Case Study : Logistic Regrerssion Case Study

Problem Statement:

Design a Logistic Regression model to correctly classify the customer based on the given set of attributes into two categories - whether the customer will be able to repay the loan or will it possibly result into NPA (Non-performing Account). The notion is that bank should not loose good a customer or retain a defaulter customer because of "False Alarm".

Import Libraries

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

pd.set_option('display.max_columns', None)
#pd.set_option('display.max_rows', None)

warnings.filterwarnings('ignore')
sns.set_style('darkgrid')
```

Import dataset and perform EDA

```
df = pd.read_csv('train.csv')
df.shape
```

```
(396030, 27)
```

```
df.head()
```

```
   loan_amnt        term  int_rate  installment grade sub_grade  \
0    10000.0   36 months     11.44       329.48     B        B4   
1     8000.0   36 months     11.99       265.68     B        B5   
2    15600.0   36 months     10.49       506.97     B        B3   
3     7200.0   36 months      6.49       220.65     A        A2   
4    24375.0   60 months     17.27       609.33     C        C5   

                 emp_title emp_length home_ownership  annual_inc  \
0                Marketing  10+ years           RENT    117000.0   
1          Credit analyst     4 years       MORTGAGE     65000.0   
2             Statistician   < 1 year           RENT     43057.0   
3          Client Advocate    6 years           RENT     54000.0   
4  Destiny Management Inc.    9 years       MORTGAGE     55000.0   

  verification_status   issue_d  loan_status             purpose  \
0        Not Verified  Jan-2015   Fully Paid            vacation   
1        Not Verified  Jan-2015   Fully Paid  debt_consolidation   
2     Source Verified  Jan-2015   Fully Paid         credit_card   
3        Not Verified  Nov-2014   Fully Paid         credit_card   
```

```
4            Verified  Apr-2013  Charged Off         credit_card

                        title    dti earliest_cr_line  open_acc  pub_rec
\
0                    Vacation  26.24         Jun-1990      16.0      0.0

1          Debt consolidation  22.05         Jul-2004      17.0      0.0

2     Credit card refinancing  12.79         Aug-2007      13.0      0.0

3     Credit card refinancing   2.60         Sep-2006       6.0      0.0

4       Credit Card Refinance  33.95         Mar-1999      13.0      0.0


   revol_bal  revol_util  total_acc initial_list_status
application_type  \
0    36369.0        41.8       25.0                   w
INDIVIDUAL
1    20131.0        53.3       27.0                   f
INDIVIDUAL
2    11987.0        92.2       26.0                   f
INDIVIDUAL
3     5472.0        21.5       13.0                   f
INDIVIDUAL
4    24584.0        69.8       43.0                   f
INDIVIDUAL

   mort_acc  pub_rec_bankruptcies  \
0       0.0                   0.0
1       3.0                   0.0
2       0.0                   0.0
3       0.0                   0.0
4       1.0                   0.0

                                              address
0     0174 Michelle Gateway\r\nMendozaberg, OK 22690
1  1076 Carney Fort Apt. 347\r\nLoganmouth, SD 05113
2  87025 Mark Dale Apt. 269\r\nNew Sabrina, WV 05113
3            823 Reid Ford\r\nDelacruzside, MA 00813
4             679 Luna Roads\r\nGreggshire, VA 11650

#Check for dupliicate values
df.duplicated().sum()

0

#Check for null values
df.isna().sum().sort_values(ascending=False)
```

```
mort_acc                37795
emp_title               22927
emp_length              18301
title                    1755
pub_rec_bankruptcies      535
revol_util                276
loan_amnt                   0
dti                         0
application_type            0
initial_list_status         0
total_acc                   0
revol_bal                   0
pub_rec                     0
open_acc                    0
earliest_cr_line            0
purpose                     0
term                        0
loan_status                 0
issue_d                     0
verification_status         0
annual_inc                  0
home_ownership              0
sub_grade                   0
grade                       0
installment                 0
int_rate                    0
address                     0
dtype: int64
```

```
#Check for percentage of null values
round(df.isna().sum()/len(df)*100,2).sort_values(ascending=False)
```

```
mort_acc                9.54
emp_title               5.79
emp_length              4.62
title                   0.44
pub_rec_bankruptcies    0.14
revol_util              0.07
loan_amnt               0.00
dti                     0.00
application_type        0.00
initial_list_status     0.00
total_acc               0.00
revol_bal               0.00
pub_rec                 0.00
open_acc                0.00
earliest_cr_line        0.00
purpose                 0.00
term                    0.00
loan_status             0.00
```

```
issue_d                 0.00
verification_status     0.00
annual_inc              0.00
home_ownership          0.00
sub_grade               0.00
grade                   0.00
installment             0.00
int_rate                0.00
address                 0.00
dtype: float64
```

```
#Check dataframe.info(). Get the null values and datatypes
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 396030 entries, 0 to 396029
Data columns (total 27 columns):
 #   Column                Non-Null Count   Dtype  
---  ------                --------------   -----  
 0   loan_amnt             396030 non-null  float64
 1   term                  396030 non-null  object 
 2   int_rate              396030 non-null  float64
 3   installment           396030 non-null  float64
 4   grade                 396030 non-null  object 
 5   sub_grade             396030 non-null  object 
 6   emp_title             373103 non-null  object 
 7   emp_length            377729 non-null  object 
 8   home_ownership        396030 non-null  object 
 9   annual_inc            396030 non-null  float64
 10  verification_status   396030 non-null  object 
 11  issue_d               396030 non-null  object 
 12  loan_status           396030 non-null  object 
 13  purpose               396030 non-null  object 
 14  title                 394275 non-null  object 
 15  dti                   396030 non-null  float64
 16  earliest_cr_line      396030 non-null  object 
 17  open_acc              396030 non-null  float64
 18  pub_rec               396030 non-null  float64
 19  revol_bal             396030 non-null  float64
 20  revol_util            395754 non-null  float64
 21  total_acc             396030 non-null  float64
 22  initial_list_status   396030 non-null  object 
 23  application_type      396030 non-null  object 
 24  mort_acc              358235 non-null  float64
 25  pub_rec_bankruptcies  395495 non-null  float64
 26  address               396030 non-null  object 
dtypes: float64(12), object(15)
memory usage: 81.6+ MB
```

```python
#Missing Value Treatments upon analysis
#NaN values are replaced as below

df.loc[df['emp_title'].isna(),'emp_title'] = 'No Employee Title'
df.loc[df['emp_length'].isna(),'emp_length'] = 'Unavailable'
df.loc[df['title'].isna(),'title'] = 'Unavailable'
df.loc[df['revol_util'].isna(),'revol_util'] = 0.0
df.loc[df['mort_acc'].isna(),'mort_acc'] = 0.0
df.loc[df['pub_rec_bankruptcies'].isna(),'pub_rec_bankruptcies'] = 0.0

#Check for missing values
df.isna().sum()
```

```
loan_amnt               0
term                    0
int_rate                0
installment             0
grade                   0
sub_grade               0
emp_title               0
emp_length              0
home_ownership          0
annual_inc              0
verification_status     0
issue_d                 0
loan_status             0
purpose                 0
title                   0
dti                     0
earliest_cr_line        0
open_acc                0
pub_rec                 0
revol_bal               0
revol_util              0
total_acc               0
initial_list_status     0
application_type        0
mort_acc                0
pub_rec_bankruptcies    0
address                 0
dtype: int64
```

```python
#Get stats of numeric/continuous variables
df.describe()
```

```
           loan_amnt       int_rate    installment    annual_inc  \
count  396030.000000  396030.000000  396030.000000  3.960300e+05
mean    14113.888089      13.639400     431.849698  7.420318e+04
std      8357.441341       4.472157     250.727790  6.163762e+04
min       500.000000       5.320000      16.080000  0.000000e+00
```

```
25%      8000.000000      10.490000     250.330000  4.500000e+04
50%     12000.000000      13.330000     375.430000  6.400000e+04
75%     20000.000000      16.490000     567.300000  9.000000e+04
max     40000.000000      30.990000    1533.810000  8.706582e+06

                 dti       open_acc        pub_rec     revol_bal  \
count  396030.000000  396030.000000  396030.000000  3.960300e+05
mean       17.379514      11.311153       0.178191  1.584454e+04
std        18.019092       5.137649       0.530671  2.059184e+04
min         0.000000       0.000000       0.000000  0.000000e+00
25%        11.280000       8.000000       0.000000  6.025000e+03
50%        16.910000      10.000000       0.000000  1.118100e+04
75%        22.980000      14.000000       0.000000  1.962000e+04
max      9999.000000      90.000000      86.000000  1.743266e+06

          revol_util      total_acc        mort_acc
pub_rec_bankruptcies
count  396030.000000  396030.000000  396030.000000
396030.000000
mean       53.754260      25.414744       1.640873
0.121483
std        24.484857      11.886991       2.111249
0.355962
min         0.000000       2.000000       0.000000
0.000000
25%        35.800000      17.000000       0.000000
0.000000
50%        54.800000      24.000000       1.000000
0.000000
75%        72.900000      32.000000       3.000000
0.000000
max       892.300000     151.000000      34.000000
8.000000

#Get stats of categorical variables
df.describe(include='object')

              term   grade sub_grade          emp_title emp_length  \
count       396030  396030    396030             396030     396030
unique           2       7        35             173106         12
top      36 months       B        B3  No Employee Title  10+ years
freq        302005  116018     26655              22927     126041

       home_ownership verification_status   issue_d loan_status  \
count          396030              396030    396030      396030
unique              6                   3       115           2
top          MORTGAGE            Verified  Oct-2014  Fully Paid
freq           198348              139563     14846      318357

                   purpose               title earliest_cr_line  \
```

```
count                   396030                 396030           396030
unique                      14                  48818              684
top     debt_consolidation  Debt consolidation        Oct-2000
freq                    234507                 152472             3017

       initial_list_status application_type
address
count                   396030           396030
396030
unique                       2                3
393700
top                          f       INDIVIDUAL  USCGC Smith\r\nFPO AE
70466
freq                    238066           395319
8
```

Feature Engineering

```
#Perform Encoding
df.loc[df['pub_rec'] >= 1,'pub_rec'] = 1
df.loc[df['mort_acc'] >= 1, 'mort_acc'] = 1
df.loc[df['pub_rec_bankruptcies'] >= 1, 'pub_rec_bankruptcies'] = 1
df.loc[df['term'] ==' 36 months', 'term'] = 36
df.loc[df['term'] ==' 60 months', 'term'] = 60
df['term'] = df['term'].astype('int64')

#Split issue_date into month and year
df[['issue_month', 'issue_year']] = df['issue_d'].str.split('-',
expand=True)
df.drop(['issue_d'], axis=1, inplace=True)

#Split er_cr_line date into month and year
df[['er_cr_line_m', 'er_cr_line_y']] =
df['earliest_cr_line'].str.split('-', expand=True)
df.drop(['earliest_cr_line'], axis=1, inplace=True)

#Split address into State and Zip code
df[['address_state', 'address_zip']] = df['address'].str.split(','
                                                                      ,
expand=True)[1].str.split(' '
                                                                       ,expan
d=True)[[1,2]]
df.drop(['address'], axis=1, inplace=True)

#Make emp_title, purpose and title as uppercase fields
df['emp_title'] = df['emp_title'].str.upper()
df['purpose'] = df['purpose'].str.upper()
df['title'] = df['title'].str.upper()
```

Outliers Detection

```
df1 = df.copy()

#Removing some extreme outliers values for annual income
print(np.percentile(df['annual_inc'], 50))
print(np.percentile(df['annual_inc'], 99))
print(np.percentile(df['annual_inc'], 99.99))
print(round(df.loc[df['annual_inc'] >
210000.0].shape[0]/len(df),2)*100)
df = df.loc[~(df['annual_inc'] > np.percentile(df['annual_inc'], 99))]
```

```
64000.0
250000.0
1250000.0
2.0
```

```
#Removing some extreme outliers values for pub_rec
print(np.percentile(df['pub_rec'], 50))
print(np.percentile(df['pub_rec'], 99))
print(np.percentile(df['pub_rec'], 99.99))
print(round(df.loc[df['pub_rec'] > 9.0].shape[0]/len(df),2)*100)
df = df.loc[~(df['pub_rec'] > np.percentile(df['pub_rec'], 99.99))]
```

```
0.0
1.0
1.0
0.0
```

```
#Removing some extreme outliers values for pub_rec_bankruptcies
print(np.percentile(df['pub_rec_bankruptcies'], 50))
print(np.percentile(df['pub_rec_bankruptcies'], 99))
print(np.percentile(df['pub_rec_bankruptcies'], 99.99))
print(round(df.loc[df['pub_rec_bankruptcies'] >
5.0].shape[0]/len(df),2)*100)
df = df.loc[~(df['pub_rec_bankruptcies'] >
np.percentile(df['pub_rec_bankruptcies'], 99.99))]
```

```
0.0
1.0
1.0
0.0
```

```
#Define Outlier Detection function based on IQR and Percentile

def detect_outliers(df,col):
    q1 = np.quantile(df[col],0.25)
    q3 = np.quantile(df[col],0.75)
    iqr = q3-q1
    lb = q1 - 1.5*iqr
    ub = q3 + 1.5*iqr
    outlier = df.loc[(df[col] < lb) | (df[col] > ub)]
```

```
    return round(outlier.shape[0]/df.shape[0]*100,2)

def detect_outliers_percentile(df,col):
    q1 = np.quantile(df[col],0.25)
    q3 = np.quantile(df[col],0.75)
    p = np.percentile(df[col],99.99)
    iqr = q3-q1
    lb = q1 - 1.5*iqr
    ub = q3 + 1.5*iqr
    outlier = df.loc[(df[col] < lb) | (df[col] > p)]
    return round(outlier.shape[0]/df.shape[0]*100,2)

#Print percentage of outliers for each cont. variable
print(f"Outlier Percentage")
print(f"loan_amnt            = {detect_outliers(df,'loan_amnt')}%")
print(f"int_rate             = {detect_outliers(df,'int_rate')}%")
print(f"installment          = {detect_outliers(df,'installment')}%")
print(f"annual_inc           = {detect_outliers(df,'annual_inc')}%")
print(f"dti                  = {detect_outliers(df,'dti')}%")
print(f"open_acc             = {detect_outliers(df,'open_acc')}%")
print(f"pub_rec              = 
{detect_outliers_percentile(df,'pub_rec')}%")
print(f"revol_bal            = {detect_outliers(df,'revol_bal')}%")
print(f"revol_util           = {detect_outliers(df,'revol_util')}%")
print(f"total_acc            = {detect_outliers(df,'total_acc')}%")
print(f"mort_acc             = {detect_outliers(df,'mort_acc')}%")
print(f"pub_rec_bankruptcies = 
{detect_outliers(df,'pub_rec_bankruptcies')}%")

Outlier Percentage
loan_amnt            = 0.04%
int_rate             = 0.79%
installment          = 2.74%
annual_inc           = 3.52%
dti                  = 0.07%
open_acc             = 2.57%
pub_rec              = 0.0%
revol_bal            = 5.23%
revol_util           = 0.0%
total_acc            = 2.11%
mort_acc             = 0.0%
pub_rec_bankruptcies = 11.45%
```

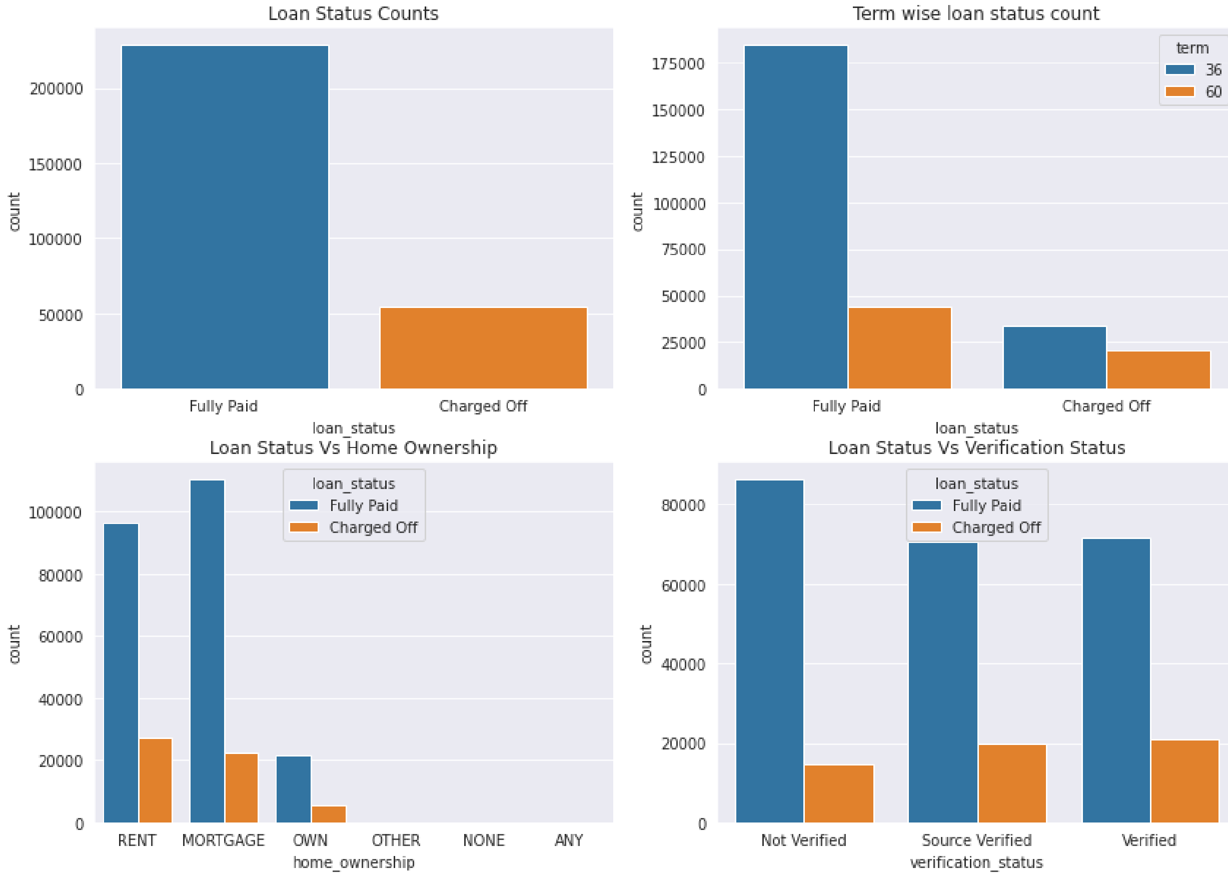
Outliers Treatment

```
#Define function to remove outliers based on IQR

def remove_outliers(df,col):
    q1 = np.quantile(df[col],0.25)
    q3 = np.quantile(df[col],0.75)
```

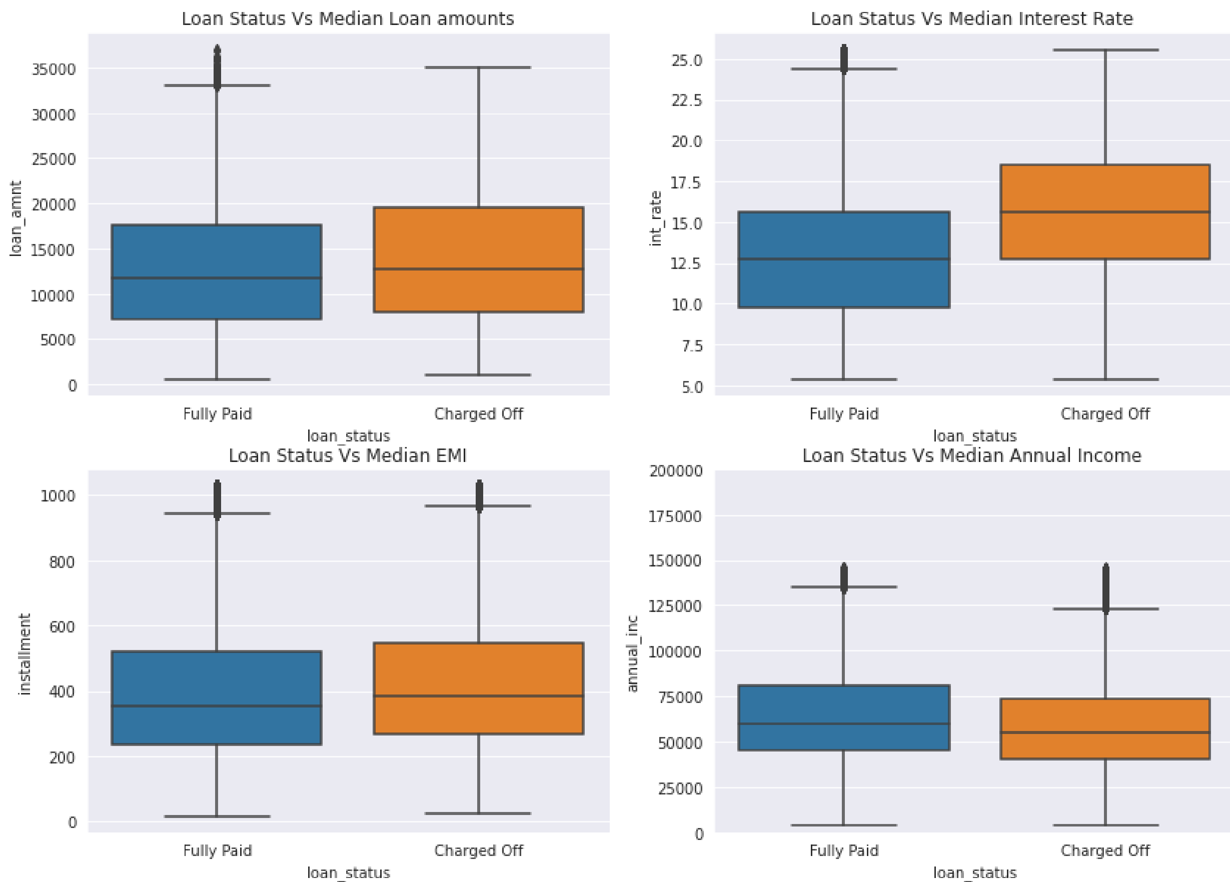
```
    iqr = q3-q1
    lb = q1 - 1.5*iqr
    ub = q3 + 1.5*iqr
    return df.loc[~((df[col] < lb) | (df[col] > ub))]

# def remove_outliers_percentile(df,col):
#     q1 = np.quantile(df[col],0.25)
#     q3 = np.quantile(df[col],0.75)
#     p = np.percentile(df[col],99.99)
#     iqr = q3-q1
#     lb = q1 - 1.5*iqr
#     ub = q3 + 1.5*iqr
#     return df.loc[~((df[col] < lb) | (df[col] > p))]

#Remove outliers from cont. variables mentioned below
df = remove_outliers(df, 'loan_amnt')
df = remove_outliers(df, 'int_rate')
df = remove_outliers(df, 'installment')
df = remove_outliers(df, 'annual_inc')
df = remove_outliers(df, 'dti')
df = remove_outliers(df, 'pub_rec')
df = remove_outliers(df, 'revol_bal')
df = remove_outliers(df, 'revol_util')
df = remove_outliers(df, 'open_acc')
df = remove_outliers(df, 'total_acc')
df = remove_outliers(df, 'mort_acc')
df = remove_outliers(df, 'pub_rec_bankruptcies')
```

Univariate/Bivariate Analysis

```
#Countplots of various categorical features w.r.t. to target variable
loan_status
plt.figure(figsize=(14,10))
plt.subplot(2,2,1)
sns.countplot(data=df, x='loan_status')
plt.title('Loan Status Counts')
plt.subplot(2,2,2)
sns.countplot(data=df, x='loan_status', hue='term')
plt.title('Term wise loan status count')
plt.subplot(2,2,3)
sns.countplot(data=df, x='home_ownership', hue='loan_status')
plt.title('Loan Status Vs Home Ownership')
plt.subplot(2,2,4)
sns.countplot(data=df, x='verification_status', hue='loan_status')
plt.title('Loan Status Vs Verification Status')
plt.show()
```




```python
#Boxplot of various cont. features w.r.t. target variable loan_status
plt.figure(figsize=(14,10))
plt.subplot(2,2,1)
sns.boxplot(data=df, x='loan_status', y='loan_amnt')
plt.title('Loan Status Vs Median Loan amounts')
plt.subplot(2,2,2)
sns.boxplot(data=df, x='loan_status', y='int_rate')
plt.title('Loan Status Vs Median Interest Rate ')
plt.subplot(2,2,3)
sns.boxplot(data=df, x='loan_status', y='installment')
plt.title('Loan Status Vs Median EMI')
plt.subplot(2,2,4)
sns.boxplot(data=df, x='loan_status', y='annual_inc')
plt.ylim(bottom=0, top=200000)
plt.title('Loan Status Vs Median Annual Income ')
plt.show()
```



Observation1: Median interest rate of Charged Off customers is significantly higher than those of Fully Paid

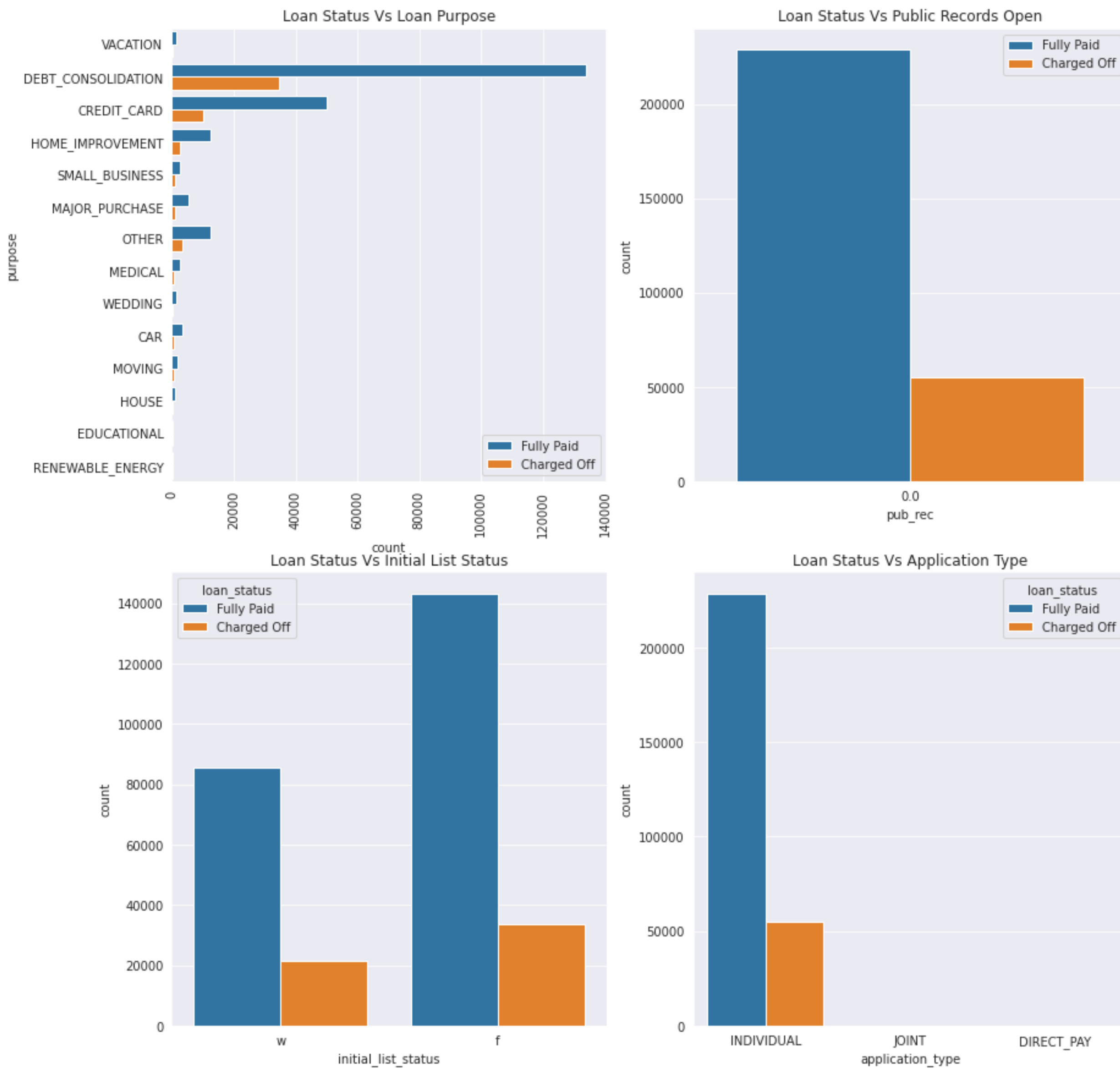
Observation2: Median annual income of Charged Off customers is lower than those of Fully Paid

Observation3: Median EMI of Charged Off is higher than those of Fully Paid

Observation4: Median loan amount of Charged Off is higher than those of Fully Paid

```
#Countplot of categorical variables w.r.t. target variable loan_status
plt.figure(figsize=(14,15))
plt.subplot(2,2,1)
sns.countplot(data=df, y='purpose', hue='loan_status')
plt.xticks(rotation=90)
plt.title('Loan Status Vs Loan Purpose')
plt.legend(loc=4)
plt.subplot(2,2,2)
sns.countplot(data=df, x='pub_rec',hue='loan_status')
#plt.xlim(left=0,right=10)
plt.title('Loan Status Vs Public Records Open')
plt.legend(loc=1)
plt.subplot(2,2,3)
sns.countplot(data=df, x='initial_list_status', hue='loan_status')
plt.title('Loan Status Vs Initial List Status')
```

```python
plt.subplot(2,2,4)
sns.countplot(data=df, x='application_type',hue='loan_status')
#plt.xlim(left=0,right=10)
plt.title('Loan Status Vs Application Type')
#plt.legend(loc=1)
plt.show()
```

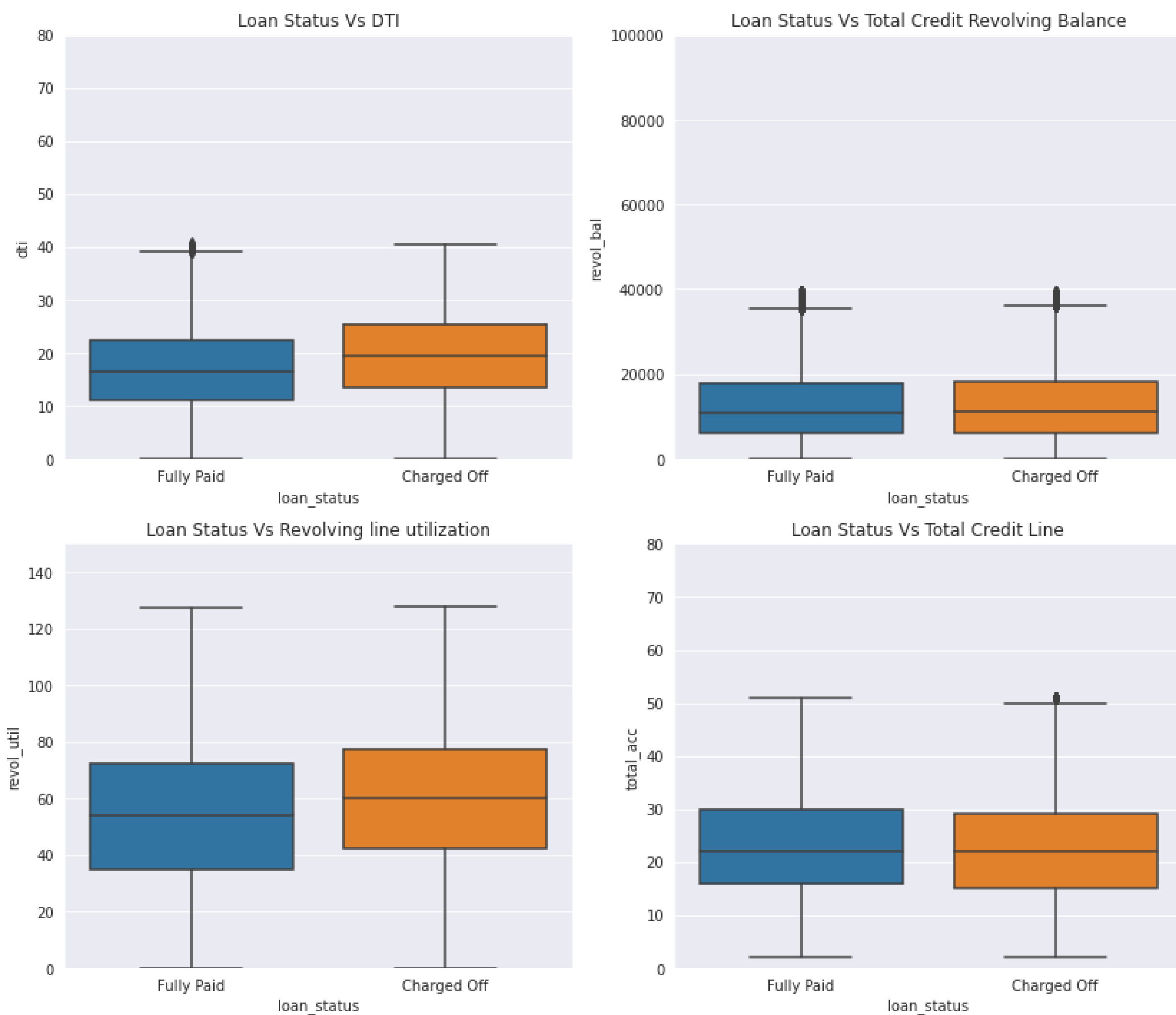


Observation1: Top 2 loan purpose categories are Debit Consolidation and Credit Card

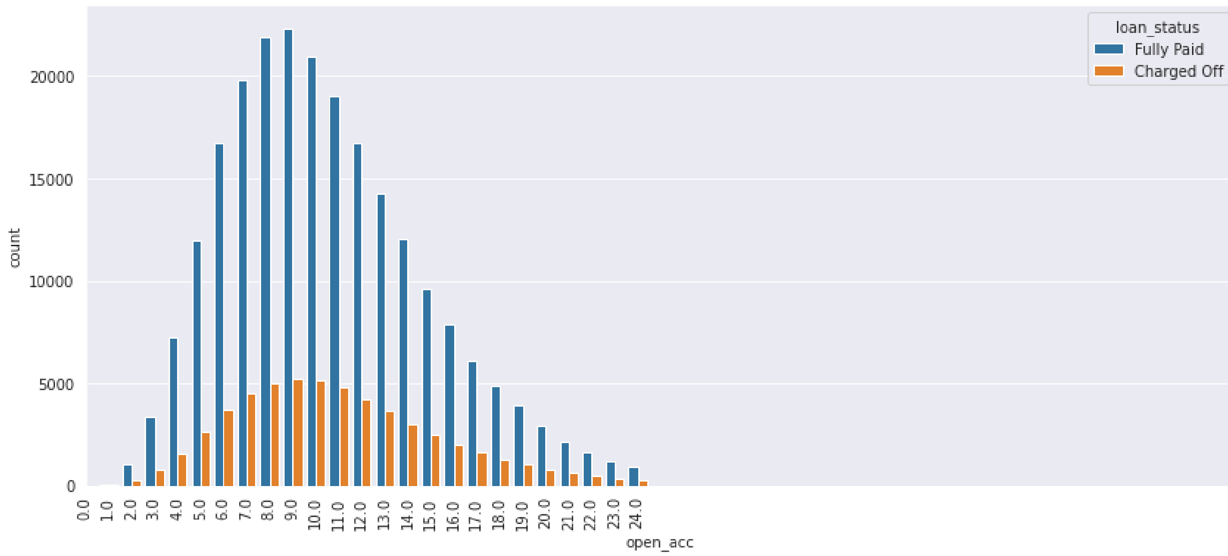
Observation2: Topmost loan type application is INDIVIDUAL

```python
#Box plot of various cont. features w.r.t. target variable loan_status

plt.figure(figsize=(14,12))
```

```
plt.subplot(2,2,1)
sns.boxplot(data=df, x='loan_status', y='dti')
plt.ylim(bottom=0,top=80)
plt.title('Loan Status Vs DTI')
plt.subplot(2,2,2)
sns.boxplot(data=df, x='loan_status', y='revol_bal')
plt.ylim(bottom=0, top=100000)
plt.title('Loan Status Vs Total Credit Revolving Balance')
plt.subplot(2,2,3)
sns.boxplot(data=df, x='loan_status', y='revol_util')
plt.ylim(bottom=0,top=150)
plt.title('Loan Status Vs Revolving line utilization')
plt.subplot(2,2,4)
sns.boxplot(data=df, x='loan_status', y='total_acc')
plt.ylim(bottom=0, top=80)
plt.title('Loan Status Vs Total Credit Line')
plt.show()
```



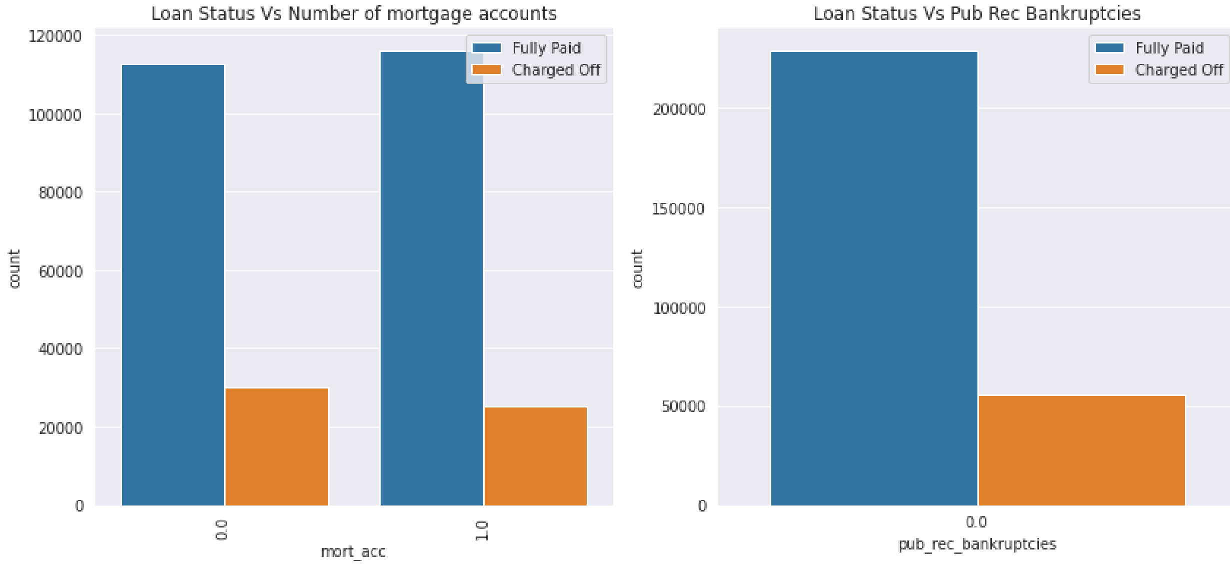
```
#Countplot of categorical variable open_acc w.r.t. target variable
loan_status

plt.figure(figsize=(14,6))
sns.countplot(data=df, x='open_acc',hue='loan_status')
plt.xlim(left=0,right=50)
plt.xticks(rotation=90)
plt.show()
```



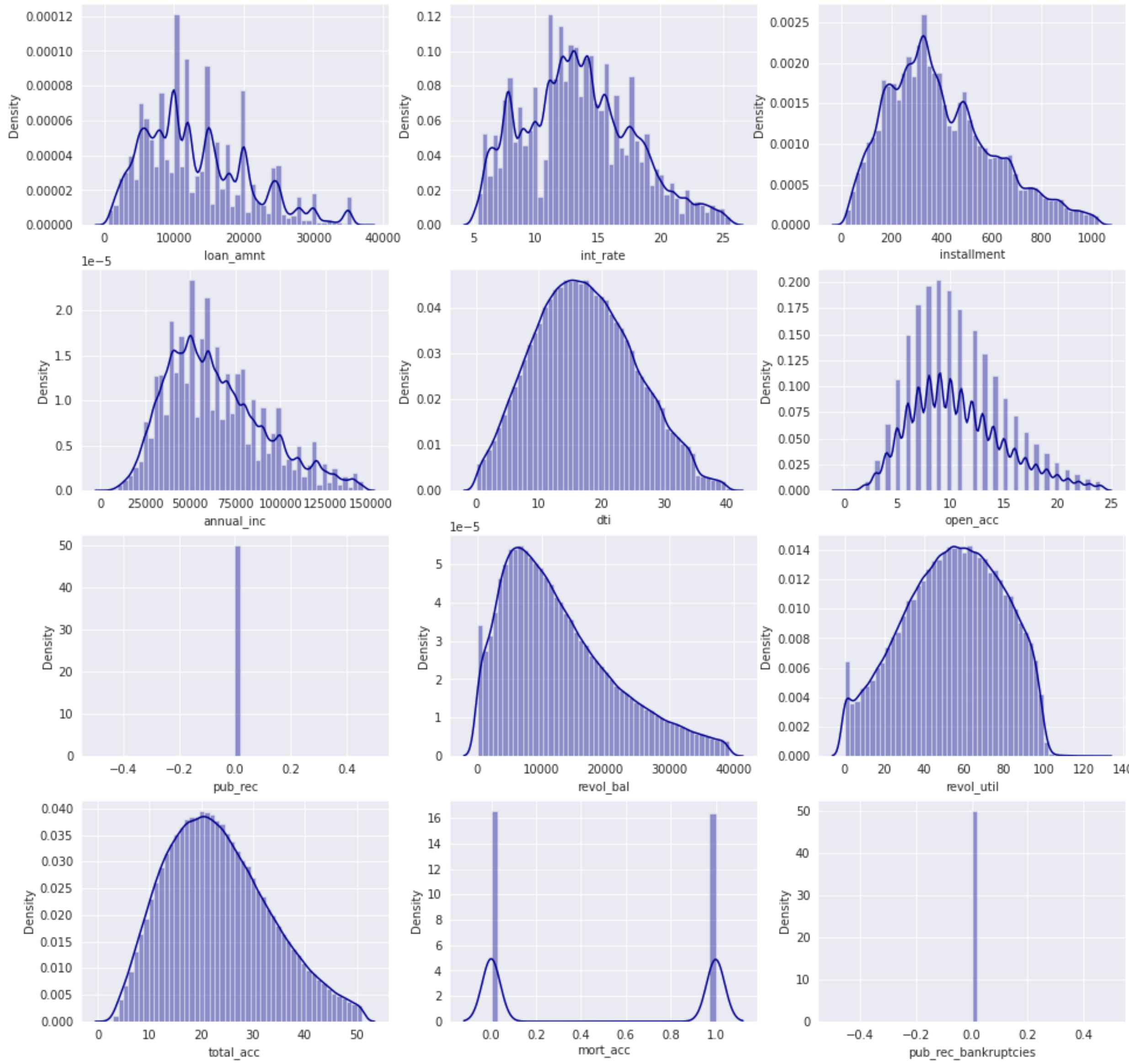
Observation1: open_acc is fairly graphically normall distributed

Observation2: Charged Off and Fully Paid have same distribution

```
#Countplot for various categorical features w.r.t. target variable
loan_status

plt.figure(figsize=(14,6))
plt.subplot(1,2,1)
sns.countplot(data=df, x='mort_acc',hue='loan_status')
plt.xticks(rotation=90)
plt.title('Loan Status Vs Number of mortgage accounts')
plt.legend(loc=1)
plt.subplot(1,2,2)
sns.countplot(data=df, x='pub_rec_bankruptcies',hue='loan_status')
#plt.xlim(left=0,right=10)
plt.title('Loan Status Vs Pub Rec Bankruptcies')
plt.legend(loc=1)
plt.show()
```

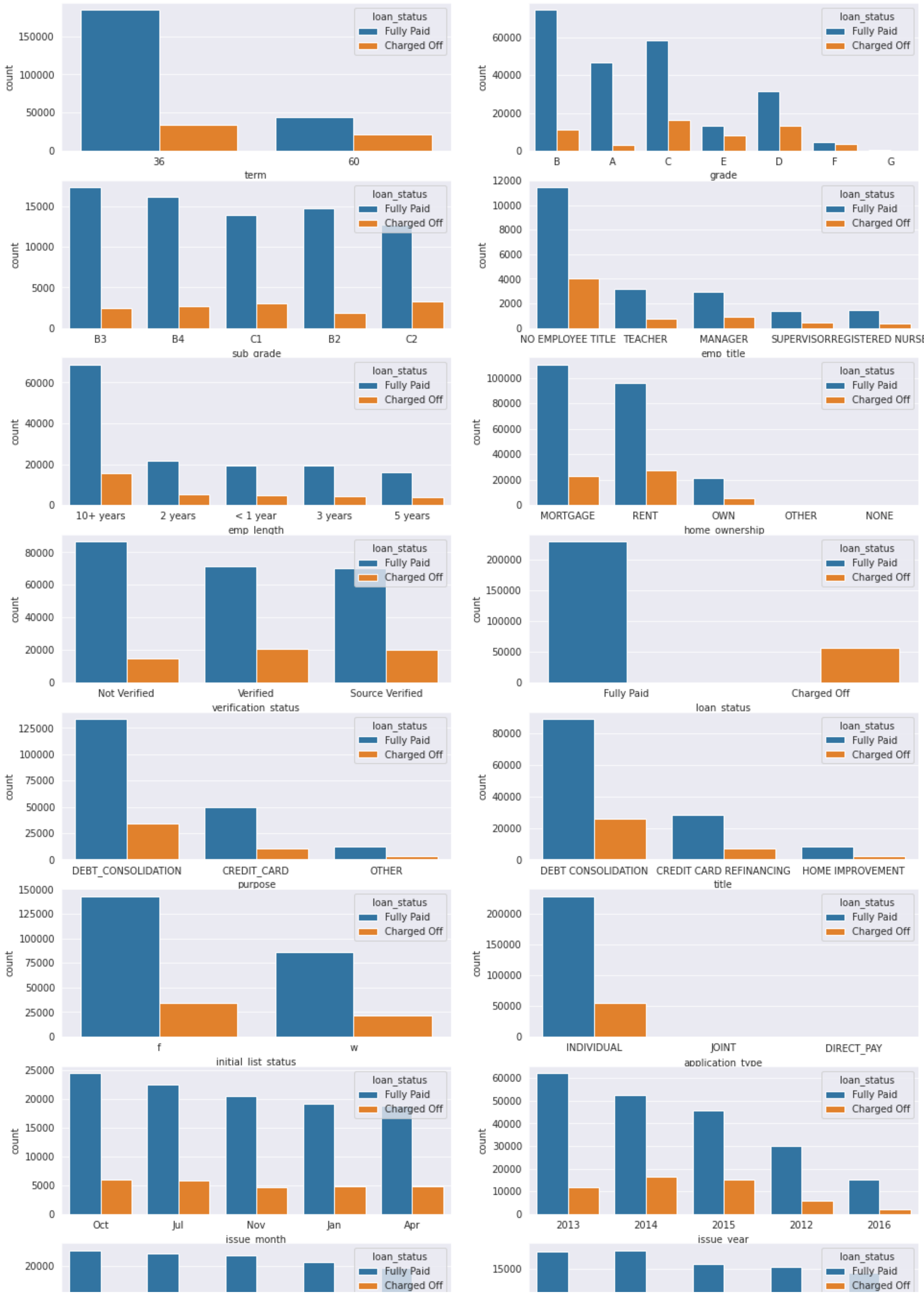



```
#Distribution plot for cont. variables

fig,axes = plt.subplots(4,3,figsize=(16,16))
sns.distplot(df['loan_amnt'],ax=axes[0,0],color='darkblue')
sns.distplot(df['int_rate'],ax=axes[0,1],color='darkblue')
sns.distplot(df['installment'],ax=axes[0,2],color='darkblue')
sns.distplot(df['annual_inc'],ax=axes[1,0],color='darkblue')
sns.distplot(df['dti'],ax=axes[1,1],color='darkblue')
sns.distplot(df['open_acc'],ax=axes[1,2],color='darkblue')
sns.distplot(df['pub_rec'],ax=axes[2,0],color='darkblue')
sns.distplot(df['revol_bal'],ax=axes[2,1],color='darkblue')
sns.distplot(df['revol_util'],ax=axes[2,2],color='darkblue')
sns.distplot(df['total_acc'],ax=axes[3,0],color='darkblue')
sns.distplot(df['mort_acc'],ax=axes[3,1],color='darkblue')
sns.distplot(df['pub_rec_bankruptcies'],ax=axes[3,2],color='darkblue')
plt.show()
```



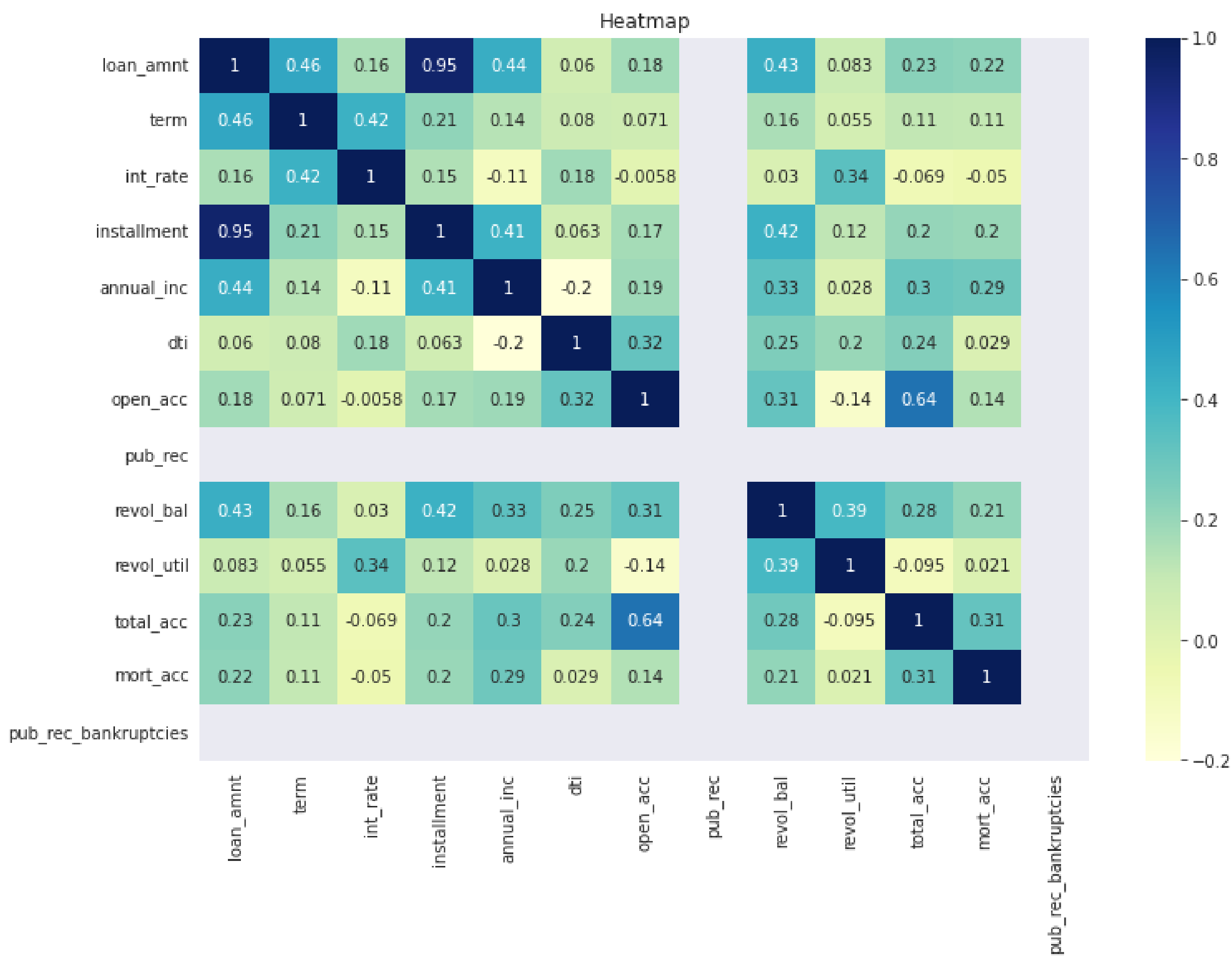

```
#Countplots for categorical variables

top = 5
fig,axes = plt.subplots(9,2,figsize=(16,30))
sns.countplot(df['term'],ax=axes[0,0],hue=df['loan_status'])
sns.countplot(df['grade'],ax=axes[0,1],hue=df['loan_status'])
sns.countplot(df['sub_grade'],ax=axes[1,0],hue=df['loan_status'],order
=df['sub_grade'].value_counts().iloc[:top].index)
sns.countplot(df['emp_title'],ax=axes[1,1],hue=df['loan_status'],order
=df['emp_title'].value_counts().iloc[:top].index)
sns.countplot(df['emp_length'],ax=axes[2,0],hue=df['loan_status'],orde
r=df['emp_length'].value_counts().iloc[:top].index)
sns.countplot(df['home_ownership'],ax=axes[2,1],hue=df['loan_status'],
order=df['home_ownership'].value_counts().iloc[:top].index)
```

```
sns.countplot(df['verification_status'],ax=axes[3,0],hue=df['loan_stat
us'],order=df['verification_status'].value_counts().iloc[:top].index)
sns.countplot(df['loan_status'],ax=axes[3,1],hue=df['loan_status'],ord
er=df['loan_status'].value_counts().iloc[:top].index)
sns.countplot(df['purpose'],ax=axes[4,0],hue=df['loan_status'],order=d
f['purpose'].value_counts().iloc[:3].index)
sns.countplot(df['title'],ax=axes[4,1],hue=df['loan_status'],order=df[
'title'].value_counts().iloc[:3].index)
sns.countplot(df['initial_list_status'],ax=axes[5,0],hue=df['loan_stat
us'],order=df['initial_list_status'].value_counts().iloc[:top].index)
sns.countplot(df['application_type'],ax=axes[5,1],hue=df['loan_status'
],order=df['application_type'].value_counts().iloc[:top].index)
sns.countplot(df['issue_month'],ax=axes[6,0],hue=df['loan_status'],ord
er=df['issue_month'].value_counts().iloc[:top].index)
sns.countplot(df['issue_year'],ax=axes[6,1],hue=df['loan_status'],orde
r=df['issue_year'].value_counts().iloc[:top].index)
sns.countplot(df['er_cr_line_m'],ax=axes[7,0],hue=df['loan_status'],or
der=df['er_cr_line_m'].value_counts().iloc[:top].index)
sns.countplot(df['er_cr_line_y'],ax=axes[7,1],hue=df['loan_status'],or
der=df['er_cr_line_y'].value_counts().iloc[:top].index)
sns.countplot(df['address_state'],ax=axes[8,0],hue=df['loan_status'],o
rder=df['address_state'].value_counts().iloc[:top].index)
sns.countplot(df['address_zip'],ax=axes[8,1],hue=df['loan_status'],ord
er=df['address_zip'].value_counts().iloc[:top].index)
plt.show()
```


loan_status
Fully Paid
Charged Off
count
term
36
60
grade
B
A
C
E
D
F
G
sub_grade
B3
B4
C1
B2
C2
emp_title
NO EMPLOYEE TITLE
TEACHER
MANAGER
SUPERVISOR
REGISTERED NURSE
emp_length
10+ years
2 years
< 1 year
3 years
5 years
home_ownership
MORTGAGE
RENT
OWN
OTHER
NONE
verification_status
Not Verified
Verified
Source Verified
loan_status
Fully Paid
Charged Off
purpose
DEBT_CONSOLIDATION
CREDIT_CARD
OTHER
title
DEBT CONSOLIDATION
CREDIT CARD REFINANCING
HOME IMPROVEMENT
initial_list_status
f
w
application_type
INDIVIDUAL
JOINT
DIRECT_PAY
issue_month
Oct
Jul
Nov
Jan
Apr
issue_year
2013
2014
2015
2012
2016

Correlation

```python
#Prepare corr dataframe and plot heatmap

plt.figure(figsize=(12,8))
df_corr = df.corr()
sns.heatmap(df_corr, cmap='YlGnBu', annot=True)
plt.title('Heatmap')
plt.show()
```



Observation1: Installment and loan_amnt are highly correlated

Observation2: open_acc and total_acc are having fairly good positive correlation

Data Preparation for ML

```python
df1 = df.copy()

#Drop the variables which didn't show any significant impact on loan_status in above analysis

df1.drop(['emp_title'
```

```
          ,'emp_length'
          ,'initial_list_status'
          ,'issue_month'
          ,'issue_year'
          ,'er_cr_line_m'
          ,'er_cr_line_y'
          ,'address_state'
          ,'address_zip'
          ,'application_type'
          ,'verification_status'
          ,'purpose'
          ,'title'
          ,'sub_grade'],axis=1,inplace=True)

#OneHotEncode variable home_ownership

df1 = pd.get_dummies(df1,
prefix=['home_ownership'] ,columns=['home_ownership'])

#Binary encode target variable loan_status

loan_status_dict = {
    'Fully Paid':1,
    'Charged Off':0
}
df1['loan_status'] = df1['loan_status'].map(loan_status_dict)

#OneHotEncode variable grade

df1 = pd.get_dummies(df1, prefix=['grade'], columns=['grade'])

#df1 = pd.get_dummies(df1, prefix=['sub_grade'],
columns=['sub_grade'])

df1.head()
```

```
   loan_amnt  term  int_rate  installment  annual_inc  loan_status
dti  \
0    10000.0    36     11.44       329.48    117000.0            1
26.24
1     8000.0    36     11.99       265.68     65000.0            1
22.05
2    15600.0    36     10.49       506.97     43057.0            1
12.79
3     7200.0    36      6.49       220.65     54000.0            1
2.60
4    24375.0    60     17.27       609.33     55000.0            0
33.95

   open_acc  pub_rec  revol_bal  revol_util  total_acc  mort_acc  \
0      16.0      0.0    36369.0        41.8       25.0       0.0
```

```
1      17.0      0.0    20131.0          53.3         27.0         1.0
2      13.0      0.0    11987.0          92.2         26.0         0.0
3       6.0      0.0     5472.0          21.5         13.0         0.0
4      13.0      0.0    24584.0          69.8         43.0         1.0

   pub_rec_bankruptcies  home_ownership_ANY
home_ownership_MORTGAGE  \
0                   0.0                   0                         0

1                   0.0                   0                         1

2                   0.0                   0                         0

3                   0.0                   0                         0

4                   0.0                   0                         1


   home_ownership_NONE  home_ownership_OTHER  home_ownership_OWN  \
0                    0                     0                   0
1                    0                     0                   0
2                    0                     0                   0
3                    0                     0                   0
4                    0                     0                   0

   home_ownership_RENT  grade_A  grade_B  grade_C  grade_D  grade_E
grade_F  \
0                    1        0        1        0        0        0
0
1                    0        0        1        0        0        0
0
2                    1        0        1        0        0        0
0
3                    1        1        0        0        0        0
0
4                    0        0        0        1        0        0
0

   grade_G
0        0
1        0
2        0
3        0
4        0
```

Build ML model

```
#Import libraries

from sklearn.preprocessing import StandardScaler
```

```python
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import precision_score, recall_score, f1_score
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay,
classification_report
from sklearn.metrics import roc_curve, roc_auc_score,
plot_confusion_matrix
from sklearn.metrics import precision_recall_curve, auc
from sklearn.model_selection import train_test_split

#Prepare X and y dataset i.e. independent and dependent datasets

X = df1.drop(['loan_status'], axis=1)
y = df1['loan_status']

#Split the data into train and test

X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=42)
print(X_train.shape)
print(X_test.shape)
print(y_train.shape)
print(y_test.shape)
```

```
(227172, 26)
(56794, 26)
(227172,)
(56794,)
```

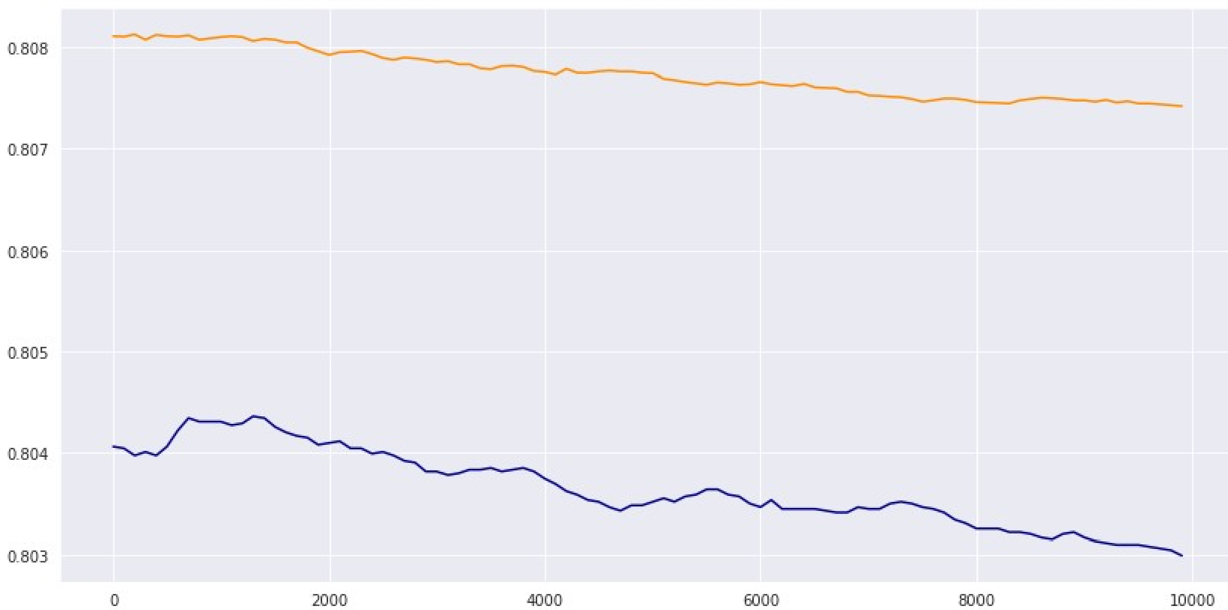
```python
#Standardize the data

scaler = StandardScaler()
scaler.fit(X_train)
X_train = scaler.transform(X_train)
X_test = scaler.transform(X_test)
X_train = pd.DataFrame(X_train, columns=X.columns)
X_test = pd.DataFrame(X_test, columns=X.columns)

#Fit the Model on training data

model = LogisticRegression()
model.fit(X_train, y_train)
```

```
LogisticRegression()
```

```python
#Predit the data on test dataset

y_pred = model.predict(X_test)

print(f'Logistic Regression Model Score: ',end='')
print(round(model.score(X_test, y_test)*100,2))
```

```
Logistic Regression Model Score: 80.4
```

```
#Try with different regularization factor lamda and choose the best to
build the model

lamb = np.arange(0.01, 10000, 100)

train_scores = []
test_scores = []

for lam in lamb:
    model = LogisticRegression(C = 1/lam)
    model.fit(X_train, y_train)

    tr_score = model.score(X_train, y_train)
    te_score = model.score(X_test, y_test)

    train_scores.append(tr_score)
    test_scores.append(te_score)

#Plot the train and test scores with respect lambda values i.e.
regularization factore

plt.figure(figsize=(14,7))
sns.lineplot(np.arange(0.01,10000,100),test_scores,color='darkblue')
sns.lineplot(np.arange(0.01,10000,100),train_scores,color='darkorange'
)
plt.show()
```




```
#Check the index of best test score and the check the best test score

print(np.argmax(test_scores))
test_scores[9]
```

```
13
```

```
0.8043103144698384
```

```
#Calculate the best lambda value based on the index of best test score

best_lamb = 0.01 + 100*13

#Fit the model using best lambda

model = LogisticRegression(C=1/best_lamb)
model.fit(X_train, y_train)
```

```
LogisticRegression(C=0.0007692248521165222)
```

```
#Predict the y_values and y_probability values

y_pred = model.predict(X_test)
y_pred_proba = model.predict_proba(X_test)

#Print model score

print(f'Logistic Regression Model Score with best lambda: ',end='')
print(round(model.score(X_test, y_test)*100,2))
```

```
Logistic Regression Model Score with best lambda: 80.44
```

```
#Collect the model coefficients and print those in dataframe format
coeff_df = pd.DataFrame()
coeff_df['Coefficients'] = X_train.columns
coeff_df['Weights'] = model.coef_[0]
coeff_df['ABS_Weights'] = abs(coeff_df['Weights'])

#Sort the coeff in the order of their importance
coeff_df = coeff_df.sort_values(['ABS_Weights'], ascending=False)
```

Weights of features (coefficients)

```
#Display variable weights

coeff_df
```

	Coefficients	Weights	ABS_Weights
19	grade_A	0.241030	0.241030
1	term	-0.207522	0.207522
4	annual_inc	0.202030	0.202030
5	dti	-0.174596	0.174596
23	grade_E	-0.143177	0.143177
22	grade_D	-0.141095	0.141095
2	int_rate	-0.115519	0.115519
20	grade_B	0.105582	0.105582
6	open_acc	-0.104445	0.104445

```
24                    grade_F -0.099762     0.099762
9                  revol_util -0.077259     0.077259
21                    grade_C -0.076903     0.076903
10                  total_acc  0.076287     0.076287
3                 installment -0.064834     0.064834
8                   revol_bal  0.062070     0.062070
18        home_ownership_RENT -0.055433     0.055433
14    home_ownership_MORTGAGE  0.054988     0.054988
0                   loan_amnt -0.049475     0.049475
25                    grade_G -0.020348     0.020348
13         home_ownership_ANY  0.007065     0.007065
15        home_ownership_NONE -0.003831     0.003831
11                   mort_acc  0.003496     0.003496
16       home_ownership_OTHER  0.001490     0.001490
17         home_ownership_OWN  0.000091     0.000091
12       pub_rec_bankruptcies  0.000000     0.000000
7                     pub_rec  0.000000     0.000000
```

```
#Top 5 important features

coeff_df.head(5)
```

```
   Coefficients   Weights  ABS_Weights
19      grade_A  0.241030     0.241030
1          term -0.207522     0.207522
4    annual_inc  0.202030     0.202030
5           dti -0.174596     0.174596
23      grade_E -0.143177     0.143177
```

```
#Logistic Regression model intercept

model.intercept_
```

```
array([1.60102577])
```

Confusion Matrix

```
#Create confusion matrix and print the matrix

cm = confusion_matrix(y_test, y_pred)
cm_df = pd.DataFrame(cm, index=np.unique(y_test),
columns=np.unique(y_test))

cm_df
```

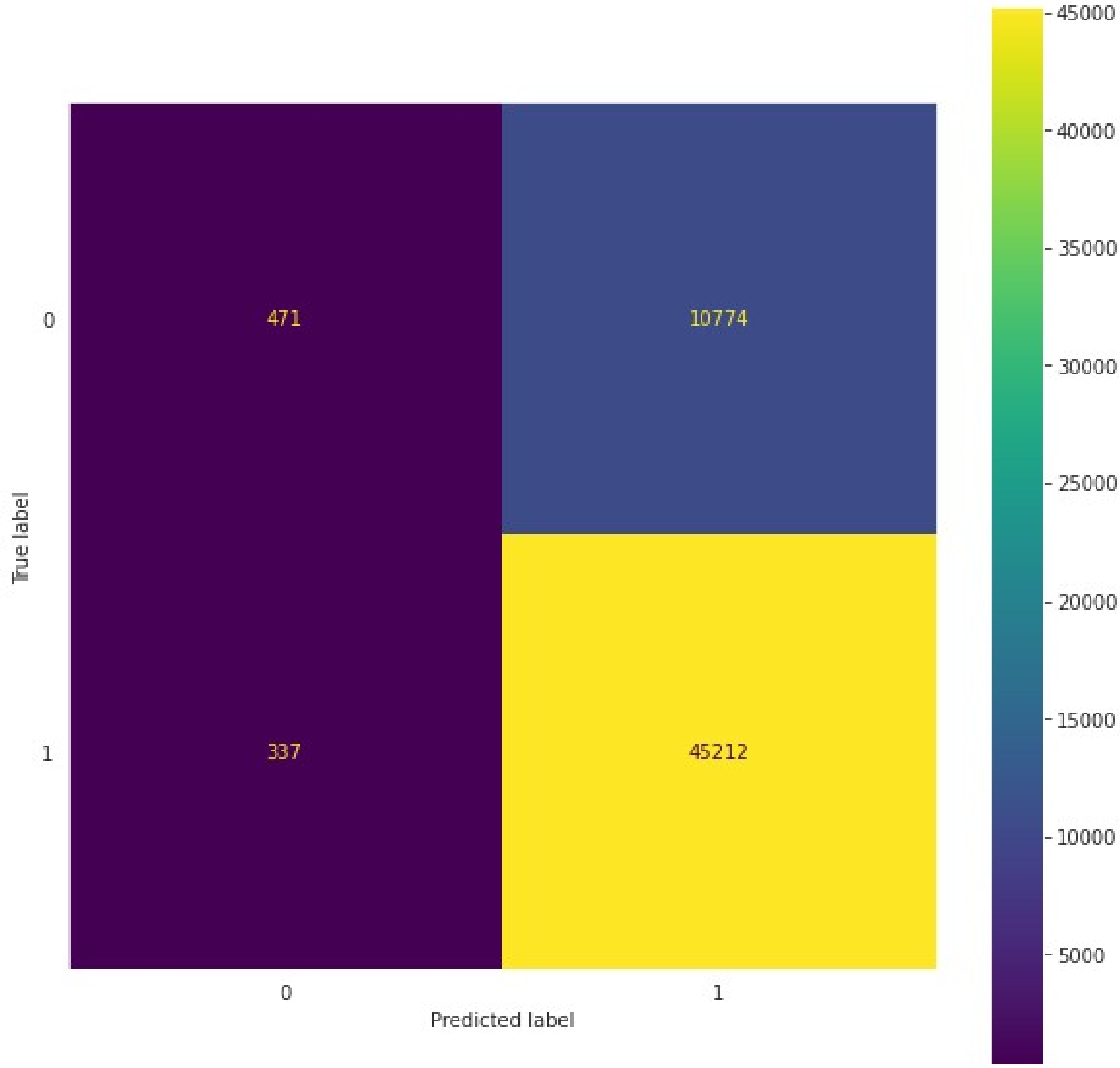
	0	1
0	471	10774
1	337	45212

Class 0 : Charged Off (Here considering as negative class)

Class 1 : Fully Paid (Here considering as positive class)

1. TN = 471
2. TP = 45212
3. FP = 10774
4. FN = 337
5. Actual Negative (Charged Off) = 471 + 10774 = 11245
6. Actual Positive (Fully Paid) = 337 + 45212 = 45549
7. Predicted Negative (Charged Off) = 471 + 337 = 808
8. Predicted Positive (Fully Paid) = 10774 + 45212 = 55986

```
#Plot confusion Matrix

fig, ax = plt.subplots(figsize=(10, 10))
plot_confusion_matrix(model, X_test, y_test, ax=ax)
plt.grid()
plt.show()
```




```
#Plot Confusion Matrix using different method

# fig, ax = plt.subplots(figsize=(10, 10))
# ConfusionMatrixDisplay(cm).plot(ax=ax);
# plt.grid()
# plt.show()
```

Classification Report

```
#Print classification report

print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       0.58      0.04      0.08     11245
           1       0.81      0.99      0.89     45549

    accuracy                           0.80     56794
   macro avg       0.70      0.52      0.48     56794
weighted avg       0.76      0.80      0.73     56794
```

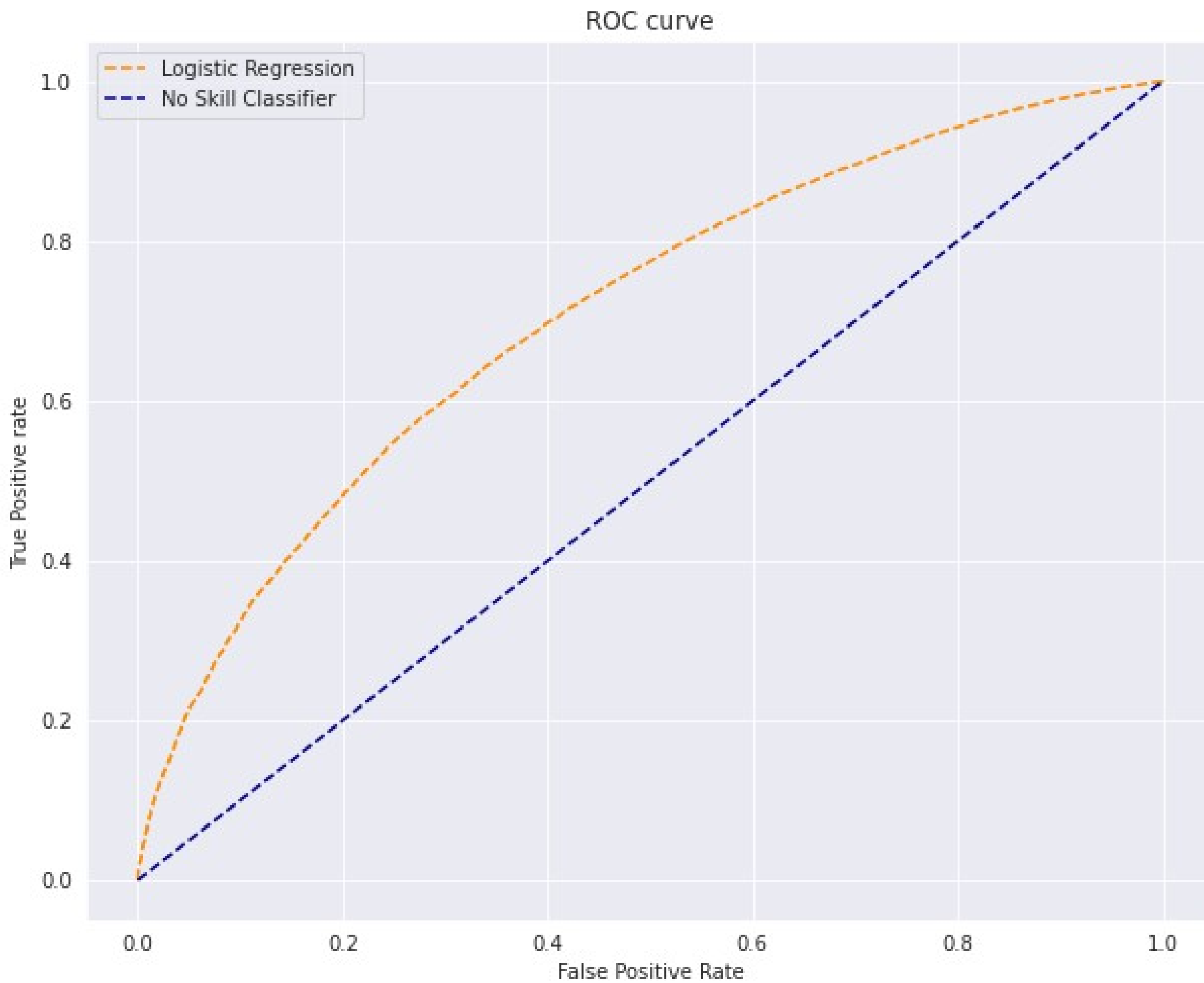
Observations from classification report:

1. Precision : 0.81
2. Recall : 0.99
3. F1-score : 0.89
4. Accuracy : 0.80

```
print('Precision Score:', precision_score(y_test,y_pred).round(2))
print('Recall Score:', recall_score(y_test,y_pred).round(2))
print('F1 Score:', f1_score(y_test,y_pred).round(2))

Precision Score: 0.81
Recall Score: 0.99
F1 Score: 0.89
```

ROC AUC Curve

```
#Plot ROC curve
#ROC Curve summarizes trade off between TPR and FPR

random_probs = [0 for i in range(len(y_test))]

p_fpr, p_tpr, _ = roc_curve(y_test, random_probs, pos_label=1)

fpr, tpr, thresh = roc_curve(y_test, y_pred_proba[:,1], pos_label=1)

plt.figure(figsize=(10,8))
plt.plot(fpr, tpr, linestyle='--',color='darkorange', label='Logistic
Regression')
plt.plot(p_fpr, p_tpr, linestyle='--', color='darkblue', label='No
Skill Classifier')
plt.title('ROC curve')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive rate')
plt.legend(loc='best')
plt.show()
```




```
roc_auc_score(y_test, y_pred_proba[:,1]).round(2)
```

```
0.71
```

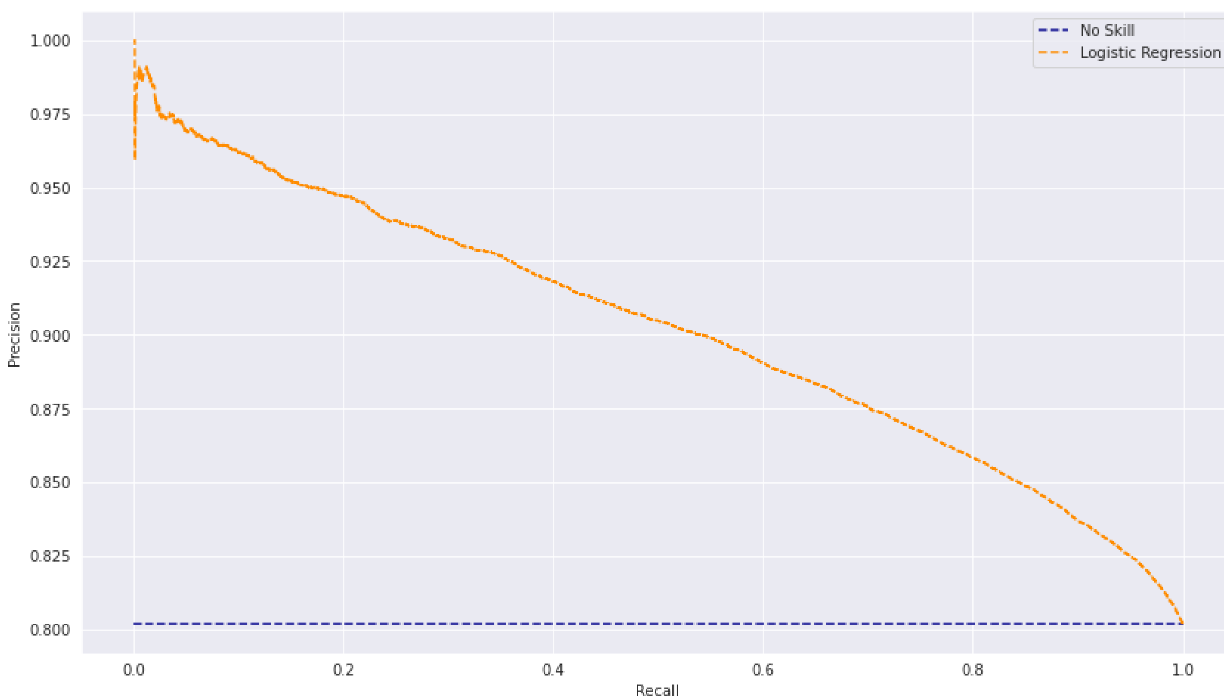
Observations: (Answers to trade off questions)

1. Area under the ROC curve = 71%. That means we can say that the performance of the model is 0.71
2. Ideal scenario would be more TPR and lower FPR
3. Plot shows that True Positives increase at the cost of generating more False Positives
4. That means in order to find more Fully Paid customers, the model will have more chances of mistakenly classifying Charged Off customers as Fully Paid customers which might result in NPAs.
5. To avoid the NPAs, there is a necessity of bringing down the FPR while keeping the TPR in shape.
6. The model can detect the real defaulters when FPs (False Positives) are pushed towards left on x-axis

7. Once FPs (False Positives) towards left on X-axis the AUC will increase and hence the model performance
8. While FPs are moved towards left on X-axis, TPs need to remain high there on Y-axis

Precision Recall Curve

```
#Plot precision recall curve
#Reviewing both precision and recall is useful in cases where there is
an imbalance in the observations
#between the two classes.

precision, recall, thresholds = precision_recall_curve(y_test,
y_pred_proba[:,1])

no_skill = len(y_test[y_test==1]) / len(y_test)

plt.figure(figsize=(14,8))
plt.plot([0, 1], [no_skill, no_skill], linestyle='--', label='No
Skill', color='darkblue')
plt.plot(recall, precision, linestyle='--', label='Logistic
Regression', color='darkorange')
plt.xlabel('Recall')
plt.ylabel('Precision')
plt.legend(loc='best')
plt.show()
```




```
auc(recall, precision).round(3)

0.902
```

Observations: (Answering Trade Off question)

1. Precision recall curve is more useful in case of imbalanced data.
2. Calculation of precision and recall do not make use of the true negatives. So, it focuses on the correct prediction of one of the class. In our case that class is Class 1 i.e. Fully Paid customers
3. If you see the confusion matrix, the upper left box just won't be used in these calculations.
4. AUC = 90.4% which is failry good.
5. We can see that as the recall increases the precision is falling down.
6. For a strong model, both the recall and precision should be high
7. For a good trade off the precision needs to stay high on y-axis as recall progress towards right on x-axis
8. This shows that in order to increase the performance of model, precision needs to be improved
9. Increase precision means, there needs to be low FPs (False Positives)
10. So, here we need to focus more on reducing the FPs

Extra analysis for questionaire and recommendations

```
#Loan Status for term = 60 months
print(df.loc[df['term']==' 60 months']
['loan_status'].value_counts(normalize=True))

print('--------------')
#Loan Status for term = 36 months
print(df.loc[df['term']==' 36 months']
['loan_status'].value_counts(normalize=True))

print('--------------')
#Loan status for grade A
print(df.loc[df['grade']=='A']
['loan_status'].value_counts(normalize=True))

print('--------------')
#Median annual income of defaulters
print(np.percentile(df.loc[df['loan_status'] == 'Charged Off']
['annual_inc'],50))

print('--------------')
#Median annual income of fully paid customers
print(np.percentile(df.loc[df['loan_status'] == 'Fully Paid']
['annual_inc'],50))

print('--------------')
#Median dti ratio of Charged Off customers
print(np.percentile(df.loc[df['loan_status'] == 'Charged Off']
['dti'],50))
```

```python
print('--------------')
#Median dti ratio of Fully Paid customers
print(np.percentile(df.loc[df['loan_status'] == 'Fully Paid']
['dti'],50))

print('--------------')
print(df.loc[df['grade']=='E']
['loan_status'].value_counts(normalize=True))

print('--------------')
print(df.loc[df['grade']=='D']
['loan_status'].value_counts(normalize=True))

print('--------------')
print(np.percentile(df.loc[df['loan_status'] == 'Charged Off']
['int_rate'],50))

print('--------------')
print(np.percentile(df.loc[df['loan_status'] == 'Fully Paid']
['int_rate'],50))
```

```
Series([], Name: loan_status, dtype: float64)
--------------
Series([], Name: loan_status, dtype: float64)
--------------
Fully Paid     0.936621
Charged Off    0.063379
Name: loan_status, dtype: float64
--------------
55000.0
--------------
60000.0
--------------
19.34
--------------
16.45
--------------
Fully Paid     0.618436
Charged Off    0.381564
Name: loan_status, dtype: float64
--------------
Fully Paid     0.704555
Charged Off    0.295445
Name: loan_status, dtype: float64
--------------
15.61
--------------
12.69
```

Questionaire

Question 1: What percentage of customers have fully paid their Loan Amount?

Answer: 80.38%

Question 2: Comment about the correlation between Loan Amount and Installment features?

Answer: Loan amount and installment has very strong positive correlation of 0.95

Question 3: The majority of people have home ownership as _______.

Answer: Mortgage i.e. 50.08%

Question 4: People with grades 'A' are more likely to fully pay their loan. (T/F)

Answer: True. Out of All people with grade A, 93.71% are Fully Paid and only 6.29% are Charged Off

Question 5: Name the top 2 afforded job titles.

Answer: Teacher and Manager.

Question 6: Thinking from a bank's perspective, which metric should our primary focus be on..

```
a. ROC AUC
b. Precision
c. Recall
d. F1 Score
```

Answer:

```
1. Bank's primary focus should be on ROC AUC
2. Because bank needs to reduce FPR (False Positive Rate) and needs to
increase the TPR (True Positive Rate).
3. In common man's term, Bank should not classify Charged Off
customers as Fully Paid i.e. False Positives
4. And bank should not classify Fully Paid customers as Charged Off
i.e. False Negatives
```

Question 6: How does the gap in precision and recall affect the bank?

Answer:

```
1. A perfect precision recall curve is depicted as a point (1,1).
2. High performance model is represented by a curve that bows towards
point (1,1) above the flat line of no skill.
3. So, the gap between precision and recall will affect the bank. As
the gap widens, there will be increase in incorrect predictions.
```

```
4. Good precision means less False Positives. i.e. Less NPA loan accounts.
5. Good recall means less False Negatives. i.e. not loosing on good customer.
```

Question 7: Which were the features that heavily affected the outcome?

Answer: Top 5 Features that affected the outcome are -

```
1. Grade
2. Term
3. Annual income
4. dti
5. int_rate
```

Question 8: Will the results be affected by geographical location? (Yes/No)

Answer: No. The results will not be affected by the geographical locaion. See the bar graph plotted above.

Business Recommendations

1. Customers with Grade A are the most reliable on the repayments. Bank can extend the credit line to these customers and should focus and adding more new customers to list of borrowers. 93% of these have a track record of repaying their loan.

2. The term period of 60 months is a trouble when it comes to Charged Off accounts. 32% of accounts from 60 months term period turned into NPA based on the data available. So, here needs to rethink on the repayment terms.

3. The median annual income of Charged Off customers is 59K which is 6K less than median annual income of Fully Paid customers (65K). Please revisit the annual income thresholds while extending the credit lines to the customers.

4. The median dti ratio of Charged Off customers is 19.34 which is 3 points higher than the fully paid customers. Please give it a thought. This feature tops in first 5 most impactful features.

5. 37% of the grade E and 28% of the grade D customers are defaulters from historical data. The needs to put more stringent criteria and the grade E and D customers.

6. Median interest rates of defaulter customers are 2.62% higher than those of regular. Median interest rate of regualr customers is 12.99% and for defaulters it's found that median interest rate is 15.61%. If the customer interest rates crawl above the alarming thresholds then that account is more probably more prone to become an NPA

7. Apart from this, the bank needs to focus more on improving the precision of correctly identifying the Charged Off customer. Becuase the current historical data

trend shows that the bank is not so accurate in classifying the Charged Off customers. However these customers often get the green pass as a result of high FPR (False Positive Rate).