1. **Problem Statement:**

LoanTap, an innovative online platform, specializes in offering customized loan products tailored to the needs of millennials. They aim to revolutionize the traditional loan segment by providing instant, flexible loans with consumer-friendly terms to salaried professionals and businessmen. LoanTap now seeks to enhance its credit evaluation process by developing a predictive model to determine whether to extend a credit line to individuals and, if approved, suggest appropriate repayment terms.

2. **Approach:**

Review the dataset provided by LoanTap, examining attributes such as age, income, employment status, and credit score. Employ machine learning algorithms like logistic regression or random forest to build a predictive model for determining creditworthiness based on the identified attributes. Assess the model's performance using metrics like accuracy, precision, recall, and F1-score through cross-validation. For creditworthy individuals, propose appropriate repayment terms including loan amount, interest rate, and tenure based on their risk profile and financial capacity. Integrate the developed predictive model into LoanTap's existing system to automate credit evaluation and streamline the loan approval process, enhancing customer experience and minimizing default risks.

Please visit the google colab link for any missing data,graph,observation and recomendations

In PDF there are some graphs missing and observations too missing. Please visit the link for evaluation of marks.

https://colab.research.google.com/drive/1l8NQhtyiS2LzYrnzuR79tMMXl4tv-ti4?usp=sharing

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import LabelEncoder
from sklearn.preprocessing import OneHotEncoder
from sklearn.preprocessing import OrdinalEncoder
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import MinMaxScaler
```

```
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import confusion_matrix
from sklearn.metrics import classification_report
from sklearn.metrics import precision_score
from sklearn.metrics import recall_score
from sklearn.metrics import f1_score
from sklearn.metrics import roc_curve
from sklearn.metrics import roc_auc_score
from sklearn.metrics import precision_recall_curve
from sklearn.metrics import accuracy_score
from statsmodels.stats.outliers_influence import variance_inflation_factor
from imblearn.over_sampling import SMOTE
import warnings
warnings.filterwarnings("ignore")
from sklearn.metrics import ConfusionMatrixDisplay
```

```
!gdown 1EBAgscDx0Is-LEHR2KEmHCd_AdzO9UtY
```

```
Downloading...
From: https://drive.google.com/uc?id=1EBAgscDx0Is-LEHR2KEmHCd_AdzO9UtY
To: /content/Loantap.csv
100% 100M/100M [00:01<00:00, 52.7MB/s]
```

```
df= pd.read_csv('Loantap.csv')
df.head()
```

	loan_amnt	term	int_rate	installment	grade	sub_grade	emp_title	emp_length	home_ownership	annual_inc	...	open_acc	pub_rec	revol_bal	revol_util	total_acc	init
0	10000.0	36 months	11.44	329.48	B	B4	Marketing	10+ years	RENT	117000.0	...	16.0	0.0	36369.0	41.8	25.0	
1	8000.0	36 months	11.99	265.68	B	B5	Credit analyst	4 years	MORTGAGE	65000.0	...	17.0	0.0	20131.0	53.3	27.0	
2	15600.0	36 months	10.49	506.97	B	B3	Statistician	< 1 year	RENT	43057.0	...	13.0	0.0	11987.0	92.2	26.0	
3	7200.0	36 months	6.49	220.65	A	A2	Client Advocate	6 years	RENT	54000.0	...	6.0	0.0	5472.0	21.5	13.0	
4	24375.0	60 months	17.27	609.33	C	C5	Destiny Management Inc.	9 years	MORTGAGE	55000.0	...	13.0	0.0	24584.0	69.8	43.0	

5 rows × 27 columns

```
df.shape
```

```
(396030, 27)
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 396030 entries, 0 to 396029
Data columns (total 27 columns):
 #   Column                Non-Null Count   Dtype  
---  ------                --------------   -----  
 0   loan_amnt             396030 non-null  float64
 1   term                  396030 non-null  object 
 2   int_rate              396030 non-null  float64
 3   installment           396030 non-null  float64
 4   grade                 396030 non-null  object 
 5   sub_grade             396030 non-null  object 
 6   emp_title             373103 non-null  object 
 7   emp_length            377729 non-null  object 
 8   home_ownership        396030 non-null  object 
 9   annual_inc            396030 non-null  float64
 10  verification_status   396030 non-null  object 
 11  issue_d               396030 non-null  object 
 12  loan_status           396030 non-null  object 
 13  purpose               396030 non-null  object 
 14  title                 394274 non-null  object 
 15  dti                   396030 non-null  float64
 16  earliest_cr_line      396030 non-null  object 
```

```
 17  open_acc              396030 non-null  float64
 18  pub_rec               396030 non-null  float64
 19  revol_bal             396030 non-null  float64
 20  revol_util            395754 non-null  float64
 21  total_acc             396030 non-null  float64
 22  initial_list_status   396030 non-null  object
 23  application_type      396030 non-null  object
 24  mort_acc              358235 non-null  float64
 25  pub_rec_bankruptcies  395495 non-null  float64
 26  address               396030 non-null  object
dtypes: float64(12), object(15)
memory usage: 81.6+ MB
```

Observation:-

Given the dataset containing the mixture of 'Numerical' and 'Categorical' data along with the need to preprocess certain 'Categorical' columns for analysis, an initial step of data extraction and conversion will be conducted to ensure their Suitability for future analysis

```
df.describe()
```

	loan_amnt	int_rate	installment	annual_inc	dti	open_acc	pub_rec	revol_bal	revol_util	total_acc	mort_acc	pub_rec_bai
count	396030.000000	396030.000000	396030.000000	3.960300e+05	396030.000000	396030.000000	396030.000000	3.960300e+05	395754.000000	396030.000000	358235.000000	395
mean	14113.888089	13.639400	431.849698	7.420318e+04	17.379514	11.311153	0.178191	1.584454e+04	53.791749	25.414744	1.813991	
std	8357.441341	4.472157	250.727790	6.163762e+04	18.019092	5.137649	0.530671	2.059184e+04	24.452193	11.886991	2.147930	
min	500.000000	5.320000	16.080000	0.000000e+00	0.000000	0.000000	0.000000	0.000000e+00	0.000000	2.000000	0.000000	
25%	8000.000000	10.490000	250.330000	4.500000e+04	11.280000	8.000000	0.000000	6.025000e+03	35.800000	17.000000	0.000000	
50%	12000.000000	13.330000	375.430000	6.400000e+04	16.910000	10.000000	0.000000	1.118100e+04	54.800000	24.000000	1.000000	
75%	20000.000000	16.490000	567.300000	9.000000e+04	22.980000	14.000000	0.000000	1.962000e+04	72.900000	32.000000	3.000000	
max	40000.000000	30.990000	1533.810000	8.706582e+06	9999.000000	90.000000	86.000000	1.743266e+06	892.300000	151.000000	34.000000	

```
df.describe(include='object')
```

	term	grade	sub_grade	emp_title	emp_length	home_ownership	verification_status	issue_d	loan_status	purpose	title	earliest_cr_line	initial_list
count	396030	396030	396030	373103	377729	396030	396030	396030	396030	396030	394274	396030	
unique	2	7	35	173105	11	6	3	115	2	14	48816	684	
top	36 months	B	B3	Teacher	10+ years	MORTGAGE	Verified	Oct-2014	Fully Paid	debt_consolidation	Debt consolidation	Oct-2000	
freq	302005	116018	26655	4389	126041	198348	139563	14846	318357	234507	152472	3017	

```
df.duplicated().sum()
```

```
0
```

Here we have no **Duplicate** values in dataset.

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

```
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
```

Extracting the Year from the 'Earliest Credit Line' column and converting its data type from String to Integer to create the Earliest Year column.

```
df['earliest_year']= df['earliest_cr_line'].str.split('-').str[-1]
df['earliest_year'] = pd.to_numeric(df['earliest_year'])
```

Extraction of Pincode from Address column from the dataset:-

```
df['pin_code']= df['address'].str.split(' ').str[-1]
```

Extracting Year from 'Issue_d' column and Converting the datatype of 'Issued Year' column from String to Integer.

```
df['issued_year'] = df['issue_d'].str.split('-').str[-1]
df['issued_year'] = pd.to_numeric(df['issued_year'])
```

```
columns_drop = ['earliest_cr_line', 'address', 'issue_d']
df= df.drop (columns= columns_drop)
```

Observation-

The dataset contains both Categorical and Numerical data. Converting Categorical data to Nimerical data type offers several advantages-

1. Memory Effeciency
2. Faster operations
3. Ordered Categories

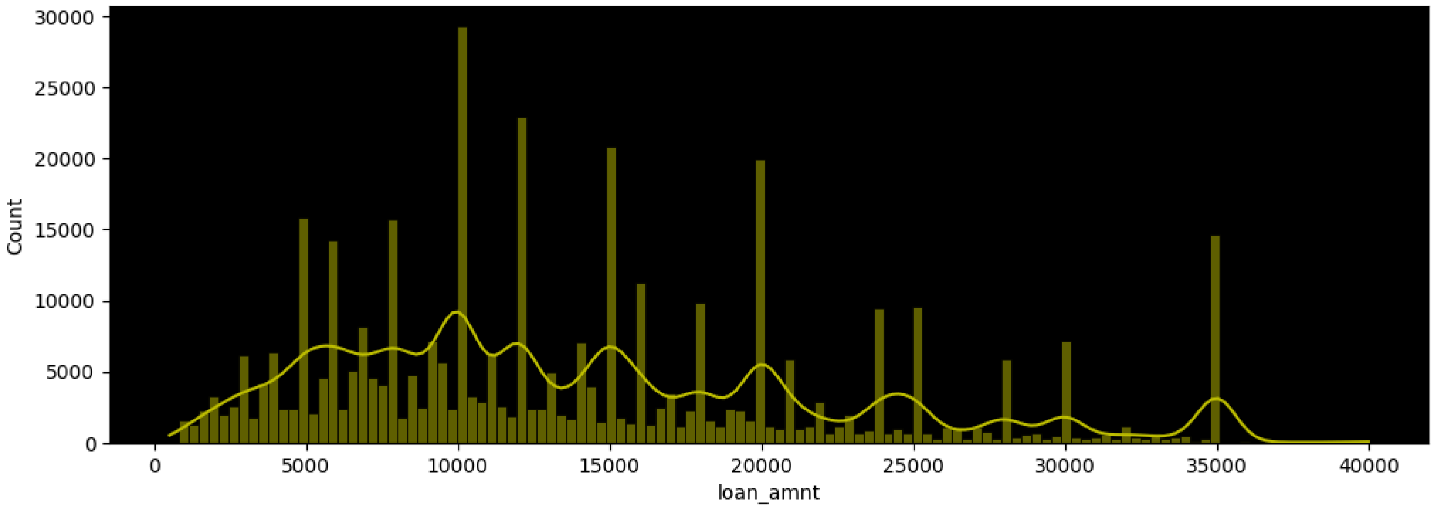
Converting Categorical data from Object Datatype to Category Datatype-

```
for column in ( 'term' , 'grade', 'sub_grade', 'emp_title', 'emp_length','home_ownership', 'verification_status' , 'loan_status', 'purpose' , 'title' , 'initial_list_status' ,'app
  df[column] = df[column].astype('category')
```

Analysis on Univariate with Continuous

Univaraite analysis of Individual columns aids in understanding the data Distribution. For Categorical columns, its crucial to ascertain whether the data exhibits any discernible categorization or if the column comprises random value that offer no actionable insights

```
plt.figure(figsize=(12,4))
sns.histplot(df['loan_amnt'],kde=True,color='y')
ax= plt.gca()
ax.set_facecolor('Black')
```



Observation

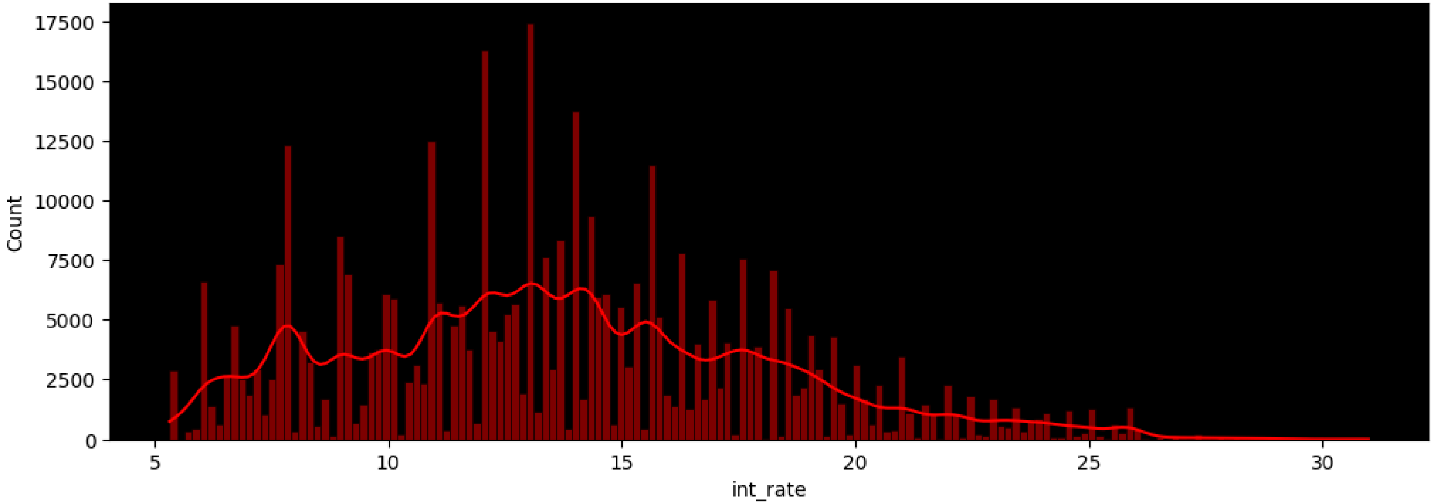
The graph depicts that the significant number of individuals have taken loan of $10000, which appears to be most common loan amount.

Furthermore, it is evident that loan amounts are distributed across various values, indicating that loans have been taken at almost every value

```
continuous= df.select_dtypes('float64').columns.to_list()
continuous
```

```
['loan_amnt',
 'int_rate',
 'installment',
 'annual_inc',
 'dti',
 'open_acc',
 'pub_rec',
 'revol_bal',
 'revol_util',
 'total_acc',
 'mort_acc',
 'pub_rec_bankruptcies']
```

```
plt.figure(figsize=(12,4))
sns.histplot(df['int_rate'],kde=True,color='r')
ax= plt.gca()
ax.set_facecolor('Black')
```



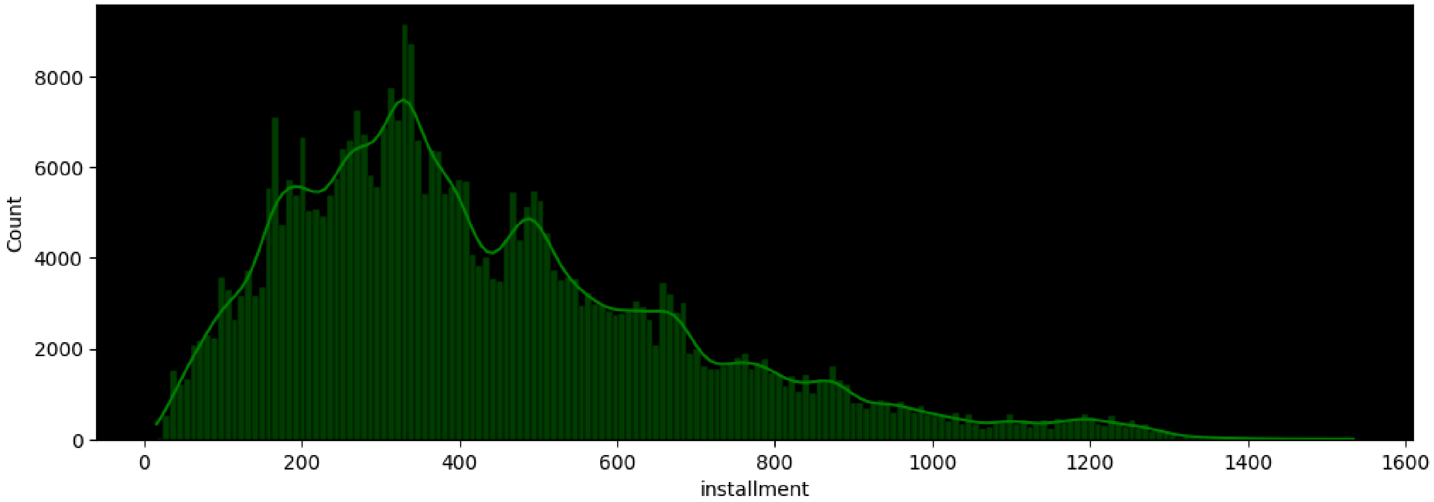
Observation

The graph displays the Interest rate chosen by individuals who have taken out loan.

According to the graph, the highest interest rates are predominantly within the range of 10% to 15%.

Specifically , the majority of individuals have selected interest rates between 12% and 14% indicating their prefrence for loans at this rate.

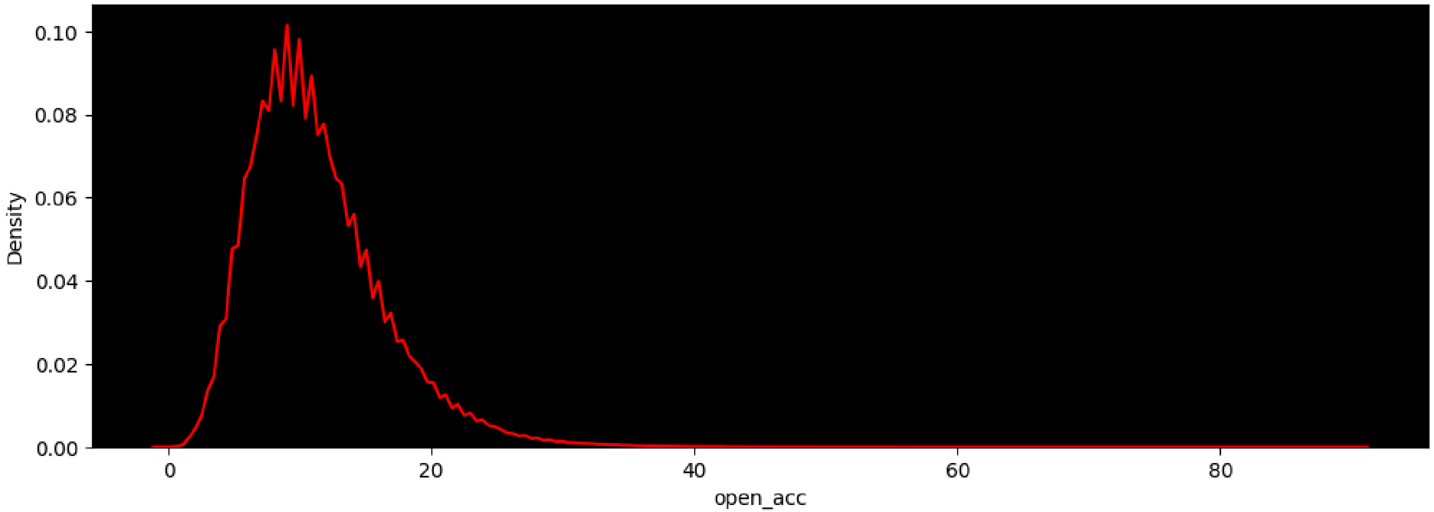
```
plt.figure(figsize=(12,4))
sns.histplot(df['installment'],kde=True,color='g')
ax= plt.gca()
ax.set_facecolor('Black')
```



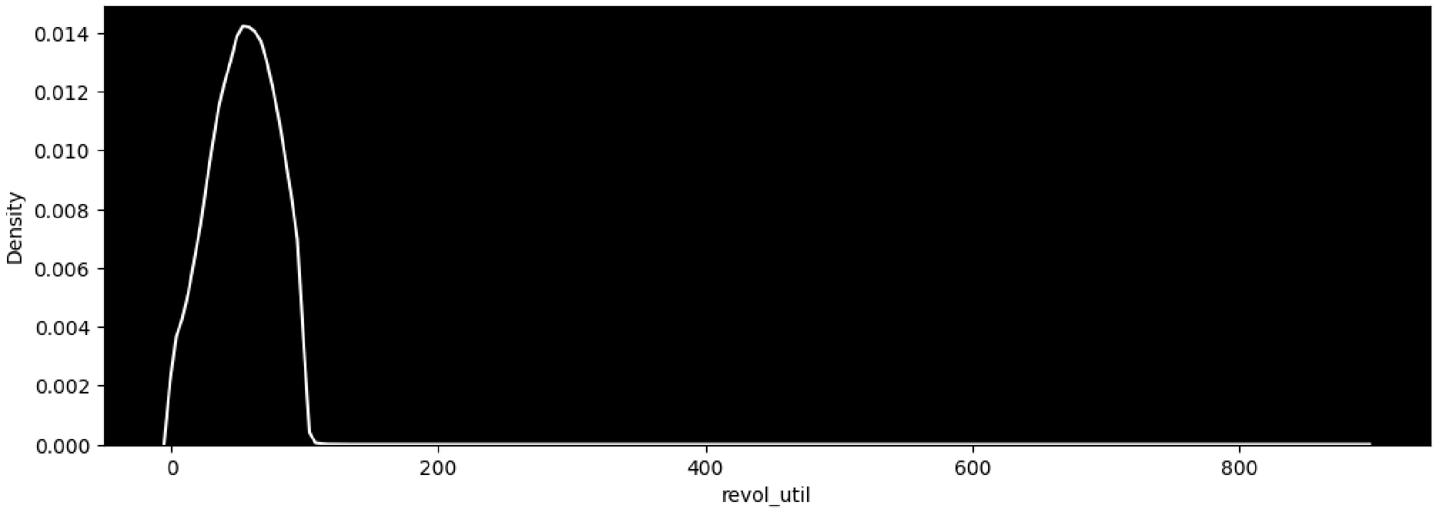
Observation

The graph represents the monthly installment amount paid by individuals who have taken out loans. It indicates that the most common installment amount falls within the range of 200-400, with individuals repaying their loan amount on specified dates throughout the month.

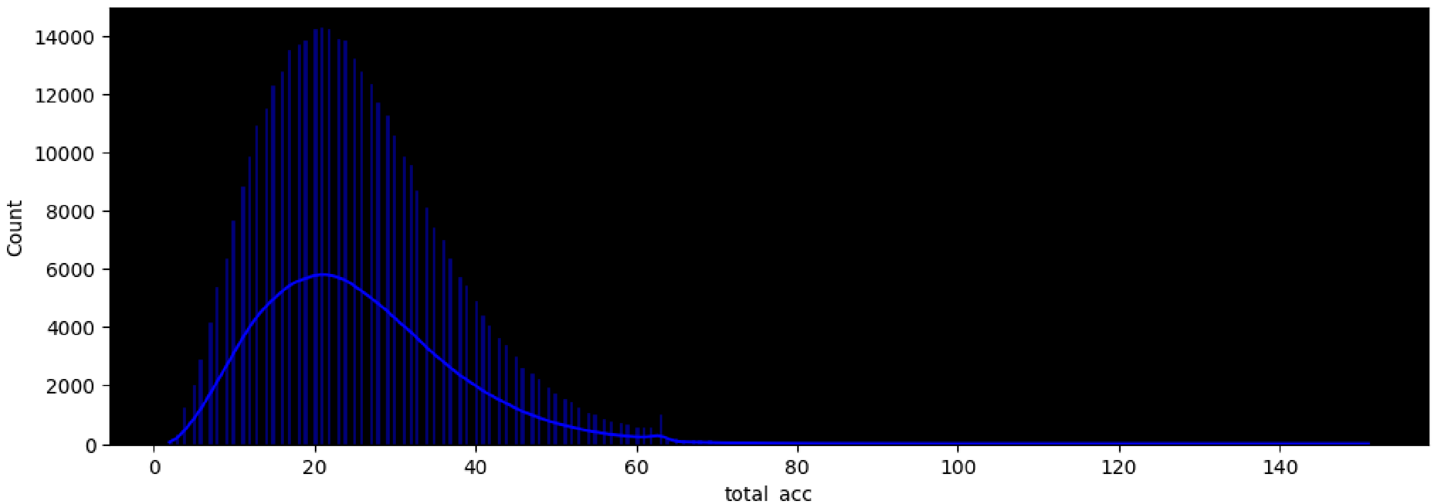
```
plt.figure(figsize=(12,4))
sns.kdeplot(df['open_acc'],color='red')
ax= plt.gca()
ax.set_facecolor('Black')
```



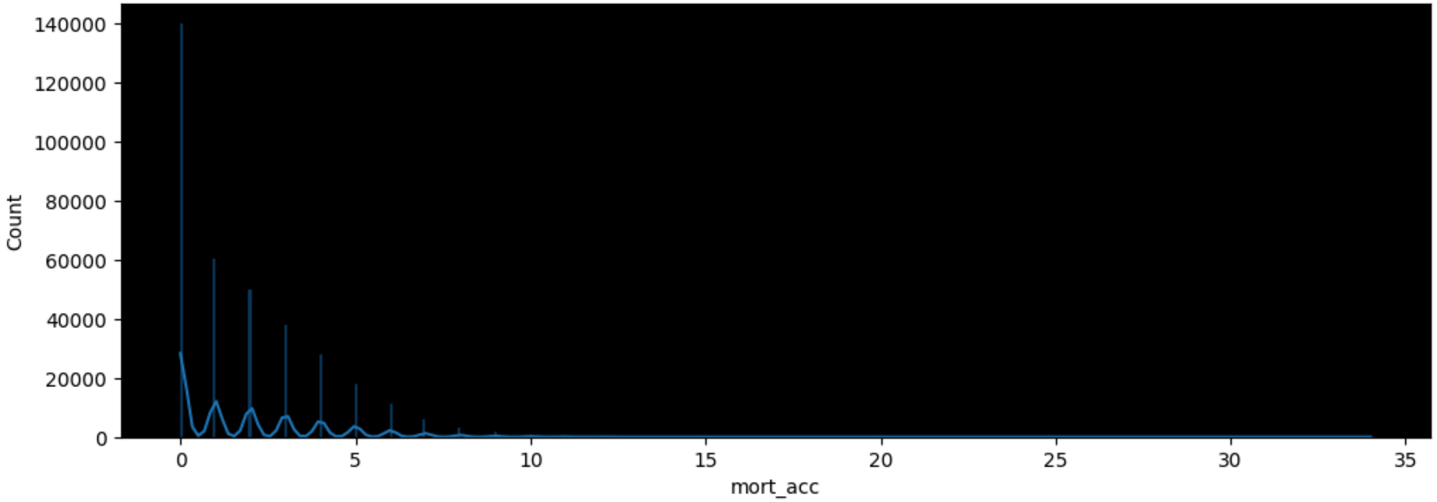

```
plt.figure(figsize=(12,4))
sns.kdeplot(df['revol_util'],color='white')
ax= plt.gca()
ax.set_facecolor('Black')
```



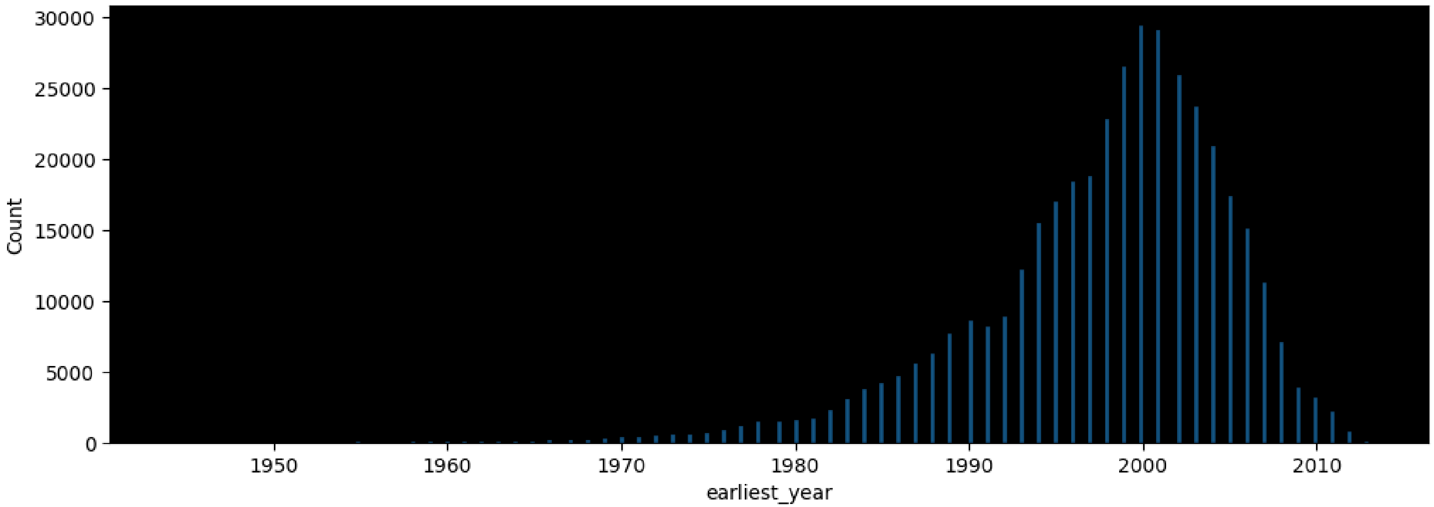

```
plt.figure(figsize=(12,4))
sns.histplot(df['total_acc'],kde=True,color='blue')
ax= plt.gca()
ax.set_facecolor('Black')
```



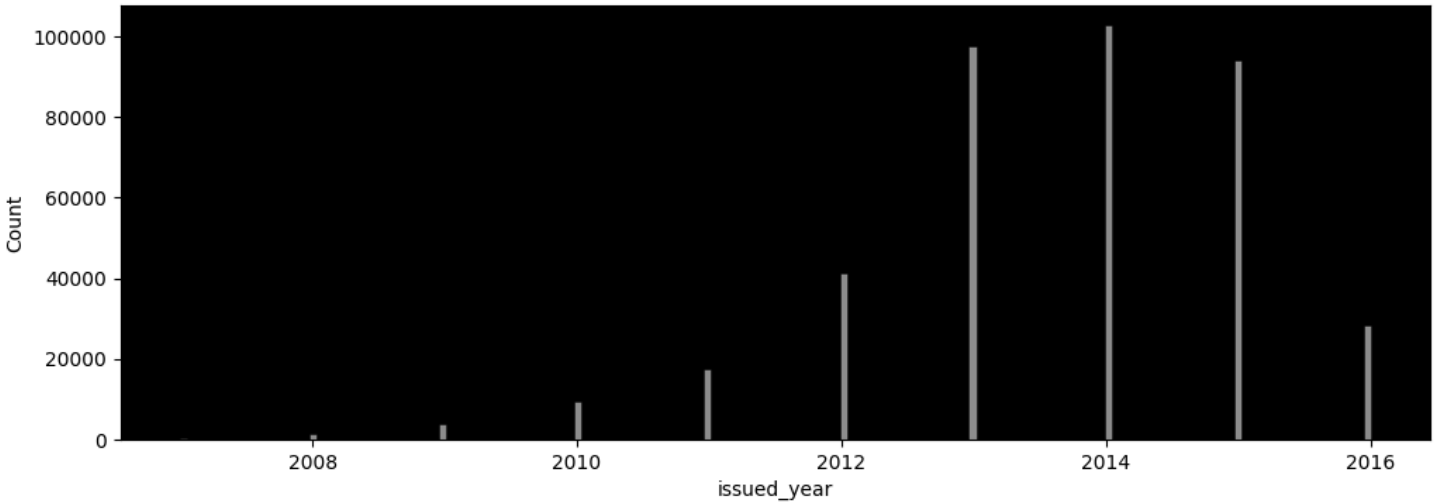
```
plt.figure(figsize=(12,4))
sns.histplot(df['mort_acc'],kde=True)
ax= plt.gca()
ax.set_facecolor('Black')
```




```
plt.figure(figsize=(12,4))
sns.histplot(df['earliest_year'])
ax= plt.gca().set_facecolor('Black')
plt.show()
```




```
plt.figure(figsize=(12,4))
sns.histplot(df['issued_year'],color='silver')
ax= plt.gca().set_facecolor('Black')
plt.show()
```



Univariate Analysis with Categorical Values

```
for column in ( 'term' , 'grade', 'sub_grade', 'emp_title', 'emp_length','home_ownership', 'verification_status' , 'loan_status', 'purpose' , 'title' , 'initial_list_status' ,'app
  print(f" {column}:{'-->'* (2-len(column))}{df[column].nunique()}")
```

```
term:2
grade:7
sub_grade:35
emp_title:173105
emp_length:11
home_ownership:6
verification_status:3
loan_status:2
purpose:14
title:48816
initial_list_status:2
application_type:3
earliest_year:65
pin_code:10
```

Observation

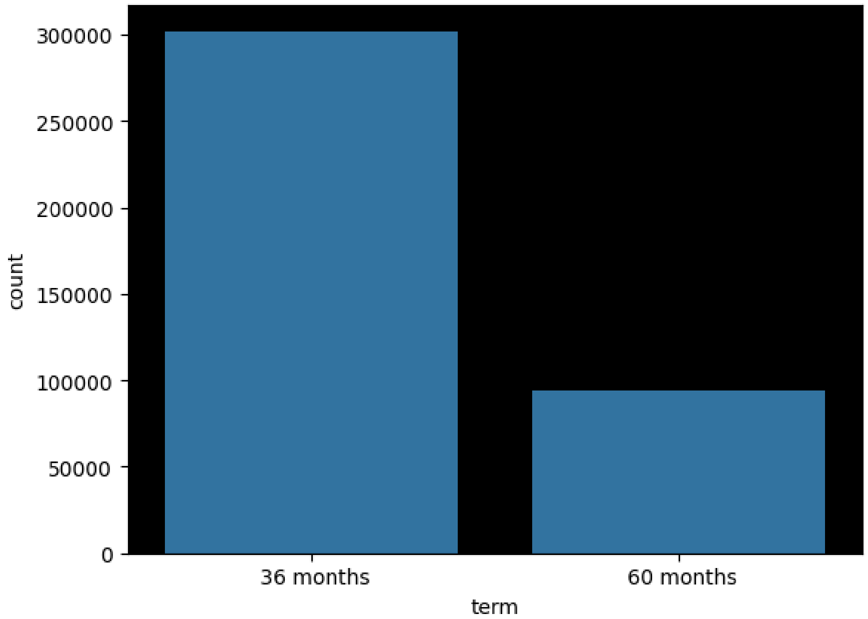
After examining the unique values above, it is evident that the 'employee title' and 'title' columns lack a discrenible pattern. The large number of unique values, numbering in the hundreds of thousands, indicate the organized categorization. Consequently these columns will be omitted from further analysis as they offer limited potential for deriving meaningful insights

```
category_column_drop= ['emp_title','title']
df= df.drop(columns=category_column_drop)
```

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

```
term
 36 months    76.258112
 60 months    23.741888
Name: proportion, dtype: float64
```

```
sns.countplot(data=df, x=df['term'])
ax=plt.gca()
ax.set_facecolor('Black')
plt.show()
```



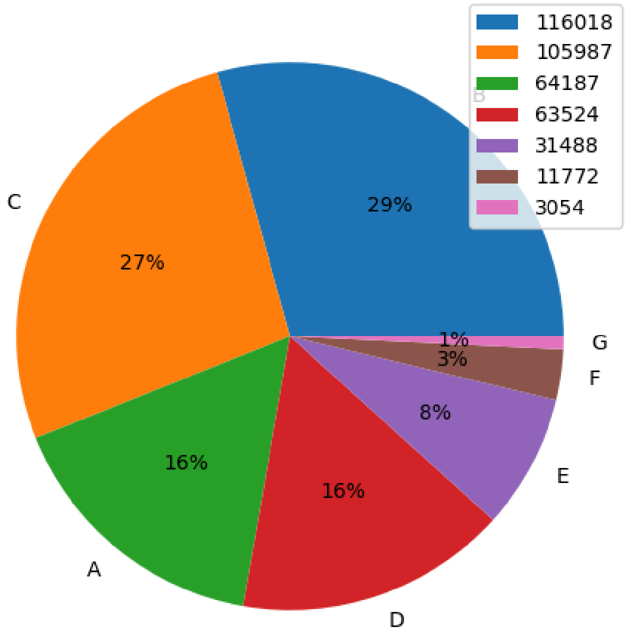
Observation

The graph illustrates the loan tenure options of 36 months and 60 months chosen by indivudials.

It is evident that the majority of individuals have opted for 36 months tenure, while fewer have selected 60 months tenure.

Thus we can infer that most people prefer the 36 months loan term based on graph.

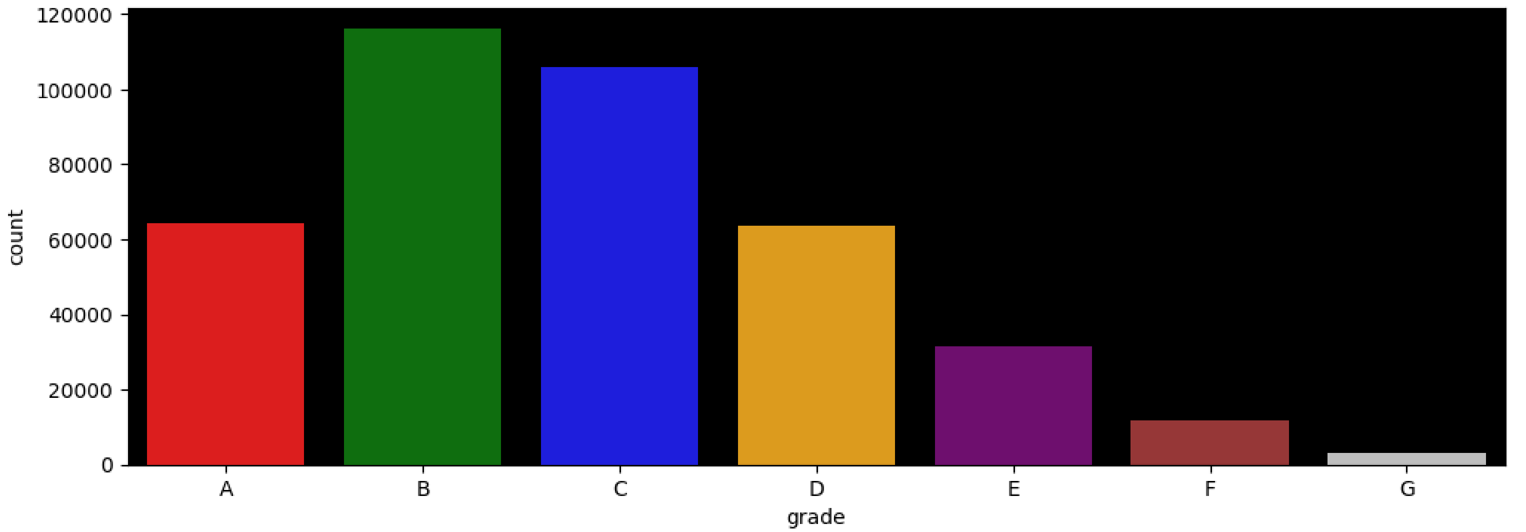
```
plt.figure(figsize=(12,6))
plt.pie(df['grade'].value_counts(),labels=df['grade'].value_counts().index, autopct='%.0f%%')
plt.legend(labels=df['grade'].value_counts(),loc='upper right')
plt.show()
```



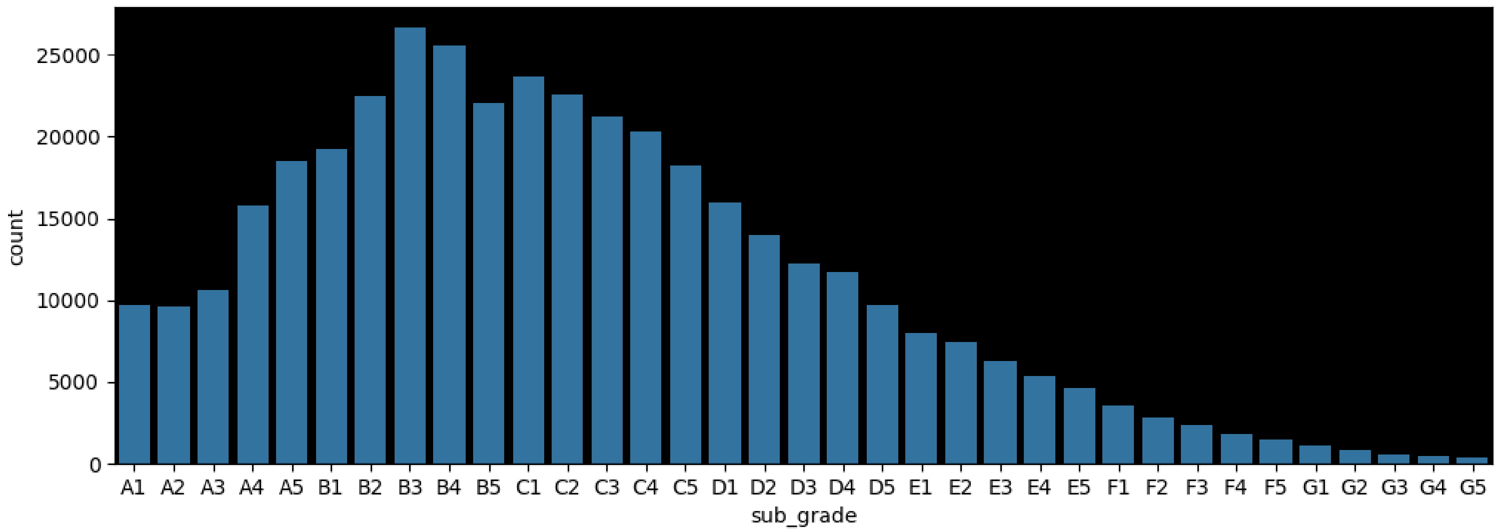
Observation

The graph displays the distribution of loan grades and the corresponding percentage of individuals categorized within each grade. It shows that the highest percentage of people are assigned the "B" grade, while the lowest percentage are assigned "G" grade.

```
plt.figure(figsize=(12,4))
colors = ['red', 'green', 'blue', 'orange', 'purple','brown','silver']
sns.countplot(data= df, x=df['grade'],palette=colors)
ax= plt.gca()
ax.set_facecolor('Black')
```



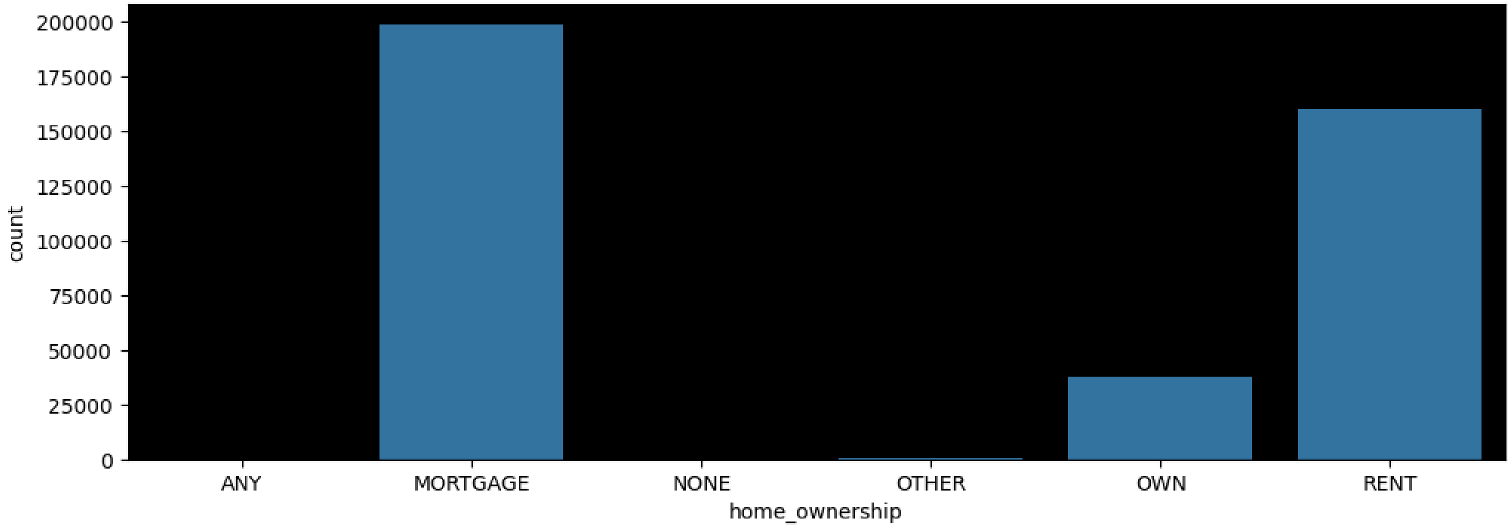

```
plt.figure(figsize=(12,4))
sns.countplot(data= df, x=df['sub_grade'])
ax= plt.gca()
ax.set_facecolor('Black')
plt.show()
```



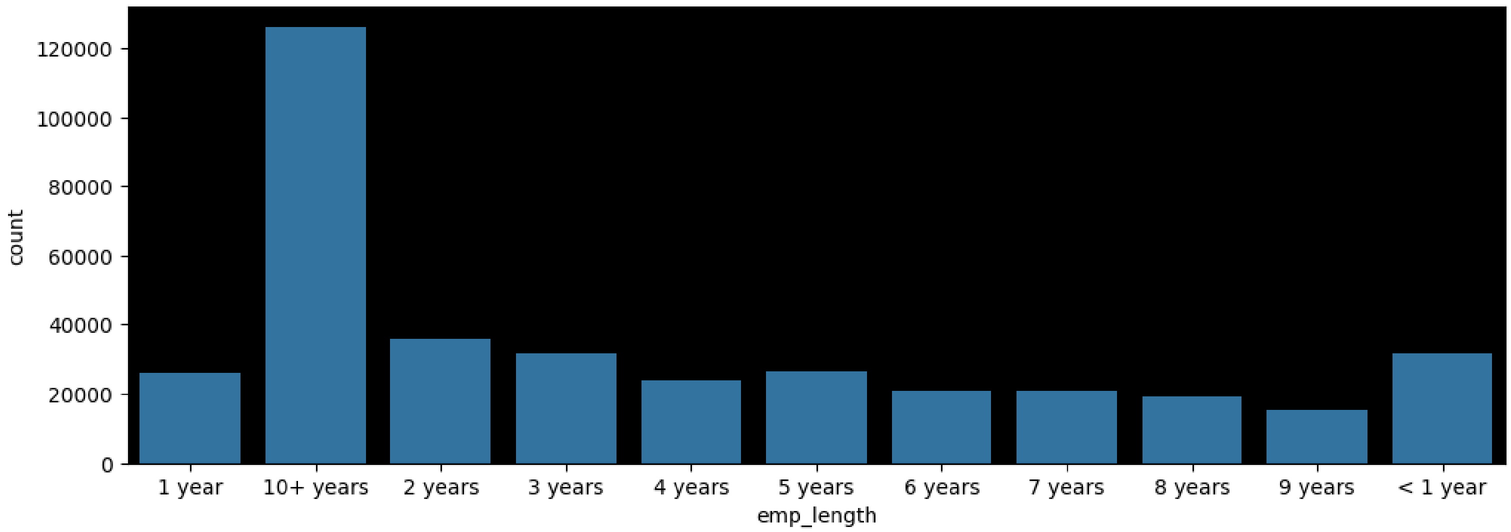
Observation

Within the loan grades , LoanTap futher subdivides them into subgrades. Notably the subgrade "B" contains the largest number of instances, indicating that a significant portion of the population falls within this category.

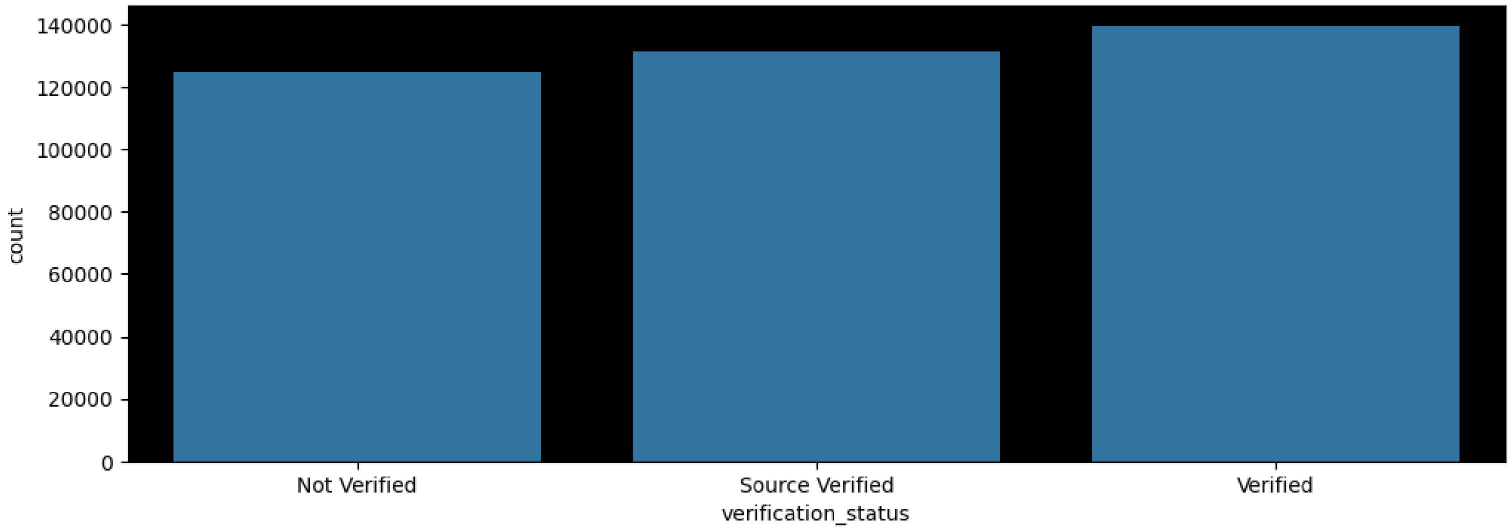
```
plt.figure(figsize=(12,4))
sns.countplot(data= df, x=df['home_ownership'])
ax= plt.gca()
ax.set_facecolor('Black')
plt.show()
```



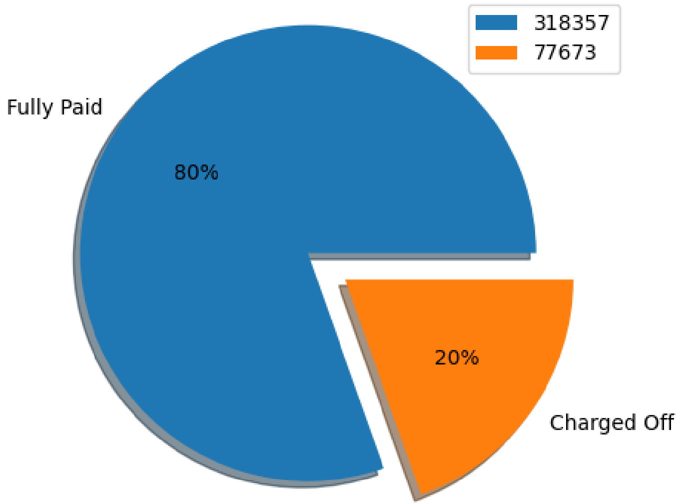

```
plt.figure(figsize=(12,4))
sns.countplot(data= df, x=df['emp_length'])
ax= plt.gca()
ax.set_facecolor('Black')
plt.show()
```



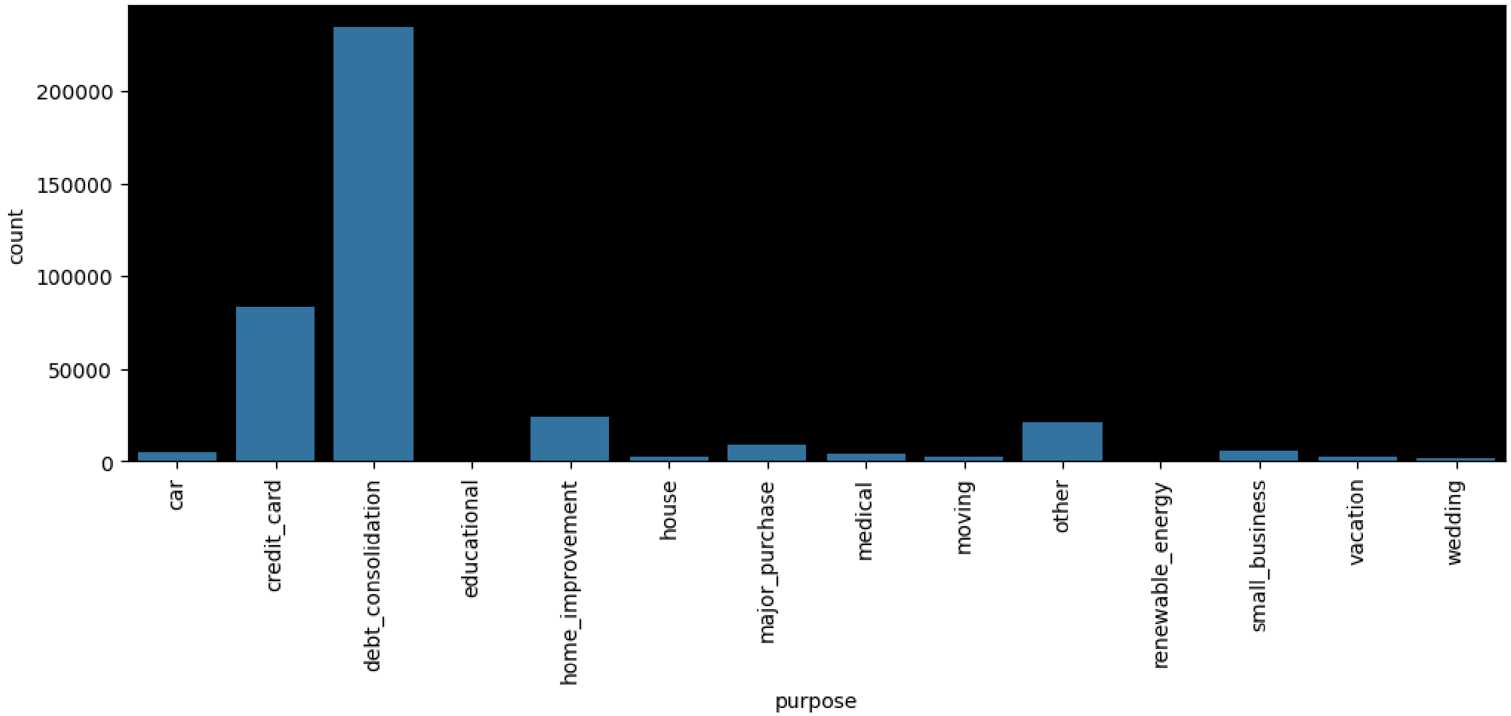

```
plt.figure(figsize=(12,4))
sns.countplot(data= df, x=df['verification_status'])
ax= plt.gca()
ax.set_facecolor('Black')
plt.show()
```



```
plt.figure(figsize=(12,5))
plt.pie(df['loan_status'].value_counts(),labels=df['loan_status'].value_counts().index,autopct='%.0f%%', explode=[0.2,0],shadow= True)
plt.legend(labels=df['loan_status'].value_counts(), loc='upper right')
plt.show()
```




```
plt.figure(figsize=(12,4))
sns.countplot(data= df, x=df['purpose'])
ax= plt.gca()
ax.set_facecolor('Black')
plt.xticks(rotation=90)
plt.show()
```

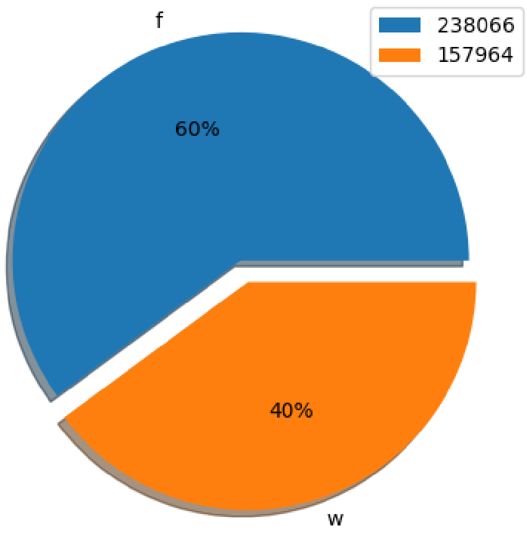


Observation

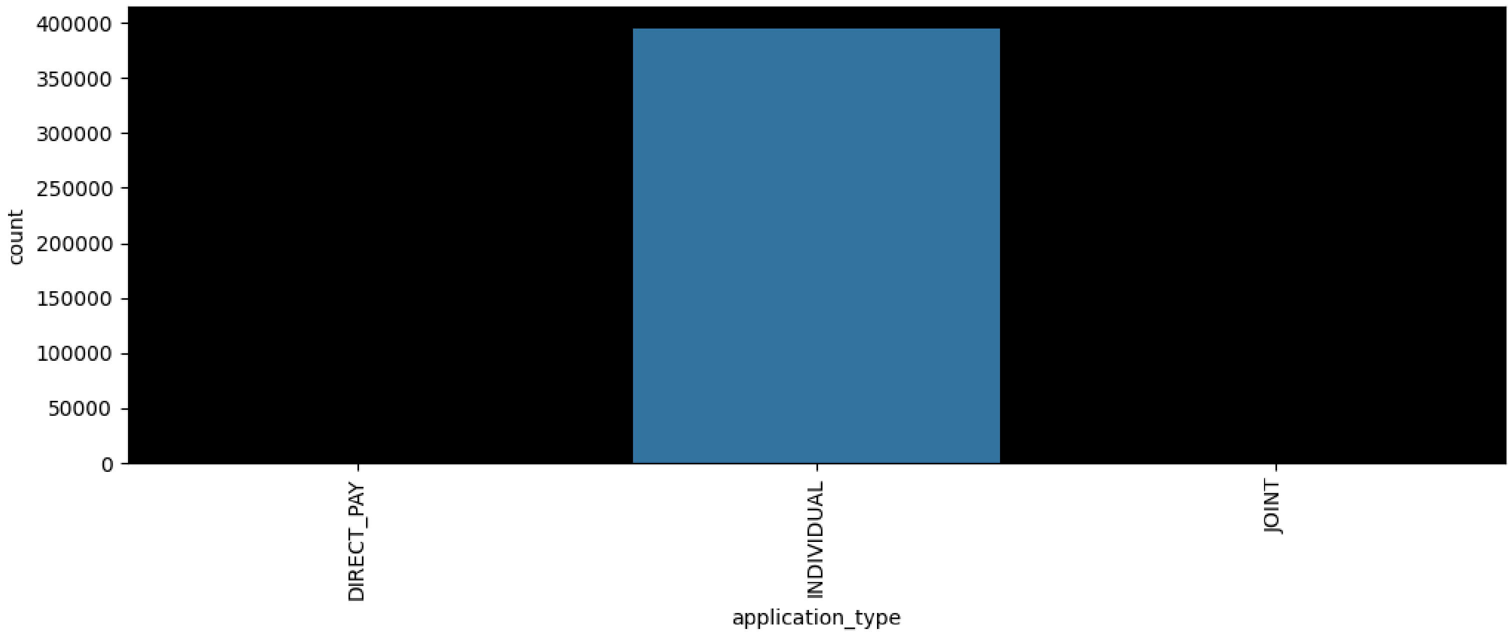
The graph reveals that the majority of individuals primarily use their cards for debt consolidation, with credit cards usage following closely behind.

This suggests that people are increasingly utilizing cards to manage and pay off their debts, indicating a focus on financial responsibility and fulfillment of financial needs.

```
plt.figure(figsize=(12,5))
plt.pie(df['initial_list_status'].value_counts(),labels=df['initial_list_status'].value_counts().index,autopct='%.0f%%', explode=[0.1,0],shadow= True)
plt.legend(labels=df['initial_list_status'].value_counts(), loc='upper right')
plt.show()
```




```
plt.figure(figsize=(12,4))
sns.countplot(data= df, x=df['application_type'])
ax= plt.gca()
ax.set_facecolor('Black')
plt.xticks(rotation=90)
plt.show()
```

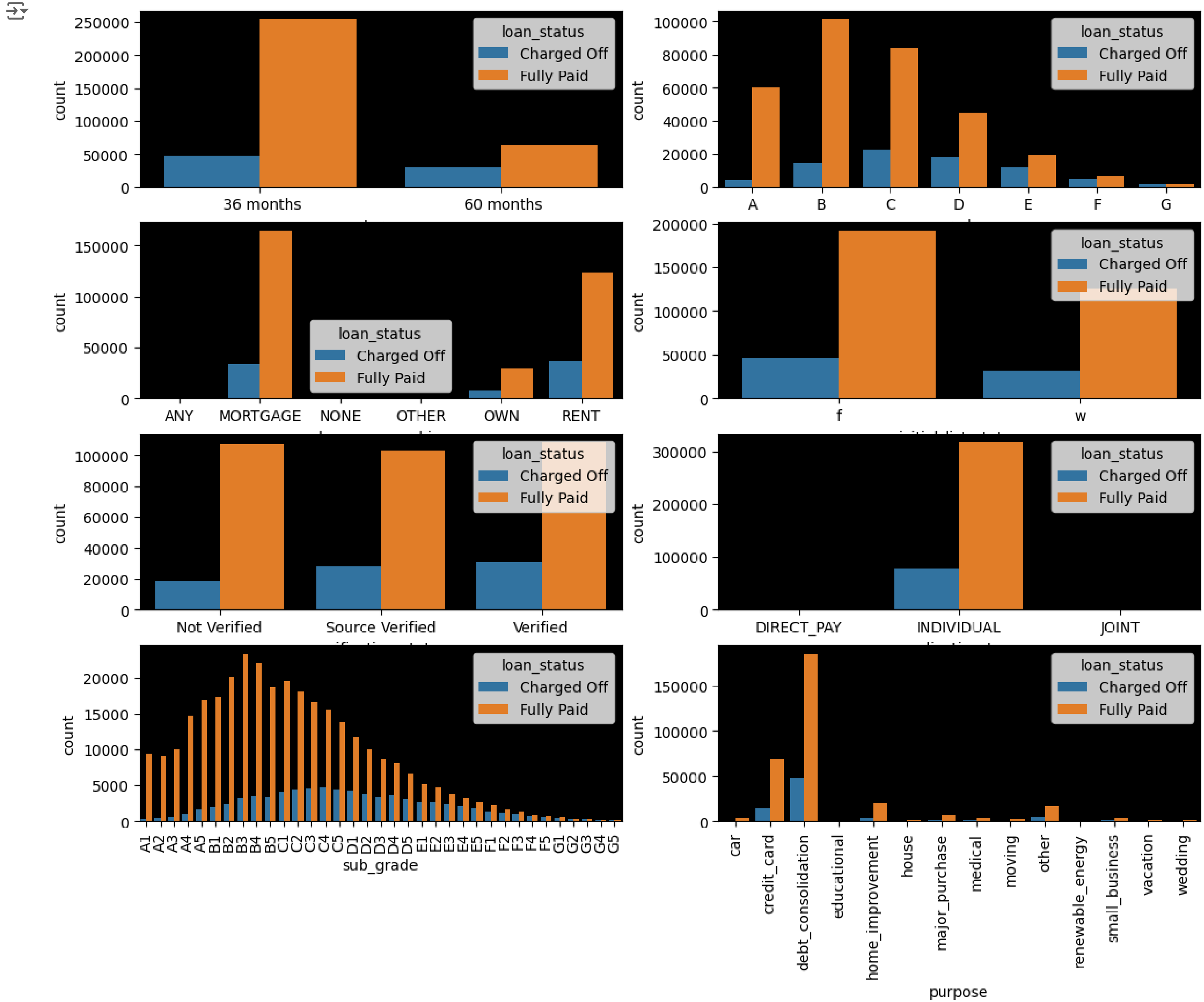



```
df['application_type'].value_counts(normalize=True)
```

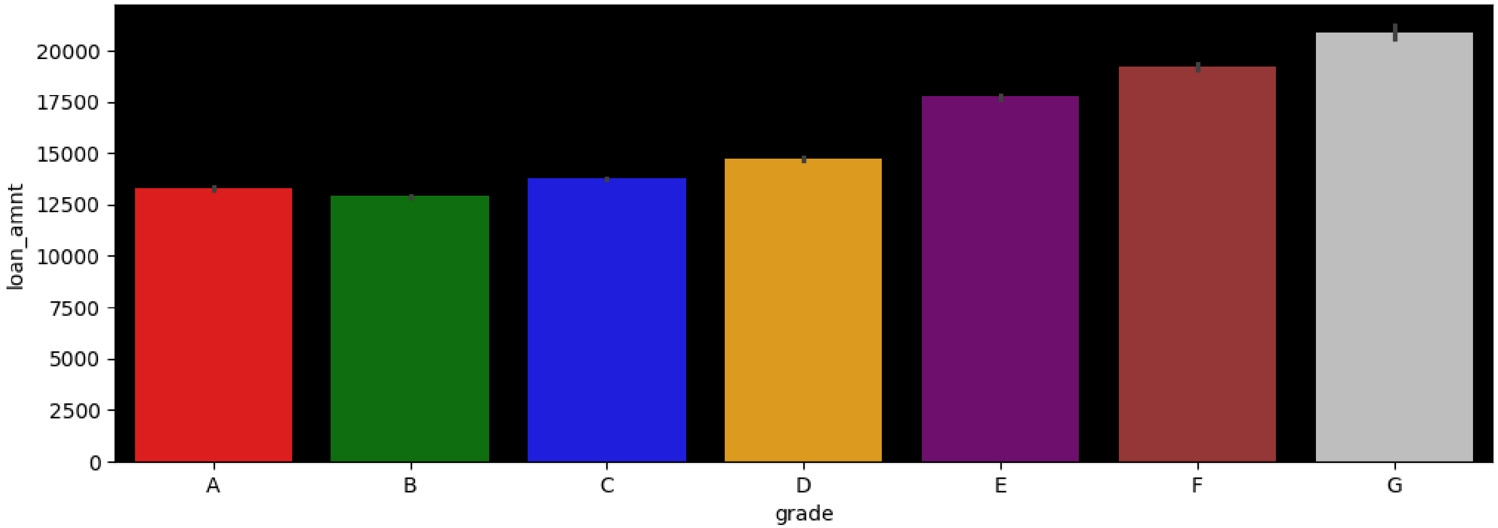
```
application_type
INDIVIDUAL    0.998205
JOINT         0.001073
DIRECT_PAY    0.000722
Name: proportion, dtype: float64
```

Bi-Variate Analysis

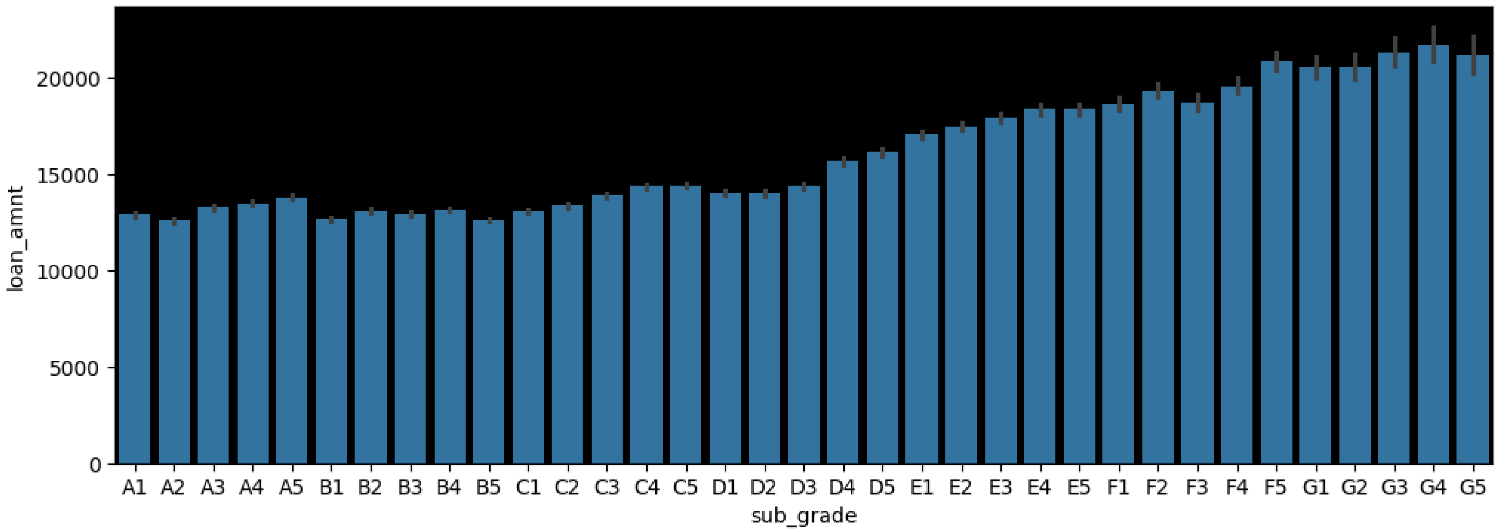
```
plt.figure(figsize=(13,10))

plt.subplot(4,2,1)
sns.countplot(data=df, x='term',hue='loan_status')
plt.gca().set_facecolor('black');

plt.subplot(4,2,2)
sns.countplot(data=df, x='grade',hue='loan_status')
plt.gca().set_facecolor('black');

plt.subplot(4,2,3)
sns.countplot(data=df, x='home_ownership',hue='loan_status')
plt.gca().set_facecolor('black');

plt.subplot(4,2,4)
sns.countplot(data=df, x='initial_list_status',hue='loan_status')
plt.gca().set_facecolor('black');

plt.subplot(4,2,5)
sns.countplot(data=df, x='verification_status',hue='loan_status')
plt.gca().set_facecolor('black');

plt.subplot(4,2,6)
sns.countplot(data=df, x='application_type',hue='loan_status')
plt.gca().set_facecolor('black');

plt.subplot(4,2,7)
sns.countplot(data=df, x='sub_grade',hue='loan_status')
plt.xticks(rotation=90)
plt.gca().set_facecolor('black');

plt.subplot(4,2,8)
sns.countplot(data=df, x='purpose',hue='loan_status')
plt.xticks(rotation=90)
plt.gca().set_facecolor('black');

plt.show()
```


loan_status
Charged Off
Fully Paid
count
36 months
60 months
A
B
C
D
E
F
G
ANY
MORTGAGE
NONE
OTHER
OWN
RENT
f
w
Not Verified
Source Verified
Verified
DIRECT_PAY
INDIVIDUAL
JOINT
sub_grade
purpose
car
credit_card
debt_consolidation
educational
home_improvement
house
major_purchase
medical
moving
other
renewable_energy
small_business
vacation
wedding

```
plt.figure(figsize=(12,4))
colors = ['red', 'green', 'blue', 'orange', 'purple','brown','silver']
sns.barplot(data= df, x=df['grade'],y=df['loan_amnt'],palette=colors)
ax= plt.gca()
ax.set_facecolor('Black')
```



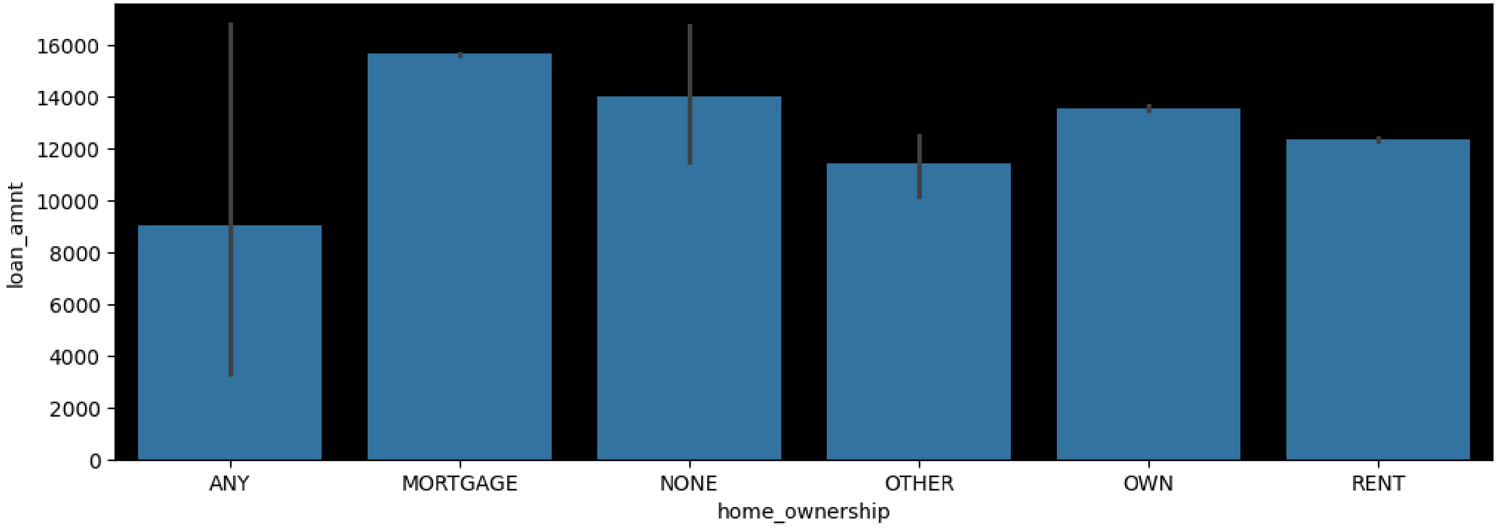

```
plt.figure(figsize=(12,4))
sns.barplot(data= df, x=df['sub_grade'],y=df['loan_amnt'])
ax= plt.gca()
ax.set_facecolor('Black')
```



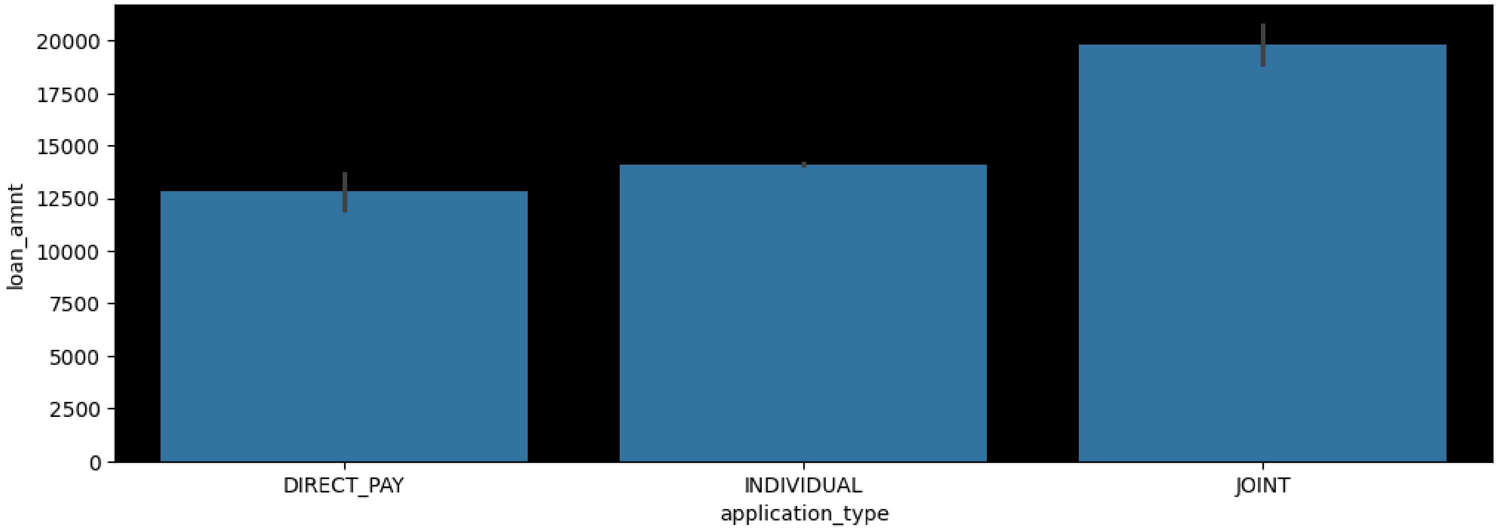
Observation

Based on the Graph, it can be infered that there is saturation point across all subgrades, with the highest loan amounts observed in the grade "G"

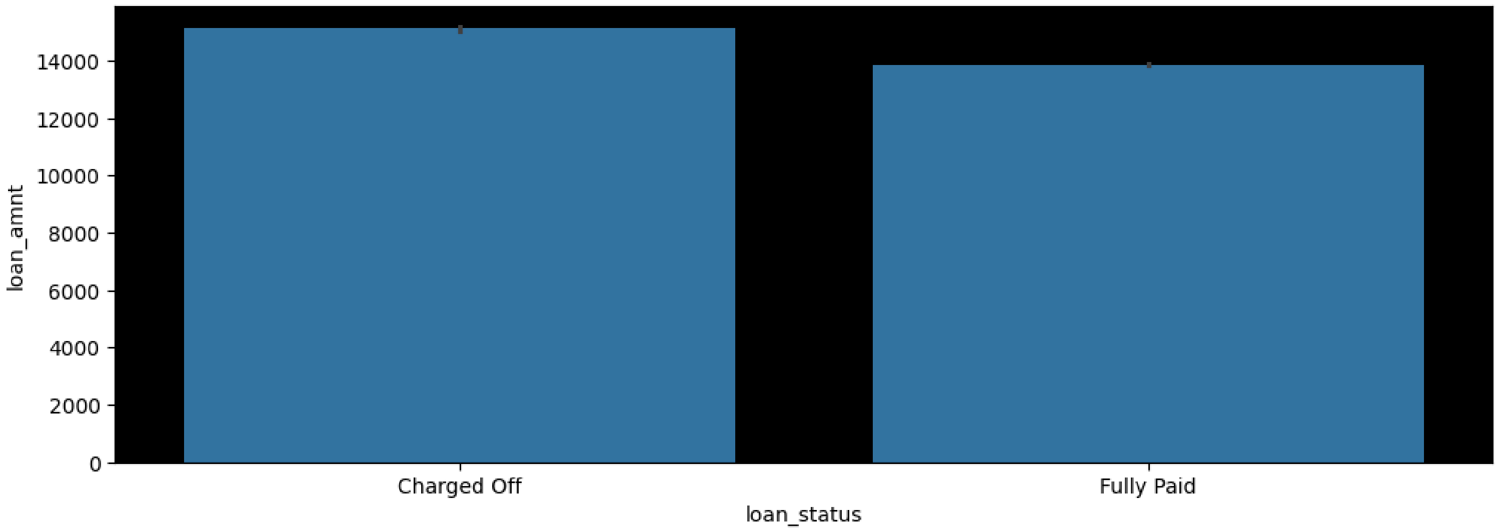
```
plt.figure(figsize=(12,4))
sns.barplot(data= df, x=df['home_ownership'],y=df['loan_amnt'])
ax= plt.gca()
ax.set_facecolor('Black')
```



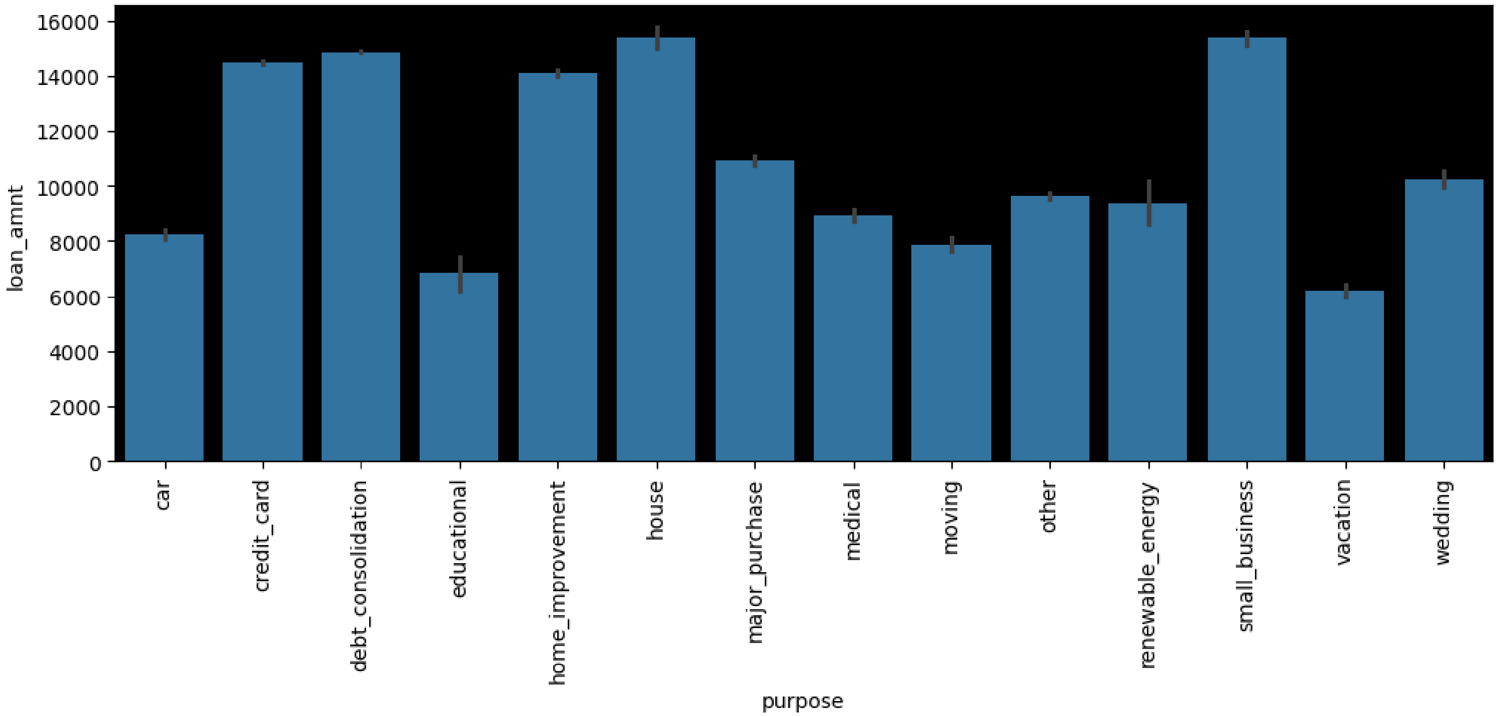

```
plt.figure(figsize=(12,4))
sns.barplot(data= df, x=df['application_type'],y=df['loan_amnt'])
ax= plt.gca()
ax.set_facecolor('Black')
```



```
plt.figure(figsize=(12,4))
sns.barplot(data= df, x=df['loan_status'],y=df['loan_amnt'])
ax= plt.gca()
ax.set_facecolor('Black')
```

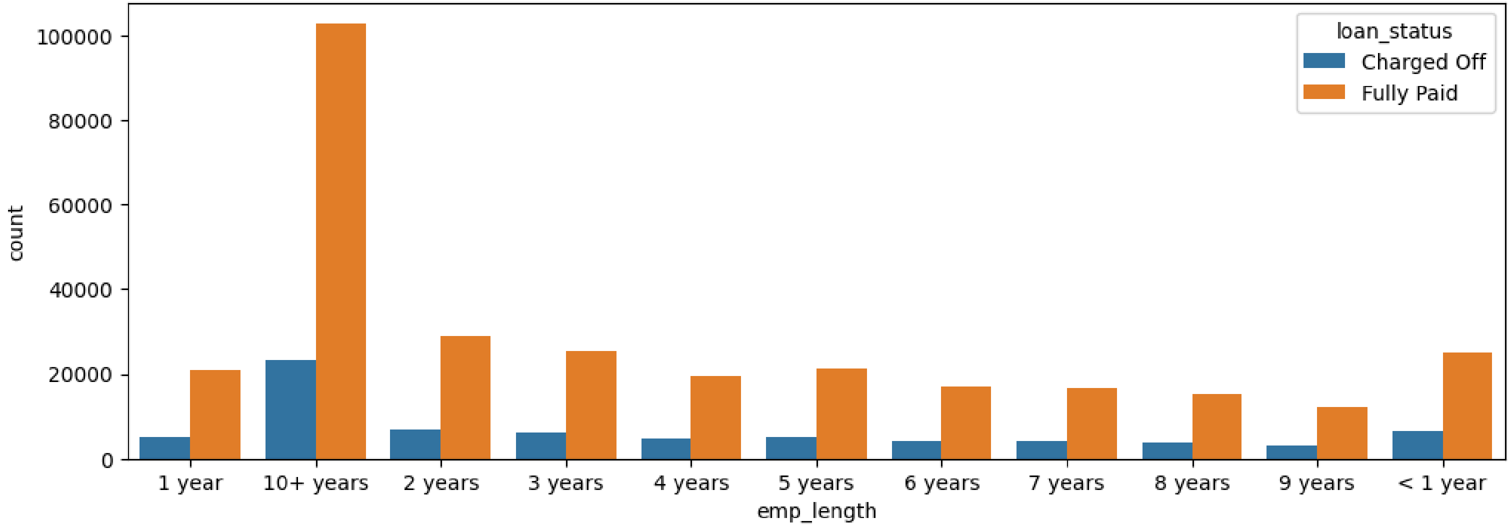



```
plt.figure(figsize=(12,4))
sns.barplot(data= df, x=df['purpose'],y=df['loan_amnt'])
ax= plt.gca()
plt.xticks(rotation=90)
ax.set_facecolor('Black')
```




```
plt.figure(figsize=(12,4))
sns.countplot(x=df['emp_length'], hue=df['loan_status'])
```

```
<Axes: xlabel='emp_length', ylabel='count'>
```




```
df.columns
```

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

```
plt.figure(figsize=(18,6))

plt.subplot(1,2,1)
sns.histplot(data=df, x='annual_inc', bins=30)
plt.xlabel(f'Annual Income\n\nFig.1')
plt.ylabel('No. of Loan Applicants')
plt.title('Annual Income vs No. of Loan Applicants')
plt.gca().set_facecolor('black')

plt.subplot(1,2,2)
sns.scatterplot(data=df, x=df['loan_amnt'],y=df['annual_inc'], c='red')
plt.xlabel(f'Loan Amount\n\nFig.2')
plt.ylabel('Annual Income')
plt.title('Loan Amount vs Annual Income')
plt.gca().set_facecolor('black')
plt.show()
```

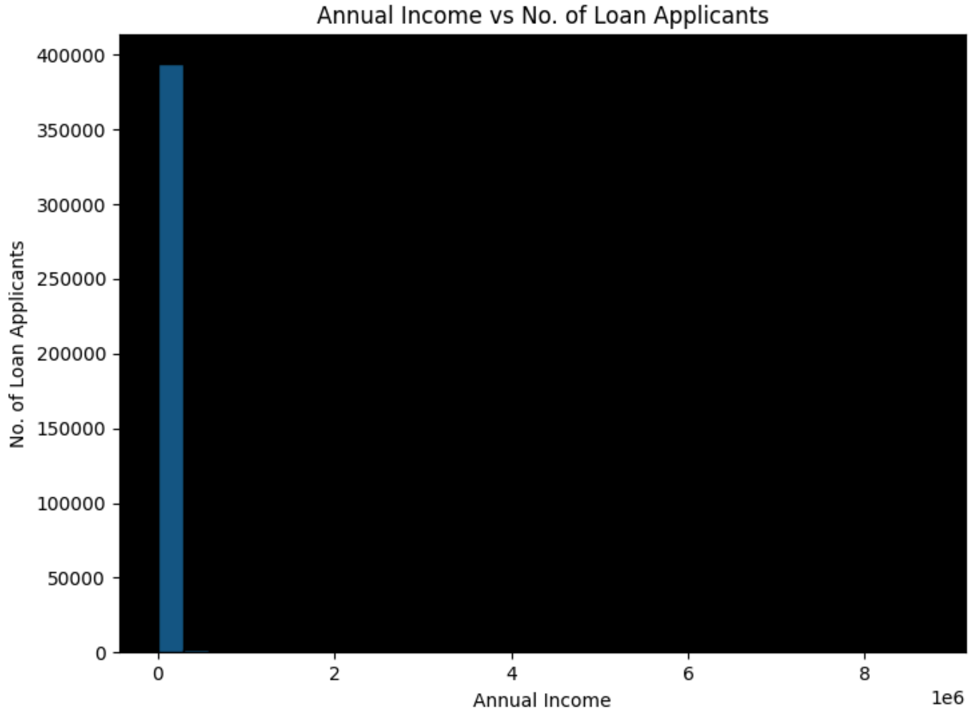


Fig.1

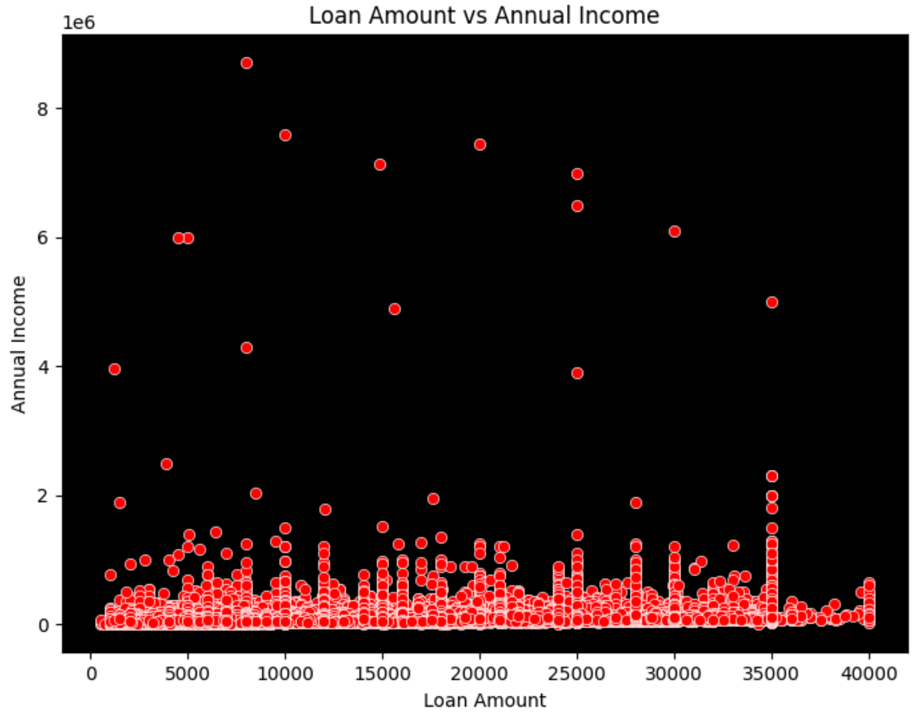


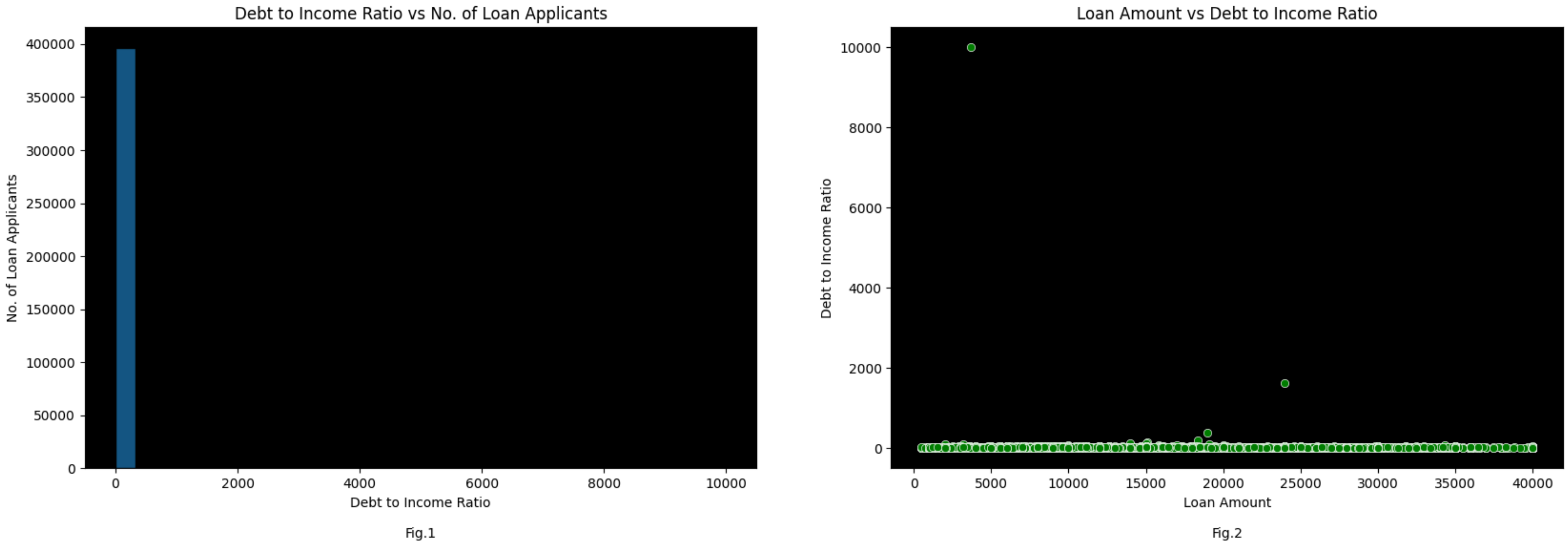
Fig.2

Observation

1. In figure 1, it is noticible that the majority of the applicants have income of approx less than $300,000 per year, with only small number of applicants reporting very high incomes. This trend is also evident in Fig 2 , where data points are densly clustered at the lower end, with only a few points scattered sparsely above.

2. The scattered points knowns as Outliers pose a risk of biasing the results of our modeling predictions. Therefore it is advisible to remove these outliers from the dataset to ensure thr accuracy and reliablity of our analysis.

```
plt.figure(figsize=(20,6))

plt.subplot(1,2,1)
sns.histplot(data=df, x='dti', bins=30)
plt.xlabel(f'Debt to Income Ratio\n\nFig.1')
plt.ylabel('No. of Loan Applicants')
plt.title('Debt to Income Ratio vs No. of Loan Applicants')
plt.gca().set_facecolor('black')

plt.subplot(1,2,2)
sns.scatterplot(data=df, x=df['loan_amnt'],y=df['dti'], c='green')
plt.xlabel(f'Loan Amount\n\nFig.2')
plt.ylabel('Debt to Income Ratio')
plt.title('Loan Amount vs Debt to Income Ratio')
plt.gca().set_facecolor('black')
plt.show()
```



Observation

1. Fig 1 illustrates that the majority of applicants have Debt to Income Ratio of approx less than 50, with only a small number reporting very high ratios, This pattern is also evident in Fig 2, where most data points are tightly clustred at the lower end, while only a few points are scattered more widely above.

2. The scattered points knowns as Outliers pose a risk of biasing the results of our modeling predictions. Therefore it is advisible to remove these outliers from the dataset to ensure thr accuracy and reliablity of our analysis.

```
plt.figure(figsize=(20,6))

plt.subplot(1,2,1)
sns.histplot(data=df, x='pub_rec', bins=30)
plt.xlabel(f'Public Credit Record (-ve record)\n\nFig.1')
plt.ylabel('No. of Loan Applicants')
plt.title('Public Credit Record (-ve record) vs No. of Loan Applicants')
plt.gca().set_facecolor('black')

plt.subplot(1,2,2)
sns.scatterplot(data=df, x=df['loan_amnt'],y=df['pub_rec'], c='orange')
plt.xlabel(f'Loan Amount\n\nFig.2')
plt.ylabel('Public Credit Record (-ve record)')
plt.title('Loan Amount vs Public Credit Record (-ve record)')
plt.gca().set_facecolor('black')
plt.show()
```

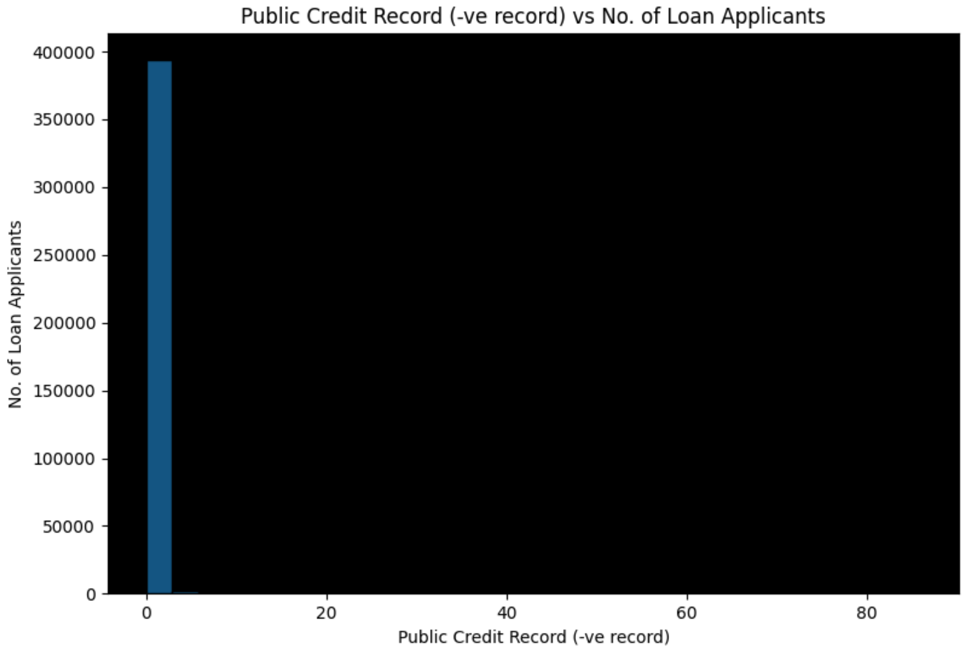


Fig.1

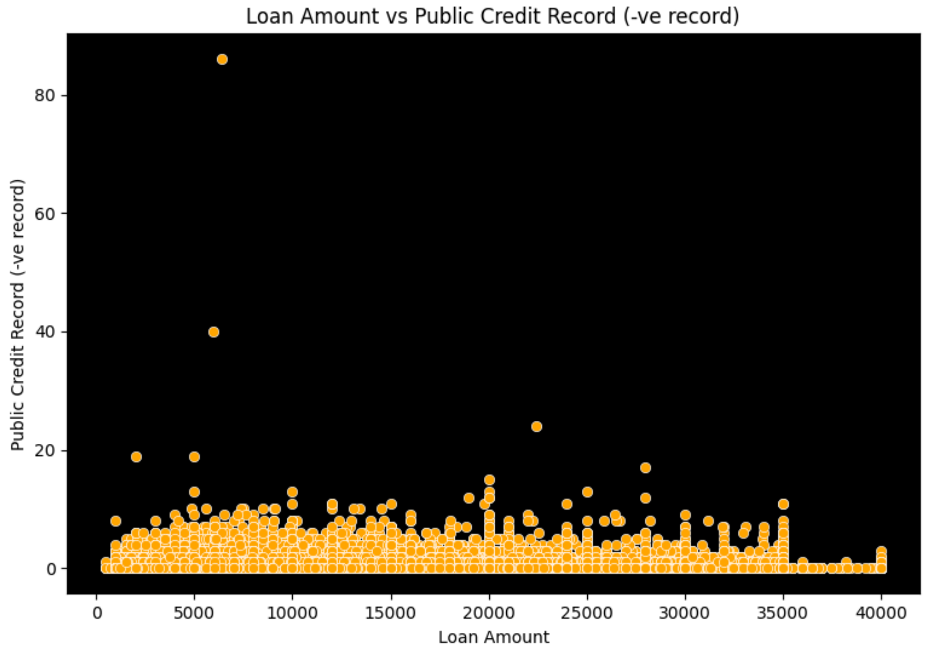


Fig.2

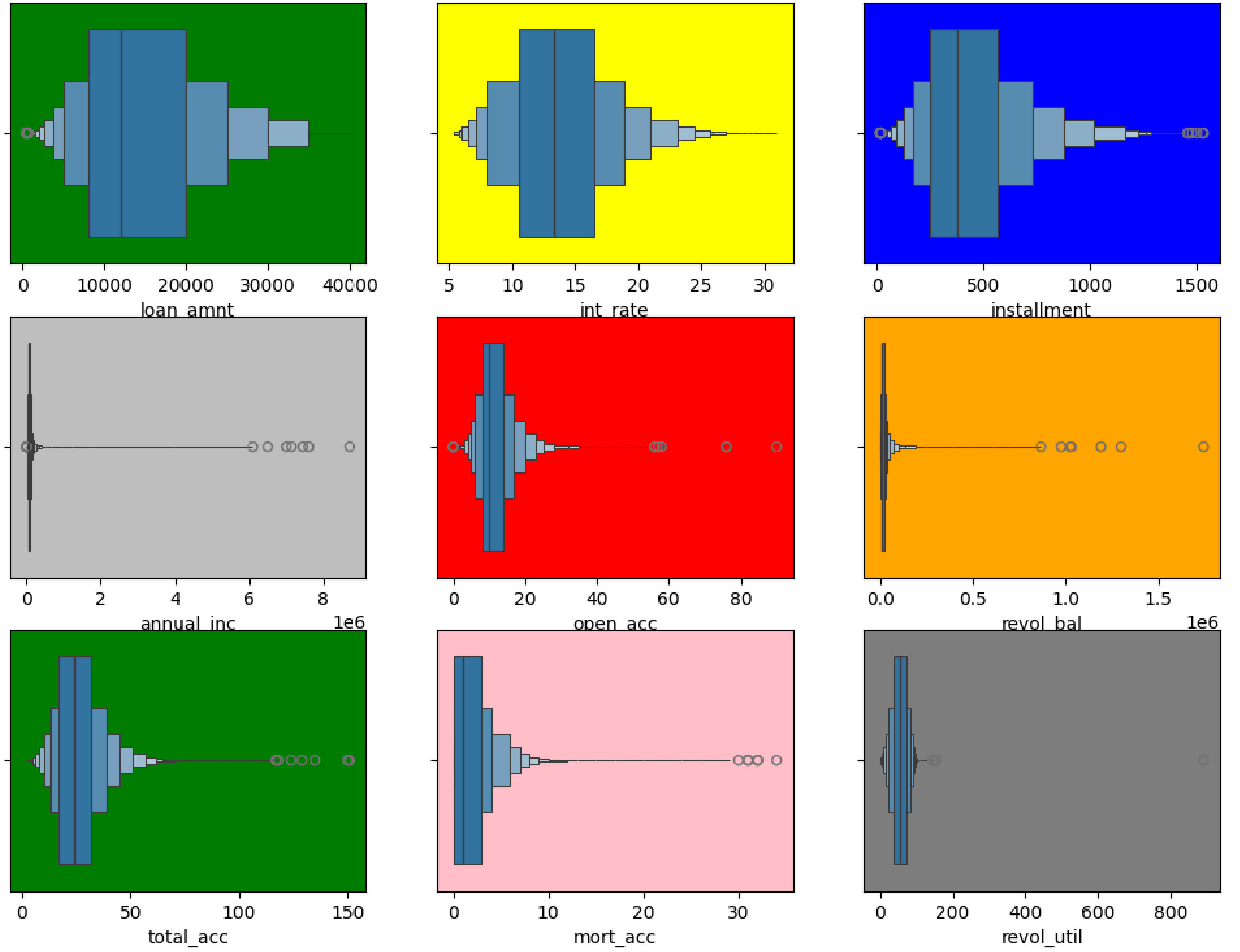
Observation

1. Fig 1 illustrates that the majority of applicants have fewer than 6 bankruptcy records, with only a small number reporting very high ratios, This pattern is also evident in Fig 2, where most data points are tightly clustred at the lower end, while only a few points are scattered more widely above.

2. The scattered points knowns as Outliers pose a risk of biasing the results of our modeling predictions. Therefore it is advisible to remove these outliers from the dataset to ensure thr accuracy and reliablity of our analysis.

Checking for outliers in Data Features

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

plt.subplot(4,3,1)
sns.boxenplot(data=df, x= df['loan_amnt'])
plt.gca().set_facecolor('green')

plt.subplot(4,3,2)
sns.boxenplot(data=df, x= df['int_rate'])
plt.gca().set_facecolor('yellow')

plt.subplot(4,3,3)
sns.boxenplot(data=df, x= df['installment'])
plt.gca().set_facecolor('blue')

plt.subplot(4,3,4)
sns.boxenplot(data=df, x= df['annual_inc'])
plt.gca().set_facecolor('silver')

plt.subplot(4,3,5)
sns.boxenplot(data=df, x= df['open_acc'])
plt.gca().set_facecolor('red')


plt.subplot(4,3,6)
sns.boxenplot(data=df, x= df['revol_bal'])
plt.gca().set_facecolor('orange')

plt.subplot(4,3,7)
sns.boxenplot(data=df, x= df['total_acc'])
plt.gca().set_facecolor('green')

plt.subplot(4,3,8)
sns.boxenplot(data=df, x= df['mort_acc'])
plt.gca().set_facecolor('pink')

plt.subplot(4,3,9)
sns.boxenplot(data=df, x= df['revol_util'])
plt.gca().set_facecolor('gray')

plt.show()
```



Data Preprocessing

```
df.duplicated().sum()
```

```
0
```

Observation

There are No Duplicate values present in Data Set.

Analyse Missing Values-

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

```
loan_amnt                   0
term                        0
int_rate                    0
installment                 0
grade                       0
sub_grade                   0
emp_length              18301
home_ownership              0
annual_inc                  0
verification_status         0
loan_status                 0
purpose                     0
dti                         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
earliest_year               0
pin_code                    0
issued_year                 0
dtype: int64
```

```
missing_values= df[['emp_length','revol_util','mort_acc','pub_rec_bankruptcies']]
missing_values.isna().sum()
```

```
emp_length              18301
revol_util                276
mort_acc                37795
pub_rec_bankruptcies      535
dtype: int64
```

```
column_mode= df['emp_length'].mode()[0]
df['emp_length'] = df['emp_length'].fillna(column_mode)
```

```
si= SimpleImputer(strategy= 'mean')
df['mort_acc']= si.fit_transform(df[['mort_acc']])
```

```
si= SimpleImputer(strategy= 'mean')
df['pub_rec_bankruptcies']= si.fit_transform(df[['pub_rec_bankruptcies']])
```

```
si= SimpleImputer(strategy= 'mean')
df['revol_util']= si.fit_transform(df[['revol_util']])
```

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

```
loan_amnt               0
term                    0
int_rate                0
installment             0
grade                   0
sub_grade               0
emp_length              0
home_ownership          0
annual_inc              0
verification_status     0
loan_status             0
purpose                 0
dti                     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
earliest_year           0
pin_code                0
issued_year             0
dtype: int64
```

```
df.describe()
```

	loan_amnt	int_rate	installment	annual_inc	dti	open_acc	pub_rec	revol_bal	revol_util	total_acc	mort_acc	pub_rec_ba
count	396030.000000	396030.000000	396030.000000	3.960300e+05	396030.000000	396030.000000	396030.000000	3.960300e+05	396030.000000	396030.000000	396030.000000	396
mean	14113.888089	13.639400	431.849698	7.420318e+04	17.379514	11.311153	0.178191	1.584454e+04	53.791749	25.414744	1.813991	
std	8357.441341	4.472157	250.727790	6.163762e+04	18.019092	5.137649	0.530671	2.059184e+04	24.443671	11.886991	2.042867	
min	500.000000	5.320000	16.080000	0.000000e+00	0.000000	0.000000	0.000000	0.000000e+00	0.000000	2.000000	0.000000	
25%	8000.000000	10.490000	250.330000	4.500000e+04	11.280000	8.000000	0.000000	6.025000e+03	35.900000	17.000000	0.000000	
50%	12000.000000	13.330000	375.430000	6.400000e+04	16.910000	10.000000	0.000000	1.118100e+04	54.800000	24.000000	1.000000	
75%	20000.000000	16.490000	567.300000	9.000000e+04	22.980000	14.000000	0.000000	1.962000e+04	72.900000	32.000000	3.000000	
max	40000.000000	30.990000	1533.810000	8.706582e+06	9999.000000	90.000000	86.000000	1.743266e+06	892.300000	151.000000	34.000000	

```
df.describe(include= 'category')
```

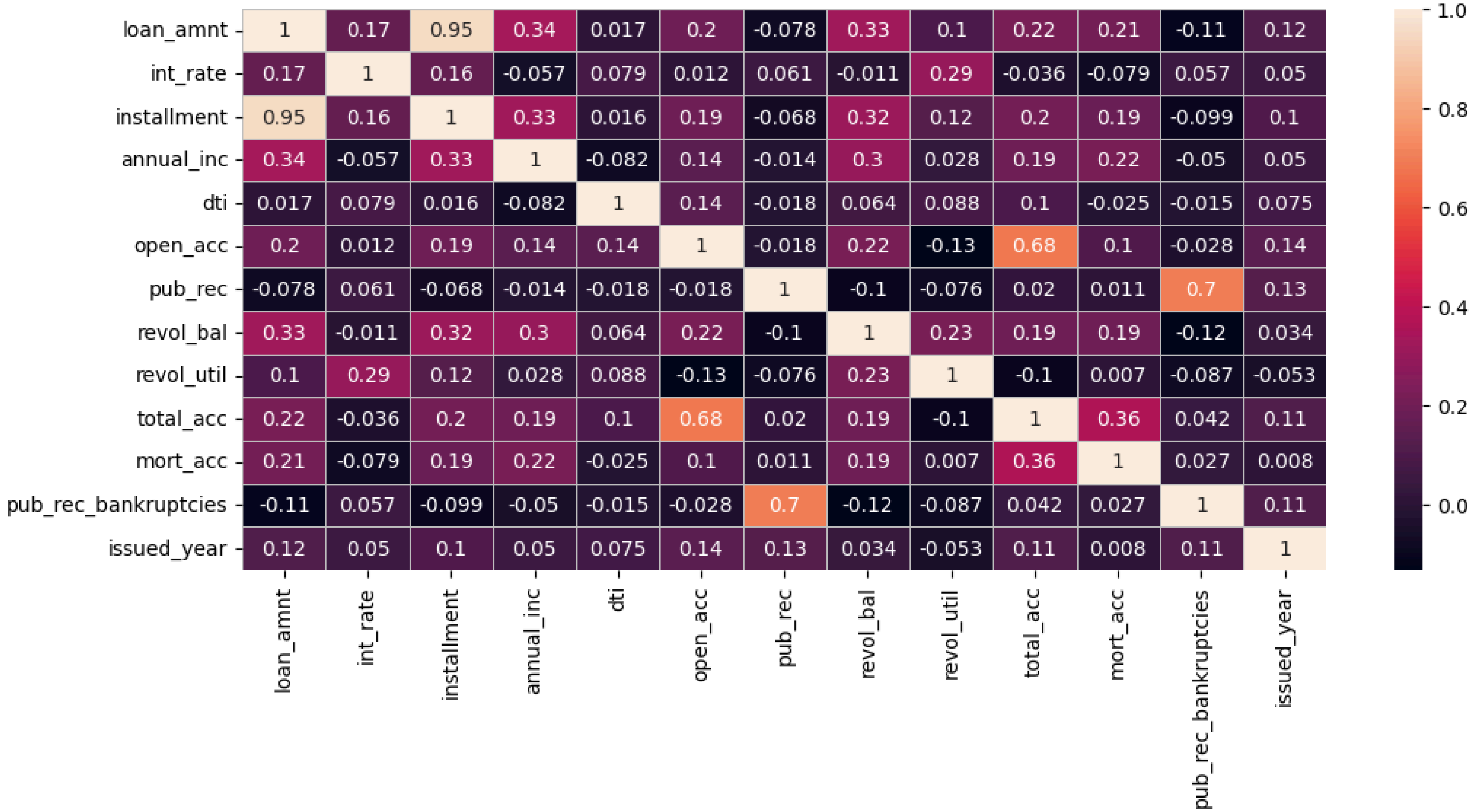
	term	grade	sub_grade	emp_length	home_ownership	verification_status	loan_status	purpose	initial_list_status	application_type
count	396030	396030	396030	396030	396030	396030	396030	396030	396030	396030
unique	2	7	35	11	6	3	2	14	2	3
top	36 months	B	B3	10+ years	MORTGAGE	Verified	Fully Paid	debt_consolidation	f	INDIVIDUAL
freq	302005	116018	26655	144342	198348	139563	318357	234507	238066	395319

```
column_drop_1= ['term' , 'grade', 'sub_grade', 'emp_length','home_ownership', 'verification_status' , 'loan_status', 'purpose'  , 'initial_list_status' ,'application_type', 'earli
df1= df.drop(columns= column_drop_1)
df1
```

	loan_amnt	int_rate	installment	annual_inc	dti	open_acc	pub_rec	revol_bal	revol_util	total_acc	mort_acc	pub_rec_bankruptcies	issued_year
0	10000.0	11.44	329.48	117000.0	26.24	16.0	0.0	36369.0	41.8	25.0	0.000000	0.0	2015
1	8000.0	11.99	265.68	65000.0	22.05	17.0	0.0	20131.0	53.3	27.0	3.000000	0.0	2015
2	15600.0	10.49	506.97	43057.0	12.79	13.0	0.0	11987.0	92.2	26.0	0.000000	0.0	2015
3	7200.0	6.49	220.65	54000.0	2.60	6.0	0.0	5472.0	21.5	13.0	0.000000	0.0	2014
4	24375.0	17.27	609.33	55000.0	33.95	13.0	0.0	24584.0	69.8	43.0	1.000000	0.0	2013
...	...	...	...	...	...	...	...	...	...	...	...	...	...
396025	10000.0	10.99	217.38	40000.0	15.63	6.0	0.0	1990.0	34.3	23.0	0.000000	0.0	2015
396026	21000.0	12.29	700.42	110000.0	21.45	6.0	0.0	43263.0	95.7	8.0	1.000000	0.0	2015
396027	5000.0	9.99	161.32	56500.0	17.56	15.0	0.0	32704.0	66.9	23.0	0.000000	0.0	2013
396028	21000.0	15.31	503.02	64000.0	15.88	9.0	0.0	15704.0	53.8	20.0	5.000000	0.0	2012
396029	2000.0	13.61	67.98	42996.0	8.32	3.0	0.0	4292.0	91.3	19.0	1.813991	0.0	2010

396030 rows × 13 columns

```
plt.figure(figsize=(12,5))
sns.heatmap(df1.corr(),annot= True, linecolor= 'silver',linewidths='0.6')
plt.show()
```



Observation-

- The Correlation analysis reveals significant positive correlation among certain varaibles. Specifically the loan amount and installment exhibits a strong correlation of 0.95, indicating a substantial relationship.
- Aditionally,open accounts and total accounts demonstrates a notable correlation of 0.67, suggesting a positive association.
- Moreover there exists a meaningful correlation of 0.70 between public records and public record bankruptcies indicating their interconnectedness

Outlier Treatment

```
q1= np.quantile(df['loan_amnt'],0.25)
q3= np.quantile(df['loan_amnt'],0.75)
IQR= q3-q1
Lower_whisker= q1-(1.5*IQR)
upper_whisker= q3+(1.5*IQR)
df[(df['loan_amnt']< Lower_whisker) | (df['loan_amnt']> upper_whisker)]
df= df[(df['loan_amnt'] > Lower_whisker) & (df['loan_amnt'] < upper_whisker)]
df.shape
```

```
(395836, 25)
```

Observation-

- The Distribution of loan amounts in the dataset deviates significantly from the normal distribution indicating a high presence of outliers.
- To ensure data accuracy and facilitate precise analysis we have opted to remove these outliers from dataset.

```
q1= np.quantile(df['int_rate'],0.25)
q3= np.quantile(df['int_rate'],0.75)
IQR= q3-q1
Lower_whisker= q1-(1.5*IQR)
upper_whisker= q3+(1.5*IQR)
df[(df['int_rate']< Lower_whisker) | (df['int_rate']> upper_whisker)][:5]
```

	loan_amnt	term	int_rate	installment	grade	sub_grade	emp_length	home_ownership	annual_inc	verification_status	...	revol_bal	revol_util	total_acc	initial_list
96	12625.0	60 months	25.78	376.36	F	F5	7 years	MORTGAGE	43000.0	Verified	...	19993.0	55.7	31.0	
97	13400.0	60 months	25.83	399.86	G	G2	10+ years	MORTGAGE	56000.0	Verified	...	28845.0	84.5	44.0	
133	13075.0	60 months	27.31	401.68	G	G2	10+ years	MORTGAGE	54777.0	Source Verified	...	3845.0	59.2	27.0	
168	11800.0	60 months	28.99	374.49	G	G5	10+ years	RENT	44011.0	Verified	...	6313.0	67.2	13.0	
204	34350.0	60 months	28.99	1090.13	G	G5	3 years	RENT	84000.0	Verified	...	8400.0	85.7	23.0	

5 rows × 25 columns

Observation-

- Regarding the interest rate, numerous outliers are present in the dataset. However its essential to note that these outliers play a significant role in the data as they are influenced by factors such as loan amount and tenure.
- Therefore it is advisible not to remove these outliers from dataset, as they contribute valuable information to our analysis.

```
q1= np.quantile(df['installment'],0.25)
q3= np.quantile(df['installment'],0.75)
IQR= q3-q1
Lower_whisker= q1-(1.5*IQR)
upper_whisker= q3+(1.5*IQR)
df[(df['installment']< Lower_whisker) | (df['installment']> upper_whisker)][:5]
```

	loan_amnt	term	int_rate	installment	grade	sub_grade	emp_length	home_ownership	annual_inc	verification_status	...	revol_bal	revol_util	total_acc	initial_list
11	35000.0	36 months	14.64	1207.13	C	C3	8 years	MORTGAGE	130000.00	Verified	...	81263.0	18.7	61.0	
18	34000.0	36 months	7.90	1063.87	A	A4	10+ years	RENT	130580.00	Verified	...	8767.0	11.9	36.0	
57	35000.0	36 months	14.16	1198.94	C	C2	9 years	MORTGAGE	118497.84	Verified	...	8148.0	83.1	59.0	
95	30000.0	36 months	16.49	1061.99	D	D3	10+ years	RENT	101000.00	Verified	...	6080.0	76.0	15.0	
103	30000.0	36 months	15.31	1044.52	C	C2	9 years	MORTGAGE	108000.00	Verified	...	19430.0	84.8	15.0	

5 rows × 25 columns

```
q1= np.quantile(df['annual_inc'],0.25)
q3= np.quantile(df['annual_inc'],0.75)
IQR= q3-q1
Lower_whisker= q1-(1.5*IQR)
upper_whisker= q3+(1.5*IQR)
df[(df['annual_inc']< Lower_whisker) | (df['annual_inc']> upper_whisker)][:5]
```

	loan_amnt	term	int_rate	installment	grade	sub_grade	emp_length	home_ownership	annual_inc	verification_status	...	revol_bal	revol_util	total_acc	initial_list
87	30000.0	60 months	24.70	875.28	G	G1	5 years	MORTGAGE	187321.0	Verified	...	54810.0	93.4	52.0	
139	20000.0	36 months	10.37	648.83	B	B3	< 1 year	MORTGAGE	170000.0	Verified	...	140820.0	76.2	19.0	
195	24000.0	60 months	24.50	697.42	F	F3	10+ years	MORTGAGE	224000.0	Verified	...	5807.0	58.1	32.0	
221	25000.0	60 months	12.49	562.33	B	B5	10+ years	RENT	170000.0	Verified	...	2390.0	5.4	13.0	
228	35000.0	36 months	12.99	1179.12	C	C2	10+ years	MORTGAGE	350000.0	Verified	...	216194.0	45.4	43.0	

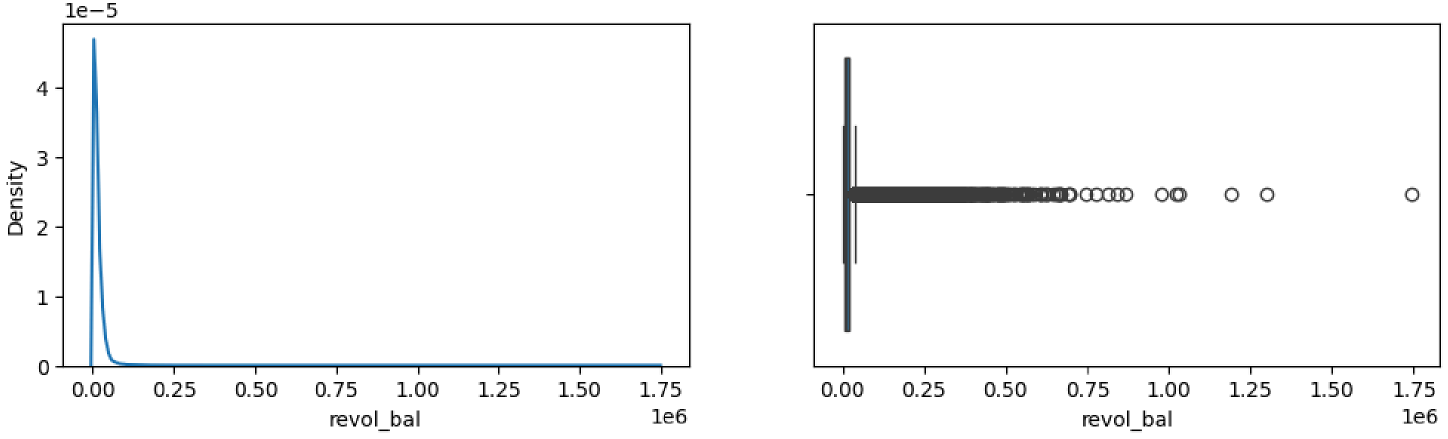
5 rows × 25 columns

```
q1= np.quantile(df['open_acc'],0.25)
q3= np.quantile(df['open_acc'],0.75)
IQR= q3-q1
Lower_whisker= q1-(1.5*IQR)
upper_whisker= q3+(1.5*IQR)
df[(df['open_acc']< Lower_whisker) | (df['open_acc']> upper_whisker)][:5]
```

	loan_amnt	term	int_rate	installment	grade	sub_grade	emp_length	home_ownership	annual_inc	verification_status	...	revol_bal	revol_util	total_acc	initial_list
11	35000.0	36 months	14.64	1207.13	C	C3	8 years	MORTGAGE	130000.0	Verified	...	81263.0	18.7	61.0	
170	35000.0	60 months	23.10	988.68	E	E4	8 years	MORTGAGE	125388.0	Verified	...	128741.0	58.6	59.0	
191	35000.0	60 months	17.57	880.61	D	D4	10+ years	MORTGAGE	150000.0	Source Verified	...	44777.0	62.7	52.0	
346	20400.0	60 months	18.24	520.70	D	D5	4 years	RENT	51000.0	Source Verified	...	13284.0	26.0	38.0	
364	25000.0	60 months	11.44	549.07	B	B4	10+ years	MORTGAGE	99000.0	Verified	...	29067.0	39.2	49.0	

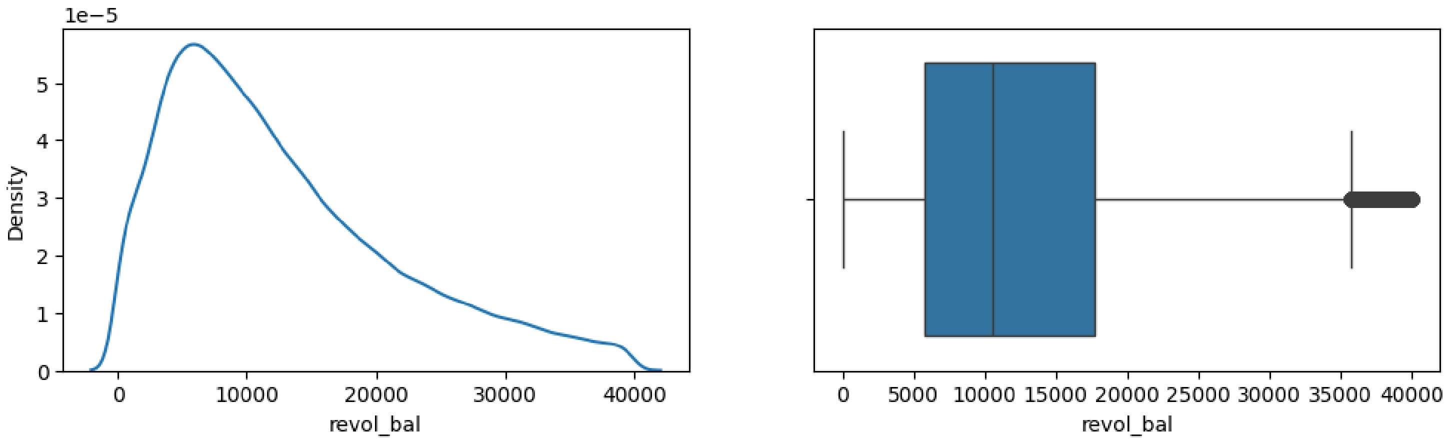
5 rows × 25 columns

```
plt.figure(figsize=(12,3))
plt.subplot(1,2,1)
sns.kdeplot(df['revol_bal'])
plt.subplot(1,2,2)
sns.boxplot(x=df['revol_bal'])
plt.show()
```

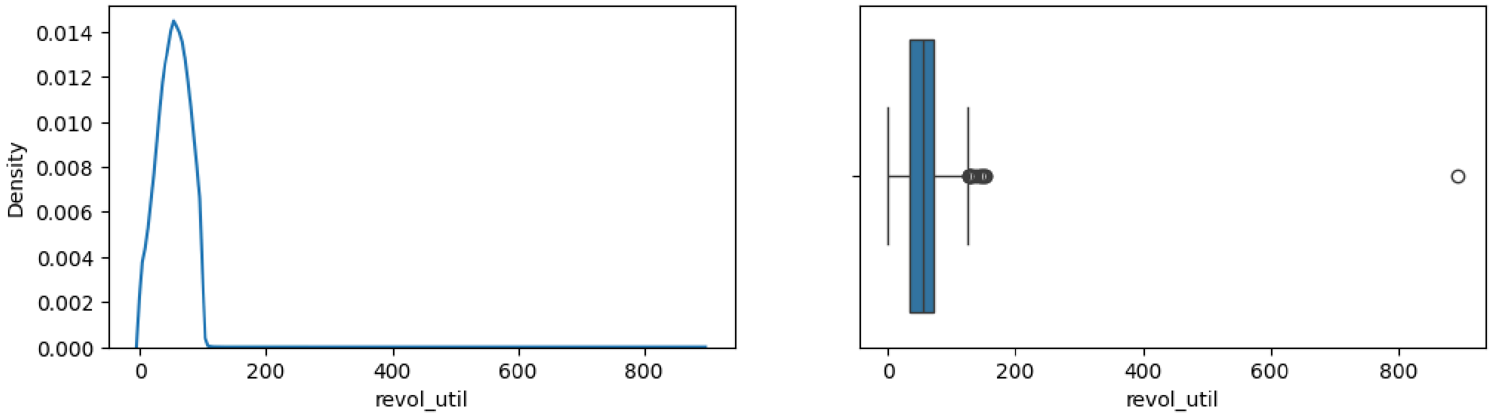



```
q1= np.quantile(df['revol_bal'],0.25)
q3= np.quantile(df['revol_bal'],0.75)
IQR= q3-q1
Lower_whisker= q1-(1.5*IQR)
upper_whisker= q3+(1.5*IQR)
df[(df['revol_bal']< Lower_whisker) | (df['revol_bal']> upper_whisker)]
df= df[(df['revol_bal'] > Lower_whisker) & (df['revol_bal'] < upper_whisker)]
```

```
plt.figure(figsize=(12,3))
plt.subplot(1,2,1)
sns.kdeplot(df['revol_bal'])
plt.subplot(1,2,2)
sns.boxplot(x=df['revol_bal'])
plt.show()
```




```
plt.figure(figsize=(12,3))
plt.subplot(1,2,1)
sns.kdeplot(df['revol_util'])
plt.subplot(1,2,2)
sns.boxplot(x=df['revol_util'])
plt.show()
```



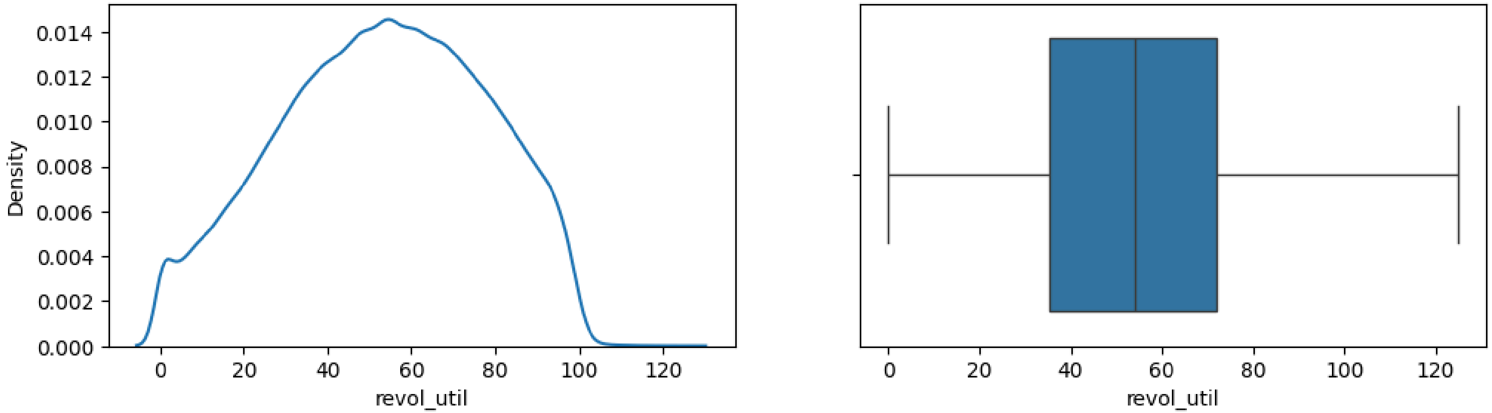
Observation-

- THe Graph illustrates a pronounced right skewness, indicating a concentration of values towards the higher end and a subsequent decline in density towards the lower end.

- Additionally the boxplot reveals the substantial range of continuous values. To ensure data conformity and achieve a more normalised distribution, we remove excess values and outliers from dataset.

```
q1= np.quantile(df['revol_util'],0.25)
q3= np.quantile(df['revol_util'],0.75)
IQR= q3-q1
Lower_whisker= q1-(1.5*IQR)
upper_whisker= q3+(1.5*IQR)
df[(df['revol_util']< Lower_whisker) | (df['revol_util']> upper_whisker)]
df= df[(df['revol_util'] > Lower_whisker) & (df['revol_util'] < upper_whisker)]
```

```
plt.figure(figsize=(12,3))
plt.subplot(1,2,1)
sns.kdeplot(df['revol_util'])
plt.subplot(1,2,2)
sns.boxplot(x=df['revol_util'])
plt.show()
```



Observation-

- Currently, the data exhibits a closer approximation to a normal distribution. Furthermore examination through the boxplot indicates the absence of outliers.
- With these observations, the data is now primed for accurate prediction and formulation, enhancing its overall quality and realibility.

Feature Engineering

Performing Label Encoding for the Column initial list status-

```
le= LabelEncoder()
le
```

```
▾ LabelEncoder
LabelEncoder()
```

```
df['loan_status']= df['loan_status'].replace('Fully Paid',1)
df['loan_status']= df['loan_status'].replace('Charged Off',0)
df['loan_status']
```

```
0         1
1         1
2         1
3         1
4         0
         ..
396024    1
396025    1
396027    1
396028    1
396029    1
Name: loan_status, Length: 374589, dtype: category
Categories (2, int64): [0, 1]
```

```
df['initial_list_status'] = le.fit_transform(df['initial_list_status'])
```

```
df['initial_list_status'][:5]
```

```
0    1
1    0
2    0
3    0
4    0
Name: initial_list_status, dtype: int64
```

Observation-

Label Encoding was applied to the status column, representing whether individuals obtained loan approval ("w" for approved) and ("f" for not approved). In this encoding scheme, "w" is represented as 1 and "f" as 0 in the dataset

Converting the "term" column which contains object values representing terms in months into integer value for 36 months and 60 months in the dataset.

```
df['months']= df['term'].str.split(' ').str[-2]
df['months']= pd.to_numeric(df['months'])
df['emp_length']= df['emp_length'].str.split(' ').str[-2]
df['updt_emp_length_yrs']= df['emp_length'].replace('10+','10')
df['updt_emp_length_yrs']= pd.to_numeric(df['updt_emp_length_yrs'])
df= df.drop(columns=['term','emp_length'])
```

Performong the Target Column Loan Status-

```
df['loan_status']= le.fit_transform(df['loan_status'])
df['loan_status'][:5]
```

```
0    1
1    1
2    1
3    1
4    0
Name: loan_status, dtype: int64
```

Observation-

The Target volumn has been label encoded with "fully paid" represented by 0 and "charged off" as 1

To Prepare the dataset for Logestic Regression Modelling and analysis, we will focus on retaining the most revelant columns while eliminating unnecessary ones. This

ensures that the data is streamlined for effective modelling, prioritizing features essential for the analysis

```
df.shape
```

```
(374589, 25)
```

Performing One Hot Encoding or with Dummy vlaues for the Modelling-

```
df[:2]
```

	loan_amnt	int_rate	installment	grade	sub_grade	home_ownership	annual_inc	verification_status	loan_status	purpose	...	total_acc	initial_list_status	applic
0	10000.0	11.44	329.48	B	B4	RENT	117000.0	Not Verified	1	vacation	...	25.0	1	
1	8000.0	11.99	265.68	B	B5	MORTGAGE	65000.0	Not Verified	1	debt_consolidation	...	27.0	0	

2 rows × 25 columns

```
for column in ['grade', 'sub_grade', 'home_ownership', 'verification_status', 'purpose', 'initial_list_status', 'application_type', 'earliest_year', 'pin_code']:
  df[column]= df[column].astype(str)
df['earliest_year'] =df['earliest_year'].astype(int)
```

Data Preprocessing for Modelling-

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

```
for column in ['grade', 'sub_grade', 'home_ownership', 'verification_status', 'purpose', 'initial_list_status', 'application_type', 'earliest_year', 'pin_code']:
    X[column] = le.fit_transform(X[column])
```

We will now proceed to prepare the dataset for the ***Testing and Training*** phase of the Algorithm

```
X.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 374589 entries, 0 to 396029
Data columns (total 24 columns):
 #   Column                Non-Null Count   Dtype  
---  ------                --------------   -----  
 0   loan_amnt             374589 non-null  float64
 1   int_rate              374589 non-null  float64
 2   installment           374589 non-null  float64
 3   grade                 374589 non-null  int64  
 4   sub_grade             374589 non-null  int64  
 5   home_ownership        374589 non-null  int64  
 6   annual_inc            374589 non-null  float64
 7   verification_status   374589 non-null  int64  
 8   purpose               374589 non-null  int64  
 9   dti                   374589 non-null  float64
 10  open_acc              374589 non-null  float64
 11  pub_rec               374589 non-null  float64
 12  revol_bal             374589 non-null  float64
 13  revol_util            374589 non-null  float64
 14  total_acc             374589 non-null  float64
 15  initial_list_status   374589 non-null  int64  
 16  application_type      374589 non-null  int64  
 17  mort_acc              374589 non-null  float64
 18  pub_rec_bankruptcies  374589 non-null  float64
 19  earliest_year         374589 non-null  int64  
 20  pin_code              374589 non-null  int64  
 21  issued_year           374589 non-null  int64  
 22  months                374589 non-null  int64  
 23  updt_emp_length_yrs   374589 non-null  int64  
dtypes: float64(12), int64(12)
memory usage: 71.4 MB
```

```
print(X.shape)
print(y.shape)
```

```
(374589, 24)
(374589,)
```

```
X_train,X_test,y_train,y_test= train_test_split(X,y,test_size=0.3,random_state=42)
X_val, X_test, y_val,y_test= train_test_split(X_test,y_test,test_size=0.5, random_state=43)
```

```
print(X_train.shape)
print(y_train.shape)
print(X_val.shape)
print(y_val.shape)
print(X_test.shape)
print(y_test.shape)
```

```
(262212, 24)
(262212,)
(56188, 24)
(56188,)
(56189, 24)
(56189,)
```

```
X_train[:2]
```

	loan_amnt	int_rate	installment	grade	sub_grade	home_ownership	annual_inc	verification_status	purpose	dti	...	total_acc	initial_list_status	application_typ
365865	5600.0	14.64	193.15	2	12	5	65000.0	2	9	3.45	...	23.0	0	
302179	10000.0	12.35	333.82	1	8	5	59000.0	0	1	15.07	...	15.0	1	

2 rows × 24 columns

```
X_test[:2]
```

	loan_amnt	int_rate	installment	grade	sub_grade	home_ownership	annual_inc	verification_status	purpose	dti	...	total_acc	initial_list_status	application_type
78071	9600.0	15.10	333.26	2	11	5	55000.0	0	2	13.37	...	17.0	0	1
70575	2000.0	11.53	65.99	1	9	1	75000.0	1	2	9.14	...	48.0	1	1

2 rows × 24 columns

```
y_train.value_counts()
```

```
loan_status
1    210476
0     51736
Name: count, dtype: int64
```

Observation-

- The value count above reveal an imbalance in distribution of outcomes '1' and '0' within the Dataset. To address this imbalance, the SMOTE (Synthetic Minority Over Sampling Technique) method can be employed. SMOTE overssamples the minority class by generating synthetic instances based on Nearest Neighbour Concept.
- Its important to note that oversampling will only be applied to the training data. This ensures that the model is trained on balanced data while maintaining the original distribution of outcomes in validation and testing dataset.

```
smote= SMOTE(random_state=42)
X_train,y_train = smote.fit_resample(X_train,y_train)
```

```
print(f'Training Data:\n{y_train.value_counts()}')
```

```
Training Data:
loan_status
1    210476
0    210476
Name: count, dtype: int64
```

Assumptions Multicollinearity Checking by VIF Score-

```
vif_data= pd.DataFrame()
vif_data["Variable"] = X_train.columns
vif_data["VIF"]= [variance_inflation_factor(X_train.values,i) for i in range(X_train.shape[1])]
print(pd.DataFrame(vif_data))
```

```
                Variable         VIF
0              loan_amnt  257.851457
1               int_rate  269.331757
2            installment  228.372297
3                  grade   44.507717
4              sub_grade  163.100710
5         home_ownership    4.867771
6             annual_inc    3.667304
7    verification_status    2.912113
8                purpose    2.610996
9                    dti    2.050445
10              open_acc   14.637792
11               pub_rec    1.920004
12             revol_bal    5.947938
13            revol_util   10.517768
14             total_acc   14.050187
15   initial_list_status    1.546250
16      application_type  523.357791
17              mort_acc    2.762600
18  pub_rec_bankruptcies    2.016470
19         earliest_year   65.937061
20              pin_code    4.780966
21           issued_year  752.321718
22                months  132.437312
23   updt_emp_length_yrs    4.689605
```

Observation-

* Based on VIF (Varaince Inflation Factor) values observed above, it is evident that several columns exhibit collinearity as indicated by high VIF scores.

* Collinearity must be addressed to uphold the stability and interpretability of the model

```
X_train = X_train.drop(columns = ['int_rate','installment','sub_grade','application_type', 'earliest_year','issued_year','months', 'total_acc'])
```

```
vif_data= pd.DataFrame()
vif_data["Variable"] = X_train.columns
vif_data["VIF"]= [variance_inflation_factor(X_train.values,i) for i in range(X_train.shape[1])]
print(vif_data.sort_values(by = ['VIF'],ascending= False))
```

```
                Variable       VIF
10            revol_util  7.751816
7               open_acc  6.591057
0              loan_amnt  6.337188
9              revol_bal  5.557774
1                  grade  4.308686
14              pin_code  4.296104
15   updt_emp_length_yrs  4.096614
2         home_ownership  3.746142
3             annual_inc  3.567457
4    verification_status  2.887075
5                purpose  2.334305
12              mort_acc  2.293153
6                    dti  2.026394
13  pub_rec_bankruptcies  1.993900
8                pub_rec  1.913557
11   initial_list_status  1.448615
```

Note-

Remove the collinear columns from validation and testing data also to get and fit the responsiveness of the data with equal shape and size.

```
X_val= X_val.drop(columns = ['int_rate','installment','sub_grade','application_type', 'earliest_year','issued_year','months', 'total_acc'])
X_test= X_test.drop(columns = ['int_rate','installment','sub_grade','application_type', 'earliest_year','issued_year','months', 'total_acc'])
```

Scaling Via MINMAXSCALER()

1) **The MinMaxScaler operates by scaling each features values to a range between 0 and 1. This is achieved by subtracting the minimum value from each feature and then Dividing by the range, which is the difference between the original maximum and original minimum values.**

2) **By employing MinMaxScaler, the distribution shape of original data is maintained, ensuring that the intrinsic information within the dataset remains unchanged.**

```
scaling= MinMaxScaler()
scaling
```

```
▾ MinMaxScaler
MinMaxScaler()
```

```
X_train = pd.DataFrame(scaling.fit_transform(X_train), columns= X_train.columns)
X_train[:2]
```

	loan_amnt	grade	home_ownership	annual_inc	verification_status	purpose	dti	open_acc	pub_rec	revol_bal	revol_util	initial_list_status	mort_acc	pub_rec_bank
0	0.136364	0.333333	1.0	0.008553	1.0	0.692308	0.000345	0.078947	0.0	0.103851	0.354451	0.0	0.0	
1	0.254011	0.166667	1.0	0.007763	0.0	0.076923	0.001507	0.078947	0.0	0.283946	0.711307	1.0	0.0	

```
X_val= pd.DataFrame(scaling.transform(X_val),columns=X_val.columns)
X_val[:2]
```

	loan_amnt	grade	home_ownership	annual_inc	verification_status	purpose	dti	open_acc	pub_rec	revol_bal	revol_util	initial_list_status	mort_acc	pub_rec_bankrup
0	0.183155	0.5	1.0	0.004605	0.5	0.384615	0.002912	0.236842	0.0	0.022081	0.150762	0.0	0.0000	
1	0.788770	0.5	0.2	0.009211	1.0	0.153846	0.001126	0.118421	0.0	0.329357	0.403368	0.0	0.0625	

```
X_test= pd.DataFrame(scaling.transform(X_test),columns= X_test.columns)
X_test[:2]
```

	loan_amnt	grade	home_ownership	annual_inc	verification_status	purpose	dti	open_acc	pub_rec	revol_bal	revol_util	initial_list_status	mort_acc	pub_rec_bank
0	0.243316	0.333333	1.0	0.007237	0.0	0.153846	0.001337	0.105263	0.0	0.234959	0.697674	0.0	0.00000	
1	0.040107	0.166667	0.2	0.009868	0.5	0.153846	0.000914	0.197368	0.0	0.559690	0.620690	1.0	0.21875	

Lets Prepare for the Logistic Regression for the Analysis with the Algorithm-

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

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

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

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

```
pd.Series((zip(X.columns,model.coef_[0])))
```

```
0               (loan_amnt, -1.3511910839050891)
1                 (int_rate, -1.976777259735695)
2             (installment, 0.12328774082464017)
3                    (grade, 26.127558885182953)
4                (sub_grade, 0.6300021713947044)
5           (home_ownership, 0.2539785964990364)
6               (annual_inc, -13.96676278587435)
7     (verification_status, -2.4244759415231165)
8                 (purpose, -9.130796708394934)
9                      (dti, 0.5814339338256844)
10               (open_acc, -1.026778036691934)
11                 (pub_rec, 0.836718250044083)
12               (revol_bal, 3.013385953482211)
13            (revol_util, -0.28045587280899226)
14              (total_acc, -3.0013471908004905)
15     (initial_list_status, 0.1396805854533711)
dtype: object
```

```
y_predval= model.predict(X_val)
y_predval
```

```
array([0, 0, 1, ..., 0, 1, 0])
```

```
y_pred= model.predict(X_test)
y_pred
```

```
array([0, 1, 1, ..., 1, 0, 1])
```

Actual and Predicted values for the Validation Data

```
test1= pd.DataFrame({"Actual": y_val, "Predicted":y_predval})
test1[:10]
```

	Actual	Predicted
151016	1	0
346251	0	0
352698	1	1
32684	1	0
7401	1	1
55279	1	0
240079	1	1
131477	1	1
216743	1	1
217320	1	0

Actual and Predicted values for the Test Data

```
test1= pd.DataFrame({"Actual": y_test, "Predicted":y_pred})
test1[:10]
```

	Actual	Predicted
78071	1	0
70575	1	1
319702	1	1
24059	1	1
129453	0	0
57366	1	1

```
r2= model.score(X_val,y_val)
r2
```

```
0.675233145867445
```

Check for Residuals-

```
Error= test1['Actual']- test1['Predicted']
```