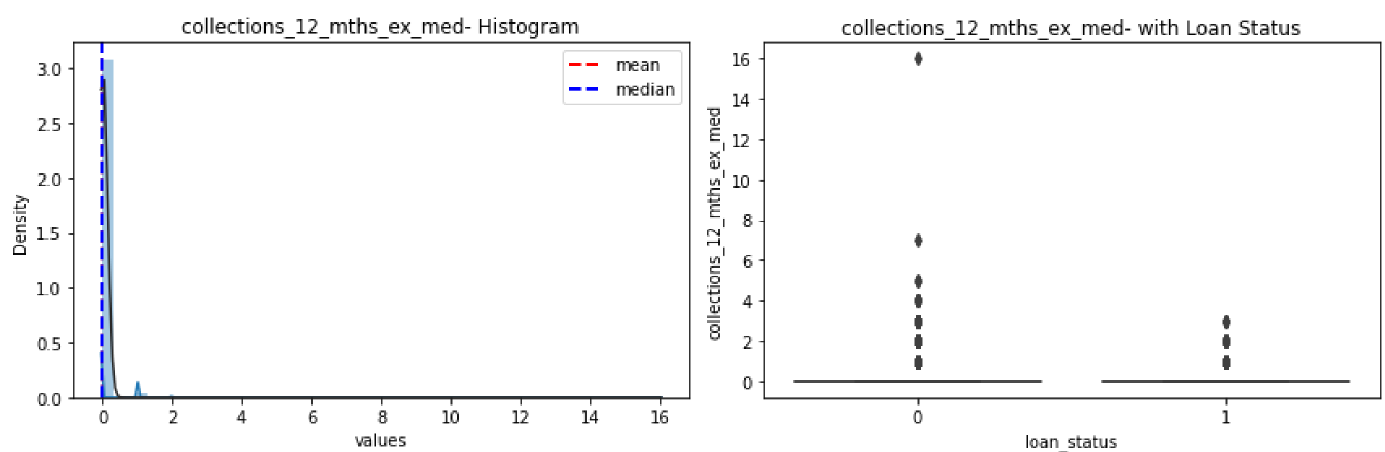
Out[129]:

	Feature_Name	Count	Q1	Q2	Q3	mean	min	max	variance	std_dev	skewness	kurtosi
22	collections_12_mths_ex_med	270000	0.0	0.0	0.0	0.014259	0.0	16.0	0.02	0.13346	16.792144	929.2838

In [130…
```
visualise_features(train_df,'collections_12_mths_ex_med','discrete')
```



In [131…
```
visualise_features(train_df,'collections_12_mths_ex_med','continous')
```



In [132…
```
train_df.groupby('loan_status')['collections_12_mths_ex_med'].describe()
```

Out[132]:

loan_status	count	mean	std	min	25%	50%	75%	max
0	206178.0	0.016801	0.145249	0.0	0.0	0.0	0.0	16.0
1	63822.0	0.006048	0.084311	0.0	0.0	0.0	0.0	3.0

7.34 Inference:

```
1.This feature doesnt differentiate between both the classes
```

7.35 mths_since_last_major_derog:

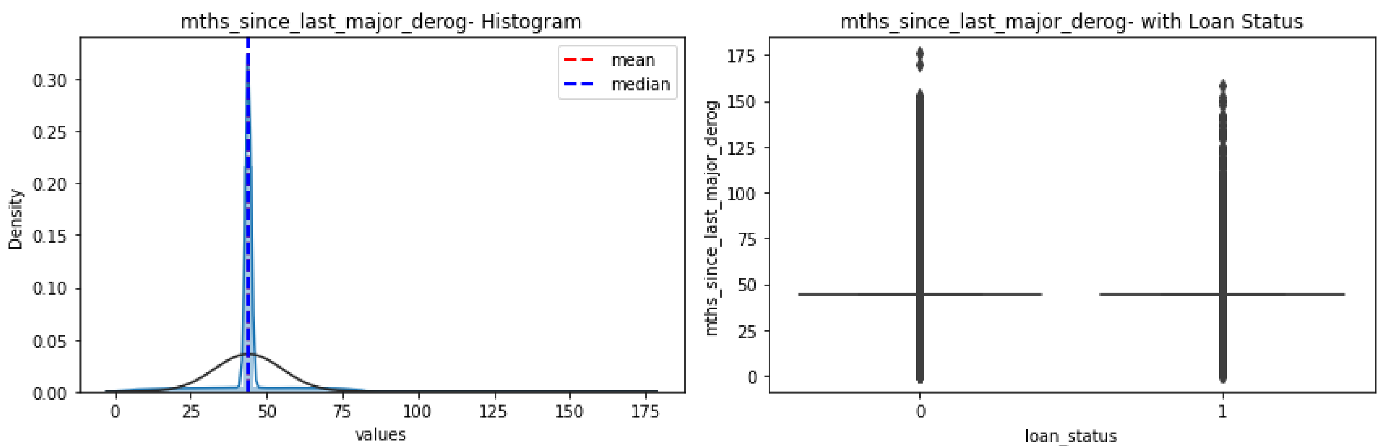
```
1.months since most recent 90 day or worse rating
“Derogatory” is seen as negative to lenders, and can include late payments,
collection accounts, bankruptcy, charge-offs and other negative marks on your
credit report. This can impact your ability to qualify for new credit.
```

In [133…
```
summary_df[summary_df['Feature_Name']=='mths_since_last_major_derog']
```

Out[133]:

	Feature_Name	Count	Q1	Q2	Q3	mean	min	max	variance	std_dev	skewness	[illegible]
23	mths_since_last_major_derog	270000	44.0	44.0	44.0	44.014659	0.0	176.0	122.91	11.086417	0.547339	8

In [134…
```
visualise_features(train_df,'mths_since_last_major_derog','continous')
```



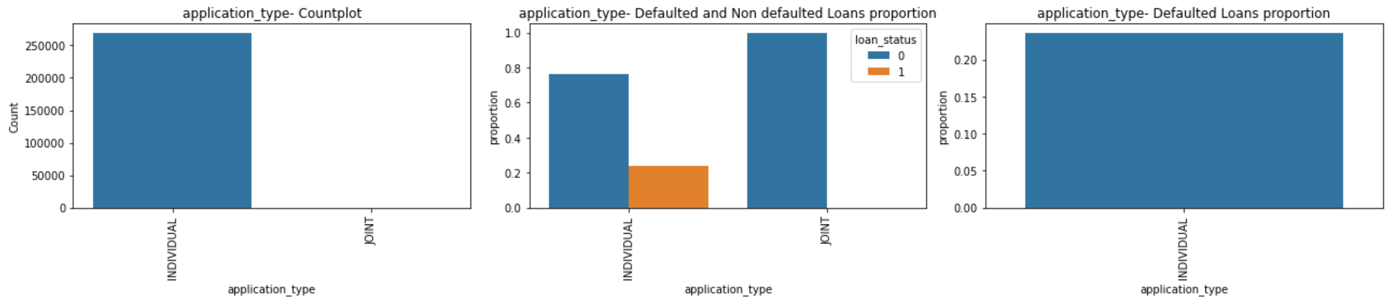
7.35 Inference:

1.This feature doesnt differentiate between both the classes

7.36 application_type:

indicates when the member is an individual or joint

In [135…
```
visualise_features(train_df,'application_type','discrete')
```



7.36 Inference:

```
1.Individual loans are more prone to defaulting
```

7.37 verification_status_joint: Deleted since most of the entries were null

7.38 last_week_pay

indicates how long (in weeks) a member has paid EMI after batch enrolled

In [136…

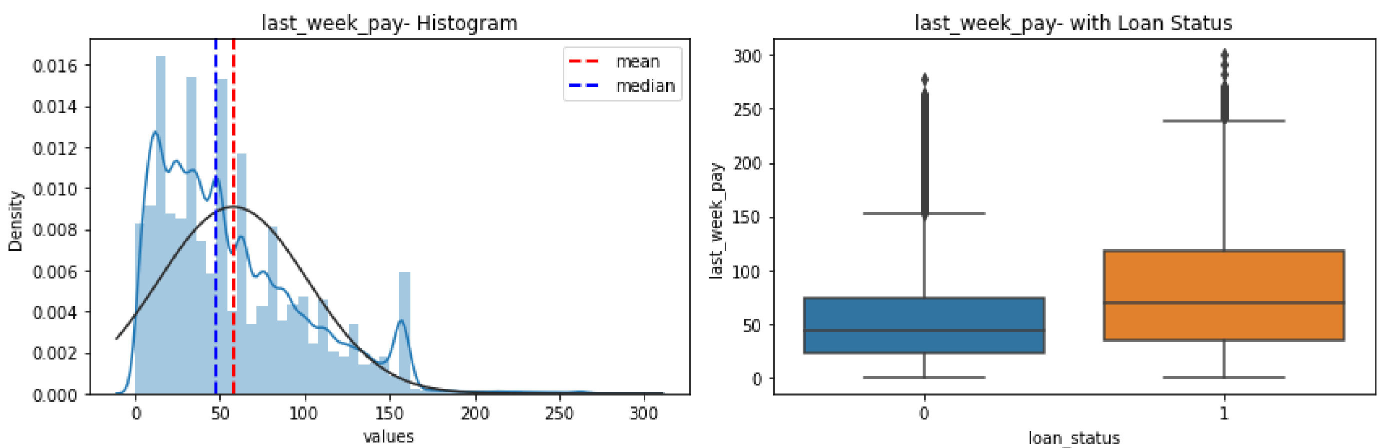
```
summary_df[summary_df['Feature_Name']=='last_week_pay']
```

Out[136]:

	Feature_Name	Count	Q1	Q2	Q3	mean	min	max	variance	std_dev	skewness	kurtosis	ske
24	last_week_pay	270000	22.0	48.0	83.0	57.919267	0.0	300.0	1929.09	43.921408	1.034416	0.807722	

In [137…

```
visualise_features(train_df,'last_week_pay','continous')
```



In [138…

```
train_df.groupby('loan_status')['last_week_pay'].describe()
```

Out[138]:

loan_status	count	mean	std	min	25%	50%	75%	max
0	206178.0	51.551596	38.889805	0.0	22.0	43.0	74.0	278.0
1	63822.0	78.490129	52.163652	0.0	35.0	69.0	117.0	300.0

Inference:

```
1.there are more defaulters in when the no of weeks is more.
```

7.40 acc_now_delinq

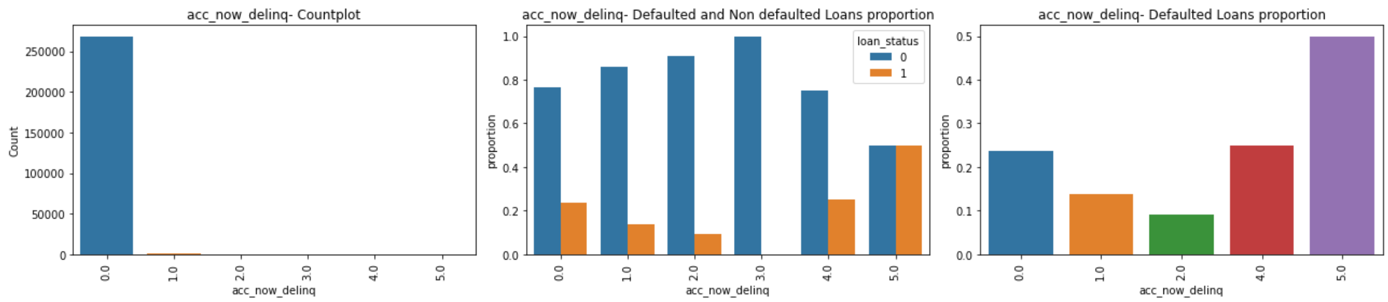
number of accounts on which the member is delinquent

In [139...
```
summary_df[summary_df['Feature_Name']=='acc_now_delinq']
```

Out[139]:

	Feature_Name	Count	Q1	Q2	Q3	mean	min	max	variance	std_dev	skewness	kurtosis	skewnes
25	acc_now_delinq	270000	0.0	0.0	0.0	0.00493	0.0	5.0	0.01	0.076894	19.496813	541.919393	Higl

In [140...
```
visualise_features(train_df,'acc_now_delinq','discrete')
```



7.40 Inference:

```
1.The variance of this column is very less
2. Most of the data have entry as 0.
3.Not useful to classify the loan_status
```

7.41 tot_coll_amt:

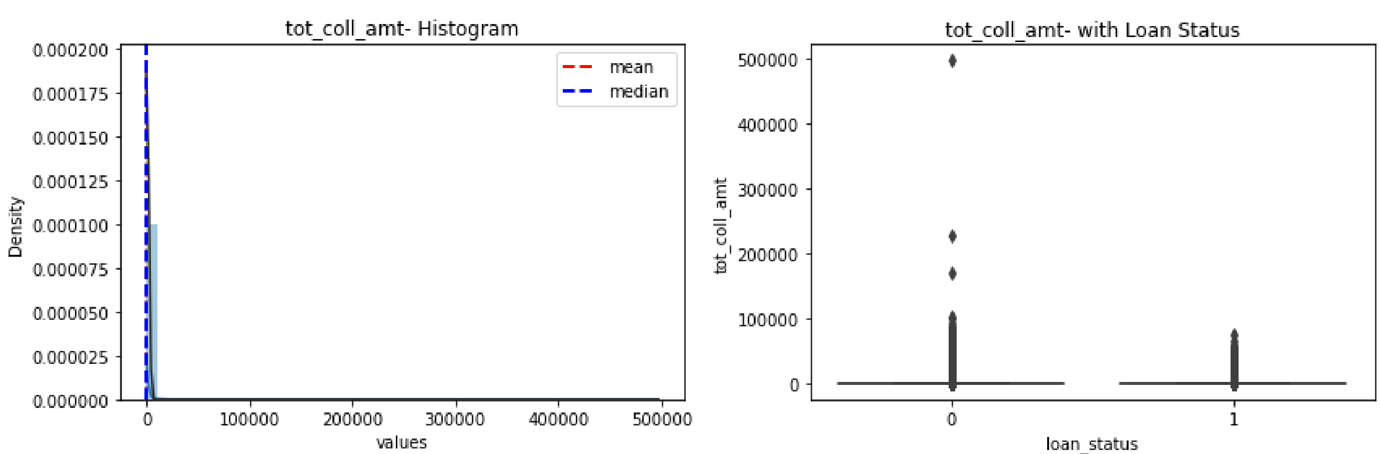
total collection amount ever owed

In [141...
```
summary_df[summary_df['Feature_Name']=='tot_coll_amt']
```

Out[141]:

	Feature_Name	Count	Q1	Q2	Q3	mean	min	max	variance	std_dev	skewness	kur
26	tot_coll_amt	270000	0.0	0.0	0.0	197.023778	0.0	496651.0	3797256.98	1948.655172	81.955557	16838.1

In [142...
```
visualise_features(train_df,'tot_coll_amt','continous')
```



In [143...
```
train_df.groupby('loan_status')['tot_coll_amt'].describe()
```

Out[143]:

loan_status	count	mean	std	min	25%	50%	75%	max
0	206178.0	219.131896	2102.867234	0.0	0.0	0.0	0.0	496651.0
1	63822.0	125.603146	1331.243320	0.0	0.0	0.0	0.0	75081.0

7.41 Inferences:

```
1. Most of the data have entry as 0.
2.Not useful to classify the loan_status
```

7.42 tot_cur_bal:

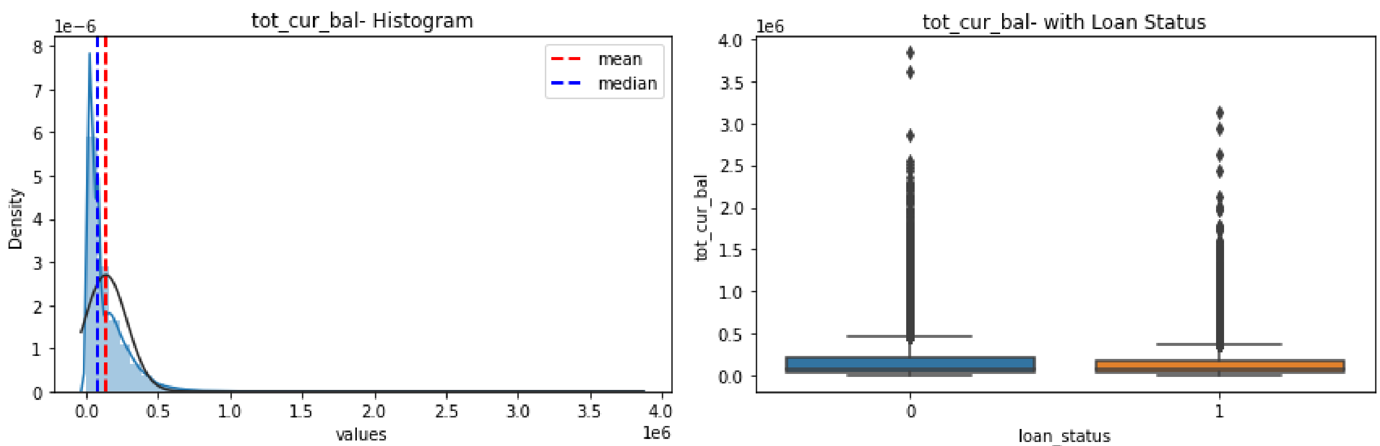
total current balance of all accounts

In [144...
```
summary_df[summary_df['Feature_Name']=='tot_cur_bal']
```

Out[144]:

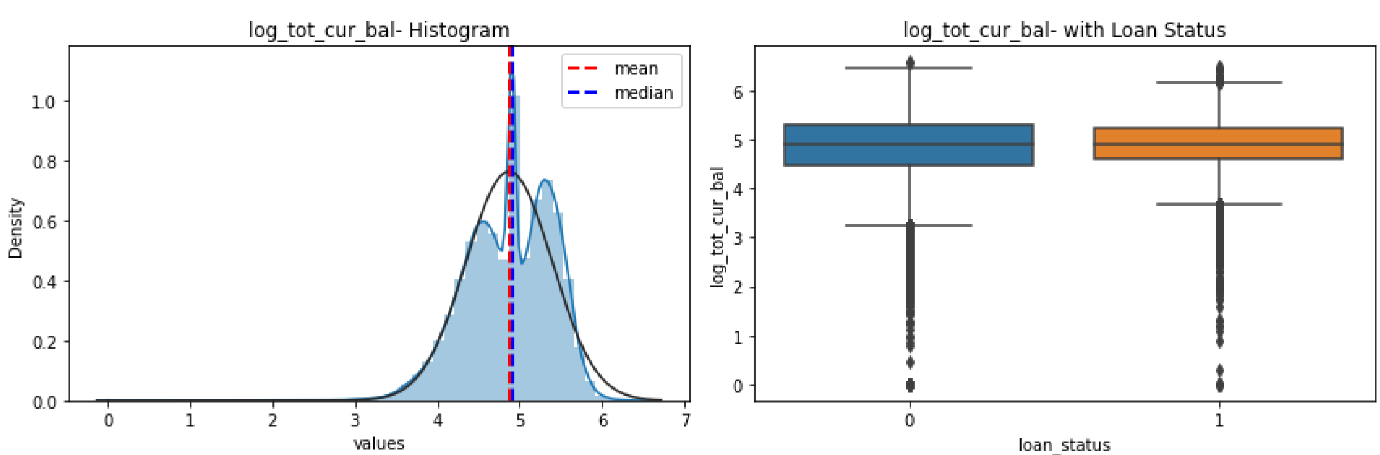
	Feature_Name	Count	Q1	Q2	Q3	mean	min	max	variance	std_d
27	tot_cur_bal	270000	32171.0	80335.0	195986.25	134838.58143	0.0	3840795.0	2.184540e+10	147801.8793

In [145...
```
visualise_features(train_df,'tot_cur_bal','continous')
```



In [146...
```
train_df['log_tot_cur_bal']=train_df['tot_cur_bal'].apply(lambda x: np.log10(x+1))
```

In [147...
```
visualise_features(train_df,'log_tot_cur_bal','continous')
```



In [148...
```
train_df.groupby('loan_status')['log_tot_cur_bal'].describe()
```

Out[148]:

loan_status	count	mean	std	min	25%	50%	75%	max
0	206178.0	4.869571	0.533165	0.0	4.484858	4.90491	5.307736	6.584421
1	63822.0	4.884635	0.483972	0.0	4.615047	4.90491	5.232675	6.495383

7.42 Inferences:

```
1.The means for both the classes are same.
2.Not useful to classify the loan_status.
```

7.43 total_rev_hi_lim

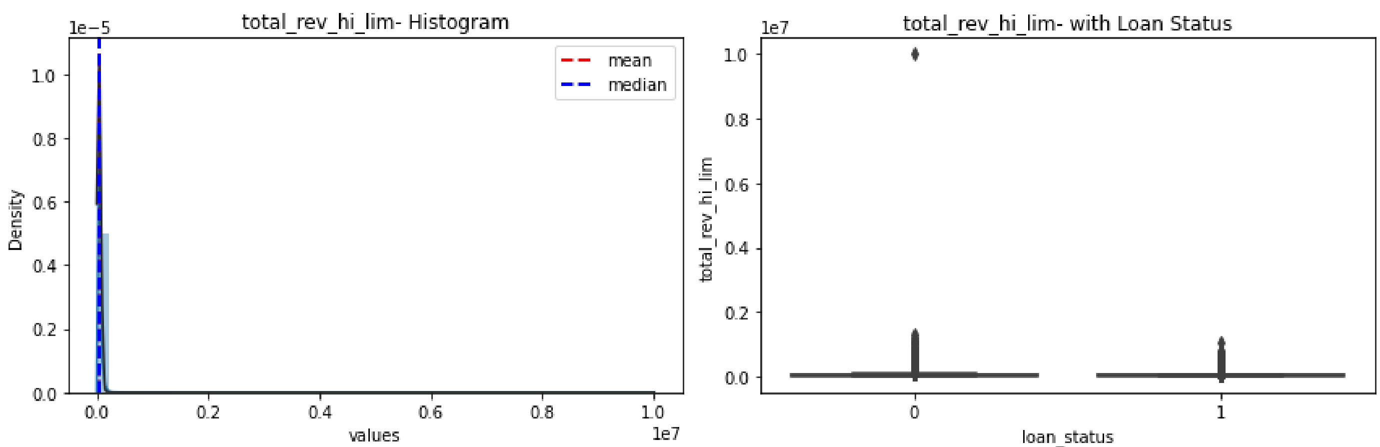
total revolving credit limit

In [149…
```
summary_df[summary_df['Feature_Name']=='total_rev_hi_lim']
```

Out[149]:

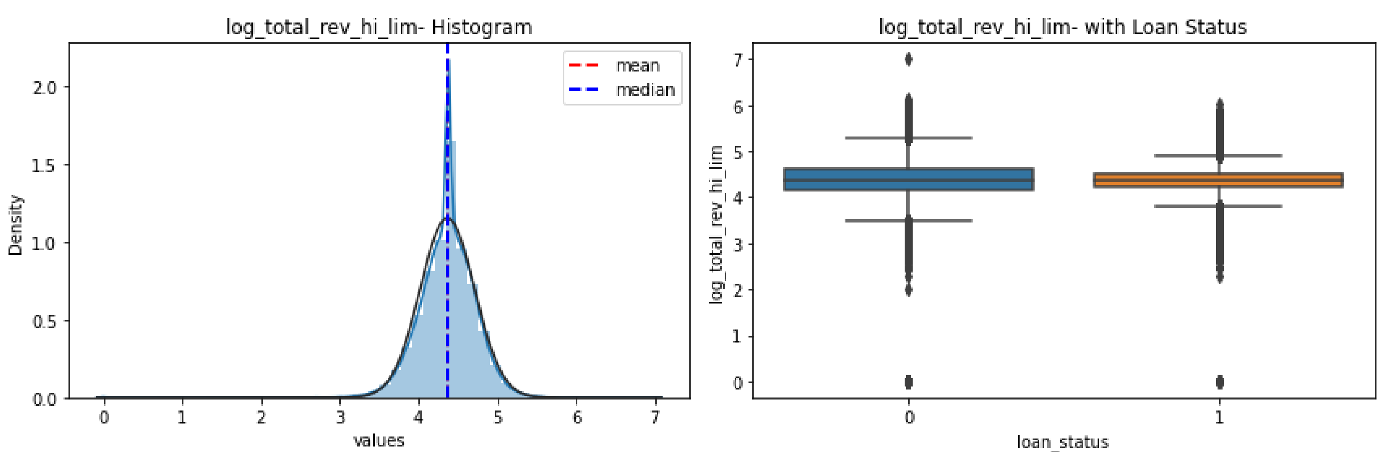
	Feature_Name	Count	Q1	Q2	Q3	mean	min	max	variance	std_dev
28	total_rev_hi_lim	270000	14700.0	23800.0	38000.0	31420.347526	0.0	9999999.0	1.308518e+09	36173.444006

In [150…
```
visualise_features(train_df,'total_rev_hi_lim','continous')
```



In [151…
```
train_df['log_total_rev_hi_lim']=train_df['total_rev_hi_lim'].apply(lambda x: np.log10(x+1))
```

In [152…
```
visualise_features(train_df,'log_total_rev_hi_lim','continous')
```



In [153...
```
train_df.groupby('loan_status')['log_total_rev_hi_lim'].describe()
```

Out[153]:

loan_status	count	mean	std	min	25%	50%	75%	max
0	206178.0	4.369623	0.357694	0.0	4.155366	4.376595	4.600984	7.000000
1	63822.0	4.355994	0.304199	0.0	4.220134	4.376595	4.492774	6.013048

7.43 Inferences:

```
1.The means for both the classes are same.
2.Not useful to classify the loan_status.
```

In [154...
```
backup_train_df=train_df
```

In [155...
```
backup_train_df.to_csv('train_df_processed.csv')
```

In [156...
```
backup_test_df=test_df
backup_test_df.to_csv('test_df_processed.csv')
```

In [157...
```
train_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 270000 entries, 0 to 269999
Data columns (total 47 columns):
 #   Column                      Non-Null Count   Dtype  
---  ------                      --------------   -----  
 0   loan_amnt                   270000 non-null  int64  
 1   funded_amnt                 270000 non-null  int64  
 2   funded_amnt_inv             270000 non-null  float64
 3   term                        270000 non-null  int64  
 4   int_rate                    270000 non-null  float64
 5   grade                       270000 non-null  object 
 6   sub_grade                   270000 non-null  object 
 7   emp_title                   270000 non-null  object 
 8   emp_length                  270000 non-null  float64
 9   home_ownership              270000 non-null  object 
 10  annual_inc                  270000 non-null  float64
 11  verification_status         270000 non-null  object 
 12  pymnt_plan                  270000 non-null  object 
 13  purpose                     270000 non-null  object 
 14  title                       270000 non-null  object 
 15  zip_code                    270000 non-null  int64  
 16  addr_state                  270000 non-null  object 
 17  dti                         270000 non-null  float64
 18  delinq_2yrs                 270000 non-null  float64
 19  inq_last_6mths              270000 non-null  float64
 20  mths_since_last_delinq      270000 non-null  float64
 21  mths_since_last_record      270000 non-null  float64
 22  open_acc                    270000 non-null  float64
 23  pub_rec                     270000 non-null  float64
 24  revol_bal                   270000 non-null  int64  
 25  revol_util                  270000 non-null  float64
 26  total_acc                   270000 non-null  float64
 27  initial_list_status         270000 non-null  object 
 28  total_rec_int               270000 non-null  float64
 29  total_rec_late_fee          270000 non-null  float64
 30  recoveries                  270000 non-null  float64
 31  collection_recovery_fee     270000 non-null  float64
 32  collections_12_mths_ex_med  270000 non-null  float64
 33  mths_since_last_major_derog 270000 non-null  float64
 34  application_type            270000 non-null  object 
 35  last_week_pay               270000 non-null  float64
 36  acc_now_delinq              270000 non-null  float64
 37  tot_coll_amt                270000 non-null  float64
 38  tot_cur_bal                 270000 non-null  float64
 39  total_rev_hi_lim            270000 non-null  float64
 40  loan_status                 270000 non-null  int64  
 41  log_annual_inc              270000 non-null  float64
 42  log_mths_since_last_delinq  270000 non-null  float64
 43  log_revol_bal               270000 non-null  float64
 44  log_total_rec_int           270000 non-null  float64
 45  log_tot_cur_bal             270000 non-null  float64
 46  log_total_rev_hi_lim        270000 non-null  float64
dtypes: float64(30), int64(6), object(11)
memory usage: 96.8+ MB
```

In [158…

```
test_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 262428 entries, 0 to 262427
Data columns (total 41 columns):
 #   Column                      Non-Null Count   Dtype  
---  ------                      --------------   -----  
 0   loan_amnt                   262428 non-null  int64  
 1   funded_amnt                 262428 non-null  int64  
 2   funded_amnt_inv             262428 non-null  float64
 3   term                        262428 non-null  int64  
 4   int_rate                    262428 non-null  float64
 5   grade                       262428 non-null  object 
 6   sub_grade                   262428 non-null  object 
 7   emp_title                   262428 non-null  object 
 8   emp_length                  262428 non-null  float64
 9   home_ownership              262428 non-null  object 
 10  annual_inc                  262428 non-null  float64
 11  verification_status         262428 non-null  object 
 12  pymnt_plan                  262428 non-null  object 
 13  purpose                     262428 non-null  object 
 14  title                       262428 non-null  object 
 15  zip_code                    262428 non-null  int64  
 16  addr_state                  262428 non-null  object 
 17  dti                         262428 non-null  float64
 18  delinq_2yrs                 262428 non-null  float64
 19  inq_last_6mths              262428 non-null  float64
 20  mths_since_last_delinq      262428 non-null  float64
 21  mths_since_last_record      262428 non-null  float64
 22  open_acc                    262428 non-null  float64
 23  pub_rec                     262428 non-null  float64
 24  revol_bal                   262428 non-null  float64
 25  revol_util                  262428 non-null  float64
 26  total_acc                   262428 non-null  float64
 27  initial_list_status         262428 non-null  object 
 28  total_rec_int               262428 non-null  float64
 29  total_rec_late_fee          262428 non-null  float64
 30  recoveries                  262428 non-null  float64
 31  collection_recovery_fee     262428 non-null  float64
 32  collections_12_mths_ex_med  262428 non-null  float64
 33  mths_since_last_major_derog 262428 non-null  float64
 34  application_type            262428 non-null  object 
 35  last_week_pay               262428 non-null  float64
 36  acc_now_delinq              262428 non-null  float64
 37  tot_coll_amt                262428 non-null  float64
 38  tot_cur_bal                 262428 non-null  float64
 39  total_rev_hi_lim            262428 non-null  float64
 40  loan_status                 262428 non-null  int64  
dtypes: float64(25), int64(5), object(11)
memory usage: 82.1+ MB
```

> All the features are analysed in the EDA and the features which donot contribute to predicting Y target variable are selected and dropped

In [159…
```
#drop the numeric features which donot differentiate both the classes
train_df.drop(['revol_bal','annual_inc','total_rec_int' ,'tot_cur_bal' ,'total_rev_hi_lim','mths_
test_df.drop(['revol_bal','annual_inc','total_rec_int' ,'tot_cur_bal' ,'total_rev_hi_lim','mths_
```

In [160…
```
#drop the categorical features which donot differentiate both the classes
train_df.drop(['addr_state','pymnt_plan','sub_grade','title','emp_title'],inplace=True,axis=1)
test_df.drop(['addr_state','pymnt_plan','sub_grade','title','emp_title'],inplace=True,axis=1)
```

In [161…

```
label_encode(train_df,['grade'])
label_encode(test_df,['grade'])
```

In [162…

```
#Among all the categorical features the following ones are selected after EDA.
selected_cat_col_list=['home_ownership','verification_status','purpose','initial_list_status','ap
```

In [163…

```
train_df_final=ohe_encode(train_df,selected_cat_col_list)
test_df_final=ohe_encode(test_df,selected_cat_col_list)
```

In [164…

```
indp_var_list=list(train_df_final.columns)
indp_var_list.remove('loan_status')
```

In [165…

```
X=train_df_final[indp_var_list]
y=train_df_final['loan_status']
```

In [166…

```
vif_=calculate_vif(X)
vif_.T
```

Out[166]:

	1	0	2	24	29	26	28
Features	funded_amnt	loan_amnt	funded_amnt_inv	log_annual_inc	log_total_rev_hi_lim	log_revol_bal	log_tot_cur_bal
VIF	3959.6	2730.44	1041.27	512.44	494.19	235.49	195.25

2 rows × 50 columns

In [169…

```
## cols with high vif are dropped after they are analysed by removing them individually
X.drop(['funded_amnt','funded_amnt_inv','log_annual_inc','log_total_rev_hi_lim','log_revol_bal',
```

In [170…

```
vif_=calculate_vif(X)
vif_
```

Out[170]:

	Features	VIF
6	open_acc	5.03
0	loan_amnt	4.94
2	emp_length	3.73
1	grade	3.35
3	zip_code	3.22
9	recoveries	2.97
10	collection_recovery_fee	2.92
12	last_week_pay	2.65
19	verification_status_Verified	2.35
18	verification_status_Source Verified	2.32
32	initial_list_status_w	2.05
17	home_ownership_RENT	1.81
5	inq_last_6mths	1.62
20	purpose_credit_card	1.39
16	home_ownership_OWN	1.18
4	delinq_2yrs	1.17
7	pub_rec	1.14
22	purpose_home_improvement	1.11
27	purpose_other	1.10
24	purpose_major_purchase	1.03
29	purpose_small_business	1.03
26	purpose_moving	1.02
25	purpose_medical	1.02
11	collections_12_mths_ex_med	1.02
13	acc_now_delinq	1.02
8	total_rec_late_fee	1.02
14	tot_coll_amt	1.02
31	purpose_wedding	1.01
30	purpose_vacation	1.01
23	purpose_house	1.01
28	purpose_renewable_energy	1.00
21	purpose_educational	1.00
15	home_ownership_OTHER	1.00
33	application_type_JOINT	1.00

In [171…

```
X_train,X_test,y_train,y_test = train_test_split(X,y,test_size=0.20,random_state=42,stratify=y)
```

In [172...
```
#normalise the features which were of int/float type
num_feature_list=list(X.select_dtypes(exclude='uint8').columns)
```

In [173...
```
for col in num_feature_list:
    X_train[col] = z_score_standardization(X_train[col])
    X_test[col] = z_score_standardization(X_test[col])
```

In [174...
```
smote=SMOTE(random_state=20)
X_train_sm, y_train_sm = smote.fit_resample(X_train, y_train)
print('Before Resampling dataset shape %s' % Counter(y_train))
print('Resampled dataset shape %s' % Counter(y_train_sm))
```

```
Before Resampling dataset shape Counter({0: 164942, 1: 51058})
Resampled dataset shape Counter({0: 164942, 1: 164942})
```

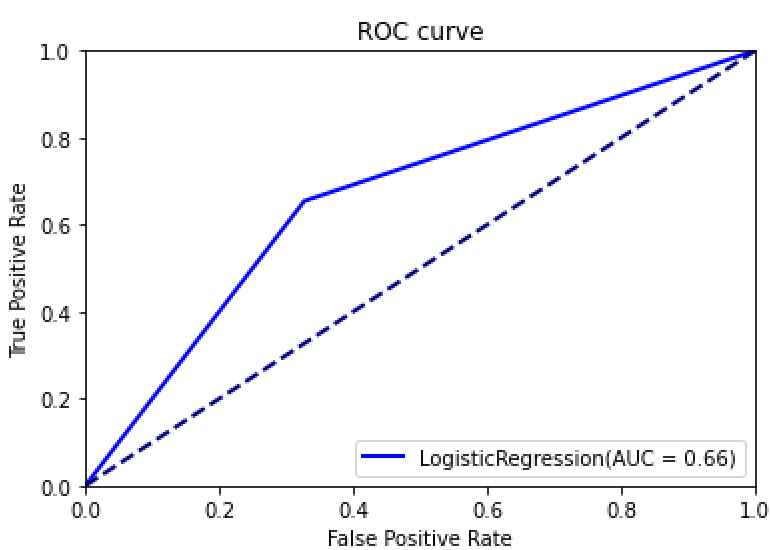
In [185...
```
logreg=LogisticRegression(random_state=42)
logreg.fit(X_train_sm, y_train_sm)
y_test_pred_lr=logreg.predict(X_test)
y_test_pred_prob_lr=logreg.predict_proba(X_test)
probs_lr=y_test_pred_prob_lr[:,1]
```

In [176...
```
train_acc_LogReg=logreg.score(X_train_sm, y_train_sm)
test_acc_LogReg=logreg.score(X_test, y_test)
print("Training Accuracy={}%".format(np.round(train_acc_LogReg,2)*100))
print("Testing Accuracy={}%".format(np.round(test_acc_LogReg,2)*100))
print(classification_report(y_test,y_test_pred_lr))
```

```
Training Accuracy=69.0%
Testing Accuracy=67.0%
              precision    recall  f1-score   support

           0       0.86      0.67      0.76     41236
           1       0.38      0.65      0.48     12764

    accuracy                           0.67     54000
   macro avg       0.62      0.66      0.62     54000
weighted avg       0.75      0.67      0.69     54000
```

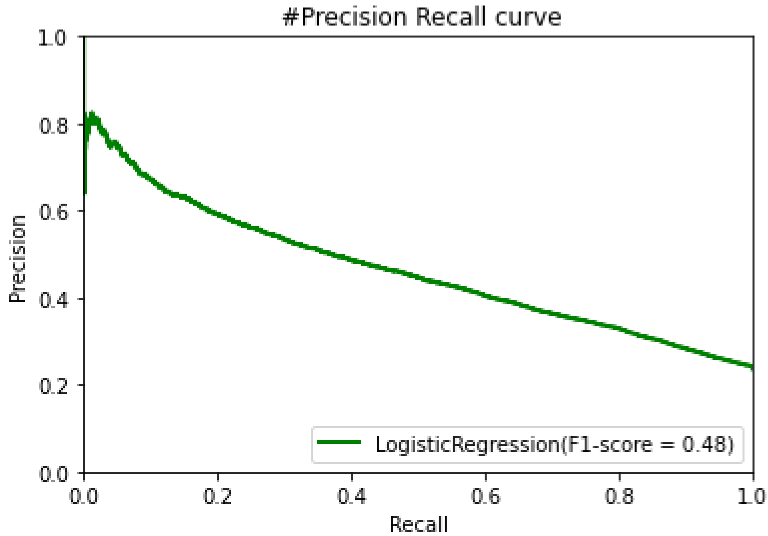
In [194...
```
prec_LogReg=precision_score(y_test,y_test_pred_lr)
recall_LogReg=recall_score(y_test,y_test_pred_lr)
F1score_LogReg=f1_score(y_test,y_test_pred_lr)
```

In [177...
```
plot_AUC(y_test,y_test_pred_lr,'LogisticRegression')
```



In [187…

```
plot_PR_Curve(y_test,probs_lr,'LogisticRegression',f1_score(y_test,y_test_pred_lr))
```



In [188…

```
log_reg_stats=build_logistic_model(X_train_sm,y_train_sm)
```

```
Warning: Maximum number of iterations has been exceeded.
         Current function value: 0.580549
         Iterations: 35
                           Logit Regression Results
==============================================================================
Dep. Variable:            loan_status   No. Observations:               329884
Model:                          Logit   Df Residuals:                   329850
Method:                           MLE   Df Model:                           33
Date:                Mon, 07 Nov 2022   Pseudo R-squ.:                  0.1624
Time:                        14:27:30   Log-Likelihood:            -1.9151e+05
converged:                      False   LL-Null:                   -2.2866e+05
Covariance Type:            nonrobust   LLR p-value:                     0.000
==============================================================================
=======
                                          coef    std err          z      P>|z|      [0.025
0.975]
------------------------------------------------------------------------------------------------
-------
loan_amnt                              -0.1706      0.005    -37.050      0.000      -0.180
-0.162
grade                                  -0.1283      0.004    -29.121      0.000      -0.137
-0.120
emp_length                             -0.0420      0.004    -10.374      0.000      -0.050
-0.034
zip_code                                0.0646      0.004     16.506      0.000       0.057
  0.072
delinq_2yrs                            -0.1403      0.005    -30.928      0.000      -0.149
-0.131
inq_last_6mths                          0.1955      0.004     47.238      0.000       0.187
  0.204
open_acc                               -0.1442      0.004    -33.416      0.000      -0.153
-0.136
pub_rec                                -0.1178      0.005    -25.311      0.000      -0.127
-0.109
total_rec_late_fee                     -0.0484      0.004    -10.809      0.000      -0.057
-0.040
recoveries                            -11.7969      0.393    -29.981      0.000     -12.568
-11.026
collection_recovery_fee                 3.8786      0.545      7.118      0.000       2.811
  4.946
collections_12_mths_ex_med             -0.0810      0.005    -15.865      0.000      -0.091
-0.071
last_week_pay                           0.3535      0.004     85.945      0.000       0.345
  0.362
acc_now_delinq                         -0.0115      0.004     -2.594      0.009      -0.020
-0.003
tot_coll_amt                           -0.0705      0.006    -11.995      0.000      -0.082
-0.059
home_ownership_OTHER                    0.9693      0.379      2.558      0.011       0.227
  1.712
home_ownership_OWN                     -0.6698      0.015    -44.280      0.000      -0.699
-0.640
home_ownership_RENT                    -0.3718      0.009    -42.151      0.000      -0.389
-0.354
verification_status_Source Verified    -0.5044      0.010    -51.285      0.000      -0.524
-0.485
verification_status_Verified           -0.2360      0.010    -22.977      0.000      -0.256
-0.216
purpose_credit_card                    -0.5938      0.010    -59.322      0.000      -0.613
-0.574
purpose_educational                     0.6743      0.314      2.150      0.032       0.059
  1.289
```

```
purpose_home_improvement                   -0.7403      0.019    -38.977      0.000      -0.778
-0.703
purpose_house                              -0.5030      0.076     -6.583      0.000      -0.653
-0.353
purpose_major_purchase                     -0.8165      0.033    -24.849      0.000      -0.881
-0.752
purpose_medical                            -0.9999      0.049    -20.299      0.000      -1.096
-0.903
purpose_moving                             -0.8288      0.059    -14.051      0.000      -0.944
-0.713
purpose_other                              -0.7113      0.021    -34.268      0.000      -0.752
-0.671
purpose_renewable_energy                   -0.8977      0.196     -4.588      0.000      -1.281
-0.514
purpose_small_business                     -0.6155      0.044    -14.086      0.000      -0.701
-0.530
purpose_vacation                           -1.2521      0.071    -17.690      0.000      -1.391
-1.113
purpose_wedding                             0.5590      0.106      5.259      0.000       0.351
  0.767
initial_list_status_w                      -1.0635      0.008   -127.120      0.000      -1.080
-1.047
application_type_JOINT                    -19.6797   2387.545     -0.008      0.993   -4699.182     4
659.823
===============================================================================================
=======
```

In [189…

```
features_scores=corr_F_P_scores(X,y)
features_scores
```

Out[189]:

	Correlation	Fscore	Pvalue
loan_amnt	-0.095343	2476.850	0.000
grade	-0.058680	932.893	0.000
emp_length	-0.028059	212.732	0.000
zip_code	0.025419	174.563	0.000
delinq_2yrs	-0.046496	584.975	0.000
inq_last_6mths	0.087834	2099.175	0.000
open_acc	-0.064131	1115.023	0.000
pub_rec	-0.049138	653.488	0.000
total_rec_late_fee	-0.003907	4.122	0.042
recoveries	-0.063569	1095.480	0.000
collection_recovery_fee	-0.044280	530.436	0.000
collections_12_mths_ex_med	-0.034231	316.745	0.000
last_week_pay	0.260580	19668.948	0.000
acc_now_delinq	-0.015262	62.903	0.000
tot_coll_amt	-0.020392	112.318	0.000
home_ownership_OTHER	0.020807	116.945	0.000
home_ownership_OWN	-0.022209	133.239	0.000
home_ownership_RENT	0.005358	7.750	0.005
verification_status_Source Verified	-0.094344	2424.791	0.000
verification_status_Verified	0.030366	249.189	0.000
purpose_credit_card	-0.039329	418.264	0.000
purpose_educational	0.028355	217.255	0.000
purpose_home_improvement	0.009128	22.500	0.000
purpose_house	0.020773	116.560	0.000
purpose_major_purchase	0.023938	154.803	0.000
purpose_medical	0.010605	30.370	0.000
purpose_moving	0.011480	35.586	0.000
purpose_other	0.018047	87.964	0.000
purpose_renewable_energy	0.008624	20.083	0.000
purpose_small_business	0.026562	190.625	0.000
purpose_vacation	0.005165	7.202	0.007
purpose_wedding	0.063134	1080.501	0.000
initial_list_status_w	-0.227494	14735.949	0.000
application_type_JOINT	-0.012718	43.676	0.000

Random Forest Classifier

In [190...
```
X_train1,X_test1,y_train1,y_test1 = train_test_split(X,y,test_size=0.20,random_state=42,stratify
```

In [191...
```
X_train_sm1, y_train_sm1 = smote.fit_resample(X_train1, y_train1)
print('Before Resampling dataset shape %s' % Counter(y_train1))
print('Resampled dataset shape %s' % Counter(y_train_sm1))
```

```
Before Resampling dataset shape Counter({0: 164942, 1: 51058})
Resampled dataset shape Counter({0: 164942, 1: 164942})
```

In [195...
```
class_weights={0:1,1:100}
#give more importance to 1(100 times more) as compared to 0.
rf_classifier=RandomForestClassifier(random_state=21,class_weight=class_weights)
rf_classifier.fit(X_train_sm1,y_train_sm1)
y_train_pred_rf=rf_classifier.predict(X_train_sm1)
y_test_pred_rf=rf_classifier.predict(X_test1)
y_test_pred_prob_rf=rf_classifier.predict_proba(X_test1)
```

In [196...
```
print("Training Accuracy={}%".format(np.round(accuracy_score(y_train_sm1,y_train_pred_rf),2)*100
print("Testing Accuracy={}%".format(np.round(accuracy_score(y_test1,y_test_pred_rf),2)*100))
print(classification_report(y_test1,y_test_pred_rf))
```

```
Training Accuracy=100.0%
Testing Accuracy=79.0%
              precision    recall  f1-score   support

           0       0.82      0.94      0.87     41236
           1       0.61      0.33      0.43     12764

    accuracy                           0.79     54000
   macro avg       0.72      0.63      0.65     54000
weighted avg       0.77      0.79      0.77     54000
```

In [197...
```
#model
rf_model = RandomForestClassifier()
#Implement RandomSearchCV
model_params = {
            "n_estimators" :  [1000,1500],
             "criterion": ["entropy"],
            }

random_search_rf = RandomizedSearchCV(rf_model, param_distributions = model_params,
                                       scoring = 'recall',
                                       return_train_score = True,
                                       random_state = 42,
                                       cv = 5,
                                       verbose = 5,n_jobs=-1)
random_search_rf.fit(X_train_sm1,y_train_sm1)
```

```
Fitting 5 folds for each of 2 candidates, totalling 10 fits
```

Out[197]:

```
▸ RandomizedSearchCV
▸ estimator: RandomForestClassifier
    ▸ RandomForestClassifier
```

In [200...
```
print(random_search_rf.best_estimator_)
print(random_search_rf.best_params_)
```

```
RandomForestClassifier(criterion='entropy', n_estimators=1000)
{'n_estimators': 1000, 'criterion': 'entropy'}
```

In [201…
```
rf_classifier_hyp=random_search_rf.best_estimator_
rf_classifier_hyp.fit(X_train_sm1,y_train_sm1)
```

Out[201]:
```
RandomForestClassifier
RandomForestClassifier(criterion='entropy', n_estimators=1000)
```

In [ ]:
```
#After Random search the best estimator found is
#RandomForestClassifier(criterion='entropy', n_estimators=1000)
```

In [202…
```
y_train_pred_rf_hyp=rf_classifier_hyp.predict(X_train_sm1)
y_test_pred_rf_hyp=rf_classifier_hyp.predict(X_test1)
y_test_pred_prob_rf_rcv=rf_classifier_hyp.predict_proba(X_test1)
```

In [311…
```
random_search_rf.best_estimator_
```

Out[311]:
```
RandomForestClassifier
RandomForestClassifier(criterion='entropy', n_estimators=1000)
```

In [312…
```
#recover the best model
rf_best_model = random_search_rf.best_estimator_
rf_best_model_df=pd.DataFrame(random_search_rf.cv_results_)
rf_best_model_df.to_csv("rf_randomsearch_08nov.csv")
```

In [203…
```
train_acc_RandomForest=accuracy_score(y_train_sm1,y_train_pred_rf_hyp)
test_acc_RandomForest=accuracy_score(y_test1,y_test_pred_rf_hyp)
prec_RandomForest=precision_score(y_test1,y_test_pred_rf_hyp)
recall_RandomForest=recall_score(y_test1,y_test_pred_rf_hyp)
F1score_RandomForest=f1_score(y_test1,y_test_pred_rf_hyp)
```

In [204…
```
print("Training Accuracy={}%".format(np.round(accuracy_score(y_train_sm1,y_train_pred_rf_hyp),2)
print("Testing Accuracy={}%".format(np.round(accuracy_score(y_test1,y_test_pred_rf_hyp),2)*100))
print(classification_report(y_test1,y_test_pred_rf_hyp))
```

```
Training Accuracy=100.0%
Testing Accuracy=80.0%
              precision    recall  f1-score   support

           0       0.82      0.94      0.87     41236
           1       0.62      0.35      0.44     12764

    accuracy                           0.80     54000
   macro avg       0.72      0.64      0.66     54000
weighted avg       0.77      0.80      0.77     54000
```

Adjust the threshold

In [205…
```
y_test_pred_prob_rf_hyp=rf_classifier_hyp.predict_proba(X_test1)
probs_rf_hyp = y_test_pred_prob_rf_hyp[:,1]
```

In [206…
```
# define thresholds
thresholds = np.arange(0, 1, 0.001)
# evaluate each threshold
f1scores = [f1_score(y_test1, to_labels(probs_rf_hyp, t)) for t in thresholds]
# get best threshold
```

```
ix = np.argmax(f1scores)
print('Threshold=%.3f, F-Score=%.5f' % (thresholds[ix], f1scores[ix]))
```

```
Threshold=0.342, F-Score=0.51188
```

In [209…

```
y_test_pred_rf_th = np.where(probs_rf_hyp>= 0.342, 1, 0)
```

In [210…

```
print("Testing Accuracy={}%".format(np.round(accuracy_score(y_test1,y_test_pred_rf_th),2)*100))
print(classification_report(y_test1,y_test_pred_rf_th))
```

```
Testing Accuracy=75.0%
              precision    recall  f1-score   support

           0       0.85      0.81      0.83     41236
           1       0.47      0.56      0.51     12764

    accuracy                           0.75     54000
   macro avg       0.66      0.68      0.67     54000
weighted avg       0.76      0.75      0.76     54000
```

In [211…

```
y_train_pred_rf_th=rf_classifier_hyp.predict(X_train_sm1)
```

In [212…

```
train_acc_RandomForest1=accuracy_score(y_train_sm1,y_train_pred_rf_th)
test_acc_RandomForest1=accuracy_score(y_test1,y_test_pred_rf_th)
prec_RandomForest1=precision_score(y_test1,y_test_pred_rf_th)
recall_RandomForest1=recall_score(y_test1,y_test_pred_rf_th)
F1score_RandomForest1=f1_score(y_test1,y_test_pred_rf_th)
```

Adaboost classifier

In [218…

```
abc = AdaBoostClassifier(n_estimators=2000,learning_rate=0.01, random_state=42)
# Train Adaboost Classifer
abc_model = abc.fit(X_train_sm1,y_train_sm1)
```

In [219…

```
y_train_pred_abc=abc_model.predict(X_train_sm1)
y_test_pred_abc=abc_model.predict(X_test1)
```

In [220…

```
print("Training Accuracy={}%".format(np.round(accuracy_score(y_train_sm1,y_train_pred_abc),2)*10
print("Testing Accuracy={}%".format(np.round(accuracy_score(y_test1,y_test_pred_abc),2)*100))
```

```
Training Accuracy=80.0%
Testing Accuracy=73.0%
```

In [221…

```
print(classification_report(y_test1,y_test_pred_abc))
```

```
              precision    recall  f1-score   support

           0       0.84      0.80      0.82     41236
           1       0.45      0.51      0.48     12764

    accuracy                           0.73     54000
   macro avg       0.64      0.66      0.65     54000
weighted avg       0.75      0.73      0.74     54000
```

In [222…

```
train_acc_adaboost=accuracy_score(y_train_sm1,y_train_pred_abc)
test_acc_adaboost=accuracy_score(y_test1,y_test_pred_abc)
prec_adaboost=precision_score(y_test1,y_test_pred_abc)
recall_adaboost=recall_score(y_test1,y_test_pred_abc)
F1score_adaboost=f1_score(y_test1,y_test_pred_abc)
```

In [223…
```
parameters_abc = {
    'n_estimators': [1000,1500,2000],
    'learning_rate': [0.01,0.1],
}
abc_grid = GridSearchCV(abc, parameters_abc, cv=5, verbose=5, n_jobs=-1,scoring='recall')
abc_grid.fit(X_train_sm1, y_train_sm1)
```

```
Fitting 5 folds for each of 6 candidates, totalling 30 fits
```

Out[223]:

```
▸ GridSearchCV
▸ estimator: AdaBoostClassifier
    ▸ AdaBoostClassifier
```

In [ ]:
```
#After grid search the best estimator found is
#AdaBoostClassifier(learning_rate=0.01, n_estimators=1000, random_state=42)
```

In [308…
```
#recover the best model
abc_best_model = abc_grid.best_estimator_
abc_best_model_df=pd.DataFrame(abc_grid.cv_results_)
abc_best_model_df.to_csv("abc_gridseach_8nov.csv")
```

In [225…
```
abc_best_model.fit(X_train_sm1,y_train_sm1)
y_train_pred_abc_grid=abc_best_model.predict(X_train_sm1)
y_test_pred_abc_grid=abc_best_model.predict(X_test1)
```

In [226…
```
print("Training Accuracy={}%".format(np.round(accuracy_score(y_train_sm1,y_train_pred_abc_grid),
print("Testing Accuracy={}%".format(np.round(accuracy_score(y_test1,y_test_pred_abc_grid),2)*100
print(classification_report(y_test1,y_test_pred_abc_grid))
```

```
Training Accuracy=78.0%
Testing Accuracy=72.0%
              precision    recall  f1-score   support

           0       0.85      0.77      0.81     41236
           1       0.42      0.55      0.48     12764

    accuracy                           0.72     54000
   macro avg       0.64      0.66      0.64     54000
weighted avg       0.75      0.72      0.73     54000
```

In [227…
```
train_acc_adaboost1=accuracy_score(y_train_sm1,y_train_pred_abc_grid)
test_acc_adaboost1=accuracy_score(y_test1,y_test_pred_abc_grid)
prec_adaboost1=precision_score(y_test1,y_test_pred_abc_grid)
recall_adaboost1=recall_score(y_test1,y_test_pred_abc_grid)
F1score_adaboost1=f1_score(y_test1,y_test_pred_abc_grid)
```

In [230…
```
# predict probabilities
y_test_pred_prob_abc = abc_best_model.predict_proba(X_test1)
# keep probabilities for the positive outcome only
probs_abc_hyp = y_test_pred_prob_abc[:, 1]
```

In [231…
```
# define thresholds
thresholds = np.arange(0, 1, 0.001)
# evaluate each threshold
scores = [f1_score(y_test1, to_labels(probs_abc_hyp, t)) for t in thresholds]
# get best threshold
```

```
ix = np.argmax(scores)
print('Threshold=%.3f, F-Score=%.5f' % (thresholds[ix], scores[ix]))
```

```
Threshold=0.499, F-Score=0.48141
```

In [235...

```
y_test1_pred_abc_grid = np.where(probs_abc_hyp>= 0.499, 1, 0)
```

In [237...

```
print("Testing Accuracy={}%".format(np.round(accuracy_score(y_test1,y_test1_pred_abc_grid),2)*10
print(classification_report(y_test1,y_test1_pred_abc_grid))
```

```
Testing Accuracy=71.0%
              precision    recall  f1-score   support

           0       0.85      0.75      0.80     41236
           1       0.42      0.57      0.48     12764

    accuracy                           0.71     54000
   macro avg       0.63      0.66      0.64     54000
weighted avg       0.75      0.71      0.72     54000
```

In [238...

```
train_acc_adaboost2=accuracy_score(y_train_sm1,y_train_pred_abc_grid)
test_acc_adaboost2=accuracy_score(y_test1,y_test1_pred_abc_grid)
prec_adaboost2=precision_score(y_test1,y_test1_pred_abc_grid)
recall_adaboost2=recall_score(y_test1,y_test1_pred_abc_grid)
F1score_adaboost2=f1_score(y_test1,y_test1_pred_abc_grid)
```

Gradboost classifier

In [239...

```
grd_boost = GradientBoostingClassifier(learning_rate=0.01, n_estimators=2000)
grd_boost.fit(X_train_sm1,y_train_sm1)
y_train_pred_grd=grd_boost.predict(X_train_sm1)
y_test_pred_grd=grd_boost.predict(X_test1)
```

In [240...

```
print("Training Accuracy={}%".format(np.round(accuracy_score(y_train_sm1,y_train_pred_grd),2)*10
print("Testing Accuracy={}%".format(np.round(accuracy_score(y_test1,y_test_pred_grd),2)*100))
print(classification_report(y_test1,y_test_pred_abc))
```

```
Training Accuracy=86.0%
Testing Accuracy=79.0%
              precision    recall  f1-score   support

           0       0.84      0.80      0.82     41236
           1       0.45      0.51      0.48     12764

    accuracy                           0.73     54000
   macro avg       0.64      0.66      0.65     54000
weighted avg       0.75      0.73      0.74     54000
```

In [241...

```
train_acc_Gradientboost=accuracy_score(y_train_sm1,y_train_pred_grd)
test_acc_Gradientboost=accuracy_score(y_test1,y_test_pred_grd)
prec_Gradientboost=precision_score(y_test1,y_test_pred_grd)
recall_Gradientboost=recall_score(y_test1,y_test_pred_grd)
F1score_Gradientboost=f1_score(y_test1,y_test_pred_grd)
```

In [242...

```
parameters_grd = {
    "n_estimators":[1000,1500,2000],
    "learning_rate":[0.01,0.1,0.2]
}
```

```
grd_clf = GridSearchCV(grd_boost, parameters_grd, cv=5, verbose=5, n_jobs=-1,scoring='recall')
grd_clf.fit(X_train_sm1, y_train_sm1)
```

```
Fitting 5 folds for each of 9 candidates, totalling 45 fits
```

Out[242]:

```
GridSearchCV
estimator: GradientBoostingClassifier
GradientBoostingClassifier
```

In [ ]:

```
#After grid search the best estimator found is
#GradientBoostingClassifier(learning_rate=0.2, n_estimators=2000)
```

In [253...

```
#recover the best model
grd_best_model = grd_clf.best_estimator_
grd_best_model_df=pd.DataFrame(grd_clf.cv_results_)
grd_best_model_df.to_csv("grd_gridseach_08.csv")
```

In [254...

```
grd_best_model.fit(X_train_sm1,y_train_sm1)
y_train_pred_grd_gcv=grd_best_model.predict(X_train_sm1)
y_test_pred_grd_gcv=grd_best_model.predict(X_test1)
```

In [255...

```
print("Training Accuracy={}%".format(np.round(accuracy_score(y_train_sm1,y_train_pred_grd_gcv),2
print("Testing Accuracy={}%".format(np.round(accuracy_score(y_test1,y_test_pred_grd_gcv),2)*100)
print(classification_report(y_test1,y_test_pred_grd_gcv))
```

```
Training Accuracy=89.0%
Testing Accuracy=82.0%
              precision    recall  f1-score   support

           0       0.83      0.97      0.89     41236
           1       0.76      0.36      0.49     12764

    accuracy                           0.82     54000
   macro avg       0.80      0.66      0.69     54000
weighted avg       0.81      0.82      0.80     54000
```

In [266...

```
train_acc_Gradientboost1=accuracy_score(y_train_sm1,y_train_pred_grd_gcv)
test_acc_Gradientboost1=accuracy_score(y_test1,y_test_pred_grd_gcv)
prec_Gradientboost1=precision_score(y_test1,y_test_pred_grd_gcv)
recall_Gradientboost1=recall_score(y_test1,y_test_pred_grd_gcv)
F1score_Gradientboost1=f1_score(y_test1,y_test_pred_grd_gcv)
```

In [260...

```
# predict probabilities
y_test_pred_prob_grd = grd_best_model.predict_proba(X_test1)
# keep probabilities for the positive outcome only
probs_grd_hyp = y_test_pred_prob_grd[:, 1]
```

In [261...

```
# define thresholds
thresholds = np.arange(0, 1, 0.001)
# evaluate each threshold
scores_grd = [f1_score(y_test1, to_labels(probs_grd_hyp, t)) for t in thresholds]
# get best threshold
ix = np.argmax(scores_grd)
print('Threshold=%.3f, F-Score=%.5f' % (thresholds[ix], scores_grd[ix]))
```

```
Threshold=0.304, F-Score=0.56099
```

In [264...

```
y_test1_pred_grd = np.where(probs_grd_hyp>= 0.34, 1, 0)
```

In [265...

```
print("Testing Accuracy={}%".format(np.round(accuracy_score(y_test1,y_test1_pred_grd),2)*100))
print(classification_report(y_test1,y_test1_pred_grd))
```

```
Testing Accuracy=80.0%
              precision    recall  f1-score   support

           0       0.86      0.88      0.87     41236
           1       0.59      0.53      0.55     12764

    accuracy                           0.80     54000
   macro avg       0.72      0.71      0.71     54000
weighted avg       0.79      0.80      0.80     54000
```

In [267...

```
train_acc_Gradientboost2=accuracy_score(y_train_sm1,y_train_pred_grd)
test_acc_Gradientboost2=accuracy_score(y_test1,y_test1_pred_grd)
prec_Gradientboost2=precision_score(y_test1,y_test1_pred_grd)
recall_Gradientboost2=recall_score(y_test1,y_test1_pred_grd)
F1score_Gradientboost2=f1_score(y_test1,y_test1_pred_grd)
```

In [281...

```
model_performance_summary={

'model':['LogisticRegression','RandomForest','Adaboost',
         'Gradientboost'],

'Training_Accuracy': [train_acc_LogReg,
                      train_acc_RandomForest1,
                      train_acc_adaboost2,
                      train_acc_Gradientboost2],
'Testing_Accuracy': [test_acc_LogReg,
                     test_acc_RandomForest1,
                     test_acc_adaboost2,
                     test_acc_Gradientboost2],
'Precission':[prec_LogReg,
              prec_RandomForest1,
              prec_adaboost2,
              prec_Gradientboost],
'Recall':[recall_LogReg,
          recall_RandomForest1,
          recall_adaboost2,
          recall_Gradientboost2],
'F1score':[F1score_LogReg,
           F1score_RandomForest1,
           F1score_adaboost2,
           F1score_Gradientboost2]
}
```

In [282...

```
summary_df=pd.DataFrame.from_dict(model_performance_summary)
```

In [283...

```
summary_df
```

Out[283]:

	model	Training_Accuracy	Testing_Accuracy	Precission	Recall	F1score
0	LogisticRegression	0.693235	0.668722	0.382621	0.654419	0.482902
1	RandomForest	1.000000	0.749704	0.474809	0.555233	0.511882
2	Adaboost	0.783394	0.710667	0.417646	0.568160	0.481413
3	Gradientboost	0.858738	0.800185	0.606457	0.527107	0.554978

In [268…
```
final_columns_unseen=X.columns
```

In [270…
```
X_unseen=train_df_final[final_columns_unseen]
y_unseen=train_df_final['loan_status']
```

In [271…
```
y_pred_grd_unseen=grd_best_model.predict(X_unseen)
```

In [272…
```
accuracy_score(y_unseen,y_pred_grd_unseen)
```

Out[272]:
```
0.8292555555555555
```

In [273…
```
print(classification_report(y_unseen,y_pred_grd_unseen))
```

```
              precision    recall  f1-score   support

           0       0.83      0.97      0.90    206178
           1       0.80      0.37      0.51     63822

    accuracy                           0.83    270000
   macro avg       0.82      0.67      0.70    270000
weighted avg       0.82      0.83      0.80    270000
```

In [274…
```
# predict probabilities
yhat_unseen = grd_best_model.predict_proba(X_unseen)
# keep probabilities for the positive outcome only
probs_unseen = yhat_unseen[:, 1]
```

In [299…
```
y_pred_unseen = np.where(probs_unseen>= 0.303, 1, 0)
```

In [300…
```
print(classification_report(y_unseen,y_pred_unseen))
```

```
              precision    recall  f1-score   support

           0       0.88      0.86      0.87    206178
           1       0.57      0.61      0.59     63822

    accuracy                           0.80    270000
   macro avg       0.72      0.73      0.73    270000
weighted avg       0.80      0.80      0.80    270000
```

In [284…
```
acc_unseen=accuracy_score(y_unseen,y_pred_unseen)
prec_unseen=precision_score(y_unseen,y_pred_unseen)
recall_unseen=recall_score(y_unseen,y_pred_unseen)
F1score_unseen=f1_score(y_unseen,y_pred_unseen)
```

In [295…
```
valid_summary={
              'Model':'Gradientboost',
              'Accuracy':[acc_unseen],
              'Precision':[prec_unseen],
              'Recall':[recall_unseen],
              'F1_Score':[F1score_unseen]
             }
```

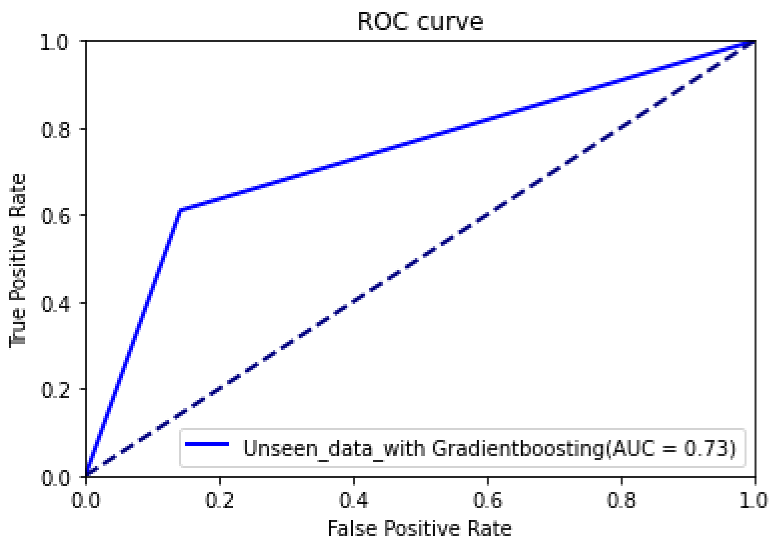
In [296…
```
valid_summary_df=pd.DataFrame.from_dict(valid_summary)
valid_summary_df
```

Out[296]:

	Model	Accuracy	Precision	Recall	F1_Score
0	Gradientboost	0.799481	0.571014	0.609915	0.589824

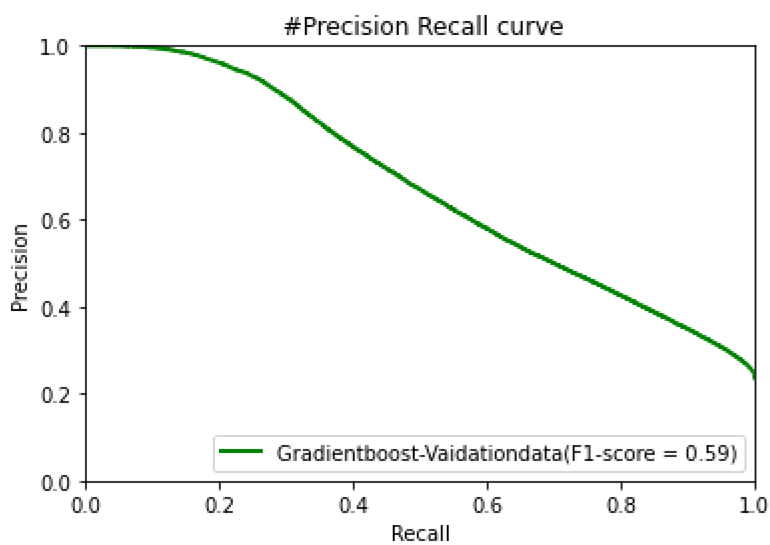
In [279...

```
plot_AUC(y_unseen,y_pred_unseen,'Gradientboost-Vaidationdata')
```



In [294...

```
plot_PR_Curve(y_unseen,probs_unseen,'Gradientboost-Vaidationdata',f1_score(y_unseen,y_pred_unseen
```



In [ ]: