Importing necessary libraries -

In [ ]:

```
import pandas as pd
import numpy as np
import seaborn as sns
from scipy import stats
import matplotlib.pyplot as plt
from sklearn.linear_model import LogisticRegression
from sklearn import metrics
from sklearn.metrics import confusion_matrix
from sklearn.metrics import classification_report
from sklearn.metrics import roc_auc_score
from sklearn.metrics import roc_curve
from sklearn.metrics import precision_recall_curve
from sklearn.model_selection import train_test_split, KFold, cross_val_score
from sklearn.preprocessing import MinMaxScaler
from sklearn.metrics import (
    accuracy_score, confusion_matrix, classification_report,
    roc_auc_score, roc_curve, auc,
    plot_confusion_matrix, plot_roc_curve
)
from statsmodels.stats.outliers_influence import variance_inflation_factor
from imblearn.over_sampling import SMOTE
```

```
/usr/local/lib/python3.7/dist-packages/statsmodels/tools/_testing.py:1
9: FutureWarning: pandas.util.testing is deprecated. Use the functions
in the public API at pandas.testing instead.
  import pandas.util.testing as tm
```

In [1]:

```
import pandas as pd
pd.set_option('display.max_columns', 500)
```

Here is the information on this particular data set:

0. loan_amnt : The listed amount of the loan applied for by the borrower. If at some point in time, the credit department reduces the loan amount, then it will be reflected in this value.
1. term : The number of payments on the loan. Values are in months and can be either 36 or 60.
2. int_rate : Interest Rate on the loan
3. installment : The monthly payment owed by the borrower if the loan originates.
4. grade LC : assigned loan grade
5. sub_grade LC : assigned loan subgrade
6. emp_title : The job title supplied by the Borrower when applying for the loan.
7. emp_length : Employment length in years. Possible values are between 0 and 10 where 0 means less than one year and 10 means ten or more years.
8. home_ownership : The home ownership status provided by the borrower during registration or obtained from the credit report. Our values are: RENT, OWN, MORTGAGE, OTHER
9. annual_inc : The self-reported annual income provided by the borrower during registration.
10. verification_status : Indicates if income was verified by LC, not verified, or if the income source was verified
11. issue_d : The month which the loan was funded
12. loan_status : Current status of the loan
13. purpose : A category provided by the borrower for the loan request.

13. purpose : A category provided by the borrower for the loan request.
14. title : The loan title provided by the borrower
15. zip_code : The first 3 numbers of the zip code provided by the borrower in the loan application.
16. addr_state : The state provided by the borrower in the loan application
17. dti : A ratio calculated using the borrower’s total monthly debt payments on the total debt obligations, excluding mortgage and the requested LC loan, divided by the borrower’s self-reported monthly income.
18. earliest_cr_line : The month the borrower's earliest reported credit line was opened
19. open_acc : The number of open credit lines in the borrower's credit file.
20. pub_rec : Number of derogatory public records
21. revol_bal : Total credit revolving balance
22. revol_util : Revolving line utilization rate, or the amount of credit the borrower is using relative to all available revolving credit.
23. total_acc : The total number of credit lines currently in the borrower's credit file
24. initial_list_status : The initial listing status of the loan. Possible values are – W, F
25. application_type : Indicates whether the loan is an individual application or a joint application with two co-borrowers
26. mort_acc : Number of mortgage accounts.
27. pub_rec_bankruptcies : Number of public record bankruptcies

Reading the data file -

In [ ]:

```
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

In [ ]:

```
!ls
```

```
drive  logistic_regression.csv  sample_data
```

In [2]:

```
data = pd.read_csv('logistic_regression.csv')
data.head()
```

Out[2]:

_acc	initial_list_status	application_type	mort_acc	pub_rec_bankruptcies	address
25.0	w	INDIVIDUAL	0.0	0.0	0174 Michelle Gateway\r\nMendozaberg, OK 22690
27.0	f	INDIVIDUAL	3.0	0.0	1076 Carney Fort Apt. 347\r\nLoganmouth, SD 05113
26.0	f	INDIVIDUAL	0.0	0.0	87025 Mark Dale Apt. 269\r\nNew Sabrina, WV 05113
13.0	f	INDIVIDUAL	0.0	0.0	823 Reid Ford\r\nDelacruzside, MA 00813
43.0	f	INDIVIDUAL	1.0	0.0	679 Luna Roads\r\nGreggshire, VA 11650

In [ ]:

```
# Shape of the dataset -
print("No. of rows: ", data.shape[0])
print("No. of columns: ", data.shape[1])
```

```
No. of rows:  231746
No. of columns:  27
```

In [ ]:

```
# Checking the distribution of outcome labels -
data.loan_status.value_counts(normalize=True)*100
```

Out[13]:

```
Fully Paid     80.423395
Charged Off    19.576605
Name: loan_status, dtype: float64
```

In [ ]:

```
# Statistical summary of the dataset -
data.describe(include='all')s
```

Out[14]:

int_rate	installment	grade	sub_grade	emp_title	emp_length	home_ownership	annual_in
5.000000	231746.000000	231746	231746	218320	221005	231746	2.317460e+0
NaN	NaN	7	35	109777	11	6	Na
NaN	NaN	B	B3	Teacher	10+ years	MORTGAGE	Na
NaN	NaN	67866	15546	2557	73880	116104	Na
3.640928	431.586377	NaN	NaN	NaN	NaN	NaN	7.429370e+0
4.466482	250.592582	NaN	NaN	NaN	NaN	NaN	6.027247e+0
5.320000	16.250000	NaN	NaN	NaN	NaN	NaN	2.500000e+0
0.490000	250.340000	NaN	NaN	NaN	NaN	NaN	4.500000e+0
3.330000	375.430000	NaN	NaN	NaN	NaN	NaN	6.400000e+0
5.490000	567.040000	NaN	NaN	NaN	NaN	NaN	9.000000e+0
0.990000	1533.810000	NaN	NaN	NaN	NaN	NaN	7.446395e+0

In [ ]:

```
data.info()
```

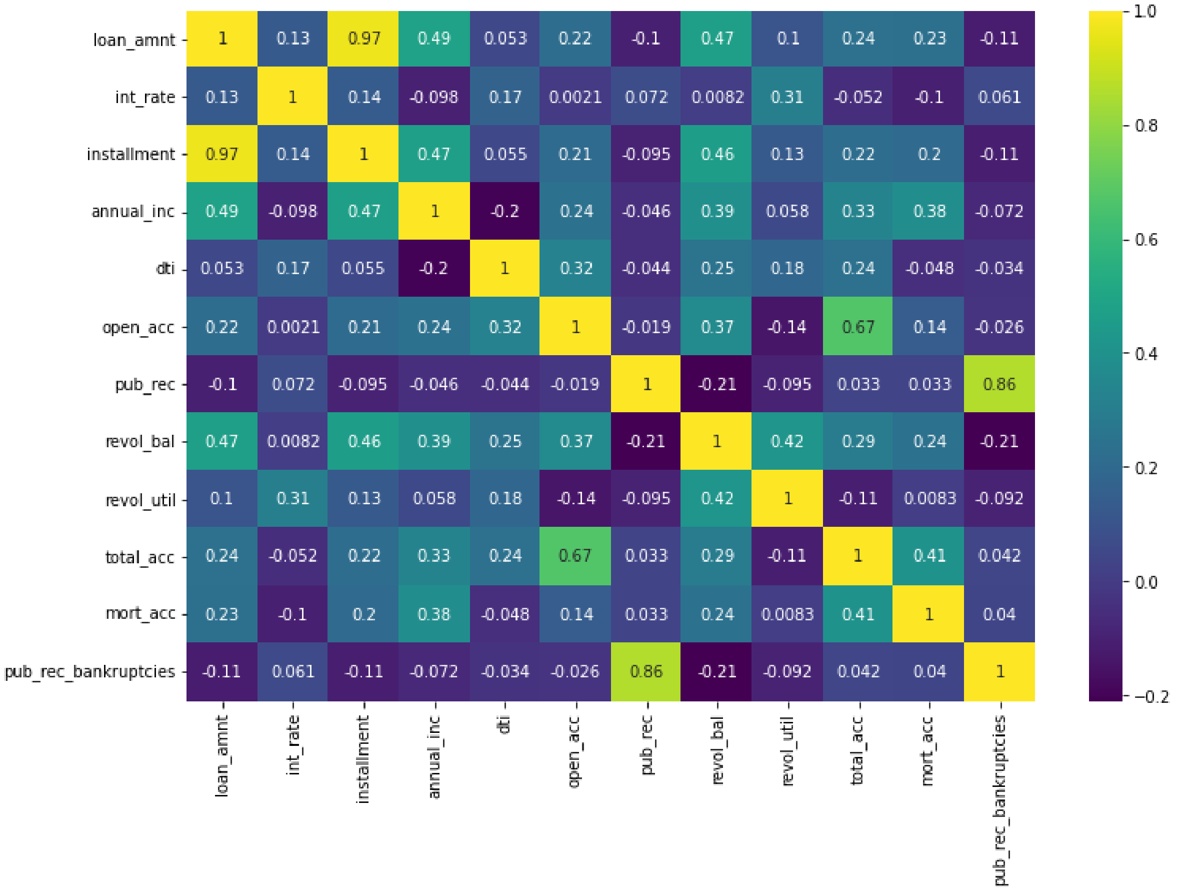
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 231746 entries, 0 to 231745
Data columns (total 27 columns):
 #   Column                Non-Null Count   Dtype  
---  ------                --------------   -----  
 0   loan_amnt             231746 non-null  float64
 1   term                  231746 non-null  object 
 2   int_rate              231746 non-null  float64
 3   installment           231746 non-null  float64
 4   grade                 231746 non-null  object 
 5   sub_grade             231746 non-null  object 
 6   emp_title             218320 non-null  object 
 7   emp_length            221005 non-null  object 
 8   home_ownership        231746 non-null  object 
 9   annual_inc            231746 non-null  float64
 10  verification_status   231746 non-null  object 
 11  issue_d               231746 non-null  object 
 12  loan_status           231746 non-null  object 
 13  purpose               231746 non-null  object 
 14  title                 230723 non-null  object 
 15  dti                   231746 non-null  float64
 16  earliest_cr_line      231746 non-null  object 
 17  open_acc              231746 non-null  float64
 18  pub_rec               231746 non-null  float64
 19  revol_bal             231746 non-null  float64
 20  revol_util            231576 non-null  float64
 21  total_acc             231746 non-null  float64
 22  initial_list_status   231746 non-null  object 
 23  application_type      231746 non-null  object 
 24  mort_acc              209558 non-null  float64
 25  pub_rec_bankruptcies  231426 non-null  float64
 26  address               231745 non-null  object 
dtypes: float64(12), object(15)
memory usage: 47.7+ MB
```

Correlation Heatmap -

A correlation heatmap is a heatmap that shows a 2D correlation matrix between two discrete dimensions, using colored cells to represent data from usually a monochromatic scale. The values of the first dimension appear as the rows of the table while of the second dimension as a column. The color of the cell is proportional to the number of measurements that match the dimensional value. This makes correlation heatmaps ideal for data analysis since it makes patterns easily readable and highlights the differences and variation in the same data. A correlation heatmap, like a regular heatmap, is assisted by a colorbar making data easily readable and comprehensible.

In [ ]:

```
plt.figure(figsize=(12, 8))
sns.heatmap(data.corr(method='spearman'), annot=True, cmap='viridis')
plt.show()
```



We noticed almost perfect correlation between "loan_amnt" the "installment" feature.

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

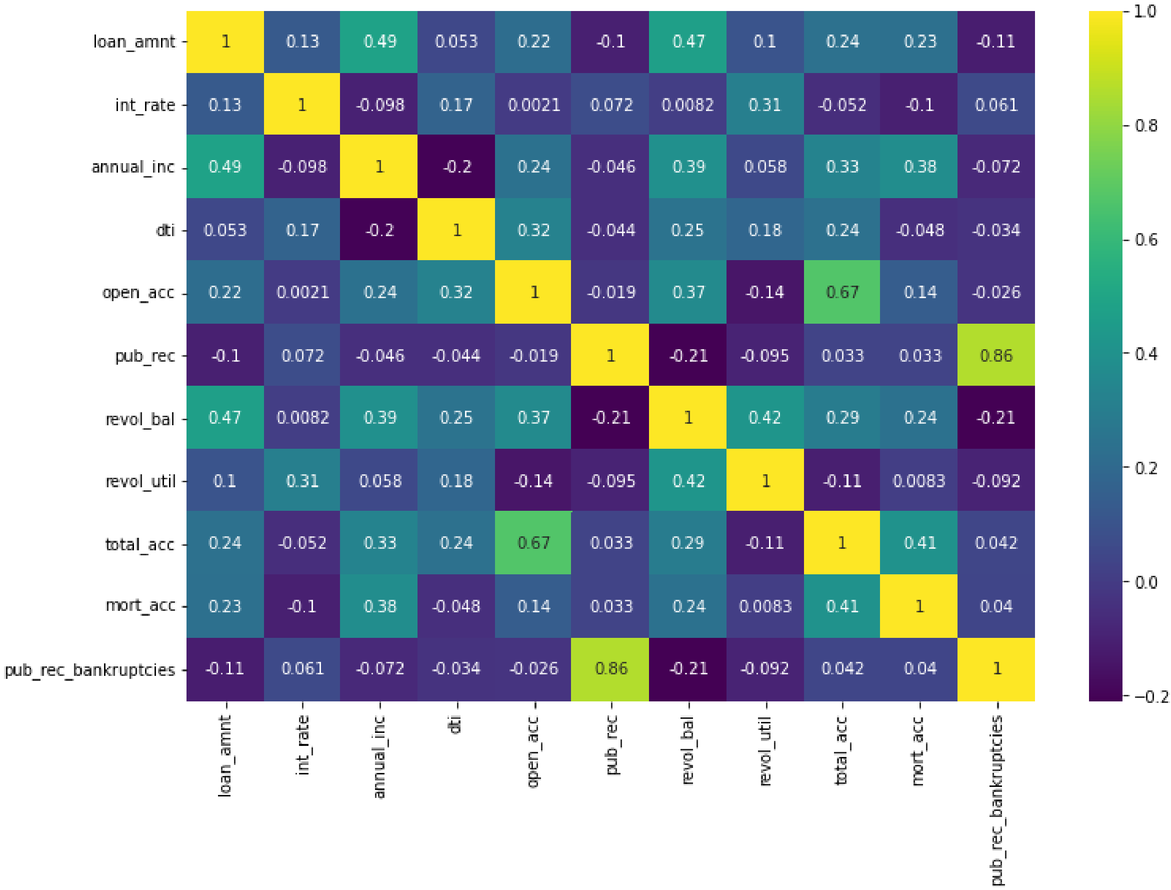
So, we can drop either one of those columns.

In [ ]:

```
data.drop(columns=['installment'], axis=1, inplace=True)
```

In [ ]:

```
plt.figure(figsize=(12, 8))
sns.heatmap(data.corr(method='spearman'), annot=True, cmap='viridis')
plt.show()
```



Data Exploration -

1. The no of people those who have fully paid are 318357 and that of Charged Off are 77673.

In [ ]:

```
data.groupby(by='loan_status')['loan_amnt'].describe()
```

Out[19]:

	count	mean	std	min	25%	50%	75%	max
loan_status								
Charged Off	45368.0	15135.654536	8484.848789	1000.0	8700.0	14000.0	20000.0	40000.0
Fully Paid	186378.0	13857.548101	8302.548155	500.0	7500.0	12000.0	19200.0	40000.0

2. The majority of people have home ownership as Mortgage and Rent.

In [ ]:

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

Out[20]:

```
MORTGAGE    116104
RENT         93551
OWN          22010
OTHER           59
NONE            19
ANY              3
Name: home_ownership, dtype: int64
```

3. Combininging the minority classes as 'OTHER'.

In [ ]:

```
ata.home_ownership == 'ANY') | (data.home_ownership == 'NONE'), 'home_ownership'] =
wnership.value_counts()
```

Out[21]:

```
MORTGAGE    116104
RENT         93551
OWN          22010
OTHER           81
Name: home_ownership, dtype: int64
```

In [ ]:

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

Out[22]:

```
MORTGAGE    116104
RENT         93551
OWN          22010
OTHER           81
Name: home_ownership, dtype: int64
```

In [ ]:

```
# Checking the distribution of 'Other' -
data.loc[data['home_ownership']=='OTHER', 'loan_status'].value_counts()
```

Out[23]:

```
Fully Paid     64
Charged Off    17
Name: loan_status, dtype: int64
```

4. Coverting string to date-time format.

In [ ]:

```
data['issue_d'] = pd.to_datetime(data['issue_d'])
data['earliest_cr_line'] = pd.to_datetime(data['earliest_cr_line'])
```

5. Saw some issues in title (Looks like it was filled manually and needs some fixing).

In [ ]:

```
data['title'].value_counts()[:20]
```

Out[25]:

```
Debt consolidation           89183
Credit card refinancing      30086
Home improvement              8932
Other                         7597
Debt Consolidation            6854
Major purchase                2887
Consolidation                 2305
debt consolidation            2055
Business                      1701
Debt Consolidation Loan       1673
Medical expenses              1605
Car financing                 1242
Credit Card Consolidation     1049
Vacation                      1025
Moving and relocation          986
consolidation                  971
Personal Loan                  913
Home Improvement               746
Consolidation Loan             739
Home buying                    674
Name: title, dtype: int64
```

In [ ]:

```
data['title'] = data.title.str.lower()
```

In [ ]:

```
data.title.value_counts()[:10]
```

Out[27]:

```
debt consolidation           98370
credit card refinancing      30256
home improvement             10011
other                         7637
consolidation                 3344
major purchase                3024
debt consolidation loan       2059
business                      1749
medical expenses              1652
credit card consolidation     1567
Name: title, dtype: int64
```

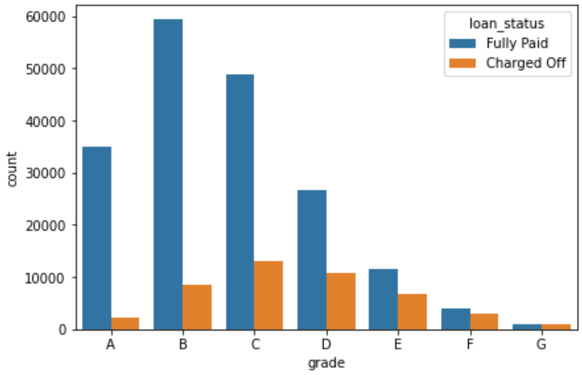
Visualization -

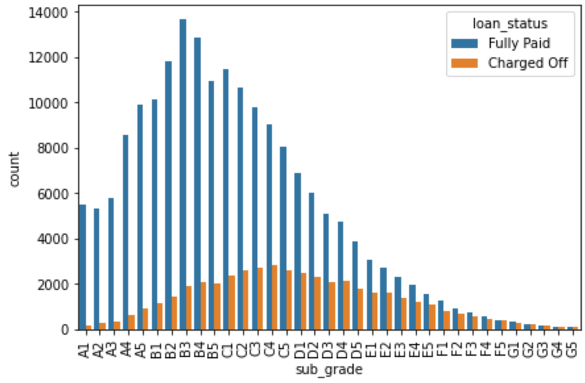
The grade of majority of people those who have fully paid the loan is 'B' and have subgrade 'B3'.

So from where we can infer that people with grade 'B' and subgrade 'B3' are more likely to fully pay the loan.

In [ ]:

```
plt.figure(figsize=(15, 10))

plt.subplot(2, 2, 1)
grade = sorted(data.grade.unique().tolist())
sns.countplot(x='grade', data=data, hue='loan_status', order=grade)

plt.subplot(2, 2, 2)
sub_grade = sorted(data.sub_grade.unique().tolist())
g = sns.countplot(x='sub_grade', data=data, hue='loan_status', order=sub_grade)
g.set_xticklabels(g.get_xticklabels(), rotation=90);
```





In [ ]:

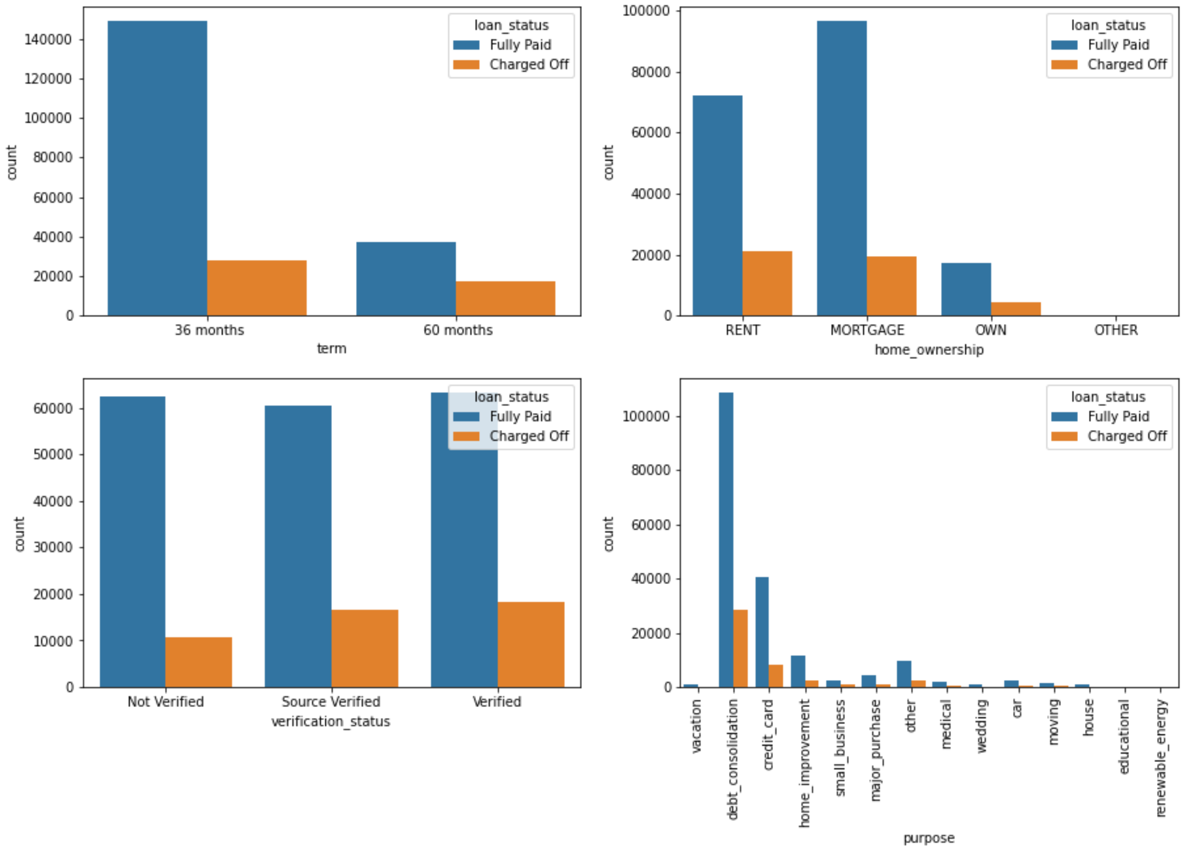
```
grade
```

Out[30]:

```
['A', 'B', 'C', 'D', 'E', 'F', 'G']
```

In [ ]:

```
plt.figure(figsize=(15, 20))

plt.subplot(4, 2, 1)
sns.countplot(x='term', data=data, hue='loan_status')

plt.subplot(4, 2, 2)
sns.countplot(x='home_ownership', data=data, hue='loan_status')

plt.subplot(4, 2, 3)
sns.countplot(x='verification_status', data=data, hue='loan_status')

plt.subplot(4, 2, 4)
g = sns.countplot(x='purpose', data=data, hue='loan_status')
g.set_xticklabels(g.get_xticklabels(), rotation=90);
```



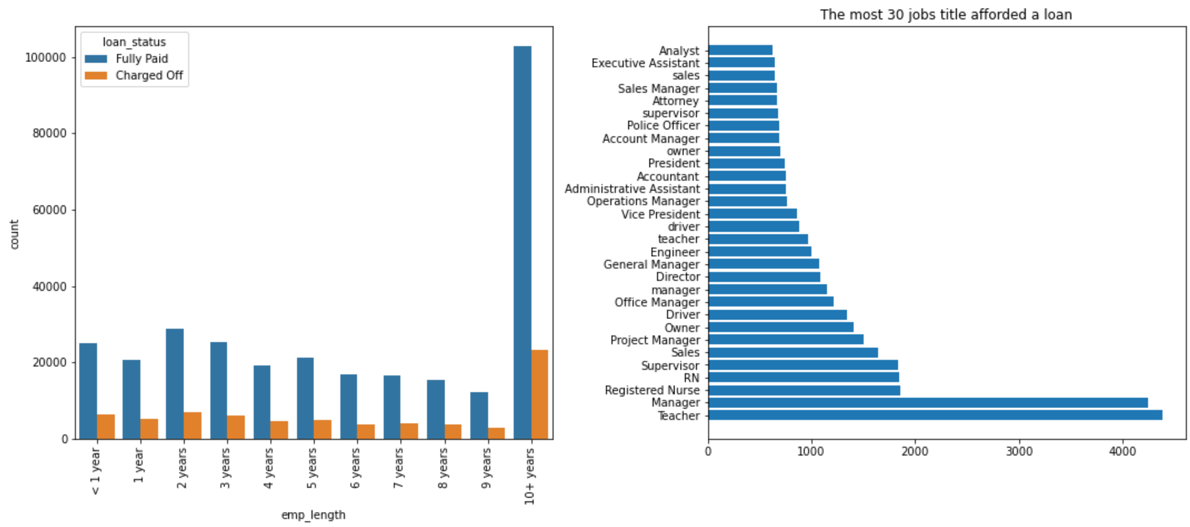
In [ ]:

```

```

Manager and Teacher are the most afforded loan job titles.

In [ ]:

```
plt.figure(figsize=(15, 12))

plt.subplot(2, 2, 1)
order = ['< 1 year', '1 year', '2 years', '3 years', '4 years', '5 years',
         '6 years', '7 years', '8 years', '9 years', '10+ years',]
g = sns.countplot(x='emp_length', data=data, hue='loan_status', order=order)
g.set_xticklabels(g.get_xticklabels(), rotation=90);

plt.subplot(2, 2, 2)
plt.barh(data.emp_title.value_counts()[:30].index, data.emp_title.value_counts()[:30
plt.title("The most 30 jobs title afforded a loan")
plt.tight_layout()
```



Feature Engineering -

In [ ]:

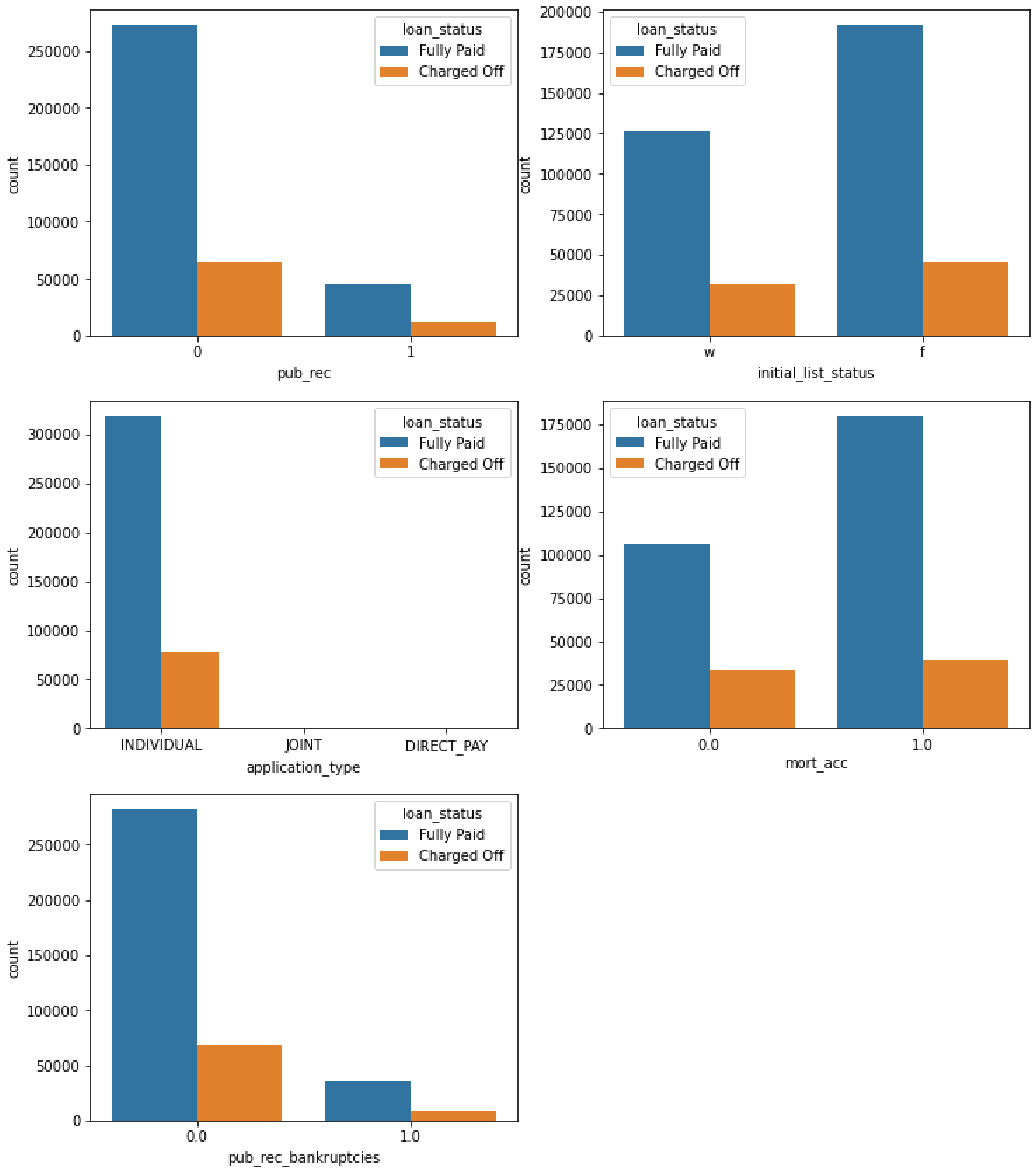
```
def pub_rec(number):
    if number == 0.0:
        return 0
    else:
        return 1

def mort_acc(number):
    if number == 0.0:
        return 0
    elif number >= 1.0:
        return 1
    else:
        return number

def pub_rec_bankruptcies(number):
    if number == 0.0:
        return 0
    elif number >= 1.0:
        return 1
    else:
        return number
```

In [ ]:

```
data['pub_rec'] = data.pub_rec.apply(pub_rec)
data['mort_acc'] = data.mort_acc.apply(mort_acc)
data['pub_rec_bankruptcies'] = data.pub_rec_bankruptcies.apply(pub_rec_bankruptcies)
```

In [ ]:

```
plt.figure(figsize=(12, 30))

plt.subplot(6, 2, 1)
sns.countplot(x='pub_rec', data=data, hue='loan_status')

plt.subplot(6, 2, 2)
sns.countplot(x='initial_list_status', data=data, hue='loan_status')

plt.subplot(6, 2, 3)
sns.countplot(x='application_type', data=data, hue='loan_status')

plt.subplot(6, 2, 4)
sns.countplot(x='mort_acc', data=data, hue='loan_status')

plt.subplot(6, 2, 5)
sns.countplot(x='pub_rec_bankruptcies', data=data, hue='loan_status')

plt.show()
```



In [ ]:

```
# Mapping of target variable -
data['loan_status'] = data.loan_status.map({'Fully Paid':0, 'Charged Off':1})
```

In [ ]:

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

Out[25]:

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

Very Important: Mean Target Imputation

In [ ]:

```
data.groupby(by='total_acc').mean()
```

Out[26]:

loan_status	dti	open_acc	pub_rec	revol_bal	revol_util	mort_acc	pub_rec_bankrupt
0.222222	2.279444	1.611111	0.000000	2860.166667	53.527778	0.000000	0.00C
0.220183	6.502813	2.611621	0.033639	3382.807339	49.991022	0.046243	0.015
0.214055	8.411963	3.324717	0.033118	4874.231826	58.477400	0.062140	0.019
0.203156	10.118328	3.921598	0.055720	5475.253452	56.890311	0.090789	0.039
0.215874	11.222542	4.511119	0.076634	6546.374957	57.812483	0.121983	0.05C
...	...	...	...	...	...	...	
1.000000	14.040000	43.000000	0.000000	25497.000000	75.400000	1.000000	0.00C
0.000000	8.900000	48.000000	0.000000	27659.000000	8.300000	1.000000	0.00C
0.000000	33.850000	57.000000	0.000000	35715.000000	50.800000	1.000000	0.00C
0.000000	6.630000	40.000000	0.000000	39065.000000	44.400000	1.000000	0.00C
1.000000	12.650000	26.000000	0.000000	46643.000000	71.500000	0.000000	0.00C

In [ ]:

```
= data.groupby(by='total_acc').mean().mort_acc
of mort_acc according to total_acc_avg (you can pick any variable for your understan
```

In [ ]:

```
def fill_mort_acc(total_acc, mort_acc):
    if np.isnan(mort_acc):
        return total_acc_avg[total_acc].round()
    else:
        return mort_acc
```

In [ ]:

```
data['mort_acc'] = data.apply(lambda x: fill_mort_acc(x['total_acc'], x['mort_acc']))
```

In [ ]:

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

Out[30]:

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

In [ ]:

```
# Current no. of rows -
data.shape
```

Out[31]:

```
(396030, 26)
```

In [ ]:

```
# Dropping rows with null values - # do your own reserach
data.dropna(inplace=True)
```

In [ ]:

```
# Remaining no. of rows -
data.shape
```

Out[33]:

```
(370622, 26)
```

Outlier Detection & Treatment -

In [ ]:

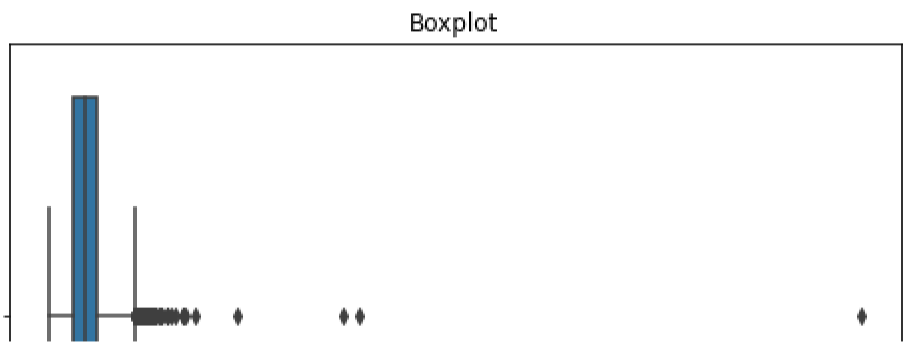
```
numerical_data = data.select_dtypes(include='number')
num_cols = numerical_data.columns
len(num_cols)
```

Out[34]:

```
12
```

In [ ]:

```
def box_plot(col):
    plt.figure(figsize=(8, 5))
    sns.boxplot(x=data[col])
    plt.title('Boxplot')
    plt.show()

for col in num_cols:
    box_plot(col)
```



In [ ]:

```
for col in num_cols:
    mean = data[col].mean()
    std = data[col].std()

    upper_limit = mean+3*std
    lower_limit = mean-3*std

    data = data[(data[col]<upper_limit) & (data[col]>lower_limit)]

data.shape
```

Out[36]:

```
(354519, 26)
```

Data Preprocessing -

In [ ]:

```
# Term -
data.term.unique()
```

Out[37]:

```
array([' 36 months', ' 60 months'], dtype=object)
```

In [ ]:

```
term_values = {' 36 months': 36, ' 60 months': 60}
data['term'] = data.term.map(term_values)
```

In [ ]:

```
# Initial List Status -
data['initial_list_status'].unique()
```

Out[39]:

```
array(['w', 'f'], dtype=object)
```

In [ ]:

```
list_status = {'w': 0, 'f': 1}
data['initial_list_status'] = data.initial_list_status.map(list_status)
```

In [ ]:

```
# Let's fetch ZIP from address and then drop the remaining details -
data['zip_code'] = data.address.apply(lambda x: x[-5:])
```

In [ ]:

```
data['zip_code'].value_counts(normalize=True)*100
```

Out[42]:

```
70466    14.382022
30723    14.277373
22690    14.268347
48052    14.127028
00813    11.610097
29597    11.537322
05113    11.516731
93700     2.774746
11650     2.772771
86630     2.733563
Name: zip_code, dtype: float64
```

In [ ]:

```
# Dropping some variables which IMO we can let go for now -
data.drop(columns=['issue_d', 'emp_title', 'title', 'sub_grade',
                   'address', 'earliest_cr_line', 'emp_length'],
                   axis=1, inplace=True)
#target encoding - freqency mapping
#a - number of rows
#b
```

One-hot Encoding -

In [ ]:

```
dummies = ['purpose', 'zip_code', 'grade', 'verification_status', 'application_type'
data = pd.get_dummies(data, columns=dummies, drop_first=True)
```

In [ ]:

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

data.head()
```

Out[45]:

	loan_amnt	term	int_rate	annual_inc	loan_status	dti	open_acc	pub_rec	revol_bal	revo
0	10000.0	36	11.44	117000.0	0	26.24	16.0	0	36369.0	
1	8000.0	36	11.99	65000.0	0	22.05	17.0	0	20131.0	
2	15600.0	36	10.49	43057.0	0	12.79	13.0	0	11987.0	
3	7200.0	36	6.49	54000.0	0	2.60	6.0	0	5472.0	
4	24375.0	60	17.27	55000.0	1	33.95	13.0	0	24584.0	

In [ ]:

```
data.shape
```

Out[46]:

```
(354519, 49)
```

Data Preparation for Modeling -

In [ ]:

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

In [ ]:

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.30,
                                                    stratify=y, random_state=42)
```

In [ ]:

```
print(X_train.shape)
print(X_test.shape)
```

```
(248163, 48)
(106356, 48)
```

MinMaxScaler -

For each value in a feature, MinMaxScaler subtracts the minimum value in the feature and then divides by the range. The range is the difference between the original maximum and original minimum.

MinMaxScaler preserves the shape of the original distribution. It doesn't meaningfully change the information embedded in the original data.

In [ ]:

```
scaler = MinMaxScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
```

Logistic Regression

In [ ]:

```
logreg = LogisticRegression(max_iter=1000)
logreg.fit(X_train, y_train)
```

Out[51]:

```
LogisticRegression(max_iter=1000)
```

In [ ]:

```
y_pred = logreg.predict(X_test)
print('Accuracy of Logistic Regression Classifier on test set: {:.3f}'.format(logreg
```

```
Accuracy of Logistic Regression Classifier on test set: 0.890
```

Confusion Matrix -

In [ ]:

```
confusion_matrix = confusion_matrix(y_test, y_pred)
print(confusion_matrix)
```

```
[[85365   523]
 [11131  9337]]
```

Classification Report -

In [ ]:

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

```
              precision    recall  f1-score   support

           0       0.88      0.99      0.94     85888
           1       0.95      0.46      0.62     20468

    accuracy                           0.89    106356
   macro avg       0.92      0.73      0.78    106356
weighted avg       0.90      0.89      0.87    106356
```

ROC Curve -

An ROC curve (receiver operating characteristic curve) is a graph showing the performance of a classification model at all classification thresholds. This curve plots two parameters:

- True Positive Rate
- False Positive Rate

True Positive Rate (TPR) is a synonym for recall and is therefore defined as follows:

- TPR=(TP)/(TP+FN)

False Positive Rate (FPR) is defined as follows:

- FPR=(FP)/(FP+TN)

An ROC curve plots TPR vs. FPR at different classification thresholds. Lowering the classification threshold classifies more items as positive, thus increasing both False Positives and True Positives. The following figure shows a typical ROC curve.

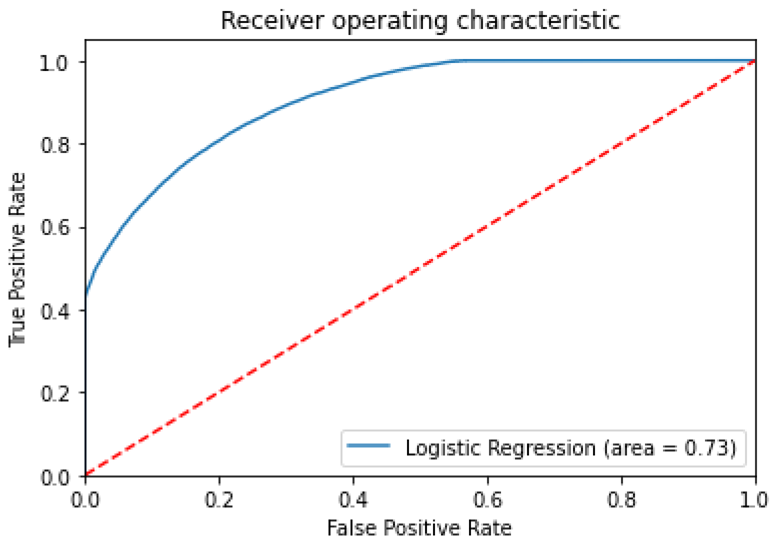
AUC (Area under the ROC Curve) -

AUC stands for "Area under the ROC Curve." That is, AUC measures the entire two-dimensional area underneath the entire ROC curve (think integral calculus) from (0,0) to (1,1).

AUC provides an aggregate measure of performance across all possible classification thresholds. One way of interpreting AUC is as the probability that the model ranks a random positive example more highly than a random negative example. For example, given the following examples, which are arranged from left to right in ascending order of logistic regression predictions:

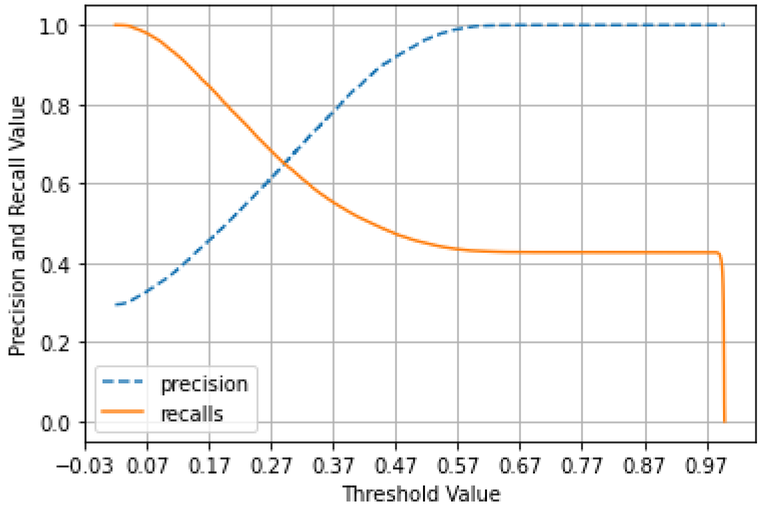
In [ ]:

```
logit_roc_auc = roc_auc_score(y_test, logreg.predict(X_test))
fpr, tpr, thresholds = roc_curve(y_test, logreg.predict_proba(X_test)[:,1])
plt.figure()
plt.plot(fpr, tpr, label='Logistic Regression (area = %0.2f)' % logit_roc_auc)
plt.plot([0, 1], [0, 1],'r--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver operating characteristic')
plt.legend(loc="lower right")
plt.savefig('Log_ROC')
plt.show()
```



In [ ]:

```
def precision_recall_curve_plot(y_test, pred_proba_c1):
    precisions, recalls, thresholds = precision_recall_curve(y_test, pred_proba_c1)

    threshold_boundary = thresholds.shape[0]
    # plot precision
    plt.plot(thresholds, precisions[0:threshold_boundary], linestyle='--', label='pr
    # plot recall
    plt.plot(thresholds, recalls[0:threshold_boundary], label='recalls')

    start, end = plt.xlim()
    plt.xticks(np.round(np.arange(start, end, 0.1), 2))

    plt.xlabel('Threshold Value'); plt.ylabel('Precision and Recall Value')
    plt.legend(); plt.grid()
    plt.show()

precision_recall_curve_plot(y_test, logreg.predict_proba(X_test)[:,1])
```



Multicollinearity check using Variance Inflation Factor (VIF) -

Multicollinearity occurs when two or more independent variables are highly correlated with one another in a regression model. Multicollinearity can be a problem in a regression model because we would not be able to distinguish between the individual effects of the independent variables on the dependent variable.

Multicollinearity can be detected via various methods. One such method is Variance Inflation Factor aka VIF. In VIF method, we pick each independent feature and regress it against all of the other independent features. VIF score of an independent variable represents how well the variable is explained by other independent variables.

VIF = 1/1-R2

In [ ]:

```
def calc_vif(X):
    # Calculating the VIF
    vif = pd.DataFrame()
    vif['Feature'] = 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

calc_vif(X)[:5]
```

Out[57]:

	Feature	VIF
43	application_type_INDIVIDUAL	156.97
2	int_rate	122.82
14	purpose_debt_consolidation	51.00
1	term	27.30
13	purpose_credit_card	18.48

In [ ]:

```
X.drop(columns=['application_type_INDIVIDUAL'], axis=1, inplace=True)
calc_vif(X)[:5]
```

Out[58]:

	Feature	VIF
2	int_rate	103.43
14	purpose_debt_consolidation	27.49
1	term	24.31
5	open_acc	13.75
9	total_acc	12.69

In [ ]:

```
X.drop(columns=['int_rate'], axis=1, inplace=True)
calc_vif(X)[:5]
```

Out[59]:

	Feature	VIF
1	term	23.35
13	purpose_debt_consolidation	22.35
4	open_acc	13.64
8	total_acc	12.69
7	revol_util	9.06

In [ ]:

```
X.drop(columns=['term'], axis=1, inplace=True)
calc_vif(X)[:5]
```

Out[60]:

	Feature	VIF
12	purpose_debt_consolidation	18.37
3	open_acc	13.64
7	total_acc	12.65
6	revol_util	9.04
1	annual_inc	8.03

In [ ]:

```
X.drop(columns=['purpose_debt_consolidation'], axis=1, inplace=True)
calc_vif(X)[:5]
```

Out[61]:

	Feature	VIF
3	open_acc	13.09
7	total_acc	12.64
6	revol_util	8.31
1	annual_inc	7.70
2	dti	7.58

In [ ]:

```
X.drop(columns=['open_acc'], axis=1, inplace=True)
calc_vif(X)[:5]
```

Out[62]:

	Feature	VIF
6	total_acc	8.23
5	revol_util	8.00
1	annual_inc	7.60
2	dti	7.02
0	loan_amnt	6.72

In [ ]:

```
X = scaler.fit_transform(X)

kfold = KFold(n_splits=5)
accuracy = np.mean(cross_val_score(logreg, X, y, cv=kfold, scoring='accuracy', n_jok
print("Cross Validation accuracy: {:.3f}".format(accuracy))
```

```
Cross Validation accuracy: 0.891
```

Oversampling using SMOTE

In [ ]:

```
sm = SMOTE(random_state=42)
X_train_res, y_train_res = sm.fit_resample(X_train, y_train.ravel())
```

In [ ]:

```
print('After OverSampling, the shape of train_X: {}'.format(X_train_res.shape))
print('After OverSampling, the shape of train_y: {} \n'.format(y_train_res.shape))

print("After OverSampling, counts of label '1': {}".format(sum(y_train_res == 1)))
print("After OverSampling, counts of label '0': {}".format(sum(y_train_res == 0)))
```

```
After OverSampling, the shape of train_X: (400810, 48)
After OverSampling, the shape of train_y: (400810,)

After OverSampling, counts of label '1': 200405
After OverSampling, counts of label '0': 200405
```

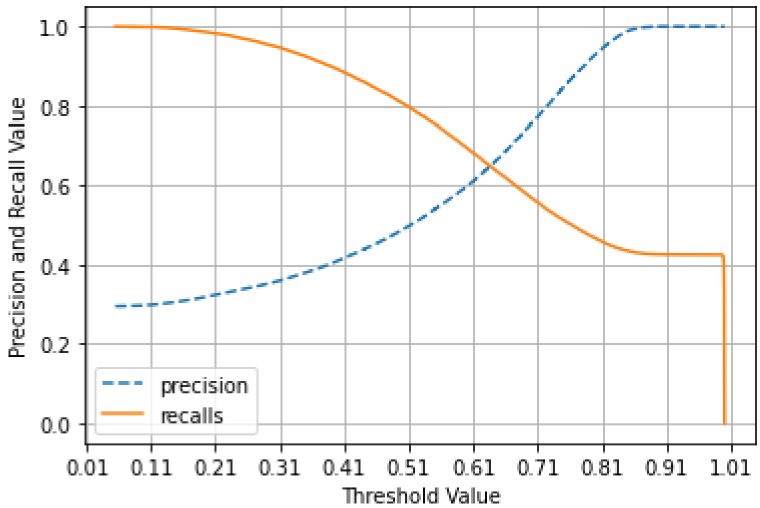
In [ ]:

```
lr1 = LogisticRegression(max_iter=1000)
lr1.fit(X_train_res, y_train_res)
predictions = lr1.predict(X_test)

# Classification Report
print(classification_report(y_test, predictions))
```

```
              precision    recall  f1-score   support

           0       0.95      0.80      0.87     85888
           1       0.49      0.81      0.61     20468

    accuracy                           0.80    106356
   macro avg       0.72      0.80      0.74    106356
weighted avg       0.86      0.80      0.82    106356
```

In [ ]:

```
def precision_recall_curve_plot(y_test, pred_proba_c1):
    precisions, recalls, thresholds = precision_recall_curve(y_test, pred_proba_c1)

    threshold_boundary = thresholds.shape[0]
    # plot precision
    plt.plot(thresholds, precisions[0:threshold_boundary], linestyle='--', label='pr
    # plot recall
    plt.plot(thresholds, recalls[0:threshold_boundary], label='recalls')

    start, end = plt.xlim()
    plt.xticks(np.round(np.arange(start, end, 0.1), 2))

    plt.xlabel('Threshold Value'); plt.ylabel('Precision and Recall Value')
    plt.legend(); plt.grid()
    plt.show()

precision_recall_curve_plot(y_test, lr1.predict_proba(X_test)[:,1])
```



In [ ]:

```
#alternative method
#We can try fixing the imbalance using class weights as well
```