LoanTap - Logistic Regression

LoanTap is an online platform committed to delivering customized loan products to millennials. They innovate in an otherwise dull loan segment, to deliver instant, flexible loans on consumer friendly terms to salaried professionals and businessmen. The data science team at LoanTap is building an underwriting layer to determine the creditworthiness of MSMEs as well as individuals.

LoanTap deploys formal credit to salaried individuals and businesses 4 main financial instruments:

- Personal Loan
- EMI Free Loan
- Personal Overdraft
- Advance Salary Loan

This case study will focus on the underwriting process behind Personal Loan only

Problem Statement:

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

Importing Libraries

```
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 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 # To decide on the best performing model
from sklearn.preprocessing import MinMaxScaler
from statsmodels.stats.outliers_influence import variance_inflation_factor # Multicolinearity?
from imblearn.over_sampling import SMOTE # Oversampling
```

```
!gdown 1ZPYj7CZCfxntE8p2Lze_4QO4MyEOy6_d
```

```
Downloading...
From: https://drive.google.com/uc?id=1ZPYj7CZCfxntE8p2Lze_4QO4MyEOy6_d
To: /content/logistic_regression.csv
100% 100M/100M [00:00<00:00, 247MB/s]
```

```
df = pd.read_csv('logistic_regression.csv')
```

```
df.head()
```

	loan_amnt	term	int_rate	installment	grade	sub_grade	emp_title	emp_length	home_ownership	annual_inc	verification_status
0	10000.0	36 months	11.44	329.48	B	B4	Marketing	10+ years	RENT	117000.0	Not Verified
1	8000.0	36 months	11.99	265.68	B	B5	Credit analyst	4 years	MORTGAGE	65000.0	Not Verified
2	15600.0	36 months	10.49	506.97	B	B3	Statistician	< 1 year	RENT	43057.0	Source Verified
3	7200.0	36 months	6.49	220.65	A	A2	Client Advocate	6 years	RENT	54000.0	Not Verified
4	24375.0	60 months	17.27	609.33	C	C5	Destiny Management Inc.	9 years	MORTGAGE	55000.0	Verified

```
df.shape
```

```
(396030, 27)
```

```
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                 394274 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
```

```
df.describe().T
```

	count	mean	std	min	25%	50%	75%	max
loan_amnt	396030.0	14113.888089	8357.441341	500.00	8000.00	12000.00	20000.00	40000.00
int_rate	396030.0	13.639400	4.472157	5.32	10.49	13.33	16.49	30.99
installment	396030.0	431.849698	250.727790	16.08	250.33	375.43	567.30	1533.81
annual_inc	396030.0	74203.175798	61637.621158	0.00	45000.00	64000.00	90000.00	8706582.00
dti	396030.0	17.379514	18.019092	0.00	11.28	16.91	22.98	9999.00
open_acc	396030.0	11.311153	5.137649	0.00	8.00	10.00	14.00	90.00
pub_rec	396030.0	0.178191	0.530671	0.00	0.00	0.00	0.00	86.00
revol_bal	396030.0	15844.539853	20591.836109	0.00	6025.00	11181.00	19620.00	1743266.00
revol_util	395754.0	53.791749	24.452193	0.00	35.80	54.80	72.90	892.30
total_acc	396030.0	25.414744	11.886991	2.00	17.00	24.00	32.00	151.00
mort_acc	358235.0	1.813991	2.147930	0.00	0.00	1.00	3.00	34.00
pub_rec_bankruptcies	395495.0	0.121648	0.356174	0.00	0.00	0.00	0.00	8.00

```
df.isna().sum()
```

	0
loan_amnt	0
term	0
int_rate	0
installment	0
grade	0
sub_grade	0
emp_title	22927
emp_length	18301
home_ownership	0
annual_inc	0
verification_status	0
issue_d	0
loan_status	0
purpose	0
title	1756
dti	0
earliest_cr_line	0
open_acc	0
pub_rec	0
revol_bal	0
revol_util	276
total_acc	0
initial_list_status	0
application_type	0
mort_acc	37795
pub_rec_bankruptcies	535
address	0

dtype: int64

There are null values in 6 columns in which 3 are numerical and 3 are categorical. categorical columns can be filled with mode and numerical can be filled with mean of their respective columns

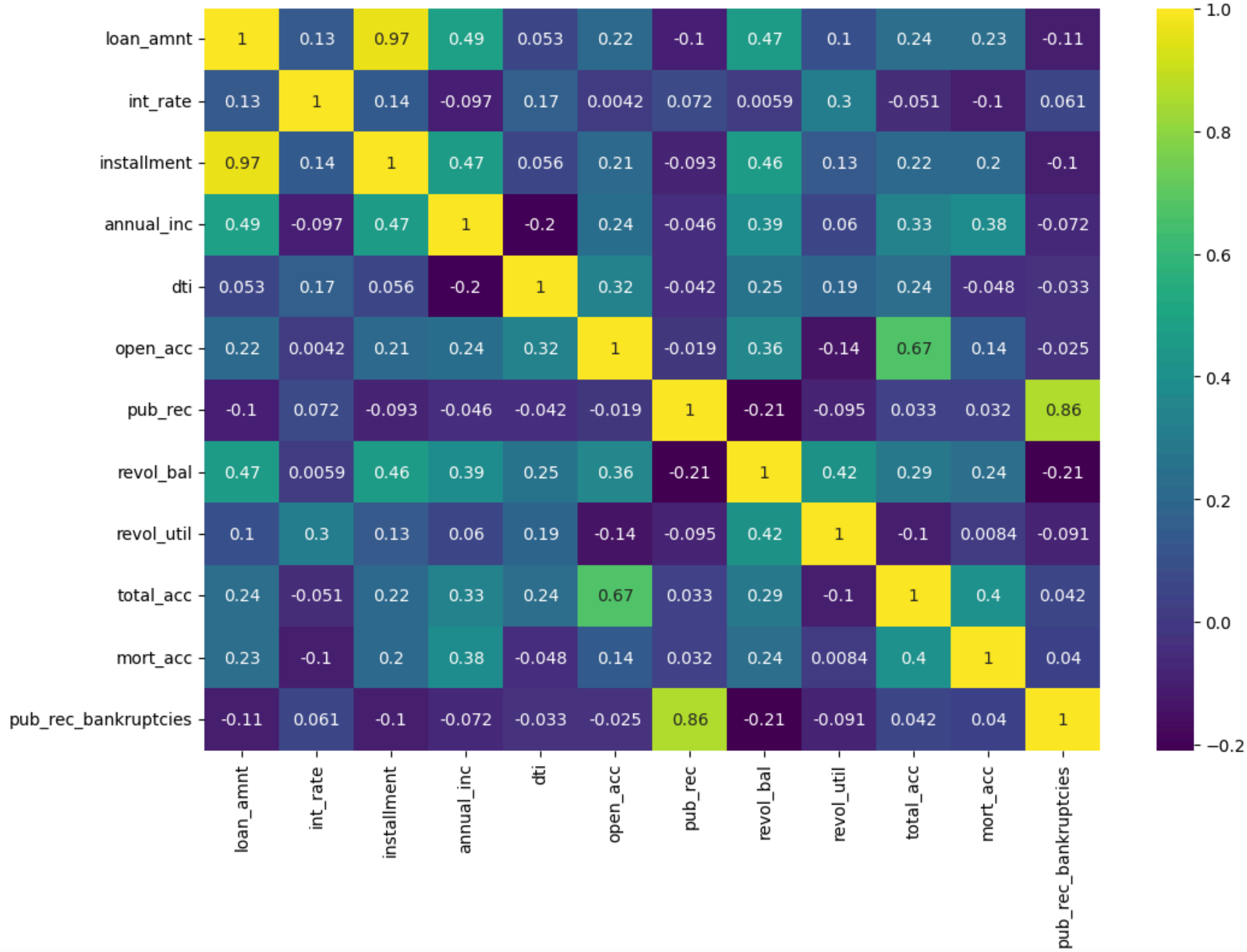
```
df.loan_status.value_counts(normalize=True)*100
```

loan_status	proportion
Fully Paid	80.387092
Charged Off	19.612908

dtype: float64

```
plt.figure(figsize=(12, 8))
numeric_df = df.select_dtypes(include=['number'])
sns.heatmap(numeric_df.corr(method='spearman'), annot=True, cmap='viridis')
```

```
<Axes: >
```



From the above heat map we can see almost perfect correlation between "loan_amnt" the "installment" feature.

```
#dropping installment feature
df.drop(columns=['installment'], axis=1, inplace=True)
```

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

loan_status	count	mean	std	min	25%	50%	75%	max
Charged Off	77673.0	15126.300967	8505.090557	1000.0	8525.0	14000.0	20000.0	40000.0
Fully Paid	318357.0	13866.878771	8302.319699	500.0	7500.0	12000.0	19225.0	40000.0

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

home_ownership	count
MORTGAGE	198348
RENT	159790
OWN	37746
OTHER	112
NONE	31
ANY	3

dtype: int64

Combining NONE and ANY into OTHER

```
df.loc[(df.home_ownership == 'ANY') | (df.home_ownership == 'NONE'), 'home_ownership'] = 'OTHER'
df.home_ownership.value_counts()
```

home_ownership	count
MORTGAGE	198348
RENT	159790
OWN	37746
OTHER	146

dtype: int64

```
df.loc[df['home_ownership']=='OTHER', 'loan_status'].value_counts()
```

loan_status	count
Fully Paid	123
Charged Off	23

dtype: int64

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

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

title	count
Debt consolidation	152472
Credit card refinancing	51487
Home improvement	15264
Other	12930
Debt Consolidation	11608
Major purchase	4769
Consolidation	3852
debt consolidation	3547
Business	2949
Debt Consolidation Loan	2864
Medical expenses	2742
Car financing	2139
Credit Card Consolidation	1775
Vacation	1717
Moving and relocation	1689
consolidation	1595
Personal Loan	1591
Consolidation Loan	1299
Home Improvement	1268
Home buying	1183

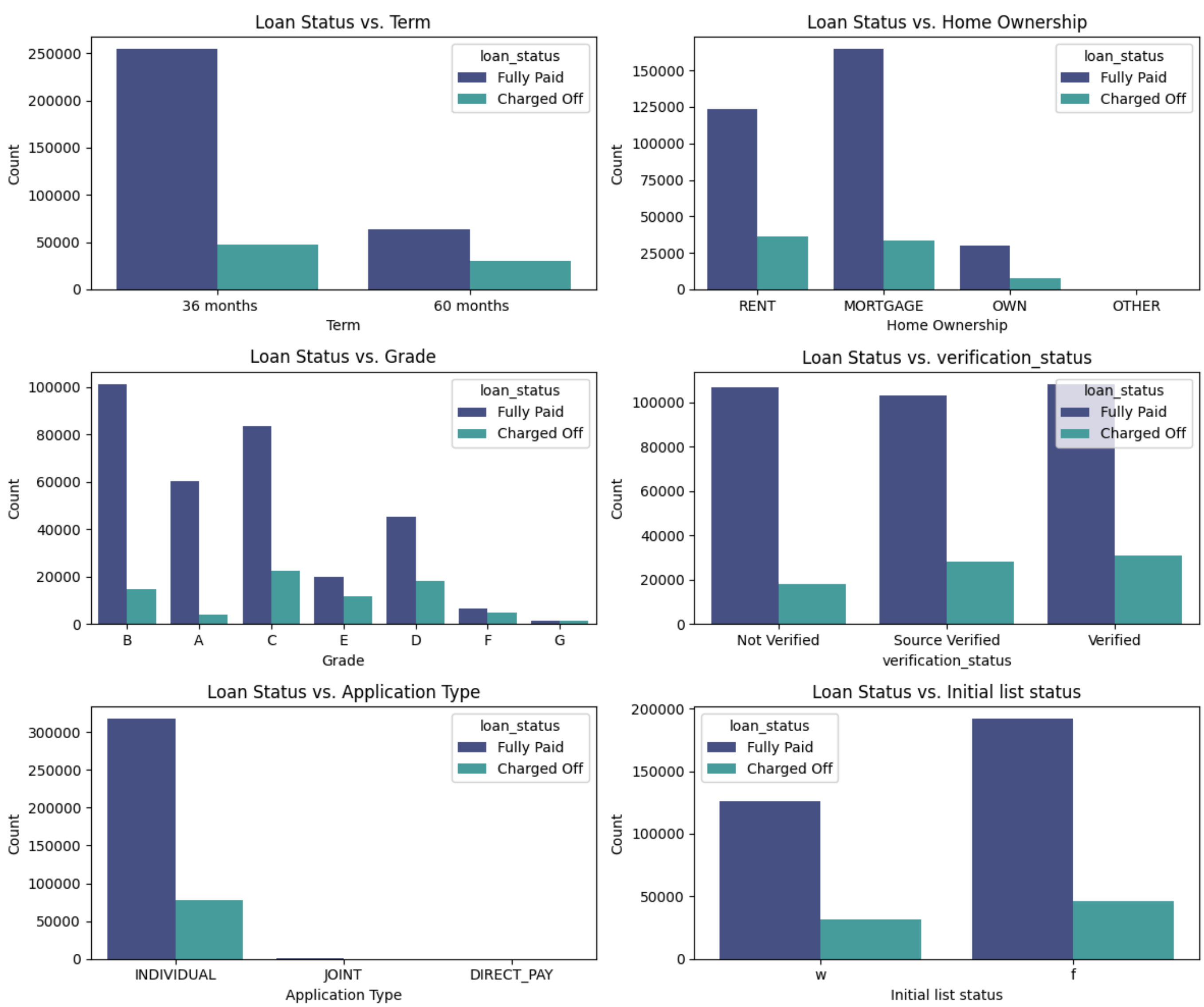
dtype: int64

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

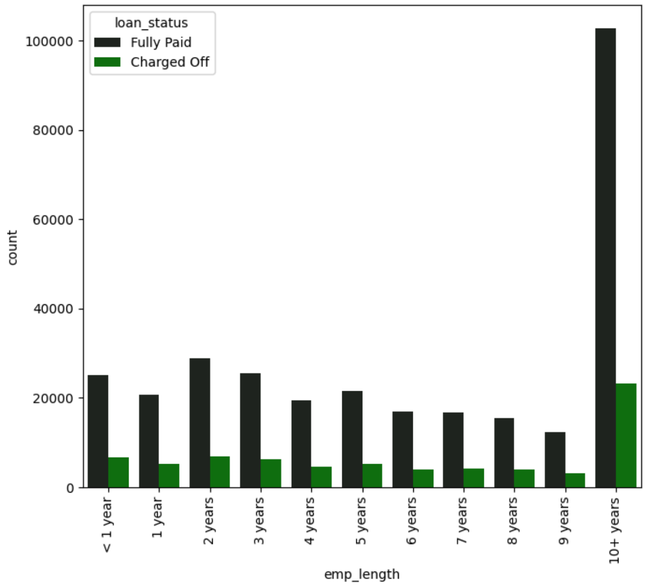
Data Visualization

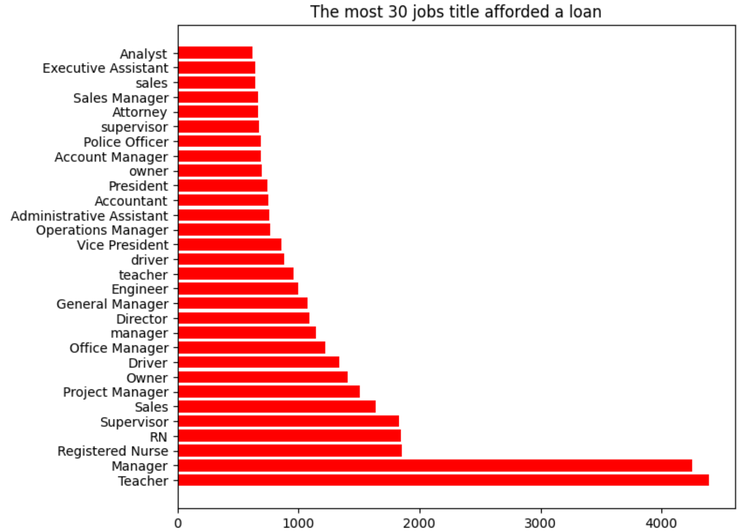
```
fig, axes = plt.subplots(nrows=3, ncols=2, figsize=(12, 10))

sns.countplot(x='term', hue='loan_status', data=df, ax=axes[0,0], palette='mako')
axes[0,0].set_title('Loan Status vs. Term')
axes[0,0].set_xlabel('Term')
axes[0,0].set_ylabel('Count')

sns.countplot(x='home_ownership', hue='loan_status', data=df, ax=axes[0,1], palette='mako')
axes[0,1].set_title('Loan Status vs. Home Ownership')
axes[0,1].set_xlabel('Home Ownership')
axes[0,1].set_ylabel('Count')

sns.countplot(x='grade', hue='loan_status', data=df, ax=axes[1,0], palette='mako')
axes[1,0].set_title('Loan Status vs. Grade')
axes[1,0].set_xlabel('Grade')
axes[1,0].set_ylabel('Count')

sns.countplot(x='verification_status', hue='loan_status', data=df, ax=axes[1,1], palette='mako')
axes[1,1].set_title('Loan Status vs. verification_status')
axes[1,1].set_xlabel('verification_status')
axes[1,1].set_ylabel('Count')

sns.countplot(x='application_type', hue='loan_status', data=df, ax=axes[2,0], palette='mako')
axes[2,0].set_title('Loan Status vs. Application Type')
axes[2,0].set_xlabel('Application Type')
axes[2,0].set_ylabel('Count')

sns.countplot(x='initial_list_status', hue='loan_status', data=df, ax=axes[2,1], palette='mako')
axes[2,1].set_title('Loan Status vs. Initial list status')
axes[2,1].set_xlabel('Initial list status')
axes[2,1].set_ylabel('Count')
```

```
plt.tight_layout()
plt.show()
```




```
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=df, hue='loan_status', order=order,color='green')
g.set_xticklabels(g.get_xticklabels(), rotation=90);

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





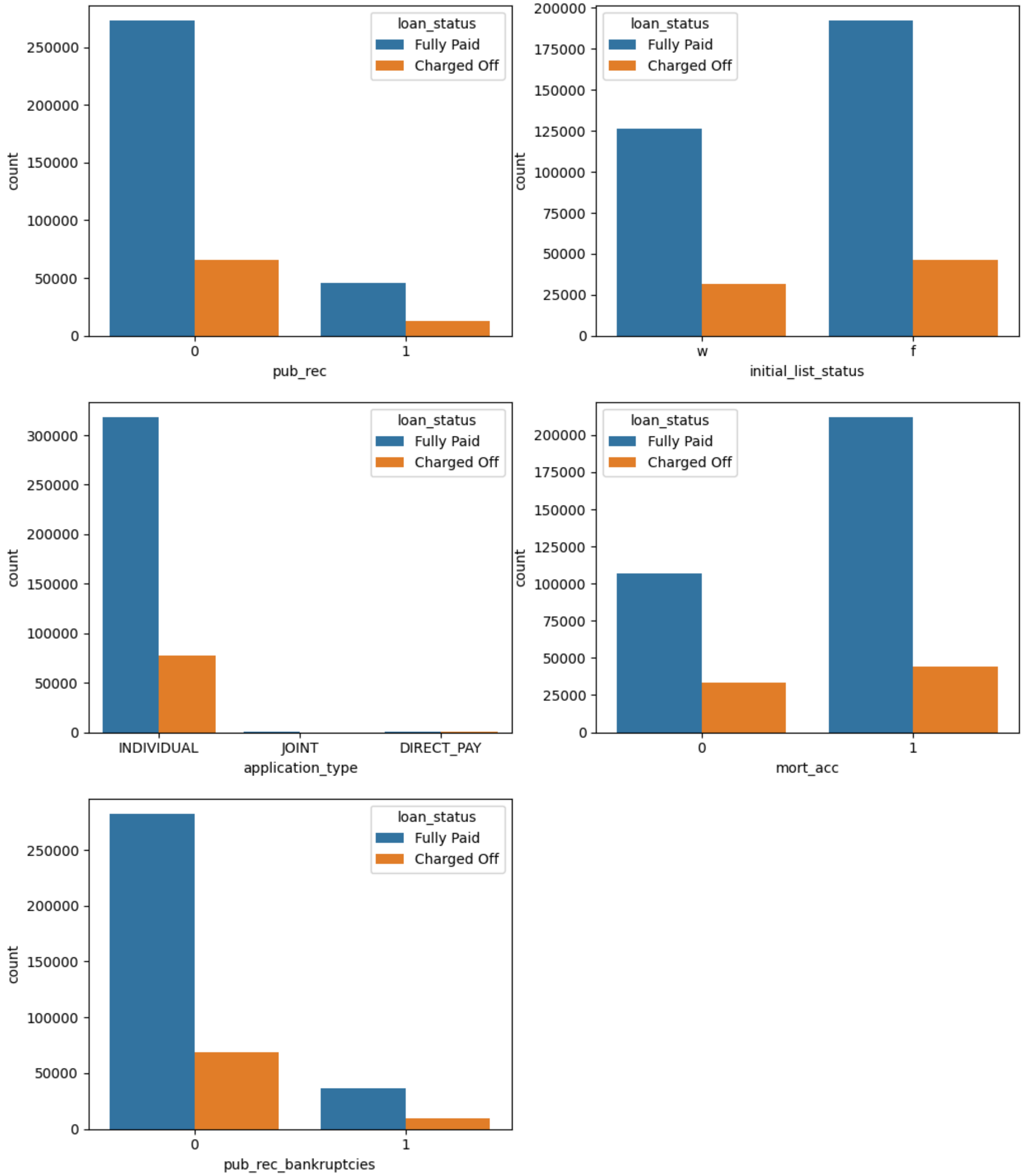
Observations:

- More people take loans for 36 months than for 60 months.
- Most people who take loans have a house under mortgage, followed by those who rent, and then those who own their house. Other types are very few.
- The number of people in each verification status group is almost the same.
- Most loan applications are from individuals, not joint applications.
- Grade B has the highest number of people who have fully paid their loans.
- In Grade B, sub-grade B3 has the most people who paid off their loans.
- Very few people fall under Grade G.
- Sub-grade A1 has the least number of defaulters, which means people in this group are more reliable

Data Preprocessing using Feautre Engineering

```
def pub_rec(number):
    if number == 0.0:
        return 0
    else:
        return 1 # Whether someone has public derogatory records or not (flag)

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


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

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


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

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

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

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

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

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

plt.show()
```




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

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

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

```
numeric_df.head()
```

total_acc	loan_amnt	int_rate	annual_inc	dti	open_acc	pub_rec	revol_bal	revol_util	mort_acc	pub_rec_bankruptcies
2.0	6672.222222	15.801111	64277.777778	2.279444	1.611111	0.000000	2860.166667	53.527778	0.000000	0.000000
3.0	6042.966361	15.615566	41270.753884	6.502813	2.611621	0.045872	3382.807339	49.991022	0.052023	0.015480
4.0	7587.399031	15.069491	42426.565969	8.411963	3.324717	0.041195	4874.231826	58.477400	0.066743	0.022951
5.0	7845.734714	14.917564	44394.098003	10.118328	3.921598	0.071499	5475.253452	56.890311	0.103289	0.041171
6.0	8529.019843	14.651752	48470.001156	11.222542	4.511119	0.104003	6546.374957	57.812483	0.151293	0.055077

Next steps: Generate code with numeric_df View recommended plots New interactive sheet

```
total_acc_avg = numeric_df.groupby(by='total_acc').mean().mort_acc
```

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

```
df['mort_acc'] = df.apply(lambda x: fill_mort_acc(x['total_acc'], x['mort_acc']), axis=1)
```

```
df.isnull().sum()
```

	0
loan_amnt	0
term	0
int_rate	0
grade	0
sub_grade	0
emp_title	22927
emp_length	18301
home_ownership	0
annual_inc	0
verification_status	0
issue_d	0
loan_status	0
purpose	0
title	1756
dti	0
earliest_cr_line	0
open_acc	0
pub_rec	0
revol_bal	0
revol_util	276
total_acc	0
initial_list_status	0
application_type	0
mort_acc	0
pub_rec_bankruptcies	0
address	0

dtype: int64

```
df.shape
```

```
(396030, 26)
```

```
df.dropna(inplace=True)
```

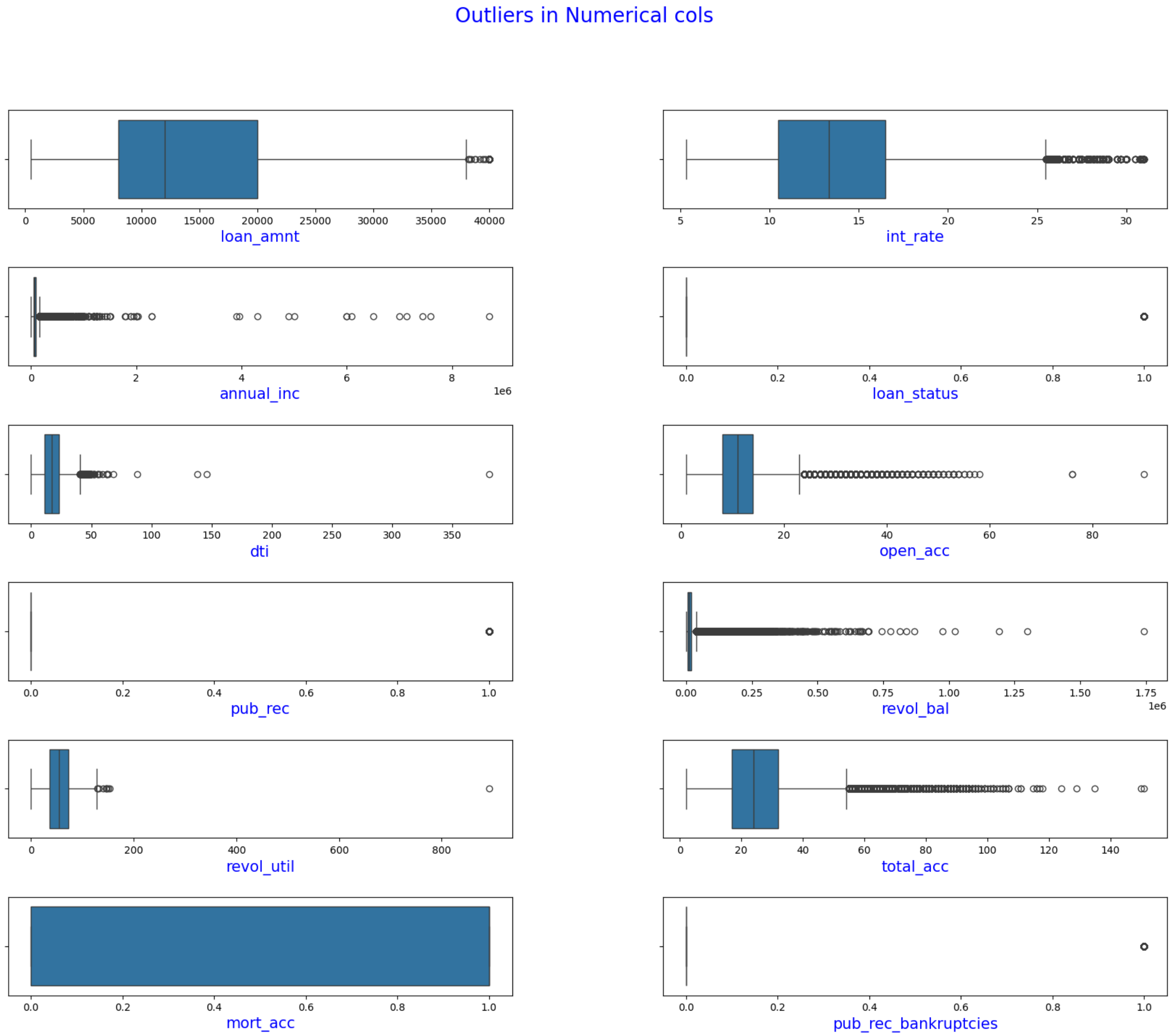
```
df.shape
```

```
(371125, 26)
```

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

```
12
```

```
fig = plt.figure(figsize=(20,18))
for i,col in enumerate(num_cols):
    plt.subplot(int(len(num_cols)/2 +1), 2, i+1)
    plt.subplots_adjust(left=0.1, right=0.9, top=0.9, bottom=0.1, wspace=0.3, hspace=0.6)
    sns.boxplot(x=df[col] )
    plt.xlabel(col,fontsize =15, color = 'blue')
    #plt.ylabel("count of bikes", fontsize = 15, color = 'blue')
fig.suptitle("Outliers in Numerical cols ", fontsize= 20, color = 'blue')
plt.show()
```


Outliers in Numerical cols
loan_amnt
0
5000
10000
15000
20000
25000
30000
35000
40000
int_rate
5
10
15
20
25
30
annual_inc
0
2
4
6
8
1e6
loan_status
0.0
0.2
0.4
0.6
0.8
1.0
dti
0
50
100
150
200
250
300
350
open_acc
0
20
40
60
80
pub_rec
revol_bal
0.00
0.25
0.50
0.75
1.00
1.25
1.50
1.75
1e6
revol_util
0
200
400
600
800
total_acc
0
20
40
60
80
100
120
140
mort_acc
pub_rec_bankruptcies

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

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

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

df.shape
```

```
(355004, 26)
```

```
df['term']=df['term'].str.strip()
map = {'36 months':36,'60 months':60}
df['term']=df['term'].map(map)
```

```
df['initial_list_status'].unique()
```

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

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

```
df['zip_code']=df['address'].apply(lambda x:x[-5:])
```

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

	proportion
zip_code	
70466	14.378711
30723	14.282656
22690	14.269135
48052	14.125193
00813	11.611982
29597	11.537053
05113	11.517053
93700	2.773772
11650	2.771236
86630	2.733209

dtype: float64

```
#dropping unnecessary columns
df.drop(columns=['issue_d', 'emp_title', 'title', 'sub_grade',
                   'address', 'earliest_cr_line', 'emp_length'],
                   axis=1, inplace=True)
```

Encoding

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

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

df.head()
```

	loan_amnt	term	int_rate	annual_inc	loan_status	dti	open_acc	pub_rec	revol_bal	revol_util	total_acc	initial_list_status	mo
0	10000.0	36	11.44	117000.0	0	26.24	16.0	0	36369.0	41.8	25.0	0	
1	8000.0	36	11.99	65000.0	0	22.05	17.0	0	20131.0	53.3	27.0	1	
2	15600.0	36	10.49	43057.0	0	12.79	13.0	0	11987.0	92.2	26.0	1	
3	7200.0	36	6.49	54000.0	0	2.60	6.0	0	5472.0	21.5	13.0	1	
4	24375.0	60	17.27	55000.0	1	33.95	13.0	0	24584.0	69.8	43.0	1	

```
df.shape
```

```
(355004, 49)
```

Splitting the data into train and test

```
X = df.drop(columns=['loan_status'])
y = df['loan_status']
```

```
X.shape
```

```
(355004, 48)
```

```
y.shape
```

```
(355004,)
```

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

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

```
(248502, 48)
(106502, 48)
```

```
from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
```

Logistic Regression

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

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

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

```
Accuracy of Logistic Regression Classifier on test set: 0.891
```

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

```
[[85434   576]
 [11071  9421]]
```

The accuracy of our first model is 89.11%, which looks good. But since our dataset is imbalanced, accuracy alone might not give the full picture. In such cases, accuracy can be misleading. So, we will look at some other evaluation metrics to better understand how well our model is performing.

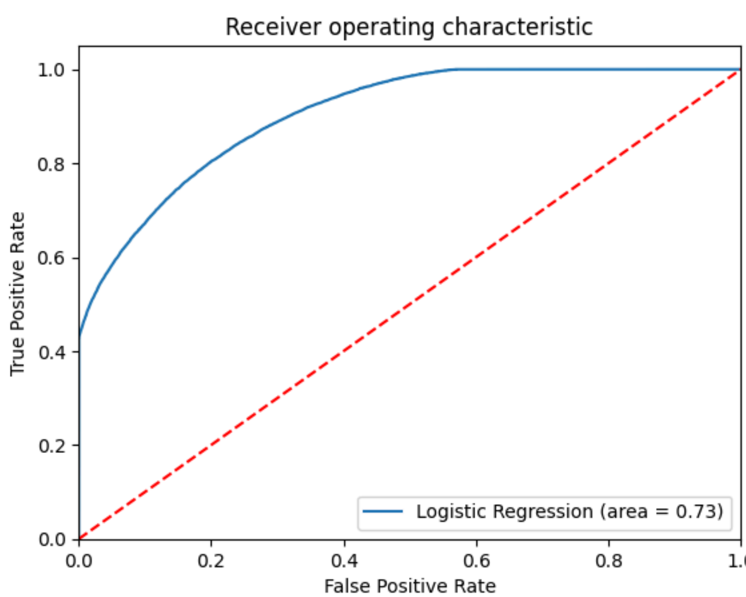
```
from sklearn.metrics import classification_report, roc_auc_score, precision_recall_curve, auc, roc_curve,confusion_matrix
```

```
print("Classification Report:")
print(classification_report(y_test, y_pred))
```

```
Classification Report:
              precision    recall  f1-score   support

           0       0.89      0.99      0.94     86010
           1       0.94      0.46      0.62     20492

    accuracy                           0.89    106502
   macro avg       0.91      0.73      0.78    106502
weighted avg       0.90      0.89      0.87    106502
```

ROC Curve

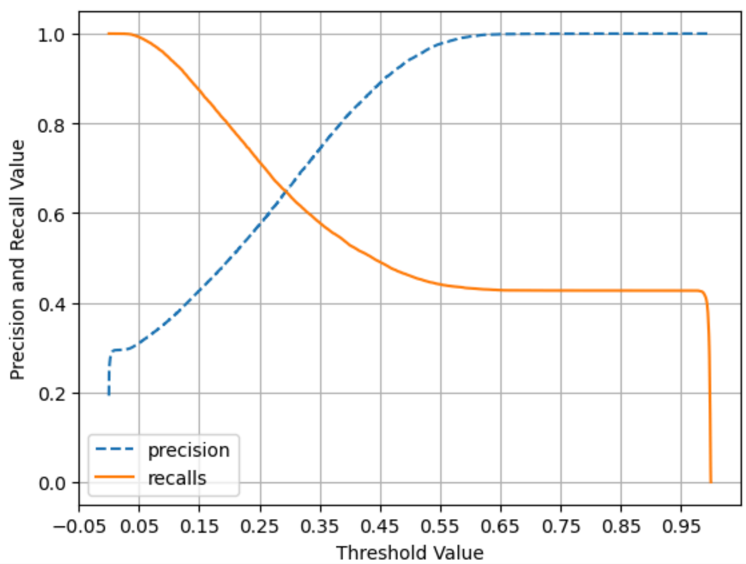
```
logit_roc_auc = roc_auc_score(y_test, logreg.predict(X_test)) # Actual Values and predicted categories
fpr, tpr, thresholds = roc_curve(y_test, logreg.predict_proba(X_test)[:,1]) # Actual values and the probability values
plt.figure()
plt.plot(fpr, tpr, label='Logistic Regression (area = %0.2f)' % 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()
```



Precision-Recall Curve

```
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='precision')
    # 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])
```




```
X = scaler.fit_transform(X)

kfold = KFold(n_splits=5)
accuracy = np.mean(cross_val_score(logreg, X, y, cv=kfold, scoring='accuracy', n_jobs=-1))
print("Cross Validation accuracy: {:.3f}".format(accuracy))
```

```
Cross Validation accuracy: 0.891
```

```
from imblearn.over_sampling import SMOTE
```

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

```
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)))
```

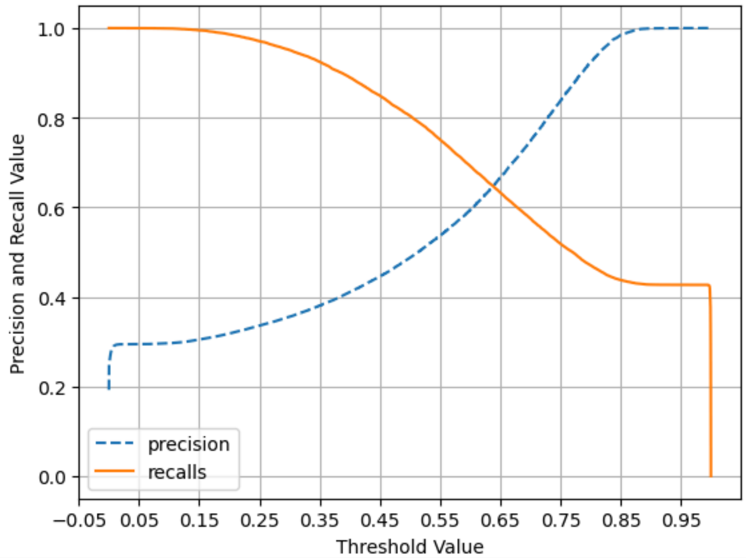
```
After OverSampling, the shape of train_X: (401374, 48)
After OverSampling, the shape of train_y: (401374,)

After OverSampling, counts of label '1': 200687
After OverSampling, counts of label '0': 200687
```

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

```
              precision    recall  f1-score   support

           0       0.94      0.80      0.87     86010
           1       0.49      0.80      0.61     20492

    accuracy                           0.80    106502
   macro avg       0.72      0.80      0.74    106502
weighted avg       0.86      0.80      0.82    106502
```

```
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]
    plt.plot(thresholds, precisions[0:threshold_boundary], linestyle='--', label='precision')
    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])
```



Insights

- More people prefer 36-month loans over 60-month loans.
- Loan distribution based on homeownership follows the order: Mortgage > Rent > Own, with fewer borrowers in other categories.
- Verification status remains balanced across different customer groups.
- Individual loan applications are the most common.
- Most borrowers in Grade B have successfully repaid their loans, with sub-grade B3 having the highest repayment rate.
- Only a small number of borrowers fall under Grade G.
- The lowest default rate is observed in sub-grade A1, indicating reliable borrowers.
- Precision for predicting debtors (class 0) is high.
- Precision for identifying defaulters (class 1) is also strong, with a 94% chance that predicted defaulters are indeed defaulters.
- Sensitivity for debtors is high, but sensitivity for defaulters is lower, leading to more false negatives, as confirmed by the confusion matrix.
- Teachers, managers, nurses, and supervisors are among the most frequent loan applicants.

Recommendations

- Implement strict monitoring for high-interest loans, as they have a 40% default risk.
- Promote low-interest loans, as their probability of repayment exceeds 90%.
- Encourage joint loans, as they have the highest likelihood of full repayment.
- Offer flexible loan terms to help customers align payments with their income levels.
- Target high-earning job roles for loan distribution, as repayment expectations are stronger.
- Maintain rigorous approval processes for loans related to education, medical needs, and other essential purposes to build customer trust.
- Use alternative credit assessment methods like utility payment history and spending behavior to minimize defaults.
- Strengthen partnerships with credit bureaus to improve borrower evaluations and reduce risk.
- Regularly update loan policies to ensure compliance with regulatory standards and enhance loan disbursement strategies.

Start coding or generate with AI.

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