Problem statment:

Aim of the Project

The aim of this project is to develop and enhance an online portal, LoanTap, which is dedicated to providing millennials with personalized lending packages. LoanTap seeks to bring innovation to the traditional loan market by offering salaried professionals and business owners quick and exible loans with affordable conditions. The project aims to streamline the loan process, making it more accessible and appealing to the millennial demographic, ultimately improving the user experience and satisfaction.

```
!pip install --upgrade scikit-learn
!pip install missingno
```

```
Requirement already satisfied: scikit-learn in /usr/local/lib/python3.11/dist-packages (1.6.1)
Requirement already satisfied: numpy>=1.19.5 in /usr/local/lib/python3.11/dist-packages (from scikit-learn) (1.26.4)
Requirement already satisfied: scipy>=1.6.0 in /usr/local/lib/python3.11/dist-packages (from scikit-learn) (1.14.1)
Requirement already satisfied: joblib>=1.2.0 in /usr/local/lib/python3.11/dist-packages (from scikit-learn) (1.4.2)
Requirement already satisfied: threadpoolctl>=3.1.0 in /usr/local/lib/python3.11/dist-packages (from scikit-learn) (3.5.0)
Requirement already satisfied: missingno in /usr/local/lib/python3.11/dist-packages (0.5.2)
Requirement already satisfied: numpy in /usr/local/lib/python3.11/dist-packages (from missingno) (1.26.4)
Requirement already satisfied: matplotlib in /usr/local/lib/python3.11/dist-packages (from missingno) (3.10.0)
Requirement already satisfied: scipy in /usr/local/lib/python3.11/dist-packages (from missingno) (1.14.1)
Requirement already satisfied: seaborn in /usr/local/lib/python3.11/dist-packages (from missingno) (0.13.2)
Requirement already satisfied: contourpy>=1.0.1 in /usr/local/lib/python3.11/dist-packages (from matplotlib->missingno) (1.3.1)
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.11/dist-packages (from matplotlib->missingno) (0.12.1)
Requirement already satisfied: fonttools>=4.22.0 in /usr/local/lib/python3.11/dist-packages (from matplotlib->missingno) (4.56.0)
Requirement already satisfied: kiwisolver>=1.3.1 in /usr/local/lib/python3.11/dist-packages (from matplotlib->missingno) (1.4.8)
Requirement already satisfied: packaging>=20.0 in /usr/local/lib/python3.11/dist-packages (from matplotlib->missingno) (24.2)
Requirement already satisfied: pillow>=8 in /usr/local/lib/python3.11/dist-packages (from matplotlib->missingno) (11.1.0)
Requirement already satisfied: pyparsing>=2.3.1 in /usr/local/lib/python3.11/dist-packages (from matplotlib->missingno) (3.2.1)
Requirement already satisfied: python-dateutil>=2.7 in /usr/local/lib/python3.11/dist-packages (from matplotlib->missingno) (2.8.2)
Requirement already satisfied: pandas>=1.2 in /usr/local/lib/python3.11/dist-packages (from seaborn->missingno) (2.2.2)
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.11/dist-packages (from pandas>=1.2->seaborn->missingno) (2025
Requirement already satisfied: tzdata>=2022.7 in /usr/local/lib/python3.11/dist-packages (from pandas>=1.2->seaborn->missingno) (202
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.11/dist-packages (from python-dateutil>=2.7->matplotlib->missingno
```

```
#Importing necessary libraries
import pandas as pd
import numpy as np
import seaborn as sns
from scipy import stats
import matplotlib.pyplot as plt
from sklearn.linear_model import LogisticRegression
from sklearn import metrics
from sklearn.metrics import confusion_matrix
from sklearn.metrics import classification_report
from sklearn.metrics import roc_auc_score
from sklearn.metrics import roc_curve
from sklearn.metrics import precision_recall_curve
from sklearn.model_selection import train_test_split, KFold, cross_val_score
from sklearn.preprocessing import MinMaxScaler
from yellowbrick.classifier import ROCAUC
from statsmodels.stats.outliers_influence import variance_inflation_factor
from imblearn.over_sampling import SMOTE
```

Here is the information on this particular data set:

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

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11. loan_status : Current status of the loan
12. purpose : A category provided by the borrower for the loan request.
13. title : The loan title provided by the borrower
14. zip_code : The rst 3 numbers of the zip code provided by the borrower in the loan application. 1 . addr_state : The state provided by the borrower in the loan application
15. dti : A ratio calculated using the borrower's total monthly debt payments on the total debt obligations, excluding mortgage and the requested LC loan, divided by the borrower's self-reported monthly income. 1 . earliest_cr_line : The month the borrower's earliest reported credit line was opened
16. open_acc : The number of open credit lines in the borrower's credit le.
17. pub_rec : Number of derogatory public records
18. revol_bal : Total credit revolving balance
19. revol_util : Revolving line utilization rate, or the amount of credit the borrower is using relative to all available revolving credit.
20. total_acc : The total number of credit lines currently in the borrower's credit le
21. initial_list_status : The initial listing status of the loan. Possible values are – W, F
22. application_type : Indicates whether the loan is an individual application or a joint application with two co-borrowers 2 . mort_acc : Number of mortgage accounts.
23. pub_rec_bankruptcies : Number of public record bankruptcies

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

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount("/content/drive", force_remount=True).
```

```
data = pd.read_csv('/content/drive/MyDrive/CSV datasets/logistic_regression.csv')
data.head()
```

	loan_amnt	term	int_rate	installment	grade	sub_grade	emp_title	emp_length	home_ownership	annual_inc	...	open_acc	pu
0	10000.0	36 months	11.44	329.48	B	B4	Marketing	10+ years	RENT	117000.0	...	16.0	
1	8000.0	36 months	11.99	265.68	B	B5	Credit analyst	4 years	MORTGAGE	65000.0	...	17.0	
2	15600.0	36 months	10.49	506.97	B	B3	Statistician	< 1 year	RENT	43057.0	...	13.0	
3	7200.0	36 months	6.49	220.65	A	A2	Client Advocate	6 years	RENT	54000.0	...	6.0	
4	24375.0	60 months	17.27	609.33	C	C5	Destiny Management Inc.	9 years	MORTGAGE	55000.0	...	13.0	

5 rows × 27 columns

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

```
No. of rows:  396030
No. of columns:  27
```

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

	proportion
loan_status	
Fully Paid	80.387092
Charged Off	19.612908

dtype: float64

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

	loan_amnt	term	int_rate	installment	grade	sub_grade	emp_title	emp_length	home_ownership	annual_inc
count	396030.000000	396030	396030.000000	396030.000000	396030	396030	373103	377729	396030	3.960300e+05
unique	NaN	2	NaN	NaN	7	35	173105	11	6	NaN
top	NaN	36 months	NaN	NaN	B	B3	Teacher	10+ years	MORTGAGE	NaN
freq	NaN	302005	NaN	NaN	116018	26655	4389	126041	198348	NaN
mean	14113.888089	NaN	13.639400	431.849698	NaN	NaN	NaN	NaN	NaN	7.420318e+04
std	8357.441341	NaN	4.472157	250.727790	NaN	NaN	NaN	NaN	NaN	6.163762e+04
min	500.000000	NaN	5.320000	16.080000	NaN	NaN	NaN	NaN	NaN	0.000000e+00
25%	8000.000000	NaN	10.490000	250.330000	NaN	NaN	NaN	NaN	NaN	4.500000e+04
50%	12000.000000	NaN	13.330000	375.430000	NaN	NaN	NaN	NaN	NaN	6.400000e+04
75%	20000.000000	NaN	16.490000	567.300000	NaN	NaN	NaN	NaN	NaN	9.000000e+04
max	40000.000000	NaN	30.990000	1533.810000	NaN	NaN	NaN	NaN	NaN	8.706582e+06

11 rows × 27 columns

```
data.columns
```

```
Index(['loan_amnt', 'term', 'int_rate', 'installment', 'annual_inc',
       'loan_status', 'dti', 'open_acc', 'pub_rec', 'revol_bal', 'revol_util',
       'total_acc', 'initial_list_status', 'mort_acc', 'pub_rec_bankruptcies',
       'purpose_credit_card', 'purpose_debt_consolidation',
       'purpose_educational', 'purpose_home_improvement', 'purpose_house',
       'purpose_major_purchase', 'purpose_medical', 'purpose_moving',
       'purpose_other', 'purpose_renewable_energy', 'purpose_small_business',
       'purpose_vacation', 'purpose_wedding', 'zip_code_05113',
       'zip_code_11650', 'zip_code_22690', 'zip_code_29597', 'zip_code_30723',
       'zip_code_48052', 'zip_code_70466', 'zip_code_86630', 'zip_code_93700',
       'grade_B', 'grade_C', 'grade_D', 'grade_E', 'grade_F', 'grade_G',
       'verification_status_Source Verified', 'verification_status_Verified',
       'application_type_INDIVIDUAL', 'application_type_JOINT',
       'home_ownership_OTHER', 'home_ownership_OWN', 'home_ownership_RENT'],
      dtype='object')
```

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 396030 entries, 0 to 396029
Data columns (total 27 columns):
 #   Column                Non-Null Count   Dtype  
---  ------                --------------   -----  
 0   loan_amnt             396030 non-null  float64
 1   term                  396030 non-null  object 
 2   int_rate              396030 non-null  float64
 3   installment           396030 non-null  float64
 4   grade                 396030 non-null  object 
 5   sub_grade             396030 non-null  object 
 6   emp_title             373103 non-null  object 
 7   emp_length            377729 non-null  object 
 8   home_ownership        396030 non-null  object 
 9   annual_inc            396030 non-null  float64
 10  verification_status   396030 non-null  object 
 11  issue_d               396030 non-null  object 
 12  loan_status           396030 non-null  object 
 13  purpose               396030 non-null  object 
 14  title                 394274 non-null  object 
 15  dti                   396030 non-null  float64
 16  earliest_cr_line      396030 non-null  object 
 17  open_acc              396030 non-null  float64
 18  pub_rec               396030 non-null  float64
 19  revol_bal             396030 non-null  float64
 20  revol_util            395754 non-null  float64
 21  total_acc             396030 non-null  float64
 22  initial_list_status   396030 non-null  object 
 23  application_type      396030 non-null  object 
 24  mort_acc              358235 non-null  float64
 25  pub_rec_bankruptcies  395495 non-null  float64
 26  address               396030 non-null  object 
dtypes: float64(12), object(15)
memory usage: 81.6+ MB
```

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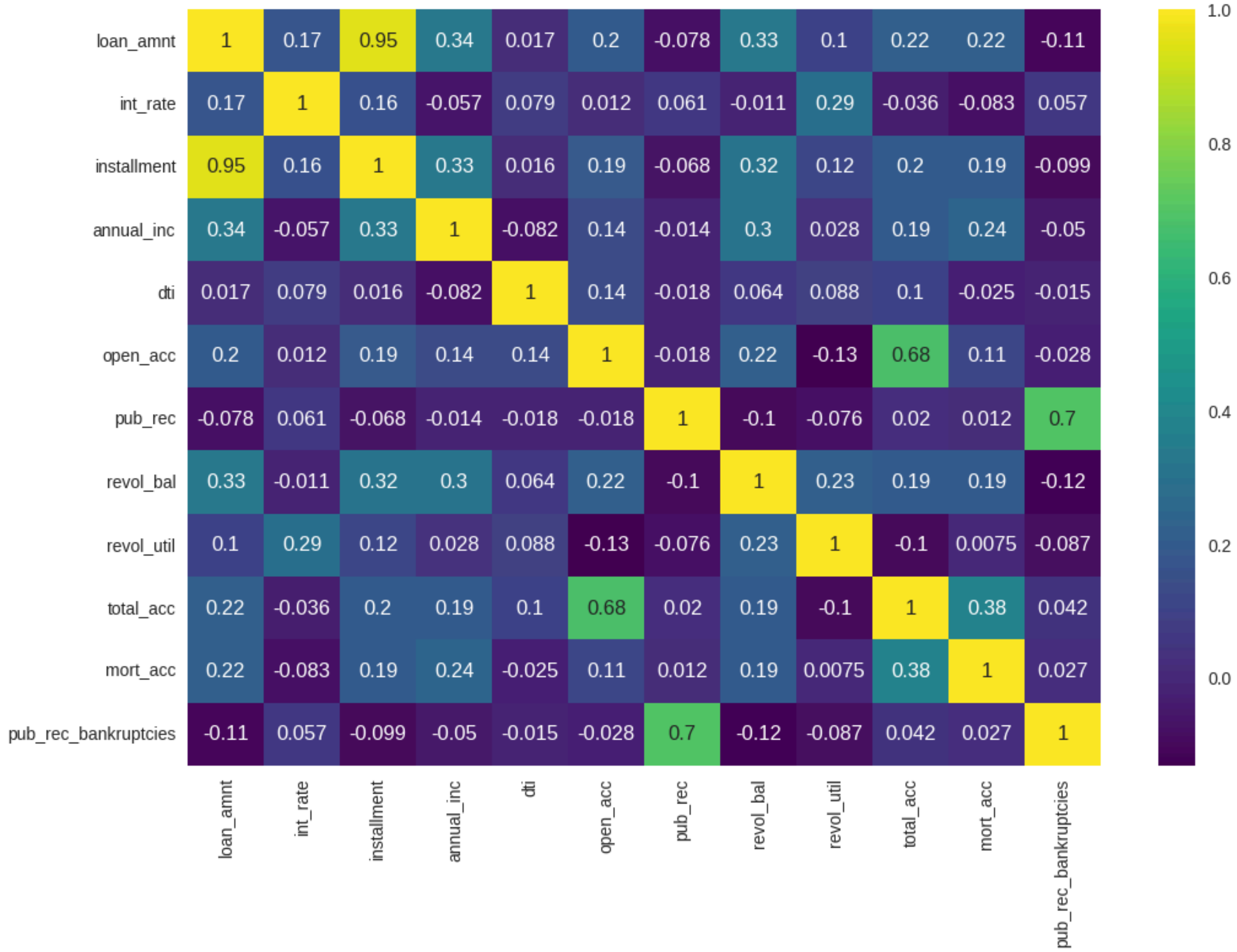
A correlation heatmap is a heatmap that shows a 2D correlation matrix between two discrete dimensions, using colored cells to represent data from usually a monochromatic scale. The values of the rst dimension appear as the rows of the table while of the second dimension as a column. The color of the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

```
plt.figure(figsize=(12, 8))
sns.heatmap(data.select_dtypes(include=np.number).corr(method='pearson'), annot=True, cmap='viridis')
plt.show()
```



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

installment: The monthly payment owed by the borrower if the loan originates.

loan_amnt: The listed amount of the loan applied for by the borrower. If at some point in time, the credit department reduces the loan amount, then it will be re ected in this value. So, we can drop either one of those columns

Data Exploration

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

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

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

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

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

The majority of people have home ownership as Mortgage and Rent

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

home_ownership	count
MORTGAGE	198348
RENT	159790
OWN	37746
OTHER	146

Combininging the minority classes as 'OTHER'.

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

home_ownership	count
MORTGAGE	198348
RENT	159790
OWN	37746
OTHER	146

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

loan_status	count
Fully Paid	123
Charged Off	23

4. Coverting string to date-time format

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

```
<ipython-input-36-2f9ecc54f8c2>:1: UserWarning: Could not infer format, so each element will be parsed individually, falling back tc
  data['issue_d'] = pd.to_datetime(data['issue_d'])
<ipython-input-36-2f9ecc54f8c2>:2: UserWarning: Could not infer format, so each element will be parsed individually, falling back tc
  data['earliest_cr_line'] = pd.to_datetime(data['earliest_cr_line'])
```

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

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

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

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

title	count
debt consolidation	168108
credit card refinancing	51781
home improvement	17117
other	12993
consolidation	5583
major purchase	4998
debt consolidation loan	3513
business	3017
medical expenses	2820
credit card consolidation	2638

dtype: int64

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

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

```
plt.figure(figsize=(15, 10))
plt.subplot(2, 2, 1)
grade = sorted(data.grade.unique().tolist())
sns.countplot(x='grade', data=data, hue='loan_status', order=grade)
plt.subplot(2, 2, 2)
sub_grade = sorted(data.sub_grade.unique().tolist())
g = sns.countplot(x='sub_grade', data=data, hue='loan_status', order=sub_grade)
g.set_xticklabels(g.get_xticklabels(), rotation=90)
```

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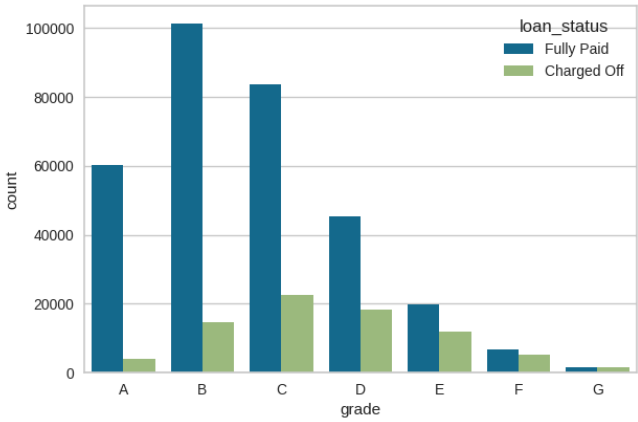
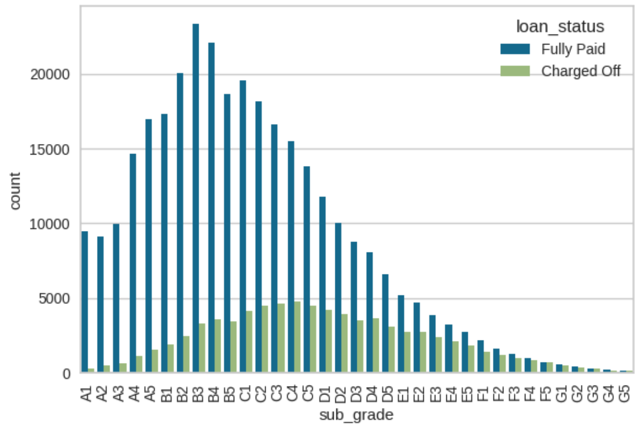
```
<ipython-input-40-e376c4a46952>:8: UserWarning: set_ticklabels() should only be used with a fixed number of ticks, i.e. after set
  g.set_xticklabels(g.get_xticklabels(), rotation=90)
[Text(0, 0, 'A1'),
 Text(1, 0, 'A2'),
 Text(2, 0, 'A3'),
 Text(3, 0, 'A4'),
 Text(4, 0, 'A5'),
 Text(5, 0, 'B1'),
 Text(6, 0, 'B2'),
 Text(7, 0, 'B3'),
 Text(8, 0, 'B4'),
 Text(9, 0, 'B5'),
 Text(10, 0, 'C1'),
 Text(11, 0, 'C2'),
 Text(12, 0, 'C3'),
 Text(13, 0, 'C4'),
 Text(14, 0, 'C5'),
 Text(15, 0, 'D1'),
 Text(16, 0, 'D2'),
 Text(17, 0, 'D3'),
 Text(18, 0, 'D4'),
 Text(19, 0, 'D5'),
 Text(20, 0, 'E1'),
 Text(21, 0, 'E2'),
 Text(22, 0, 'E3'),
 Text(23, 0, 'E4'),
 Text(24, 0, 'E5'),
 Text(25, 0, 'F1'),
 Text(26, 0, 'F2'),
 Text(27, 0, 'F3'),
 Text(28, 0, 'F4'),
 Text(29, 0, 'F5'),
 Text(30, 0, 'G1'),
 Text(31, 0, 'G2'),
 Text(32, 0, 'G3'),
 Text(33, 0, 'G4'),
 Text(34, 0, 'G5')]
```






```
plt.figure(figsize=(15, 20))
plt.subplot(4, 2, 1)
sns.countplot(x='term', data=data, hue='loan_status')
plt.subplot(4, 2, 2)
sns.countplot(x='home_ownership', data=data, hue='loan_status')
plt.subplot(4, 2, 3)
sns.countplot(x='verification_status', data=data, hue='loan_status')
plt.subplot(4, 2, 4)
g = sns.countplot(x='purpose', data=data, hue='loan_status')
g.set_xticklabels(g.get_xticklabels(), rotation=90)
```

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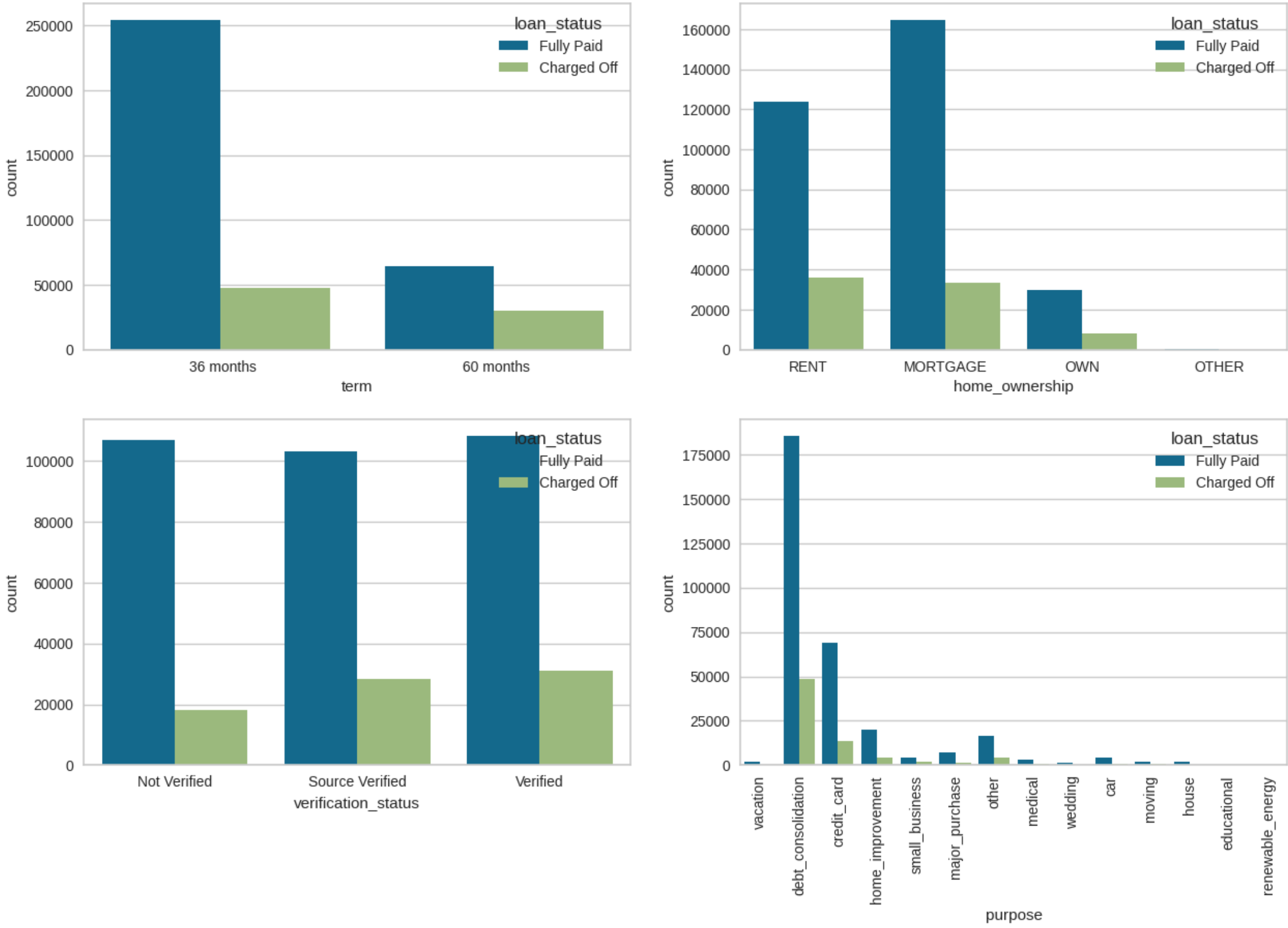
```
<ipython-input-41-9fd3c7705aaa>:10: UserWarning: set_ticklabels() should only be used with a fixed number of ticks, i.e. after se
  g.set_xticklabels(g.get_xticklabels(), rotation=90)
[Text(0, 0, 'vacation'),
 Text(1, 0, 'debt_consolidation'),
 Text(2, 0, 'credit_card'),
 Text(3, 0, 'home_improvement'),
 Text(4, 0, 'small_business'),
 Text(5, 0, 'major_purchase'),
 Text(6, 0, 'other'),
 Text(7, 0, 'medical'),
 Text(8, 0, 'wedding'),
 Text(9, 0, 'car'),
 Text(10, 0, 'moving'),
 Text(11, 0, 'house'),
 Text(12, 0, 'educational'),
 Text(13, 0, 'renewable_energy')]
```




```
plt.figure(figsize=(15, 12))
plt.subplot(2, 2, 1)
order = ['< 1 year', '1 year', '2 years', '3 years', '4 years', '5 years',
'6 years', '7 years', '8 years', '9 years', '10+ years',]
g = sns.countplot(x='emp_length', data=data, hue='loan_status', order=order)
g.set_xticklabels(g.get_xticklabels(), rotation=90);
plt.subplot(2, 2, 2)
plt.barh(data.emp_title.value_counts()[:30].index, data.emp_title.value_counts()[:30])
plt.title("The most 30 jobs title afforded a loan")
plt.tight_layout()
```

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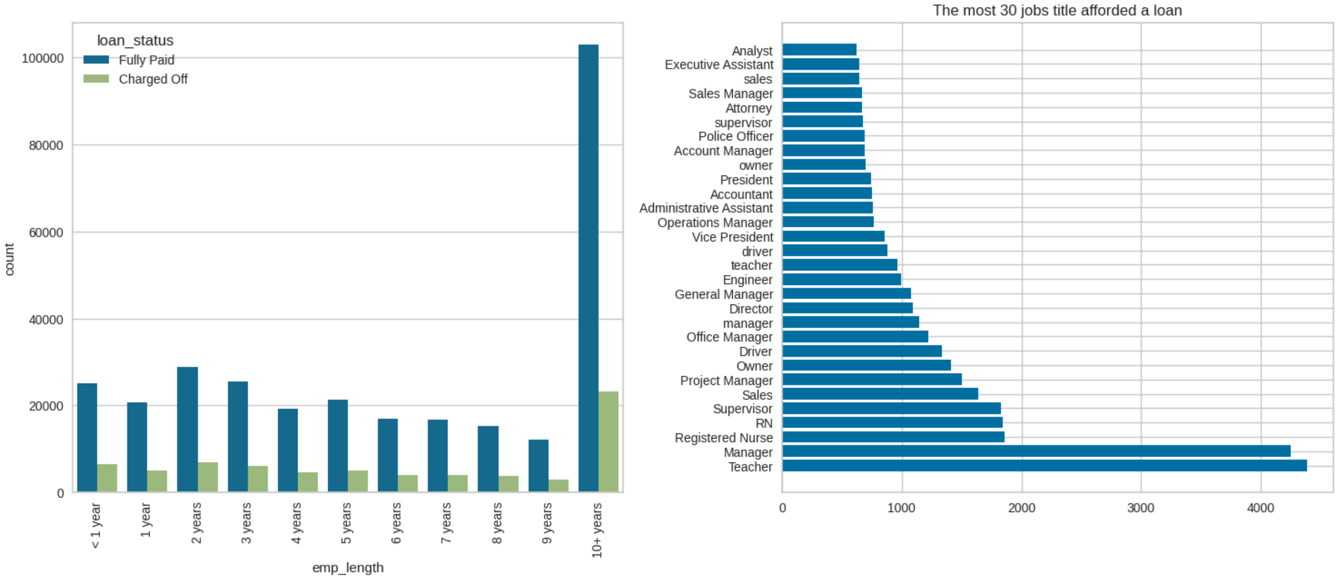
```
<ipython-input-42-4ef9e4833dc9>:6: UserWarning: set_ticklabels() should only be used with a fixed number of ticks, i.e. after set_ti
  g.set_xticklabels(g.get_xticklabels(), rotation=90);
```



Manager and Teacher are the most afforded loan job titles.

Feature Engineering

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


data['pub_rec'] = data.pub_rec.apply(pub_rec)
data['mort_acc'] = data.mort_acc.apply(mort_acc)
data['pub_rec_bankruptcies'] = data.pub_rec_bankruptcies.apply(pub_rec_bankruptcies)
plt.figure(figsize=(12, 30))
plt.subplot(6, 2, 1)
sns.countplot(x='pub_rec', data=data, hue='loan_status')
plt.subplot(6, 2, 2)
sns.countplot(x='initial_list_status', data=data, hue='loan_status')
plt.subplot(6, 2, 3)
sns.countplot(x='application_type', data=data, hue='loan_status')
plt.subplot(6, 2, 4)
sns.countplot(x='mort_acc', data=data, hue='loan_status')
plt.subplot(6, 2, 5)
sns.countplot(x='pub_rec_bankruptcies', data=data, hue='loan_status')
plt.show()
```

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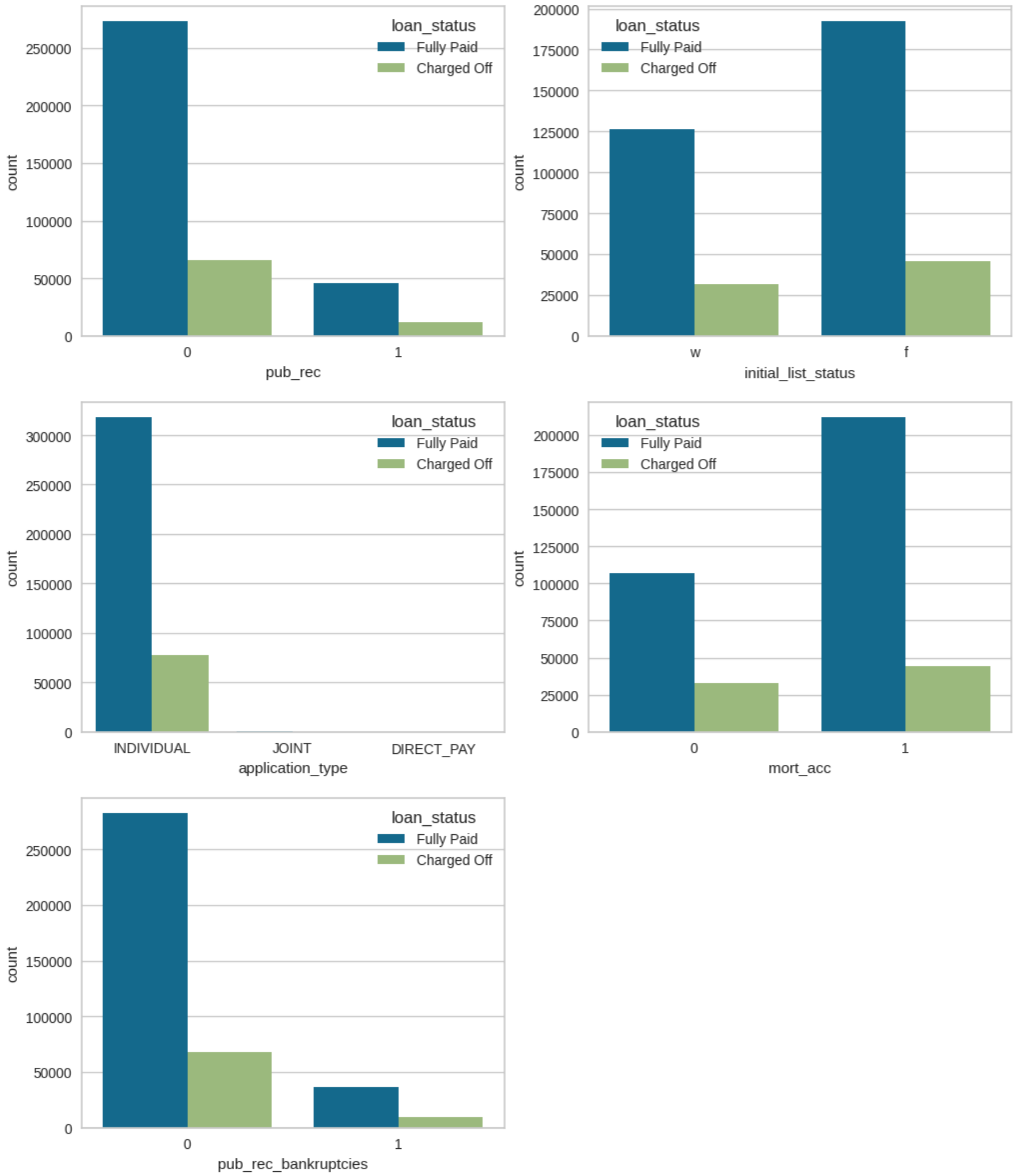


```
# Mapping of target variable
data['loan_status'] = data.loan_status.map({'Fully Paid':0, 'Charged Off':1})
```

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

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	0
loan_amnt	0.000000
term	0.000000
int_rate	0.000000
installment	0.000000
grade	0.000000
sub_grade	0.000000
emp_title	5.789208
emp_length	4.621115
home_ownership	0.000000
annual_inc	0.000000
verification_status	0.000000
issue_d	0.000000
loan_status	0.000000
purpose	0.000000
title	0.443401
dti	0.000000
earliest_cr_line	0.000000
open_acc	0.000000
pub_rec	0.000000
revol_bal	0.000000
revol_util	0.069692
total_acc	0.000000
initial_list_status	0.000000
application_type	0.000000
mort_acc	0.000000
pub_rec_bankruptcies	0.000000
address	0.000000

Very Important: Mean Target Imputation

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

total_acc	loan_amnt	int_rate	installment	annual_inc	loan_status	dti	open_acc	pub_rec	revol_bal	revol_util
2.0	6672.222222	15.801111	210.881667	64277.777778	0.222222	2.279444	1.611111	0.000000	2860.166667	53.527778
3.0	6042.966361	15.615566	198.728318	41270.753884	0.220183	6.502813	2.611621	0.033639	3382.807339	49.991022
4.0	7587.399031	15.069491	250.050194	42426.565969	0.214055	8.411963	3.324717	0.033118	4874.231826	58.477400
5.0	7845.734714	14.917564	256.190325	44394.098003	0.203156	10.118328	3.921598	0.055720	5475.253452	56.890311
6.0	8529.019843	14.651752	278.518228	48470.001156	0.215874	11.222542	4.511119	0.076634	6546.374957	57.812483
...	...	...	...	...	...	...	...	...	...	...
124.0	23200.000000	17.860000	587.370000	66000.000000	1.000000	14.040000	43.000000	0.000000	25497.000000	75.400000
129.0	25000.000000	7.890000	505.600000	200000.000000	0.000000	8.900000	48.000000	0.000000	27659.000000	8.300000
135.0	24000.000000	15.410000	576.140000	82000.000000	0.000000	33.850000	57.000000	0.000000	35715.000000	50.800000
150.0	35000.000000	8.670000	1107.630000	189000.000000	0.000000	6.630000	40.000000	0.000000	39065.000000	44.400000
151.0	35000.000000	13.990000	1196.050000	160000.000000	1.000000	12.650000	26.000000	0.000000	46643.000000	71.500000

118 rows × 12 columns

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```
total_acc_avg = data.groupby(by='total_acc')['mort_acc'].mean()
# Saving mean of mort_acc according to total_acc_avg
```

```
# Specifying 'mort_acc' column ensures only numeric data is used for calculating the mean.


def fill_mort_acc(total_acc, mort_acc):
    if np.isnan(mort_acc):
        return total_acc_avg[total_acc].round()
    else:
        return mort_acc
data['mort_acc'] = data.apply(lambda x: fill_mort_acc(x['total_acc'], x['mort_acc']), axis=1)
data.isnull().sum()/len(data)*100
```

	0
loan_amnt	0.000000
term	0.000000
int_rate	0.000000
installment	0.000000
grade	0.000000
sub_grade	0.000000
emp_title	5.789208
emp_length	4.621115
home_ownership	0.000000
annual_inc	0.000000
verification_status	0.000000
issue_d	0.000000
loan_status	0.000000
purpose	0.000000
title	0.443401
dti	0.000000
earliest_cr_line	0.000000
open_acc	0.000000
pub_rec	0.000000
revol_bal	0.000000
revol_util	0.069692
total_acc	0.000000
initial_list_status	0.000000
application_type	0.000000
mort_acc	0.000000
pub_rec_bankruptcies	0.000000
address	0.000000

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

```
(396030, 27)
```

```
 # Dropping rows with null values
data.dropna(inplace=True)
```

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

```
(371125, 27)
```

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

```
13
```

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

# Get numerical columns
num_cols = data.select_dtypes(include=[np.number]).columns.tolist()

# Determine the number of rows and columns for subplots
num_features = len(num_cols)
cols = 3  # Number of plots per row
rows = math.ceil(num_features / cols)  # Determine required rows

# Create subplots
fig, axes = plt.subplots(rows, cols, figsize=(cols * 5, rows * 4))
axes = axes.flatten()  # Flatten axes array for easy iteration

# Loop through numerical columns and plot boxplots
for i, col in enumerate(num_cols):
    sns.boxplot(x=data[col], ax=axes[i])
    axes[i].set_title(f'Boxplot of {col}')

# Remove empty subplots if any
for j in range(i + 1, len(axes)):
    fig.delaxes(axes[j])

plt.tight_layout()  # Adjust layout for better appearance
plt.show()
```

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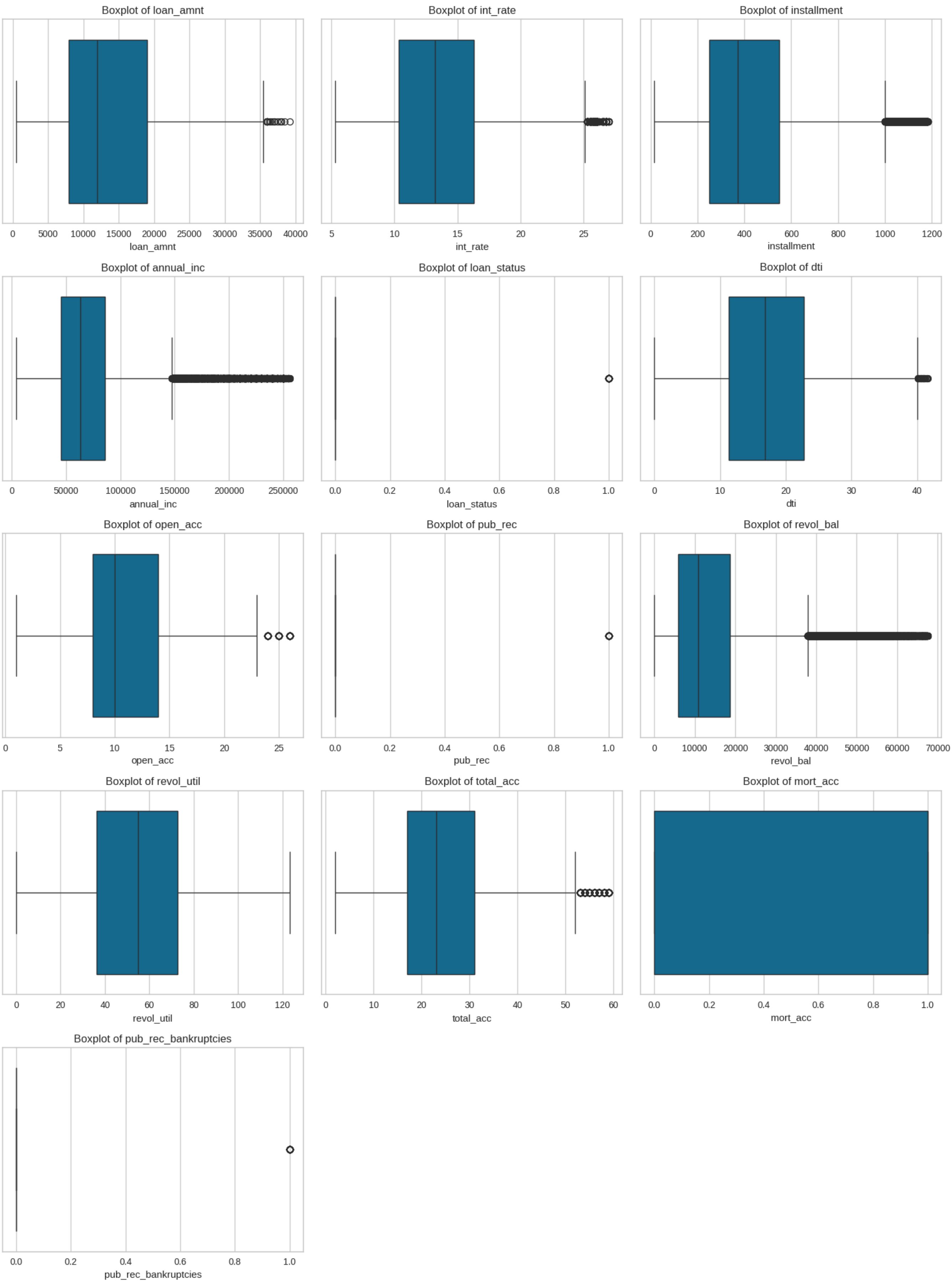

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```
for col in num_cols:
 mean = data[col].mean()
 std = data[col].std()
 upper_limit = mean+3*std
 lower_limit = mean-3*std

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

Data Preprocessing

```
data.term.unique()
```

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

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

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

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

```
 # Let's fetch ZIP from address and then drop the remaining details
data['zip_code'] = data.address.apply(lambda x: x[-5:])
data['zip_code'].value_counts(normalize=True)*100
```

zip_code	proportion
70466	14.372118
30723	14.294876
22690	14.272929
48052	14.125001
00813	11.607942
29597	11.548942
05113	11.519299
93700	2.767596
11650	2.761040
86630	2.730258

```
 # Dropping some variables which IMO we can let go for now
data.drop(columns=['issue_d', 'emp_title', 'title', 'sub_grade',
                   'address', 'earliest_cr_line', 'emp_length'],
                   axis=1, inplace=True)
```

One-hot Encoding

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

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

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	loan_amnt	term	int_rate	installment	annual_inc	loan_status	dti	open_acc	pub_rec	revol_bal	revol_util	total_acc	initi
1	8000.0	36	11.99	265.68	65000.0	0	22.05	17.0	0	20131.0	53.3	27.0	
2	15600.0	36	10.49	506.97	43057.0	0	12.79	13.0	0	11987.0	92.2	26.0	
3	7200.0	36	6.49	220.65	54000.0	0	2.60	6.0	0	5472.0	21.5	13.0	
4	24375.0	60	17.27	609.33	55000.0	1	33.95	13.0	0	24584.0	69.8	43.0	

```
data.shape
```

```
(350846, 50)
```

Logistic Regression model building

```
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score, roc_auc_score, confusion_matrix, classification_repo


# Step 1: Identify Numerical and Categorical Features
numerical_cols = X.select_dtypes(include=[np.number]).columns.tolist()
categorical_cols = X.select_dtypes(include=['object', 'category']).columns.tolist()

# Step 2: Encode Categorical Features using OneHotEncoding
if categorical_cols:
    X = pd.get_dummies(X, columns=categorical_cols, drop_first=True)  # Convert to numeric

# Step 3: Train-Test Split (80% Train, 20% Test)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42, stratify=y)

# Step 4: Standardize Only Numerical Features
scaler = StandardScaler()
X_train[numerical_cols] = scaler.fit_transform(X_train[numerical_cols])
X_test[numerical_cols] = scaler.transform(X_test[numerical_cols])

# Step 5: Train Logistic Regression Model
model = LogisticRegression(max_iter=1000)
model.fit(X_train, y_train)

# Step 6: Make Predictions
y_pred = model.predict(X_test)
y_prob = model.predict_proba(X_test)[:, 1]  # Get probability scores for ROC-AUC

# Step 7: Evaluate Model Performance
accuracy = accuracy_score(y_test, y_pred)
precision = precision_score(y_test, y_pred)
recall = recall_score(y_test, y_pred)
f1 = f1_score(y_test, y_pred)
roc_auc = roc_auc_score(y_test, y_prob)
conf_matrix = confusion_matrix(y_test, y_pred)

# Print Metrics
print(f'Accuracy: {accuracy:.4f}')
print(f'Precision: {precision:.4f}')
print(f'Recall: {recall:.4f}')
print(f'F1 Score: {f1:.4f}')
print(f'ROC AUC Score: {roc_auc:.4f}')
print("\nClassification Report:\n", classification_report(y_test, y_pred))

# Plot Confusion Matrix
plt.figure(figsize=(5,4))
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues', xticklabels=['Not Approved', 'Approved'], yticklabels=['Not Approved', 'Appı
plt.xlabel('Predicted')
```

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