Problem Statement

LoanTap aims to strengthen its underwriting process for Personal Loans by leveraging data-driven decision-making. The goal is to analyze customer attributes and financial behavior to build a robust creditworthiness model that helps determine whether a credit line should be extended to an individual.

The analysis will focus on:

Identifying Key Predictors – Determining the most significant demographic, financial, and behavioral factors that influence loan approval decisions.

Creditworthiness Assessment – Developing a predictive framework to classify individuals as eligible or ineligible for a personal loan.

Risk Profiling – Segmenting applicants into low, medium, and high-risk categories based on repayment capability and default probability.

Business Recommendations – Suggesting optimal repayment terms (tenure, EMI flexibility, interest rates) tailored to each risk profile to minimize default risk while ensuring customer satisfaction.

Through this analysis, LoanTap can improve loan approval efficiency, reduce risk exposure, and enhance customer experience by offering customized repayment solutions for personal loans.

Import Libraries

In [134…

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

from scipy.stats import ttest_ind,chi2_contingency

from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split, KFold, cross_val_score
from sklearn.preprocessing import MinMaxScaler, LabelEncoder, StandardScaler
from sklearn.metrics import (
```

```
    accuracy_score, confusion_matrix, classification_report,
    roc_auc_score, roc_curve, auc, precision_recall_curve, average_precision_s
    ConfusionMatrixDisplay, RocCurveDisplay,f1_score,recall_score,precision_sc
)

from statsmodels.stats.outliers_influence import variance_inflation_factor
from imblearn.over_sampling import SMOTE

import warnings
warnings.filterwarnings("ignore")
```

In [135…

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

Exploratory Data Analysis

In [136…

```
df.head()
```

Out[136…

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

5 rows × 27 columns

In [137…

```
# Shape of Data
df.shape
```

Out[137…

```
(396030, 27)
```

In [138…

```
# Data TYpe
```

```python
df.dtypes
```

Out[138…

	0
loan_amnt	float64
term	object
int_rate	float64
installment	float64
grade	object
sub_grade	object
emp_title	object
emp_length	object
home_ownership	object
annual_inc	float64
verification_status	object
issue_d	object
loan_status	object
purpose	object
title	object
dti	float64
earliest_cr_line	object
open_acc	float64
pub_rec	float64
revol_bal	float64
revol_util	float64
total_acc	float64
initial_list_status	object
application_type	object
mort_acc	float64
pub_rec_bankruptcies	float64
address	object

dtype: object

In [139…

```python
df.columns
```

Out[139…

```
Index(['loan_amnt', 'term', 'int_rate', 'installment', 'grade', 'sub_grade',
       'emp_title', 'emp_length', 'home_ownership', 'annual_inc',
       'verification_status', 'issue_d', 'loan_status', 'purpose', 'title',
       'dti', 'earliest_cr_line', 'open_acc', 'pub_rec', 'revol_bal',
       'revol_util', 'total_acc', 'initial_list_status', 'application_type',
       'mort_acc', 'pub_rec_bankruptcies', 'address'],
      dtype='object')
```

In [140…

```
df.nunique()
```

Out[140…

	0
loan_amnt	1397
term	2
int_rate	566
installment	55706
grade	7
sub_grade	35
emp_title	173105
emp_length	11
home_ownership	6
annual_inc	27197
verification_status	3
issue_d	115
loan_status	2
purpose	14
title	48816
dti	4262
earliest_cr_line	684
open_acc	61
pub_rec	20
revol_bal	55622
revol_util	1226
total_acc	118
initial_list_status	2
application_type	3
mort_acc	33
pub_rec_bankruptcies	9
address	393700

dtype: int64

In [141…

```
df.emp_length.unique()
```

Out[141…
```
array(['10+ years', '4 years', '< 1 year', '6 years', '9 years',
       '2 years', '3 years', '8 years', '7 years', '5 years', '1 year',
       nan], dtype=object)
```

In [142…
```
# convert term column to category and remove months character from it
df['term'] = df['term'].str.replace(' months', '')
df['term'] = df['term'].astype('category')
```

In [142…
```

```

In [143…
```
# Convert grade to category
df['grade'] = df['grade'].astype('category')
# Convert Subgrade to category
df['sub_grade'] = df['sub_grade'].astype('category')
# Cpmvert home_ownership to category
df['home_ownership'] = df['home_ownership'].astype('category')
# Convert verification_status to category
df['verification_status'] = df['verification_status'].astype('category')
# Convert loan_status to category
df['loan_status'] = df['loan_status'].astype('category')
# Convert purpose to category
df['purpose'] = df['purpose'].astype('category')
# Convert initial_list_status to category
df['initial_list_status'] = df['initial_list_status'].astype('category')
# convert application type to category
df['application_type'] = df['application_type'].astype('category')
```

In [144…
```
# Missing value detection
df.isnull().sum()
```

Out[144…

	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

In [145…

```
# Statistical summary
df.describe().T
```

Out[145…

	count	mean	std	min	25%
loan_amnt	396030.0	14113.888089	8357.441341	500.00	8000.00
int_rate	396030.0	13.639400	4.472157	5.32	10.49
installment	396030.0	431.849698	250.727790	16.08	250.33
annual_inc	396030.0	74203.175798	61637.621158	0.00	45000.00
dti	396030.0	17.379514	18.019092	0.00	11.28
open_acc	396030.0	11.311153	5.137649	0.00	8.00
pub_rec	396030.0	0.178191	0.530671	0.00	0.00
revol_bal	396030.0	15844.539853	20591.836109	0.00	6025.00
revol_util	395754.0	53.791749	24.452193	0.00	35.80
total_acc	396030.0	25.414744	11.886991	2.00	17.00
mort_acc	358235.0	1.813991	2.147930	0.00	0.00
pub_rec_bankruptcies	395495.0	0.121648	0.356174	0.00	0.00

In [146…

```
# Statistical summary of categorical data
df.describe(include='object').T
```

Out[146…

	count	unique	top	freq
emp_title	373103	173105	Teacher	4389
emp_length	377729	11	10+ years	126041
issue_d	396030	115	Oct-2014	14846
title	394274	48816	Debt consolidation	152472
earliest_cr_line	396030	684	Oct-2000	3017
address	396030	393700	USS Johnson\r\nFPO AE 48052	8

Univariate Analysis

In [147…

```
# univariate Analysis of categorical features
df.select_dtypes(include='object').describe().T
#
```

Out[147…

	count	unique	top	freq
emp_title	373103	173105	Teacher	4389
emp_length	377729	11	10+ years	126041
issue_d	396030	115	Oct-2014	14846
title	394274	48816	Debt consolidation	152472
earliest_cr_line	396030	684	Oct-2000	3017
address	396030	393700	USS Johnson\r\nFPO AE 48052	8

Duplicate Detection

In [148…
```
df[df.duplicated()]
```

Out[148…

loan_amnt	term	int_rate	installment	grade	sub_grade	emp_title	emp_leng

0 rows × 27 columns

Insights

- The dataset does not contain any duplicates.

Null Detection

In [149…
```
df.isna().any()[df.isna().any()]
```

Out[149…

	0
emp_title	True
emp_length	True
title	True
revol_util	True
mort_acc	True
pub_rec_bankruptcies	True

dtype: bool

In [150…
```
df.isna().sum().sort_values(ascending=False)
```

Out[150…

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

dtype: int64

In [151…

```
def missing_data(df):
    total_missing_df = df.isnull().sum().sort_values(ascending =False)
    percent_missing_df = (df.isnull().sum()/df.isna().count()*100).sort_values
```

```
    missing_data_df = pd.concat([total_missing_df, percent_missing_df], axis=1
    return missing_data_df

missing_pct = missing_data(df)
missing_pct[missing_pct['Total']>0]
```

Out[151…

	Total	Percent
mort_acc	37795	9.543469
emp_title	22927	5.789208
emp_length	18301	4.621115
title	1756	0.443401
pub_rec_bankruptcies	535	0.135091
revol_util	276	0.069692

Insight

1. emp_title has 5.78% missing values
2. emp_length has 4.62% missing values
3. title has 0.43% missing values
4. revol_until has 0.07% missing values
5. mort_acc has 9.56% missing values
6. pub_rec_bankruptcies has 0.13% missing values

> Action

> Following columns has missing values

- Since ML algorithm do not work on columns which has missing values so we need to impute these missing values.

In [152…

```
df.isna().sum().sum()
# since there are 67446 rows are null , we cant drop na ...
```

Out[152…

```
np.int64(81590)
```

In [153…

```
#checking the unique values for columns
for _ in df.columns:
    print()
    print(f'Total Unique Values in {_} column are :- {df[_].nunique()}')
    print(f'Unique Values in {_} column are :-\n {df[_].unique()}')
    print(f'Value_counts of {_} column :-\n {df[_].value_counts()}')
    print()
    print('-'*120)
```

```
Total Unique Values in loan_amnt column are :- 1397
Unique Values in loan_amnt column are :-
 [10000.  8000. 15600. ... 36275. 36475.   725.]
Value_counts of loan_amnt column :-
 loan_amnt
10000.0    27668
12000.0    21366
15000.0    19903
20000.0    18969
35000.0    14576
           ...
39200.0        1
38750.0        1
36275.0        1
36475.0        1
725.0          1
Name: count, Length: 1397, dtype: int64

--------------------------------------------------------------------------------
----------------------------------------

Total Unique Values in term column are :- 2
Unique Values in term column are :-
 [' 36', ' 60']
Categories (2, object): [' 36', ' 60']
Value_counts of term column :-
 term
36    302005
60     94025
Name: count, dtype: int64

--------------------------------------------------------------------------------
----------------------------------------

Total Unique Values in int_rate column are :- 566
Unique Values in int_rate column are :-
 [11.44 11.99 10.49  6.49 17.27 13.33  5.32 11.14 10.99 16.29 13.11 14.64
  9.17 12.29  6.62  8.39 21.98  7.9   6.97  6.99 15.61 11.36 13.35 12.12
  9.99  8.19 18.75  6.03 14.99 16.78 13.67 13.98 16.99 19.91 17.86 21.49
 12.99 18.54  7.89 17.1  18.25 11.67  6.24  8.18 12.35 14.16 17.56 18.55
 22.15 10.39 15.99 16.07 24.99  9.67 19.19 21.   12.69 10.74  6.68 19.22
 11.49 16.55 19.97 24.7  13.49 18.24 16.49 25.78 25.83 18.64  7.51 13.99
 15.22 15.31  7.69 19.53 10.16  7.62  9.75 13.68 15.88 14.65  6.92 23.83
 10.75 18.49 20.31 17.57 27.31 19.99 22.99 12.59 10.37 14.33 13.53 22.45
 24.5  17.99  9.16 12.49 11.55 17.76 28.99 23.1  20.49 22.7  10.15  6.89
 19.52  8.9  14.3   9.49 25.99 24.08 13.05 14.98 16.59 11.26 25.89 14.48
 21.99 23.99  5.99 14.47 11.53  8.67  8.59 10.64 23.28 25.44  9.71 16.2
 19.24 24.11 15.8  15.96 14.49 18.99  5.79 19.29 14.54 14.09  9.25 19.05
 17.77 18.92 20.75 10.65 18.85 10.59 12.85 11.39 13.65 13.06  7.12 20.99
 13.61 12.73 14.46 16.24 25.49  7.39 10.78 20.8   7.88 15.95 12.39 21.18
 21.97 15.77  6.39 10.   12.53 13.43  7.49 25.57 21.48 18.39 11.47  7.26
 15.68 19.04 14.31 24.24  5.42 23.43 19.47  6.54 23.32 17.58 14.72  7.66
  9.76 13.23 13.48 12.42  9.8  11.71 14.27 21.15 22.95  8.49 17.74 15.59
 13.72  9.45  7.29 15.1  11.86 19.72 14.35 11.22 15.62 15.81 12.41 28.67
```

```
 11.48 13.66  9.91 23.76 17.14 18.84 12.23  6.17  8.94 14.22 19.03 25.29
  8.99  9.88 15.58 27.49  8.07 22.47 19.2  13.44 22.4  12.79 18.2  13.18
  7.24 14.84  5.93 15.28 13.85 25.28  8.    9.62 12.05 15.7  20.2  13.57
 21.67  7.4  25.8  12.68 11.83  7.37 11.11 14.85 16.   11.12 23.63  6.
  7.99  7.91 14.83 21.7  26.06 16.77 27.34 12.21  7.68 15.27 19.69  9.63
  7.14 20.5  16.02 12.84  7.74 15.33 19.79 22.2  18.62 17.49 16.89 15.21
 14.79 18.67  9.32 15.41 15.65 23.5  22.9  11.34 22.11 19.48 14.75 28.14
 13.22 23.4  23.13 28.18 12.88 22.06 24.49 16.45 21.6  28.49  8.38  6.76
 10.83 13.79  8.88 17.88 17.97 14.26  6.91 13.47  8.6  27.88  8.63 10.25
 14.91 12.74 10.96 25.88  7.43 16.4  20.25 24.89 12.87 20.16 14.17 12.18
 17.51 13.92 20.53 26.77 10.62 26.49 16.32 12.61 21.36 14.61 15.37 20.3
 14.59 16.7  19.89 10.95 18.17 18.21 17.93 22.39 24.83 13.8  19.42 23.7
  7.59 13.17 18.09 13.04 25.69  9.07 15.23 14.42 23.33 16.69 10.36 14.96
 10.38 26.24 24.2  12.98 20.85 13.36 26.57 23.52 22.78 13.16 15.13 25.11
 13.55 10.51 11.78  7.05 11.46 21.28 12.09 16.35  8.7  26.99 14.11 26.14
 16.82 23.26 18.79 10.28 19.36 18.3  17.06 17.19  7.75 17.34 20.89 22.35
 19.66 13.62 22.74 11.89 23.59  8.24 20.62 11.97 15.2  20.48 12.36 10.71
 25.09 20.11 27.79 29.49 11.58 19.13 11.66 13.75 30.74  9.38 27.99 11.59
  9.64 25.65  9.96 19.41 14.18 10.08 17.43 24.74 14.74 17.04 15.57 30.49
 17.8  10.91 14.82 29.96 12.92 12.22 15.45 11.72 10.2  14.7  20.69 15.05
 24.33 14.93 10.33 16.95 28.88 11.03 28.34 21.22 18.07  9.33 12.17 19.74
 20.9  20.03 17.39 29.67 12.04 23.22 10.01 22.48 24.76 13.3  20.77 10.14
 14.5  30.94  8.32 13.24 21.59 21.27 24.52 11.54 10.46 13.87 30.99  9.51
  9.83 19.39 12.86 30.79 21.74 11.09 16.11 17.26 22.85 18.91 18.43  9.2
 21.14 12.62 21.21 29.99 14.88 13.12 30.89 16.08 12.54 28.69 12.8  11.28
 23.91 22.94 19.16 20.86 11.63 19.82 11.41 21.82 12.72 20.4   9.7  18.72
 18.36 14.25 13.84 18.78 17.15 15.25 16.63 16.15 11.91 14.07  9.01 15.01
 21.64 15.83 18.53  7.42 12.67 15.76 16.33 30.84 13.93 14.12 14.28 20.17
 24.59 20.52 17.03 17.9  14.67 15.38 17.46 14.62 14.38 24.4  22.64 17.54
 17.44 15.07]
Value_counts of int_rate column :-
 int_rate
10.99    12411
12.99     9632
15.61     9350
11.99     8582
8.90      8019
         ...
14.38        1
24.40        1
22.64        1
17.54        1
17.44        1
Name: count, Length: 566, dtype: int64

--------------------------------------------------------------------------------
-----------------------------------------

Total Unique Values in installment column are :- 55706
Unique Values in installment column are :-
 [329.48 265.68 506.97 ... 343.14 118.13 572.44]
Value_counts of installment column :-
 installment
327.34     968
```

```
332.10     791
491.01     736
336.90     686
392.81     683
          ...
1146.14      1
218.49       1
961.66       1
569.10       1
555.96       1
Name: count, Length: 55706, dtype: int64

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-----------------------------------------

Total Unique Values in grade column are :- 7
Unique Values in grade column are :-
 ['B', 'A', 'C', 'E', 'D', 'F', 'G']
Categories (7, object): ['A', 'B', 'C', 'D', 'E', 'F', 'G']
Value_counts of grade column :-
 grade
B    116018
C    105987
A     64187
D     63524
E     31488
F     11772
G      3054
Name: count, dtype: int64

--------------------------------------------------------------------------------
-----------------------------------------

Total Unique Values in sub_grade column are :- 35
Unique Values in sub_grade column are :-
 ['B4', 'B5', 'B3', 'A2', 'C5', ..., 'F3', 'G5', 'G4', 'F2', 'G3']
Length: 35
Categories (35, object): ['A1', 'A2', 'A3', 'A4', ..., 'G2', 'G3', 'G4', 'G5']
Value_counts of sub_grade column :-
 sub_grade
B3    26655
B4    25601
C1    23662
C2    22580
B2    22495
B5    22085
C3    21221
C4    20280
B1    19182
A5    18526
C5    18244
D1    15993
A4    15789
D2    13951
```

```
D3    12223
D4    11657
A3    10576
A1     9729
D5     9700
A2     9567
E1     7917
E2     7431
E3     6207
E4     5361
E5     4572
F1     3536
F2     2766
F3     2286
F4     1787
F5     1397
G1     1058
G2      754
G3      552
G4      374
G5      316
Name: count, dtype: int64

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Total Unique Values in emp_title column are :- 173105
Unique Values in emp_title column are :-
 ['Marketing' 'Credit analyst ' 'Statistician' ...
 "Michael's Arts & Crafts" 'licensed bankere' 'Gracon Services, Inc']
Value_counts of emp_title column :-
 emp_title
Teacher                      4389
Manager                      4250
Registered Nurse             1856
RN                           1846
Supervisor                   1830
                             ...
OMIV Supervisor                 1
SVP, Technology                 1
sikorsky                        1
Postman                         1
Sr. Facilities Caretaker        1
Name: count, Length: 173105, dtype: int64

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Total Unique Values in emp_length column are :- 11
Unique Values in emp_length column are :-
 ['10+ years' '4 years' '< 1 year' '6 years' '9 years' '2 years' '3 years'
 '8 years' '7 years' '5 years' '1 year' nan]
Value_counts of emp_length column :-
 emp_length
```

```
10+ years    126041
2 years       35827
< 1 year      31725
3 years       31665
5 years       26495
1 year        25882
4 years       23952
6 years       20841
7 years       20819
8 years       19168
9 years       15314
Name: count, dtype: int64

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Total Unique Values in home_ownership column are :- 6
Unique Values in home_ownership column are :-
 ['RENT', 'MORTGAGE', 'OWN', 'OTHER', 'NONE', 'ANY']
Categories (6, object): ['ANY', 'MORTGAGE', 'NONE', 'OTHER', 'OWN', 'RENT']
Value_counts of home_ownership column :-
 home_ownership
MORTGAGE    198348
RENT        159790
OWN          37746
OTHER          112
NONE            31
ANY              3
Name: count, dtype: int64

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Total Unique Values in annual_inc column are :- 27197
Unique Values in annual_inc column are :-
 [117000.    65000.    43057.   ...  36111.    47212.    31789.88]
Value_counts of annual_inc column :-
 annual_inc
60000.0    15313
50000.0    13303
65000.0    11333
70000.0    10674
40000.0    10629
           ...
67842.0        1
72179.0        1
50416.0        1
46820.8        1
87622.0        1
Name: count, Length: 27197, dtype: int64

--------------------------------------------------------------------------------
-----------------------------------------
```

```
Total Unique Values in verification_status column are :- 3
Unique Values in verification_status column are :-
 ['Not Verified', 'Source Verified', 'Verified']
Categories (3, object): ['Not Verified', 'Source Verified', 'Verified']
Value_counts of verification_status column :-
 verification_status
Verified           139563
Source Verified    131385
Not Verified       125082
Name: count, dtype: int64

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Total Unique Values in issue_d column are :- 115
Unique Values in issue_d column are :-
 ['Jan-2015' 'Nov-2014' 'Apr-2013' 'Sep-2015' 'Sep-2012' 'Oct-2014'
 'Apr-2012' 'Jun-2013' 'May-2014' 'Dec-2015' 'Apr-2015' 'Oct-2012'
 'Jul-2014' 'Feb-2013' 'Oct-2015' 'Jan-2014' 'Mar-2016' 'Apr-2014'
 'Jun-2011' 'Apr-2010' 'Jun-2014' 'Oct-2013' 'May-2013' 'Feb-2015'
 'Oct-2011' 'Jun-2015' 'Aug-2013' 'Feb-2014' 'Dec-2011' 'Mar-2013'
 'Jun-2016' 'Mar-2014' 'Nov-2013' 'Dec-2014' 'Apr-2016' 'Sep-2013'
 'May-2016' 'Jul-2015' 'Jul-2013' 'Aug-2014' 'May-2008' 'Mar-2010'
 'Dec-2013' 'Mar-2012' 'Mar-2015' 'Sep-2011' 'Jul-2012' 'Dec-2012'
 'Sep-2014' 'Nov-2012' 'Nov-2015' 'Jan-2011' 'May-2012' 'Feb-2016'
 'Jun-2012' 'Aug-2012' 'Jan-2016' 'May-2015' 'Oct-2016' 'Aug-2015'
 'Jul-2016' 'May-2009' 'Aug-2016' 'Jan-2012' 'Jan-2013' 'Nov-2010'
 'Jul-2011' 'Mar-2011' 'Feb-2012' 'May-2011' 'Aug-2010' 'Nov-2016'
 'Jul-2010' 'Sep-2010' 'Dec-2010' 'Feb-2011' 'Jun-2009' 'Aug-2011'
 'Dec-2016' 'Mar-2009' 'Jun-2010' 'May-2010' 'Nov-2011' 'Sep-2016'
 'Oct-2009' 'Mar-2008' 'Nov-2008' 'Dec-2009' 'Oct-2010' 'Sep-2009'
 'Oct-2007' 'Aug-2009' 'Jul-2009' 'Nov-2009' 'Jan-2010' 'Dec-2008'
 'Feb-2009' 'Oct-2008' 'Apr-2009' 'Feb-2010' 'Apr-2011' 'Apr-2008'
 'Aug-2008' 'Jan-2009' 'Feb-2008' 'Aug-2007' 'Sep-2008' 'Dec-2007'
 'Jan-2008' 'Sep-2007' 'Jun-2008' 'Jul-2008' 'Jun-2007' 'Nov-2007'
 'Jul-2007']
Value_counts of issue_d column :-
 issue_d
Oct-2014    14846
Jul-2014    12609
Jan-2015    11705
Dec-2013    10618
Nov-2013    10496
            ...
Aug-2007       26
Sep-2008       25
Nov-2007       22
Sep-2007       15
Jun-2007        1
Name: count, Length: 115, dtype: int64

--------------------------------------------------------------------------------
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```

```
Total Unique Values in loan_status column are :- 2
Unique Values in loan_status column are :-
 ['Fully Paid', 'Charged Off']
Categories (2, object): ['Charged Off', 'Fully Paid']
Value_counts of loan_status column :-
 loan_status
Fully Paid     318357
Charged Off     77673
Name: count, dtype: int64

--------------------------------------------------------------------------------
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Total Unique Values in purpose column are :- 14
Unique Values in purpose column are :-
 ['vacation', 'debt_consolidation', 'credit_card', 'home_improvement', 'small_b
usiness', ..., 'car', 'moving', 'house', 'educational', 'renewable_energy']
Length: 14
Categories (14, object): ['car', 'credit_card', 'debt_consolidation', 'educatio
nal', ...,
                          'renewable_energy', 'small_business', 'vacation', 'we
dding']
Value_counts of purpose column :-
 purpose
debt_consolidation    234507
credit_card            83019
home_improvement       24030
other                  21185
major_purchase          8790
small_business          5701
car                     4697
medical                 4196
moving                  2854
vacation                2452
house                   2201
wedding                 1812
renewable_energy         329
educational              257
Name: count, dtype: int64

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Total Unique Values in title column are :- 48816
Unique Values in title column are :-
 ['Vacation' 'Debt consolidation' 'Credit card refinancing' ...
 'Credit buster ' 'Loanforpayoff' 'Toxic Debt Payoff']
Value_counts of title column :-
 title
Debt consolidation         152472
Credit card refinancing     51487
Home improvement            15264
Other                       12930
Debt Consolidation          11608
```

```
                            ...
creditcardrefi                  1
Debt/Home                       1
Peace Of Mind Loan              1
Blazer repair                   1
Out of my rut                   1
Name: count, Length: 48816, dtype: int64

--------------------------------------------------------------------------------
-----------------------------------------

Total Unique Values in dti column are :- 4262
Unique Values in dti column are :-
 [26.24 22.05 12.79 ... 40.56 47.09 55.53]
Value_counts of dti column :-
 dti
0.00       313
14.40      310
19.20      302
16.80      301
18.00      300
          ...
47.05        1
46.52        1
1622.00      1
40.21        1
189.90       1
Name: count, Length: 4262, dtype: int64

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Total Unique Values in earliest_cr_line column are :- 684
Unique Values in earliest_cr_line column are :-
 ['Jun-1990' 'Jul-2004' 'Aug-2007' 'Sep-2006' 'Mar-1999' 'Jan-2005'
 'Aug-2005' 'Sep-1994' 'Jun-1994' 'Dec-1997' 'Dec-1990' 'May-1984'
 'Apr-1995' 'Jan-1997' 'May-2001' 'Mar-1982' 'Sep-1996' 'Jan-1990'
 'Mar-2000' 'Jan-2006' 'Oct-2006' 'Jan-2003' 'May-2008' 'Oct-2003'
 'Jun-2004' 'Jan-1999' 'Apr-1994' 'Apr-1998' 'Jul-2007' 'Apr-2002'
 'Oct-2007' 'Jun-2009' 'May-1997' 'Jul-2006' 'Sep-2003' 'Aug-1992'
 'Dec-1988' 'Feb-2002' 'Jan-1992' 'Aug-2001' 'Dec-2010' 'Oct-1999'
 'Sep-2004' 'Aug-1994' 'Jul-2003' 'Apr-2000' 'Dec-2004' 'Jun-1995'
 'Dec-2003' 'Jul-1994' 'Oct-1990' 'Dec-2001' 'Apr-1999' 'Feb-1995'
 'May-2003' 'Oct-2002' 'Mar-2004' 'Aug-2003' 'Oct-2000' 'Nov-2004'
 'Mar-2010' 'Mar-1996' 'May-1994' 'Jun-1996' 'Nov-1986' 'Jan-2001'
 'Jan-2002' 'Mar-2001' 'Sep-2012' 'Apr-2006' 'May-1998' 'Dec-2002'
 'Nov-2003' 'Oct-2005' 'May-1990' 'Jun-2003' 'Jun-2001' 'Jan-1998'
 'Oct-1978' 'Feb-2001' 'Jun-2006' 'Aug-1993' 'Apr-2001' 'Nov-2001'
 'Feb-2003' 'Jun-1993' 'Sep-1992' 'Nov-1992' 'Jun-1983' 'Oct-2001'
 'Jul-1999' 'Sep-1997' 'Nov-1993' 'Feb-1993' 'Apr-2007' 'Nov-1999'
 'Nov-2005' 'Dec-1992' 'Mar-1986' 'May-1989' 'Dec-2000' 'Mar-1991'
 'Mar-2005' 'Jun-2010' 'Dec-1998' 'Sep-2001' 'Nov-2000' 'Jan-1994'
 'Aug-2002' 'Jan-2011' 'Aug-2008' 'Jun-2005' 'Nov-1997' 'May-1996'
 'Apr-2010' 'May-1993' 'Sep-2005' 'Jun-1992' 'Apr-1986' 'Aug-1996'
```

```
'Aug-1997' 'Jul-2005' 'May-2011' 'Sep-2002' 'Jan-1989' 'Aug-1999'
'Feb-1992' 'Sep-1999' 'Jul-2001' 'May-1980' 'Oct-2008' 'Nov-2007'
'Apr-1997' 'Jun-1986' 'Sep-1998' 'Jun-1982' 'Oct-1981' 'Feb-1994'
'Dec-1984' 'Nov-1991' 'Nov-2006' 'Aug-2000' 'Oct-2004' 'Jun-2011'
'Apr-1988' 'May-2004' 'Aug-1988' 'Mar-1994' 'Aug-2004' 'Dec-2006'
'Nov-1998' 'Oct-1997' 'Mar-1989' 'Feb-1988' 'Jul-1982' 'Nov-1995'
'Mar-1997' 'Oct-1994' 'Jul-1998' 'Jun-2002' 'May-1991' 'Oct-2011'
'Sep-2007' 'Jan-2007' 'Jan-2010' 'Mar-1987' 'Feb-1997' 'Oct-1986'
'Mar-2002' 'Jul-1993' 'Mar-2007' 'Aug-1989' 'Oct-1995' 'May-2007'
'Dec-1993' 'Jun-1989' 'Apr-2004' 'Jun-1997' 'Apr-1996' 'Apr-1992'
'Oct-1998' 'Mar-1983' 'Mar-1985' 'Oct-1993' 'Feb-2000' 'Apr-2003'
'Oct-1985' 'Jul-1985' 'May-1978' 'Sep-2010' 'Oct-1996' 'Sep-2009'
'Jun-1999' 'Jan-2000' 'Sep-1987' 'Aug-1998' 'Jan-1995' 'Jul-1988'
'May-2000' 'Jun-1981' 'Feb-1998' 'Nov-1996' 'Aug-1967' 'Dec-1999'
'Aug-2006' 'Nov-2009' 'Jul-2000' 'Mar-1988' 'Jul-1992' 'Jul-1991'
'Mar-1990' 'May-1986' 'Jun-1991' 'Dec-1987' 'Jul-1996' 'Jul-1997'
'Aug-1990' 'Jan-1988' 'Dec-2005' 'Mar-2003' 'Feb-1999' 'Nov-1990'
'Jun-2000' 'Dec-1996' 'Jan-2004' 'May-1999' 'Sep-1972' 'Jul-1981'
'Sep-1993' 'Feb-2009' 'Nov-2002' 'Nov-1969' 'Jan-1993' 'May-2005'
'Sep-1982' 'Apr-1990' 'Feb-1996' 'Mar-1993' 'Apr-1978' 'Jul-1995'
'May-1995' 'Apr-1991' 'Mar-1998' 'Aug-1991' 'Jul-2002' 'Oct-1989'
'Apr-1984' 'Dec-2009' 'Sep-2000' 'Jan-1982' 'Jun-1998' 'Jan-1996'
'Nov-1987' 'May-2010' 'Jul-1989' 'Jun-1987' 'Oct-1987' 'Aug-1995'
'Feb-2004' 'Oct-1991' 'Dec-1989' 'Oct-1992' 'Feb-2005' 'Apr-1993'
'Dec-1985' 'Sep-1979' 'Feb-2007' 'Nov-1989' 'Apr-2005' 'Mar-1978'
'Sep-1985' 'Nov-1994' 'Jun-2008' 'Apr-1987' 'Dec-1983' 'Dec-2007'
'May-1979' 'May-1992' 'Jul-1990' 'Mar-1995' 'Feb-2006' 'Feb-1985'
'Sep-1989' 'Aug-2009' 'Nov-2008' 'Nov-1981' 'Jan-2008' 'Aug-1987'
'Nov-1985' 'Dec-1965' 'Sep-1995' 'Jan-1986' 'Oct-2009' 'May-2002'
'Aug-1980' 'Sep-1977' 'Sep-1988' 'Oct-1984' 'May-1988' 'Aug-1984'
'Nov-1988' 'May-1974' 'Nov-1982' 'Oct-1983' 'Sep-1991' 'Feb-1984'
'Feb-1991' 'Jan-1981' 'Jun-1985' 'Dec-1976' 'Dec-1994' 'Dec-1980'
'Sep-1984' 'Jun-2007' 'Aug-1979' 'Sep-2008' 'Apr-1983' 'Mar-2006'
'Jun-1984' 'Jul-1984' 'Jan-1985' 'Dec-1995' 'Apr-2008' 'Mar-2008'
'Jan-1983' 'Dec-1986' 'Jun-1979' 'Dec-1975' 'Nov-1983' 'Jul-1986'
'Nov-1977' 'Dec-1982' 'May-1985' 'Feb-1983' 'Aug-1982' 'Oct-1980'
'Mar-1979' 'Jan-1978' 'Mar-1984' 'May-1983' 'Jul-2008' 'Apr-1982'
'Jul-1983' 'Feb-1990' 'Dec-2008' 'Jul-1975' 'Dec-1971' 'Feb-2008'
'Mar-2011' 'Feb-1987' 'Feb-1989' 'Aug-1985' 'Jul-2010' 'Apr-1989'
'Feb-1980' 'May-2006' 'Nov-2010' 'Apr-2009' 'Feb-2010' 'May-1976'
'Feb-1981' 'Jan-2012' 'Oct-1988' 'Nov-1984' 'May-1982' 'Oct-1975'
'Jun-1988' 'May-1972' 'Apr-2013' 'Sep-1990' 'Oct-1982' 'Feb-2013'
'Mar-1992' 'Aug-1981' 'Feb-2011' 'Nov-1974' 'Feb-1978' 'Sep-1983'
'Jul-2011' 'Nov-1979' 'Aug-1983' 'Apr-1985' 'Jul-2009' 'Jan-1971'
'Jul-1987' 'Aug-1978' 'Aug-2010' 'Oct-1976' 'Aug-1986' 'Jan-1991'
'Dec-1991' 'May-2009' 'Aug-2011' 'Jun-1964' 'Jan-1974' 'May-1981'
'Jun-1972' 'Jun-1978' 'Sep-1986' 'Jan-1987' 'Jan-1975' 'Feb-1982'
'Jan-1980' 'Feb-1977' 'Sep-1980' 'Nov-1978' 'Jul-1974' 'Jun-1970'
'Jan-1984' 'Nov-1980' 'May-1987' 'Sep-1970' 'Jan-1976' 'Feb-1986'
'Oct-2010' 'Apr-1979' 'Oct-1979' 'Jan-1979' 'Sep-2011' 'Jul-1979'
'Sep-1975' 'Mar-1981' 'Aug-1971' 'Apr-1980' 'Apr-1977' 'Jan-1965'
'Nov-1976' 'Nov-1970' 'Nov-2011' 'Nov-1973' 'Sep-1981' 'Jul-1980'
'Mar-2012' 'Dec-1974' 'Mar-1977' 'Dec-1977' 'May-2012' 'Dec-1979'
'Jan-2009' 'Jan-1970' 'Dec-2011' 'Feb-1979' 'Mar-1976' 'Jan-1973'
```

```
 'Oct-1973' 'Mar-1969' 'Oct-1977' 'Mar-1975' 'Aug-1977' 'Jun-1969'
 'Oct-1963' 'Nov-1960' 'Aug-1970' 'Feb-1975' 'Sep-1974' 'May-1966'
 'Apr-1972' 'Apr-1973' 'Apr-2012' 'May-1975' 'Sep-1966' 'Feb-1969'
 'Feb-2012' 'Jan-1961' 'Aug-1973' 'Feb-1972' 'Apr-1975' 'Jul-1978'
 'Oct-1970' 'Mar-1980' 'Sep-1976' 'Apr-2011' 'Nov-2012' 'Aug-1976'
 'Jun-1975' 'Apr-1981' 'Mar-2009' 'Jun-1977' 'Apr-1971' 'Sep-1969'
 'Jun-2012' 'Apr-1976' 'Feb-1965' 'Jul-1977' 'Jun-1976' 'Mar-1973'
 'Oct-1972' 'Dec-1978' 'Nov-1967' 'Sep-1967' 'Nov-1971' 'Jun-1980'
 'May-1964' 'Feb-1971' 'May-1970' 'Apr-1970' 'Mar-1971' 'Apr-1969'
 'Jan-1963' 'Jun-1974' 'Oct-1974' 'May-1977' 'Dec-1981' 'Jan-1969'
 'Feb-1976' 'Mar-1970' 'Aug-1968' 'Feb-1970' 'Jun-1971' 'Jun-1963'
 'Jun-2013' 'Mar-1972' 'Aug-2012' 'Jan-1967' 'Feb-1968' 'Dec-1969'
 'Jan-1977' 'Jul-1970' 'Feb-1973' 'Mar-1974' 'Feb-1974' 'Dec-1960'
 'Jul-1972' 'Jul-1973' 'Sep-1964' 'Jul-1965' 'Oct-1958' 'Jul-2012'
 'Jun-1973' 'Sep-1978' 'Nov-1975' 'Jul-1963' 'Jan-1964' 'Dec-1968'
 'May-1958' 'Sep-1973' 'May-1971' 'Dec-1972' 'Aug-1965' 'Jul-1976'
 'Oct-2012' 'May-1973' 'Apr-1955' 'Apr-1966' 'Jan-1968' 'Nov-1968'
 'Oct-1969' 'Mar-2013' 'Jan-2013' 'Jul-1967' 'Oct-1965' 'Jan-1966'
 'Aug-1972' 'Jul-1969' 'May-1965' 'Jan-1953' 'Aug-1974' 'May-1968'
 'Aug-1969' 'May-2013' 'Oct-1967' 'Aug-1975' 'Apr-1974' 'Sep-1971'
 'Apr-1968' 'Jul-1971' 'Jan-1972' 'Nov-1965' 'Dec-1970' 'Dec-1973'
 'Nov-1972' 'Oct-1959' 'Oct-1962' 'Apr-1967' 'Oct-1971' 'Nov-1963'
 'Oct-1968' 'Dec-1962' 'Jun-1960' 'Jan-1960' 'Sep-2013' 'May-1969'
 'Dec-1966' 'Feb-1967' 'Dec-1967' 'Aug-1961' 'Sep-1968' 'Oct-1964'
 'Aug-1966' 'Jul-1966' 'Apr-1964' 'Sep-1962' 'Jul-2013' 'Jun-1967'
 'Apr-1965' 'Jun-1966' 'Jan-1955' 'Jan-1962' 'Feb-1964' 'Aug-1958'
 'Jul-1968' 'May-1967' 'Dec-1959' 'Sep-1963' 'Dec-2012' 'Dec-1963'
 'Jan-1944' 'Jun-1965' 'May-1962' 'Mar-1967' 'Mar-1968' 'Jan-1956'
 'Sep-1965' 'Dec-1951' 'Aug-2013' 'Jun-1968' 'Mar-1965' 'Oct-1957'
 'Nov-1966' 'Dec-1958' 'Feb-1957' 'Feb-1963' 'Mar-1963' 'Jan-1959'
 'May-1955' 'Feb-1966' 'Nov-1950' 'Mar-1964' 'Jan-1958' 'Nov-1964'
 'Sep-1961' 'Apr-1963' 'Jul-1964' 'Nov-1955' 'Jun-1957' 'Dec-1964'
 'Nov-1953' 'Apr-1961' 'Mar-1966' 'Oct-1960' 'Jul-1959' 'Jul-1961'
 'Jan-1954' 'Dec-1956' 'Mar-1962' 'Jul-1960' 'Sep-1959' 'Dec-1950'
 'Oct-1966' 'Apr-1960' 'Jul-1958' 'Nov-1954' 'Nov-1957' 'Jun-1962'
 'May-1963' 'Jul-1955' 'Oct-1950' 'Dec-1961' 'Aug-1951' 'Oct-2013'
 'Aug-1964' 'Apr-1962' 'Jun-1955' 'Jul-1962' 'Jan-1957' 'Nov-1958'
 'Jul-1951' 'Nov-1959' 'Apr-1958' 'Mar-1960' 'Sep-1957' 'Nov-1961'
 'Sep-1960' 'May-1959' 'Jun-1959' 'Feb-1962' 'Sep-1956' 'Aug-1960'
 'Feb-1961' 'Jan-1948' 'Aug-1963' 'Oct-1961' 'Aug-1962' 'Aug-1959']
Value_counts of earliest_cr_line column :-
 earliest_cr_line
Oct-2000    3017
Aug-2000    2935
Oct-2001    2896
Aug-2001    2884
Nov-2000    2736
            ...
Feb-1957       1
Nov-1950       1
May-1955       1
Sep-1961       1
Nov-1955       1
Name: count, Length: 684, dtype: int64
```

```
--------------------------------------------------------------------------------
-----------------------------------------

Total Unique Values in open_acc column are :- 61
Unique Values in open_acc column are :-
 [16. 17. 13.  6.  8. 11.  5. 30.  9. 15. 12. 10. 18.  7.  4. 14. 20. 19.
 21. 23.  3. 26. 42. 22. 25. 28.  2. 34. 24. 27. 31. 32. 33.  1. 29. 36.
 40. 35. 37. 41. 44. 39. 49. 48. 38. 51. 50. 43. 46.  0. 47. 57. 53. 58.
 52. 54. 45. 90. 56. 55. 76.]
Value_counts of open_acc column :-
 open_acc
9.0     36779
10.0    35441
8.0     35137
11.0    32695
7.0     31328
        ...
56.0        2
55.0        2
57.0        1
58.0        1
90.0        1
Name: count, Length: 61, dtype: int64

--------------------------------------------------------------------------------
-----------------------------------------

Total Unique Values in pub_rec column are :- 20
Unique Values in pub_rec column are :-
 [ 0.  1.  2.  3.  4.  6.  5.  8.  9. 10. 11.  7. 19. 13. 40. 17. 86. 12.
 24. 15.]
Value_counts of pub_rec column :-
 pub_rec
0.0     338272
1.0      49739
2.0       5476
3.0       1521
4.0        527
5.0        237
6.0        122
7.0         56
8.0         34
9.0         12
10.0        11
11.0         8
13.0         4
12.0         4
19.0         2
40.0         1
17.0         1
86.0         1
24.0         1
15.0         1
```

```
Name: count, dtype: int64

-------------------------------------------------------------------------------
-----------------------------------------

Total Unique Values in revol_bal column are :- 55622
Unique Values in revol_bal column are :-
 [ 36369.  20131.  11987. ...  34531. 151912.  29244.]
Value_counts of revol_bal column :-
 revol_bal
0.0         2128
5655.0        41
7792.0        38
6095.0        38
3953.0        37
            ...
43895.0        1
46733.0        1
36519.0        1
212269.0       1
71547.0        1
Name: count, Length: 55622, dtype: int64

-------------------------------------------------------------------------------
-----------------------------------------

Total Unique Values in revol_util column are :- 1226
Unique Values in revol_util column are :-
 [ 41.8   53.3   92.2  ...  56.26 111.4  128.1 ]
Value_counts of revol_util column :-
 revol_util
0.00      2213
53.00      752
60.00      739
61.00      734
55.00      730
          ...
146.10       1
109.30       1
108.10       1
115.30       1
37.63        1
Name: count, Length: 1226, dtype: int64

-------------------------------------------------------------------------------
-----------------------------------------

Total Unique Values in total_acc column are :- 118
Unique Values in total_acc column are :-
 [ 25.  27.  26.  13.  43.  23.  15.  40.  37.  61.  35.  22.  20.  36.
  38.   7.  18.  10.  17.  29.  16.  21.  34.   9.  14.  59.  41.  19.
  12.  30.  56.  24.  28.   8.  52.  31.  44.  39.  50.  11.  62.  32.
   5.  33.  46.  42.   6.  49.  45.  57.  48.  67.  47.  51.  58.   3.
  55.  63.  53.   4.  71.  69.  54.  64.  81.  72.  60.  68.  65.  73.
```

```
  78.  84.   2.  76.  75.  79.  87.  77. 104.  89.  70. 105.  97.  66.
 108.  74.  80.  82.  91.  93. 106.  90.  85.  88.  83. 111.  86. 101.
 135.  92.  94.  95.  99. 102. 129. 110. 124. 151. 107. 118. 150. 115.
 117.  96.  98. 100. 116. 103.]
Value_counts of total_acc column :-
 total_acc
21.0     14280
22.0     14260
20.0     14228
23.0     13923
24.0     13878
         ...
150.0        1
117.0        1
115.0        1
100.0        1
103.0        1
Name: count, Length: 118, dtype: int64

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Total Unique Values in initial_list_status column are :- 2
Unique Values in initial_list_status column are :-
 ['w', 'f']
Categories (2, object): ['f', 'w']
Value_counts of initial_list_status column :-
 initial_list_status
f    238066
w    157964
Name: count, dtype: int64

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Total Unique Values in application_type column are :- 3
Unique Values in application_type column are :-
 ['INDIVIDUAL', 'JOINT', 'DIRECT_PAY']
Categories (3, object): ['DIRECT_PAY', 'INDIVIDUAL', 'JOINT']
Value_counts of application_type column :-
 application_type
INDIVIDUAL    395319
JOINT            425
DIRECT_PAY       286
Name: count, dtype: int64

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Total Unique Values in mort_acc column are :- 33
Unique Values in mort_acc column are :-
 [ 0.  3.  1.  4.  2.  6.  5. nan 10.  7. 12. 11.  8.  9. 13. 14. 22. 34.
 15. 25. 19. 16. 17. 32. 18. 24. 21. 20. 31. 28. 30. 23. 26. 27.]
Value_counts of mort_acc column :-
```

```
 mort_acc
0.0     139777
1.0      60416
2.0      49948
3.0      38049
4.0      27887
5.0      18194
6.0      11069
7.0       6052
8.0       3121
9.0       1656
10.0       865
11.0       479
12.0       264
13.0       146
14.0       107
15.0        61
16.0        37
17.0        22
18.0        18
19.0        15
20.0        13
24.0        10
22.0         7
21.0         4
25.0         4
27.0         3
26.0         2
32.0         2
31.0         2
23.0         2
34.0         1
28.0         1
30.0         1
Name: count, dtype: int64

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-----------------------------------------

Total Unique Values in pub_rec_bankruptcies column are :- 9
Unique Values in pub_rec_bankruptcies column are :-
 [ 0.  1.  2.  3. nan  4.  5.  6.  7.  8.]
Value_counts of pub_rec_bankruptcies column :-
 pub_rec_bankruptcies
0.0    350380
1.0     42790
2.0      1847
3.0       351
4.0        82
5.0        32
6.0         7
7.0         4
8.0         2
Name: count, dtype: int64
```

```
--------------------------------------------------------------------------------
-----------------------------------------

Total Unique Values in address column are :- 393700
Unique Values in address column are :-
 ['0174 Michelle Gateway\r\nMendozaberg, OK 22690'
 '1076 Carney Fort Apt. 347\r\nLoganmouth, SD 05113'
 '87025 Mark Dale Apt. 269\r\nNew Sabrina, WV 05113' ...
 '953 Matthew Points Suite 414\r\nReedfort, NY 70466'
 '7843 Blake Freeway Apt. 229\r\nNew Michael, FL 29597'
 '787 Michelle Causeway\r\nBriannaton, AR 48052']
Value_counts of address column :-
 address
USS Johnson\r\nFPO AE 48052                                  8
USNS Johnson\r\nFPO AE 05113                                 8
USS Smith\r\nFPO AP 70466                                    8
USCGC Smith\r\nFPO AE 70466                                  8
USNS Johnson\r\nFPO AP 48052                                 7
                                                            ..
8141 Cox Greens Suite 186\r\nMadisonstad, VT 05113           1
8803 Sean Highway Suite 029\r\nNorth Nicoleshire, AK 11650   1
594 Nicole Mission Apt. 620\r\nNew Patrick, NJ 00813         1
7336 Sean Groves Apt. 893\r\nDariusborough, NJ 05113         1
9160 Tucker Squares\r\nSouth Paul, MO 30723                  1
Name: count, Length: 393700, dtype: int64

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```

Null Treatment:

In [154…

```python
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
df.loc[df['emp_title'].isna(), 'emp_title'] = 'No Employee Title'
df.loc[df['title'].isna(), 'title'] = 'Unavailable'
df['emp_length'] = df['emp_length'].fillna('< 1 year')
df.loc[df['home_ownership'].isna(), 'home_ownership'] = 'ANY'
df.loc[df['annual_inc'].isna(), 'annual_inc'] = 0.0
df.loc[df['verification_status'].isna(), 'verification_status'] = 'Not Verifie
df.loc[df['issue_d'].isna(), 'issue_d'] = 'Oct-2014'
df.loc[df['loan_status'].isna(), 'loan_status'] = 'Fully Paid'
df.loc[df['purpose'].isna(), 'purpose'] = 'debt_consolidation'
df.loc[df['dti'].isna(), 'dti'] = 0.0
df.loc[df['earliest_cr_line'].isna(), 'earliest_cr_line'] = 'Oct-2000'
df.loc[df['address'].isna(), 'address'] = 'USCGC Miller\r\nFPO AE 22690'
df.loc[df['open_acc'].isna(), 'open_acc'] = 0.0
df.loc[df['pub_rec'].isna(), 'pub_rec'] = 0.0
df.loc[df['revol_bal'].isna(), 'revol_bal'] = 0.0
```

In [155…

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

Out[155…

	0
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

In [156…

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

Out[156…

	count	mean	std	min	25%
loan_amnt	396030.0	14113.888089	8357.441341	500.00	8000.00
int_rate	396030.0	13.639400	4.472157	5.32	10.49
installment	396030.0	431.849698	250.727790	16.08	250.33
annual_inc	396030.0	74203.175798	61637.621158	0.00	45000.00
dti	396030.0	17.379514	18.019092	0.00	11.28
open_acc	396030.0	11.311153	5.137649	0.00	8.00
pub_rec	396030.0	0.178191	0.530671	0.00	0.00
revol_bal	396030.0	15844.539853	20591.836109	0.00	6025.00
revol_util	396030.0	53.754260	24.484857	0.00	35.80
total_acc	396030.0	25.414744	11.886991	2.00	17.00
mort_acc	396030.0	1.640873	2.111249	0.00	0.00
pub_rec_bankruptcies	396030.0	0.121483	0.355962	0.00	0.00

In [157…

```
df.describe(include='object').T
```

Out[157…

	count	unique	top	freq
emp_title	396030	173106	No Employee Title	22927
emp_length	396030	11	10+ years	126041
issue_d	396030	115	Oct-2014	14846
title	396030	48817	Debt consolidation	152472
earliest_cr_line	396030	684	Oct-2000	3017
address	396030	393700	USS Johnson\r\nFPO AE 48052	8

Feature Engineering

In [158…

```
df['pub_rec'] = [1 if i > 1 else 0 for i in df['pub_rec']]
df['mort_acc'] = [1 if i > 1 else 0 for i in df['mort_acc']]
df['pub_rec_bankruptcies'] = [1 if i > 1 else 0 for i in df['pub_rec_bankrupto
```

In [159…

```
df.sample()
```

Out[159…

	loan_amnt	term	int_rate	installment	grade	sub_grade	emp_title	er
141742	9500.0	36	7.89	297.22	A	A5	manager	

1 rows × 27 columns

In [160…

```
#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)
```

In [161…

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

In [162…

```
df['address']
```

Out[162…

	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
...	...
396025	12951 Williams Crossing\r\nJohnnyville, DC 30723
396026	0114 Fowler Field Suite 028\r\nRachelborough, ...
396027	953 Matthew Points Suite 414\r\nReedfort, NY 7...
396028	7843 Blake Freeway Apt. 229\r\nNew Michael, FL...
396029	787 Michelle Causeway\r\nBriannaton, AR 48052

396030 rows × 1 columns

dtype: object

In [163…

```
#Split address into State and Zip code
import re
df[['state','zipcode']] = df['address'].str.extract(r'([A-Z]{2}) (\d{5})')
df.drop(['address'], axis=1, inplace=True)
```

In [164…
```
df['state'].nunique() , df['zipcode'].nunique()
```
Out[164… (54, 10)

In [165…
```
df['state'].isna().sum() , df['zipcode'].isna().sum()
```
Out[165… (np.int64(0), np.int64(0))

In [166…
```
df['emp_length_yrs'] = df['emp_length'].str.extract('(\d+)')
df.drop(['emp_length'], axis=1, inplace=True)
```
In [167…
```
df['term'] = df['term'].str.split().str[0].astype('object')
```
In [168…
```
df.sample()
```
Out[168…

	loan_amnt	term	int_rate	installment	grade	sub_grade	emp_title	h
190117	9000.0	36	15.61	314.69	C	C3	Letter Carrier	

1 rows × 30 columns

In [169…
```
df.shape
```
Out[169… (396030, 30)

In [170…
```
# List of categorical columns
cat_cols = df.select_dtypes(include='object')

# List of numerical columns
num_cols = df.select_dtypes(exclude=['object','category'])
```
In [171…
```
cat_cols.sample(3)
```
Out[171…

	term	emp_title	title	issue_month	issue_year	er_cr_line_m	e
37942	36	Director	Credit card refinancing	Jun	2014	May	
314273	36	Mechanical Assembler	Vacation	May	2015	Aug	
62001	60	Security Advisor Specialist	Debt consolidation	May	2015	Mar	

In [172…
```
num_cols.sample(3)
```

Out[172…

	loan_amnt	int_rate	installment	annual_inc	dti	open_acc	pub_rec
128931	5000.0	11.49	164.86	65000.0	7.16	11.0	0
172580	15000.0	11.99	498.15	57000.0	15.07	14.0	0
262512	5000.0	13.99	170.87	25000.0	9.03	11.0	0

In [173…

```
num_cols.skew()
```

Out[173…

	0
loan_amnt	0.777285
int_rate	0.420669
installment	0.983598
annual_inc	41.042725
dti	431.051225
open_acc	1.213019
pub_rec	6.812303
revol_bal	11.727515
revol_util	-0.074238
total_acc	0.864328
mort_acc	0.412225
pub_rec_bankruptcies	12.936099

dtype: float64

Insights

- Features are Right skewed

Action

- Need to apply log transformations in order to normalise them

---

In [174…

```
df1 = df.copy()
```

In [175…

```
df1.sample()
```

Out[175…

	loan_amnt	term	int_rate	installment	grade	sub_grade	emp_title	h
297535	10000.0	36	12.35	333.82	B	B4	Honda of Ocala	

1 rows × 30 columns

Q1. What percentage of customers have fully paid their Loan Amount?

In [176…

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

Out[176…

loan_status	proportion
Fully Paid	80.387092
Charged Off	19.612908

dtype: float64

Insights:

- Target variable distribution is 80%-20%. Data is `significantly imbalanced`

Graphical Analysis:

uni / bi / multi variate Analysis

In [177…

```
cp = ['indigo','m','darkviolet','magenta','mediumorchid','violet','purple','or
```

In [178…

```
num_cols.iloc[:,[0,2,3,4,5,6,8,9,10]].sample()
```

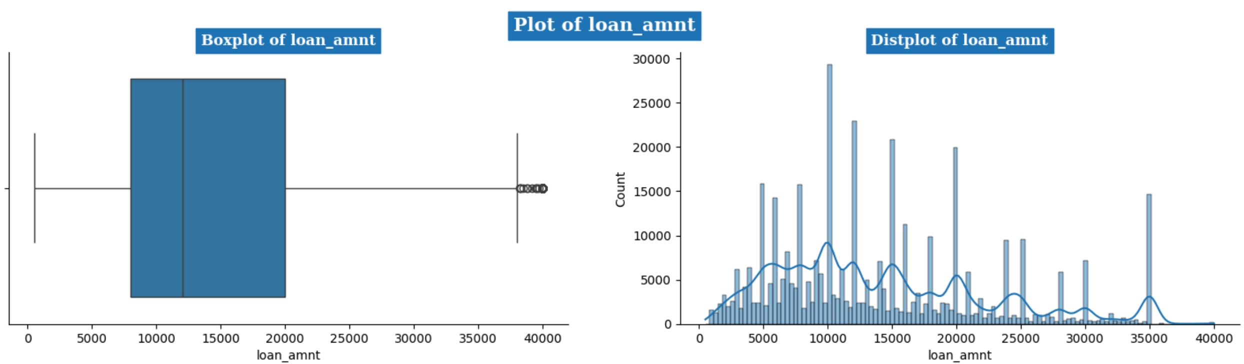
Out[178…

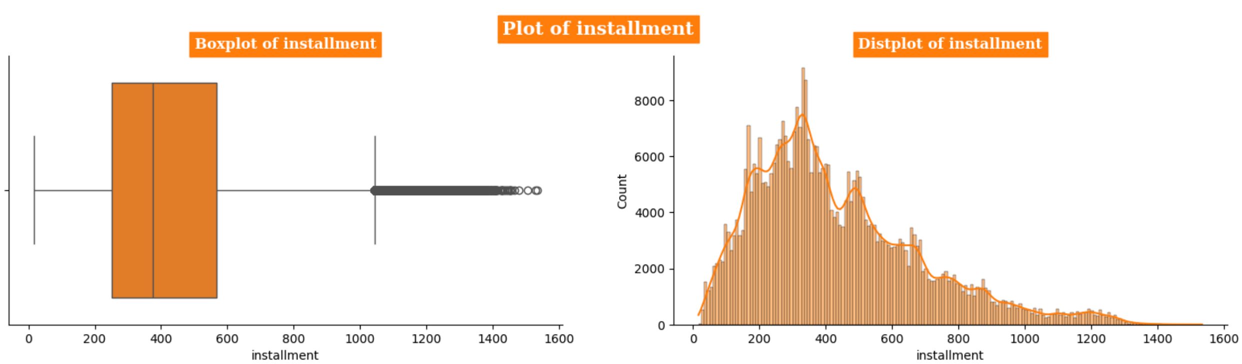
	loan_amnt	installment	annual_inc	dti	open_acc	pub_rec	revol_uti
159459	6400.0	221.39	86000.0	14.81	9.0	0	48.3

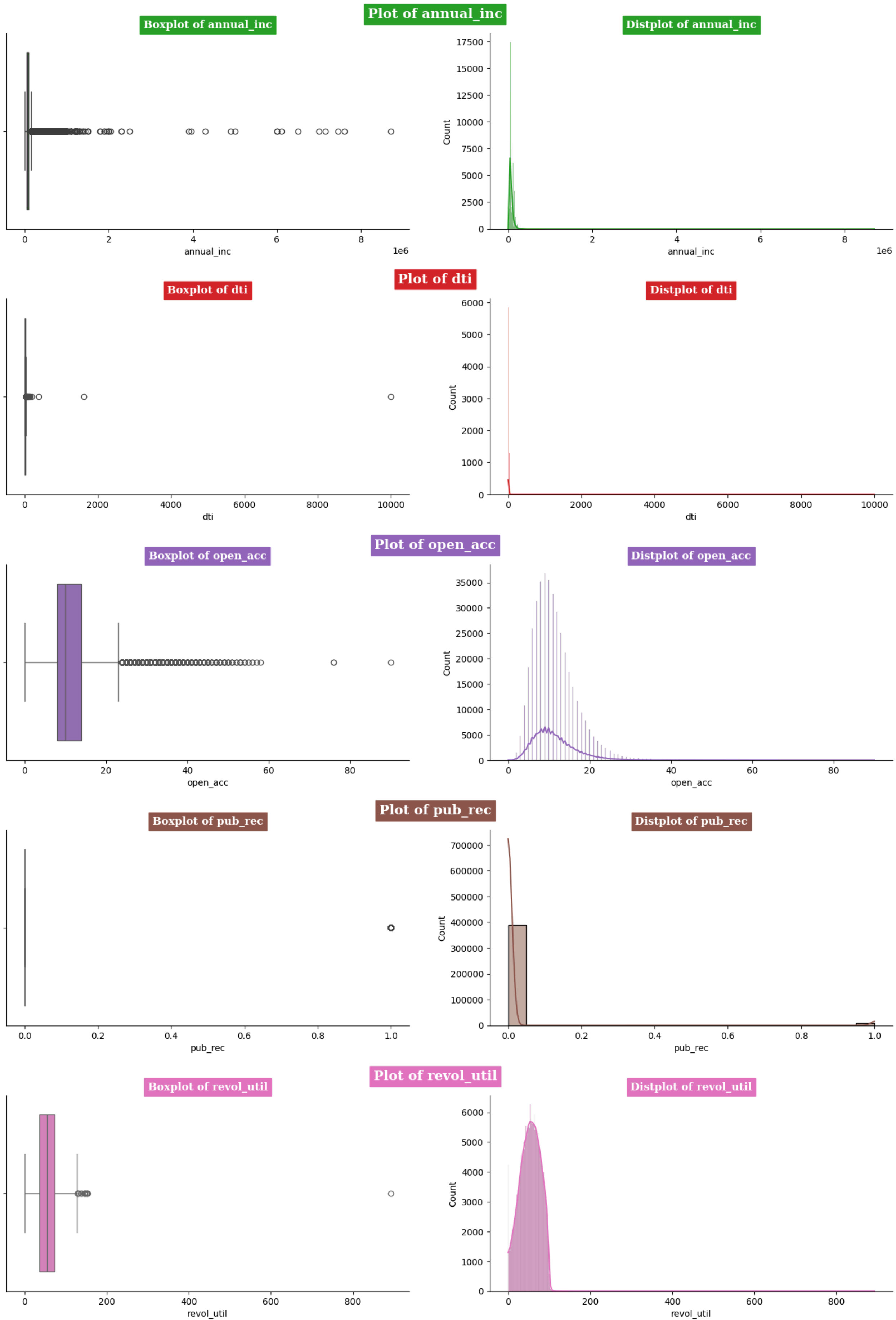
In [247…

```
import matplotlib.pyplot as plt
import seaborn as sns

# Define your own color palette
cp = ['#1f77b4', '#ff7f0e', '#2ca02c', '#d62728',
```

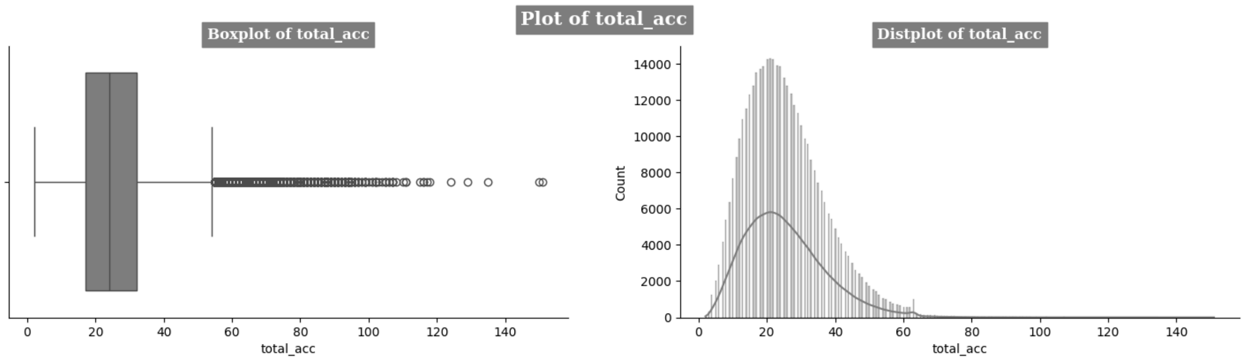
```
        '#9467bd', '#8c564b', '#e377c2', '#7f7f7f', '#bcbd22', '#17becf']

plt.style.use('default')
plt.style.use('seaborn-v0_8-bright')

outlier_graphical_cols = num_cols.iloc[:, [0,2,3,4,5,6,8,9,10]]

for i, col in enumerate(outlier_graphical_cols.columns):
    plt.figure(figsize=(18,4))
    plt.suptitle(f'Plot of {col}', fontsize=15, fontfamily='serif',
                 fontweight='bold', backgroundcolor=cp[i % len(cp)], color='w'

    plt.subplot(121)
    sns.boxplot(x=df[col], color=cp[i % len(cp)])
    plt.title(f'Boxplot of {col}', fontsize=12, fontfamily='serif',
              fontweight='bold', backgroundcolor=cp[i % len(cp)], color='w')

    plt.subplot(122)
    sns.histplot(x=df[col], kde=True, color=cp[i % len(cp)])
    plt.title(f'Distplot of {col}', fontsize=12, fontfamily='serif',
              fontweight='bold', backgroundcolor=cp[i % len(cp)], color='w')

    sns.despine()
    plt.show()
```

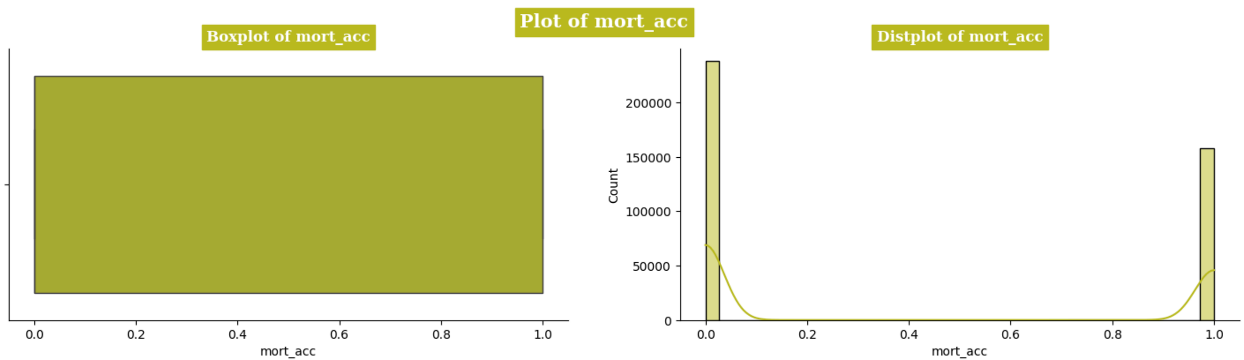






Plot of annual_inc
Boxplot of annual_inc
Distplot of annual_inc
annual_inc
1e6
Count
Plot of dti
Boxplot of dti
Distplot of dti
dti
Count
Plot of open_acc
Boxplot of open_acc
Distplot of open_acc
open_acc
Count
Plot of pub_rec
Boxplot of pub_rec
Distplot of pub_rec
pub_rec
Count
Plot of revol_util
Boxplot of revol_util
Distplot of revol_util
revol_util
Count





In [180…
```
print(plt.style.available)
```

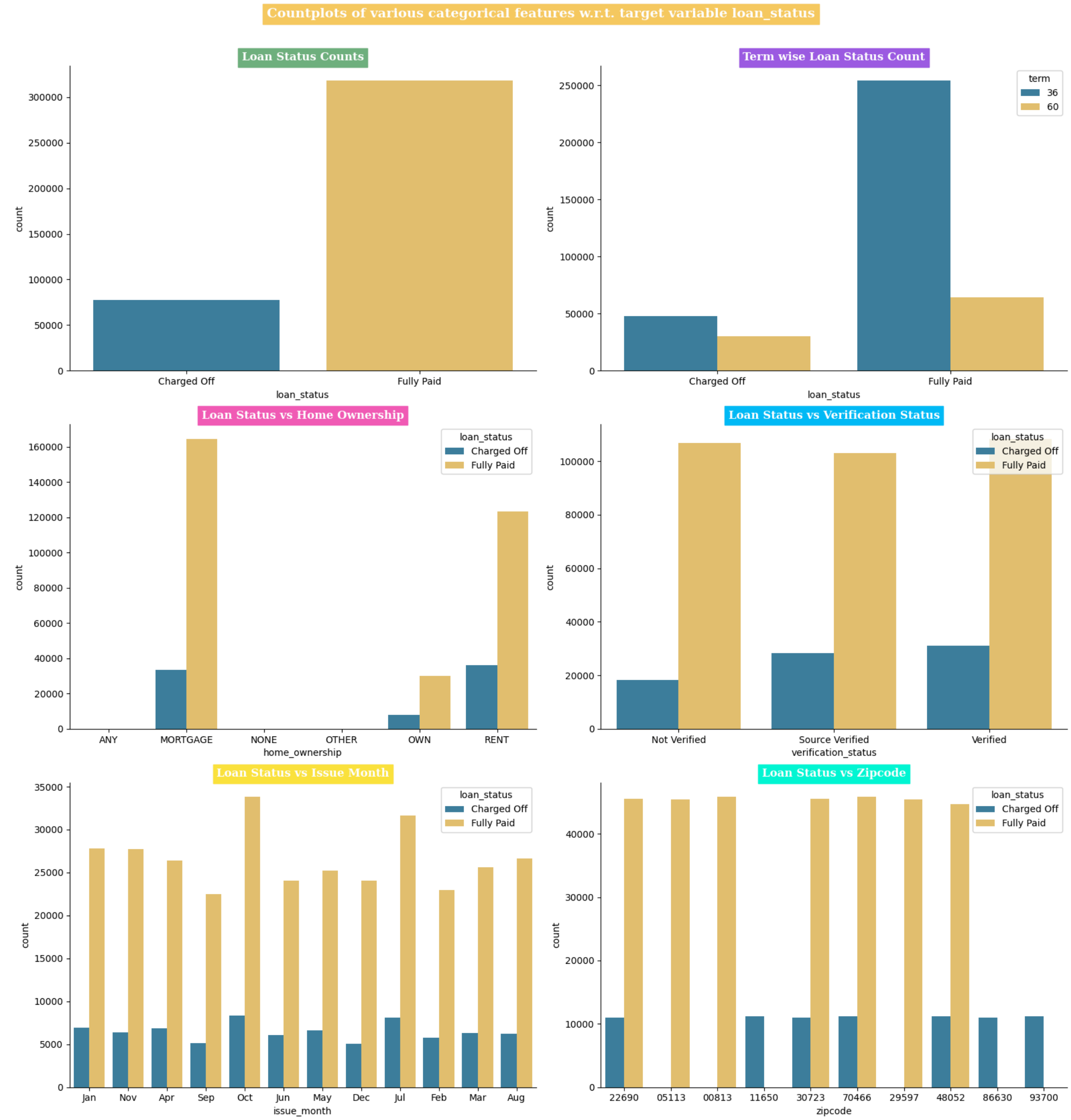
```
['Solarize_Light2', '_classic_test_patch', '_mpl-gallery', '_mpl-gallery-nogri
d', 'bmh', 'classic', 'dark_background', 'fast', 'fivethirtyeight', 'ggplot',
'grayscale', 'petroff10', 'seaborn-v0_8', 'seaborn-v0_8-bright', 'seaborn-v
0_8-colorblind', 'seaborn-v0_8-dark', 'seaborn-v0_8-dark-palette', 'seaborn-v
0_8-darkgrid', 'seaborn-v0_8-deep', 'seaborn-v0_8-muted', 'seaborn-v0_8-noteboo
k', 'seaborn-v0_8-paper', 'seaborn-v0_8-pastel', 'seaborn-v0_8-poster', 'seabor
n-v0_8-talk', 'seaborn-v0_8-ticks', 'seaborn-v0_8-white', 'seaborn-v0_8-whitegr
id', 'tableau-colorblind10']
```

Insights:

1. The analysis suggests a prevalence of outliers, prompting further investigation into outlier detection techniques.
2. Among the numerical features, Potential outliers may still be present.
3. Notably, features such as Pub_rec, Mort_acc, and Pub_rec_bankruptcies display a sparse distribution of unique values, indicating the potential benefit of generating binary features from these variables.

In [248…
```
# Define a bright, modern color palette
cp = ['#2E86AB', '#F6C85F', '#6FB07F', '#9B5DE5',
      '#F15BB5', '#00BBF9', '#FEE440', '#00F5D4']

plt.style.use('default')
plt.style.use('seaborn-v0_8-bright')

plt.figure(figsize=(16, 17))
plt.suptitle(
```

```
    'Countplots of various categorical features w.r.t. target variable loan_st
    fontsize=14, fontfamily='serif', fontweight='bold',
    backgroundcolor=cp[1], color='white'
)

# 1� Loan Status
plt.subplot(321)
sns.countplot(data=df, x='loan_status', palette=cp)
plt.title('Loan Status Counts', fontsize=12, fontfamily='serif',
          fontweight='bold', backgroundcolor=cp[2], color='white')

# 2� Term wise loan status
plt.subplot(322)
sns.countplot(data=df, x='loan_status', hue='term', palette=cp)
plt.title('Term wise Loan Status Count', fontsize=12, fontfamily='serif',
          fontweight='bold', backgroundcolor=cp[3], color='white')

# 3� Home Ownership
plt.subplot(323)
sns.countplot(data=df, x='home_ownership', hue='loan_status', palette=cp)
plt.title('Loan Status vs Home Ownership', fontsize=12, fontfamily='serif',
          fontweight='bold', backgroundcolor=cp[4], color='white')

# 4� Verification Status
plt.subplot(324)
sns.countplot(data=df, x='verification_status', hue='loan_status', palette=cp)
plt.title('Loan Status vs Verification Status', fontsize=12, fontfamily='serif
          fontweight='bold', backgroundcolor=cp[5], color='white')

# 5� Issue Month
plt.subplot(325)
sns.countplot(data=df, x='issue_month', hue='loan_status', palette=cp)
plt.title('Loan Status vs Issue Month', fontsize=12, fontfamily='serif',
          fontweight='bold', backgroundcolor=cp[6], color='white')

# 6� Zipcode
plt.subplot(326)
sns.countplot(data=df, x='zipcode', hue='loan_status', palette=cp)
plt.title('Loan Status vs Zipcode', fontsize=12, fontfamily='serif',
          fontweight='bold', backgroundcolor=cp[7], color='white')

sns.despine()
plt.tight_layout(rect=[0, 0, 1, 0.97])
plt.show()
```



In [182…

```
zip_codes = ["11650", "86630", "93700"]
states = df[df['zipcode'].isin(zip_codes)]['state']

for zip_code, state in zip(zip_codes, states):
    print(f"Zip code: {zip_code}, State: {state}")
```

```
Zip code: 11650, State: VA
Zip code: 86630, State: MI
Zip code: 93700, State: MD
```

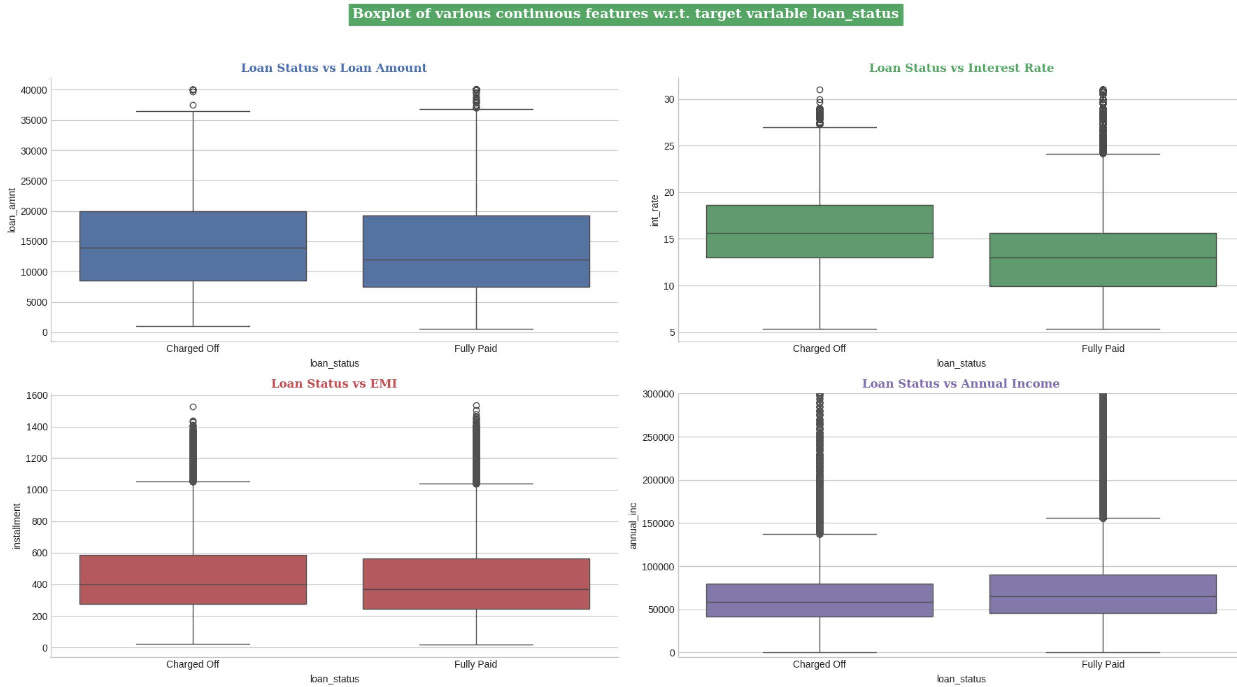
🔍Observations:

- It's been observed that loans haven't been completely repaid in zip codes 11650, 86630, and 93700.

- Loans haven't been repaid by borrowers residing in 'VA', 'MI', and 'MD'.

In [249…

```
#Boxplot of various cont. features w.r.t. target variable loan_status

cp = ['#4C72B0', '#55A868', '#C44E52', '#8172B2', '#CCB974', '#64B5CD']

plt.style.use('default')
plt.style.use('seaborn-v0_8-whitegrid')

plt.figure(figsize=(18,10))
plt.suptitle(
    'Boxplot of various continuous features w.r.t. target variable loan_status
    fontsize=14, fontfamily='serif', fontweight='bold',
    backgroundcolor=cp[1], color='white'
)

# 1◈ Loan amount
plt.subplot(221)
sns.boxplot(data=df, x='loan_status', y='loan_amnt', palette=[cp[0]])
plt.title('Loan Status vs Loan Amount', fontsize=12, fontfamily='serif',
          fontweight='bold', color=cp[0])

# 2◈ Interest rate
plt.subplot(222)
sns.boxplot(data=df, x='loan_status', y='int_rate', palette=[cp[1]])
plt.title('Loan Status vs Interest Rate', fontsize=12, fontfamily='serif',
          fontweight='bold', color=cp[1])

# 3◈ Installment
plt.subplot(223)
sns.boxplot(data=df, x='loan_status', y='installment', palette=[cp[2]])
plt.title('Loan Status vs EMI', fontsize=12, fontfamily='serif',
          fontweight='bold', color=cp[2])

# 4◈ Annual Income
plt.subplot(224)
sns.boxplot(data=df, x='loan_status', y='annual_inc', palette=[cp[3]])
plt.ylim(bottom=-5000, top=300000)
plt.title('Loan Status vs Annual Income', fontsize=12, fontfamily='serif',
          fontweight='bold', color=cp[3])

sns.despine()
plt.tight_layout(rect=[0, 0, 1, 0.95])
plt.show()
```



Observations:

- Charged Off customers exhibit a notably higher median interest rate compared to Fully Paid customers.
- The median annual income of Charged Off customers is lower than that of Fully Paid customers.
- Charged Off customers tend to have a higher median EMI compared to Fully Paid customers.
- The median loan amount for Charged Off customers surpasses that of Fully Paid customers.

In [184…

```
df.sample()
```

Out[184…

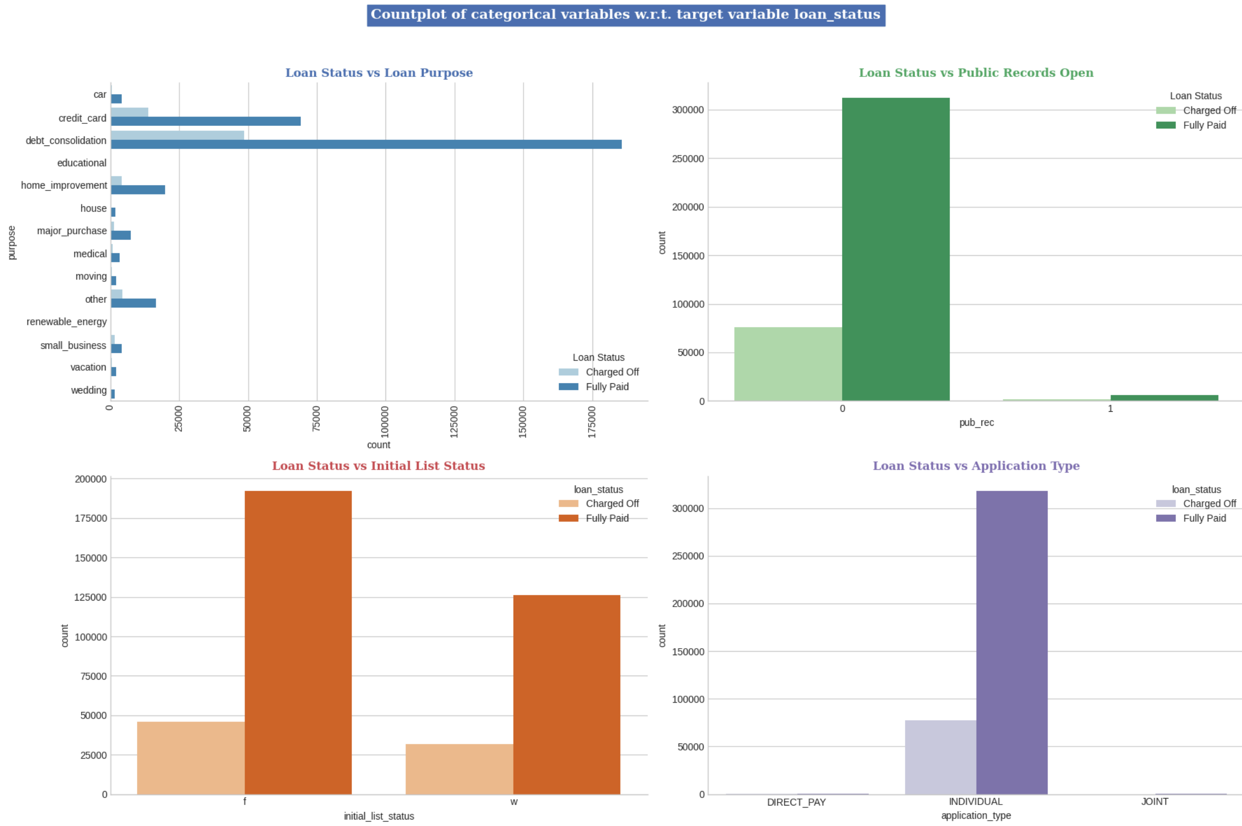
	loan_amnt	term	int_rate	installment	grade	sub_grade	emp_title	h
184308	35000.0	36	10.15	1131.82	B	B2	AGENT	

1 rows × 30 columns

In [250…

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

cp = ['#4C72B0', '#55A868', '#C44E52', '#8172B2', '#CCB974', '#64B5CD']

plt.style.use('default')
plt.style.use('seaborn-v0_8-whitegrid')

plt.figure(figsize=(18,12))
plt.suptitle(
```

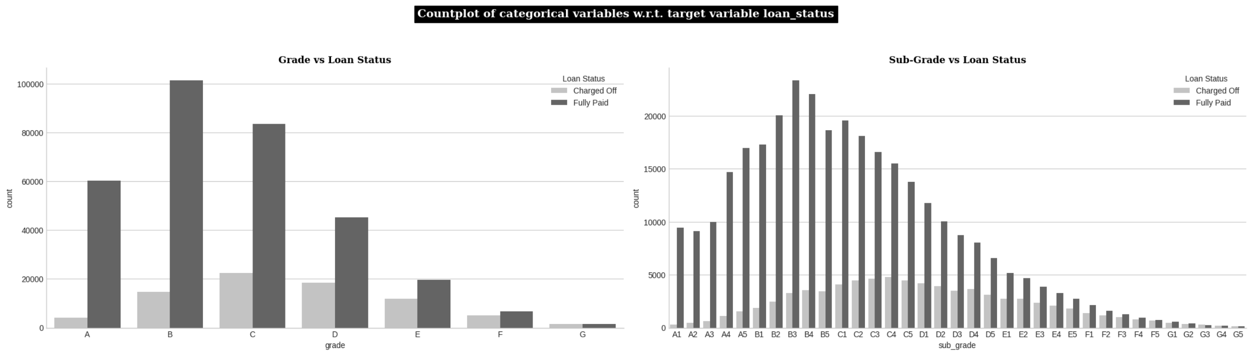
```
    'Countplot of categorical variables w.r.t. target variable loan_status',
    fontsize=14, fontfamily='serif', fontweight='bold',
    backgroundcolor=cp[0], color='white'
)

# 1️⃣ Purpose vs Loan Status
plt.subplot(221)
sns.countplot(data=df, y='purpose', hue='loan_status', palette='Blues')
plt.xticks(rotation=90)
plt.title('Loan Status vs Loan Purpose', fontsize=12, fontfamily='serif',
          fontweight='bold', color=cp[0])
plt.legend(title='Loan Status', loc='lower right')

# 2️⃣ Public Records vs Loan Status
plt.subplot(222)
sns.countplot(data=df, x='pub_rec', hue='loan_status', palette='Greens')
plt.title('Loan Status vs Public Records Open', fontsize=12, fontfamily='serif
          fontweight='bold', color=cp[1])
plt.legend(title='Loan Status', loc='upper right')

# 3️⃣ Initial List Status
plt.subplot(223)
sns.countplot(data=df, x='initial_list_status', hue='loan_status', palette='Or
plt.title('Loan Status vs Initial List Status', fontsize=12, fontfamily='serif
          fontweight='bold', color=cp[2])

# 4️⃣ Application Type
plt.subplot(224)
sns.countplot(data=df, x='application_type', hue='loan_status', palette='Purpl
plt.title('Loan Status vs Application Type', fontsize=12, fontfamily='serif',
          fontweight='bold', color=cp[3])

sns.despine()
plt.tight_layout(rect=[0, 0, 1, 0.95])
plt.show()
```



In [253…

```
plt.style.use('seaborn-v0_8-whitegrid')

# Black and white palette
cp = ['#000000', '#555555', '#AAAAAA', '#DDDDDD']

plt.figure(figsize=(22,11))
plt.suptitle(
    'Countplot of categorical variables w.r.t. target variable loan_status',
    fontsize=14, fontfamily='serif', fontweight='bold',
    backgroundcolor='black', color='white'
)

# 1� Grade vs Loan Status
plt.subplot(221)
grade = sorted(df.grade.unique().tolist())
sns.countplot(x='grade', data=df, hue='loan_status', order=grade, palette='Gre
plt.title('Grade vs Loan Status', fontsize=12, fontfamily='serif',
          fontweight='bold', color='black')
plt.legend(title='Loan Status', loc='upper right', facecolor='white', edgecolo

# 2� Sub-grade vs Loan Status
plt.subplot(222)
sub_grade = sorted(df.sub_grade.unique().tolist())
sns.countplot(x='sub_grade', data=df, hue='loan_status', order=sub_grade, pale
plt.title('Sub-Grade vs Loan Status', fontsize=12, fontfamily='serif',
          fontweight='bold', color='black')
plt.legend(title='Loan Status', loc='upper right', facecolor='white', edgecolo
```

```
sns.despine()
plt.tight_layout(rect=[0, 0, 1, 0.95])
plt.show()
```



Observations:

- Top 2 loan purpose categories are Debit Consolidation and Credit Card
- Topmost loan type application is INDIVIDUAL
- The distribution of open_acc appears to be relatively normal when visualized graphically.
- Charged Off and Fully Paid categories exhibit similar distributions.

In [187…

```
df.sample()
```

Out[187…

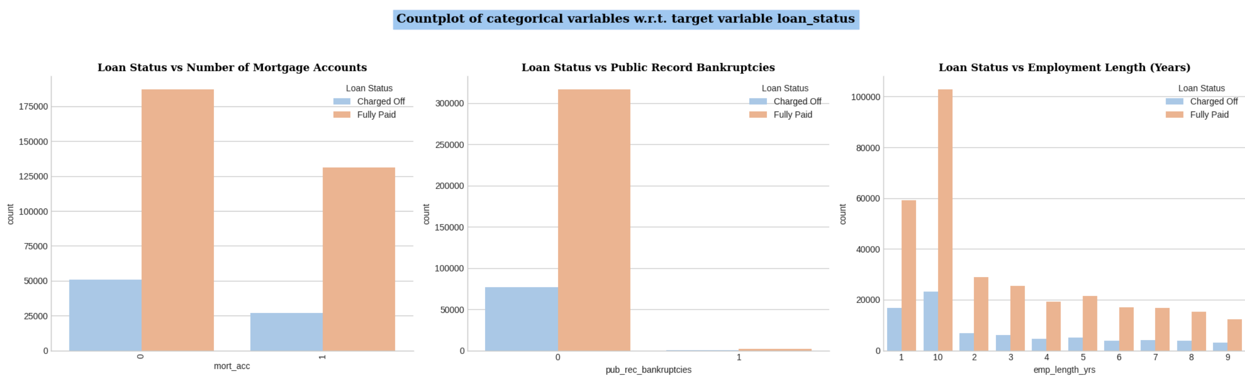
	loan_amnt	term	int_rate	installment	grade	sub_grade	emp_title	he
240416	30225.0	36	15.8	1059.64	C	C3	National Louis University	

1 rows × 30 columns

In [254…

```
#Countplot for various categorical features w.r.t. target variable loan_status
# Use a subtle whitegrid style
plt.style.use('seaborn-v0_8-whitegrid')

# Soft pastel palette (faint and classy)
cp = sns.color_palette("pastel")

plt.figure(figsize=(20,6))
plt.suptitle(
    'Countplot of categorical variables w.r.t. target variable loan_status',
    fontsize=14, fontfamily='serif', fontweight='bold',
    backgroundcolor=cp[0], color='black'
)

# 1� Mortgage Accounts
plt.subplot(131)
sns.countplot(data=df, x='mort_acc', hue='loan_status', palette=cp)
```

```
plt.xticks(rotation=90)
plt.title('Loan Status vs Number of Mortgage Accounts',
          fontsize=12, fontfamily='serif', fontweight='bold', color='black')
plt.legend(title='Loan Status', loc='upper right', facecolor='white', edgecolo

# 2️⃣ Public Record Bankruptcies
plt.subplot(132)
sns.countplot(data=df, x='pub_rec_bankruptcies', hue='loan_status', palette=cp
plt.title('Loan Status vs Public Record Bankruptcies',
          fontsize=12, fontfamily='serif', fontweight='bold', color='black')
plt.legend(title='Loan Status', loc='upper right', facecolor='white', edgecolo

# 3️⃣ Employment Length
plt.subplot(133)
order = sorted(df.emp_length_yrs.unique().tolist())
sns.countplot(data=df, x='emp_length_yrs', hue='loan_status', order=order, pal
plt.title('Loan Status vs Employment Length (Years)',
          fontsize=12, fontfamily='serif', fontweight='bold', color='black')
plt.legend(title='Loan Status', loc='upper right', facecolor='white', edgecolo

sns.despine()
plt.tight_layout(rect=[0, 0, 1, 0.93])
plt.show()
```



Q2. Comment about the correlation between Loan Amount and Installment features.

In [189…

```
df[['loan_amnt', 'installment']].corr()
```

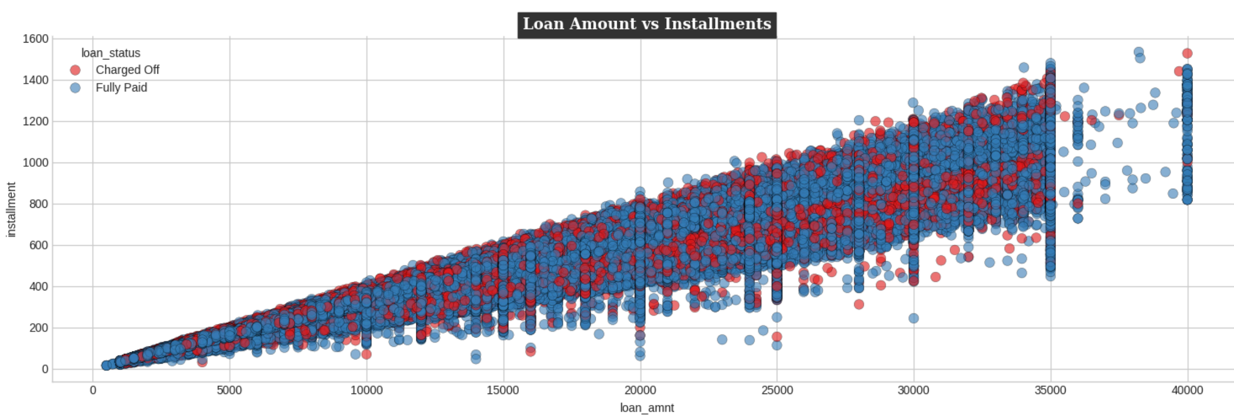
Out[189…

	loan_amnt	installment
loan_amnt	1.000000	0.953929
installment	0.953929	1.000000

In [256…

```
import matplotlib.pyplot as plt
import seaborn as sns

# Clean, bright style
```

```
plt.style.use('seaborn-v0_8-whitegrid')

# High-contrast, elegant palette (distinct but not harsh)
cp = sns.color_palette("Set1")  # vivid & clear colors

plt.figure(figsize=(15,5))
sns.scatterplot(
    data=df,
    x='loan_amnt',
    y='installment',
    alpha=0.6,                  # slightly less transparent
    hue='loan_status',
    palette=cp,
    s=70,                       # bigger points for visibility
    edgecolor='black',          # thin outline makes them pop
    linewidth=0.3
)

plt.title(
    'Loan Amount vs Installments',
    fontsize=13, fontfamily='serif', fontweight='bold',
    backgroundcolor='#333333', color='white'
)
sns.despine()
plt.tight_layout()
plt.show()
```



Insights:

The correlation coefficient measures the strength and direction of the linear relationship between two variables. In this case, the correlation coefficient between 'loan_amnt' and 'installment' is quite high, approximately 0.95, indicating a strong positive linear relationship between these two variables.

- **Loan Terms**: Understanding the relationship between loan amount and installment payments is crucial for setting appropriate loan terms. Lenders can adjust loan terms such as interest rates and repayment periods based on the borrower's ability to handle installment payments associated with different loan amounts.

- **Potential Multicollinearity**: When building predictive models, it's essential to be cautious of multicollinearity between highly correlated predictor variables. Multicollinearity can lead to unstable estimates and difficulties in interpreting the model coefficients. Therefore, it might be necessary to address multicollinearity through techniques such as variable selection or regularization.

Q3. The majority of people have home ownership as ________.

In [191…
```
(df['home_ownership'].value_counts(normalize=True)*100).to_frame()
```

Out[191…

home_ownership	proportion
MORTGAGE	50.084085
RENT	40.347953
OWN	9.531096
OTHER	0.028281
NONE	0.007828
ANY	0.000758

Insights:

- Mortgage holders comprise the majority with approximately `50.08%`, indicating that a significant portion of individuals own homes through `Mortgage` agreements.
- `Renters` constitute a substantial portion, accounting for around `40.35%` of home ownership types. This suggests a sizable demographic of individuals who opt for renting rather than owning a home.

Q4. People with grades 'A' are more likely to fully pay their loan. (T/F)

In [192…
```
pd.crosstab(df['grade'],df['loan_status'], normalize = 'index')
```

Out[192…

loan_status	Charged Off	Fully Paid
grade		
A	0.062879	0.937121
B	0.125730	0.874270
C	0.211809	0.788191
D	0.288678	0.711322
E	0.373634	0.626366
F	0.427880	0.572120
G	0.478389	0.521611

Insights:

> **Grade 'A' borrowers demonstrate a significantly high likelihood of fully repaying their loans, with approximately 93.71% of loans being fully paid**. This suggests that borrowers with the highest credit rating are more inclined to fulfill their loan obligations successfully.

- The proportion of charged-off loans for grade 'A' borrowers is relatively low, standing at approximately 6.29%. This indicates a low default rate among borrowers with the highest credit rating, emphasizing their creditworthiness and reliability in loan repayment.

Q5. Name the top 2 afforded job titles.

In [193…

```
df[df['emp_title'] != 'No Employee Title']['emp_title'].value_counts().to_fram
```

Out[193…

	count
emp_title	
Teacher	4389
Manager	4250
Registered Nurse	1856
RN	1846
Supervisor	1830

In [194…

```
df.groupby('emp_title')['loan_status'].count().sort_values(ascending=False).to
```

Out[194…

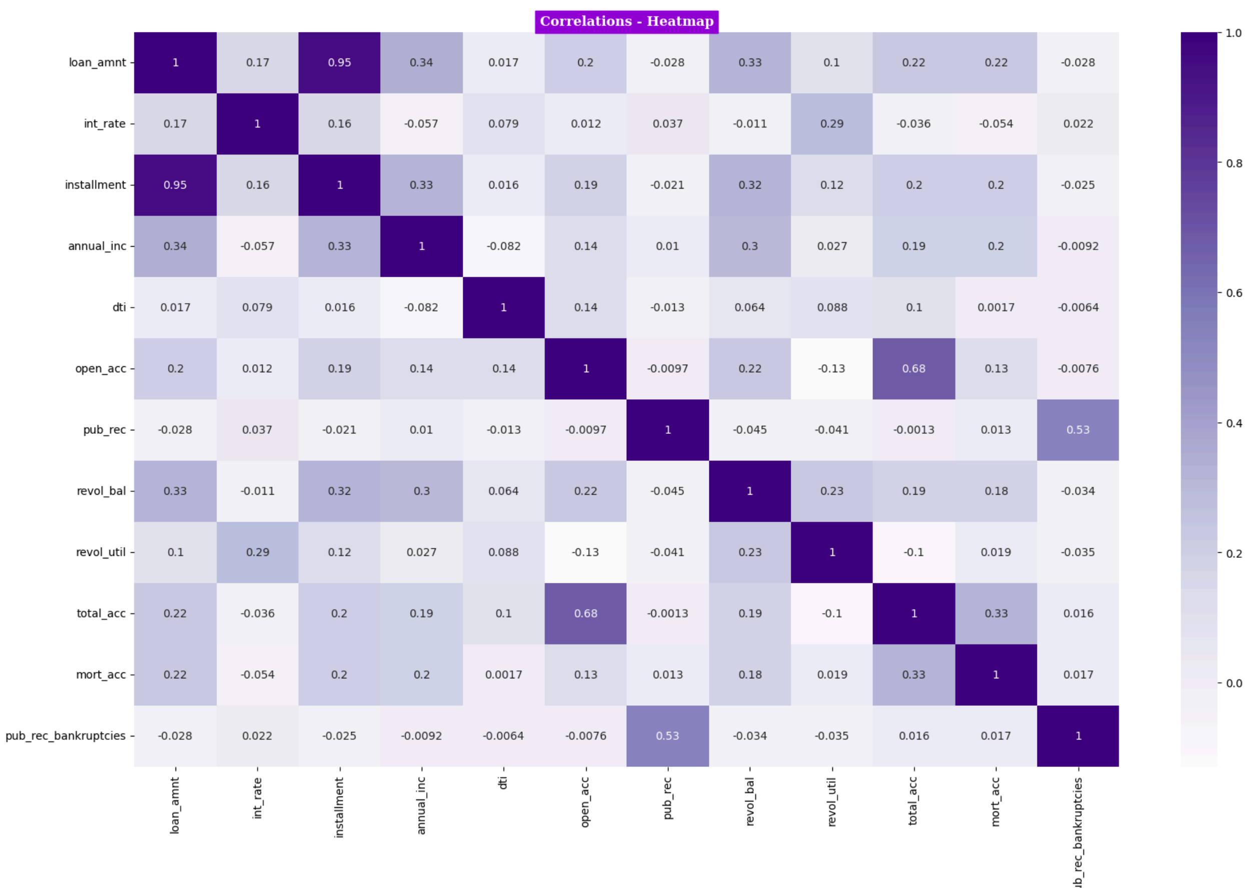
emp_title	loan_status
Teacher	4389
Manager	4250
Registered Nurse	1856
RN	1846
Supervisor	1830

Insights:

- The Most afforded job titles are `Teachers & Managers`.

In [195…

```
plt.figure(figsize=(20,12))
sns.heatmap(num_cols.corr(), annot=True, cmap='Purples')
plt.title('Correlations - Heatmap',fontsize=12,fontfamily='serif',fontweight='
plt.show()
```



Observations:

- There exists a strong correlation between loan_amnt and installment, indicating that higher loan amounts correspond to larger installment payments.
- The variables total_acc and open_acc exhibit a significant correlation.
- There is a notable correlation between pub_rec_bankruptcies and pub_rec.

Outlier Treatment:

In [196…
```
numerical_cols = df.select_dtypes(include=np.number).columns
numerical_cols
```

Out[196…
```
Index(['loan_amnt', 'int_rate', 'installment', 'annual_inc', 'dti', 'open_ac
c',
       'pub_rec', 'revol_bal', 'revol_util', 'total_acc', 'mort_acc',
       'pub_rec_bankruptcies'],
      dtype='object')
```

In [197…
```
# outlier treatment
def remove_outliers_zscore(df, threshold=2): #(considering 2 std.dev away from
    """
    Remove outliers from a DataFrame using the Z-score method.

    Parameters:
        df (DataFrame): The input DataFrame.
        threshold (float): The Z-score threshold for identifying outliers.
                           Observations with a Z-score greater than this thres
                           will be considered as outliers.

    Returns:
        DataFrame: The DataFrame with outliers removed.
    """
    # Calculate Z-scores for numerical columns
    z_scores = (df[numerical_cols] - df[numerical_cols].mean()) / df[numerical

    # Identify outliers
    outliers = np.abs(z_scores) > threshold

    # Keep non-outliers for numerical columns
    df_cleaned = df[~outliers.any(axis=1)]

    return df_cleaned

cleaned_df = remove_outliers_zscore(df1)
print(cleaned_df.shape)
```

```
(311392, 30)
```

In [198…
```
def clip_outliers_zscore(df, threshold=2):
```

```
    """
    Clip outliers in a DataFrame using the Z-score method.

    Parameters:
        df (DataFrame): The input DataFrame.
        threshold (float): The Z-score threshold for identifying outliers.
                           Observations with a Z-score greater than this thres
                           will be considered as outliers.

    Returns:
        DataFrame: The DataFrame with outliers clipped.
    """
    # Calculate Z-scores for numerical columns
    z_scores = (df[numerical_cols] - df[numerical_cols].mean()) / df[numerical

    # Clip outliers
    clipped_values = df[numerical_cols].clip(df[numerical_cols].mean() - thres
                                             df[numerical_cols].mean() + thres
                                             axis=1)

    # Assign clipped values to original DataFrame
    df_clipped = df.copy()
    df_clipped[numerical_cols] = clipped_values

    return df_clipped

clipped_df = clip_outliers_zscore(df1)
print(clipped_df.shape)
```

```
(396030, 30)
```

In [199…

```
data = cleaned_df.copy()
cp_data = clipped_df.copy()
data.sample()
```

Out[199…

	loan_amnt	term	int_rate	installment	grade	sub_grade	emp_title	h
355656	6000.0	36	17.57	215.63	D	D2	No Employee Title	

1 rows × 30 columns

In [200…

```
data['pub_rec_bankruptcies'].value_counts() , data['pub_rec'].value_counts()
```

Out[200…

```
(pub_rec_bankruptcies
 0    311392
 Name: count, dtype: int64,
 pub_rec
 0    311392
 Name: count, dtype: int64)
```

In [201…

```
cp_data['pub_rec_bankruptcies'].value_counts() , cp_data['pub_rec'].value_cour
```

Out[201… (pub_rec_bankruptcies
```
 0.000000    393705
 0.158662      2325
 Name: count, dtype: int64,
 pub_rec
 0.000000    388011
 0.301947      8019
 Name: count, dtype: int64)
```

In [202…
```
data.shape
```

Out[202…
```
(311392, 30)
```

In [203…
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 311392 entries, 0 to 396029
Data columns (total 30 columns):
 #   Column                Non-Null Count   Dtype
---  ------                --------------   -----
 0   loan_amnt             311392 non-null  float64
 1   term                  311392 non-null  object
 2   int_rate              311392 non-null  float64
 3   installment           311392 non-null  float64
 4   grade                 311392 non-null  category
 5   sub_grade             311392 non-null  category
 6   emp_title             311392 non-null  object
 7   home_ownership        311392 non-null  category
 8   annual_inc            311392 non-null  float64
 9   verification_status   311392 non-null  category
 10  loan_status           311392 non-null  category
 11  purpose               311392 non-null  category
 12  title                 311392 non-null  object
 13  dti                   311392 non-null  float64
 14  open_acc              311392 non-null  float64
 15  pub_rec               311392 non-null  int64
 16  revol_bal             311392 non-null  float64
 17  revol_util            311392 non-null  float64
 18  total_acc             311392 non-null  float64
 19  initial_list_status   311392 non-null  category
 20  application_type      311392 non-null  category
 21  mort_acc              311392 non-null  int64
 22  pub_rec_bankruptcies  311392 non-null  int64
 23  issue_month           311392 non-null  object
 24  issue_year            311392 non-null  object
 25  er_cr_line_m          311392 non-null  object
 26  er_cr_line_y          311392 non-null  object
 27  state                 311392 non-null  object
 28  zipcode               311392 non-null  object
 29  emp_length_yrs        311392 non-null  object
dtypes: category(8), float64(9), int64(3), object(10)
memory usage: 57.0+ MB
```

Manual encoding:

In [204…
```
data['loan_status']=data.loan_status.map({'Fully Paid':1, 'Charged Off':0})

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

In [205…
```
data.head()
```

Out[205…

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

5 rows × 30 columns

Feature selection - done by hypothesis testing & VIF(multicolinearity)

> Find VIF after modelling and remove features with high VIF (>5):

```
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
```

In [206…
```
cat_cols = data.select_dtypes(include=['object']).columns.tolist()
for col in cat_cols:
    chi2, p, dof, expected = chi2_contingency(pd.crosstab(data[col], data['loa
    if p > 0.05:
        print('>>>>>>> Independent feature - Not Significant:',col,' >> p valu
```

```
>>>>>>> Independent feature - Not Significant: emp_title  >> p value: 0.5367121
560200798
>>>>>>> Independent feature - Not Significant: title  >> p value: 1.0
>>>>>>> Independent feature - Not Significant: er_cr_line_m  >> p value: 0.2722
117086158036
>>>>>>> Independent feature - Not Significant: state  >> p value: 0.76047808977
373
```

In [207…

```python
## dropping cols based on correlation(heatmap,hypothesis testing)
lt = data.drop(columns=['emp_title','title','sub_grade','er_cr_line_m','er_cr_
                        'state','issue_month','issue_year','pub_rec','pub_rec_
lt.shape
```

Out[207…

```
(311392, 19)
```

In [208…

```python
lt.sample()
```

Out[208…

	loan_amnt	term	int_rate	installment	grade	home_ownership	annua
145315	10625.0	36	10.99	347.8	B	RENT	325

In [209…

```python
#### Performing OneHotEncoding on feature having multiple variable
dummies=['zipcode', 'grade','purpose','home_ownership','verification_status','
ltd = pd.get_dummies(lt, columns=dummies, drop_first=True)
```

In [210…

```python
ltd.shape
```

Out[210…

```
(311392, 50)
```

In [211…

```python
ltd.sample(8)
```

Out[211…

	loan_amnt	term	int_rate	installment	annual_inc	loan_status	dti
92145	15000.0	36	14.33	515.08	42000.0	0	15.00
1726	25000.0	60	15.22	597.64	75500.0	1	33.10
290657	6000.0	36	5.32	180.69	41175.0	1	4.14
312003	20000.0	60	21.49	546.60	45128.0	1	14.31
144406	29000.0	60	14.31	679.45	75000.0	1	14.30
101839	4500.0	36	19.05	165.07	16000.0	1	31.28
82578	10000.0	36	7.62	311.62	33000.0	1	3.53
150268	23450.0	60	20.99	634.27	63000.0	0	23.92

8 rows × 50 columns

Model:

In [212…
```
#Prepare X and y dataset i.e. independent and dependent datasets

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

In [213…
```
#Split the data into train and test
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,strati
print(X_train.shape)
print(X_test.shape)
print(y_train.shape)
print(y_test.shape)
```

```
(249113, 49)
(62279, 49)
(249113,)
(62279,)
```

Minmax scaling the data

In [214…
```
scaler = MinMaxScaler()
X_train = scaler.fit_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)
```

In [215…
```
X_train.head()
```

Out[215…

	loan_amnt	term	int_rate	installment	annual_inc	dti	open_acc	revo
0	0.379538	0.0	0.339161	0.411590	0.207250	0.465341	0.368421	0.17
1	0.643564	1.0	0.680070	0.524221	0.367868	0.252652	0.473684	0.22
2	0.168317	0.0	0.208625	0.176198	0.134712	0.357576	0.368421	0.05
3	0.379538	1.0	0.680070	0.307444	0.367868	0.449242	0.315789	0.25
4	0.368812	0.0	0.543706	0.421460	0.246109	0.315530	0.263158	0.09

5 rows × 49 columns

🏷️Model-1

In [216…
```
#Fit the Model on training data
logreg_model = LogisticRegression()
logreg_model.fit(X_train, y_train)
```

Out[216…

```
▾ LogisticRegression
LogisticRegression()
```

In [217…

```python
#Predit the data on test dataset
y_train_pred = logreg_model.predict(X_train)
y_test_pred = logreg_model.predict(X_test)
```

In [218…

```python
logreg_model.score(X_test, y_test) , logreg_model.score(X_test, y_test_pred)
```

Out[218…

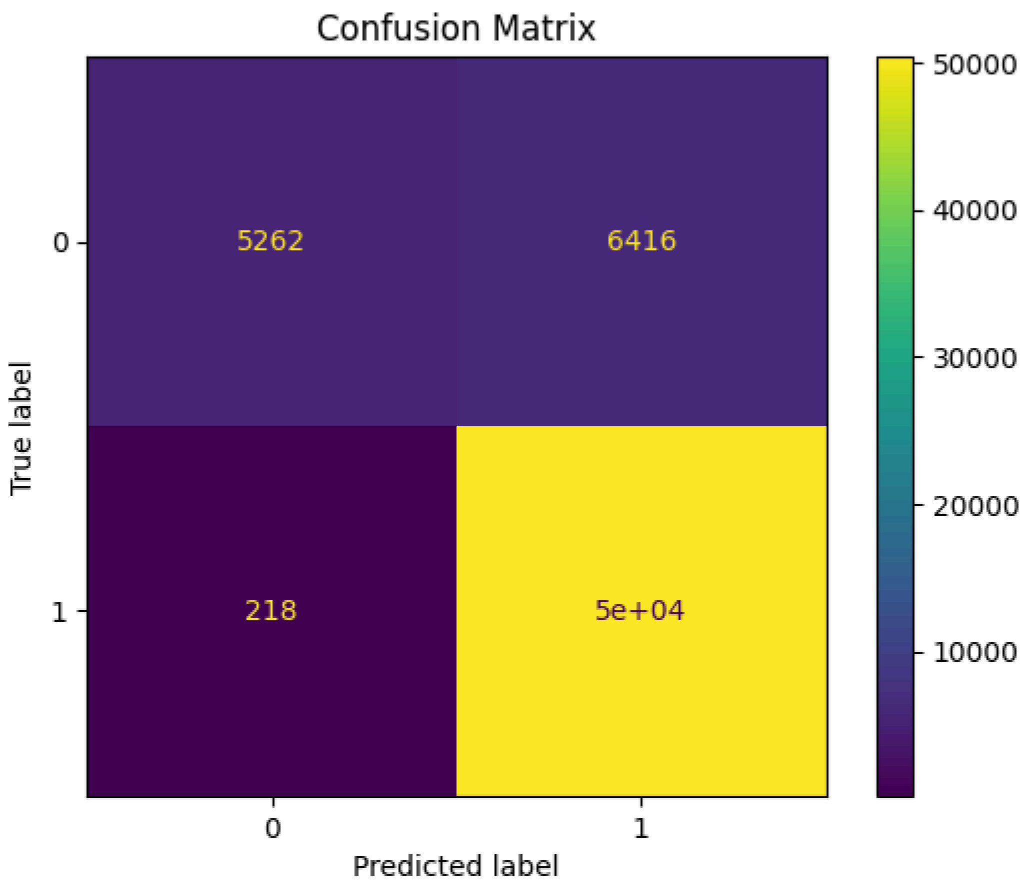
```
(0.8934793429566948, 1.0)
```

If logreg_model.score(X_test, y_test) consistently returns 1, it would imply that your model is predicting the test set perfectly, which could be a sign of overfitting, data leakage, or an issue with the evaluation process.

In [219…

```python
#Model Evaluation
print('Train Accuracy :', round(logreg_model.score(X_train, y_train), 2))
print('Train F1 Score:', round(f1_score(y_train, y_train_pred), 2))
print('Train Recall Score:', round(recall_score(y_train, y_train_pred), 2))
print('Train Precision Score:', round(precision_score(y_train, y_train_pred),

print('\nTest Accuracy :', round(logreg_model.score(X_test, y_test), 2))
print('Test F1 Score:', round(f1_score(y_test, y_test_pred), 2))
print('Test Recall Score:', round(recall_score(y_test, y_test_pred), 2))
print('Test Precision Score:', round(precision_score(y_test, y_test_pred), 2))

# Confusion Matrix
cm = confusion_matrix(y_test, y_test_pred)
disp = ConfusionMatrixDisplay(cm)
disp.plot()
plt.title('Confusion Matrix')
plt.show()
```

```
Train Accuracy : 0.89
Train F1 Score: 0.94
Train Recall Score: 1.0
Train Precision Score: 0.89

Test Accuracy : 0.89
Test F1 Score: 0.94
Test Recall Score: 1.0
Test Precision Score: 0.89
```



In [220…

```
print(classification_report(y_test,y_test_pred))
```

```
              precision    recall  f1-score   support

           0       0.96      0.45      0.61     11678
           1       0.89      1.00      0.94     50601

    accuracy                           0.89     62279
   macro avg       0.92      0.72      0.78     62279
weighted avg       0.90      0.89      0.88     62279
```

- Here the recall value for the 'charged off' is very low, Hence will build a better model

Model-2

In [221…

```
# Oversampling to balance the target variable

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

print(f"Before OverSampling, count of label 1: {sum(y_train == 1)}")
print(f"Before OverSampling, count of label 0: {sum(y_train == 0)}")
```

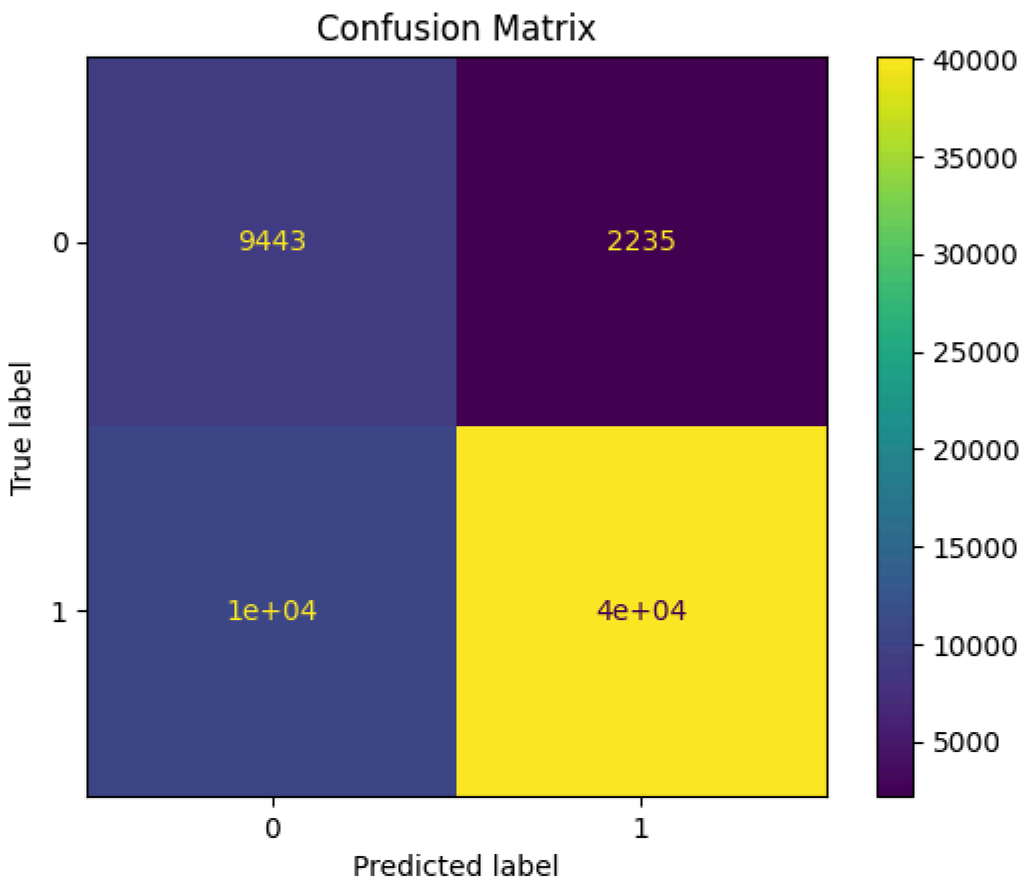
```python
print(f"After OverSampling, count of label 1: {sum(y_train_res == 1)}")
print(f"After OverSampling, count of label 0: {sum(y_train_res == 0)}")
```

```
Before OverSampling, count of label 1: 202401
Before OverSampling, count of label 0: 46712
After OverSampling, count of label 1: 202401
After OverSampling, count of label 0: 202401
```

In [222…

```python
model = LogisticRegression()
model.fit(X_train_res, y_train_res)
train_preds = model.predict(X_train)
test_preds = model.predict(X_test)

#Model Evaluation
print('Train Accuracy :', round(model.score(X_train, y_train), 2))
print('Train F1 Score:', round(f1_score(y_train, train_preds), 2))
print('Train Recall Score:', round(recall_score(y_train, train_preds), 2))
print('Train Precision Score:', round(precision_score(y_train, train_preds), 2

print('\nTest Accuracy :', round(model.score(X_test, y_test), 2))
print('Test F1 Score:', round(f1_score(y_test, test_preds), 2))
print('Test Recall Score:', round(recall_score(y_test, test_preds), 2))
print('Test Precision Score:', round(precision_score(y_test, test_preds), 2))

# Confusion Matrix
cm = confusion_matrix(y_test, test_preds)
disp = ConfusionMatrixDisplay(cm)
disp.plot()
plt.title('Confusion Matrix')
plt.show()
```

```
Train Accuracy : 0.79
Train F1 Score: 0.86
Train Recall Score: 0.79
Train Precision Score: 0.95

Test Accuracy : 0.8
Test F1 Score: 0.86
Test Recall Score: 0.79
Test Precision Score: 0.95
```



In [223…

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

```
              precision    recall  f1-score   support

           0       0.47      0.81      0.60     11678
           1       0.95      0.79      0.86     50601

    accuracy                           0.80     62279
   macro avg       0.71      0.80      0.73     62279
weighted avg       0.86      0.80      0.81     62279
```

Observations:

- The model demonstrates a high recall score, successfully identifying 80% of actual defaulters.
- However, the precision for the positive class (defaulters) is low; only 47% of predicted defaulters are actually defaulters.
- This high recall and low precision indicate that while the model is effective at flagging most defaulters, it also results in many false positives. Consequently, many deserving customers may be denied loans.

- The low precision adversely affects the F1 score, reducing it to 60%, despite an overall accuracy of 80%. This highlights the trade-off between precision and recall in the model's performance.

> Explanation :

- The model is good at catching most people who don't pay back their loans it catches 80% of them.
- But, when it says someone won't pay back, it's right only half of the time.47% So, there's a chance it's making mistakes and wrongly flagging people.
- Because of these mistakes, some people who deserve loans might not get them.
- Even though the model seems okay overall, its balance between being right and not making mistakes isn't great. It's like a seesaw; when one side goes up, the other goes down.

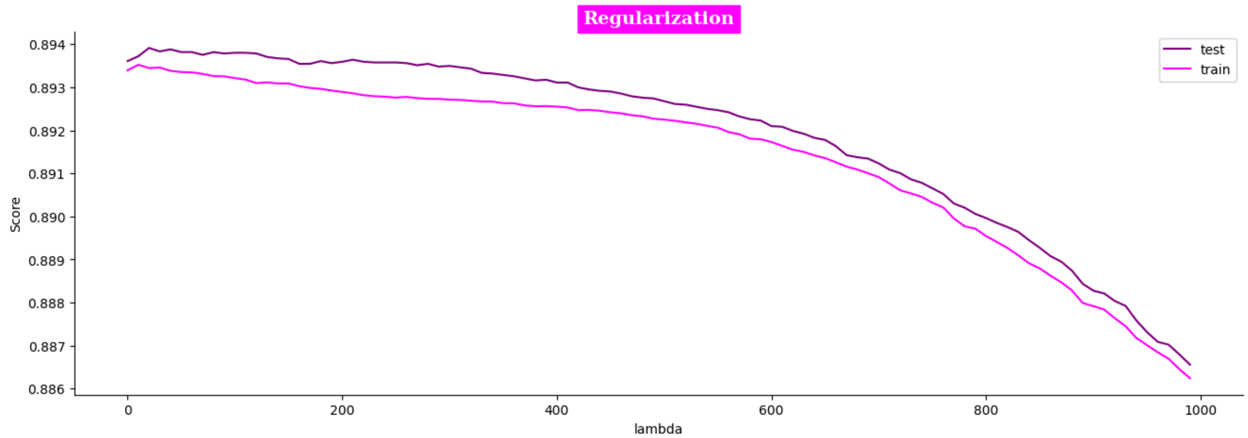
🏷️Regularization Model

In [224…

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

lamb = np.arange(0.01, 1000, 10)

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)
```

In [225…

```
#Plot the train and test scores with respect lambda values i.e. regularization
ran = np.arange(0.01, 1000, 10)
plt.figure(figsize=(16,5))
sns.lineplot(x=ran,y=test_scores,color='purple',label='test')
sns.lineplot(x=ran,y=train_scores,color='magenta',label='train')
plt.title('Regularization',fontsize=14,fontfamily='serif',fontweight='bold',ba
plt.xlabel("lambda")
plt.ylabel("Score")
sns.despine()
plt.show()
```



In [226…

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

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

```
2
0.8939128759292859
```

In [227…

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

best_lamb = 0.01 + (10*2)
best_lamb
```

Out[227… 20.01

In [228…

```
lamdba = np.argmax(test_scores)
```

In [229…

```
#Fit the model using best lambda

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

Out[229…

```
LogisticRegression
LogisticRegression(C=0.049975012493753 12)
```

In [230…

```
#Predict the y_values and y_probability values

y_reg_pred = reg_model.predict(X_test)
y_reg_pred_proba = reg_model.predict_proba(X_test)
```

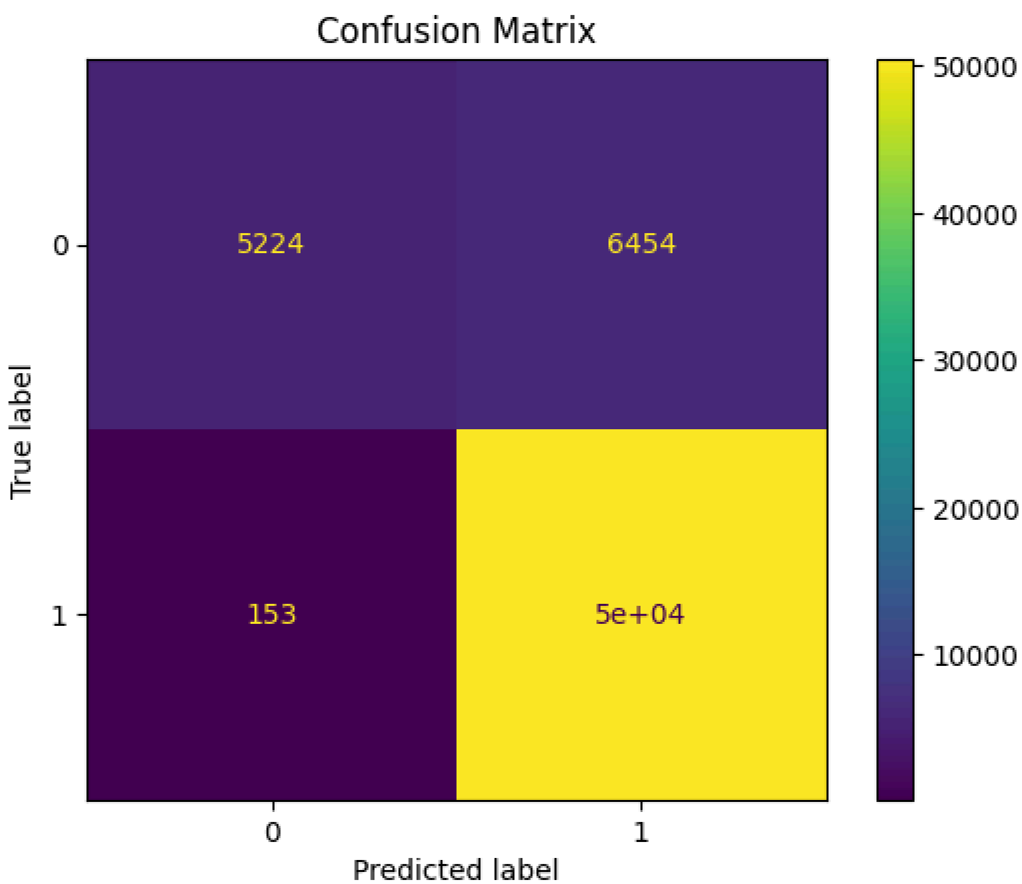
In [231…

```
#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: 88.66 %
```

In [232…

```
# Confusion Matrix
cm = confusion_matrix(y_test, y_reg_pred)
disp = ConfusionMatrixDisplay(cm)
disp.plot()
plt.title('Confusion Matrix')
plt.show()
```



In [233…

```
print(classification_report(y_test, y_reg_pred))
```

```
              precision    recall  f1-score   support

           0       0.97      0.45      0.61     11678
           1       0.89      1.00      0.94     50601

    accuracy                           0.89     62279
   macro avg       0.93      0.72      0.78     62279
weighted avg       0.90      0.89      0.88     62279
```

💡Observations from classification report:

> Regularized model

- `Precision : 89%`
- `Recall : 100%`

- `F1-score : 94%`
- `Accuracy : 89%`

🔹 K-fold - Cross_validation

- cross validation accuracy has to be approx 89%

In [234…
```
x=scaler.fit_transform(X)

kfold = KFold(n_splits=10)
accuracy = np.mean(cross_val_score(reg_model,x,y,cv=kfold,scoring='accuracy'))
print("Cross Validation accuracy : {:.3f}".format(accuracy))
```

```
Cross Validation accuracy : 0.894
```

In [235…
```
cm = confusion_matrix(y_test, y_reg_pred)
cm_df = pd.DataFrame(cm, index=['Defaulter','Fully paid'], columns=['Defaulter
cm_df
```

Out[235…

	Defaulter	Fully paid
Defaulter	5224	6454
Fully paid	153	50448

Insights:

- TN = 5223 (True Negative: Correctly predicted Charged Off)
- TP = 50450 (True Positive: Correctly predicted Fully Paid)
- FP = 6455 (False Positive: Predicted Fully Paid but actually Charged Off)
- FN = 151 (False Negative: Predicted Charged Off but actually Fully Paid)
- Actual Negative (Charged Off) = 5223 + 6455 = 11678
- Actual Positive (Fully Paid) = 151 + 50450 = 50601
- Predicted Negative (Charged Off) = 5223 + 151 = 5374
- Predicted Positive (Fully Paid) = 6455 + 50450 = 56905

In [236…
```
#Collect the model coefficients and print those in dataframe format
coeff_df = pd.DataFrame()
coeff_df['Features'] = X_train_res.columns
coeff_df['Weights'] = model.coef_[0]
coeff_df['ABS_Weights'] = abs(coeff_df['Weights'])
coeff_df = coeff_df.sort_values(['ABS_Weights'], ascending=False)
coeff_df
```

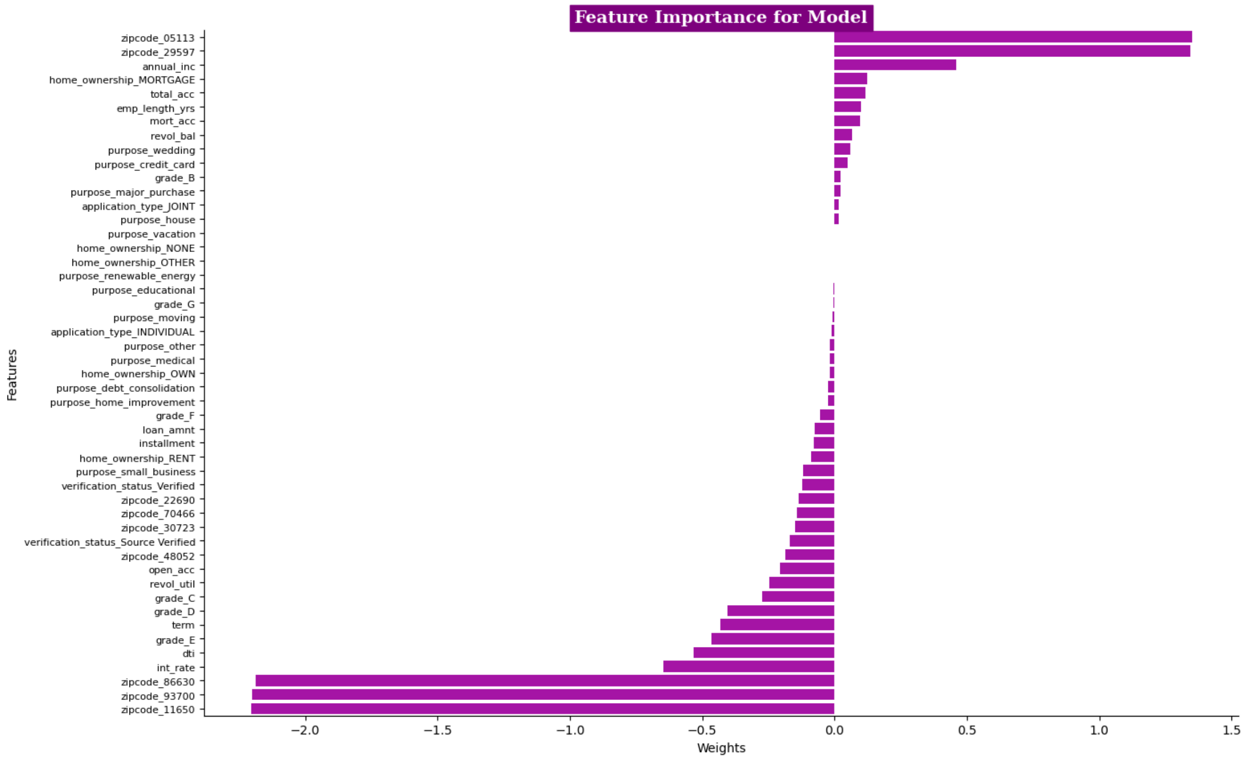
Out[236…

	Features	Weights	ABS_Weights
13	zipcode_11650	-2.205071	2.205071
20	zipcode_93700	-2.199511	2.199511
19	zipcode_86630	-2.187202	2.187202
12	zipcode_05113	1.349854	1.349854
15	zipcode_29597	1.345002	1.345002
2	int_rate	-0.647268	0.647268
5	dti	-0.533302	0.533302
24	grade_E	-0.464009	0.464009
4	annual_inc	0.460678	0.460678
1	term	-0.432346	0.432346
23	grade_D	-0.405342	0.405342
22	grade_C	-0.274999	0.274999
8	revol_util	-0.245635	0.245635
6	open_acc	-0.205268	0.205268
17	zipcode_48052	-0.185657	0.185657
45	verification_status_Source Verified	-0.170248	0.170248
16	zipcode_30723	-0.150426	0.150426
18	zipcode_70466	-0.142453	0.142453
14	zipcode_22690	-0.136254	0.136254
40	home_ownership_MORTGAGE	0.124330	0.124330
46	verification_status_Verified	-0.123013	0.123013
37	purpose_small_business	-0.117063	0.117063
9	total_acc	0.116940	0.116940
11	emp_length_yrs	0.099225	0.099225
10	mort_acc	0.097998	0.097998
44	home_ownership_RENT	-0.089612	0.089612
3	installment	-0.077029	0.077029
0	loan_amnt	-0.074132	0.074132
7	revol_bal	0.065485	0.065485
39	purpose_wedding	0.059511	0.059511
25	grade_F	-0.053116	0.053116

	Features	Weights	ABS_Weights
27	purpose_credit_card	0.050020	0.050020
30	purpose_home_improvement	-0.024664	0.024664
28	purpose_debt_consolidation	-0.024582	0.024582
21	grade_B	0.023140	0.023140
32	purpose_major_purchase	0.021931	0.021931
43	home_ownership_OWN	-0.018953	0.018953
33	purpose_medical	-0.018311	0.018311
35	purpose_other	-0.017780	0.017780
48	application_type_JOINT	0.017406	0.017406
31	purpose_house	0.017302	0.017302
47	application_type_INDIVIDUAL	-0.010355	0.010355
34	purpose_moving	-0.008649	0.008649
26	grade_G	-0.003484	0.003484
29	purpose_educational	-0.003211	0.003211
36	purpose_renewable_energy	-0.002542	0.002542
42	home_ownership_OTHER	-0.002166	0.002166
41	home_ownership_NONE	-0.001545	0.001545
38	purpose_vacation	-0.000423	0.000423

In [237…

```
imp_feature = coeff_df.sort_values(by='Weights',ascending=False)
plt.figure(figsize=(15,10))
sns.barplot(y = imp_feature['Features'],
           x = imp_feature['Weights'],color='m')
plt.title("Feature Importance for Model",fontsize=14,fontfamily='serif',fontwe
plt.xlabel("Weights")
plt.yticks(fontsize=8)
plt.ylabel("Features")
sns.despine()
plt.show()
```



In [238…

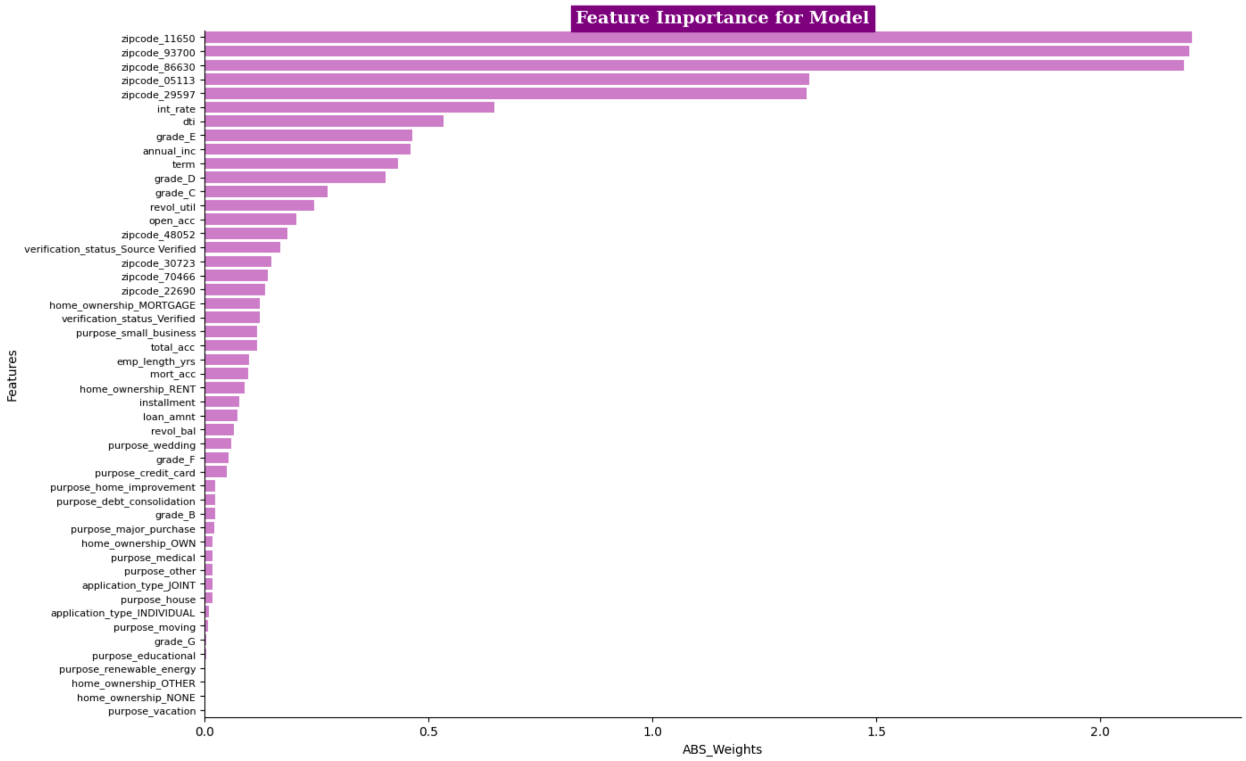
```
#Logistic Regression model intercept

model.intercept_
```

Out[238…

```
array([2.52298763])
```

In [239…

```
plt.figure(figsize=(15,10))
sns.barplot(y = coeff_df['Features'],x = coeff_df['ABS_Weights'],color='orchic
plt.title("Feature Importance for Model",fontsize=14,fontfamily='serif',fontwe
plt.xlabel("ABS_Weights")
plt.yticks(fontsize=8)
plt.ylabel("Features")
sns.despine()
plt.show()
```



Observations:

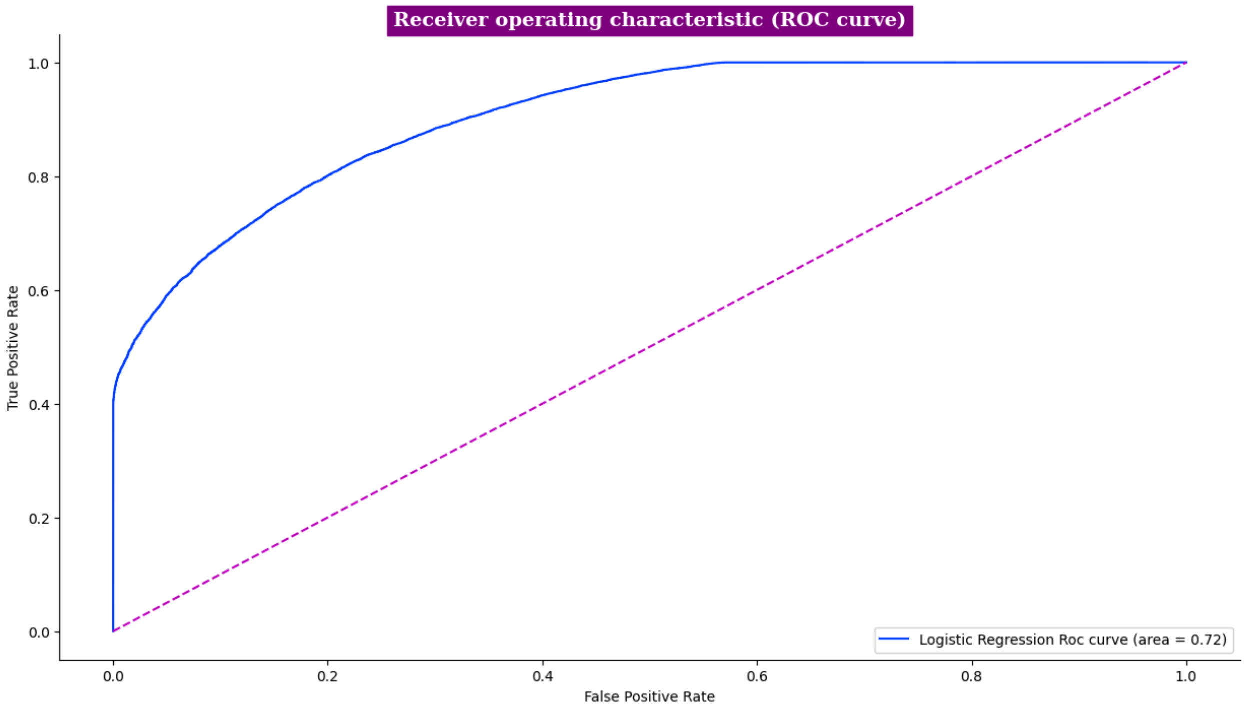
- The model has assigned significant weight to the zip_code, Annual Income, grade features, indicating that certain zip codes strongly influence the prediction of defaulters.
- Features such as dti (debt-to-income ratio), open_acc (number of open accounts), and loan_amnt (loan amount) also have high positive coefficients, highlighting their importance in predicting default risk.
- On the other hand, several zip codes have large negative coefficients, suggesting that they are associated with a lower likelihood of default.

ROC AUC curve

In [240…

```
# area under ROC curve
logit_roc_auc = roc_auc_score(y_test,y_reg_pred)

# Compute the false positive rate, true positive rate, and thresholds
fpr,tpr,thresholds = roc_curve(y_test,y_reg_pred_proba[:,1])

# Compute the area under the ROC curve
roc_auc = auc(fpr, tpr)

# plot ROC curve
plt.figure(figsize=(15,8))
plt.plot(fpr,tpr,label='Logistic Regression Roc curve (area = %0.2f)'% logit_r
plt.plot([0,1],[0,1],'m--')
```

```python
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver operating characteristic (ROC curve)',fontsize=14,fontfami
plt.legend(loc="lower right")
sns.despine()
plt.show()
```



In [241…
```python
logit_roc_auc
```

Out[241… np.float64(0.7221566085466022)

In [242…
```python
roc_auc = auc(fpr, tpr)
roc_auc
```

Out[242… np.float64(0.9036968327803755)

Insights:

Trade-off in Performance: The ROC curve area, representing model performance, is 72%. This indicates that the model effectively distinguishes between classes 72% of the time.

- Ideally, we aim for a higher True Positive Rate (TPR) and a lower False Positive Rate (FPR) to ensure accurate predictions.
- The ROC curve illustrates that as True Positives increase, there's a simultaneous increase in False Positives.
- Misclassification: This trade-off implies that while identifying more Fully

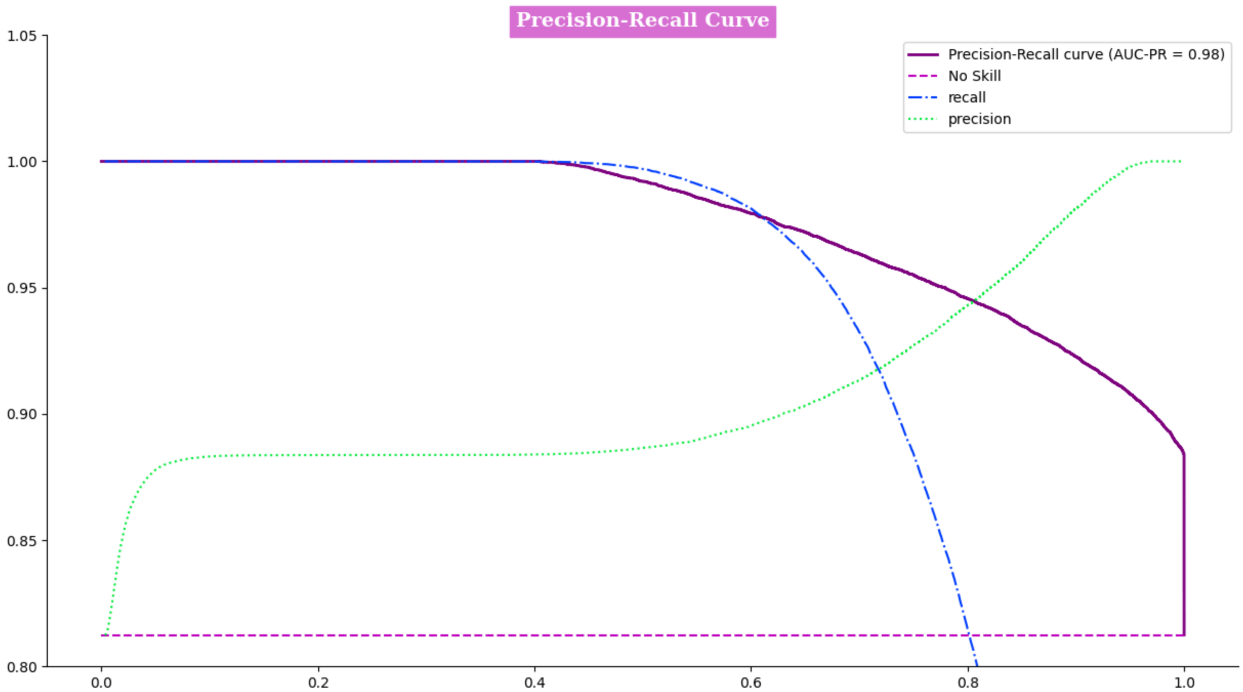
Paid customers, there's a heightened risk of misclassifying Charged Off customers as Fully Paid, potentially leading to Non-Performing Assets (NPAs).

These points emphasize the need to mitigate this risk:

- Reducing FPR while maintaining TPR is crucial to minimize misclassifications and associated risks.
- By shifting False Positives towards the left on the ROC curve, the model's overall performance, as measured by AUC, can improve.
- This improvement in AUC relies on maintaining a high True Positive Rate while reducing False Positives.

In [243…

```
precision, recall, thresholds = precision_recall_curve(y_test, y_reg_pred_prob

average_precision = average_precision_score(y_test, y_reg_pred_proba[:,1])

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

plt.figure(figsize=(15,8))
plt.plot(recall, precision, color='purple', lw=2, label=f'Precision-Recall cur
plt.plot([0, 1], [no_skill, no_skill], linestyle='--', label='No Skill', color
plt.plot(thresholds, recall[0:thresholds.shape[0]], label='recall',linestyle='
plt.plot(thresholds, precision[0:thresholds.shape[0]], label='precision',lines
# plt.xlim([0.0, 1.0])
plt.ylim([0.8, 1.05])
plt.title('Precision-Recall Curve',fontsize=14,fontfamily='serif',fontweight='
plt.legend(loc='upper right')
sns.despine()
plt.show()
```



In [244…
```
auc(recall, precision).round(3)
```

Out[244…
```
np.float64(0.975)
```

Observations:

> 💡Insight:

- The Area Under the Curve (AUC) for the precision-recall curve is 0.975. This high AUC value suggests that the model achieves excellent performance in distinguishing between positive and negative classes, showcasing strong precision-recall characteristics.
- **Precision-Recall Curve Superiority**: Precision-recall curves are pivotal, especially in imbalanced datasets, focusing on accurate predictions of the relevant class (Class 1 - Fully paid in this case).
- **Irrelevance of True Negatives**: Precision and recall computations disregard true negatives, simplifying focus to the correct prediction of Fully Paid customers.
- **AUC Strengthens Model Evaluation**: A high AUC (97.5%) underscores the model's robustness in distinguishing between classes, indicating its efficacy.
- **Precision Enhancement Priority**: Optimal model refinement centers

on elevating precision by minimizing False Positives, vital for improving overall performance and mitigating risks.

In [245…

```python
# balanced Model
lr = LogisticRegression(max_iter=1000, class_weight='balanced')

lr_model = lr.fit(X_train, y_train)

print(classification_report(y_test, lr_model.predict(X_test)))

cm_bal = confusion_matrix(y_test, lr_model.predict(X_test))
cm_bal_df = pd.DataFrame(cm_bal, index=['Defaulter','Fully paid'], columns=['D
cm_bal_df
```

```
              precision    recall  f1-score   support

           0       0.47      0.81      0.60     11678
           1       0.95      0.79      0.86     50601

    accuracy                           0.79     62279
   macro avg       0.71      0.80      0.73     62279
weighted avg       0.86      0.79      0.81     62279
```

Out[245…

	Defaulter	Fully paid
Defaulter	9468	2210
Fully paid	10586	40015

Observations from classification report:

> Balenced model

- `Precision : 95%`
- `Recall : 79%`
- `F1-score : 86%`
- `Accuracy : 79%`

💡Insights:

- TN = 9466 (True Negative: Correctly predicted Charged Off)
- TP = 40028 (True Positive: Correctly predicted Fully Paid)
- FP = 2212 (False Positive: Predicted Fully Paid but actually Charged Off)
- FN = 10573 (False Negative: Predicted Charged Off but actually Fully Paid)
- Actual Negative (Charged Off) = 9466 + 2212 = 11678
- Actual Positive (Fully Paid) = 10573 + 40028 = 50601

- Predicted Negative (Charged Off) = 9466 + 10573 = 20039
- Predicted Positive (Fully Paid) = 2212 + 40028 = 42240

In [246…
```
lr_model.intercept_
```

Out[246…
```
array([6.35576692])
```

Q6: Thinking from a bank's perspective, which metric should our primary focus be on..

a. ROC AUC

b. Precision

c. Recall

d. F1 Score

Ans:

> From a bank's perspective, minimizing risks and maximizing profitability are paramount. `ROC AUC (Receiver Operating Characteristic Area Under Curve)` is indeed a crucial metric because it encompasses both True Positive Rate (TPR) and False Positive Rate (FPR)

- Bank's primary focus should be on ROC AUC , because bank needs to reduce FPR (False Positive Rate) and needs to increase the TPR (True Positive Rate).

- Maximizing TPR ensures that the bank correctly identifies customers who fully pay their loans (reducing False Negatives), while minimizing FPR ensures that the bank doesn't wrongly classify customers as fully paid when they're actually charged off (reducing False Positives).

- By optimizing ROC AUC, the bank can strike a balance between correctly identifying creditworthy customers and minimizing the risk of defaulters, thereby enhancing the overall performance and reliability of its credit scoring model.

Another approach:

- since I'm having `High Recall` value of 100% in Regularized model(most efficient model:

> From a bank's perspective, the primary focus should be on minimizing risks while maximizing profitability. Therefore, the most relevant metric would be **Precision**.

- Precision represents the proportion of correctly predicted positive instances (e.g., customers who fully pay their loans) out of all instances predicted as positive. In the context of a bank, precision reflects the accuracy of identifying creditworthy customers who are likely to repay their loans. Maximizing precision ensures that the bank minimizes the number of false positives, which are instances where the bank incorrectly identifies customers as creditworthy when they are not. By prioritizing precision, the bank can reduce the risk of loan defaults and associated financial losses.

- While ROC AUC, Recall, and F1 Score are also important metrics, precision aligns closely with the bank's objective of minimizing risks and ensuring the quality of its loan portfolio.

Q7. How does the gap in precision and recall affect the bank?

> Ans:

- To fully understand a model’s errors, it’s important to analyze both false positives and false negatives, which are measured using metrics such as precision and recall. A low recall can be particularly risky for a bank.
- The gap between precision and recall reflects the model’s balance — a wider gap indicates a higher rate of incorrect predictions.
- High precision implies fewer false positives, meaning the bank is less likely to classify genuine customers as defaulters (resulting in fewer NPA loan accounts).
- High recall indicates fewer false negatives, ensuring the bank doesn’t miss out on good customers who are actually creditworthy.

Q8. Which were the features that heavily affected the outcome?

> Ans:

- `Address(Zipcode), Annual_Income, Grade` seems to be most important feature in our case.

- Loan duration `term`, Total Credit balance `revol_bal`, : Monthly debt vs. monthly income ratio `dti`, Interest `int_rate` also has high weights(coeffients) in the model .

Q9. Will the results be affected by geographical location? (Yes/No)

- Yes, we can see that zip_code (Address) is a very important feature so geographical location has impact on our result.

> Ans:

Business Recommendations for LoanTap

- Focus on maximizing the F1 score and area under the Precision-Recall Curve to effectively manage the precision-recall trade-off. This ensures identifying most defaulters while reducing false positives, enhancing risk management.

- Consider using more complex classifiers like Random Forests or XGBoost and perform hyperparameter tuning to enhance model performance and capture intricate relationships in the data.

- Employed stratified k-fold cross-validation to ensure representative distribution of minority class in each fold, providing reliable estimates of model performance.

> **Policy Adjustments Based on Insights**

> **Cross-Validation:**

> **Model Improvement:**

> **Optimize Loan Approval Strategy:**

- Scrutinize loans with lower grades more rigorously and consider adjusting interest rates to compensate for higher risk.
- Implement targeted strategies for high-risk zip codes, such as

additional verification steps or higher interest rates.
- Evaluate small business loans with additional financial health checks and collateral requirements to mitigate default risk.

By implementing these recommendations, LoanTap can enhance their loan approval process, minimize the risk of NPAs, and ensure sustainable growth and financial stability.

In [246…

```

```