Project 8 - LoanTap

September 9, 2022

0.1 Context:

LoanTap is an online platform committed to delivering customized loan products to millennials. They innovate in an otherwise dull loan segment, to deliver instant, flexible loans on consumer friendly terms to salaried professionals and businessmen.

The data science team at LoanTap is building an underwriting layer to determine the creditworthiness of MSMEs as well as individuals.

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

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

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

0.2 Problem Statement:

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

0.3 Data dictionary:

- loan_amnt : The listed amount of the loan applied for by the borrower. If at some point in time, the credit department reduces the loan amount, then it will be reflected in this value.
- term : The number of payments on the loan. Values are in months and can be either 36 or 60.
- int_rate : Interest Rate on the loan
- installment : The monthly payment owed by the borrower if the loan originates.
- grade : LoanTap assigned loan grade
- sub_grade : LoanTap assigned loan subgrade
- emp_title :The job title supplied by the Borrower when applying for the loan.*
- 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.
- annual_inc : The self-reported annual income provided by the borrower during registration.
- verification_status : Indicates if income was verified by LoanTap, not verified, or if the income source was verified

- issue_d : The month which the loan was funded
- loan_status : Current status of the loan - Target Variable
- purpose : A category provided by the borrower for the loan request.
- title : The loan title provided by the borrower
- dti : A ratio calculated using the borrower's total monthly debt payments on the total debt obligations, excluding mortgage and the requested LoanTap loan, divided by the borrower's self-reported monthly income.
- earliest_cr_line :The month the borrower's earliest reported credit line was opened
- open_acc : The number of open credit lines in the borrower's credit file.
- pub_rec : Number of derogatory public records
- revol_bal : Total credit revolving balance
- revol_util : Revolving line utilization rate, or the amount of credit the borrower is using relative to all available revolving credit.
- total_acc : The total number of credit lines currently in the borrower's credit file
- initial_list_status : The initial listing status of the loan. Possible values are – W, F
- application_type : Indicates whether the loan is an individual application or a joint application with two co-borrowers
- mort_acc : Number of mortgage accounts.
- pub_rec_bankruptcies : Number of public record bankruptcies
- Address: Address of the individual

[1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
from sklearn.model_selection import cross_val_score
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import OrdinalEncoder
from sklearn.preprocessing import OneHotEncoder
from sklearn.metrics import precision_score
from sklearn.metrics import recall_score
from sklearn.metrics import f1_score
from sklearn.metrics import roc_auc_score, roc_curve, precision_recall_curve,␣
 ↪auc
import warnings
warnings.filterwarnings('ignore')
```

[2]:
```
#Importing the dataset
df=pd.read_csv('LoanTap Data.csv')
```

[3]:
```
#Checking the first 5 records
df.head(5)
```

[3]:
```
   loan_amnt        term  int_rate  installment grade sub_grade  \
0    10000.0   36 months     11.44       329.48     B        B4
```

```
1     8000.0   36 months     11.99       265.68     B         B5
2    15600.0   36 months     10.49       506.97     B         B3
3     7200.0   36 months      6.49       220.65     A         A2
4    24375.0   60 months     17.27       609.33     C         C5

                 emp_title emp_length home_ownership  annual_inc  …  \
0                Marketing  10+ years           RENT    117000.0  …
1          Credit analyst    4 years       MORTGAGE     65000.0  …
2             Statistician   < 1 year           RENT     43057.0  …
3          Client Advocate    6 years           RENT     54000.0  …
4  Destiny Management Inc.    9 years       MORTGAGE     55000.0  …

  open_acc pub_rec revol_bal revol_util total_acc  initial_list_status  \
0     16.0     0.0   36369.0       41.8      25.0                    w
1     17.0     0.0   20131.0       53.3      27.0                    f
2     13.0     0.0   11987.0       92.2      26.0                    f
3      6.0     0.0    5472.0       21.5      13.0                    f
4     13.0     0.0   24584.0       69.8      43.0                    f

  application_type  mort_acc  pub_rec_bankruptcies  \
0       INDIVIDUAL       0.0                   0.0
1       INDIVIDUAL       3.0                   0.0
2       INDIVIDUAL       0.0                   0.0
3       INDIVIDUAL       0.0                   0.0
4       INDIVIDUAL       1.0                   0.0

                                              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

[5 rows x 27 columns]
```

[4]:
```python
#Number of rows and columns
df.shape
#There are 27 columns, we need to determine which columns are not important.
```

[4]: (396030, 27)

[5]:
```python
#Checking for the different columns
df.columns
```

[5]:
```
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')
```

[6]:
```
#Checking for total number of unique values for each column and a few unique␣
 ↪values for each column
for column in df.columns:
    print(column,'-',df[column].nunique(),'Number of unique values')
    print(column,'-',df[column].unique()[:5])
    print('--------------')
#Seems like there are few categorical and few continuous features
```

```
loan_amnt - 1397 Number of unique values
loan_amnt - [10000.  8000. 15600.  7200. 24375.]
--------------
term - 2 Number of unique values
term - [' 36 months' ' 60 months']
--------------
int_rate - 566 Number of unique values
int_rate - [11.44 11.99 10.49  6.49 17.27]
--------------
installment - 55706 Number of unique values
installment - [329.48 265.68 506.97 220.65 609.33]
--------------
grade - 7 Number of unique values
grade - ['B' 'A' 'C' 'E' 'D']
--------------
sub_grade - 35 Number of unique values
sub_grade - ['B4' 'B5' 'B3' 'A2' 'C5']
--------------
emp_title - 173105 Number of unique values
emp_title - ['Marketing' 'Credit analyst ' 'Statistician' 'Client Advocate'
 'Destiny Management Inc.']
--------------
emp_length - 11 Number of unique values
emp_length - ['10+ years' '4 years' '< 1 year' '6 years' '9 years']
--------------
home_ownership - 6 Number of unique values
home_ownership - ['RENT' 'MORTGAGE' 'OWN' 'OTHER' 'NONE']
--------------
annual_inc - 27197 Number of unique values
annual_inc - [117000.  65000.  43057.  54000.  55000.]
--------------
verification_status - 3 Number of unique values
verification_status - ['Not Verified' 'Source Verified' 'Verified']
--------------
issue_d - 115 Number of unique values
```

```
issue_d - ['Jan-2015' 'Nov-2014' 'Apr-2013' 'Sep-2015' 'Sep-2012']
--------------
loan_status - 2 Number of unique values
loan_status - ['Fully Paid' 'Charged Off']
--------------
purpose - 14 Number of unique values
purpose - ['vacation' 'debt_consolidation' 'credit_card' 'home_improvement'
 'small_business']
--------------
title - 48817 Number of unique values
title - ['Vacation' 'Debt consolidation' 'Credit card refinancing'
 'Credit Card Refinance' 'Home improvement']
--------------
dti - 4262 Number of unique values
dti - [26.24 22.05 12.79  2.6  33.95]
--------------
earliest_cr_line - 684 Number of unique values
earliest_cr_line - ['Jun-1990' 'Jul-2004' 'Aug-2007' 'Sep-2006' 'Mar-1999']
--------------
open_acc - 61 Number of unique values
open_acc - [16. 17. 13.  6.  8.]
--------------
pub_rec - 20 Number of unique values
pub_rec - [0. 1. 2. 3. 4.]
--------------
revol_bal - 55622 Number of unique values
revol_bal - [36369. 20131. 11987.  5472. 24584.]
--------------
revol_util - 1226 Number of unique values
revol_util - [41.8 53.3 92.2 21.5 69.8]
--------------
total_acc - 118 Number of unique values
total_acc - [25. 27. 26. 13. 43.]
--------------
initial_list_status - 2 Number of unique values
initial_list_status - ['w' 'f']
--------------
application_type - 3 Number of unique values
application_type - ['INDIVIDUAL' 'JOINT' 'DIRECT_PAY']
--------------
mort_acc - 33 Number of unique values
mort_acc - [0. 3. 1. 4. 2.]
--------------
pub_rec_bankruptcies - 9 Number of unique values
pub_rec_bankruptcies - [ 0.  1.  2.  3. nan]
--------------
address - 393700 Number of unique values
address - ['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'
 '823 Reid Ford\r\nDelacruzside, MA 00813'
 '679 Luna Roads\r\nGreggshire, VA 11650']
--------------
```

[7]:
```
#Checking for duplicate rows
df[df.duplicated()]
#There are no duplicate rows
```

[7]:
```
Empty DataFrame
Columns: [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]
Index: []

[0 rows x 27 columns]
```

[8]:
```
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                 394275 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

[9]:
```
#Dividing the dataset into train and test sets.
df_train,df_test=train_test_split(df,test_size=0.2,random_state=2)
df_train.reset_index(drop=True,inplace=True)
df_test.reset_index(drop=True,inplace=True)
```

[10]:
```
#Checking the shape of train and test sets
print(df_train.shape)
print(df_test.shape)
```

```
(316824, 27)
(79206, 27)
```

[ ]:
```

```

0.3.1 EDA, Univariate and Bivariate Analysis on Train_Data

[11]:
```
#Checking for null values in X_train
display(df_train.isna().sum())
# emp_title,emp_length,mort_acc,pub_rec_bankruptcies,revol_util,title columns␣
↪have null values
```

```
loan_amnt                   0
term                        0
int_rate                    0
installment                 0
grade                       0
sub_grade                   0
emp_title               18252
emp_length              14572
home_ownership              0
annual_inc                  0
verification_status         0
issue_d                     0
loan_status                 0
purpose                     0
title                    1418
dti                         0
earliest_cr_line            0
open_acc                    0
pub_rec                     0
```

```
revol_bal                  0
revol_util               223
total_acc                  0
initial_list_status        0
application_type           0
mort_acc               30091
pub_rec_bankruptcies     423
address                    0
dtype: int64
```

[12]:
```
#Making 2 variables to split the features into categorical and continuous␣
↪features
categorical_columns=[]
continuous_columns=[]
```

[ ]:
```

```

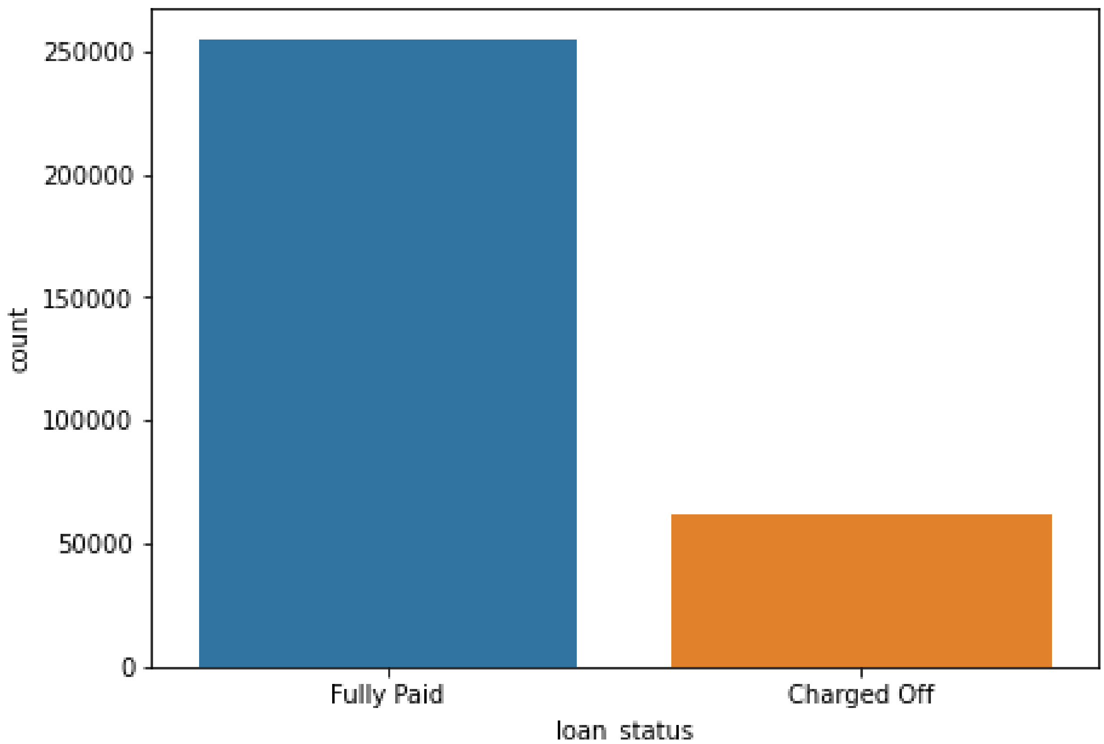
0.3.2 1) Loan_Status - Target Variable

[13]:
```
variable='loan_status'
#Checking for null values
print('Number of Null Values -',df_train[variable].isna().sum())
#There are no null values

#Checking for number of unique values
print('Number of Unique Values -',df_train[variable].nunique())
#There are 2 unique values
# This is a categorical variable. Hence we have a classification problem in␣
↪hand.
```

```
Number of Null Values - 0
Number of Unique Values - 2
```

[14]:
```
#Checking the percentage of occurence of each of the categories.
print(np.round(df_train[variable].value_counts(normalize=True)*100))
#We have imbalanced target data. Need to adopt some technique to take care of␣
↪imbalanced data.

plt.figure(figsize=(7,5))
sns.countplot(df_train[variable])
plt.show()
```

```
Fully Paid     80.0
Charged Off    20.0
Name: loan_status, dtype: float64
```



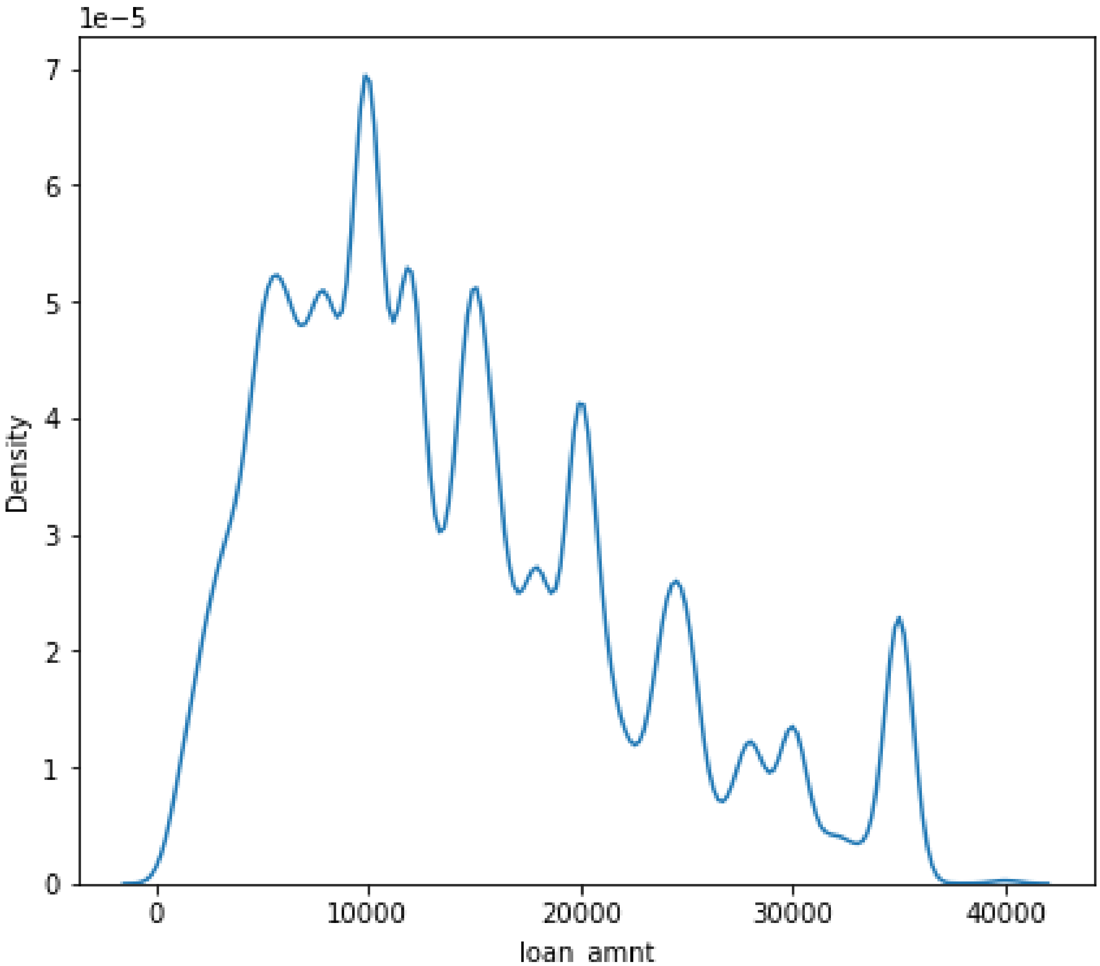
0.3.3 2) Loan_Amount

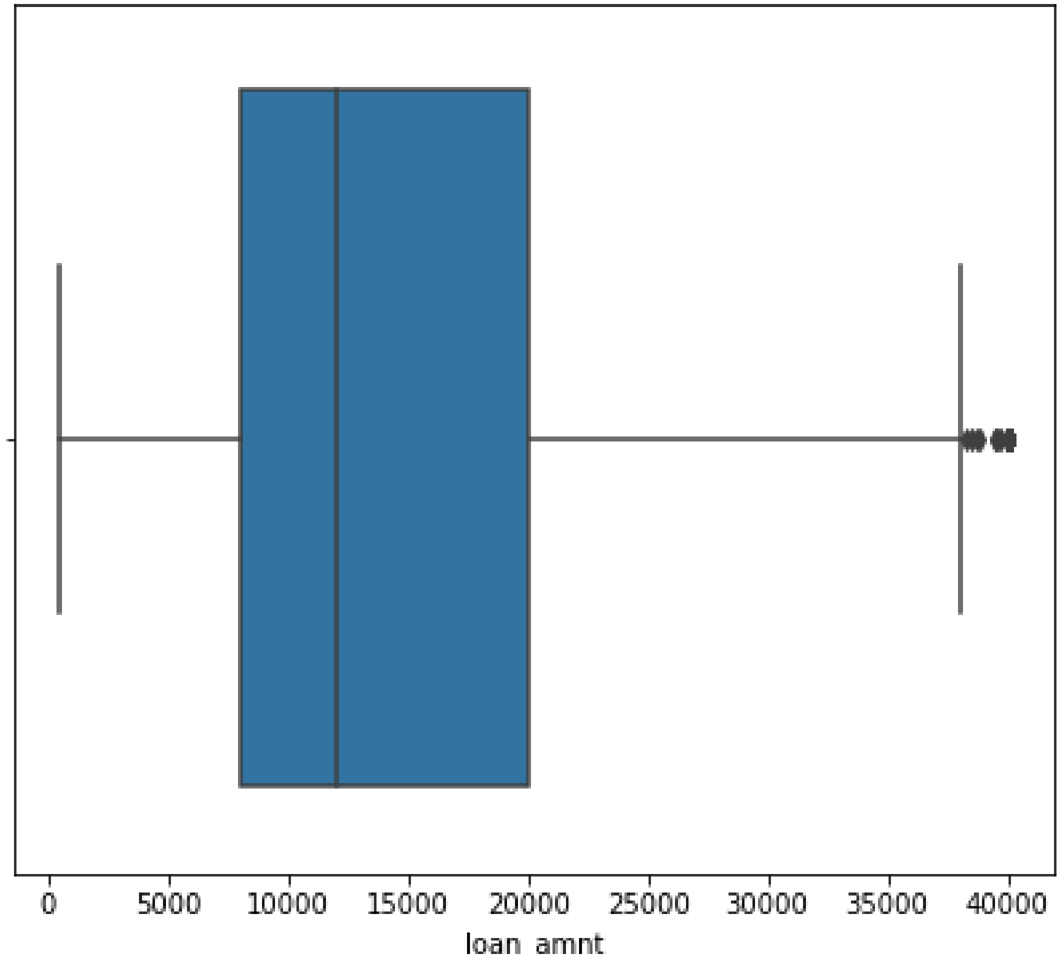
[15]:
```
variable='loan_amnt'
#Checking for null values
print('Number of Null Values -',df_train[variable].isna().sum())
#There are no null values

#Checking for number of unique values
print('Number of Unique Values -',df_train[variable].nunique())
#There are 1387 unique values
# This is a continuous variable
```

```
Number of Null Values - 0
Number of Unique Values - 1389
```

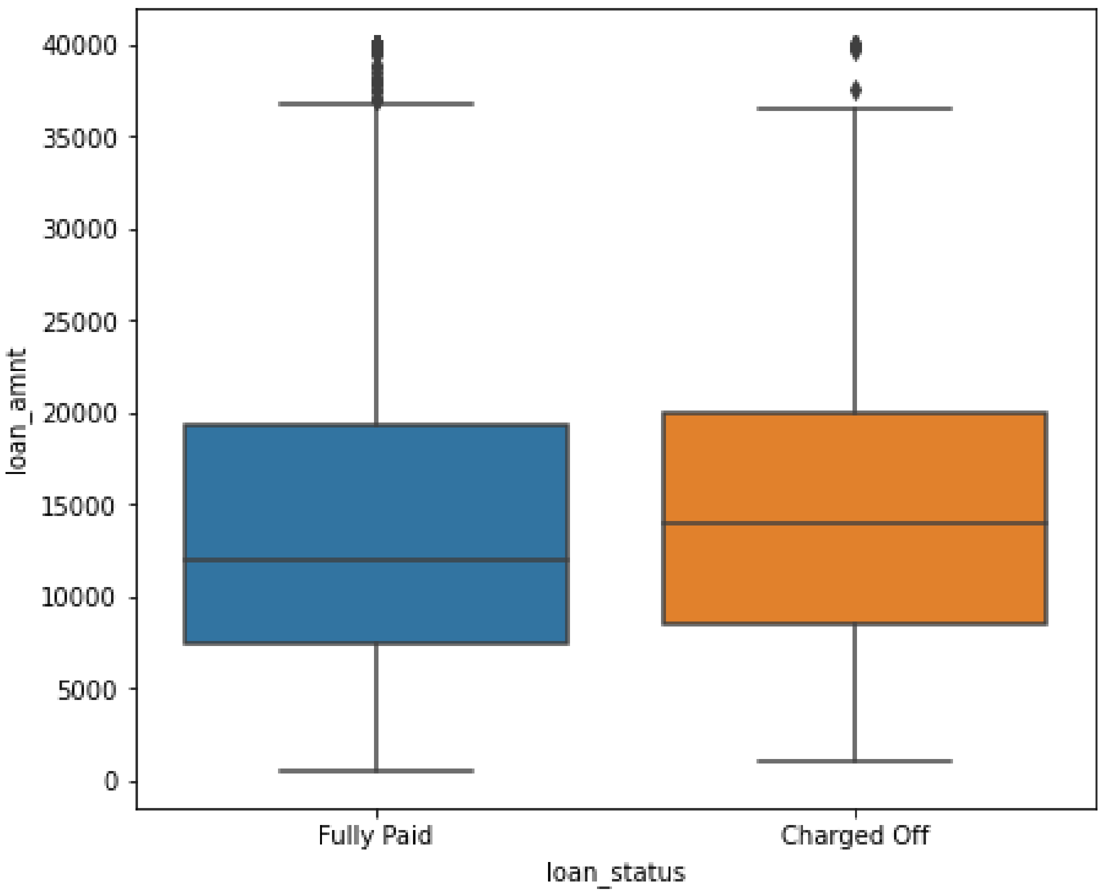
[16]:
```
plt.figure(figsize=(7,6))
sns.kdeplot(df_train[variable])
plt.show()
#Data looks right skewed

plt.figure(figsize=(7,6))
sns.boxplot(df_train[variable])
plt.show()
```

```
#There are few outliers in the data
```





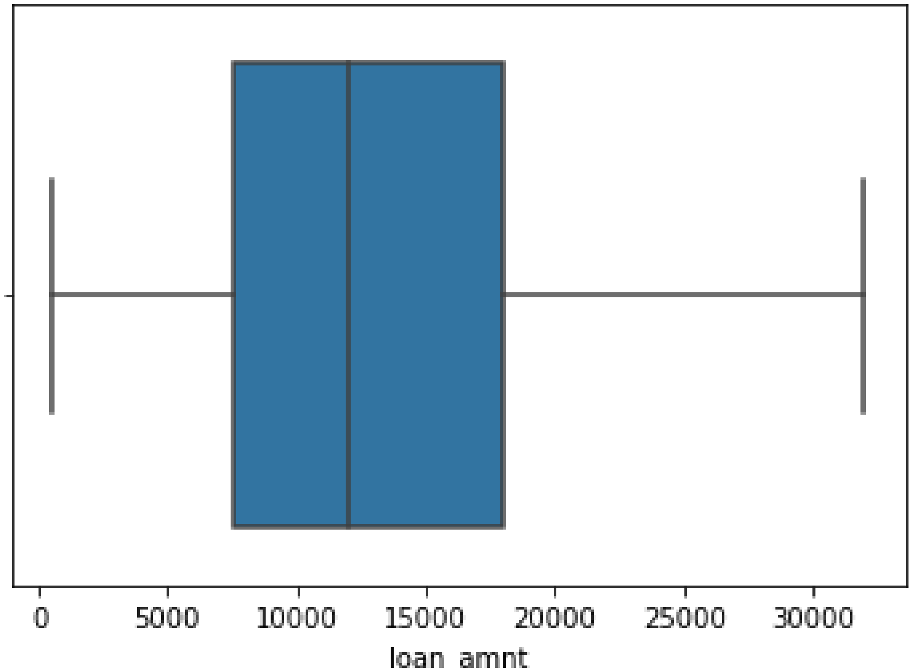
[17]:
```
#Checking Loan_Status with Loan_Amount to check if there is any relationship
plt.figure(figsize=(7,6))
sns.boxplot(data=df_train,y=variable,x='loan_status')
plt.show()
#Observation - The median loan_amount is higher for charged off loans in␣
↪comparison to fully_paid loans.
```



[18]:
```
df_train.groupby(by='loan_status').mean()[variable]
#Observation - The mean loan_amount is higher for charged off loans in␣
↪comparison to fully_paid loans.
```

[18]:
```
loan_status
Charged Off    15128.570278
Fully Paid     13871.043024
Name: loan_amnt, dtype: float64
```

[19]:
```
#Removing the outliers
q75=np.percentile(df_train[variable],75)
q25=np.percentile(df_train[variable],25)
iqr=q75-q25
sns.boxplot(df_train.loc[df_train[variable]<iqr+q75,variable])
plt.show()
df_train=df_train.loc[df_train[variable]<iqr+q75]
#The outliers have been removed
```



[20]:
```
# Since mean and median loan_amount is different for different classes,␣
↪therefore it could be an important feature.
# Since it is a continuous variable, therefore adding it to the␣
↪continuous_columns variable.
continuous_columns.append(variable)
```

[ ]:
```
```

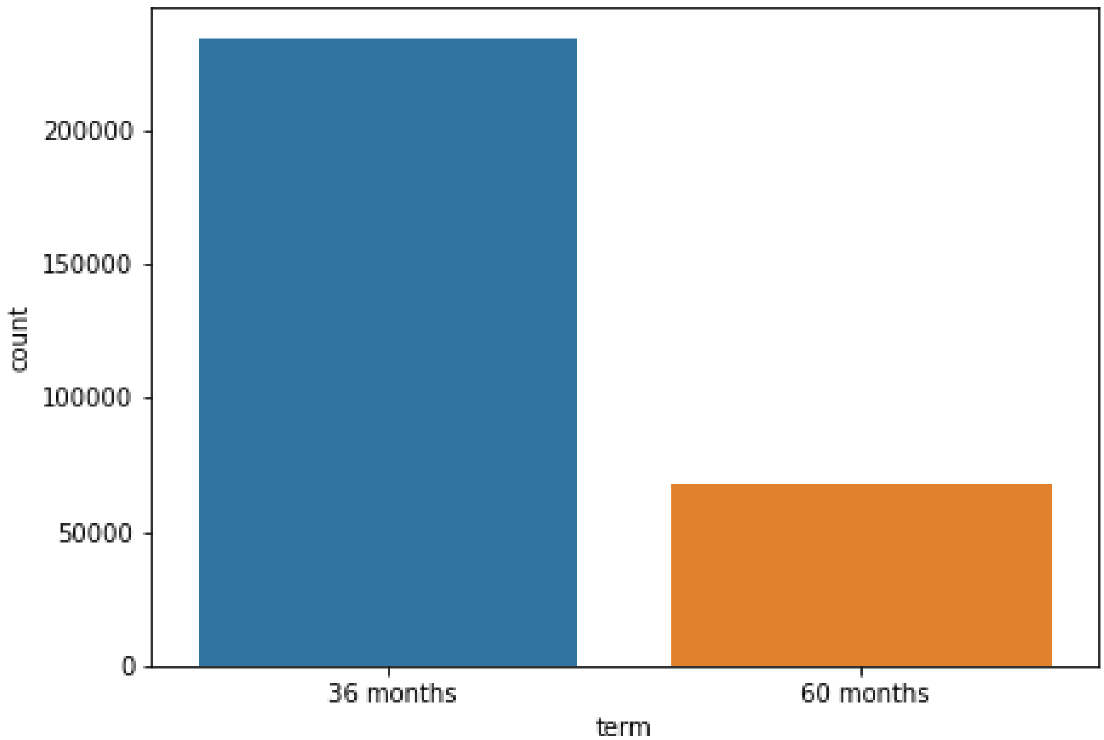
0.3.4 3) Term

[21]:
```
variable= 'term'
#Checking for null values
print('Number of Null Values -',df_train[variable].isna().sum())
#There are no null values

#Checking for number of unique values
print('Number of Unique Values -',df_train[variable].nunique())
#There are 2 unique values
# This is a categorical variable
```

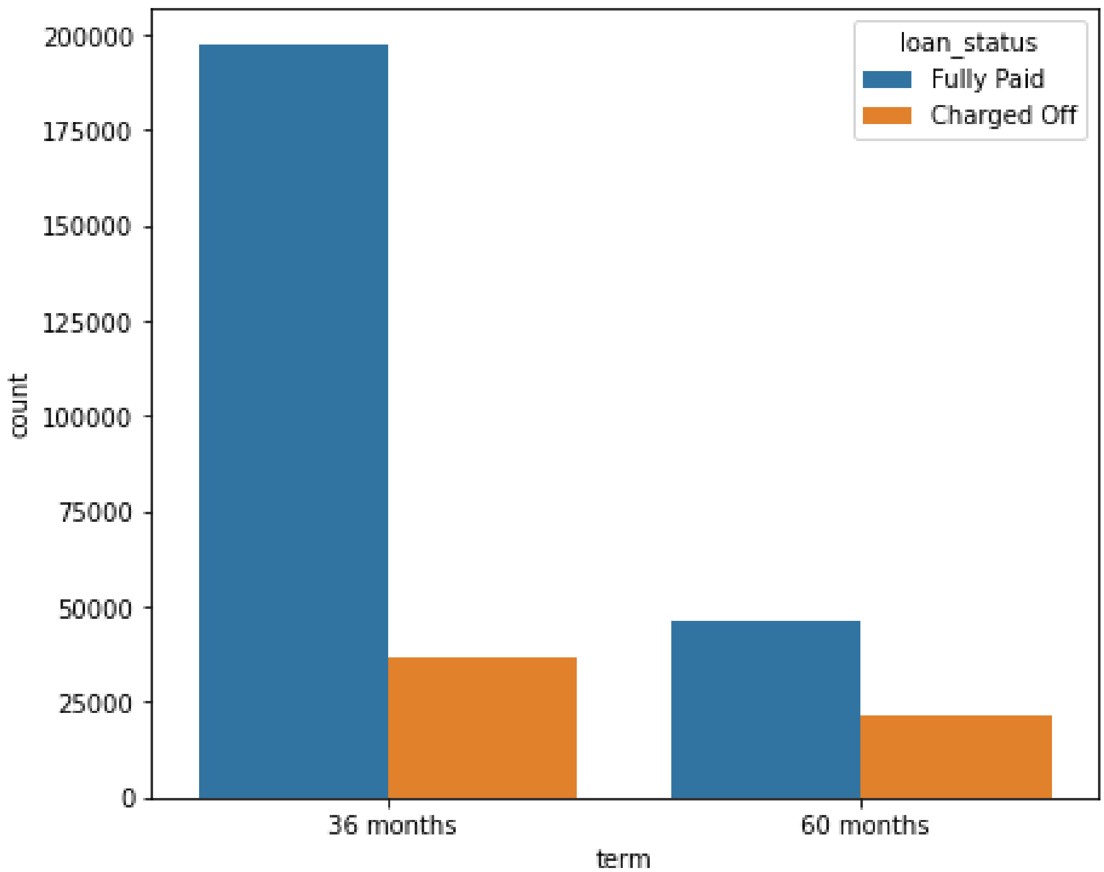
```
Number of Null Values - 0
Number of Unique Values - 2
```

[22]:
```
#Checking the percentage of occurence of each of the categories.
print(np.round(df_train[variable].value_counts(normalize=True)*100))

plt.figure(figsize=(7,5))
sns.countplot(df_train[variable])
plt.show()
#Later we can encode this data.
```

```
36 months    78.0
60 months    22.0
Name: term, dtype: float64
```



[23]:
```
#Checking Loan_Status with Term to check if there is any relationship
plt.figure(figsize=(7,6))
sns.countplot(data=df_train,x=variable,hue='loan_status')
plt.show()
#Observation - We can see different behavior for each of the 2 categories of␣
 ↪"term" variable.
```



[24]:
```
np.round(pd.
 ↪crosstab(df_train['loan_status'],df_train[variable],normalize='columns')*100)
#Observation - People who take a 60 months term loan are more likely to default.
```

[24]:
```
term          36 months   60 months
loan_status
Charged Off        16.0        32.0
Fully Paid         84.0        68.0
```

[25]:
```
# Since the charged_off probability is different for the 2 "term"␣
 ↪categories,therefore "term" could be an important feature.
# Since it is a categorical variable, therefore adding it to the␣
 ↪categorical_columns variable.
categorical_columns.append(variable)
```

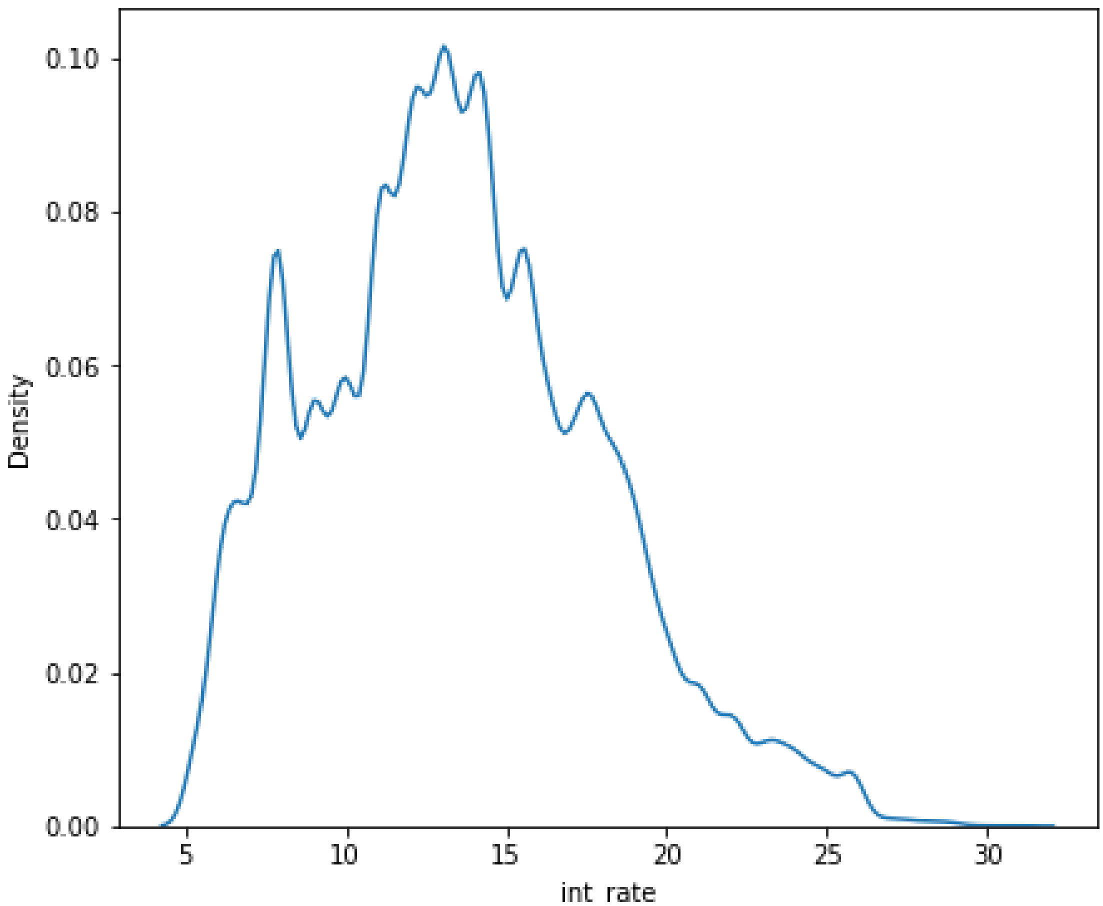
[ ]:

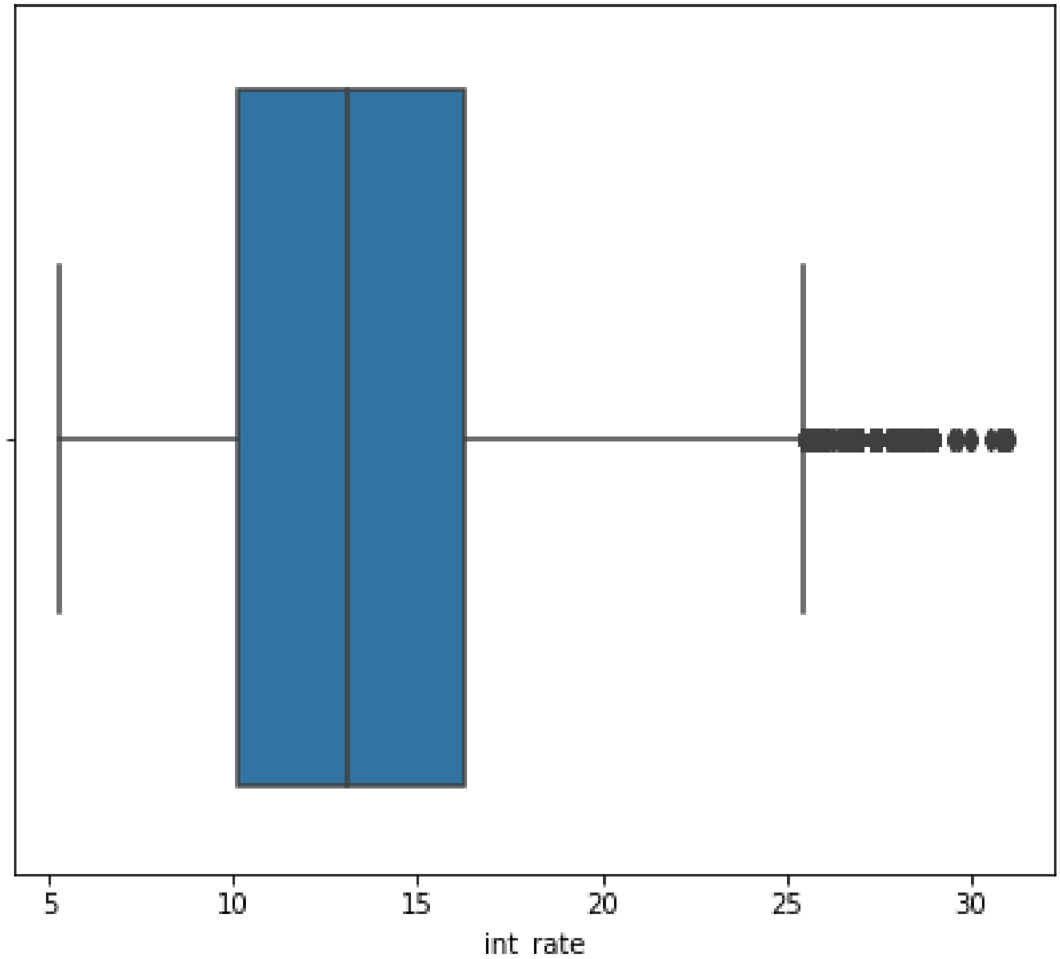
0.3.5 4) Interest_Rate

[26]:
```
variable='int_rate'
#Checking for null values
print('Number of Null Values -',df_train[variable].isna().sum())
#There are no null values

#Checking for number of unique values
print('Number of Unique Values -',df_train[variable].nunique())
#There are 565 unique values
# This is a continuous variable
```

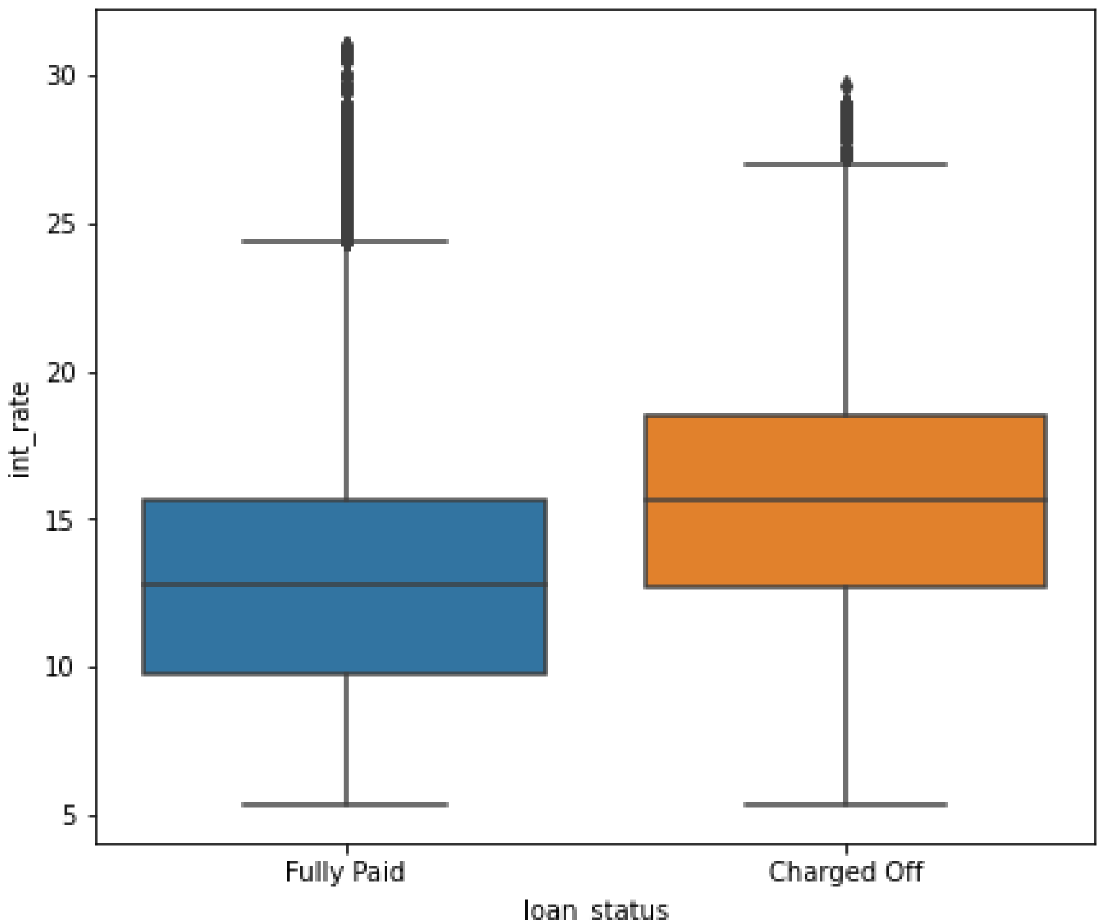
```
Number of Null Values - 0
Number of Unique Values - 559
```

[27]:
```
plt.figure(figsize=(7,6))
sns.kdeplot(df_train[variable])
plt.show()
#Data looks little right skewed

plt.figure(figsize=(7,6))
sns.boxplot(df_train[variable])
plt.show()
#Data has few outliers
```


0.10
0.08
0.06
0.04
0.02
0.00
Density
5
10
15
20
25
30
int_rate



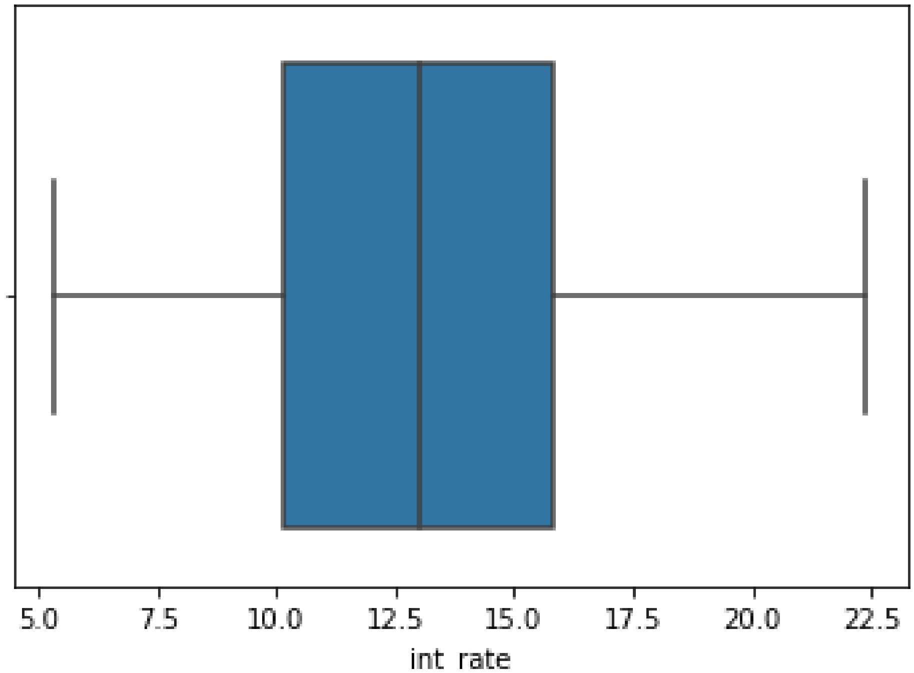
[28]:
```
#Checking Loan_Status with Interest_Rate to check if there is any relationship
plt.figure(figsize=(7,6))
sns.boxplot(data=df_train,y=variable,x='loan_status')
plt.show()
#Observation - The median interest_rate is higher for charged off loans in␣
↪comparison to fully_paid loans.
```



[29]:
```
df_train.groupby(by='loan_status').mean()[variable]
#Observation - The mean interest_rate is also higher for charged off loans in␣
↪comparison to fully_paid loans.
```

[29]:
```
loan_status
Charged Off    15.738901
Fully Paid     12.974179
Name: int_rate, dtype: float64
```

[30]:
```
#Removing the outliers
q75=np.percentile(df_train[variable],75)
q25=np.percentile(df_train[variable],25)
iqr=q75-q25
sns.boxplot(df_train.loc[df_train[variable]<iqr+q75,variable])
plt.show()
df_train=df_train.loc[df_train[variable]<iqr+q75]
#The outliers have been removed
```



[31]:
```
# Since mean and median int_rate is different for different classes, therefore␣
↪it could be an important feature.
# Since it is a continuous variable, therefore adding it to the␣
↪continuous_columns variable.
continuous_columns.append(variable)
```

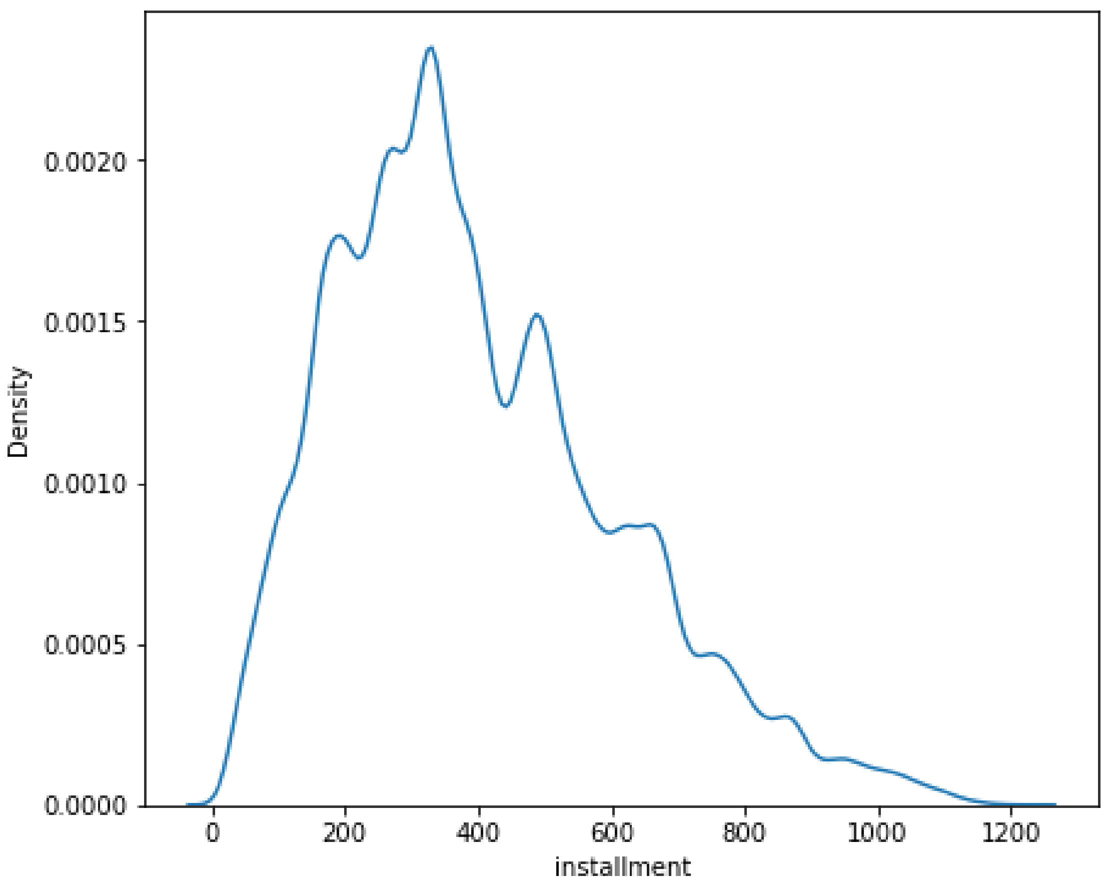
[ ]:

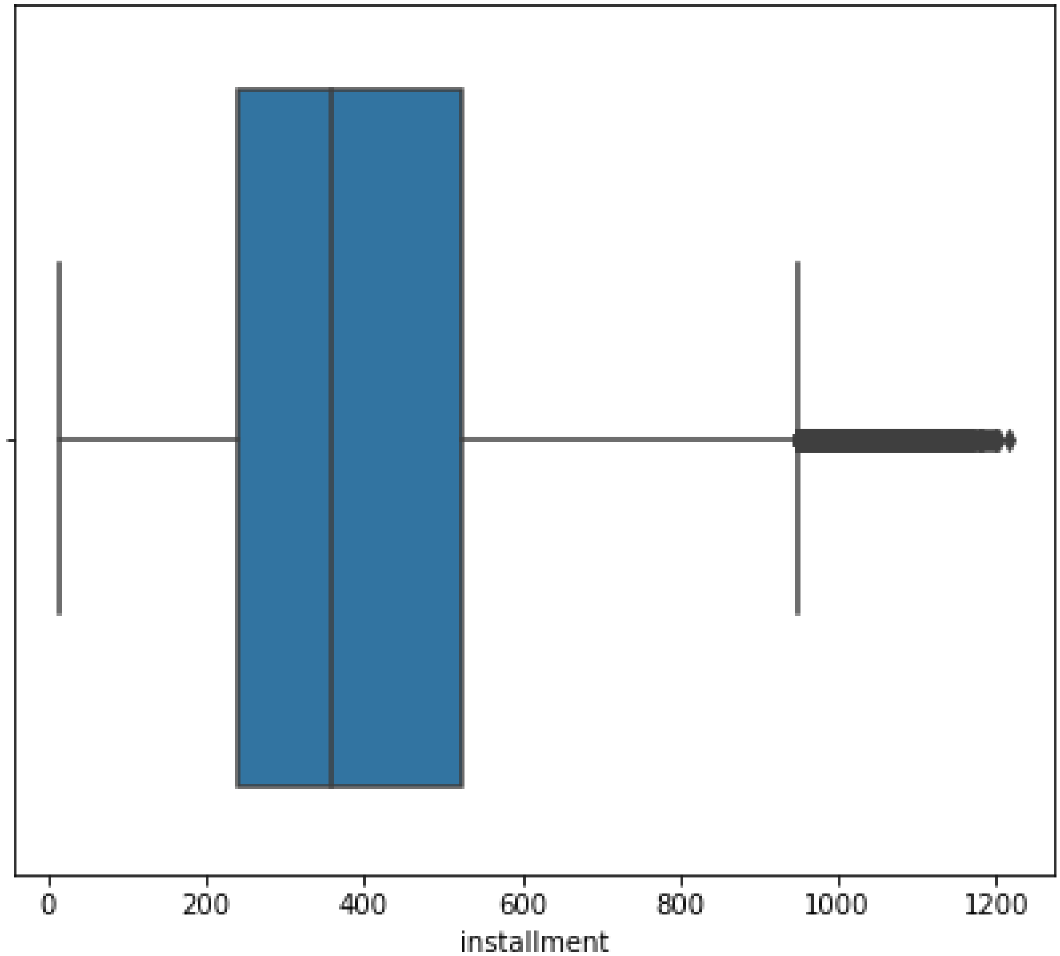
0.3.6 5) Installment__Amount

[32]:
```
variable='installment'
#Checking for null values
print('Number of Null Values -',df_train[variable].isna().sum())
#There are no null values

#Checking for number of unique values
print('Number of Unique Values -',df_train[variable].nunique())
#There are 45626 unique values
# This is a continuous variable
```

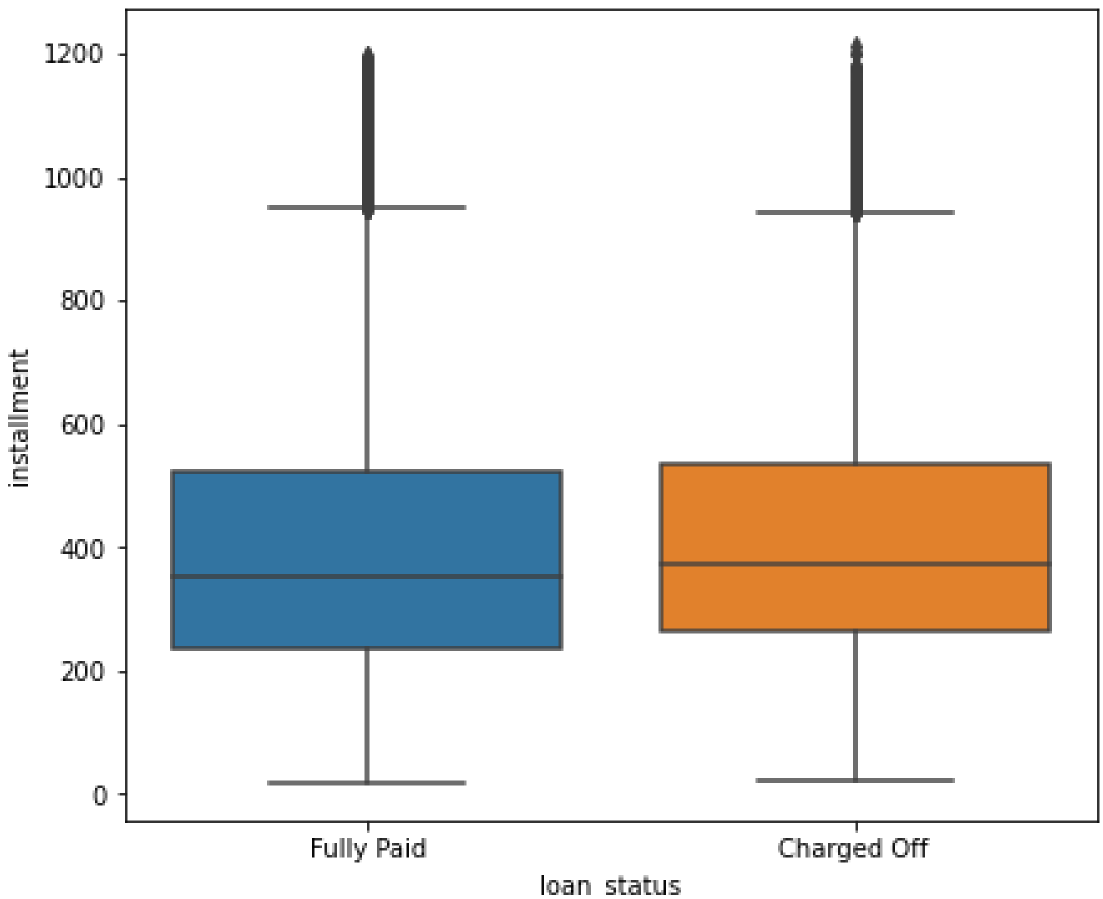
```
Number of Null Values - 0
Number of Unique Values - 45556
```

[33]:
```
plt.figure(figsize=(7,6))
sns.kdeplot(df_train[variable])
plt.show()
#Data looks right skewed

plt.figure(figsize=(7,6))
sns.boxplot(df_train[variable])
plt.show()
#There are few outliers in the data
```





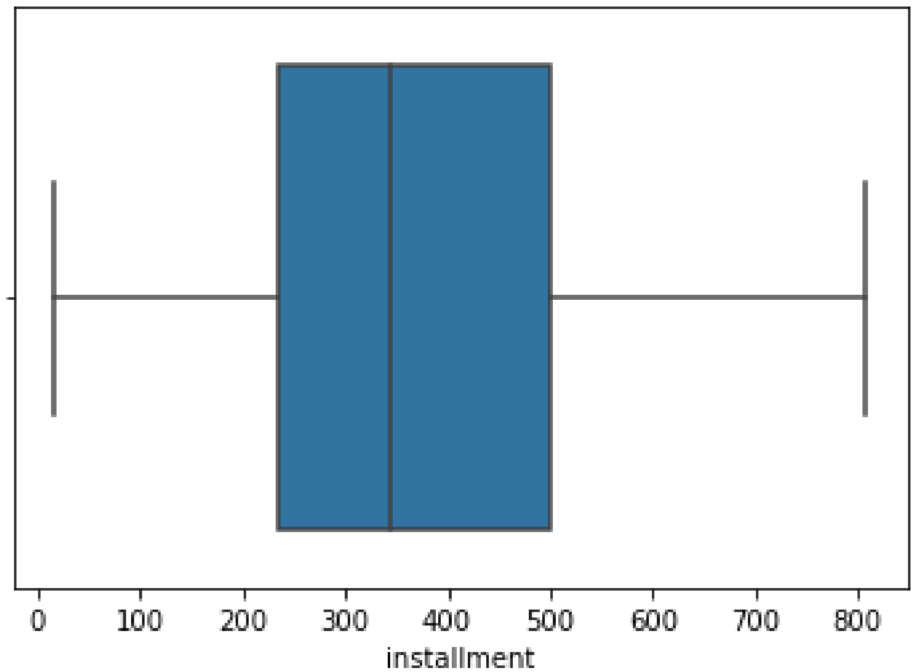
[34]:
```
#Checking Loan_Status with Installment_Amount to check if there is any␣
 ↪relationship
plt.figure(figsize=(7,6))
sns.boxplot(data=df_train,y=variable,x='loan_status')
plt.show()
#Observation - The median installment_amount is little higher for charged off␣
 ↪loans in comparison to fully_paid loans.
```



[35]:
```
df_train.groupby(by='loan_status').mean()[variable]
#Observation - The mean installment_amount is also a little higher for charged␣
↪off loans in comparison to fully_paid loans.
```

[35]:
```
loan_status
Charged Off    409.530808
Fully Paid     395.205656
Name: installment, dtype: float64
```

[36]:
```
#Removing the outliers
q75=np.percentile(df_train[variable],75)
q25=np.percentile(df_train[variable],25)
iqr=q75-q25
sns.boxplot(df_train.loc[df_train[variable]<iqr+q75,variable])
plt.show()
df_train=df_train.loc[df_train[variable]<iqr+q75]
#The outliers have been removed
```



[37]:
```
# Since mean and median loan_amount is different for different classes,␣
↪therefore it could be an important feature.
# Since it is a continuous variable, therefore adding it to the␣
↪continuous_columns variable.
continuous_columns.append(variable)
```

0.3.7 6) Grade

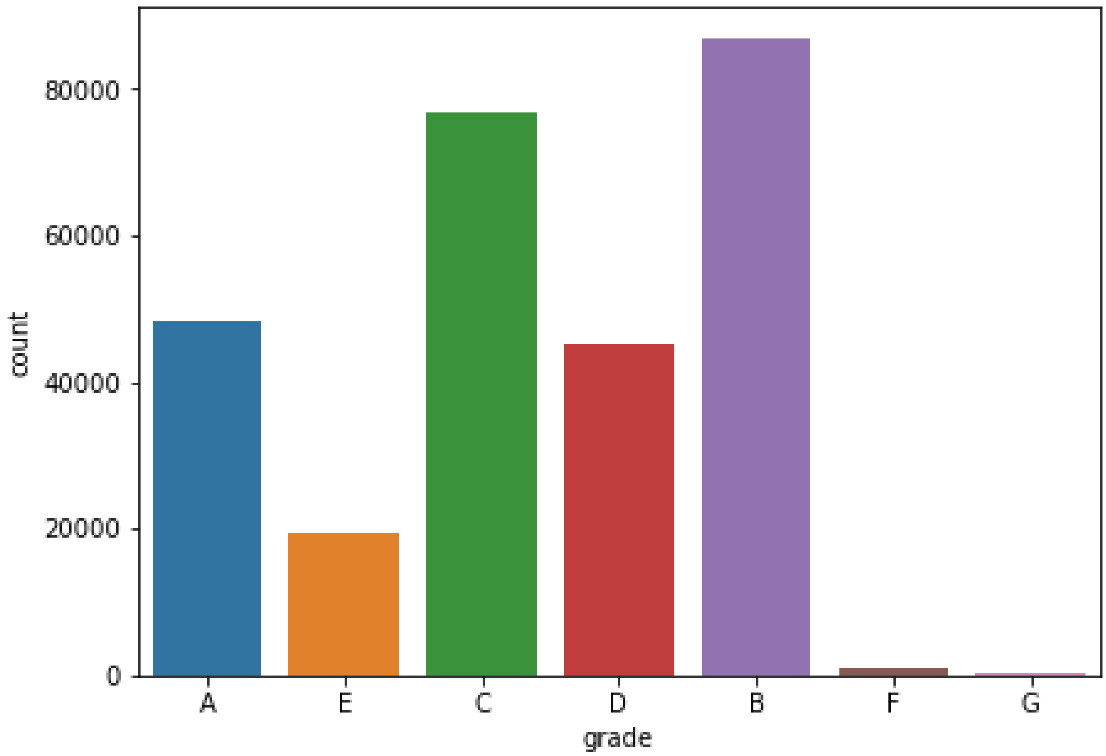
[38]:
```
variable='grade'
#Checking for null values
print('Number of Null Values -',df_train[variable].isna().sum())
#There are no null values

#Checking for number of unique values
print('Number of Unique Values -',df_train[variable].nunique())
#There are 7 unique values
# This is a categorical variable
```

```
Number of Null Values - 0
Number of Unique Values - 7
```

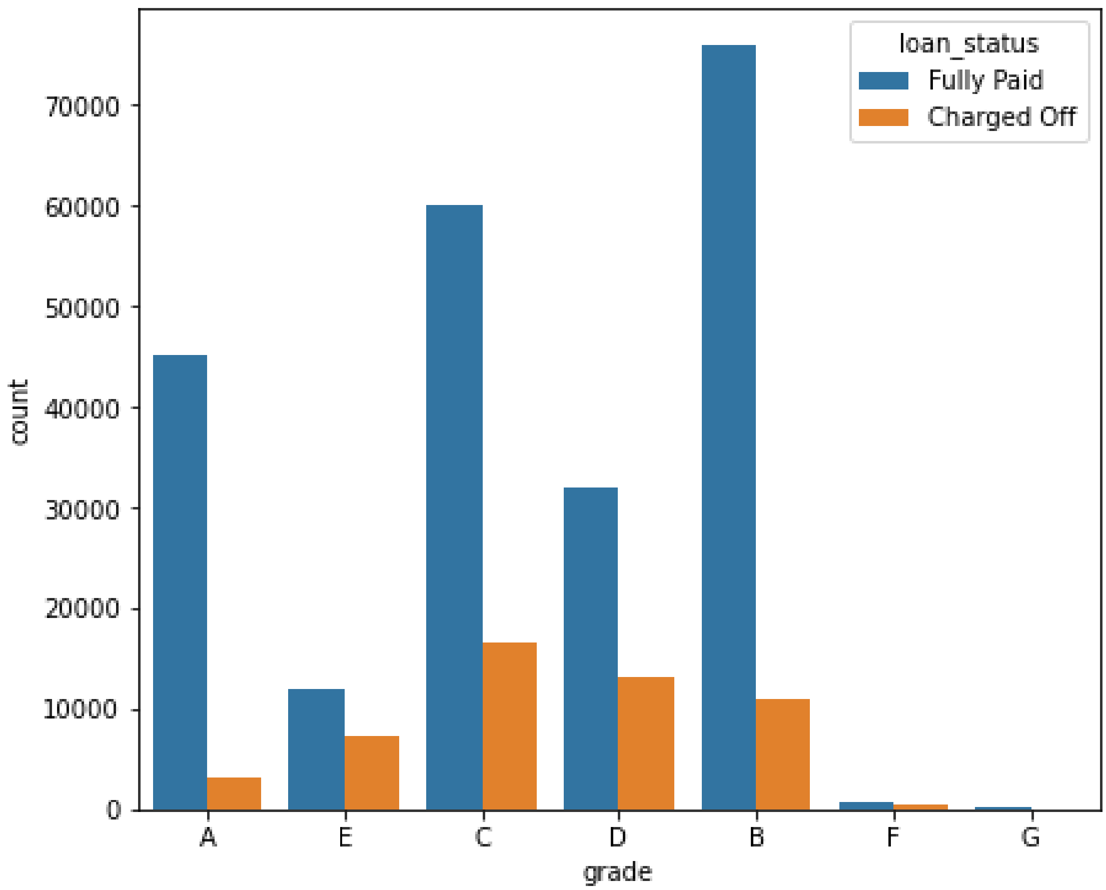
[39]:
```
#Checking the percentage of occurence of each of the categories.
print(np.round(df_train[variable].value_counts(normalize=True)*100))

plt.figure(figsize=(7,5))
```

```
sns.countplot(df_train[variable])
plt.show()
#Later we can encode this data.
```

```
B    31.0
C    28.0
A    17.0
D    16.0
E     7.0
F     0.0
G     0.0
Name: grade, dtype: float64
```



[40]:
```
#Checking Loan_Status with Grade to check if there is any relationship
plt.figure(figsize=(7,6))
sns.countplot(data=df_train,x=variable,hue='loan_status')
plt.show()
#Observation - We can see the difference in the ratio for fully_paid to␣
↪charged_off for each category of "Grade" variable.
```



[41]:
```
np.round(pd.
 ↪crosstab(df_train['loan_status'],df_train[variable],normalize='columns')*100)
#Observation - We can see that the charged off probability increases with␣
 ↪change in Grade.
```

[41]:

grade	A	B	C	D	E	F	G
loan_status							
Charged Off	6.0	13.0	22.0	29.0	38.0	37.0	28.0
Fully Paid	94.0	87.0	78.0	71.0	62.0	63.0	72.0

[42]:
```
# Since the charged_off probability is different for the "Grade"␣
 ↪categories,therefore "Grade" could be an important feature.
# Since it is a categorical variable, therefore adding it to the␣
 ↪categorical_columns variable.
categorical_columns.append(variable)
```

[ ]:
```
```

0.3.8 7) Sub_Grade

[43]:
```
variable= 'sub_grade'
#Checking for null values
print('Number of Null Values -',df_train[variable].isna().sum())
#There are no null values

#Checking for number of unique values
print('Number of Unique Values -',df_train[variable].nunique())
#There are 35 unique values
# This is a categorical variable
```

```
Number of Null Values - 0
Number of Unique Values - 35
```

[44]:
```
# Lets have a look at the relation of "Grade" with "SubGrade"
pd.crosstab(df_train[variable],df_train['grade'])
# We observe that the first letter of SubGrade is actually the grade.
# So we can ignore the first letter.
```

[44]:

grade sub_grade	A	B	C	D	E	F	G
A1	7529	0	0	0	0	0	0
A2	7351	0	0	0	0	0	0
A3	7962	0	0	0	0	0	0
A4	11708	0	0	0	0	0	0
A5	13750	0	0	0	0	0	0
B1	0	14470	0	0	0	0	0
B2	0	16905	0	0	0	0	0
B3	0	20124	0	0	0	0	0
B4	0	18947	0	0	0	0	0
B5	0	16404	0	0	0	0	0
C1	0	0	17223	0	0	0	0
C2	0	0	16276	0	0	0	0
C3	0	0	15279	0	0	0	0
C4	0	0	14717	0	0	0	0
C5	0	0	13157	0	0	0	0
D1	0	0	0	11477	0	0	0
D2	0	0	0	10128	0	0	0
D3	0	0	0	8698	0	0	0
D4	0	0	0	8060	0	0	0
D5	0	0	0	6736	0	0	0
E1	0	0	0	0	5316	0	0
E2	0	0	0	0	4982	0	0
E3	0	0	0	0	4088	0	0
E4	0	0	0	0	3146	0	0
E5	0	0	0	0	1802	0	0
F1	0	0	0	0	0	552	0

```
F2                0      0      0      0     0  151    0
F3                0      0      0      0     0  100    0
F4                0      0      0      0     0   94    0
F5                0      0      0      0     0   68    0
G1                0      0      0      0     0    0   46
G2                0      0      0      0     0    0   25
G3                0      0      0      0     0    0   17
G4                0      0      0      0     0    0   14
G5                0      0      0      0     0    0   15
```

[45]:
```
#Extracting only the second letter from grade column
df_train[variable]=df_train[variable].apply(lambda x : x[1])
df_train[variable].head()
```

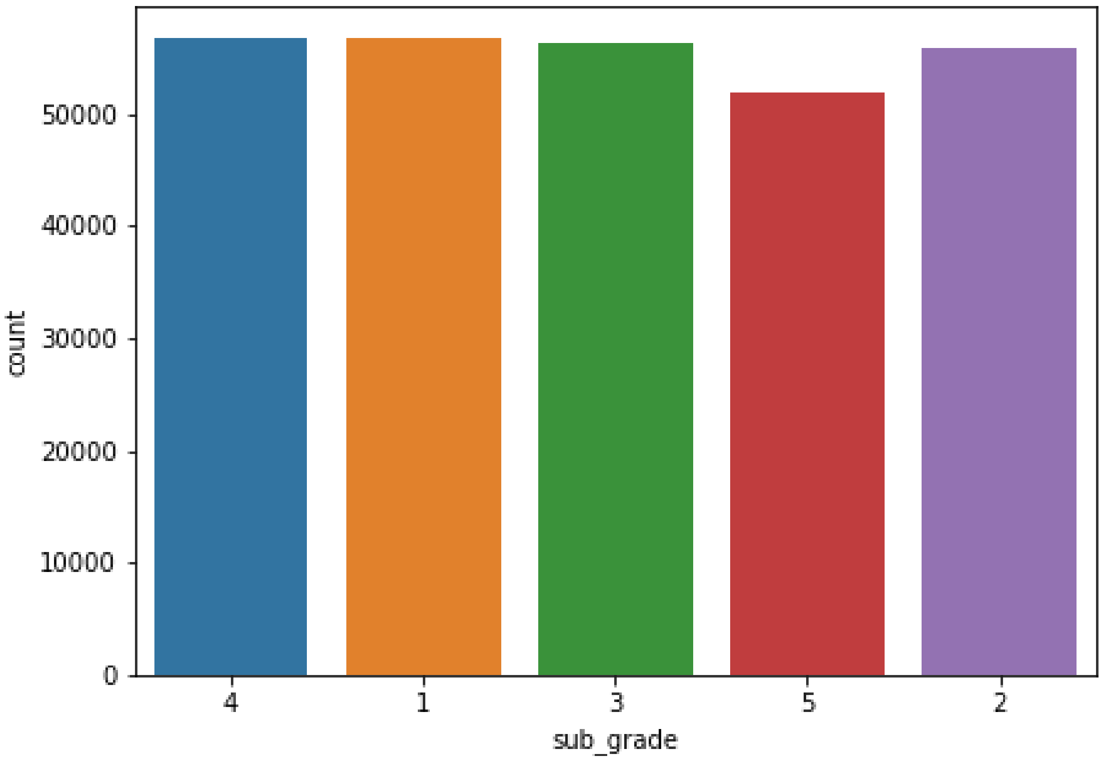
[45]:
```
0    4
1    1
2    3
3    1
4    5
Name: sub_grade, dtype: object
```

[46]:
```
#Checking for number of unique values
print('Number of Unique Values -',df_train[variable].nunique())
#There are 5 unique values
# This is a categorical variable
```

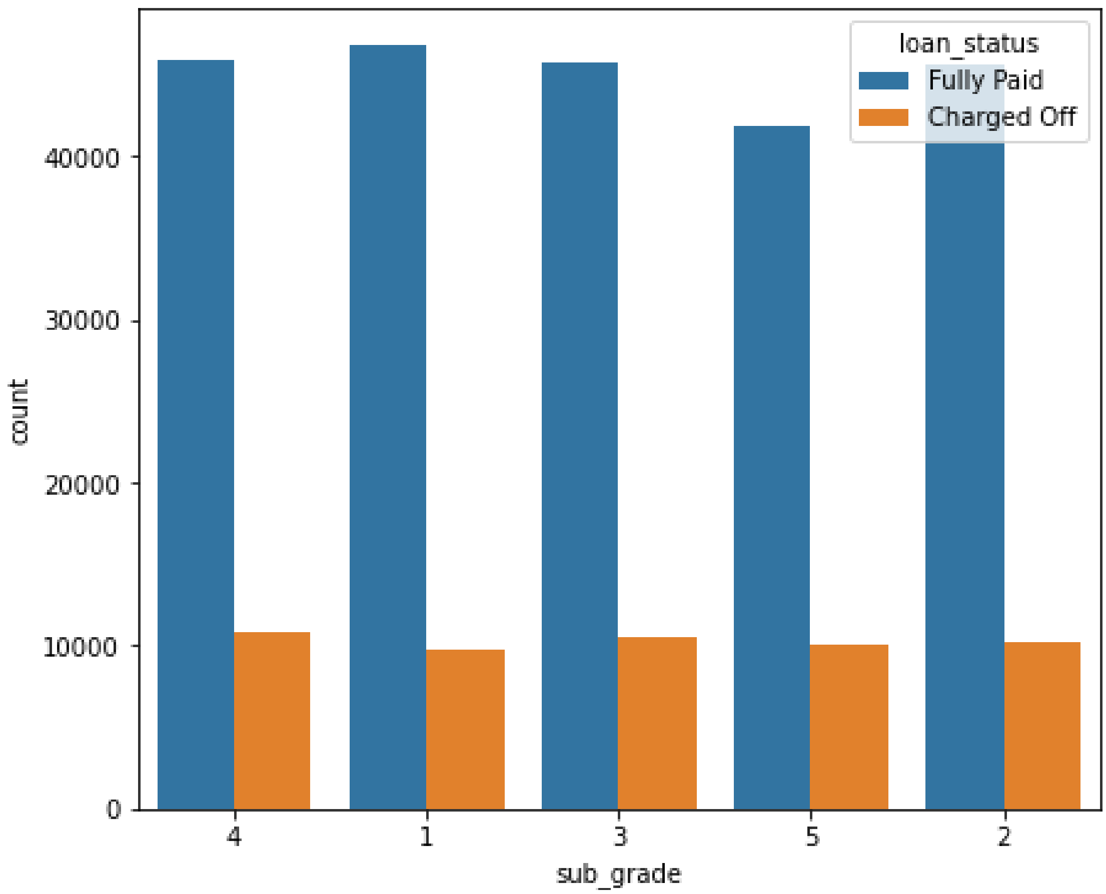
```
Number of Unique Values - 5
```

[47]:
```
#Checking the percentage of occurence of each of the categories.
print(np.round(df_train[variable].value_counts(normalize=True)*100))

plt.figure(figsize=(7,5))
sns.countplot(df_train[variable])
plt.show()
```

```
4    20.0
1    20.0
3    20.0
2    20.0
5    19.0
Name: sub_grade, dtype: float64
```



[48]:
```
#Checking Loan_Status with Term to check if there is any relationship
plt.figure(figsize=(7,6))
sns.countplot(data=df_train,x=variable,hue='loan_status')
plt.show()
#Observation - We can see almomst same behavior for each of the categories of␣
↪"sub_grade" variable.
```



[49]:
```
np.round(pd.
↪crosstab(df_train['loan_status'],df_train[variable],normalize='columns')*100)
#Observation - The charged_off percentage remains almost same for each of the␣
↪sub_grade categories.
```

[49]:
```
sub_grade       1     2     3     4     5
loan_status
Charged Off  17.0  18.0  19.0  19.0  19.0
Fully Paid   83.0  82.0  81.0  81.0  81.0
```

[50]:
```
#Since the charged_off probability is almost same for the "SubGrade"␣
↪categories,"SubGrade" may not be an important feature.
#But since "sub-grade" feature can be combined with "grade" feature, therefore␣
↪lets keep this feature.
#Since it is a categorical variable, therefore adding it to the␣
↪categorical_columns variable.

categorical_columns.append(variable)
```

[51]:
```python
#Doing same change for test data
#Extracting only the second letter from grade column
df_test[variable]=df_test[variable].apply(lambda x : x[1])
df_test[variable].head()
```

[51]:
```
0    4
1    4
2    1
3    3
4    1
Name: sub_grade, dtype: object
```

[ ]:
```python

```

0.3.9 8) Employee_Title

[52]:
```python
variable='emp_title'
#Checking for null values
print('Number of Null Values -',df_train[variable].isna().sum())
#There are no null values

#Checking for number of unique values
print('Number of Unique Values -',df_train[variable].nunique())
#There are 129430 unique values

#Checking few unique values
df[variable].unique()[:15]
# This is a categorical variable having lots of categories. So we can drop this␣
↪column.
```

```
Number of Null Values - 16343
Number of Unique Values - 129424
```

[52]:
```
array(['Marketing', 'Credit analyst ', 'Statistician', 'Client Advocate',
       'Destiny Management Inc.', 'HR Specialist',
       'Software Development Engineer', 'Office Depot',
       'Application Architect', 'Regado Biosciences', 'Sodexo',
       'Director Bureau of Equipment Inventory',
       'Social Work/Care Manager', 'Regional Counsel',
       'Pullman Regional Hospital'], dtype=object)
```

[53]:
```python
df_train.drop(columns='emp_title',inplace=True)
df_test.drop(columns='emp_title',inplace=True)
print(df_train.shape,df_test.shape)
```

```
(277317, 26) (79206, 26)
```

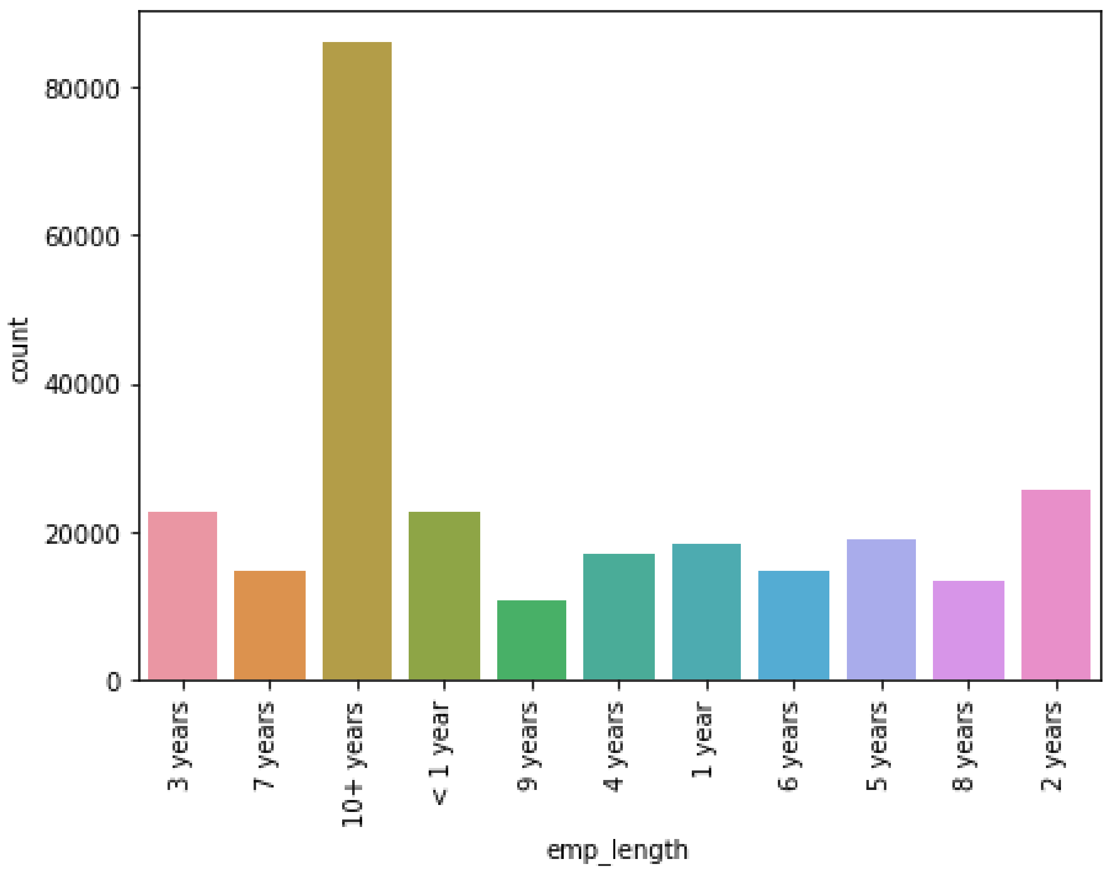
0.3.10 9) Employee_Length

[54]:
```
variable= 'emp_length'
#Checking for null values
print('Number of Null Values -',df_train[variable].isna().sum())
#There are no null values

#Checking for number of unique values
print('Number of Unique Values -',df_train[variable].nunique())
#There are 11 unique values
# This is a categorical variable

print(df[variable].unique())
#We can encode these categories.
```

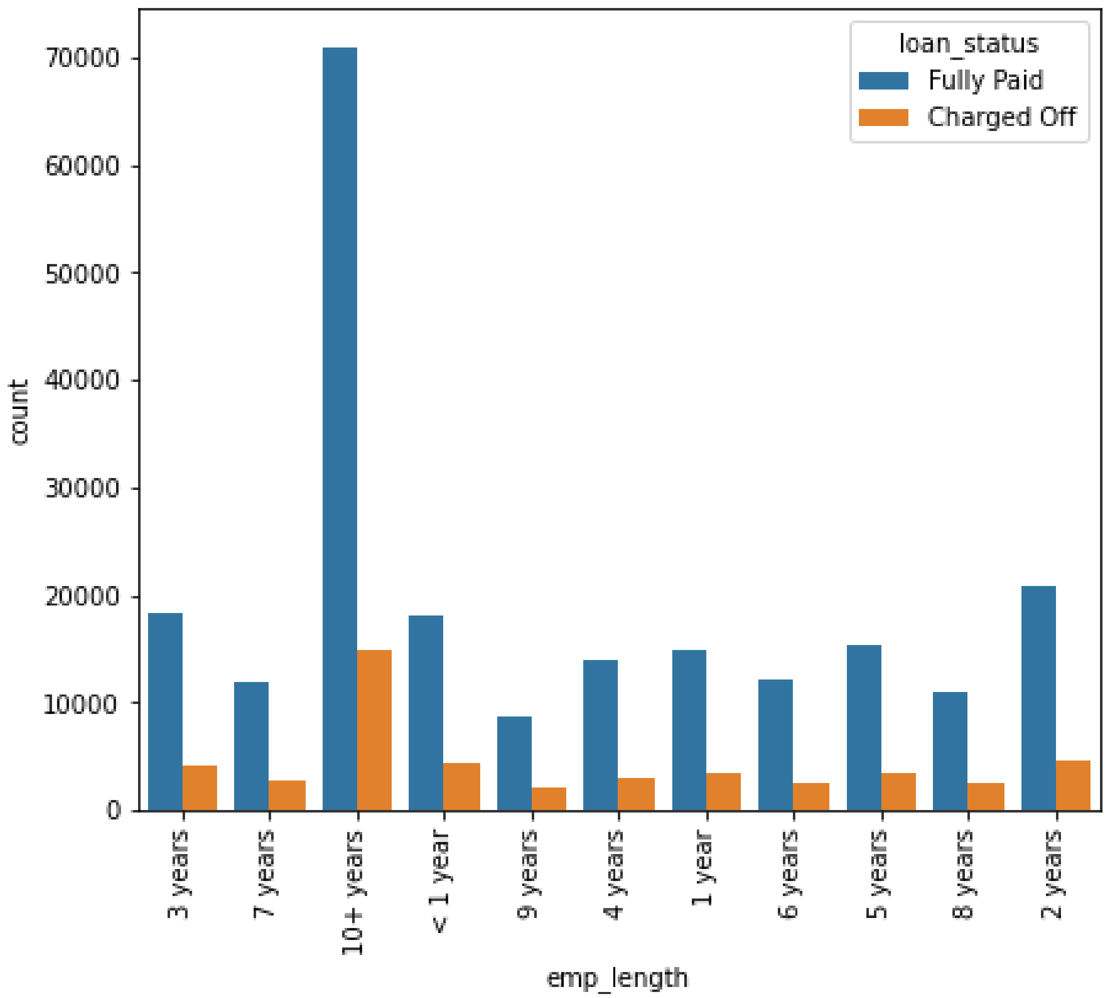
```
Number of Null Values - 13341
Number of Unique Values - 11
['10+ years' '4 years' '< 1 year' '6 years' '9 years' '2 years' '3 years'
 '8 years' '7 years' '5 years' '1 year' nan]
```

[55]:
```
#Checking the percentage of occurence of each of the categories.
print(np.round(df_train[variable].value_counts(normalize=True)*100))

plt.figure(figsize=(7,5))
sns.countplot(df_train[variable])
plt.xticks(rotation=90)
plt.show()
#Later we can encode this data.
```

```
10+ years    33.0
2 years      10.0
< 1 year      9.0
3 years       9.0
5 years       7.0
1 year        7.0
4 years       6.0
6 years       6.0
7 years       6.0
8 years       5.0
9 years       4.0
Name: emp_length, dtype: float64
```



[56]:
```
#Checking Loan_Status with Employee_Length feature to check if there is any␣
↪relationship.
plt.figure(figsize=(7,6))
sns.countplot(data=df_train,x=variable,hue='loan_status')
plt.xticks(rotation=90)
plt.show()
#Observation - We can see different behavior for the categories of␣
↪"Employee_Length" variable.
```



[57]:
```
np.round(pd.
↪crosstab(df_train['loan_status'],df_train[variable],normalize='columns')*100)
```

[57]:
```
emp_length   1 year  10+ years  2 years  3 years  4 years  5 years  6 years  \
loan_status
Charged Off    19.0       17.0     18.0     18.0     18.0     18.0     18.0
Fully Paid     81.0       83.0     82.0     82.0     82.0     82.0     82.0

emp_length   7 years  8 years  9 years  < 1 year
loan_status
Charged Off     18.0     19.0     19.0      20.0
Fully Paid      82.0     81.0     81.0      80.0
```

[58]:
```
#Since the charged_off probability is little different for the␣
↪"Employee_Length" categories,it may be an important feature.
```

```
# Since it is a categorical variable, therefore adding it to the␣
↪categorical_columns variable.
categorical_columns.append(variable)
```

[ ]:

```

```

0.3.11 10) Home_Ownership

[59]:

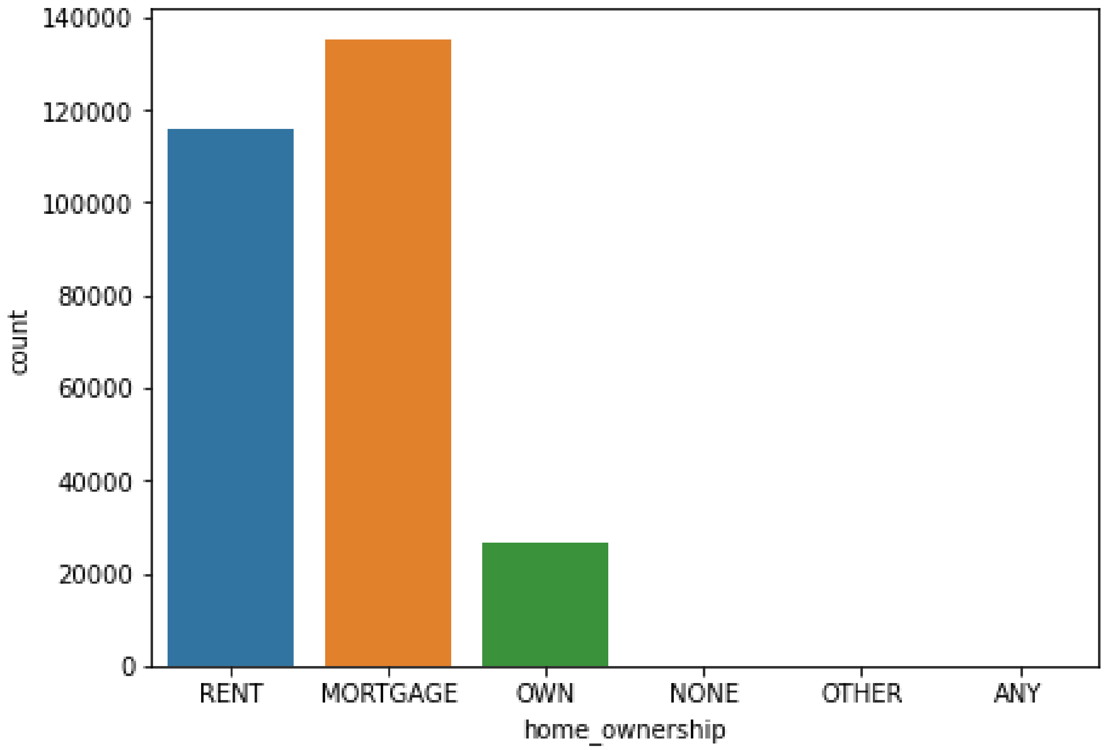
```
variable='home_ownership'
#Checking for null values
print('Number of Null Values -',df_train[variable].isna().sum())
#There are no null values

#Checking for number of unique values
print('Number of Unique Values -',df_train[variable].nunique())
#There are 6 unique values
# This is a categorical variable
```

```
Number of Null Values - 0
Number of Unique Values - 6
```

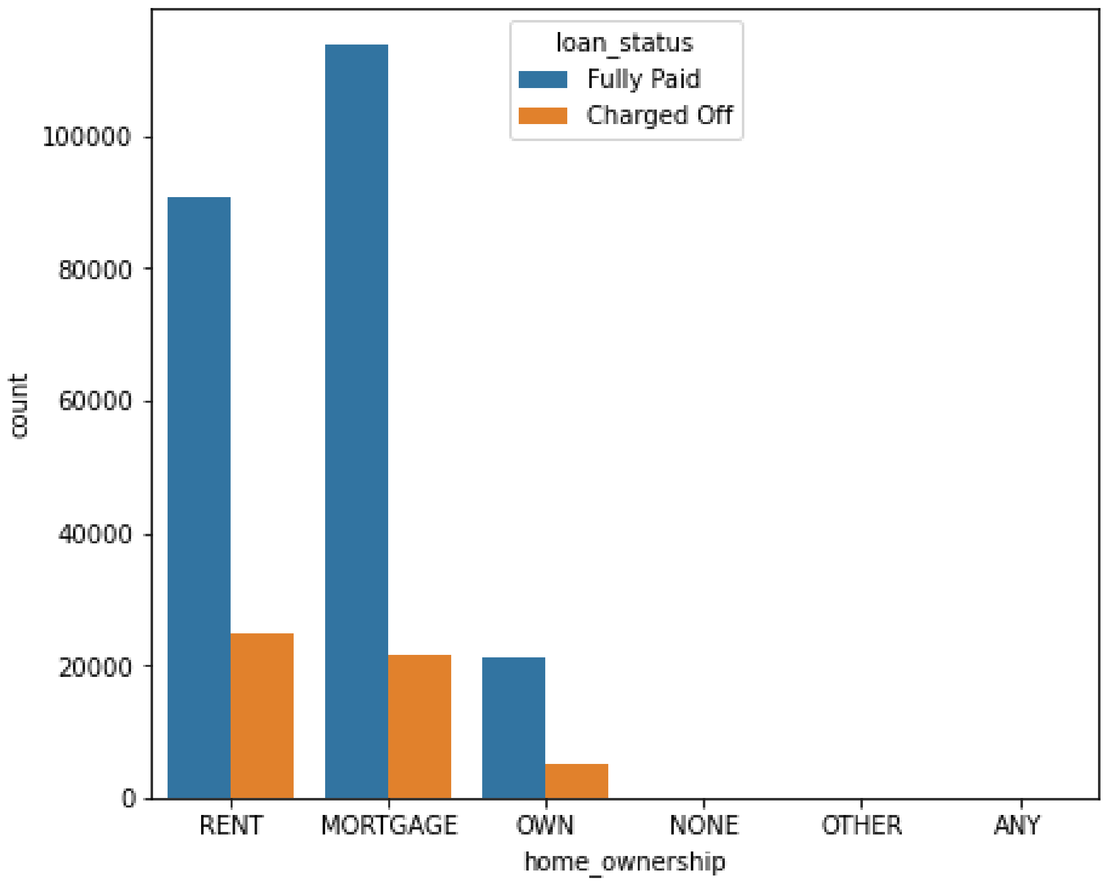
[60]:

```
#Checking the percentage of occurence of each of the categories.
print(np.round(df_train[variable].value_counts(normalize=True)*100))

plt.figure(figsize=(7,5))
sns.countplot(df_train[variable])
plt.show()
#Later we can encode this data.
```

```
MORTGAGE    49.0
RENT        42.0
OWN         10.0
OTHER        0.0
NONE         0.0
ANY          0.0
Name: home_ownership, dtype: float64
```



[61]:
```
#Checking Loan_Status with Home_Ownership to check if there is any relationship.
plt.figure(figsize=(7,6))
sns.countplot(data=df_train,x=variable,hue='loan_status')
plt.show()
#Observation - We can see different behavior for the categories of␣
↪"Home_Ownership" variable.
```



[62]:
```
np.round(pd.crosstab(df['loan_status'],df[variable],normalize='columns')*100)
```

[62]:
```
home_ownership    ANY  MORTGAGE  NONE  OTHER   OWN  RENT
loan_status
Charged Off       0.0      17.0  23.0   14.0  21.0  23.0
Fully Paid      100.0      83.0  77.0   86.0  79.0  77.0
```

[63]:
```
# Since the charged_off probability is diffrent for "Home_Ownership"␣
↪categories,itcould be an important feature.
# Since it is a categorical variable, therefore adding it to the␣
↪categorical_columns variable.
categorical_columns.append(variable)
```

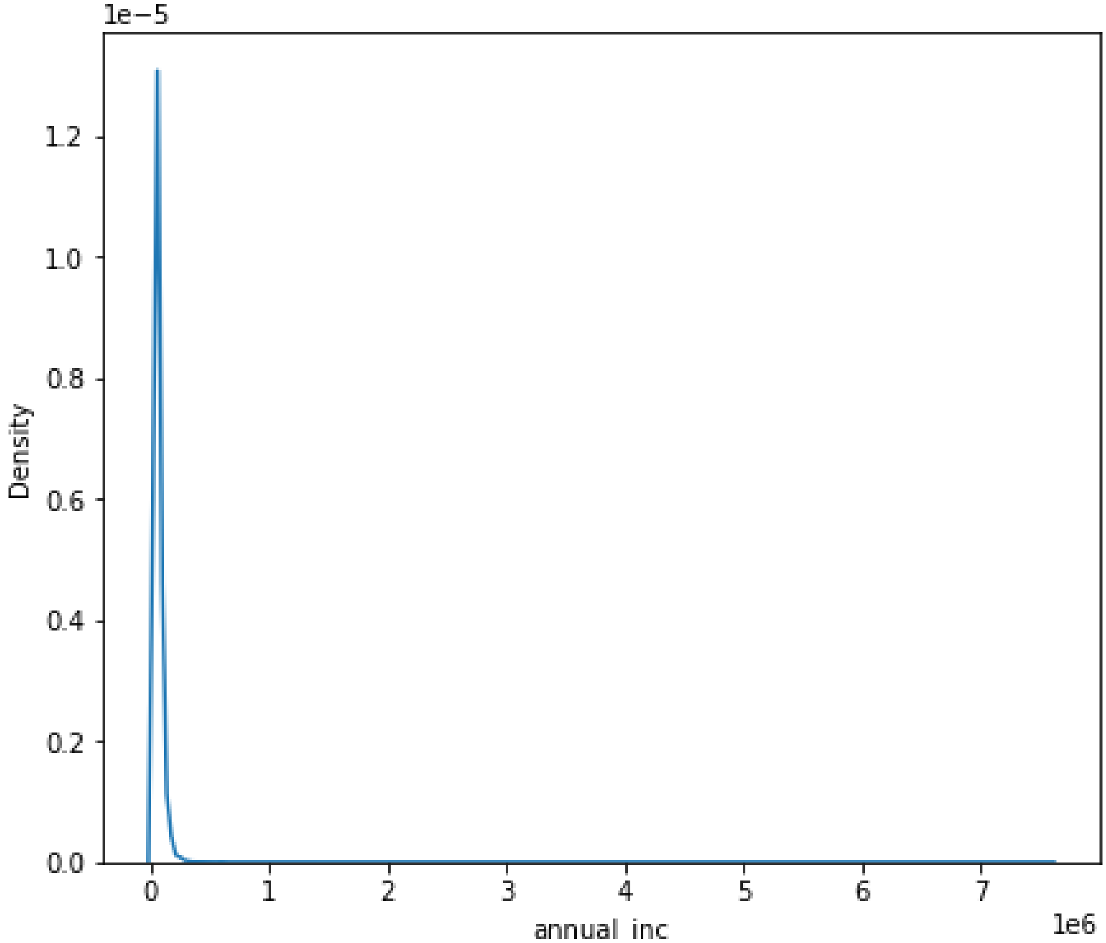
[ ]:

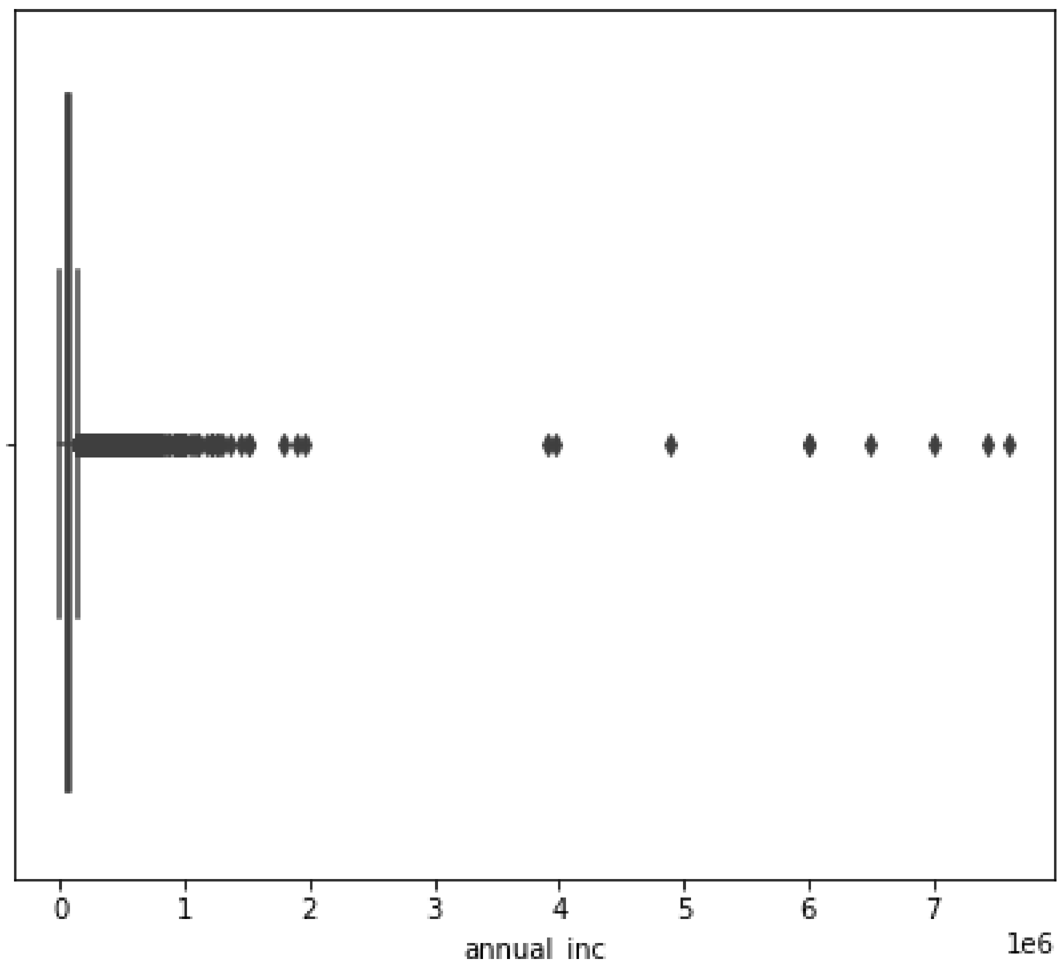
0.3.12 11) Annual_Inc

[64]:
```
variable= 'annual_inc'
#Checking for null values
print('Number of Null Values -',df_train[variable].isna().sum())
#There are no null values

#Checking for number of unique values
print('Number of Unique Values -',df_train[variable].nunique())
#There are 20381 unique values
# This is a continuous variable
```

```
Number of Null Values - 0
Number of Unique Values - 20407
```

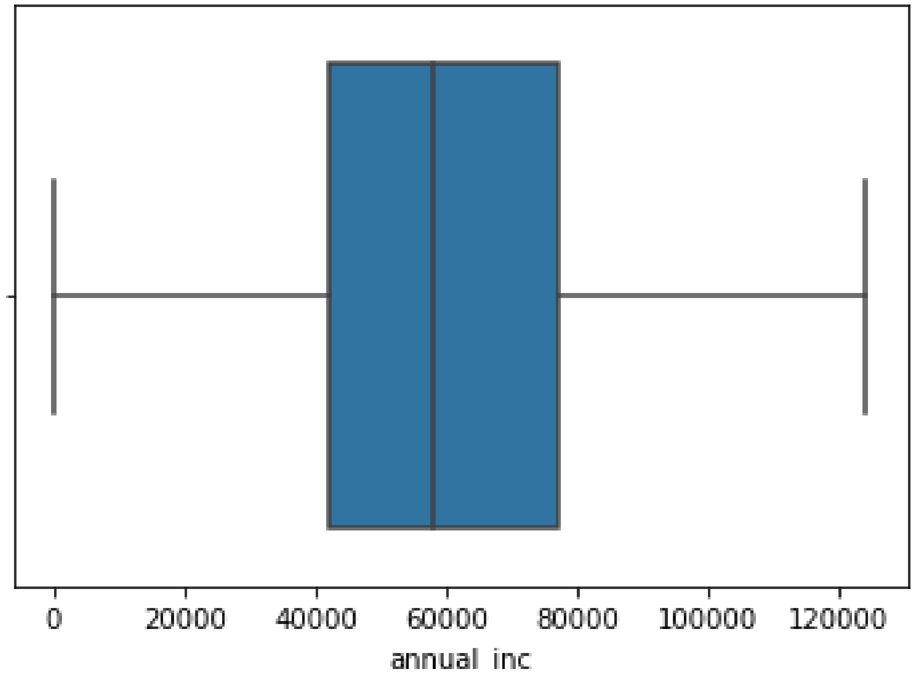
[65]:
```
plt.figure(figsize=(7,6))
sns.kdeplot(df_train[variable])
plt.show()
#Data looks heavily right skewed

plt.figure(figsize=(7,6))
sns.boxplot(df_train[variable])
plt.show()
#There are few outliers in the data
```


1e−5
1.2
1.0
0.8
0.6
0.4
0.2
0.0
Density
0
1
2
3
4
5
6
7
1e6
annual_inc

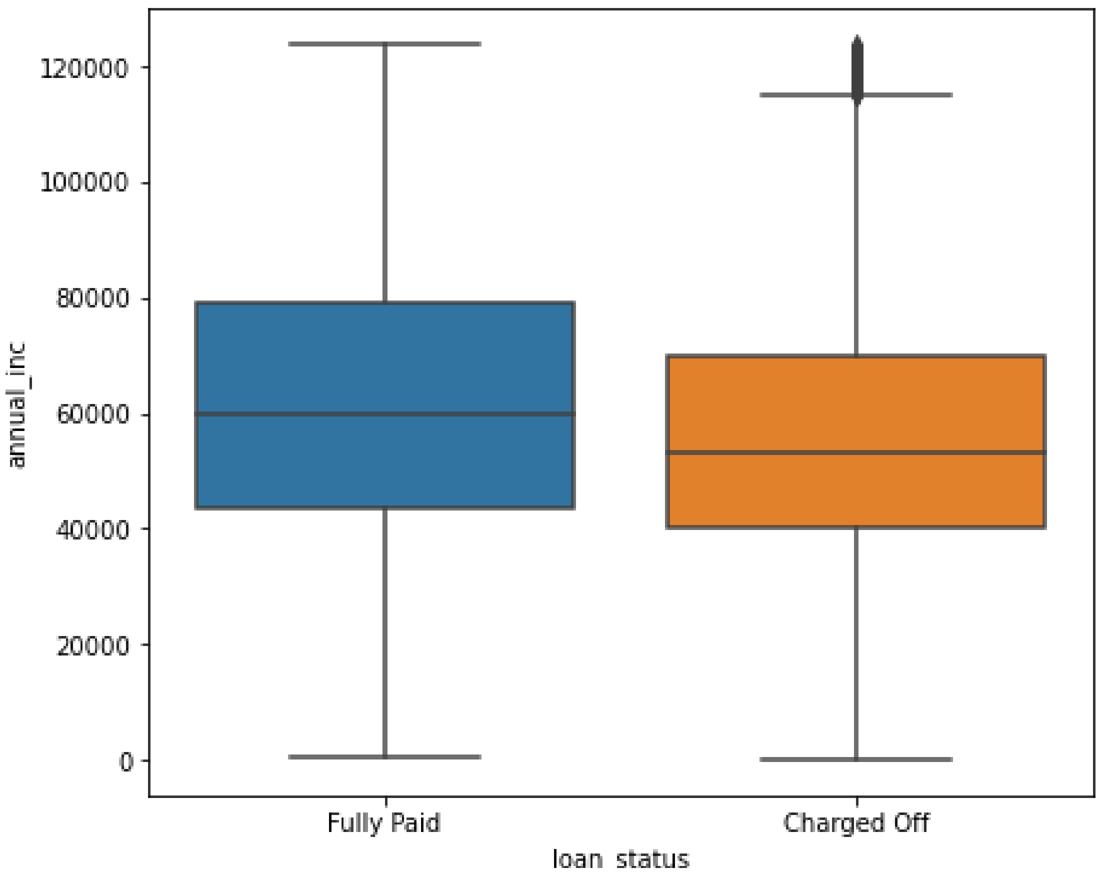


[66]:

```
#Removing the outliers
q75=np.percentile(df_train[variable],75)
q25=np.percentile(df_train[variable],25)
iqr=q75-q25
sns.boxplot(df_train.loc[df_train[variable]<iqr+q75,variable])
plt.show()
df_train=df_train.loc[df_train[variable]<iqr+q75]
#The outliers have been removed
```



[67]:
```
#Checking Loan_Status with Loan_Amount to check if there is any relationship
plt.figure(figsize=(7,6))
sns.boxplot(data=df_train,y=variable,x='loan_status')
plt.show()
#Observation - The median loan_amount is higher for fully_paid loans in␣
↪comparison to charged_off loans.
```



[68]:
```
df_train.groupby(by='loan_status').mean()[variable]
#Observation - The mean loan_amount is also higher for fully_paid loans in␣
↪comparison to charged off loans.
```

[68]:
```
loan_status
Charged Off    56691.768156
Fully Paid     62098.513881
Name: annual_inc, dtype: float64
```

[69]:
```
# Since mean and median loan_amount is different for different classes,␣
↪therefore it could be an important feature.
# Since it is a continuous variable, therefore adding it to the␣
↪continuous_columns variable.
continuous_columns.append(variable)
```

[ ]:

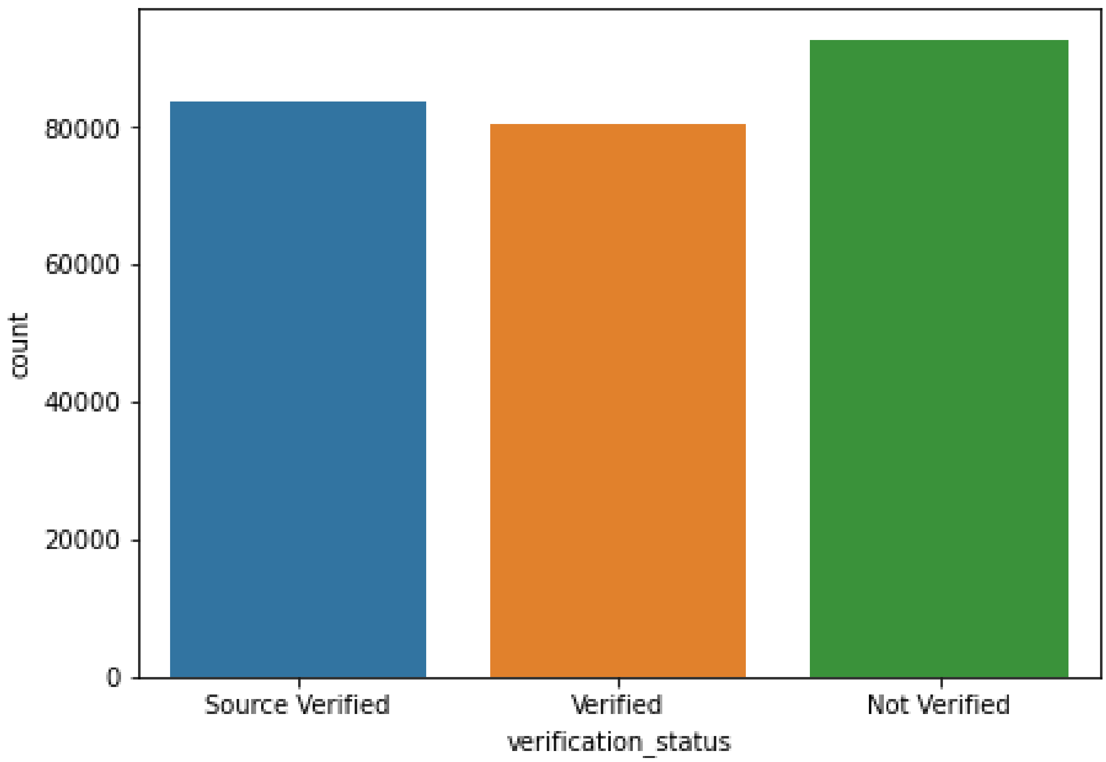
0.3.13 12) Verification_Status

[70]:
```
variable='verification_status'
#Checking for null values
print('Number of Null Values -',df_train[variable].isna().sum())
#There are no null values

#Checking for number of unique values
print('Number of Unique Values -',df_train[variable].nunique())
#There are 3 unique values
# This is a categorical variable
```

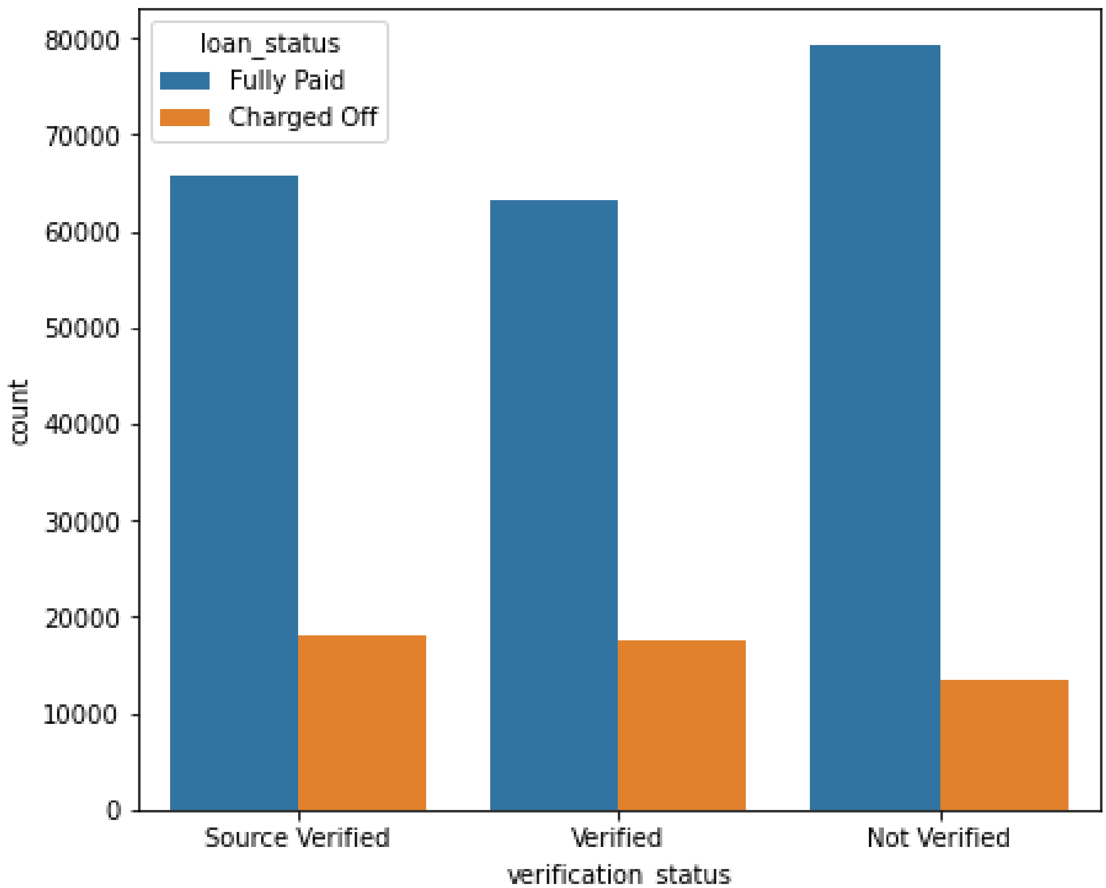
```
Number of Null Values - 0
Number of Unique Values - 3
```

[71]:
```
#Checking the percentage of occurence of each of the categories.
print(np.round(df_train[variable].value_counts(normalize=True)*100))

plt.figure(figsize=(7,5))
sns.countplot(df_train[variable])
plt.show()
#Later we can encode this data.
```

```
Not Verified       36.0
Source Verified    33.0
Verified           31.0
Name: verification_status, dtype: float64
```



[72]:
```
#Checking Loan_Status with verification_status to check if there is any␣
 ↪relationship
plt.figure(figsize=(7,6))
sns.countplot(data=df_train,x=variable,hue='loan_status')
plt.show()
#Observation - We can see different behavior for each of the 2 categories of␣
 ↪"term" variable.
```



[73]:
```
np.round(pd.
 ↪crosstab(df_train['loan_status'],df_train[variable],normalize='columns')*100)
```

[73]:
```
verification_status  Not Verified  Source Verified  Verified
loan_status
Charged Off                  15.0             21.0      22.0
Fully Paid                   85.0             79.0      78.0
```

[74]:
```
# Since the charged_off probability is diffrent for "verification_status"␣
 ↪categories, it could be an important feature.
# Since it is a categorical variable, therefore adding it to the␣
 ↪categorical_columns variable.
categorical_columns.append(variable)
```

[ ]:

0.3.14 13) Issue_d

[75]:
```python
variable='issue_d'
#Checking for null values
print('Number of Null Values -',df_train[variable].isna().sum())
#There are no null values

#Checking for number of unique values
print('Number of Unique Values -',df_train[variable].nunique())
#There are 115 unique values

#Checking few unique values
df_train[variable].unique()[:5]
```

```
Number of Null Values - 0
Number of Unique Values - 115
```

[75]:
```
array(['Dec-2013', 'Jan-2013', 'May-2014', 'Sep-2015', 'Jan-2014'],
      dtype=object)
```

[76]:
```python
#Converting it to date_time format
df_train[variable]=pd.to_datetime(df_train[variable])
df_test[variable]=pd.to_datetime(df_test[variable])
```

[ ]:
```python

```

0.3.15 14) Purpose

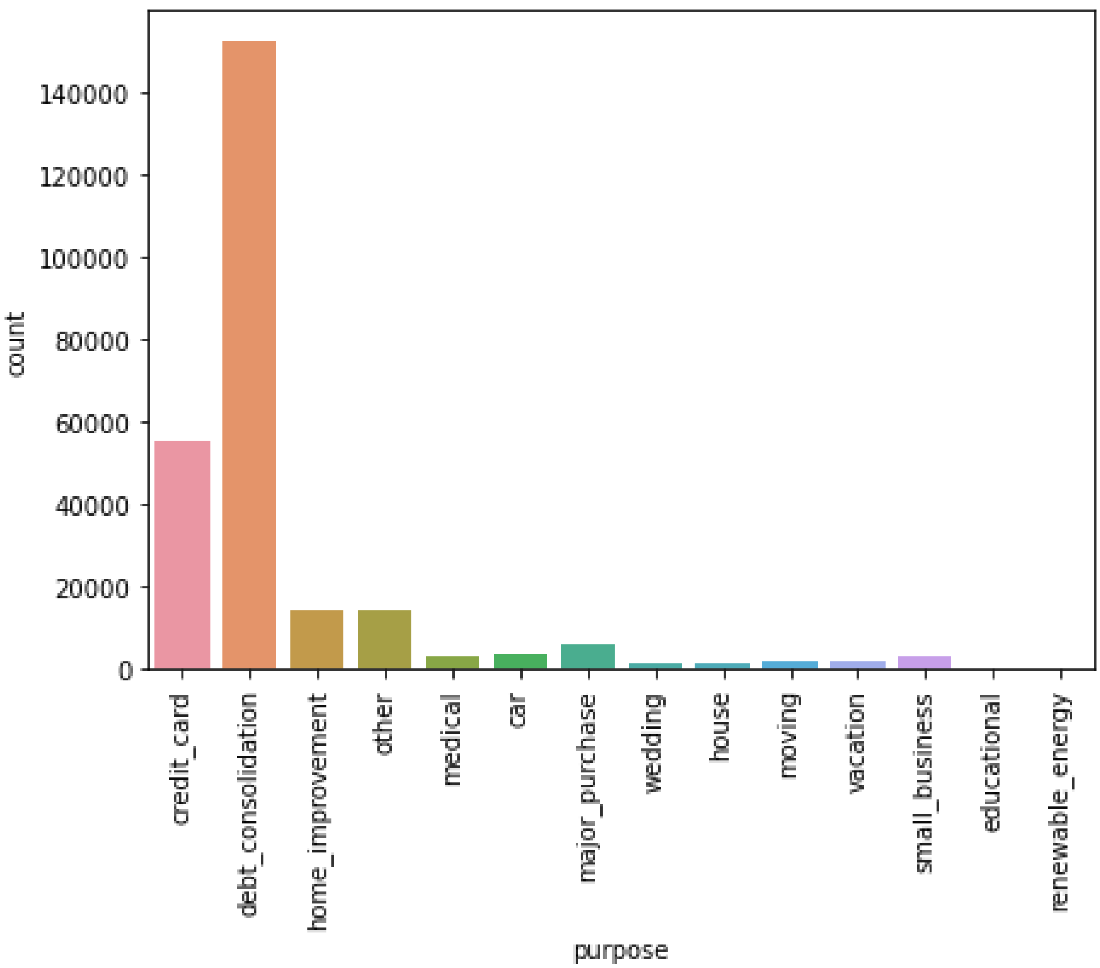
[77]:
```python
variable= 'purpose'
#Checking for null values
print('Number of Null Values -',df_train[variable].isna().sum())
#There are no null values

#Checking for number of unique values
print('Number of Unique Values -',df_train[variable].nunique())
#There are 14 unique values
# This is a categorical variable
```

```
Number of Null Values - 0
Number of Unique Values - 14
```

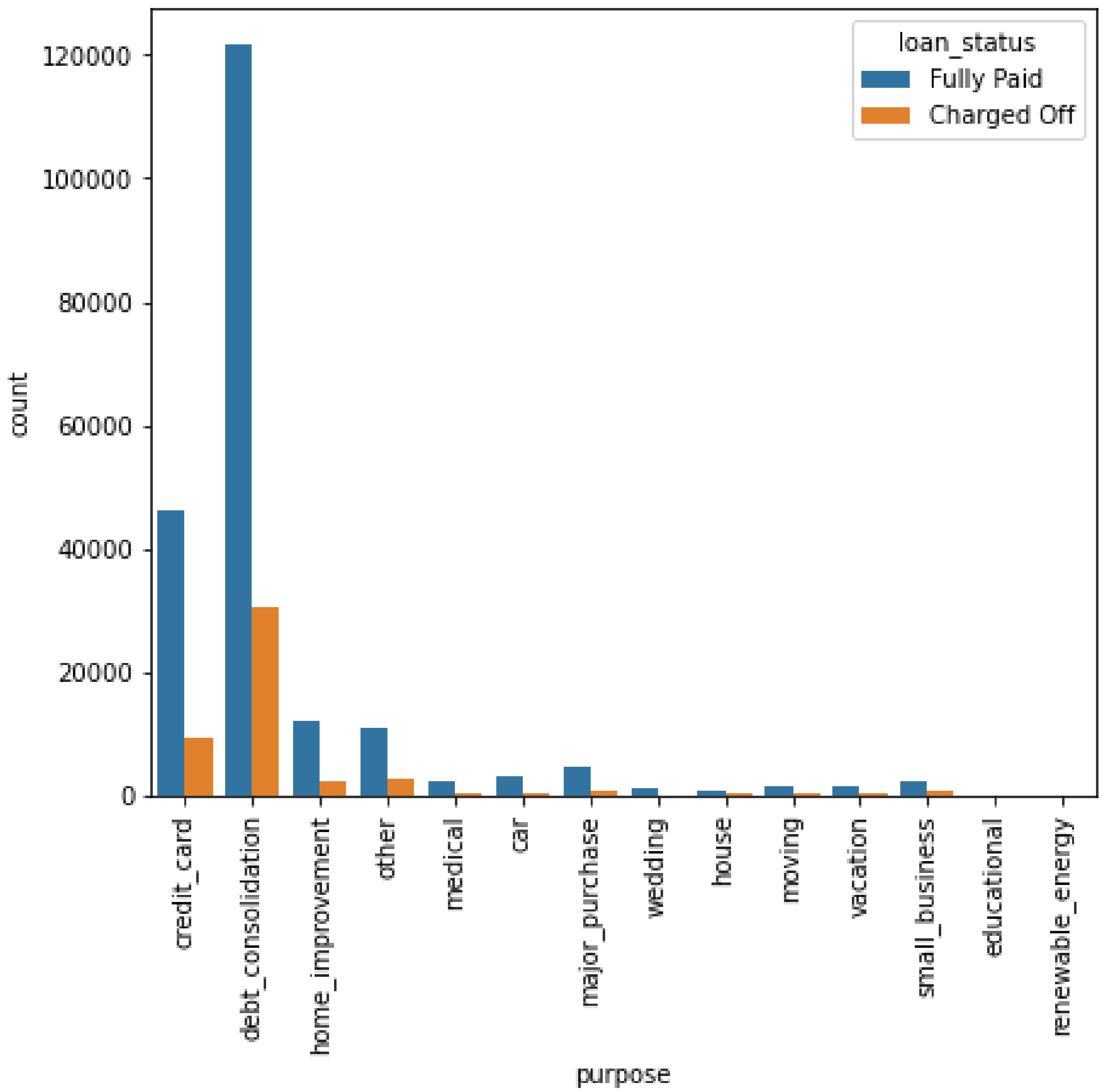
[78]:
```python
#Checking the percentage of occurence of each of the categories.
print(np.round(df_train[variable].value_counts(normalize=True)*100))

plt.figure(figsize=(7,5))
sns.countplot(df_train[variable])
plt.xticks(rotation=90)
plt.show()
```

```python
#Later we can encode this data.
```

```
debt_consolidation    59.0
credit_card           21.0
home_improvement       6.0
other                  5.0
major_purchase         2.0
car                    1.0
small_business         1.0
medical                1.0
moving                 1.0
vacation               1.0
wedding                0.0
house                  0.0
renewable_energy       0.0
educational            0.0
Name: purpose, dtype: float64
```



[79]:
```
#Checking Loan_Status with purpose to check if there is any relationship
plt.figure(figsize=(7,6))
sns.countplot(data=df_train,x=variable,hue='loan_status')
plt.xticks(rotation=90)
plt.show()
#Observation - We can see different behavior for the categories of "purpose"␣
↪variable.
```



[80]:
```
np.round(pd.
↪crosstab(df_train['loan_status'],df_train[variable],normalize='columns')*100)
```

[80]:
```
purpose        car  credit_card  debt_consolidation  educational  \
loan_status
```

```
Charged Off  12.0         17.0                20.0         16.0
Fully Paid   88.0         83.0                80.0         84.0

purpose      home_improvement  house  major_purchase  medical  moving  other  \
loan_status
Charged Off              17.0   19.0            16.0     20.0    23.0   20.0
Fully Paid               83.0   81.0            84.0     80.0    77.0   80.0

purpose      renewable_energy  small_business  vacation  wedding
loan_status
Charged Off              21.0            27.0      18.0     11.0
Fully Paid               79.0            73.0      82.0     89.0
```

[81]:
```
# Since the charged_off probability is diffrent for "purpose"␣
↪categories,therefore  itcould be an important feature.
# Since it is a categorical variable, therefore adding it to the␣
↪categorical_columns variable.
categorical_columns.append(variable)
```

[ ]:
```

```

0.3.16 15) Title

[82]:
```
variable= 'title'
#Checking for null values
print('Number of Null Values -',df_train[variable].isna().sum())
#There are 1059 null values

#Checking for number of unique values
print('Number of Unique Values -',df_train[variable].nunique())
#There are 35144 unique values
# This is a continuous variable
```

```
Number of Null Values - 1060
Number of Unique Values - 35213
```

[83]:
```
#Checking few values
df[variable].unique()[:10]
#Observation - We can drop this column since there are a lot of categories.
```

[83]:
```
array(['Vacation', 'Debt consolidation', 'Credit card refinancing',
       'Credit Card Refinance', 'Home improvement',
       'No More Credit Cards', 'Debt Consolidation', 'Business',
       'Major purchase', 'Debt Consolidation/Home Repairs'], dtype=object)
```

[84]:
```
df_train.drop(columns='title',inplace=True)
df_test.drop(columns='title',inplace=True)
print(df_train.shape,df_test.shape)
```

```
(257248, 25) (79206, 25)
```

[ ]:

```

```

0.3.17 16) DTI

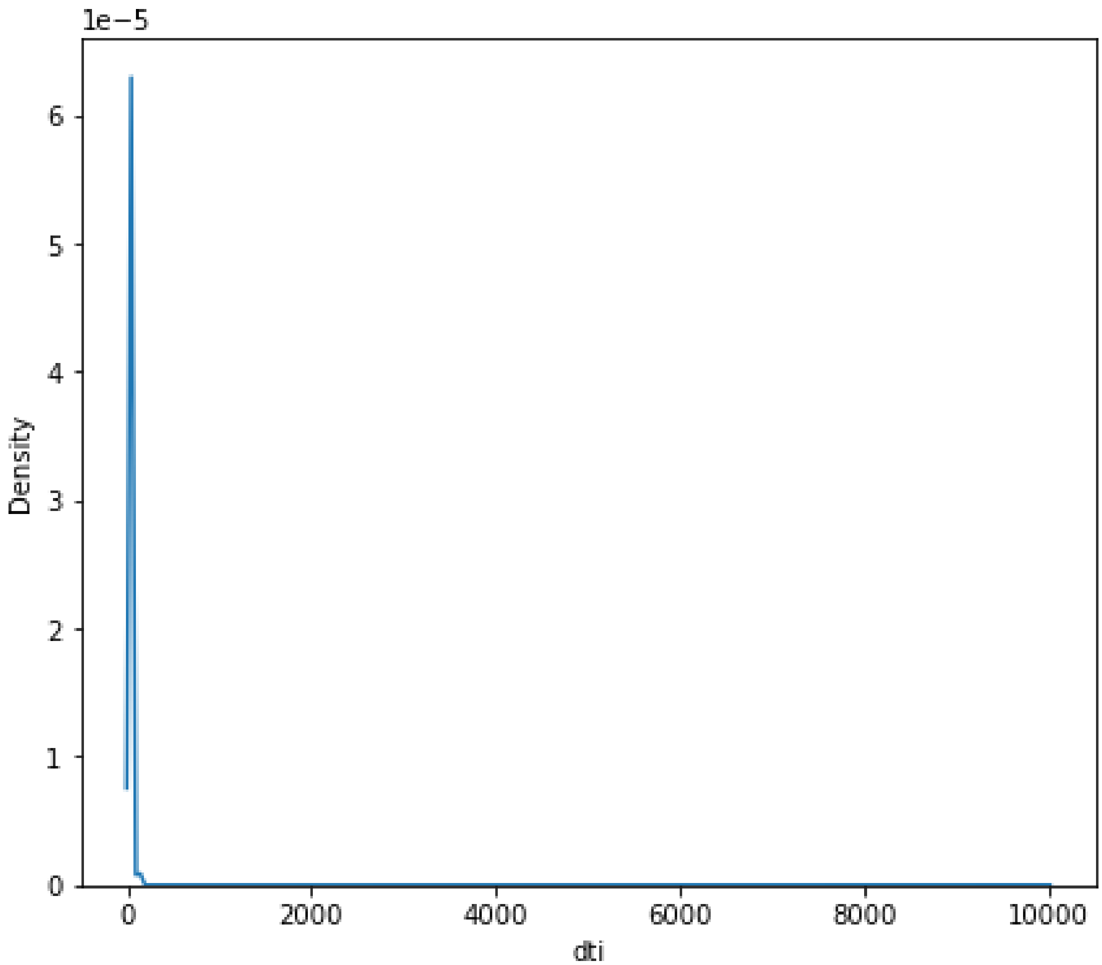
[85]:

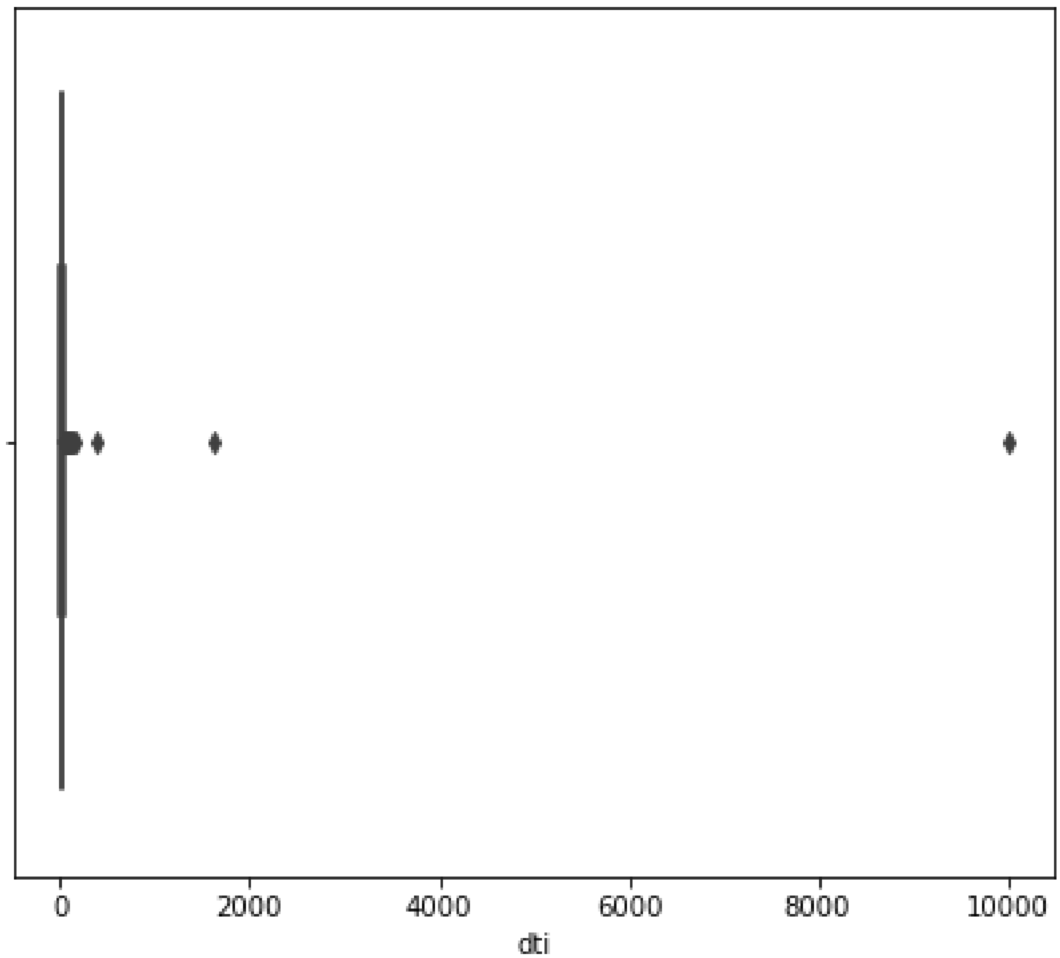
```
variable= 'dti'
#Checking for null values
print('Number of Null Values -',df_train[variable].isna().sum())
#There are no null values

#Checking for number of unique values
print('Number of Unique Values -',df_train[variable].nunique())
#There are 4157 unique values
# This is a continuous variable
```

```
Number of Null Values - 0
Number of Unique Values - 4163
```

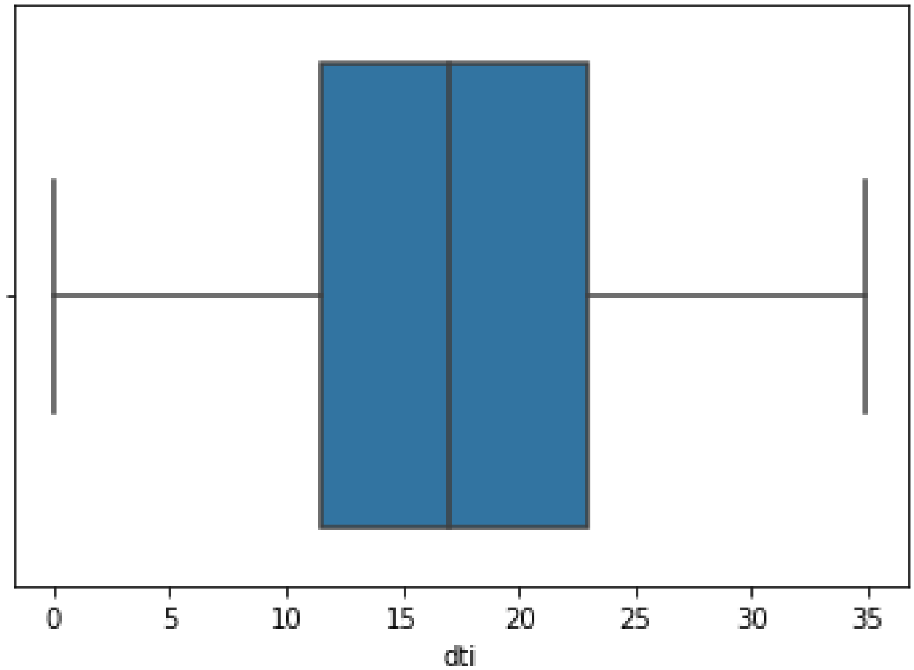
[86]:

```
plt.figure(figsize=(7,6))
sns.kdeplot(df_train[variable])
plt.show()
#Data looks right skewed

plt.figure(figsize=(7,6))
sns.boxplot(df_train[variable])
plt.show()
#There are few outliers in the data
```

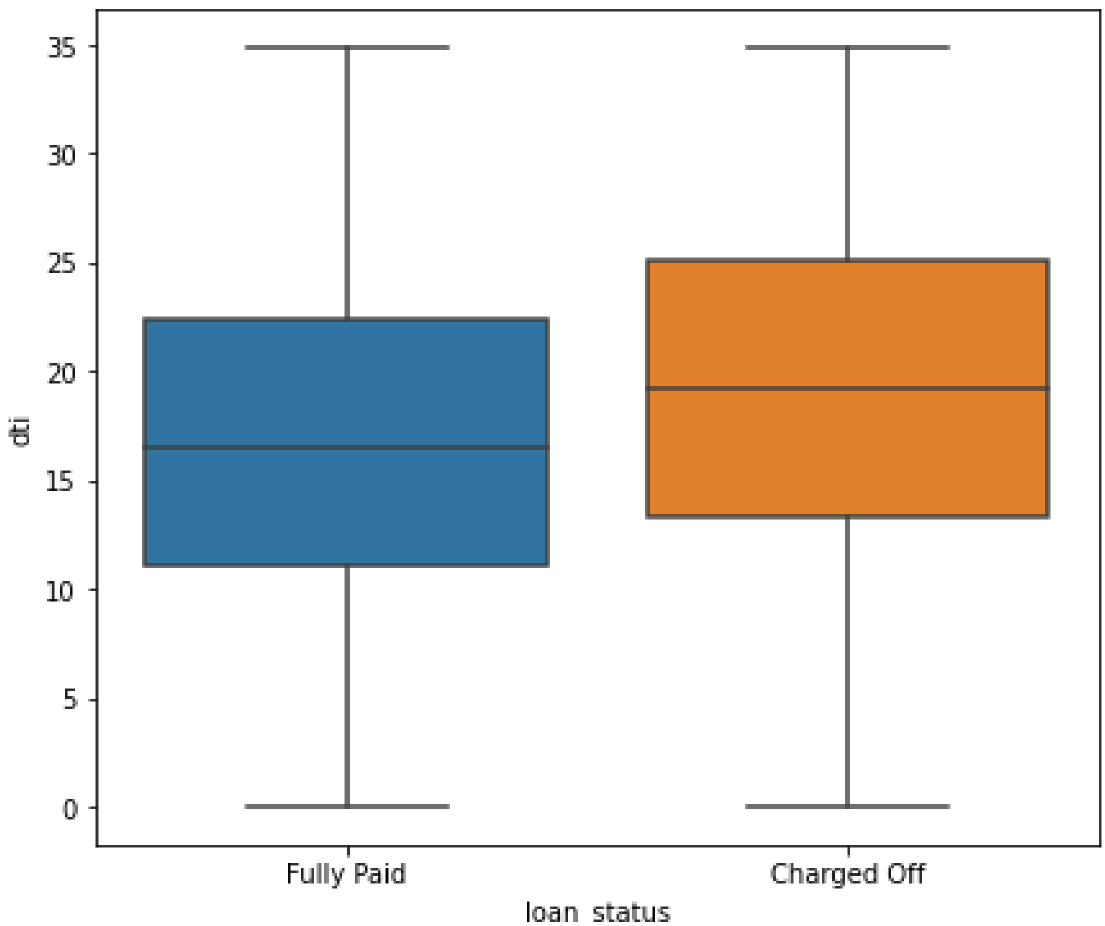

1e−5
Density
0
1
2
3
4
5
6
0
2000
4000
6000
8000
10000
dti



[87]:
```
#Removing the outliers
q75=np.percentile(df_train[variable],75)
q25=np.percentile(df_train[variable],25)
iqr=q75-q25
sns.boxplot(df_train.loc[df_train[variable]<iqr+q75,variable])
plt.show()
df_train=df_train.loc[df_train[variable]<iqr+q75]
#The outliers have been removed
```



[88]:
```
#Checking Loan_Status with dti to check if there is any relationship
plt.figure(figsize=(7,6))
sns.boxplot(data=df_train,y=variable,x='loan_status')
plt.show()
#Observation - The median dti is higher for charged off loans in comparison to␣
↪fully_paid loans.
```



[89]:
```
df_train.groupby(by='loan_status').mean()[variable]
#Observation - The mean dti is higher for charged off loans in comparison to␣
↪fully_paid loans.
```

[89]:
```
loan_status
Charged Off    19.141872
Fully Paid     16.867942
Name: dti, dtype: float64
```

[90]:
```
# Since mean and median dti is different for different classes, therefore it␣
↪could be an important feature.
# Since it is a continuous variable, therefore adding it to the␣
↪continuous_columns variable.
continuous_columns.append(variable)
```

[ ]:
```

```

0.3.18 17) Earliest_Cr_Line

[91]:
```
variable='earliest_cr_line'
#Checking for null values
print('Number of Null Values -',df_train[variable].isna().sum())
#There are no null values

#Checking for number of unique values
print('Number of Unique Values -',df_train[variable].nunique())
#There are 666 unique values
```

```
Number of Null Values - 0
Number of Unique Values - 662
```

[92]:
```
print(df_train[variable][:2])
#Converting to datetime format
df_train[variable]=pd.to_datetime(df_train[variable])
df_test[variable]=pd.to_datetime(df_test[variable])
```

```
0    Nov-2000
2    Sep-1999
Name: earliest_cr_line, dtype: object
```

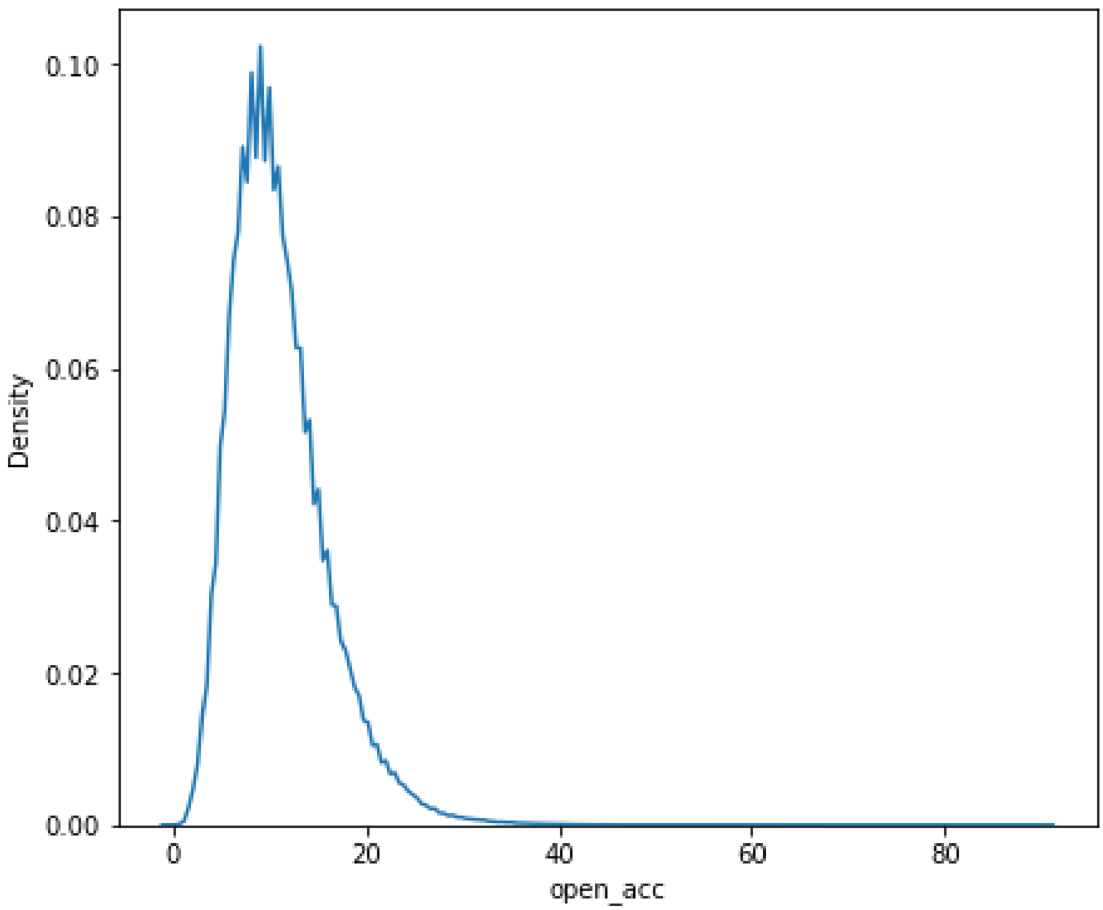
[ ]:
```

```

0.3.19 18) Open_Acc

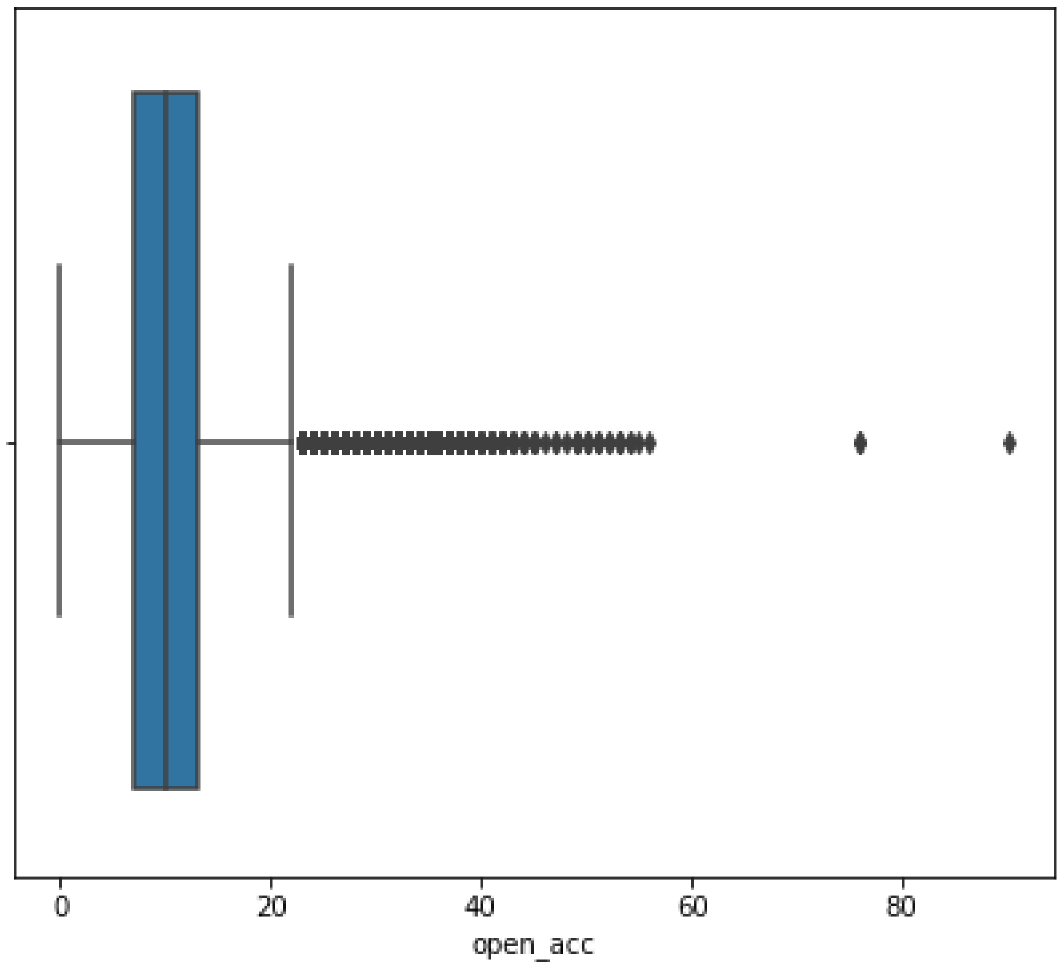
[93]:
```
variable='open_acc'
#Checking for null values
print('Number of Null Values -',df_train[variable].isna().sum())
#There are no null values

#Checking for number of unique values
print('Number of Unique Values -',df_train[variable].nunique())
#There are 59 unique values
# This is a continuous variable
```

```
Number of Null Values - 0
Number of Unique Values - 59
```

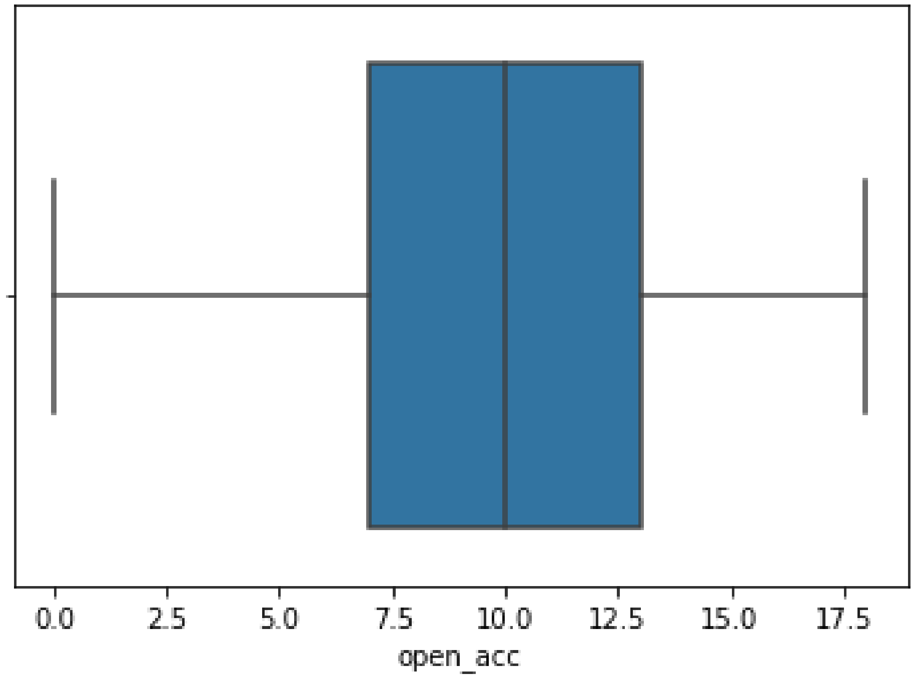
[94]:
```
plt.figure(figsize=(7,6))
sns.kdeplot(df_train[variable])
plt.show()
#Data looks right skewed

plt.figure(figsize=(7,6))
sns.boxplot(df_train[variable])
plt.show()
#There are few outliers in the data
```



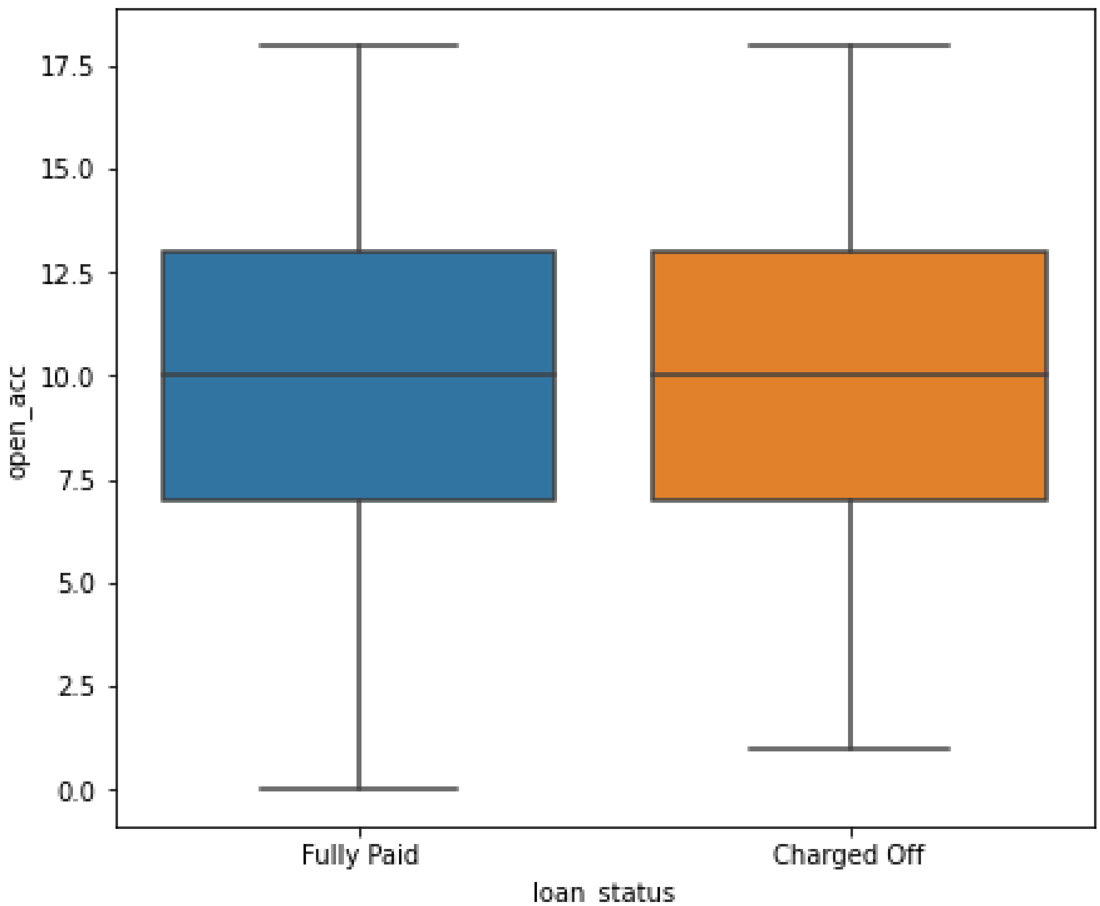
0.10
0.08
0.06
0.04
0.02
0.00
Density
0
20
40
60
80
open_acc



[95]:
```
#Removing the outliers
q75=np.percentile(df_train[variable],75)
q25=np.percentile(df_train[variable],25)
iqr=q75-q25
sns.boxplot(df_train.loc[df_train[variable]<iqr+q75,variable])
plt.show()
df_train=df_train.loc[df_train[variable]<iqr+q75]
#The outliers have been removed
```



[96]:
```
#Checking Loan_Status with Open_Acc to check if there is any relationship
plt.figure(figsize=(7,6))
sns.boxplot(data=df_train,y=variable,x='loan_status')
plt.show()
#Observation - The median open_acc is almost same for charged off loans in␣
↪comparison to fully_paid loans.
```



[97]:
```
df_train.groupby(by='loan_status').mean()[variable]
#Observation - The mean open_acc is almost same for charged off loans in␣
↪comparison to fully_paid loans.
```

[97]:
```
loan_status
Charged Off    10.165199
Fully Paid      9.961693
Name: open_acc, dtype: float64
```

[98]:
```
# Since mean and median open_acc is almost same for different classes,␣
↪therefore this feature can be ignored.
```

[ ]:
```
```

0.3.20 19) Pub_Rec

[99]:
```
variable= 'pub_rec'
#Checking for null values
print('Number of Null Values -',df_train[variable].isna().sum())
#There are no null values

#Checking for number of unique values
print('Number of Unique Values -',df_train[variable].nunique())
#There are 17 unique values
```

```
Number of Null Values - 0
Number of Unique Values - 18
```

[100]:
```
df_train[variable].unique()
```

[100]:
```
array([ 0.,  1.,  6.,  2.,  3.,  5.,  4.,  7.,  8., 10., 11., 86.,  9.,
       19., 13., 15., 12., 24.])
```

[101]:
```
df_train[variable].value_counts()
```

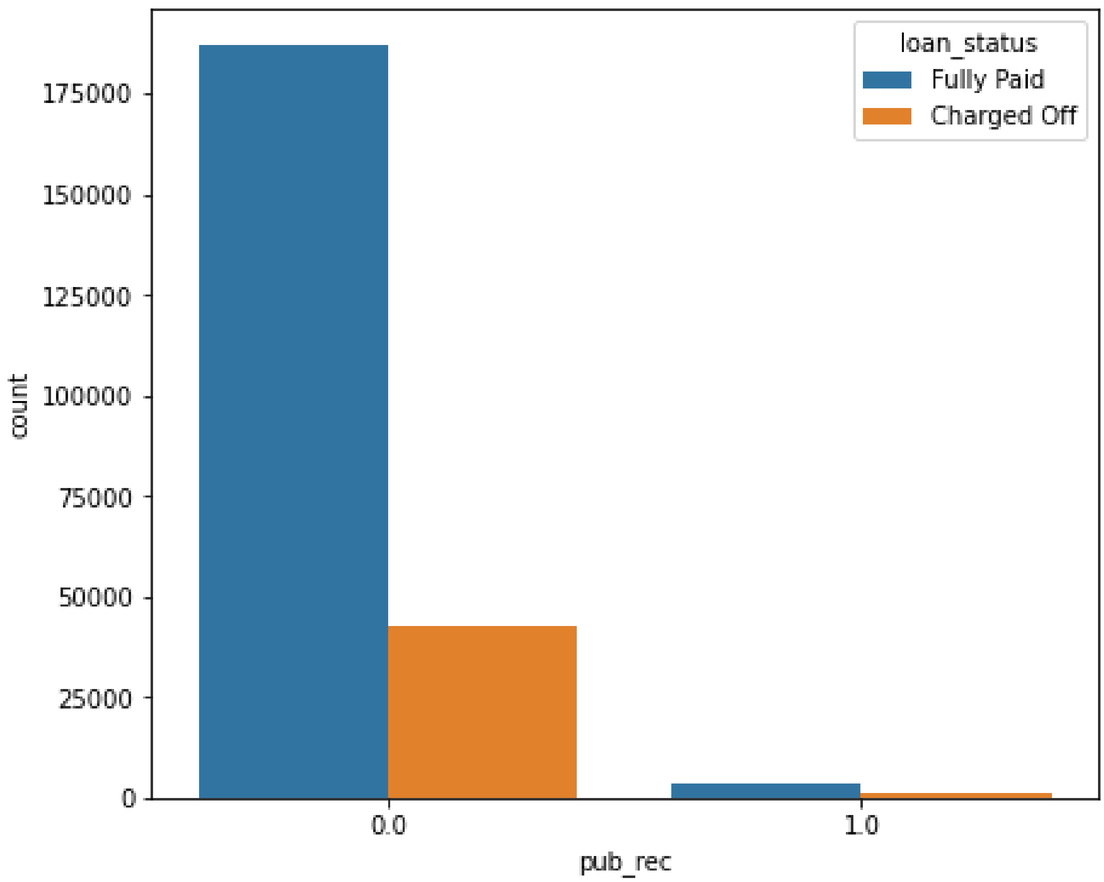
[101]:
```
0.0     197704
1.0      31493
2.0       3358
3.0        861
4.0        295
5.0        121
6.0         55
7.0         26
8.0         19
11.0         6
10.0         6
9.0          5
19.0         2
12.0         2
86.0         1
13.0         1
15.0         1
24.0         1
Name: pub_rec, dtype: int64
```

[102]:
```
#Creating flag for this feature
df_train.loc[df_train[variable]<=1,variable]=0
df_train.loc[df_train[variable]>1,variable]=1
df_test.loc[df_test[variable]<=1,variable]=0
df_test.loc[df_test[variable]>1,variable]=1
```

[103]:
```
df_train[variable].value_counts()
```

[103]:
```
0.0    229197
1.0      4760
Name: pub_rec, dtype: int64
```

[104]:
```
#Checking Loan_Status with pub_rec to check if there is any relationship
plt.figure(figsize=(7,6))
sns.countplot(data=df_train,x=variable,hue='loan_status')
plt.show()
#Observation - We can see different behavior for the categories of "pub_rec"␣
↪variable.
```



[105]:
```
np.round(pd.
↪crosstab(df_train['loan_status'],df_train[variable],normalize='columns')*100)
```

[105]:
```
pub_rec       0.0   1.0
loan_status
Charged Off  18.0  22.0
Fully Paid   82.0  78.0
```

[106]:
```
# Since it is a categorical variable, therefore adding it to the␣
↪categorical_columns variable.
categorical_columns.append(variable)
```

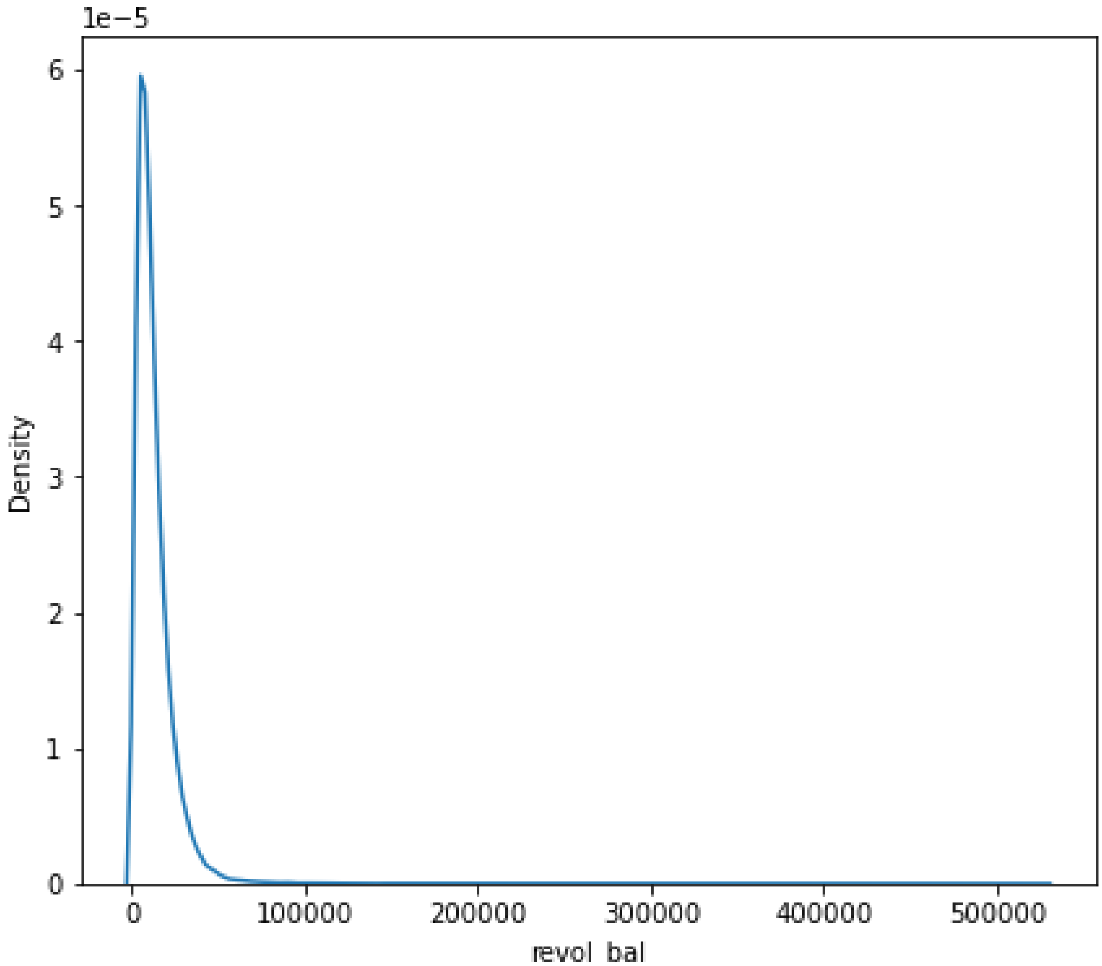
[ ]:
```

```

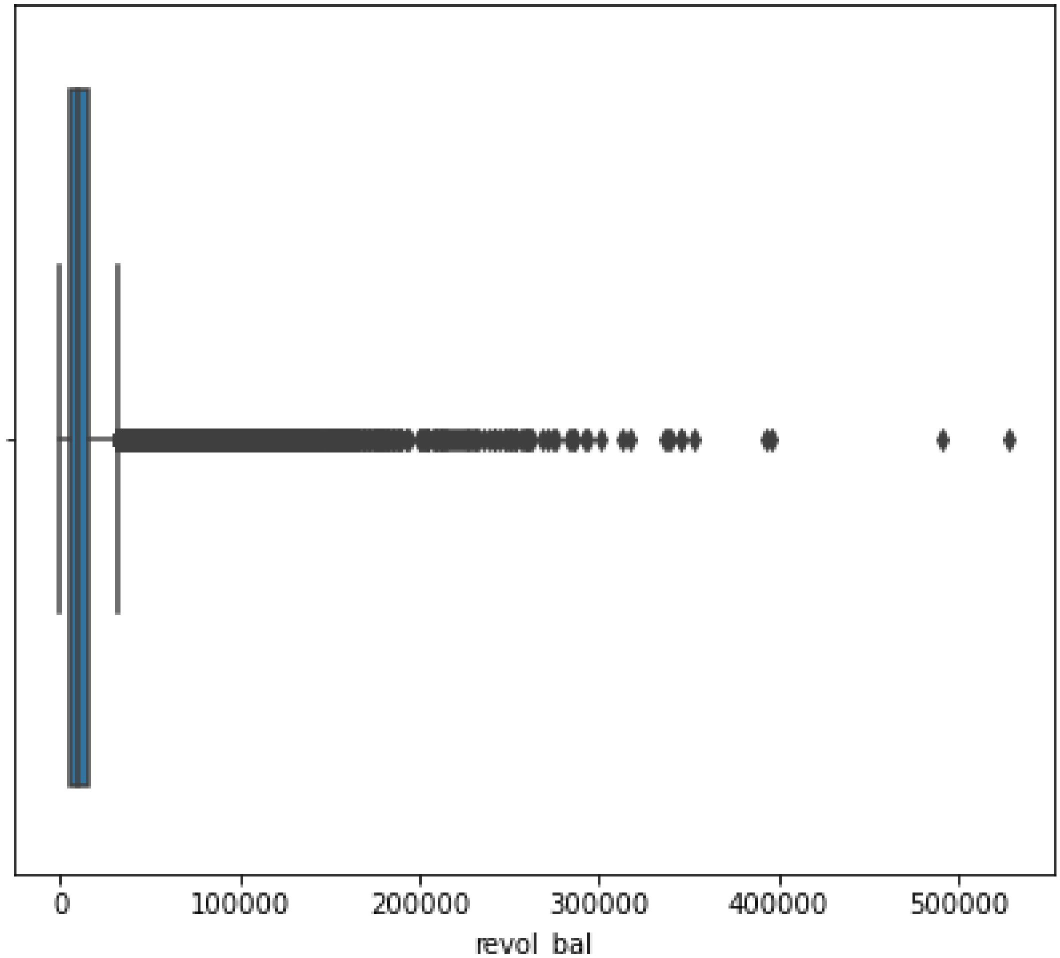
0.3.21 20) Revol_Bal

[107]:
```
variable= 'revol_bal'
#Checking for null values
print('Number of Null Values -',df_train[variable].isna().sum())
#There are no null values

#Checking for number of unique values
print('Number of Unique Values -',df_train[variable].nunique())
#There are 39632 unique values
# This is a continuous variable
```

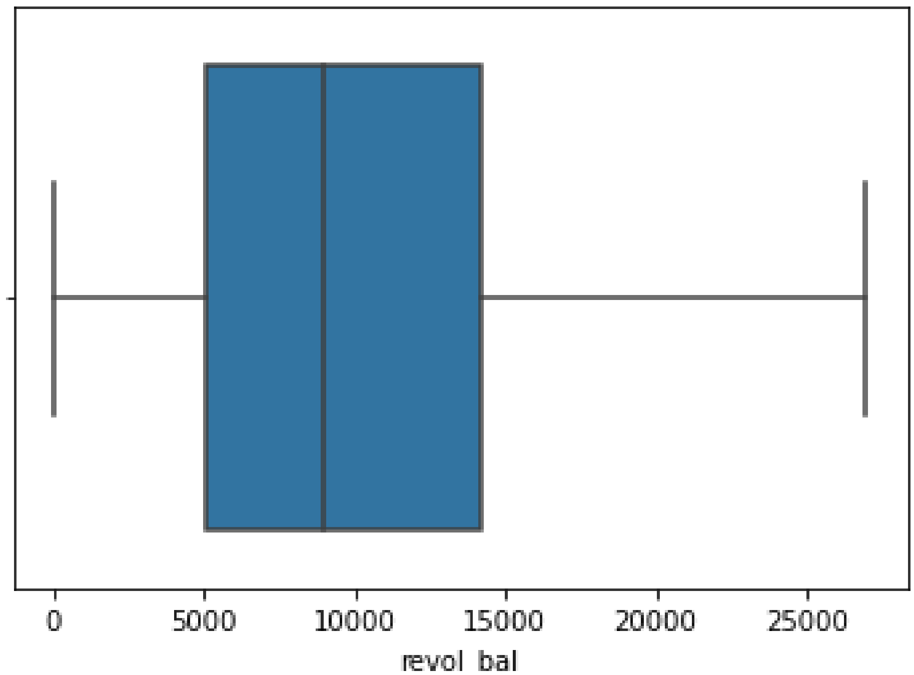
```
Number of Null Values - 0
Number of Unique Values - 39541
```

[108]:
```
plt.figure(figsize=(7,6))
sns.kdeplot(df_train[variable])
plt.show()
#Data looks right skewed

plt.figure(figsize=(7,6))
sns.boxplot(df_train[variable])
plt.show()
#There are few outliers in the data
```

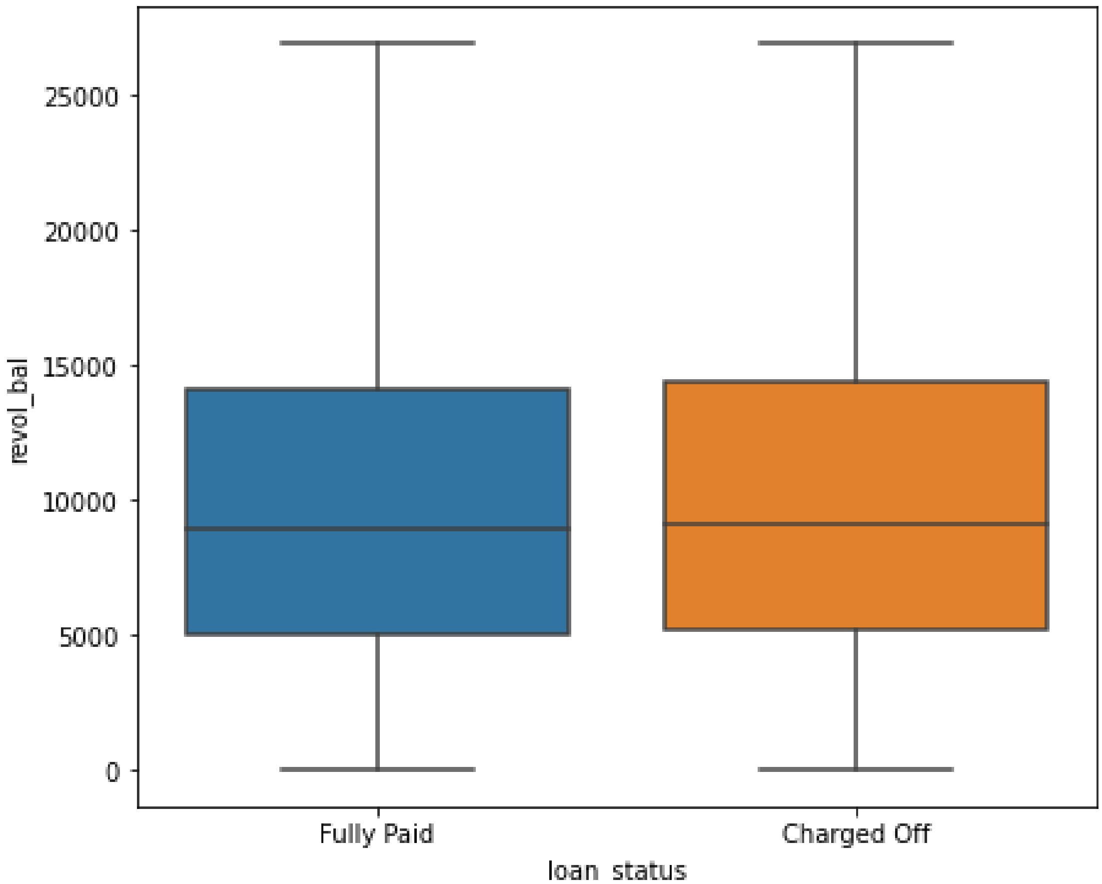

1e−5
6
5
4
3
2
1
0
Density
0
100000
200000
300000
400000
500000
revol_bal



[109]:
```
#Removing the outliers
q75=np.percentile(df_train[variable],75)
q25=np.percentile(df_train[variable],25)
iqr=q75-q25
sns.boxplot(df_train.loc[df_train[variable]<iqr+q75,variable])
plt.show()
df_train=df_train.loc[df_train[variable]<iqr+q75]
#The outliers have been removed
```



[110]:
```
#Checking Loan_Status with revol_bal to check if there is any relationship
plt.figure(figsize=(7,6))
sns.boxplot(data=df_train,y=variable,x='loan_status')
plt.show()
#Observation - The median revol_bal is almost same for charged off loans in␣
↪comparison to fully_paid loans.
```



[111]:
```
df_train.groupby(by='loan_status').mean()[variable]
#Observation - The mean revol_bal is higher for charged off loans in comparison␣
↪to fully_paid loans.
```

[111]:
```
loan_status
Charged Off    10190.947523
Fully Paid     10032.238462
Name: revol_bal, dtype: float64
```

[112]:
```
# Since it is a continuous variable, therefore adding it to the␣
↪continuous_columns variable.
continuous_columns.append(variable)
```

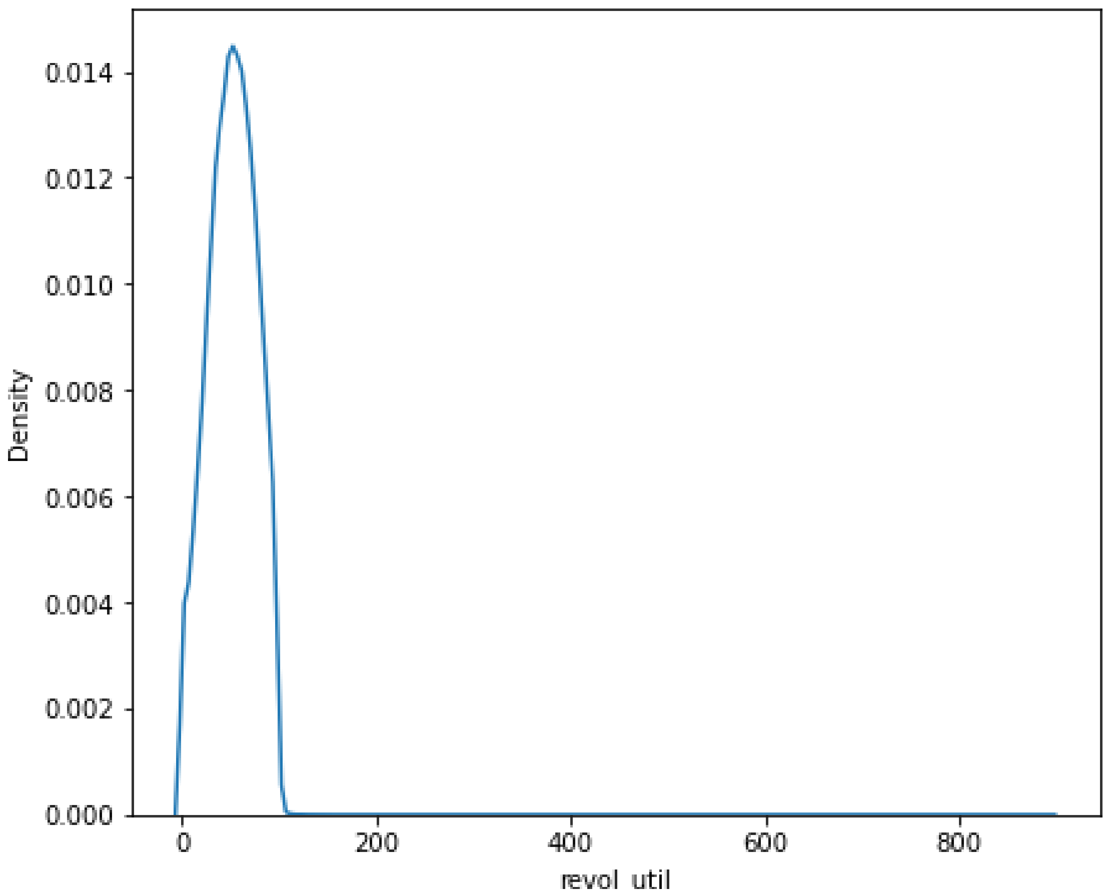
[ ]:

0.3.22 21) Revol_Util

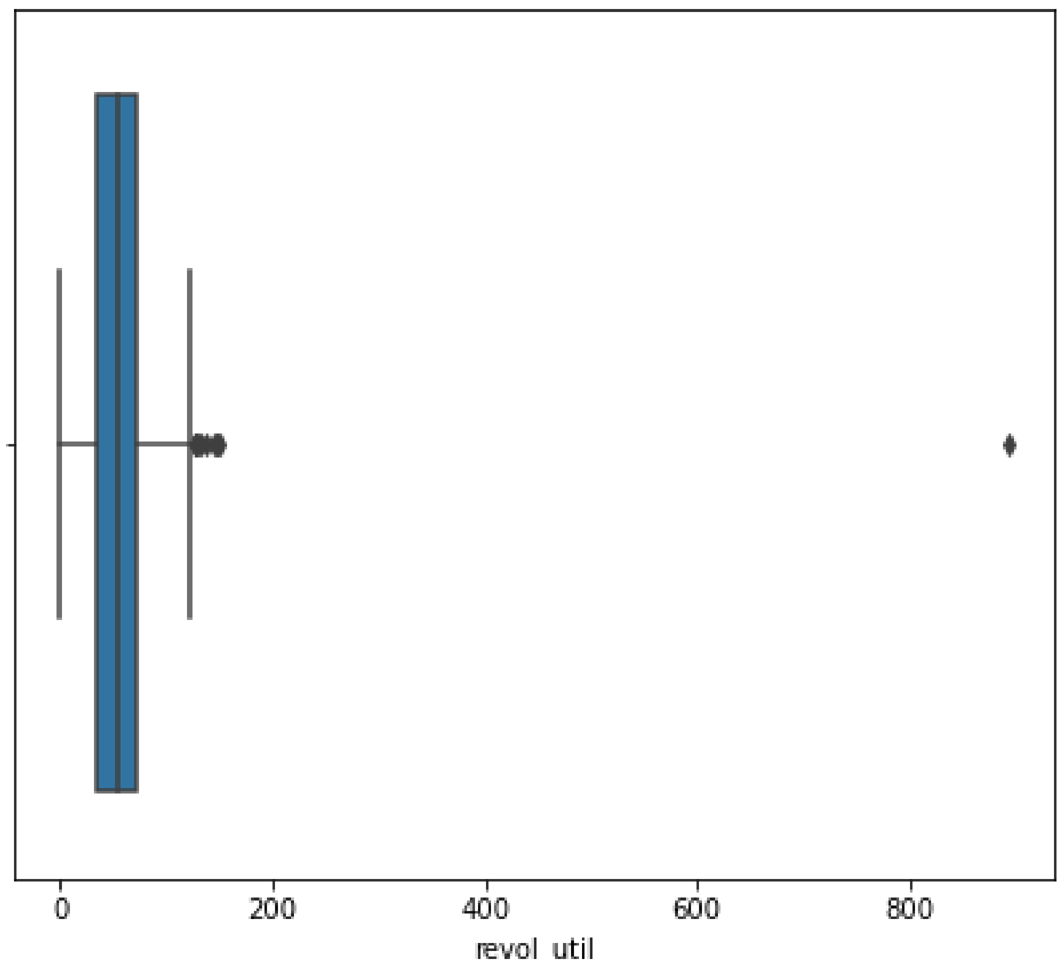
[113]:
```
variable= 'revol_util'
#Checking for null values
print('Number of Null Values -',df_train[variable].isna().sum())
#There are no null values

#Checking for number of unique values
print('Number of Unique Values -',df_train[variable].nunique())
#There are 1154 unique values
# This is a continuous variable
```

```
Number of Null Values - 154
Number of Unique Values - 1157
```

[114]:
```
plt.figure(figsize=(7,6))
sns.kdeplot(df_train[variable])
plt.show()
#Data looks right skewed

plt.figure(figsize=(7,6))
sns.boxplot(df_train[variable])
plt.show()
#There are few outliers in the data
```

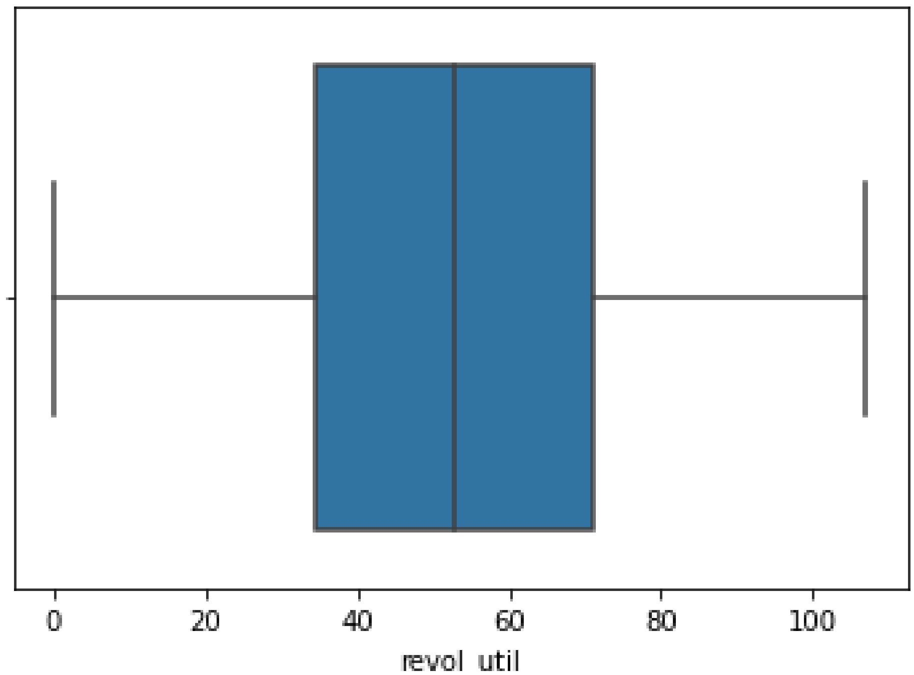


0.014
0.012
0.010
0.008
0.006
0.004
0.002
0.000
Density
0
200
400
600
800
revol_util

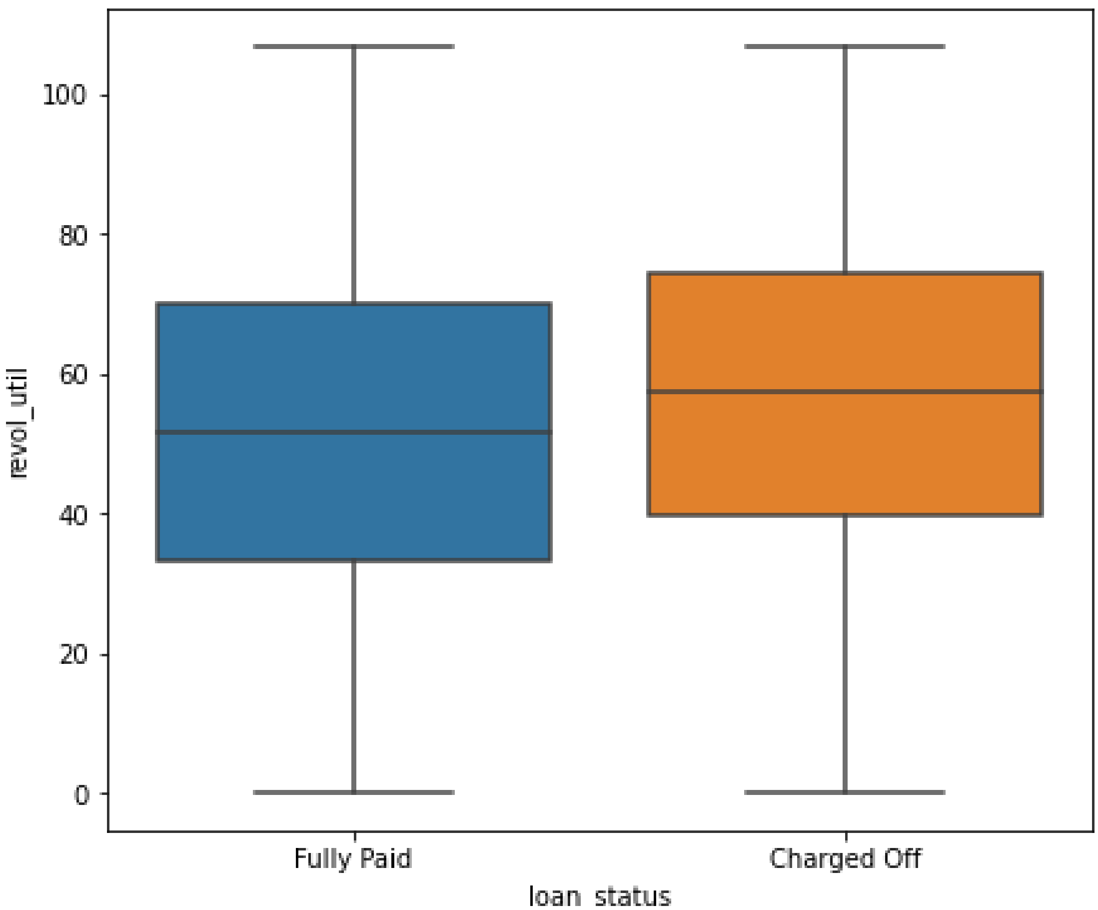


[115]:
```
#Sincce there are null values, and distribution is right skewed, therefore
↪using median imputation.
median_revol_util=df_train[variable].median()
median_revol_util
df_train[variable].fillna(median_revol_util,inplace=True)
```

[116]:
```
#Removing the outliers
q75=np.percentile(df_train[variable],75)
q25=np.percentile(df_train[variable],25)
iqr=q75-q25
sns.boxplot(df_train.loc[df_train[variable]<iqr+q75,variable])
plt.show()
df_train=df_train.loc[df_train[variable]<iqr+q75]
#The outliers have been removed
```



[117]:
```
#Checking Loan_Status with Loan_Amount to check if there is any relationship
plt.figure(figsize=(7,6))
sns.boxplot(data=df_train,y=variable,x='loan_status')
plt.show()
#Observation - The median revol_util is higher for charged off loans in␣
↪comparison to fully_paid loans.
```



[118]:
```
df_train.groupby(by='loan_status').mean()[variable]
#Observation - The mean revol_util is higher for charged off loans in␣
↪comparison to fully_paid loans.
```

[118]:
```
loan_status
Charged Off    56.297562
Fully Paid     51.318292
Name: revol_util, dtype: float64
```

[119]:
```
# Since mean and median revol_util is different for different classes,␣
↪therefore it could be an important feature.
# Since it is a continuous variable, therefore adding it to the␣
↪continuous_columns variable.
continuous_columns.append(variable)
```

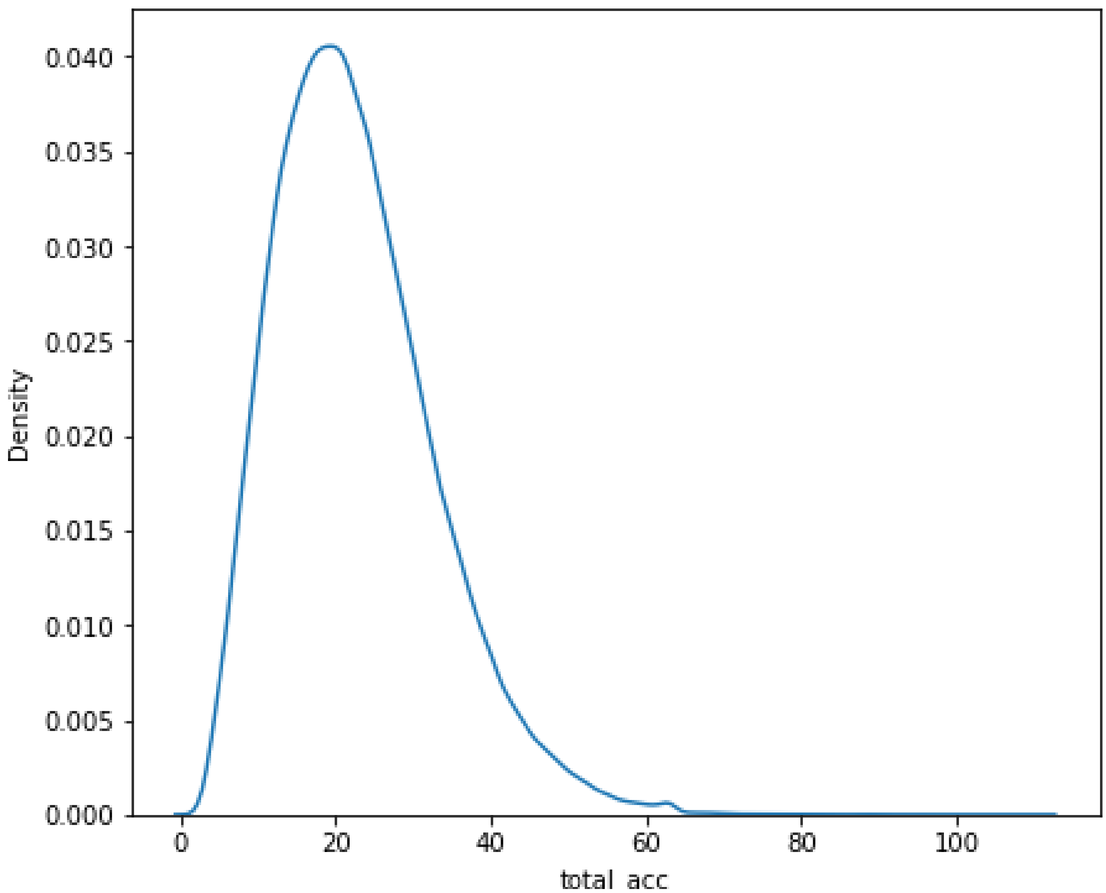
[ ]:
```

```

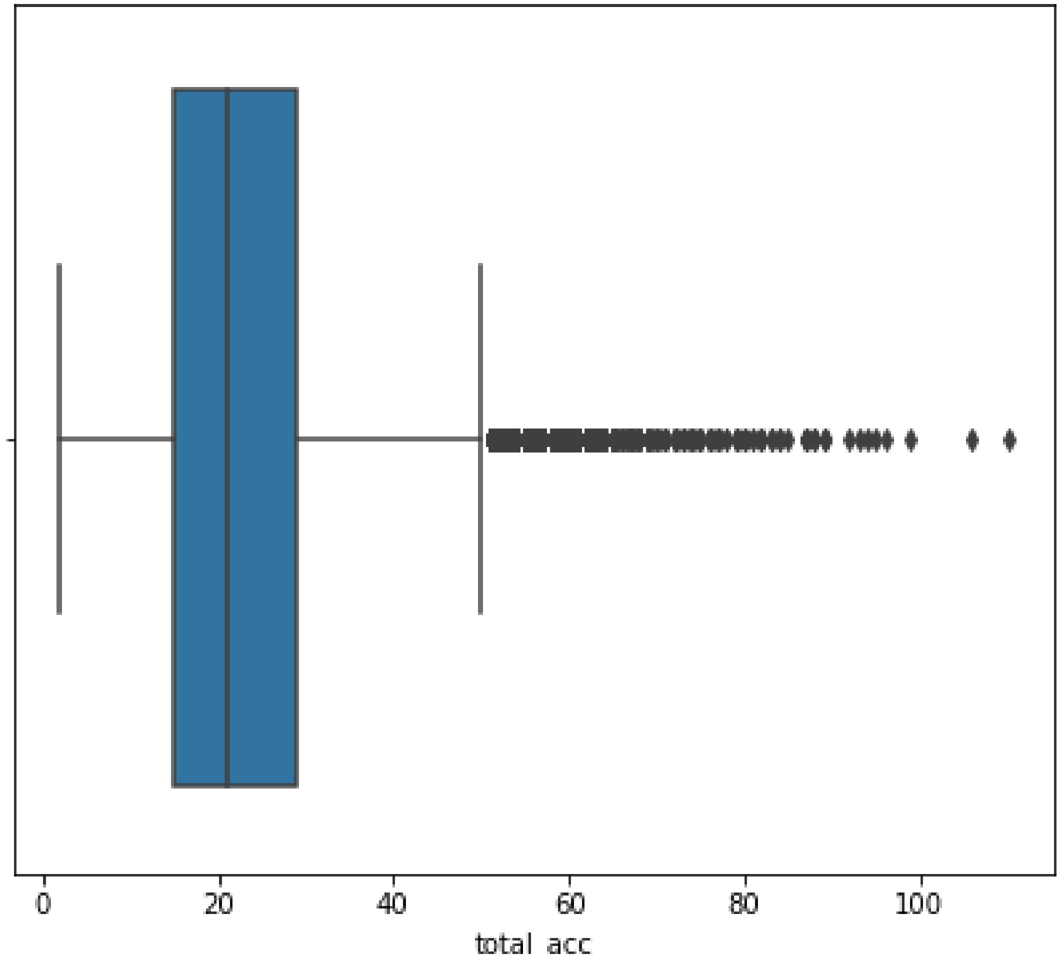
0.3.23 22) Total_Acc

[120]:
```
variable='total_acc'
#Checking for null values
print('Number of Null Values -',df_train[variable].isna().sum())
#There are no null values

#Checking for number of unique values
print('Number of Unique Values -',df_train[variable].nunique())
#There are 94 unique values
# This is a continuous variable
```

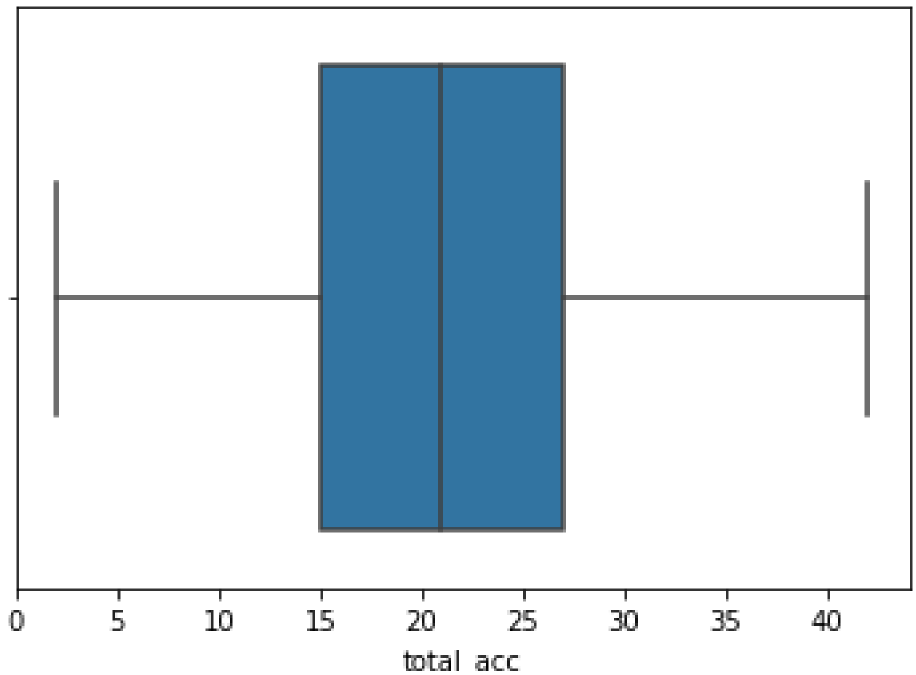
```
Number of Null Values - 0
Number of Unique Values - 95
```

[121]:
```
plt.figure(figsize=(7,6))
sns.kdeplot(df_train[variable])
plt.show()
#Data looks right skewed

plt.figure(figsize=(7,6))
sns.boxplot(df_train[variable])
plt.show()
#There are few outliers in the data
```

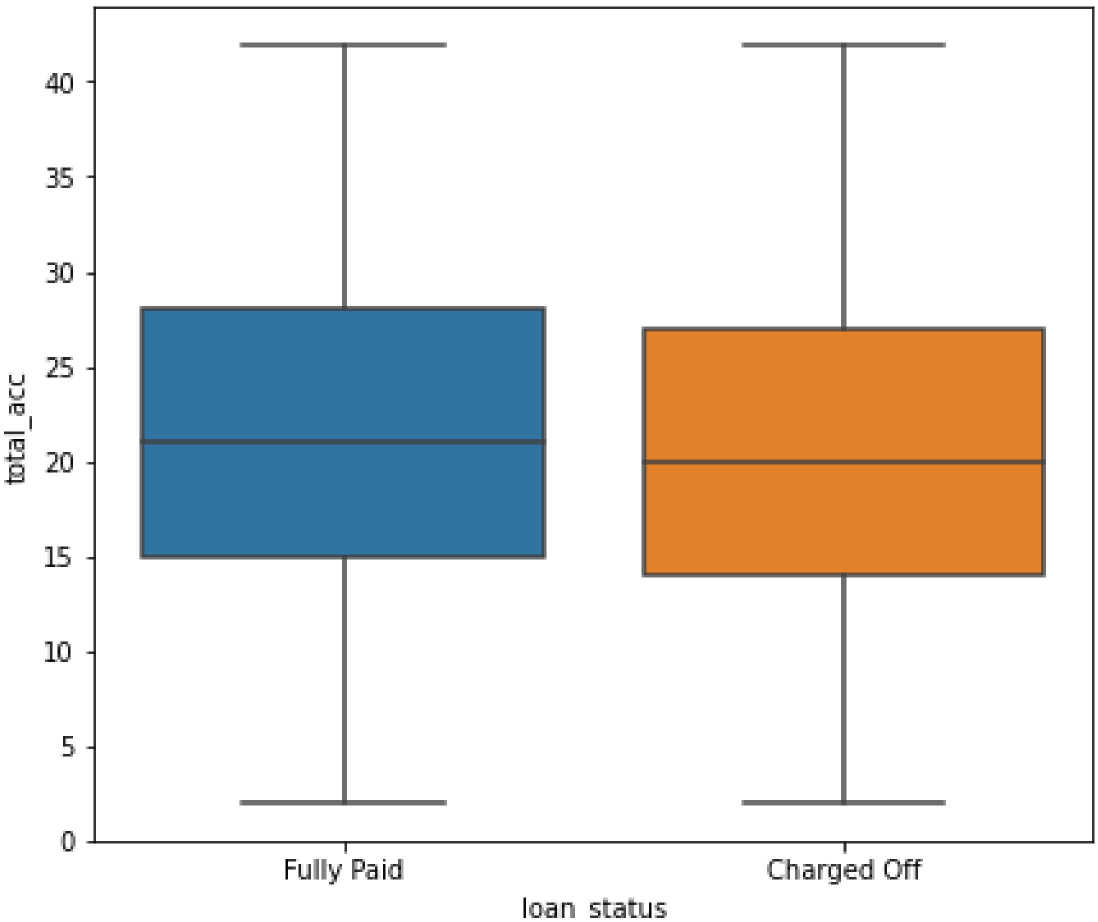

0.040
0.035
0.030
0.025
0.020
0.015
0.010
0.005
0.000
Density
0
20
40
60
80
100
total_acc



[122]:
```
#Removing the outliers
q75=np.percentile(df_train[variable],75)
q25=np.percentile(df_train[variable],25)
iqr=q75-q25
sns.boxplot(df_train.loc[df_train[variable]<iqr+q75,variable])
plt.show()
df_train=df_train.loc[df_train[variable]<iqr+q75]
# The outliers have been removed
```



[123]:
```
#Checking Loan_Status with total_acc to check if there is any relationship
plt.figure(figsize=(7,6))
sns.boxplot(data=df_train,y=variable,x='loan_status')
plt.show()
#Observation - The median total_acc is higher for fully_paid loans.
```



[124]:
```
df_train.groupby(by='loan_status').mean()[variable]
#Observation - The mean total_acc is higher for fully_paid loans.
```

[124]:
```
loan_status
Charged Off    20.892729
Fully Paid     21.489676
Name: total_acc, dtype: float64
```

[125]:
```
# Since mean and median total_acc is different for different classes, therefore␣
↪it could be an important feature.
# Since it is a continuous variable, therefore adding it to the␣
↪continuous_columns variable.
continuous_columns.append(variable)
```

[ ]:
```

```

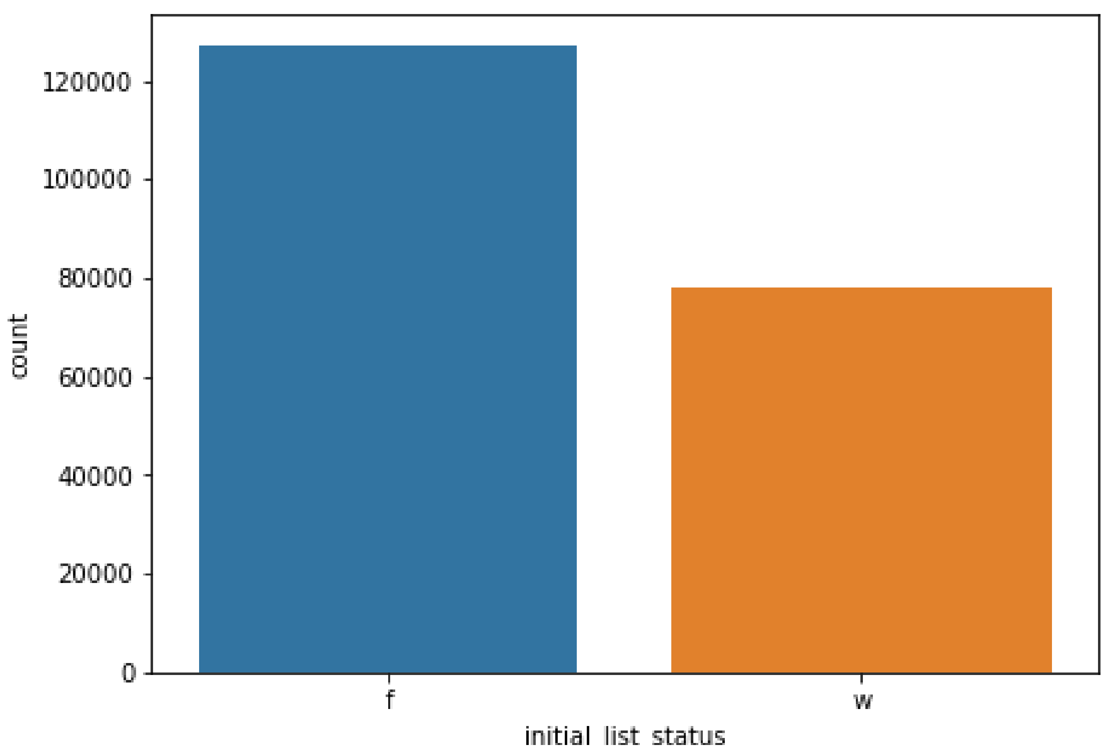
0.3.24 23) Initial_List_Status

[126]:
```python
variable= 'initial_list_status'
#Checking for null values
print('Number of Null Values -',df_train[variable].isna().sum())
#There are no null values

#Checking for number of unique values
print('Number of Unique Values -',df_train[variable].nunique())
#There are 2 unique values
# This is a categorical variable
```

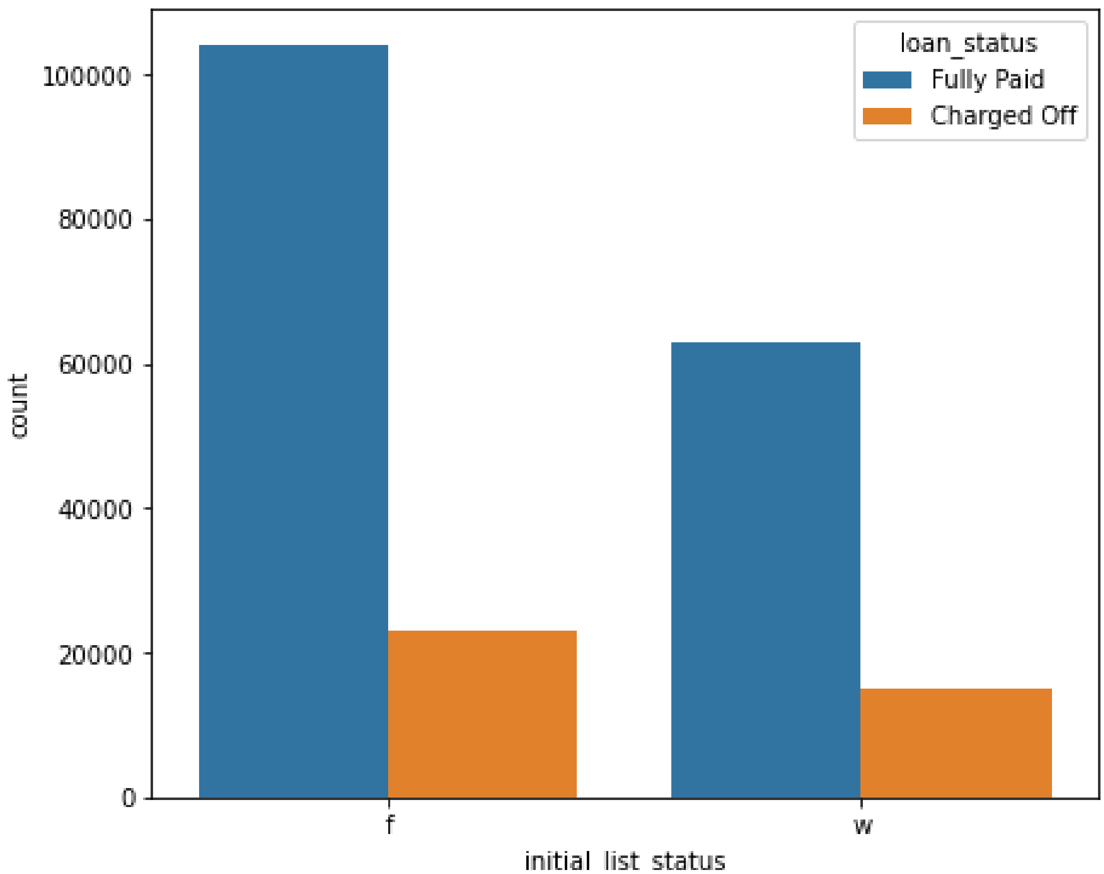
```
Number of Null Values - 0
Number of Unique Values - 2
```

[127]:
```python
#Checking the percentage of occurence of each of the categories.
print(np.round(df_train[variable].value_counts(normalize=True)*100))

plt.figure(figsize=(7,5))
sns.countplot(df_train[variable])
plt.show()
#Later we can encode this data.
```

```
f    62.0
w    38.0
Name: initial_list_status, dtype: float64
```



[128]:
```
#Checking Loan_Status with Initial_List_Status to check if there is any␣
↪relationship
plt.figure(figsize=(7,6))
sns.countplot(data=df_train,x=variable,hue='loan_status')
plt.show()
#Observation - We can see different behavior for each of the 2 categories.
```



[129]:
```
np.round(pd.
↪crosstab(df_train['loan_status'],df_train[variable],normalize='columns')*100)
```

[129]:
```
initial_list_status     f     w
loan_status
Charged Off          18.0  19.0
Fully Paid           82.0  81.0
```

[130]:
```
# Since it is a categorical variable, therefore adding it to the␣
↪categorical_columns variable.
categorical_columns.append(variable)
```

[ ]:
```

```

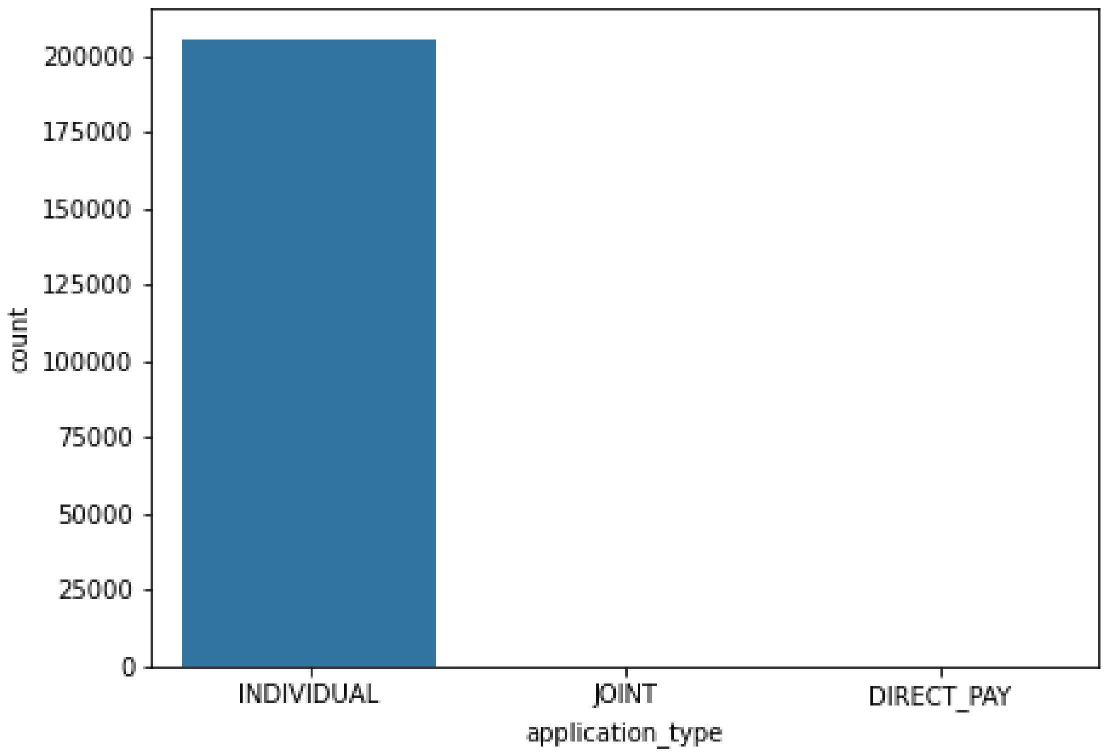
0.3.25 24) Application_Type

[131]:
```
variable= 'application_type'
#Checking for null values
print('Number of Null Values -',df_train[variable].isna().sum())
#There are no null values

#Checking for number of unique values
print('Number of Unique Values -',df_train[variable].nunique())
#There are 3 unique values
# This is a categorical variable
```

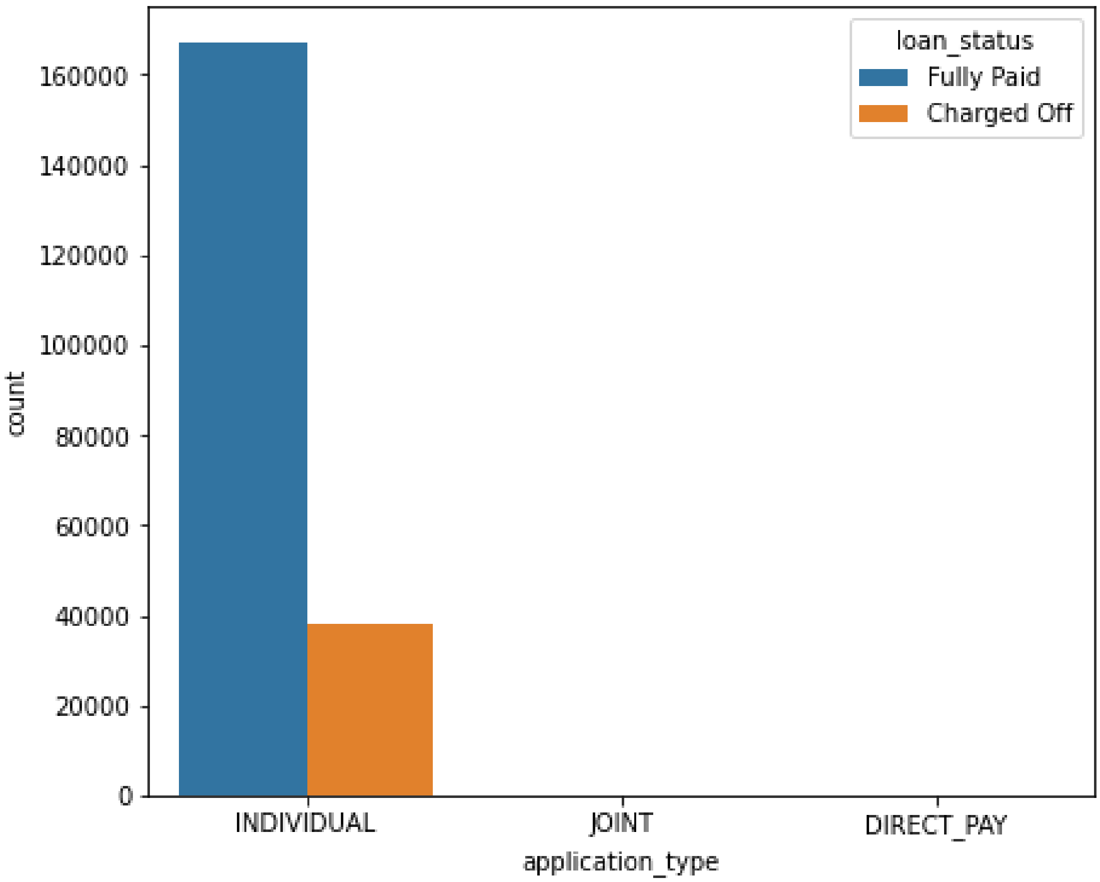
```
Number of Null Values - 0
Number of Unique Values - 3
```

[132]:
```
#Checking the percentage of occurence of each of the categories.
print(np.round(df_train[variable].value_counts(normalize=True)*100))

plt.figure(figsize=(7,5))
sns.countplot(df_train[variable])
plt.show()
#Later we can encode this data.
```

```
INDIVIDUAL    100.0
JOINT           0.0
DIRECT_PAY      0.0
Name: application_type, dtype: float64
```



[133]:
```
#Checking Loan_Status with application_type to check if there is any␣
↪relationship
plt.figure(figsize=(7,6))
sns.countplot(data=df_train,x=variable,hue='loan_status')
plt.show()
```



[134]:
```
np.round(pd.
↪crosstab(df_train['loan_status'],df_train[variable],normalize='columns')*100)
#Observation - Different charged_off percentage for different categories.
```

[134]:
```
application_type  DIRECT_PAY  INDIVIDUAL  JOINT
loan_status
Charged Off             60.0        19.0   15.0
Fully Paid              40.0        81.0   85.0
```

[135]:
```
# Since the charged_off probability is different for the categories,therefore␣
↪it could be an important feature.
# Since it is a categorical variable, therefore adding it to the␣
↪categorical_columns variable.
categorical_columns.append(variable)
```

[ ]:
```
```

0.3.26 25) Mort_Acc

[136]:
```
variable=  'mort_acc'
#Checking for null values
print('Number of Null Values -',df_train[variable].isna().sum())
#There are 23018 null values

#Checking for number of unique values
print('Number of Unique Values -',df_train[variable].nunique())
#There are 22 unique values
```

```
Number of Null Values - 23018
Number of Unique Values - 22
```

[137]:
```
df_train[variable].unique()
```

[137]:
```
array([ 2.,  0.,  3.,  1., nan,  4.,  5.,  9.,  7.,  6.,  8., 10., 11.,
       14., 13., 12., 21., 19., 17., 25., 16., 15., 18.])
```

[138]:
```
#Since there are null values, therefore using mode imputation.
mode_more_acc=df_train[variable].mode()
df_train[variable].fillna(mode_more_acc[0],inplace=True)
```

[139]:
```
df_train[variable].value_counts()
```

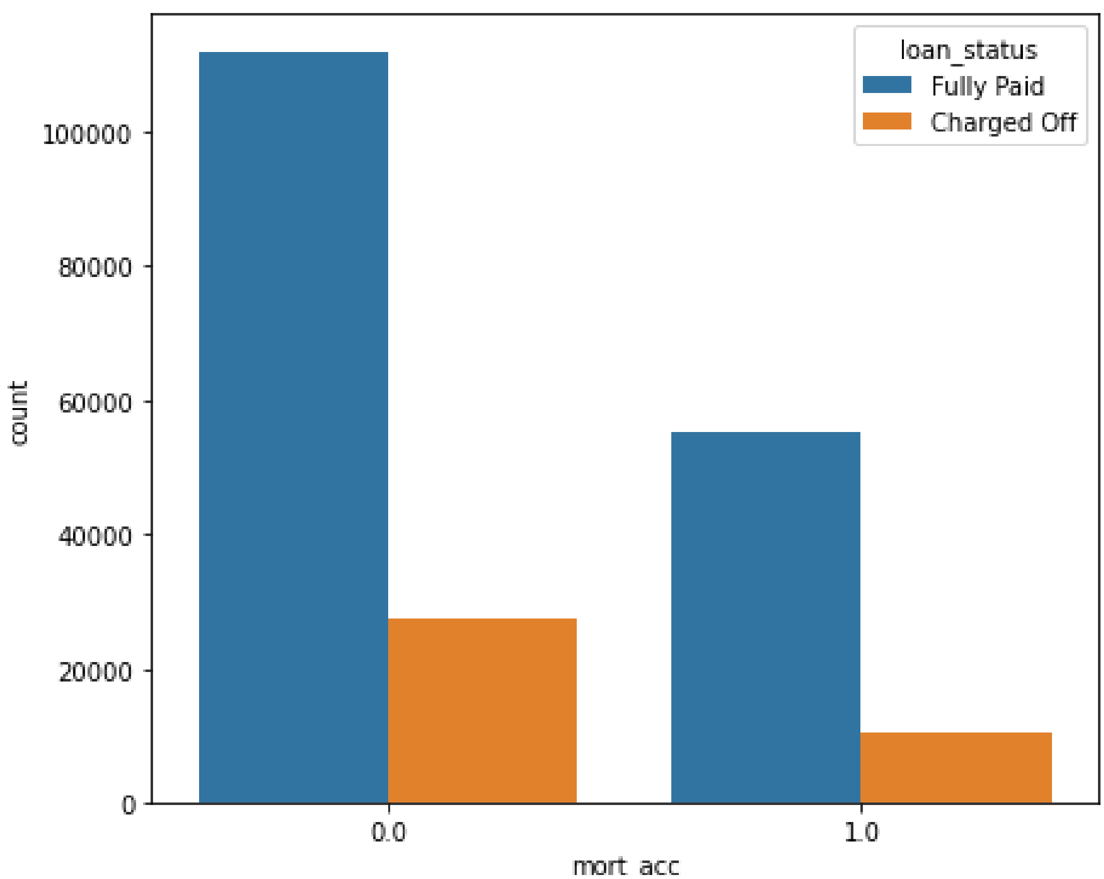
[139]:
```
0.0     106905
1.0      32562
2.0      23985
3.0      16729
4.0      11055
5.0       6634
6.0       3792
7.0       1927
8.0        942
9.0        441
10.0       214
11.0        98
12.0        56
13.0        25
14.0        17
16.0         7
19.0         3
17.0         2
15.0         2
21.0         1
25.0         1
18.0         1
Name: mort_acc, dtype: int64
```

[140]:
```
#Creating flag for this feature
df_train.loc[df_train[variable]<=1,variable]=0
df_train.loc[df_train[variable]>1,variable]=1
df_test.loc[df_test[variable]<=1,variable]=0
df_test.loc[df_test[variable]>1,variable]=1
```

[141]:
```
df_train[variable].value_counts()
```

[141]:
```
0.0    139467
1.0     65932
Name: mort_acc, dtype: int64
```

[142]:
```
#Checking Loan_Status with mort_acc to check if there is any relationship
plt.figure(figsize=(7,6))
sns.countplot(data=df_train,x=variable,hue='loan_status')
plt.show()
#Observation - We can see different behavior for the categories of "pub_rec"␣
↪variable.
```



[143]:
```
np.round(pd.
↪crosstab(df_train['loan_status'],df_train[variable],normalize='columns')*100)
```

[143]:
```
mort_acc      0.0   1.0
loan_status
Charged Off  20.0  16.0
Fully Paid   80.0  84.0
```

[144]:
```
# Since it is a categorical variable, therefore adding it to the␣
↪categorical_columns variable.
categorical_columns.append(variable)
```

[ ]:
```

```

0.3.27 26) Pub_Rec_Bankruptcies

[145]:
```
variable='pub_rec_bankruptcies'
#Checking for null values
print('Number of Null Values -',df_train[variable].isna().sum())
#There are 325 null values

#Checking for number of unique values
print('Number of Unique Values -',df_train[variable].nunique())
#There are 8 unique values
# This is a categorical variable
```

```
Number of Null Values - 325
Number of Unique Values - 8
```

[146]:
```
df_train[variable].unique()
```

[146]:
```
array([ 0.,  1.,  2.,  3., nan,  4.,  7.,  5.,  6.])
```

[147]:
```
#Since there are null values, therefore using mode imputation.
mode_pub_rec_bankruptcies=df_train[variable].mode()
df_train[variable].fillna(mode_pub_rec_bankruptcies[0],inplace=True)
```

[148]:
```
df_train[variable].value_counts()
```

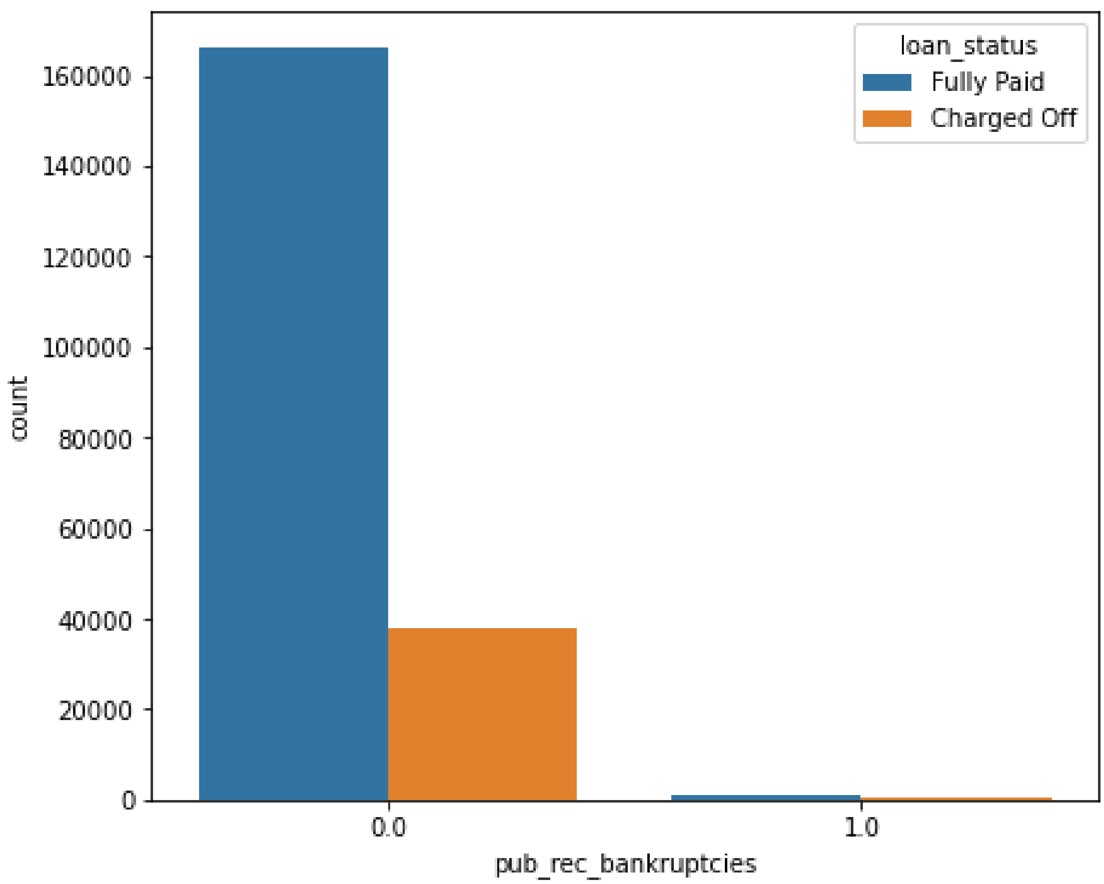
[148]:
```
0.0    178604
1.0     25405
2.0      1115
3.0       208
4.0        44
5.0        19
6.0         3
7.0         1
Name: pub_rec_bankruptcies, dtype: int64
```

[149]:
```
#Creating flag for this feature
df_train.loc[df_train[variable]<=1,variable]=0
df_train.loc[df_train[variable]>1,variable]=1
df_test.loc[df_test[variable]<=1,variable]=0
df_test.loc[df_test[variable]>1,variable]=1
```

[150]:
```
df_train[variable].value_counts()
```

[150]:
```
0.0    204009
1.0      1390
Name: pub_rec_bankruptcies, dtype: int64
```

[151]:
```
#Checking Loan_Status with pub_rec_bankruptcies to check if there is any␣
 ↪relationship
plt.figure(figsize=(7,6))
sns.countplot(data=df_train,x=variable,hue='loan_status')
plt.show()
#Observation - We can see different behavior for the categories of "pub_rec"␣
 ↪variable.
```



[152]:
```
np.round(pd.
 ↪crosstab(df_train['loan_status'],df_train[variable],normalize='columns')*100)
```

[152]:
```
pub_rec_bankruptcies   0.0   1.0
loan_status
Charged Off           19.0  22.0
Fully Paid            81.0  78.0
```

[153]:
```
# Since it is a categorical variable, therefore adding it to the␣
 ↪categorical_columns variable.
categorical_columns.append(variable)
```

[ ]:
```

```

0.3.28 27) Address

[154]:
```
variable='address'
#Checking for null values
print('Number of Null Values -',df_train[variable].isna().sum())
#There are no null values

#Checking for number of unique values
print('Number of Unique Values -',df_train[variable].nunique())
#There are 293340 unique values
# This is a continuous variable
```

```
Number of Null Values - 0
Number of Unique Values - 204701
```

[155]:
```
#Checking 1 address
df_train.loc[199642,variable]
#We can extract the pin code and state from the address.
```

[155]:
```
'1778 Spencer Flats Suite 111\r\nWest Crystal, WV 22690'
```

[ ]:
```

```

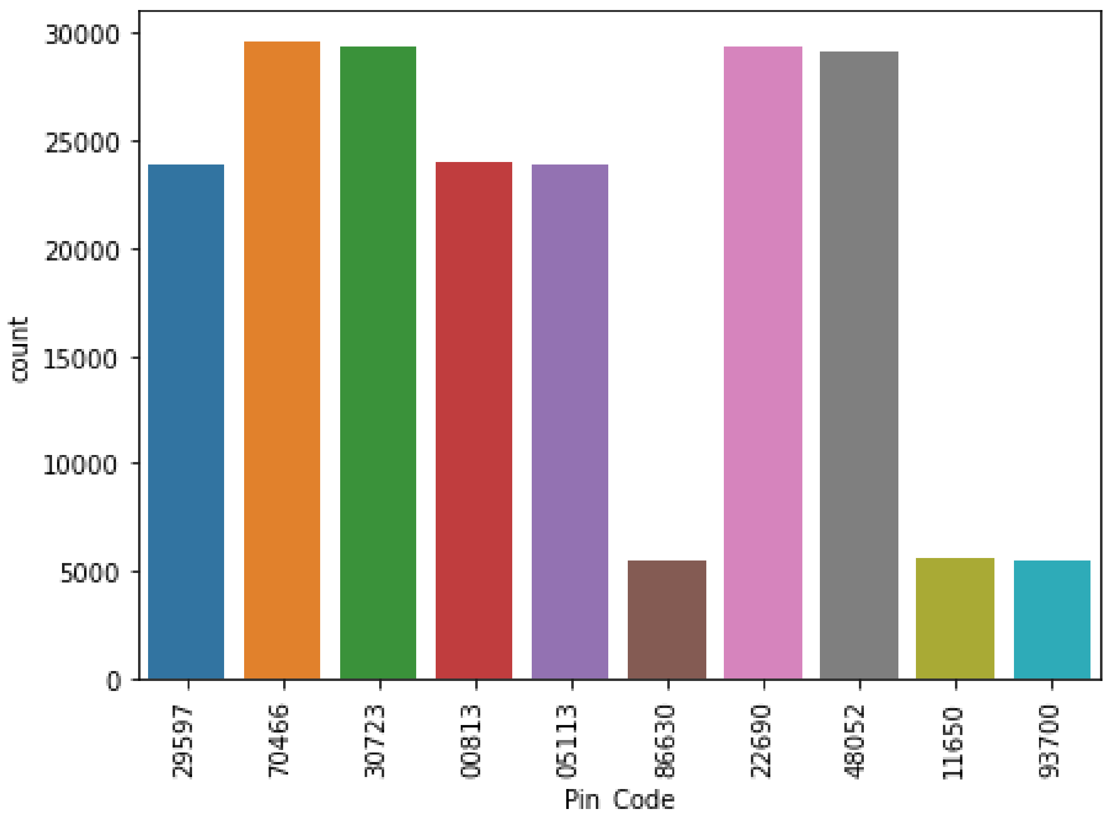
0.3.29 Feature Engineering

[156]:
```
#Extracting Pin Code and State From Address.
df_train['Pin_Code']=df_train[variable].apply(lambda x : x.split()[-1])
df_train['State']=df_train[variable].apply(lambda x : x.split()[-2])
df_test['Pin_Code']=df_test[variable].apply(lambda x : x.split()[-1])
df_test['State']=df_test[variable].apply(lambda x : x.split()[-2])
```

[157]:
```
#Checking the percentage of occurence of each of the categories of "Pin_Code".
print(np.round(df_train['Pin_Code'].value_counts(normalize=True)*100))
```

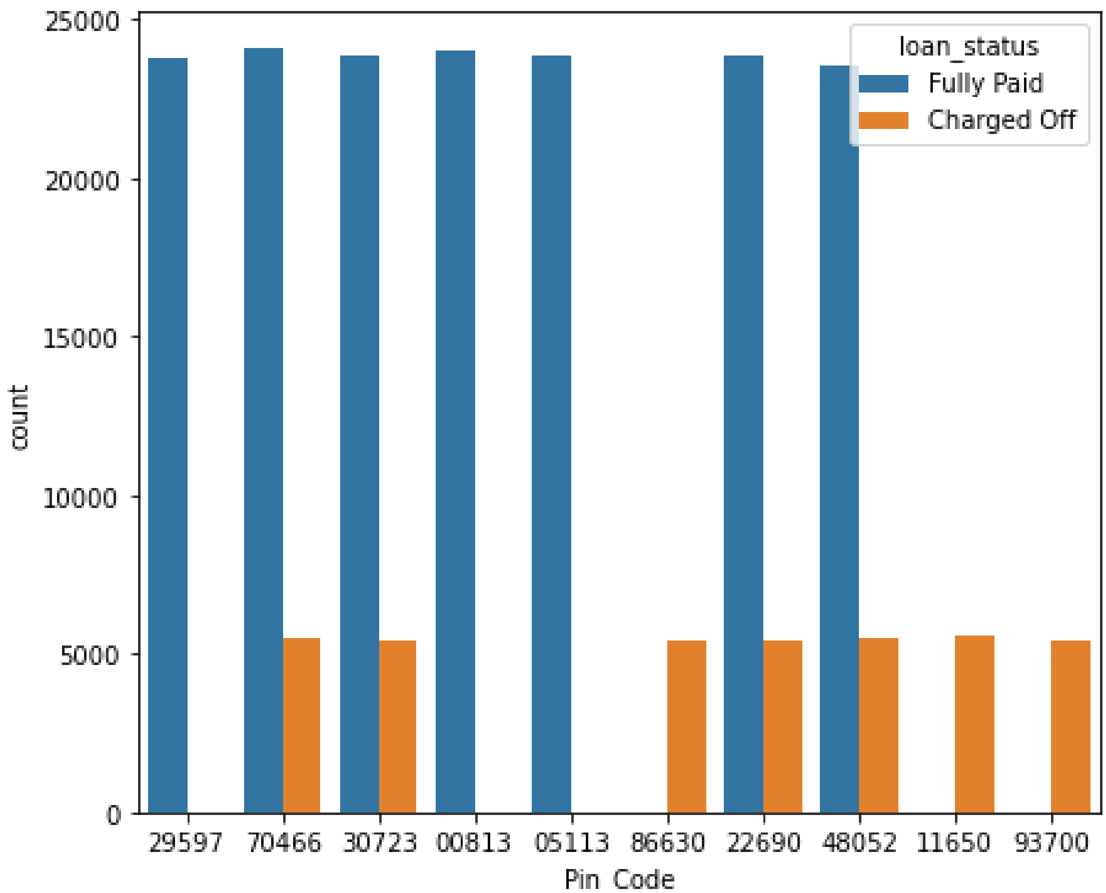
```
plt.figure(figsize=(7,5))
sns.countplot(df_train['Pin_Code'])
plt.xticks(rotation=90)
plt.show()
#Later we can encode this data.
```

```
70466    14.0
22690    14.0
30723    14.0
48052    14.0
00813    12.0
05113    12.0
29597    12.0
11650     3.0
86630     3.0
93700     3.0
Name: Pin_Code, dtype: float64
```



[158]:
```
#Checking Loan_Status with Pin_Code to check if there is any relationship
plt.figure(figsize=(7,6))
sns.countplot(data=df_train,x='Pin_Code',hue='loan_status')
```

```
plt.show()
```



[159]:
```
np.round(pd.
→crosstab(df_train['loan_status'],df_train['Pin_Code'],normalize='columns')*100)
```

[159]:
```
Pin_Code      00813  05113  11650  22690  29597  30723  48052  70466  86630  \
loan_status
Charged Off     0.0    0.0  100.0   19.0    0.0   19.0   19.0   19.0  100.0
Fully Paid    100.0  100.0    0.0   81.0  100.0   81.0   81.0   81.0    0.0

Pin_Code      93700
loan_status
Charged Off   100.0
Fully Paid      0.0
```

[160]:
```
# Since "Pin_Code" is a categorical variable, therefore adding it to the␣
→categorical_columns variable.
categorical_columns.append('Pin_Code')
```

[ ]:

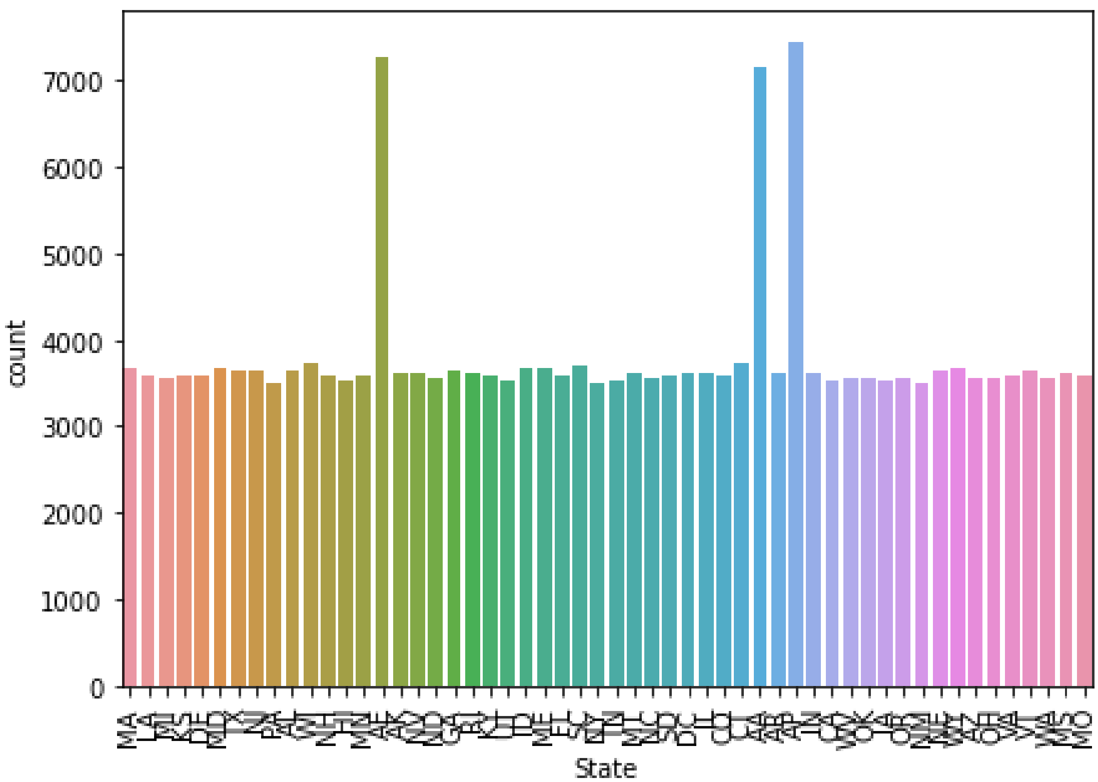
```

```

[161]:

```
#Checking the percentage of occurence of each of the categories of "State".
print(np.round(df_train['State'].value_counts(normalize=True)*100))

plt.figure(figsize=(7,5))
sns.countplot(df_train['State'])
plt.xticks(rotation=90)
plt.show()
#Later we can encode this data.
```

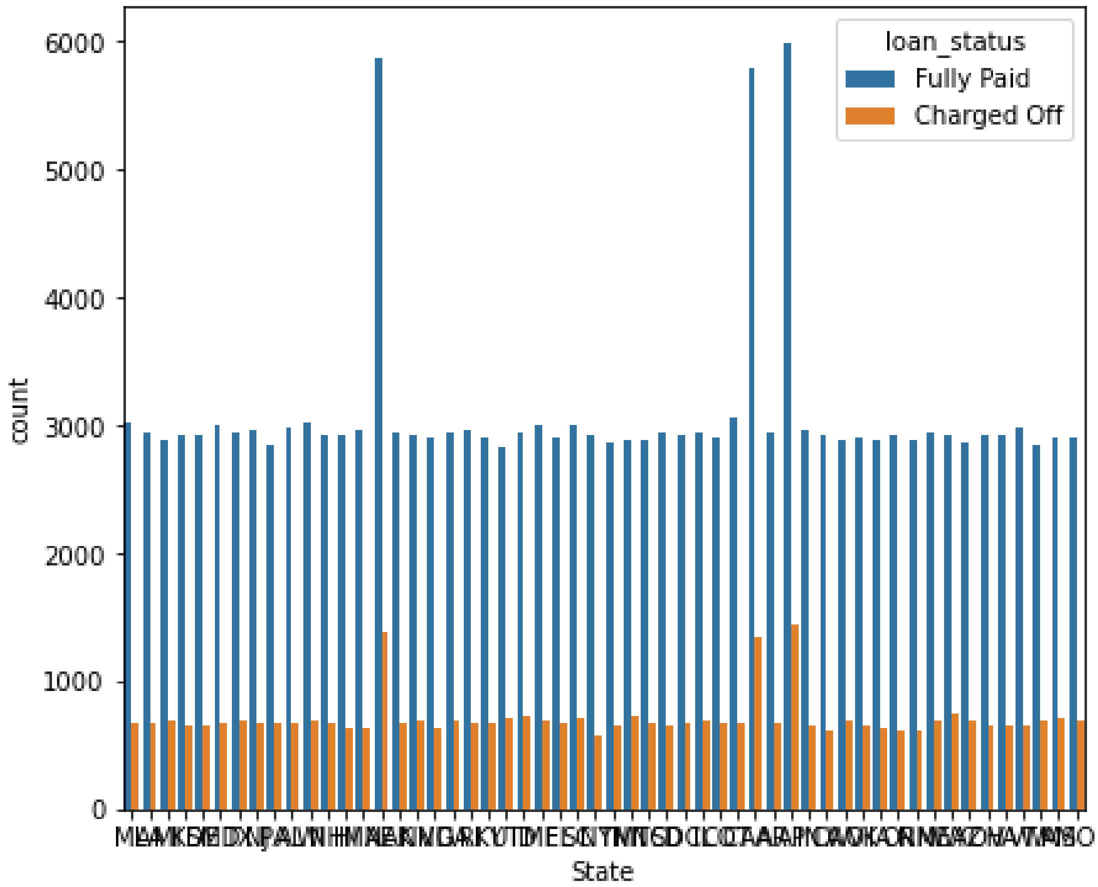
```
AP    4.0
AE    4.0
AA    3.0
CT    2.0
WI    2.0
SC    2.0
MA    2.0
ME    2.0
WY    2.0
MD    2.0
ID    2.0
AL    2.0
NJ    2.0
NE    2.0
GA    2.0
TX    2.0
VT    2.0
AK    2.0
IN    2.0
AR    2.0
RI    2.0
IL    2.0
NV    2.0
MT    2.0
MS    2.0
DC    2.0
LA    2.0
MO    2.0
MN    2.0
SD    2.0
NH    2.0
CO    2.0
VA    2.0
DE    2.0
FL    2.0
KS    2.0
KY    2.0
```

```
OH    2.0
OK    2.0
MI    2.0
WV    2.0
OR    2.0
NC    2.0
WA    2.0
AZ    2.0
ND    2.0
UT    2.0
HI    2.0
TN    2.0
CA    2.0
IA    2.0
PA    2.0
NM    2.0
NY    2.0
Name: State, dtype: float64
```



[162]:
```
#Checking Loan_Status with Pin_Code to check if there is any relationship
plt.figure(figsize=(7,6))
sns.countplot(data=df_train,x='State',hue='loan_status')
```

```
plt.show()
```



[163]:
```
np.round(pd.
↪crosstab(df_train['loan_status'],df_train['State'],normalize='columns')*100)
```

[163]:
```
State          AA    AE    AK    AL    AP    AR    AZ    CA    CO    CT  …  \
loan_status                                                              …
Charged Off  19.0  19.0  19.0  19.0  19.0  19.0  19.0  17.0  19.0  18.0  …
Fully Paid   81.0  81.0  81.0  81.0  81.0  81.0  81.0  83.0  81.0  82.0  …

State          SD    TN    TX    UT    VA    VT    WA    WI    WV    WY
loan_status
Charged Off  18.0  19.0  19.0  20.0  18.0  18.0  19.0  19.0  19.0  20.0
Fully Paid   82.0  81.0  81.0  80.0  82.0  82.0  81.0  81.0  81.0  80.0

[2 rows x 54 columns]
```

[164]:
```
# Since "State" is a categorical variable, therefore adding it to the␣
 ↪categorical_columns variable.
categorical_columns.append('State')
```

[165]:
```
#Dropping Address column
df_train.drop(columns='address',inplace=True)
```

[166]:
```
df_train.shape
```

[166]:
```
(205399, 26)
```

[ ]:
```

```

0.3.30 Interval - Number Of days between issue_date and earliest_cr_line

[167]:
```
# earliest_cr_line :The month the borrower's earliest reported credit line was␣
 ↪opened
# issue_d : The month which the loan was funded
(df_train['issue_d']-df_train['earliest_cr_line'])
```

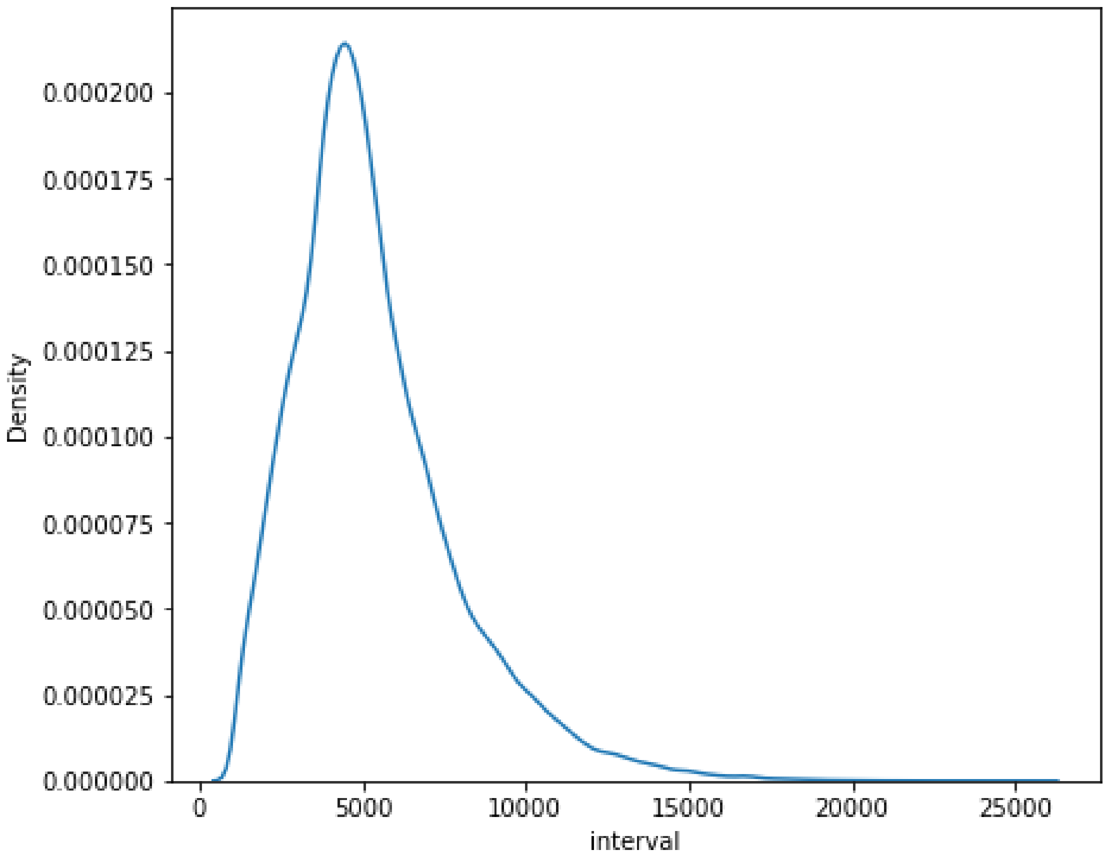
[167]:
```
0         4778 days
2         4871 days
3         6270 days
4         6909 days
5         5236 days
            …
316818    4291 days
316819    3103 days
316820    2740 days
316821    3468 days
316823    2434 days
Length: 205399, dtype: timedelta64[ns]
```

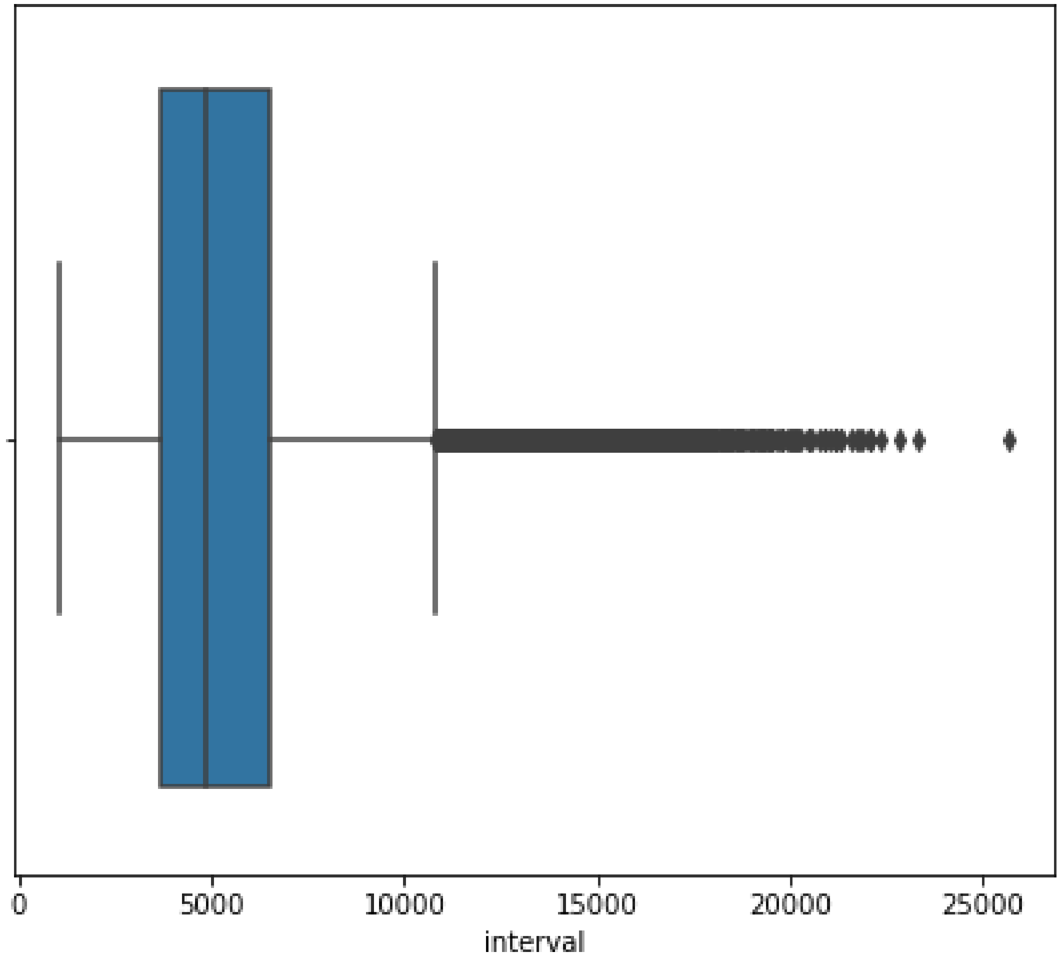
[168]:
```
df_train['interval']=(df_train['issue_d']-df_train['earliest_cr_line']).dt.days
df_test['interval']=(df_test['issue_d']-df_test['earliest_cr_line']).dt.days
```

[169]:
```
variable='interval'
#Checking for null values
print('Number of Null Values -',df_train[variable].isna().sum())
#There are no null values

#Checking for number of unique values
print('Number of Unique Values -',df_train[variable].nunique())
#There are 2234 unique values
# This is a continuous variable
```

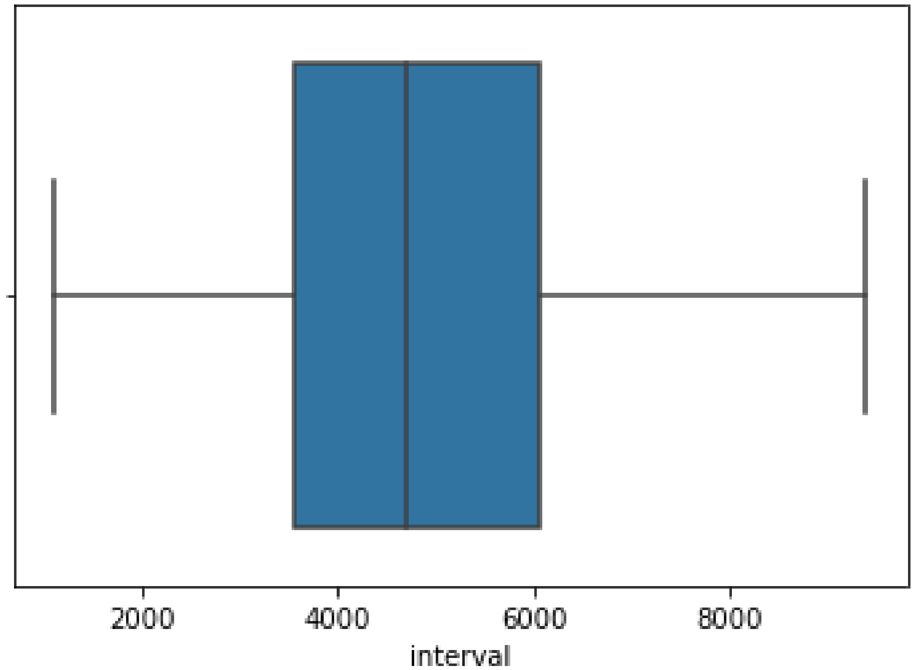
```
Number of Null Values - 0
Number of Unique Values - 2300
```

[170]:
```
plt.figure(figsize=(7,6))
sns.kdeplot(df_train[variable])
plt.show()
#Data looks right skewed

plt.figure(figsize=(7,6))
sns.boxplot(df_train[variable])
plt.show()
#There are few outliers in the data
```

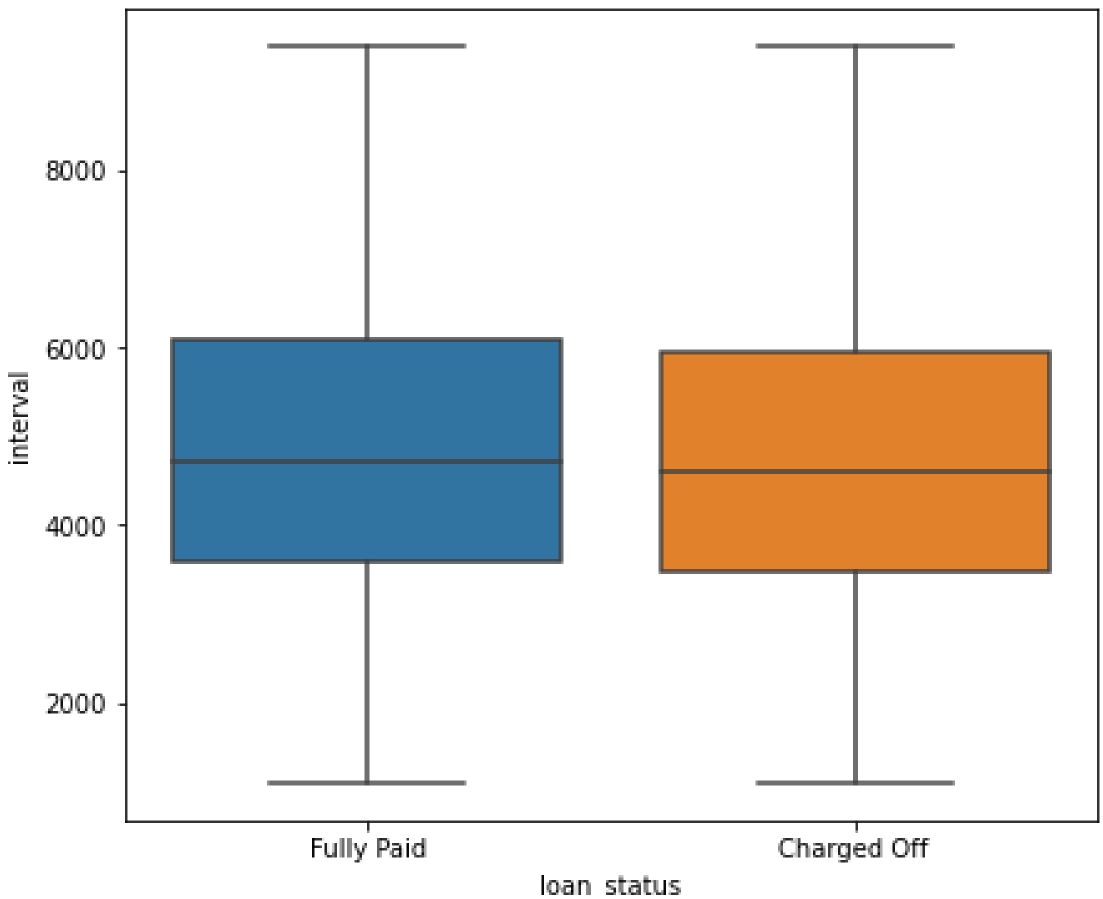




[171]:
```
#Removing the outliers
q75=np.percentile(df_train[variable],75)
q25=np.percentile(df_train[variable],25)
iqr=q75-q25
sns.boxplot(df_train.loc[df_train[variable]<iqr+q75,variable])
plt.show()
df_train=df_train.loc[df_train[variable]<iqr+q75]
#The outliers have been removed
```



[172]:
```
#Checking Loan_Status with Loan_Amount to check if there is any relationship
plt.figure(figsize=(7,6))
sns.boxplot(data=df_train,y=variable,x='loan_status')
plt.show()
#Observation - The median loan_amount is higher for charged off loans in␣
↪comparison to fully_paid loans.
```



[173]:
```
df_train.groupby(by='loan_status').mean()[variable]
#Observation - The mean loan_amount is higher for charged off loans in␣
↪comparison to fully_paid loans.
```

[173]:
```
loan_status
Charged Off    4765.899567
Fully Paid     4885.571776
Name: interval, dtype: float64
```

[174]:
```
# Since mean and median loan_amount is different for different classes,␣
↪therefore it could be an important feature.
# Since it is a continuous variable, therefore adding it to the␣
↪continuous_columns variable.
continuous_columns.append(variable)
```

[ ]:
```

```

[175]:
```
### Dropping "issue_date" and "earliest_cr_line" columns
df_train.drop(columns=['issue_d','earliest_cr_line'],inplace=True)
df_test.drop(columns=['issue_d','earliest_cr_line'],inplace=True)
```

[ ]:
```

```

0.3.31 Final Dataset

[176]:
```
y_train=df_train['loan_status']
df_train=df_train[categorical_columns+continuous_columns]
y_test=df_test['loan_status']
df_test=df_test[categorical_columns+continuous_columns]
```

[177]:
```
df_train.shape
```

[177]: (190191, 23)

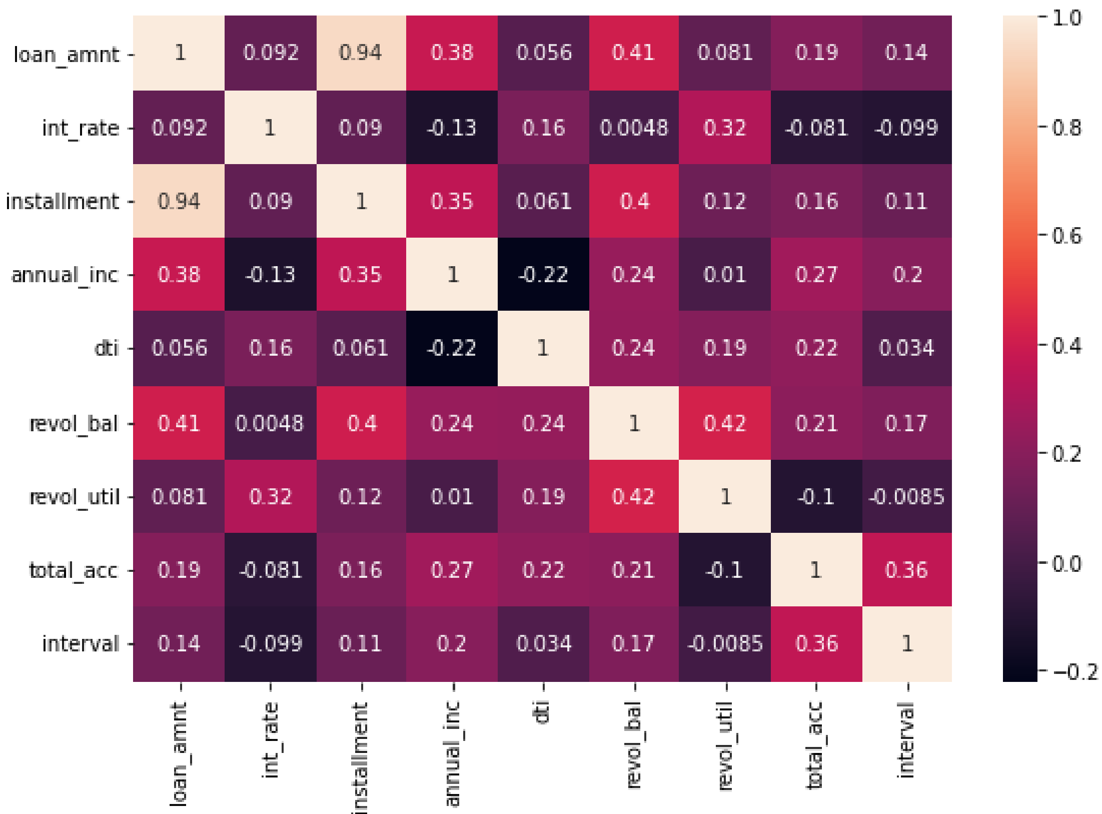
[178]:
```
df_test.shape
```

[178]: (79206, 23)

[ ]:
```

```

0.3.32 Descriptive Statistics

[179]:
```
plt.figure(figsize=(9,6))
sns.heatmap(df_train[continuous_columns].corr(),annot=True)
plt.show()
```



[180]:
```
#Continuous Variables Summary
df_train[continuous_columns].describe()
```

[180]:

	loan_amnt	int_rate	installment	annual_inc
count	190191.000000	190191.000000	190191.000000	190191.000000
mean	11308.507763	13.216712	348.357316	58122.886891
std	5986.641419	3.871707	170.528153	23318.048798
min	500.000000	5.320000	16.250000	4000.000000
25%	6550.000000	10.490000	217.660000	40000.000000
50%	10000.000000	13.110000	328.060000	55000.000000
75%	15000.000000	15.810000	466.150000	72500.000000
max	31975.000000	22.400000	807.790000	123996.000000

	dti	revol_bal	revol_util	total_acc
count	190191.000000	190191.000000	190191.000000	190191.000000
mean	16.530831	9916.130842	52.769850	21.136079
std	7.705130	6304.195266	24.237657	8.649889
min	0.000000	0.000000	0.000000	2.000000
25%	10.740000	5002.000000	35.000000	15.000000
50%	16.180000	8781.000000	53.500000	20.000000
75%	22.020000	13952.000000	71.500000	27.000000

```
max        34.940000   26972.000000     107.000000      42.000000

            interval
count  190191.000000
mean     4863.167726
std      1841.887359
min      1095.000000
25%      3562.000000
50%      4689.000000
75%      6058.000000
max      9405.000000
```

[181]:
```python
#Categorical Variables Summary
df_train[categorical_columns].describe(include='object').T
```

[181]:
```
                      count unique                 top    freq
term                 190191      2           36 months  154323
grade                190191      7                   B   60239
sub_grade            190191      5                   4   39054
emp_length           182001     11           10+ years   52990
home_ownership       190191      6                RENT   89660
verification_status  190191      3        Not Verified   72259
purpose              190191     14  debt_consolidation  112123
initial_list_status  190191      2                   f  118590
application_type     190191      3          INDIVIDUAL  190050
Pin_Code             190191     10               70466   27448
State                190191     54                  AP    6885
```

[ ]:

0.3.33 Missing Value Treatment

[182]:
```python
#Checking for columns which have missing values
for column in df_train.columns:
    print(column,df_train[column].isna().sum())
```

```
term 0
grade 0
sub_grade 0
emp_length 8190
home_ownership 0
verification_status 0
purpose 0
pub_rec 0
initial_list_status 0
application_type 0
mort_acc 0
pub_rec_bankruptcies 0
```

```
Pin_Code 0
State 0
loan_amnt 0
int_rate 0
installment 0
annual_inc 0
dti 0
revol_bal 0
revol_util 0
total_acc 0
interval 0
```

[183]:
```python
# Checking emp_length variable
df_train['emp_length'].value_counts()
```

[183]:
```
10+ years    52990
2 years      18464
3 years      16331
< 1 year     16270
5 years      13893
1 year       13412
4 years      12423
6 years      10657
7 years      10575
8 years       9527
9 years       7459
Name: emp_length, dtype: int64
```

[184]:
```python
# Imputing with Mode Value
df_train['emp_length'].fillna('10+ years',inplace=True)
```

[185]:
```python
df_train['emp_length'].isna().sum()
#All missing values imputed
```

[185]:
```
0
```

[ ]:
```python

```

0.3.34 Imputing Test Dataset

[186]:
```python
df_test['emp_length'].fillna('10+ years',inplace=True)
df_test['pub_rec_bankruptcies'].
 ↪fillna(mode_pub_rec_bankruptcies[0],inplace=True)
df_test['revol_util'].fillna(median_revol_util,inplace=True)
df_test['mort_acc'].fillna(mode_more_acc[0],inplace=True)
```

[187]:
```python
df_test.isna().sum()
```

[187]:
```
term                    0
grade                   0
sub_grade               0
emp_length              0
home_ownership          0
verification_status     0
purpose                 0
pub_rec                 0
initial_list_status     0
application_type        0
mort_acc                0
pub_rec_bankruptcies    0
Pin_Code                0
State                   0
loan_amnt               0
int_rate                0
installment             0
annual_inc              0
dti                     0
revol_bal               0
revol_util              0
total_acc               0
interval                0
dtype: int64
```

[ ]:

0.3.35 Scaling Continuous Variables

[188]:
```
scaler=StandardScaler()
df_train_scaled=scaler.fit_transform(df_train[continuous_columns])
df_train_scaled=pd.
 ↪DataFrame(data=df_train_scaled,columns=df_train[continuous_columns].columns)
df_test_scaled=scaler.transform(df_test[continuous_columns])
df_test_scaled=pd.
 ↪DataFrame(data=df_test_scaled,columns=df_test[continuous_columns].columns)
```

[189]:
```
df_train_scaled.shape
```

[189]: (190191, 9)

[190]:
```
df_train.shape
```

[190]: (190191, 23)

[ ]:

0.3.36 Encoding Categorical Variables

[191]:
```
categorical_columns
```

[191]:
```
['term',
 'grade',
 'sub_grade',
 'emp_length',
 'home_ownership',
 'verification_status',
 'purpose',
 'pub_rec',
 'initial_list_status',
 'application_type',
 'mort_acc',
 'pub_rec_bankruptcies',
 'Pin_Code',
 'State']
```

[192]:
```
#Term
print(df_train['term'].unique())
mapping={' 60 months':1,' 36 months':0}
df_train['term']=df_train['term'].map(mapping)
df_test['term']=df_test['term'].map(mapping)
```

```
[' 36 months' ' 60 months']
```

[193]:
```
#grade
print(df_train['grade'].unique())
mapping={'A':1,'B':2,'C':3,'D':4,'E':5,'F':6,'G':7}
df_train['grade']=df_train['grade'].map(mapping)
df_test['grade']=df_test['grade'].map(mapping)
```

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

[194]:
```
#sub_grade
print(df_train['sub_grade'].unique())
df_train['sub_grade']=df_train['sub_grade'].astype('int')
df_test['sub_grade']=df_test['sub_grade'].astype('int')
```

```
['4' '3' '1' '5' '2']
```

[195]:
```
#emp_length
print(df_train['emp_length'].unique())
mapping={'< 1 year':0,'1 year':1,'2 years':2,'3 years':3,'4 years':4,'5 years':
 ↪5,
         '6 years':6,'7 years':7,'8 years':8,'9 years':9,'10+ years':10}
df_train['emp_length']=df_train['emp_length'].map(mapping)
df_test['emp_length']=df_test['emp_length'].map(mapping)
```

```
['3 years' '7 years' '10+ years' '< 1 year' '1 year' '6 years' '8 years'
 '4 years' '5 years' '9 years' '2 years']
```

[196]:
```
#home_ownership
print(df_train['home_ownership'].unique())
#Using One Hot Encoding Encoder
encoder=OneHotEncoder()
home_ownership_encoded=encoder.fit_transform(df_train[['home_ownership']]).
 ↪toarray()
home_ownership_encoded_train=pd.
 ↪DataFrame(data=home_ownership_encoded,columns=encoder.categories_)
home_ownership_encoded=encoder.fit_transform(df_test[['home_ownership']]).
 ↪toarray()
home_ownership_encoded_test=pd.
 ↪DataFrame(data=home_ownership_encoded,columns=encoder.categories_)
```

```
['RENT' 'MORTGAGE' 'OWN' 'OTHER' 'NONE' 'ANY']
```

[197]:
```
home_ownership_encoded_train.shape
```

[197]:
```
(190191, 6)
```

[198]:
```
#verification_status
print(df_train['verification_status'].unique())
#Using One Hot Encoding Encoder
encoder=OneHotEncoder()
verification_status_encoded=encoder.
 ↪fit_transform(df_train[['verification_status']]).toarray()
verification_status_train=pd.
 ↪DataFrame(data=verification_status_encoded,columns=encoder.categories_)
verification_status_encoded=encoder.
 ↪fit_transform(df_test[['verification_status']]).toarray()
verification_status_test=pd.
 ↪DataFrame(data=verification_status_encoded,columns=encoder.categories_)
```

```
['Source Verified' 'Verified' 'Not Verified']
```

[199]:
```
#purpose
print(df_train['purpose'].unique())
#Using One Hot Encoding Encoder
encoder=OneHotEncoder()
purpose_encoded=encoder.fit_transform(df_train[['purpose']]).toarray()
purpose_train=pd.DataFrame(data=purpose_encoded,columns=encoder.categories_)
purpose_encoded=encoder.fit_transform(df_test[['purpose']]).toarray()
purpose_test=pd.DataFrame(data=purpose_encoded,columns=encoder.categories_)
```

```
['credit_card' 'debt_consolidation' 'home_improvement' 'medical' 'car'
 'major_purchase' 'wedding' 'house' 'moving' 'other' 'vacation'
 'small_business' 'educational' 'renewable_energy']
```

[200]:
```
#pub_rec
print(df_train['pub_rec'].unique())
df_train.loc[df_train['pub_rec']=='6+','pub_rec']=7
df_test.loc[df_test['pub_rec']=='6+','pub_rec']=7
```

```
[0. 1.]
```

[201]:
```
#initial_list_status
print(df_train['initial_list_status'].unique())
#Using One Hot Encoding Encoder
encoder=OneHotEncoder()
initial_list_status_encoded=encoder.
↪fit_transform(df_train[['application_type']]).toarray()
initial_list_status_train=pd.
↪DataFrame(data=initial_list_status_encoded,columns=encoder.categories_)
initial_list_status_encoded=encoder.
↪fit_transform(df_test[['application_type']]).toarray()
initial_list_status_test=pd.
↪DataFrame(data=initial_list_status_encoded,columns=encoder.categories_)
```

```
['f' 'w']
```

[202]:
```
#application_type
print(df_train['application_type'].unique())
#Using One Hot Encoding Encoder
encoder=OneHotEncoder()
application_type_encoded=encoder.fit_transform(df_train[['application_type']]).
↪toarray()
application_type_train=pd.
↪DataFrame(data=application_type_encoded,columns=encoder.categories_)
application_type_encoded=encoder.fit_transform(df_test[['application_type']]).
↪toarray()
application_type_test=pd.
↪DataFrame(data=application_type_encoded,columns=encoder.categories_)
```

```
['INDIVIDUAL' 'JOINT' 'DIRECT_PAY']
```

[203]:
```
#pub_rec_bankruptcies
print(df_train['pub_rec_bankruptcies'].unique())
# This categorical feature is already encoded and looks fine.
```

```
[0. 1.]
```

[204]:
```
#Pin_Code
print(df_train['Pin_Code'].unique())
#Using One Hot Encoding Encoder
encoder=OneHotEncoder()
pincode_encoded=encoder.fit_transform(df_train[['Pin_Code']]).toarray()
pincode_train=pd.DataFrame(data=pincode_encoded,columns=encoder.categories_)
```

```
pincode_encoded=encoder.fit_transform(df_test[['Pin_Code']]).toarray()
pincode_test=pd.DataFrame(data=pincode_encoded,columns=encoder.categories_)
```

```
['29597' '70466' '30723' '00813' '86630' '22690' '48052' '05113' '11650'
 '93700']
```

[205]:
```
#State
print(df_train['State'].unique())
#Using One Hot Encoding Encoder
encoder=OneHotEncoder()
State_encoded=encoder.fit_transform(df_train[['State']]).toarray()
State_train=pd.DataFrame(data=State_encoded,columns=encoder.categories_)
State_encoded=encoder.fit_transform(df_test[['State']]).toarray()
State_test=pd.DataFrame(data=State_encoded,columns=encoder.categories_)
```

```
['MA' 'LA' 'MI' 'KS' 'DE' 'MD' 'TX' 'NJ' 'PA' 'AL' 'WI' 'NH' 'HI' 'AK'
 'NV' 'AE' 'ND' 'RI' 'KY' 'UT' 'ID' 'MN' 'GA' 'ME' 'FL' 'NY' 'TN' 'MT'
 'SD' 'DC' 'IL' 'CO' 'CT' 'AA' 'AP' 'IN' 'CA' 'WV' 'NC' 'OK' 'AR' 'IA'
 'OR' 'NM' 'NE' 'WY' 'AZ' 'OH' 'VT' 'VA' 'WA' 'SC' 'MO' 'MS']
```

[ ]:
```

```

[206]:
```
#Encoding Target Variable
y_train.value_counts()
mapping={'Fully Paid':1,'Charged Off':0}
y_train=y_train.map(mapping)
y_test=y_test.map(mapping)
```

[207]:
```
### Final Check For Missing Values in Train Data
for column in df_train.columns:
    print(column,df_train[column].isna().sum())
```

```
term 0
grade 0
sub_grade 0
emp_length 0
home_ownership 0
verification_status 0
purpose 0
pub_rec 0
initial_list_status 0
application_type 0
mort_acc 0
pub_rec_bankruptcies 0
Pin_Code 0
State 0
loan_amnt 0
int_rate 0
installment 0
```

```
annual_inc 0
dti 0
revol_bal 0
revol_util 0
total_acc 0
interval 0
```

[208]:
```
### Final Check For Missing Values in Test Data
for column in df_test.columns:
    print(column,df_test[column].isna().sum())
```

```
term 0
grade 0
sub_grade 0
emp_length 0
home_ownership 0
verification_status 0
purpose 0
pub_rec 0
initial_list_status 0
application_type 0
mort_acc 0
pub_rec_bankruptcies 0
Pin_Code 0
State 0
loan_amnt 0
int_rate 0
installment 0
annual_inc 0
dti 0
revol_bal 0
revol_util 0
total_acc 0
interval 0
```

[209]:
```
df_train.reset_index(drop=True,inplace=True)
df_test.reset_index(drop=True,inplace=True)
```

[210]:
```
### Combining all one hot encoded categorical columns in train_dataset and␣
↪test_dataset
train_onehotencoded_columns=pd.
↪concat((home_ownership_encoded_train,verification_status_train,purpose_train,
                                                      ␣
↪initial_list_status_train,application_type_train,pincode_train,State_train),axis=1)
test_onehotencoded_columns=pd.
↪concat((home_ownership_encoded_test,verification_status_test,purpose_test,
                                                      ␣
↪initial_list_status_test,application_type_test,pincode_test,State_test),axis=1)
```

[211]:
```
### Combining all categorical columns in train_dataset and test_dataset
train_categorical=pd.
↪concat((df_train[['term','grade','sub_grade','emp_length','pub_rec','pub_rec_bankruptcies']],
                              train_onehotencoded_columns),axis=1)
test_categorical=pd.
↪concat((df_test[['term','grade','sub_grade','emp_length','pub_rec','pub_rec_bankruptcies']],
                              test_onehotencoded_columns),axis=1)
```

[212]:
```
### Combining continuous and categorical columns in train_dataset and␣
↪test_dataset
df_train=pd.concat((df_train[continuous_columns],train_categorical),axis=1)
df_test=pd.concat((df_test[continuous_columns],test_categorical),axis=1)
```

[213]:
```
print(df_train.shape,df_test.shape)
```

```
(190191, 108) (79206, 108)
```

[ ]:
```

```

0.3.37 Fitting The Logistic Regression Model

[214]:
```
model=LogisticRegression()
model.fit(df_train,y_train)
y_pred=model.predict(df_test)
y_pred_proba=model.predict_proba(df_test)
```

[215]:
```
# Model Coefficients
coefficients=pd.DataFrame(data=model.coef_,columns=df_train.columns)
coefficients
```

[215]:
```
   loan_amnt  int_rate  installment  annual_inc       dti  revol_bal  \
0  -0.000132 -0.024731     0.003395     0.00002 -0.005697   0.000001

   revol_util  total_acc  interval      term  …     (SD,)     (TN,)  \
0    0.001411   0.027631   0.00008 -0.002571  …  0.000104  0.000056

      (TX,)     (UT,)    (VA,)     (VT,)     (WA,)     (WI,)     (WV,)  \
0  0.000056 -0.000004  0.00006  0.000099 -0.000012  0.000042  0.000027

      (WY,)
0 -0.000026

[1 rows x 108 columns]
```

[216]:
```
coefficients.T.sort_values(by=0,ascending=False)
```

[216]:
```
                  0
total_acc  0.027631
```

```
sub_grade  0.008685
(00813,)   0.006199
(29597,)   0.006136
(05113,)   0.006134
…              …
(93700,)  -0.005631
dti       -0.005697
(11650,)  -0.005747
grade     -0.012609
int_rate  -0.024731

[108 rows x 1 columns]
```

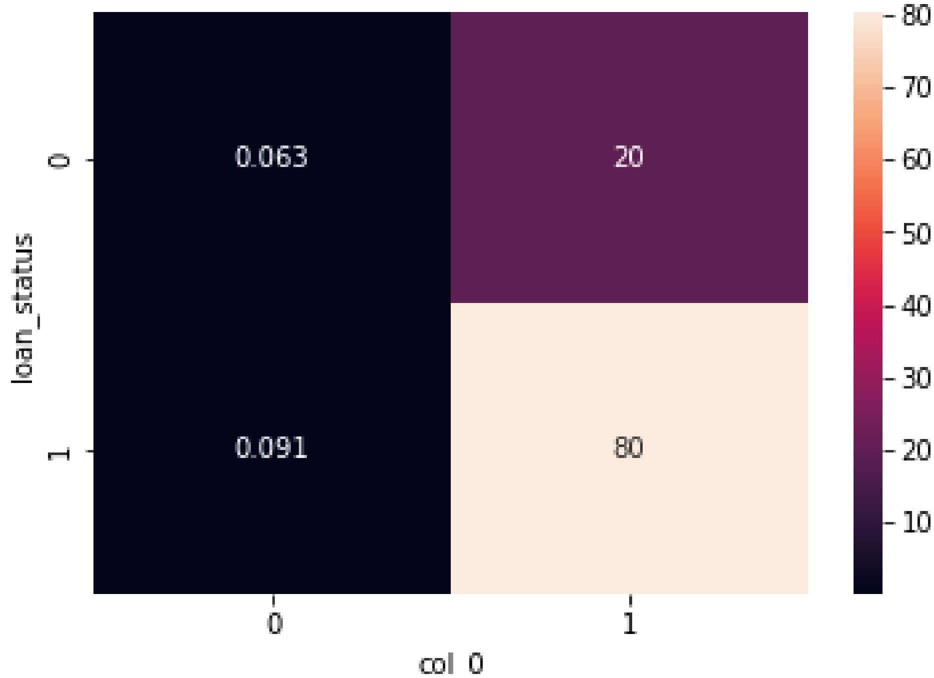
[217]:
```
#Train_Accuracy
model.score(df_train,y_train)
```

[217]: 0.8122361205314658

[218]:
```
#Test_Accuracy
model.score(df_test,y_test)
```

[218]: 0.8031462262959876

[219]:
```
#Checking the probabilities for TP,TN,FP,FN
sns.heatmap(pd.crosstab(y_test,y_pred,normalize=True)*100,annot=True)
plt.show()
#Observation - There are a lot of False Positives, and very less False
 ↪Negatives.
```



[ ]:

[220]:
```
# Precision
precision_score(y_test,y_pred)
# Precision is okayish.
```

[220]: 0.8037529715239492

[221]:
```
# Recall
recall_score(y_test,y_pred)
# Recall score is very good.
```

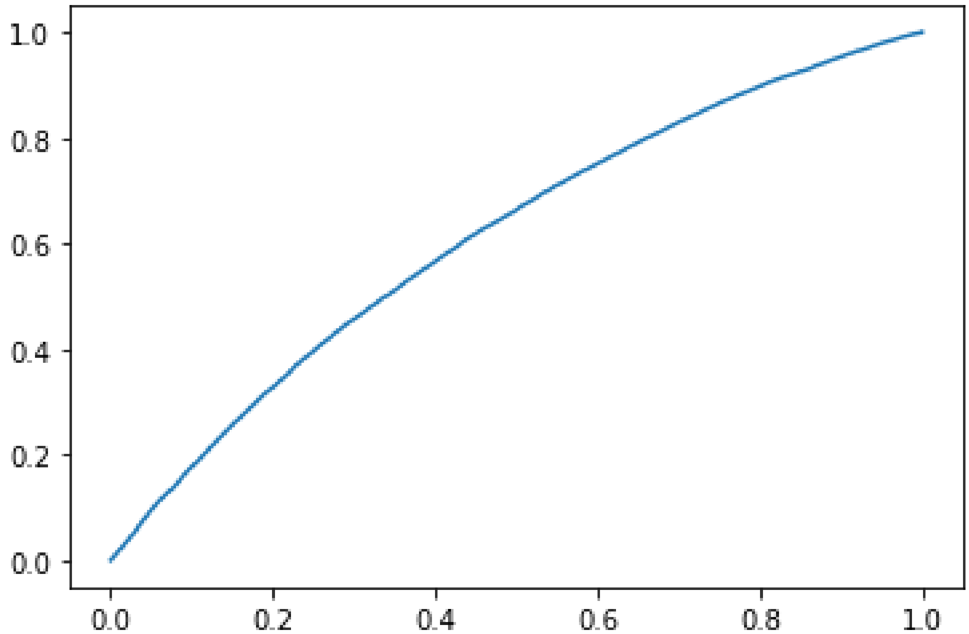
[221]: 0.9988685649632284

[222]:
```
# F1_Score
f1_score(y_test,y_pred)
# F1 Score is good.
```

[222]: 0.8907511210762332

[223]:
```
#ROC_Curve
fpr, tpr, thresholds=roc_curve(y_test,y_pred_proba[:,1])
plt.plot(fpr,tpr)
plt.plot()
#The curve is better than the average model.
```

[223]: []

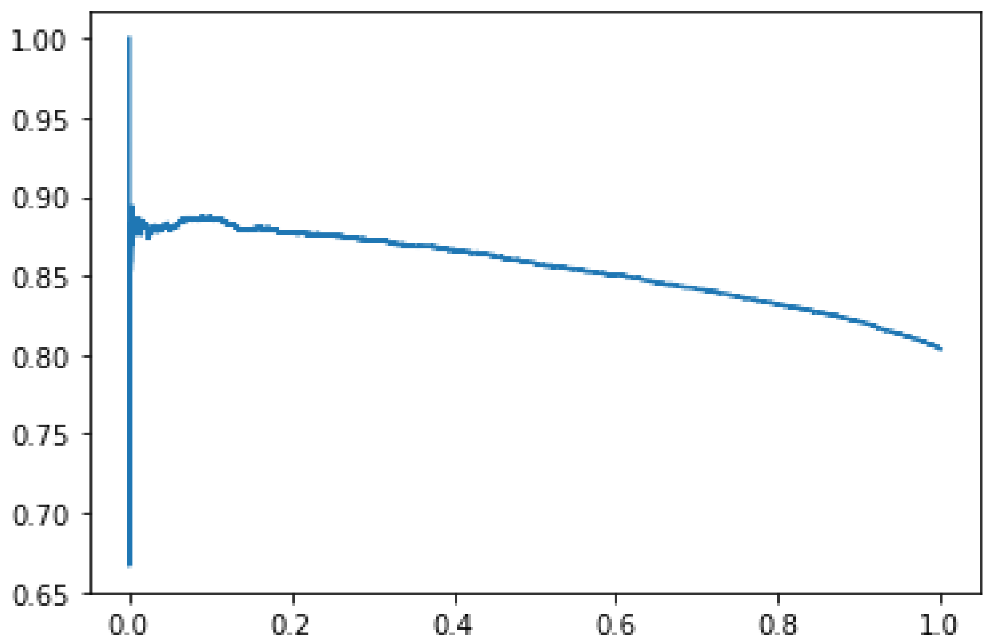


[224]:
```
#ROC_AUC
roc_auc_score(y_test,y_pred_proba[:,1])
# The ROC_AUC_Score is good.
```

[224]: 0.6142135007539065

[225]:
```
precision, recall, thresholds=precision_recall_curve(y_test,y_pred_proba[:,1])
plt.plot(recall,precision)
plt.plot()
#The curve is better than the average model.
```

[225]: []



[226]:
```
#Precision_Recall_AUC
auc(recall,precision)
# The Precision_Recall_AUC score is good
```

[226]: 0.8544597651544354

[ ]:

0.3.38 Understanding the Business Requirements

- How can we make sure that our model can detect real defaulters and there are less false positives? This is important as we can lose out on an opportunity to finance more individuals and earn interest on it.
- We can increase the probability threshold to decrease false positives to handle this situation.
- Since NPA (non-performing asset) is a real problem in this industry, it's important we play safe and shouldn't disburse loans to anyone.
- We can increase the probability threshold for the positive class to decrease false positives to handle this situation.

[ ]:

0.3.39 Actionable Insights & Recommendations

- Term is an important feature in determining the loan_status.
- Interest_Rate is an important feature in determining the loan_status.
- Loan_Amount is an important feature in determining the loan_status.

- Grade is an important feature in determining the loan_status.
- Annual_Income is an important feature in determining the loan_status.
- Verification_Status is an important feature in determining the loan_status.
- dti is an important feature in determining the loan_status.
- application_type is an important feature in determining the loan_status.

[ ]:

```

```