Lending group case study

Input as given in the case study

You work for a consumer finance company which specialises in lending various types of loans to urban customers. When the company receives a loan application, the company has to make a decision for loan approval based on the applicant's profile. Two types of risks are associated with the bank's decision:

If the applicant is likely to repay the loan, then not approving the loan results in a loss of business to the company

If the applicant is not likely to repay the loan, i.e. he/she is likely to default, then approving the loan may lead to a financial loss for the company

The data given below contains information about past loan applicants and whether they 'defaulted' or not. The aim is to identify patterns which indicate if a person is likely to default, which may be used for taking actions such as denying the loan, reducing the amount of loan, lending (to risky applicants) at a higher interest rate, etc.

In this case study, you will use EDA to understand how consumer attributes and loan attributes influence the tendency of default.

When a person applies for a loan, there are two types of decisions that could be taken by the company:

Loan accepted: If the company approves the loan, there are 3 possible scenarios described below:

Fully paid: Applicant has fully paid the loan (the principal and the interest rate)

Current: Applicant is in the process of paying the instalments, i.e. the tenure of the loan is not yet completed. These candidates are not labelled as 'defaulted'.

Charged-off: Applicant has not paid the instalments in due time for a long period of time, i.e. he/she has defaulted on the loan

Loan rejected: The company had rejected the loan (because the candidate does not meet their requirements etc.). Since the loan was rejected, there is no transactional history of those applicants with the company and so this data is not available with the company (and thus in this dataset)

Business Objectives

Risk Analytics for Loan Default Prediction

The company's business objective is to employ Exploratory Data Analysis (EDA) to identify the key driving factors (driver variables) behind loan defaults. By understanding and leveraging these indicators of default, the company aims to enhance its risk assessment and portfolio management strategies, ultimately reducing credit losses and improving its lending practices.

Importing python packages

```
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
```

Reading the loan Information CSV File

```
loan_df=pd.read_csv("loan_dataset.csv")
```

Getting General information of the dataset

```
loan_df.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 39717 entries, 0 to 39716
Columns: 111 entries, id to total_il_high_credit_limit
dtypes: float64(74), int64(13), object(24)
memory usage: 33.6+ MB
```

From the above obersvation we confirm that there are 111 Columns, with the following data types float64(74), int64(13), object(24) and a total of 39717 rows

Exploring the CSV file to look at the coloumn and row values for starting the data cleaning exercise

```
loan_df.head()

        id  member_id  loan_amnt  funded_amnt  funded_amnt_inv
term  \
0  1077501    1296599       5000         5000           4975.0    36
months
1  1077430    1314167       2500         2500           2500.0    60
months
2  1077175    1313524       2400         2400           2400.0    36
months
3  1076863    1277178      10000        10000          10000.0    36
months
4  1075358    1311748       3000         3000           3000.0    60
months

  int_rate  installment grade sub_grade  ... num_tl_90g_dpd_24m  \
0   10.65%       162.87     B        B2  ...                NaN
1   15.27%        59.83     C        C4  ...                NaN
```

```
2   15.96%        84.33     C        C5  ...                 NaN
3   13.49%       339.31     C        C1  ...                 NaN
4   12.69%        67.79     B        B5  ...                 NaN

  num_tl_op_past_12m pct_tl_nvr_dlq  percent_bc_gt_75
pub_rec_bankruptcies  \
0                NaN            NaN               NaN
0.0
1                NaN            NaN               NaN
0.0
2                NaN            NaN               NaN
0.0
3                NaN            NaN               NaN
0.0
4                NaN            NaN               NaN
0.0

  tax_liens tot_hi_cred_lim total_bal_ex_mort total_bc_limit  \
0       0.0             NaN               NaN            NaN
1       0.0             NaN               NaN            NaN
2       0.0             NaN               NaN            NaN
3       0.0             NaN               NaN            NaN
4       0.0             NaN               NaN            NaN

  total_il_high_credit_limit
0                        NaN
1                        NaN
2                        NaN
3                        NaN
4                        NaN

[5 rows x 111 columns]
```

Data Cleaning for loan dataset

Exploring Null values in the dataset

```
loan_df.isnull().sum()

id                                  0
member_id                           0
loan_amnt                           0
funded_amnt                         0
funded_amnt_inv                     0
                                ...
tax_liens                          39
tot_hi_cred_lim                 39717
total_bal_ex_mort               39717
```

```
total_bc_limit                   39717
total_il_high_credit_limit       39717
Length: 111, dtype: int64
```

Seems like there are some columns where all the values are null

Now Dropping the columns having all Nullable values

```
loan_df.dropna(axis = 1, how = 'all', inplace = True)
loan_df.head()
```

```
        id  member_id  loan_amnt  funded_amnt  funded_amnt_inv 
term  \
0  1077501    1296599       5000         5000           4975.0   36 
months
1  1077430    1314167       2500         2500           2500.0   60 
months
2  1077175    1313524       2400         2400           2400.0   36 
months
3  1076863    1277178      10000        10000          10000.0   36 
months
4  1075358    1311748       3000         3000           3000.0   60 
months

  int_rate  installment grade sub_grade  ... next_pymnt_d 
last_credit_pull_d  \
0   10.65%       162.87     B        B2  ...          NaN 
May-16
1   15.27%        59.83     C        C4  ...          NaN 
Sep-13
2   15.96%        84.33     C        C5  ...          NaN 
May-16
3   13.49%       339.31     C        C1  ...          NaN 
Apr-16
4   12.69%        67.79     B        B5  ...       Jun-16 
May-16

  collections_12_mths_ex_med  policy_code application_type 
acc_now_delinq  \
0                        0.0            1       INDIVIDUAL 
0
1                        0.0            1       INDIVIDUAL 
0
2                        0.0            1       INDIVIDUAL 
0
3                        0.0            1       INDIVIDUAL 
0
4                        0.0            1       INDIVIDUAL 
0
```

```
  chargeoff_within_12_mths delinq_amnt pub_rec_bankruptcies tax_liens
0                      0.0           0                  0.0       0.0
1                      0.0           0                  0.0       0.0
2                      0.0           0                  0.0       0.0
3                      0.0           0                  0.0       0.0
4                      0.0           0                  0.0       0.0

[5 rows x 57 columns]
```

Now we calculate the precentage of missing values in each columns

```
round(loan_df.isnull().sum()/len(loan_df.index), 2)*100
```

```
id                             0.0
member_id                      0.0
loan_amnt                      0.0
funded_amnt                    0.0
funded_amnt_inv                0.0
term                           0.0
int_rate                       0.0
installment                    0.0
grade                          0.0
sub_grade                      0.0
emp_title                      6.0
emp_length                     3.0
home_ownership                 0.0
annual_inc                     0.0
verification_status            0.0
issue_d                        0.0
loan_status                    0.0
pymnt_plan                     0.0
url                            0.0
desc                          33.0
purpose                        0.0
title                          0.0
zip_code                       0.0
addr_state                     0.0
dti                            0.0
delinq_2yrs                    0.0
earliest_cr_line               0.0
inq_last_6mths                 0.0
mths_since_last_delinq        65.0
mths_since_last_record        93.0
open_acc                       0.0
```

```
pub_rec                           0.0
revol_bal                         0.0
revol_util                        0.0
total_acc                         0.0
initial_list_status               0.0
out_prncp                         0.0
out_prncp_inv                     0.0
total_pymnt                       0.0
total_pymnt_inv                   0.0
total_rec_prncp                   0.0
total_rec_int                     0.0
total_rec_late_fee                0.0
recoveries                        0.0
collection_recovery_fee           0.0
last_pymnt_d                      0.0
last_pymnt_amnt                   0.0
next_pymnt_d                     97.0
last_credit_pull_d                0.0
collections_12_mths_ex_med        0.0
policy_code                       0.0
application_type                  0.0
acc_now_delinq                    0.0
chargeoff_within_12_mths          0.0
delinq_amnt                       0.0
pub_rec_bankruptcies              2.0
tax_liens                         0.0
dtype: float64
```

```
loan_90_percentage_missing_columns =
loan_df.columns[100*(loan_df.isnull().sum()/len(loan_df.index)) > 90]
print(loan_90_percentage_missing_columns)
loan_df = loan_df.drop(loan_90_percentage_missing_columns, axis=1)
print(loan_df.shape)
```

```
Index(['mths_since_last_record', 'next_pymnt_d'], dtype='object')
(39717, 55)
```

Now we are left with only 55 coloumns out of 111

```
loan_df.var()
```

```
id                               4.439202e+10
member_id                        7.058496e+10
loan_amnt                        5.560194e+07
funded_amnt                      5.165640e+07
funded_amnt_inv                  5.081481e+07
installment                      4.362871e+04
annual_inc                       4.069645e+09
dti                              4.460361e+01
delinq_2yrs                      2.418786e-01
```

```
inq_last_6mths                1.145369e+00
mths_since_last_delinq        4.848830e+02
open_acc                      1.936249e+01
pub_rec                       5.626382e-02
revol_bal                     2.523338e+08
total_acc                     1.299990e+02
out_prncp                     1.407547e+05
out_prncp_inv                 1.397447e+05
total_pymnt                   8.175850e+07
total_pymnt_inv               7.997139e+07
total_rec_prncp               4.992160e+07
total_rec_int                 6.802248e+06
total_rec_late_fee            5.314380e+01
recoveries                    4.743694e+05
collection_recovery_fee       2.210324e+04
last_pymnt_amnt               1.977702e+07
collections_12_mths_ex_med    0.000000e+00
policy_code                   0.000000e+00
acc_now_delinq                0.000000e+00
chargeoff_within_12_mths      0.000000e+00
delinq_amnt                   0.000000e+00
pub_rec_bankruptcies          4.174831e-02
tax_liens                     0.000000e+00
dtype: float64
```

```
loan_df.drop(['collections_12_mths_ex_med',
"policy_code",'acc_now_delinq','chargeoff_within_12_mths',
'delinq_amnt', 'tax_liens'], axis = 1, inplace = True)
```

```
loan_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 39717 entries, 0 to 39716
Data columns (total 49 columns):
 #   Column                     Non-Null Count  Dtype
---  ------                     --------------  -----
 0   id                         39717 non-null  int64
 1   member_id                  39717 non-null  int64
 2   loan_amnt                  39717 non-null  int64
 3   funded_amnt                39717 non-null  int64
 4   funded_amnt_inv            39717 non-null  float64
 5   term                       39717 non-null  object
 6   int_rate                   39717 non-null  object
 7   installment                39717 non-null  float64
 8   grade                      39717 non-null  object
 9   sub_grade                  39717 non-null  object
 10  emp_title                  37258 non-null  object
 11  emp_length                 38642 non-null  object
 12  home_ownership             39717 non-null  object
 13  annual_inc                 39717 non-null  float64
```

```
 14  verification_status      39717 non-null  object
 15  issue_d                  39717 non-null  object
 16  loan_status              39717 non-null  object
 17  pymnt_plan               39717 non-null  object
 18  url                      39717 non-null  object
 19  desc                     26777 non-null  object
 20  purpose                  39717 non-null  object
 21  title                    39706 non-null  object
 22  zip_code                 39717 non-null  object
 23  addr_state               39717 non-null  object
 24  dti                      39717 non-null  float64
 25  delinq_2yrs              39717 non-null  int64
 26  earliest_cr_line         39717 non-null  object
 27  inq_last_6mths           39717 non-null  int64
 28  mths_since_last_delinq   14035 non-null  float64
 29  open_acc                 39717 non-null  int64
 30  pub_rec                  39717 non-null  int64
 31  revol_bal                39717 non-null  int64
 32  revol_util               39667 non-null  object
 33  total_acc                39717 non-null  int64
 34  initial_list_status      39717 non-null  object
 35  out_prncp                39717 non-null  float64
 36  out_prncp_inv            39717 non-null  float64
 37  total_pymnt              39717 non-null  float64
 38  total_pymnt_inv          39717 non-null  float64
 39  total_rec_prncp          39717 non-null  float64
 40  total_rec_int            39717 non-null  float64
 41  total_rec_late_fee       39717 non-null  float64
 42  recoveries               39717 non-null  float64
 43  collection_recovery_fee  39717 non-null  float64
 44  last_pymnt_d             39646 non-null  object
 45  last_pymnt_amnt          39717 non-null  float64
 46  last_credit_pull_d       39715 non-null  object
 47  application_type         39717 non-null  object
 48  pub_rec_bankruptcies     39020 non-null  float64
dtypes: float64(16), int64(10), object(23)
memory usage: 14.8+ MB
```

Now we have 49 columns out of which some correspond to the post approval of loan and ids

We are analyzing the user details and the driving factors of loan defaulting before approving loan.

So we can safely remove the columns / variables corresponding to that scenario.

Also there are some columns such as "id", "member_id", "url", "title", "emp_title", "zip_code", "last_credit_pull_d", "addr_state".

The above features or columns doesnt contribute to the loan defaulting in any way due to irrelevant information. So removing them.

- "desc" has description (text data) which we cannot do anythhing about for now. So removing the column.
- "out_prncp_inv" , "total_pymnt_inv " are useful for investors but not contributing to the loan defaulting analysis. So removing them.
- "funded_amnt" is not needed because we only need info as to how much is funded in actual. As we have "funded_amnt_inv" , we can remove the earlier column.

List of post-approval features

- delinq_2yrs
- revol_bal
- out_prncp
- total_pymnt
- total_rec_prncp
- total_rec_int
- total_rec_late_fee
- recoveries
- collection_recovery_fee
- last_pymnt_d
- last_pymnt_amnt
- mths_since_last_delinq
- total_pymnt_inv
- out_prncp_inv
- total_pymnt_inv
- funded_amnt
- total_pymnt

```
loan_df.drop(['delinq_2yrs',
"revol_bal",'out_prncp','mths_since_last_delinq', 'last_pymnt_amnt',
'last_pymnt_d','collection_recovery_fee','recoveries','total_rec_late_
fee','total_rec_int','total_rec_prncp',"id", "member_id", "url",
"title", "emp_title", "zip_code",
"last_credit_pull_d","desc","out_prncp_inv","total_pymnt_inv","funded_
amnt","total_pymnt","pub_rec_bankruptcies"], axis = 1, inplace = True)
loan_df.head()
```

```
   loan_amnt  funded_amnt_inv        term int_rate  installment grade  
\
0       5000           4975.0   36 months   10.65%       162.87     B   

1       2500           2500.0   60 months   15.27%        59.83     C   

2       2400           2400.0   36 months   15.96%        84.33     C   

3      10000          10000.0   36 months   13.49%       339.31     C   

4       3000           3000.0   60 months   12.69%        67.79     B   


  sub_grade emp_length home_ownership  annual_inc  ... addr_state  
dti  \
0        B2  10+ years           RENT     24000.0  ...         AZ  
27.65   
1        C4   < 1 year           RENT     30000.0  ...         GA   
1.00   
2        C5  10+ years           RENT     12252.0  ...         IL   
8.72   
3        C1  10+ years           RENT     49200.0  ...         CA  
20.00   
4        B5     1 year           RENT     80000.0  ...         OR  
17.94   

  earliest_cr_line inq_last_6mths open_acc pub_rec  revol_util  
total_acc  \
0           Jan-85              1        3       0      83.70%          
9   
1           Apr-99              5        3       0       9.40%          
4   
2           Nov-01              2        2       0      98.50%         
10   
3           Feb-96              1       10       0         21%         
37   
4           Jan-96              0       15       0      53.90%         
38   

   initial_list_status  application_type  
0                    f        INDIVIDUAL  
1                    f        INDIVIDUAL  
2                    f        INDIVIDUAL  
3                    f        INDIVIDUAL  
4                    f        INDIVIDUAL  

[5 rows x 25 columns]
```

```
loan_df.shape
```

```
(39717, 25)
```

Seeing Posible loan_status

```
loan_df.loan_status.unique()
```

```
array(['Fully Paid', 'Charged Off', 'Current'], dtype=object)
```

Fixing the Missing Values

```
loan_df.isnull().sum()
```

```
loan_amnt                  0
funded_amnt_inv            0
term                       0
int_rate                   0
installment                0
grade                      0
sub_grade                  0
emp_length              1075
home_ownership             0
annual_inc                 0
verification_status        0
issue_d                    0
loan_status                0
pymnt_plan                 0
purpose                    0
addr_state                 0
dti                        0
earliest_cr_line           0
inq_last_6mths             0
open_acc                   0
pub_rec                    0
revol_util                50
total_acc                  0
initial_list_status        0
application_type           0
dtype: int64
```

Now we know that there are some missing values in the coloum emp_length and revol_util

Dropping null rows from emp_length

```
loan_df['emp_length'].value_counts()
```

```
10+ years    8879
< 1 year     4583
2 years      4388
3 years      4095
4 years      3436
5 years      3282
```

```
1 year       3240
6 years      2229
7 years      1773
8 years      1479
9 years      1258
Name: emp_length, dtype: int64
```

```
loan_df=loan_df[-(loan_df['emp_length'].isnull())]
```

```
loan_df.isnull().sum()
```

```
loan_amnt                0
funded_amnt_inv          0
term                     0
int_rate                 0
installment              0
grade                    0
sub_grade                0
emp_length               0
home_ownership           0
annual_inc               0
verification_status      0
issue_d                  0
loan_status              0
pymnt_plan               0
purpose                  0
addr_state               0
dti                      0
earliest_cr_line         0
inq_last_6mths           0
open_acc                 0
pub_rec                  0
revol_util              47
total_acc                0
initial_list_status      0
application_type         0
dtype: int64
```

Dropping null rows from revol_util

```
loan_df['revol_util'].value_counts()
```

```
0%          941
0.20%        62
63%          61
66.70%       57
40.70%       57
           ...
0.83%         1
47.36%        1
```

```
24.65%      1
10.61%      1
7.28%       1
Name: revol_util, Length: 1087, dtype: int64
```

```
loan_df=loan_df[-(loan_df['revol_util'].isnull())]
```

```
loan_df.isnull().sum()
```

```
loan_amnt               0
funded_amnt_inv         0
term                    0
int_rate                0
installment             0
grade                   0
sub_grade               0
emp_length              0
home_ownership          0
annual_inc              0
verification_status     0
issue_d                 0
loan_status             0
pymnt_plan              0
purpose                 0
addr_state              0
dti                     0
earliest_cr_line        0
inq_last_6mths          0
open_acc                0
pub_rec                 0
revol_util              0
total_acc               0
initial_list_status     0
application_type        0
dtype: int64
```

Standardising Values

Standardising values for revol_util

```
loan_df['revol_util'].value_counts()
```

```
0%        941
0.20%      62
63%        61
66.70%     57
40.70%     57
         ...
0.83%       1
47.36%      1
```

```
24.65%      1
10.61%      1
7.28%       1
Name: revol_util, Length: 1087, dtype: int64
```

```
loan_df.revol_util = pd.to_numeric(loan_df.revol_util.apply(lambda x :
x.split('%')[0]))
```

```
loan_df['revol_util'].value_counts()
```

```
0.00     941
0.20      62
63.00     61
66.70     57
40.70     57
        ...
0.83       1
47.36      1
24.65      1
10.61      1
7.28       1
Name: revol_util, Length: 1087, dtype: int64
```

Values for revol_util has been Standardized

Standardising values for int_rate

```
loan_df["int_rate"].value_counts()
```

```
10.99%    932
13.49%    813
11.49%    800
7.51%     756
7.88%     701
         ...
16.33%      1
16.15%      1
16.01%      1
10.64%      1
17.44%      1
Name: int_rate, Length: 371, dtype: int64
```

```
loan_df["int_rate"] = pd.to_numeric(loan_df["int_rate"].apply(lambda x
: x.split('%')[0]))
```

```
loan_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 38595 entries, 0 to 39716
Data columns (total 25 columns):
 #   Column               Non-Null Count  Dtype
```

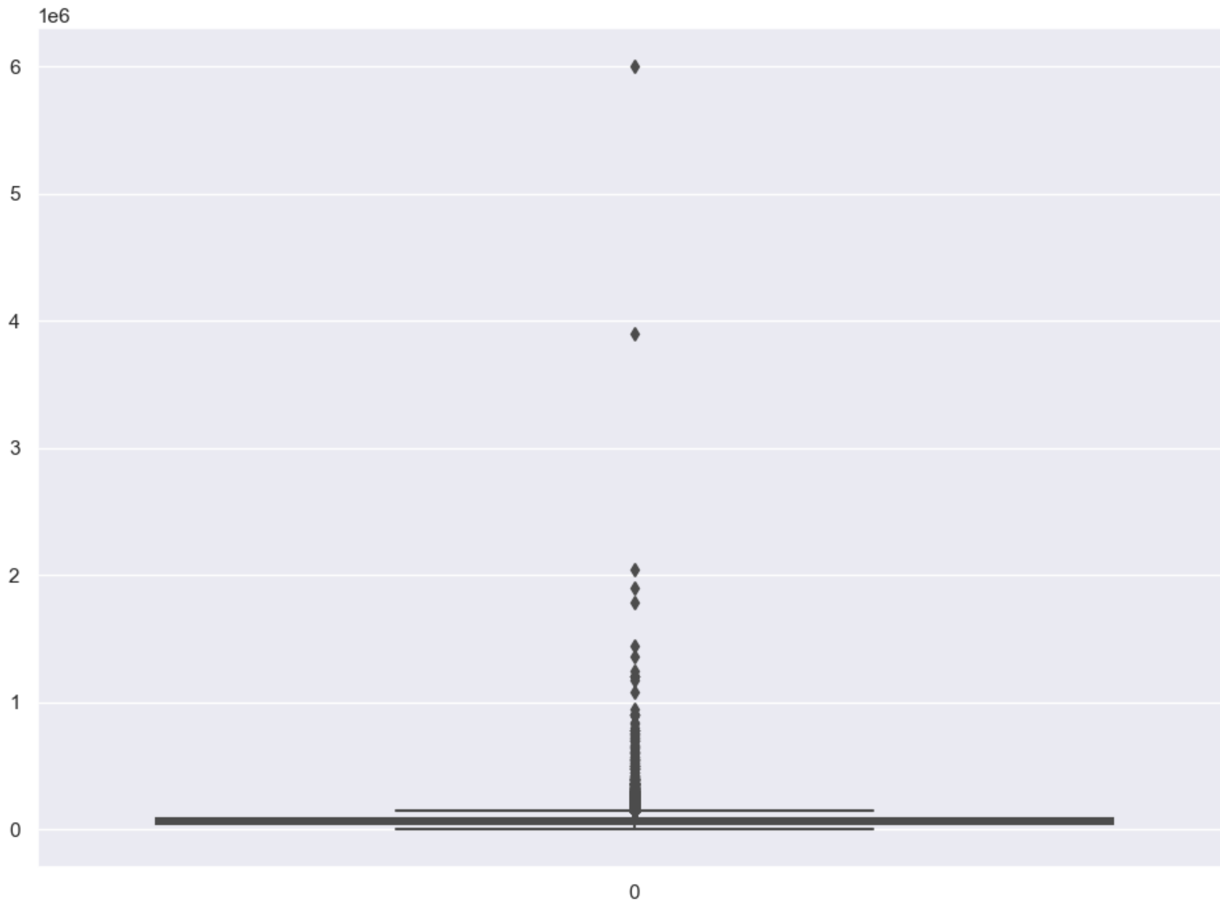
```
---  ------                 --------------  -----
 0   loan_amnt              38595 non-null  int64
 1   funded_amnt_inv        38595 non-null  float64
 2   term                   38595 non-null  object
 3   int_rate               38595 non-null  float64
 4   installment            38595 non-null  float64
 5   grade                  38595 non-null  object
 6   sub_grade              38595 non-null  object
 7   emp_length             38595 non-null  object
 8   home_ownership         38595 non-null  object
 9   annual_inc             38595 non-null  float64
 10  verification_status    38595 non-null  object
 11  issue_d                38595 non-null  object
 12  loan_status            38595 non-null  object
 13  pymnt_plan             38595 non-null  object
 14  purpose                38595 non-null  object
 15  addr_state             38595 non-null  object
 16  dti                    38595 non-null  float64
 17  earliest_cr_line       38595 non-null  object
 18  inq_last_6mths         38595 non-null  int64
 19  open_acc               38595 non-null  int64
 20  pub_rec                38595 non-null  int64
 21  revol_util             38595 non-null  float64
 22  total_acc              38595 non-null  int64
 23  initial_list_status    38595 non-null  object
 24  application_type       38595 non-null  object
dtypes: float64(6), int64(5), object(14)
memory usage: 7.7+ MB
```

Removing Outliers

Plotting Box plot for annual_inc

```
sns.boxplot(loan_df['annual_inc'])

<Axes: >
```



Removing all data after the 95 percentile

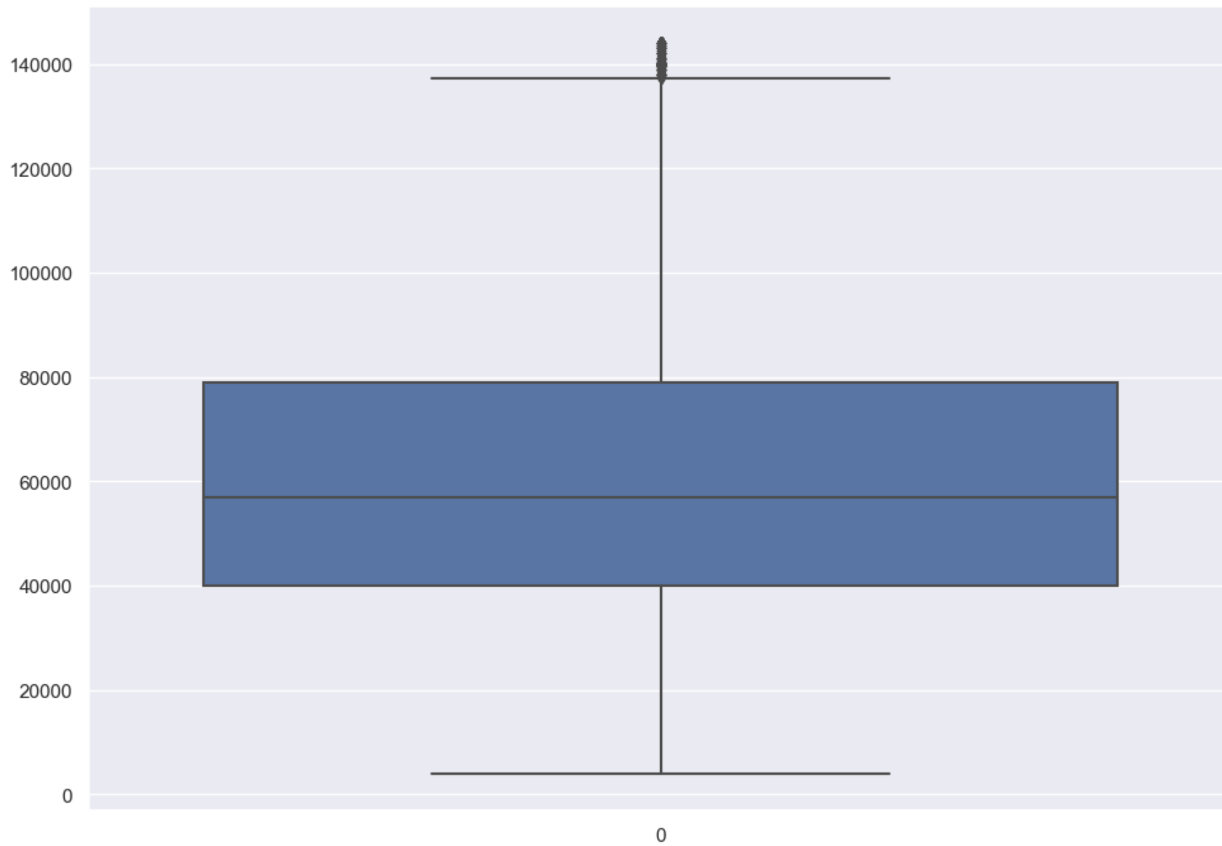
```
quantile_annual_inc = loan_df.annual_inc.quantile([0.95])
quantile_annual_inc
```

```
0.95    144000.0
Name: annual_inc, dtype: float64
```

```
per_95_annual_inc = loan_df['annual_inc'].quantile(0.95)
loan_df = loan_df[loan_df.annual_inc <= per_95_annual_inc]
```

```
sns.boxplot(loan_df['annual_inc'])
```

```
<Axes: >
```

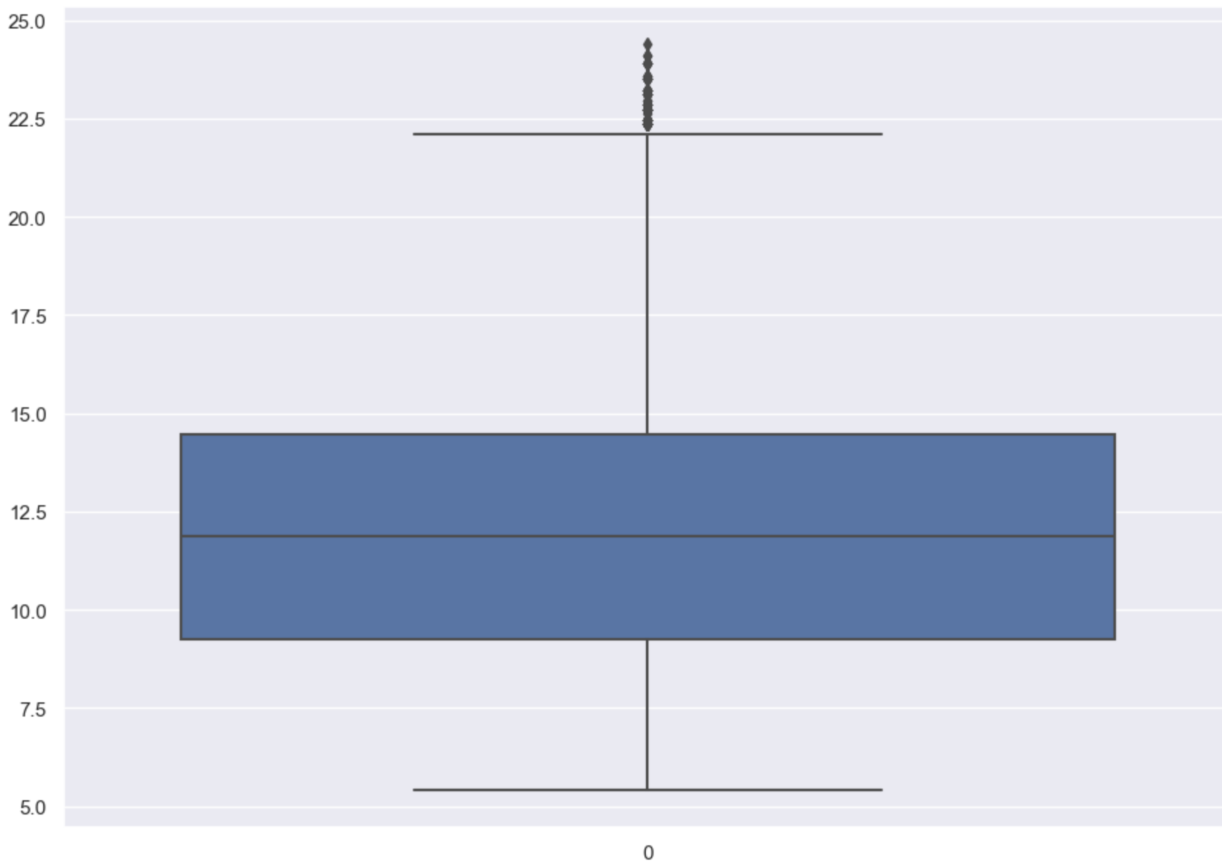


Now the values looks continuous hence we can proceed with the next steps

Plotting Box plot for int_rate

```
sns.boxplot(loan_df['int_rate'])
```

```
<Axes: >
```

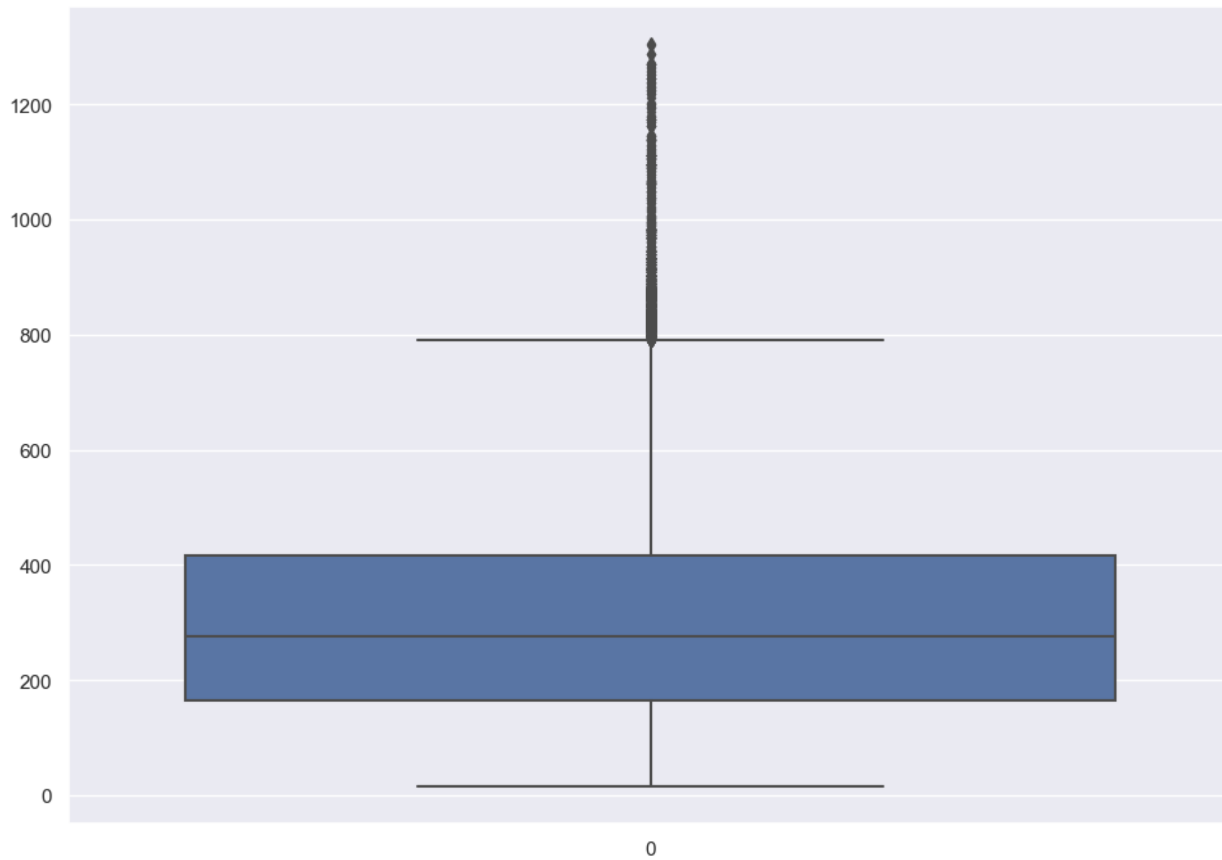


The Box plot for int rate looks continuous with minimum number of outliers hence not removing data

Plotting Box plot for installment¶

```
sns.boxplot(loan_df['installment'])
```

```
<Axes: >
```



The data is moreover continuous but there seems to be a large number of outliers in the data that needs to be cleared

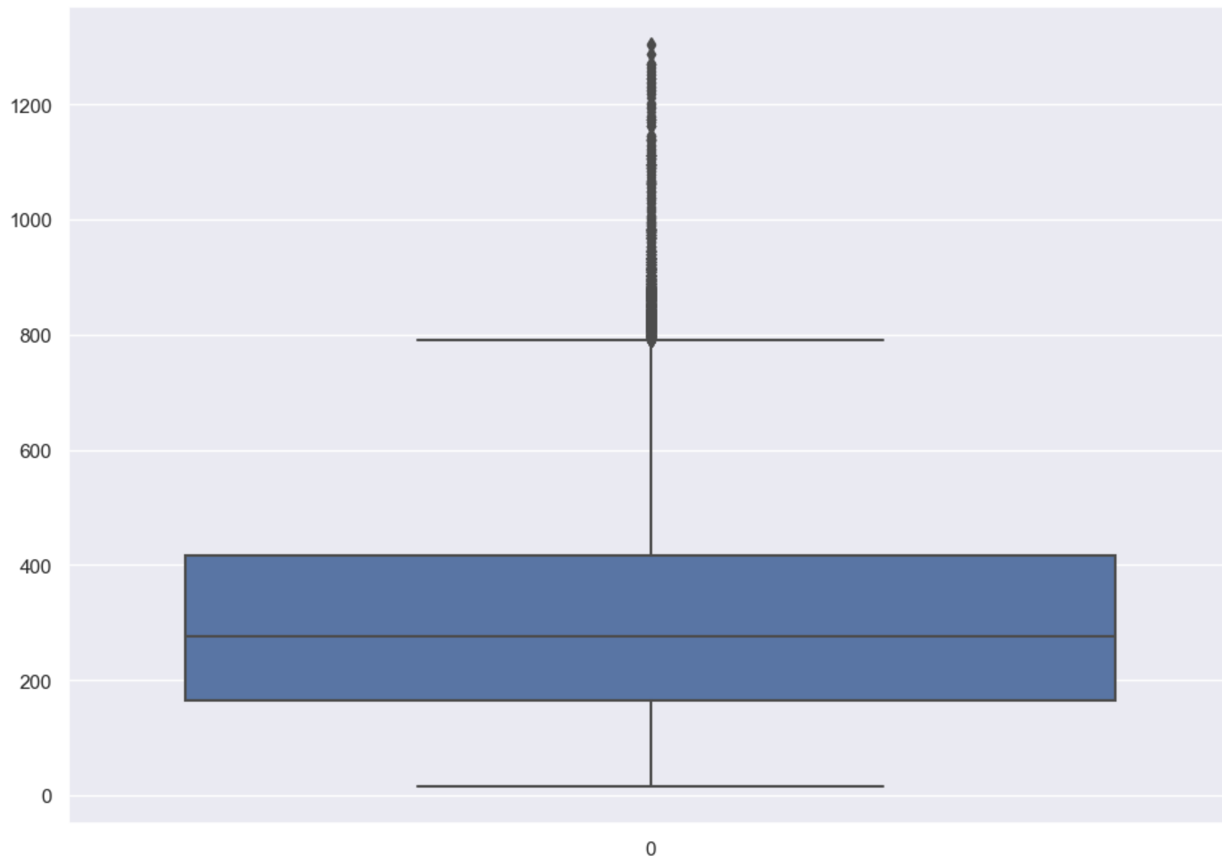
```
quantile_installment = loan_df.installment.quantile([0.5, 0.75,0.90,
0.95, 0.97,0.98, 0.99])
quantile_installment

0.50    276.0600
0.75    415.4800
0.90    594.8540
0.95    712.6080
0.97    811.7098
0.98    850.9500
0.99    902.5480
Name: installment, dtype: float64

per_95_installment = loan_df['installment'].quantile(0.95)
dt = loan_df[loan_df.installment <= per_95_installment]

sns.boxplot(loan_df['installment'])

<Axes: >
```

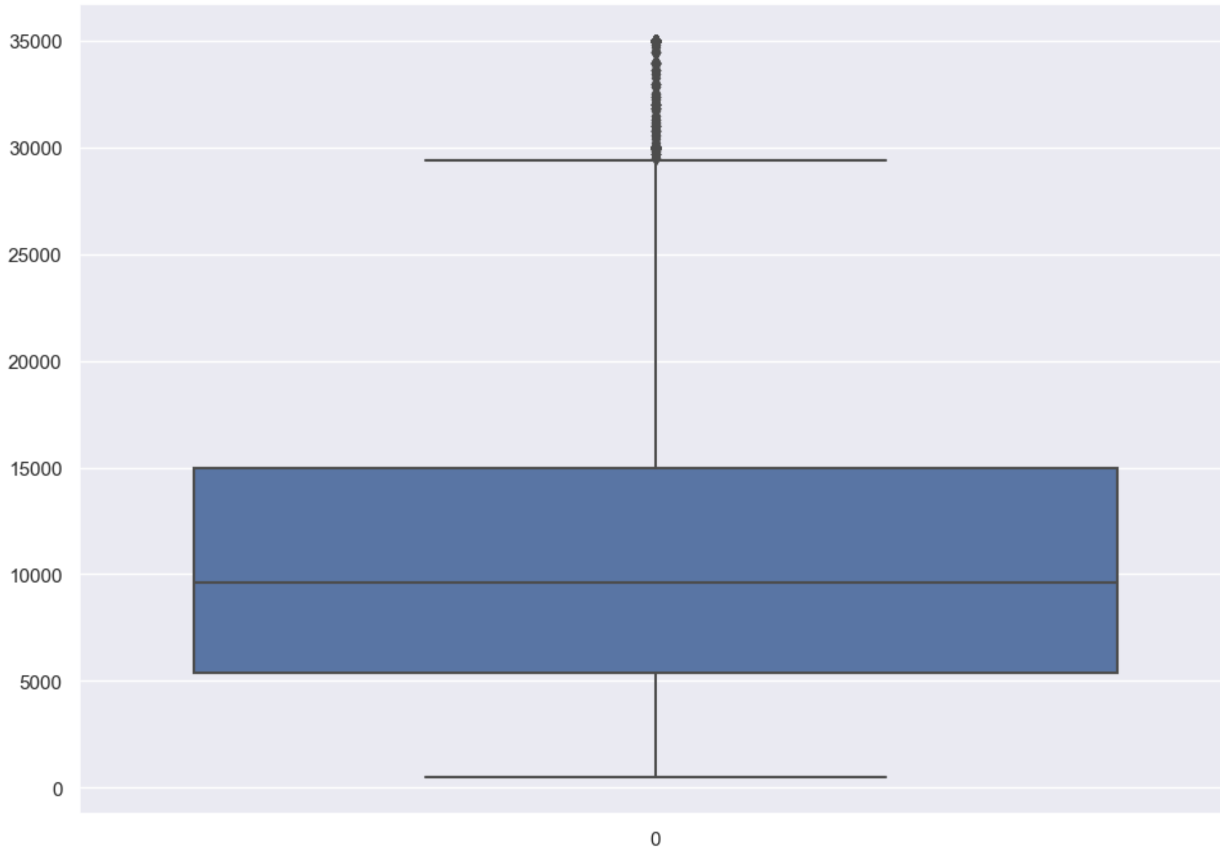


Now the data looks continous for installments

Plotting Box plot for loan amount

```
sns.boxplot(loan_df['loan_amnt'])
```

```
<Axes: >
```

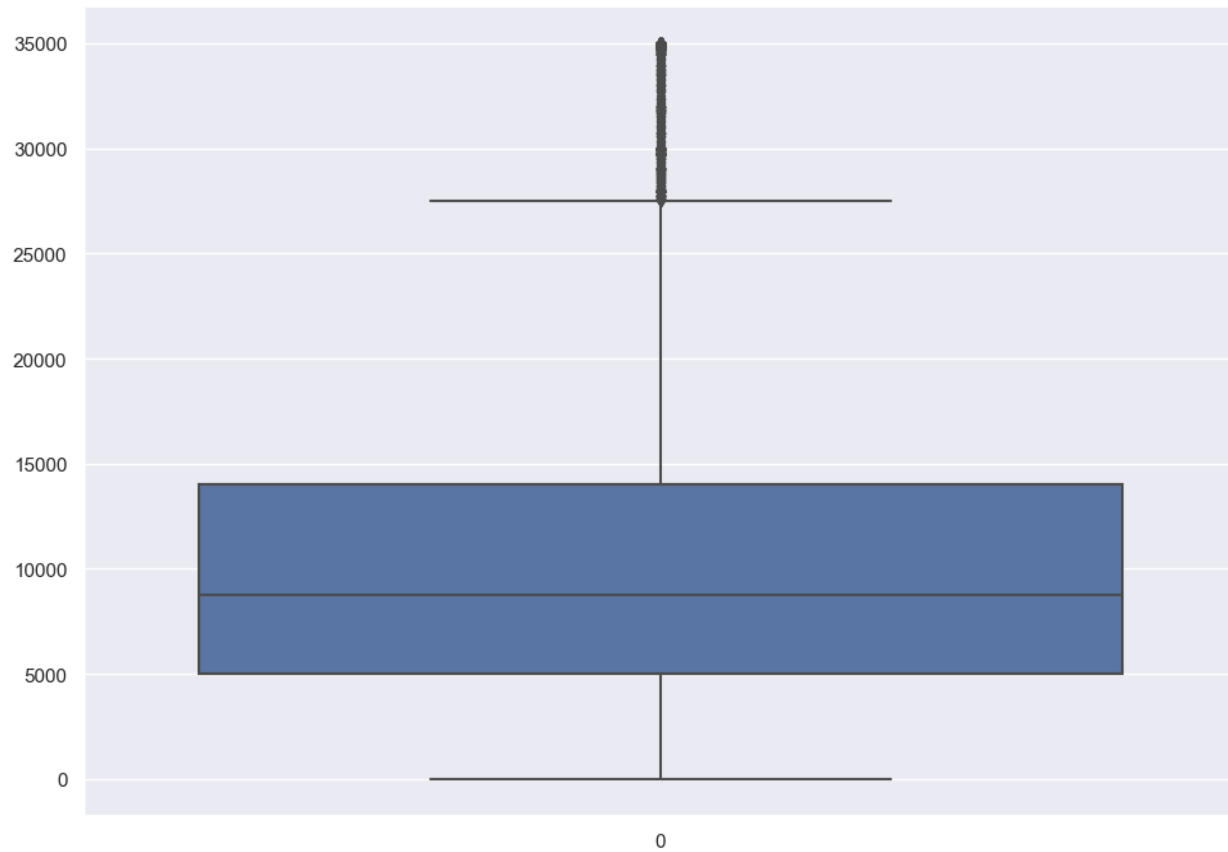


The Box plot for loan amount looks continuous with minimum number of outliers hence not removing data

Plotting Box plot for funded_amnt_inv

```
sns.boxplot(loan_df['funded_amnt_inv'])
```

```
<Axes: >
```

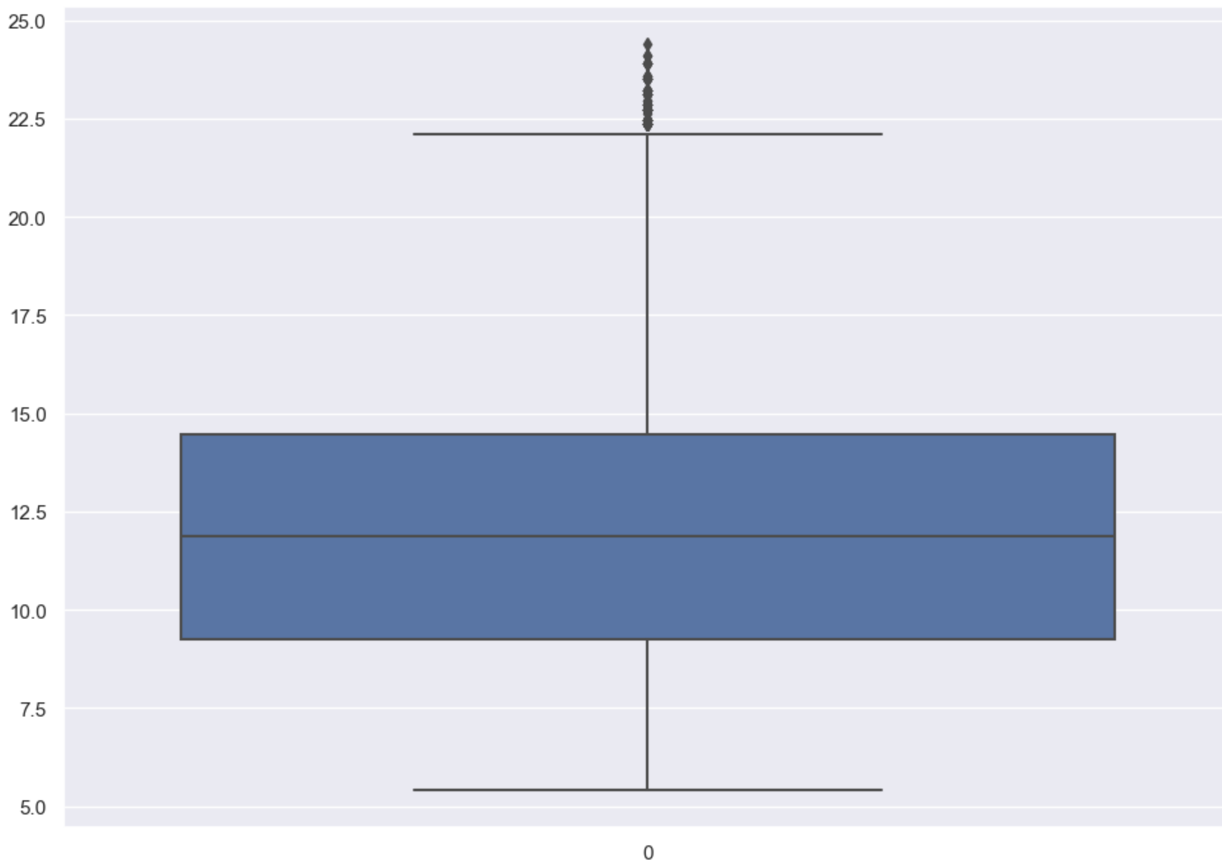


The Box plot for funded_amnt_inv looks continuous with minimum number of outliers hence not removing data

Plotting Box plot for intrest rate

```
sns.boxplot(loan_df['int_rate'])
```

```
<Axes: >
```



The Box plot for loan amount looks continuous with minimum number of outliers hence not removing data

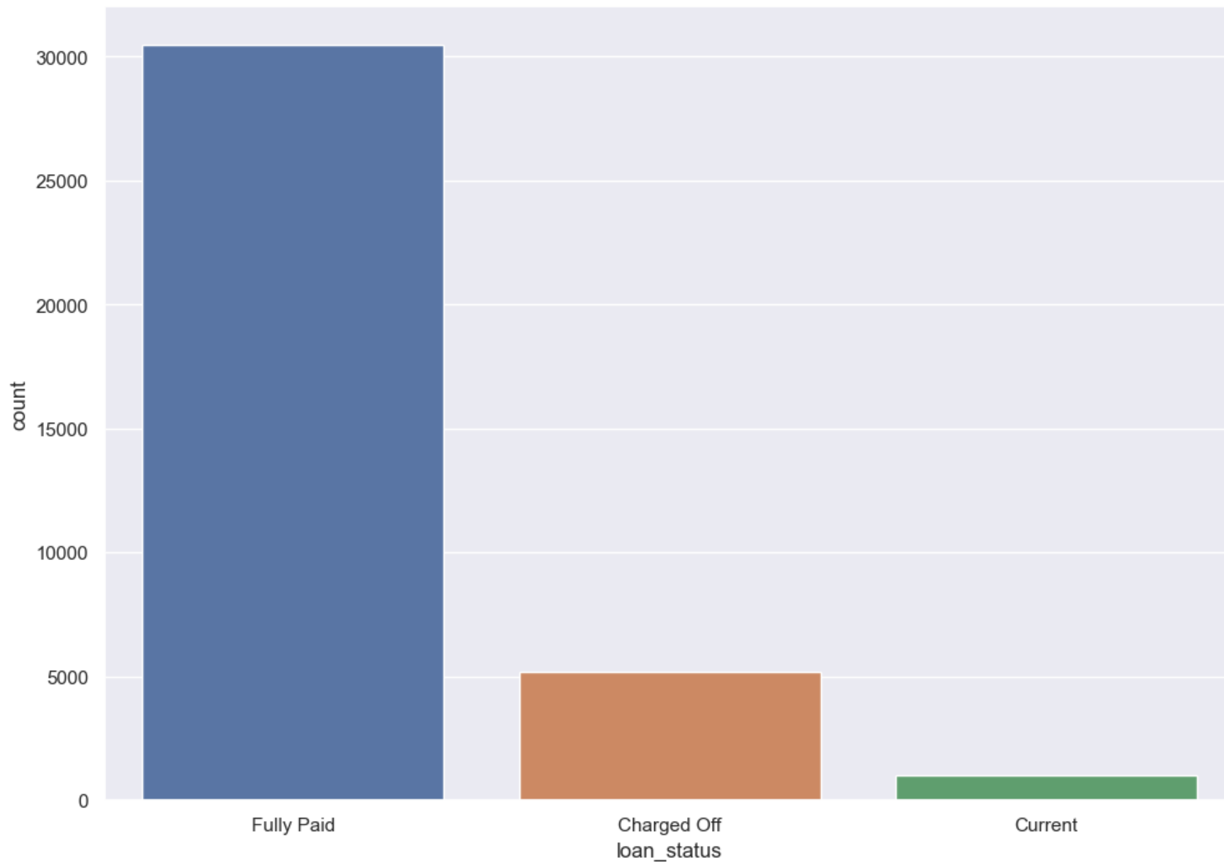
Univariate Analysis

Visualizing Categorical Columns

Plotting countplot for loan status

```
sns.countplot(x = 'loan_status', data = loan_df)
```

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



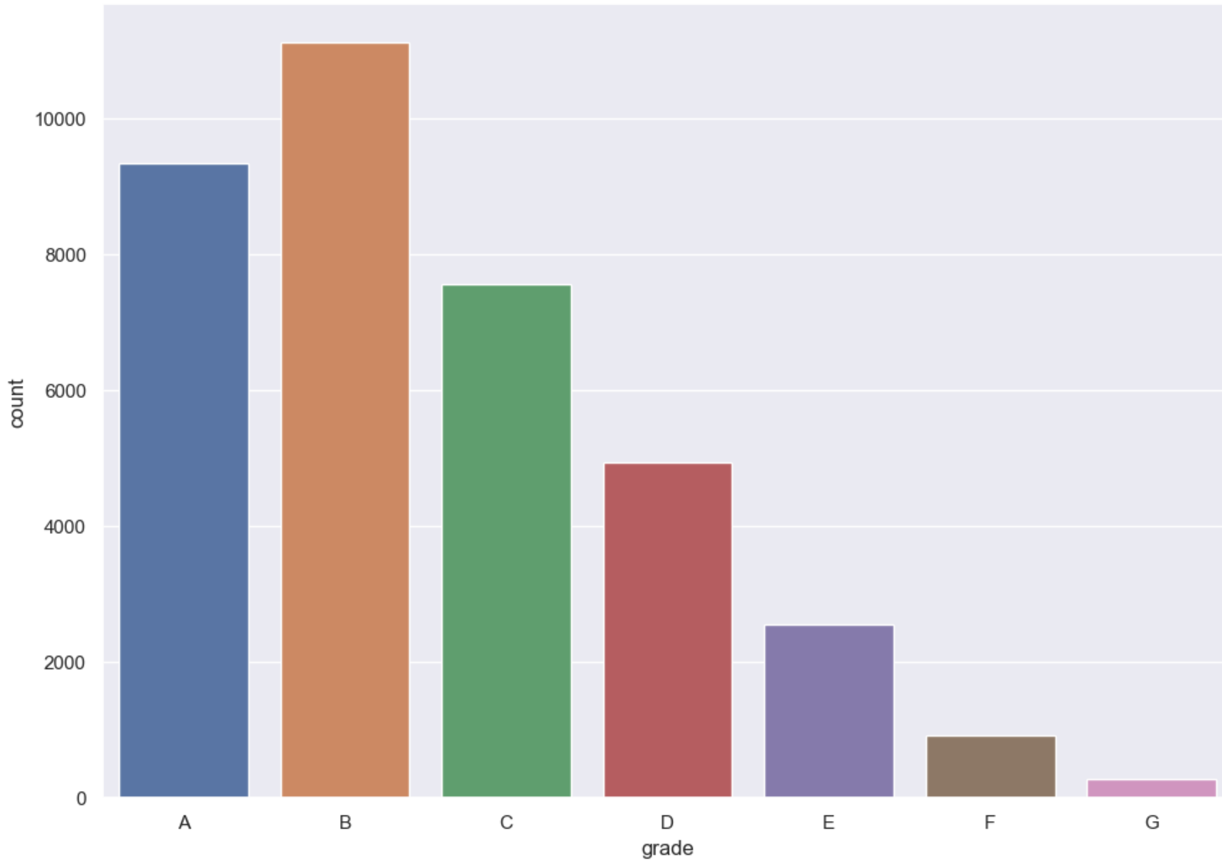
Findings

- There are a very large number of loans that are fully paid as compared to charged off

Plotting countplot for grade

```
sns.countplot(x = 'grade', data = loan_df, order = ['A', 'B', 'C',
'D', 'E', 'F', 'G'])

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



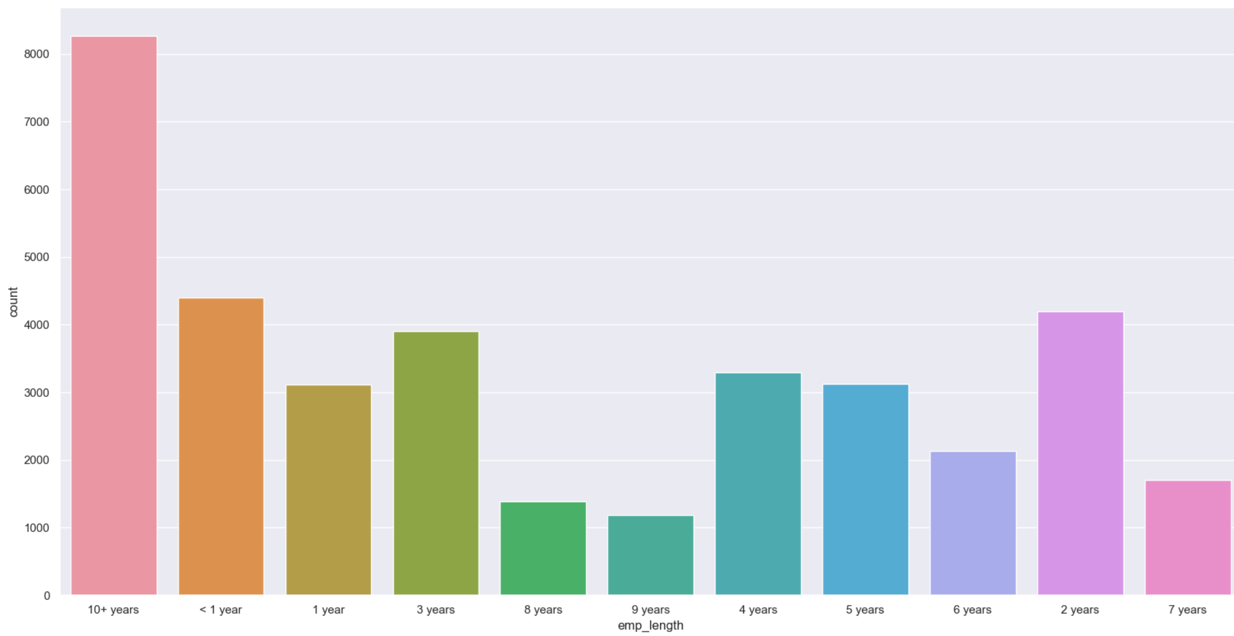
Findings

- Most of the loans were given in the grade category B

Plotting countplot for employee length

```
fig, ax = plt.subplots(figsize = (20,10))
sns.countplot(x = 'emp_length', data = loan_df)
```

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



Findings

- Most of the people who were given loan have a employee lenght greater than 10 years

Plotting countplot for verification_status

```
fig, ax = plt.subplots(figsize = (5,5))
sns.countplot(x = 'verification_status', data = loan_df)

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

Findings

- Most of the people who were given loan have a employee lenght greater than 10 years

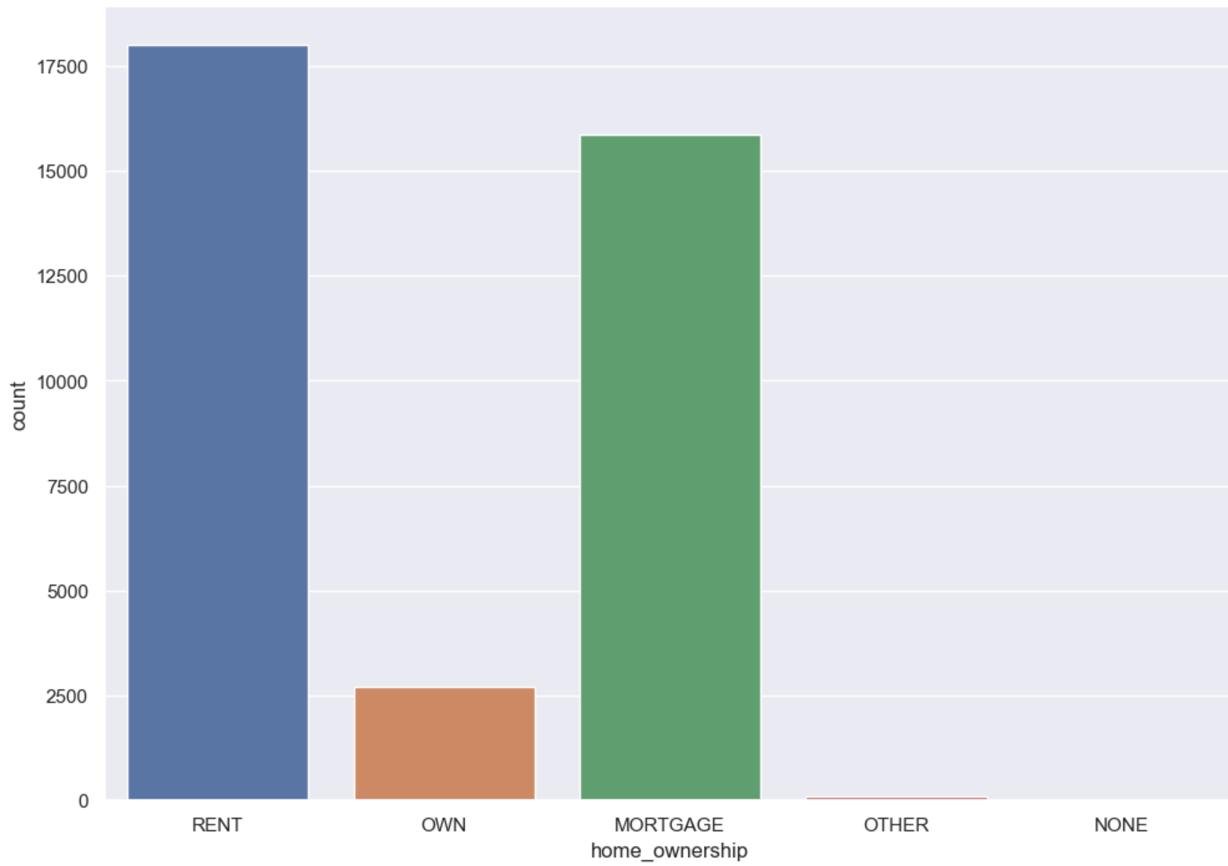
Plotting countplot for Home Ownership

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

```
RENT        17355
MORTGAGE    14824
OWN          2594
OTHER          88
NONE            3
Name: home_ownership, dtype: int64
```

```
sns.countplot(x='home_ownership', data=loan_df)
```

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



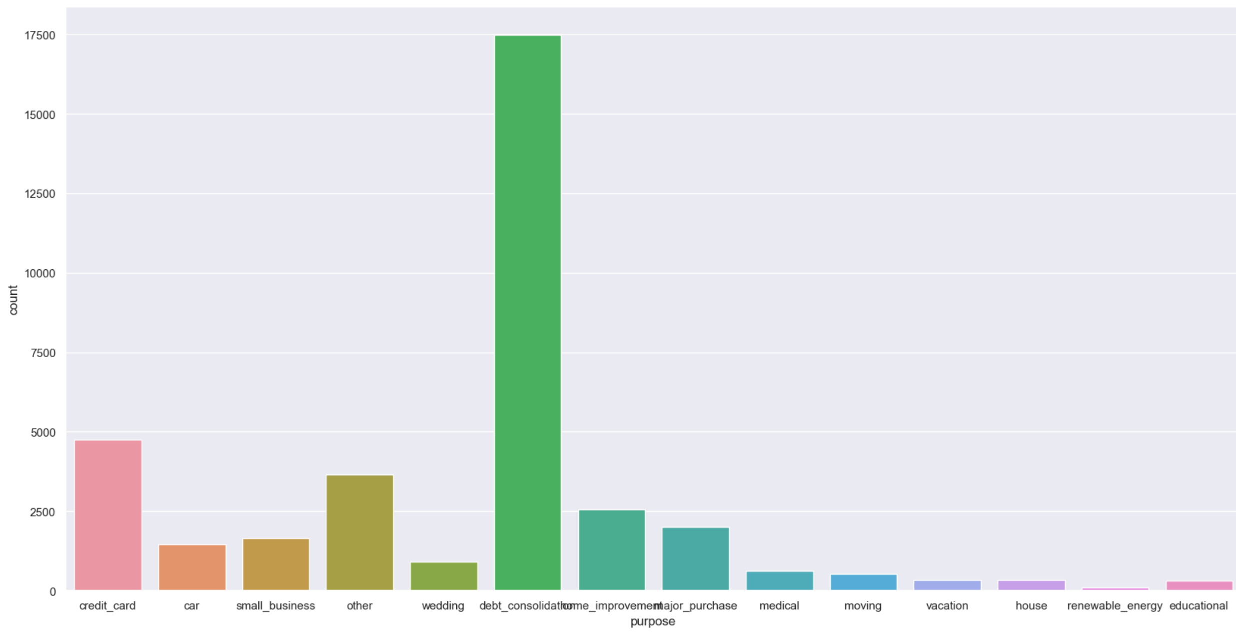
Findings

- Most of the people who were given a loan live on rent

Plotting countplot for loan purpose

```
fig, ax = plt.subplots(figsize = (20,10))
sns.countplot(x ='purpose', data=loan_df)

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



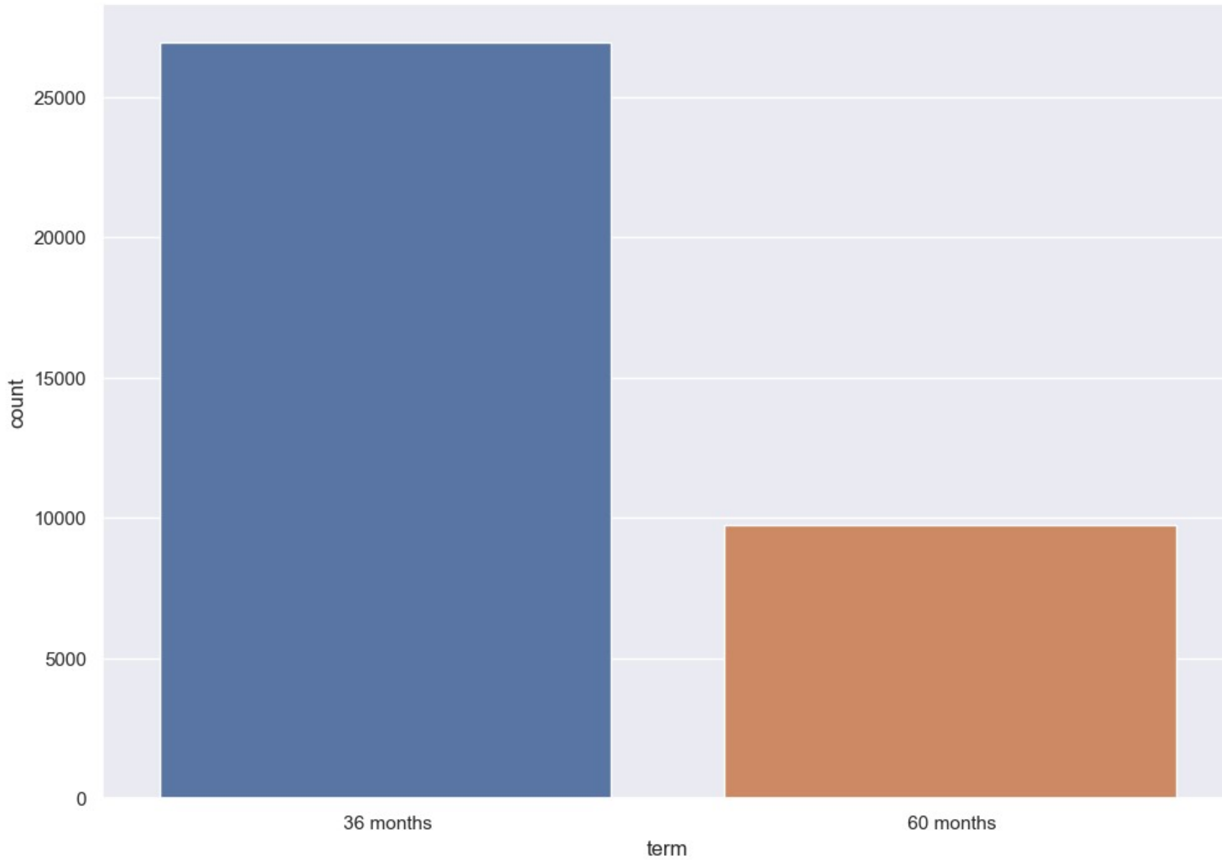
Findings

- Most of loans were given to people for the debt consolidation

Plotting countplot for loan term

```
sns.countplot(x='term', data=loan_df)
```

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



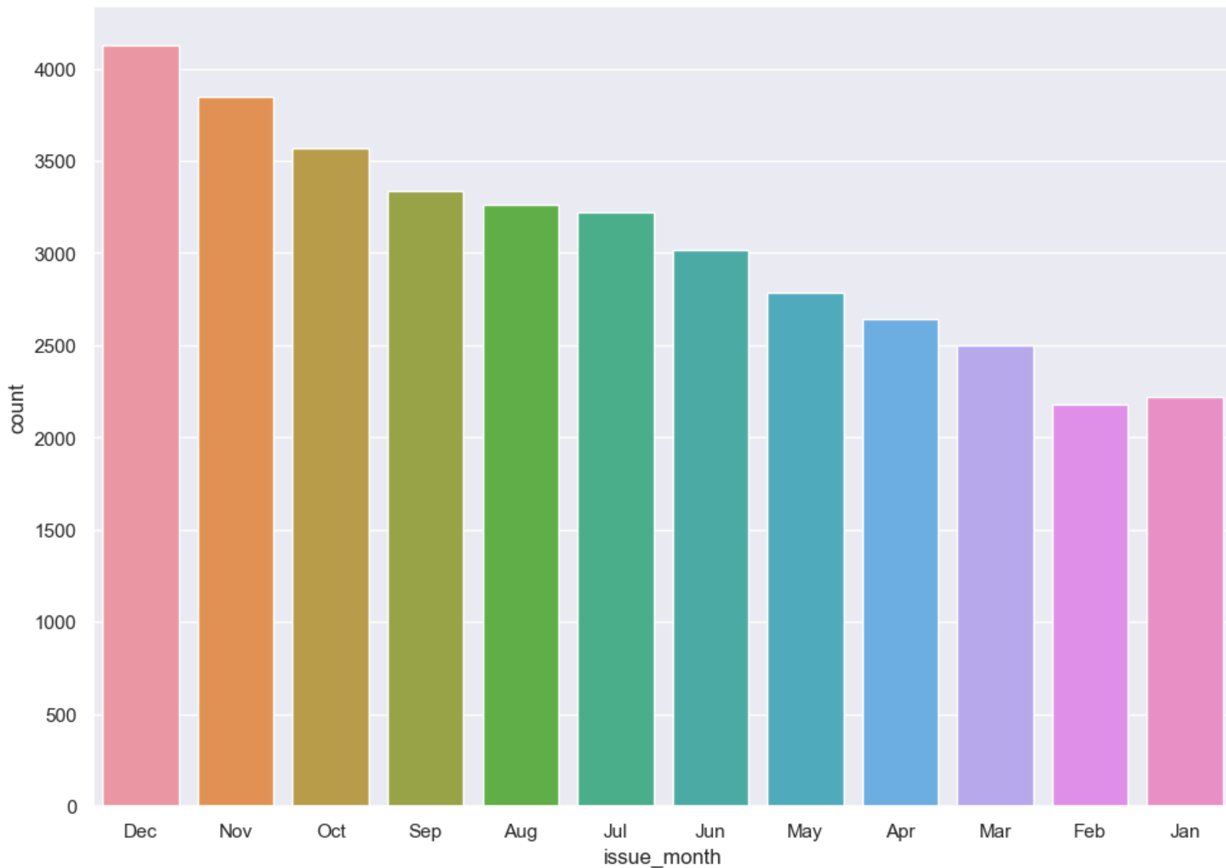
Findings

- Most of the people were given a loan for a period of 36 months

Analyzing Issue Date of the loan by spliting it into years and months

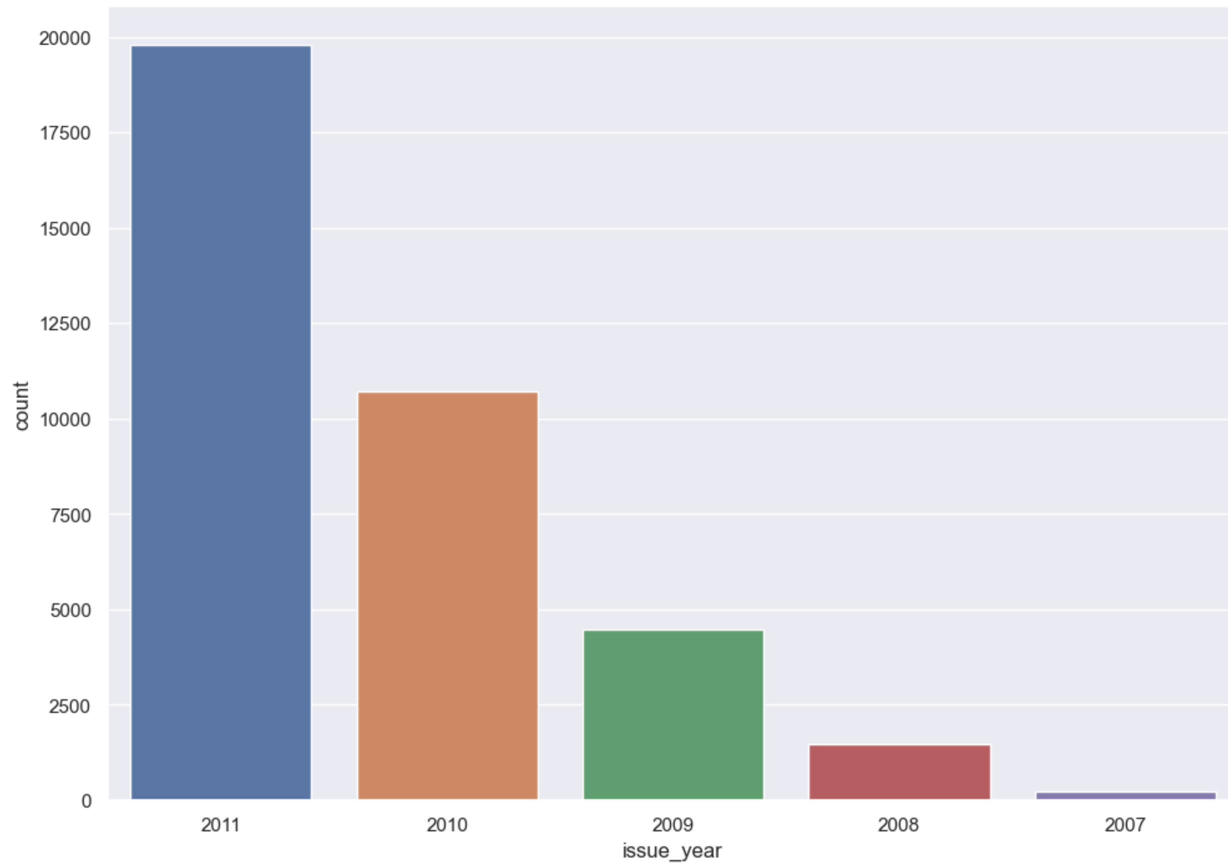
```
loan_df_month_year = loan_df['issue_d'].str.partition("-", True)
loan_df['issue_year']='20' + loan_df_month_year[2]
loan_df['issue_month']=loan_df_month_year[0]
sns.countplot(x='issue_month', data=loan_df)

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




```python
sns.countplot(x='issue_year', data=loan_df)
```

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



Findings

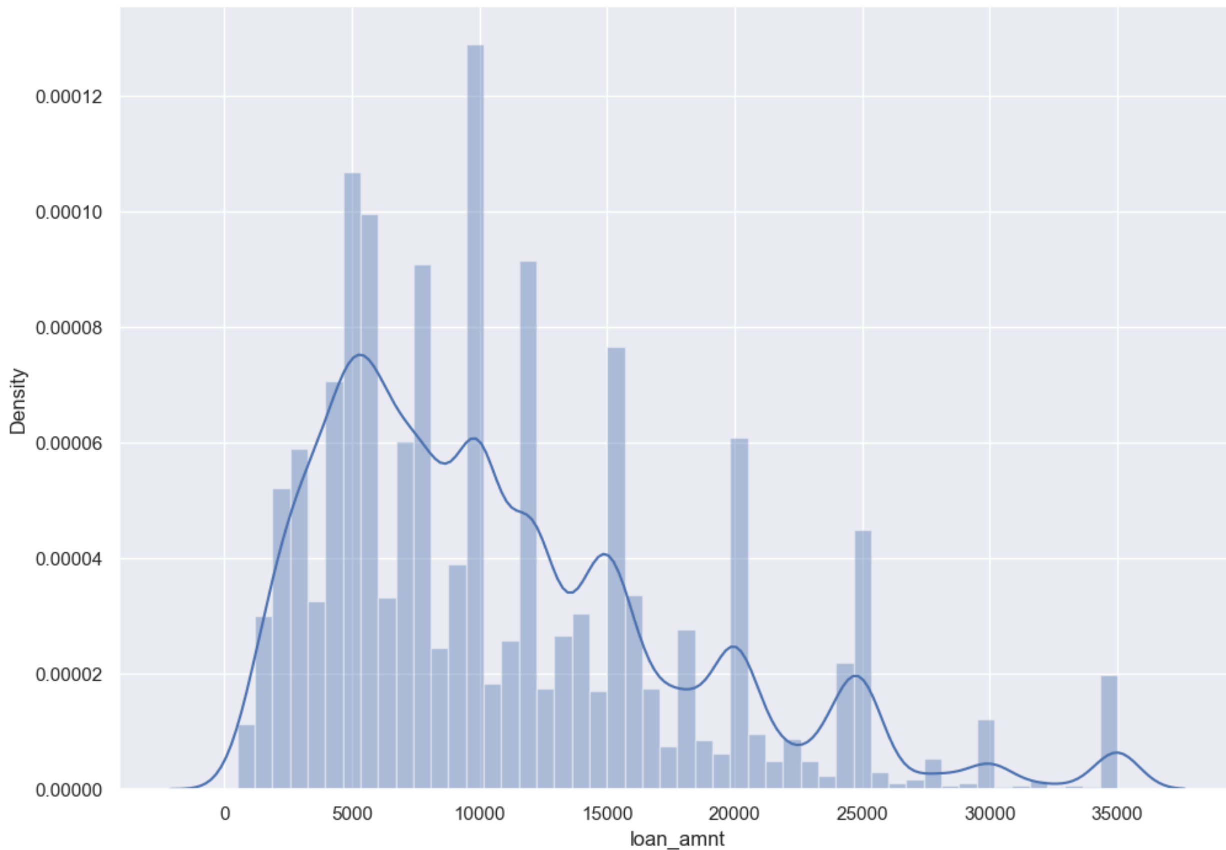
- Most of the people were given a loan in the month of december
- Most of the people were given a loan for year 2011
- The number of loans gien increases as the months are incresing

Analysisng Numerical data

Analysing loan_amnt , interest rate and installments

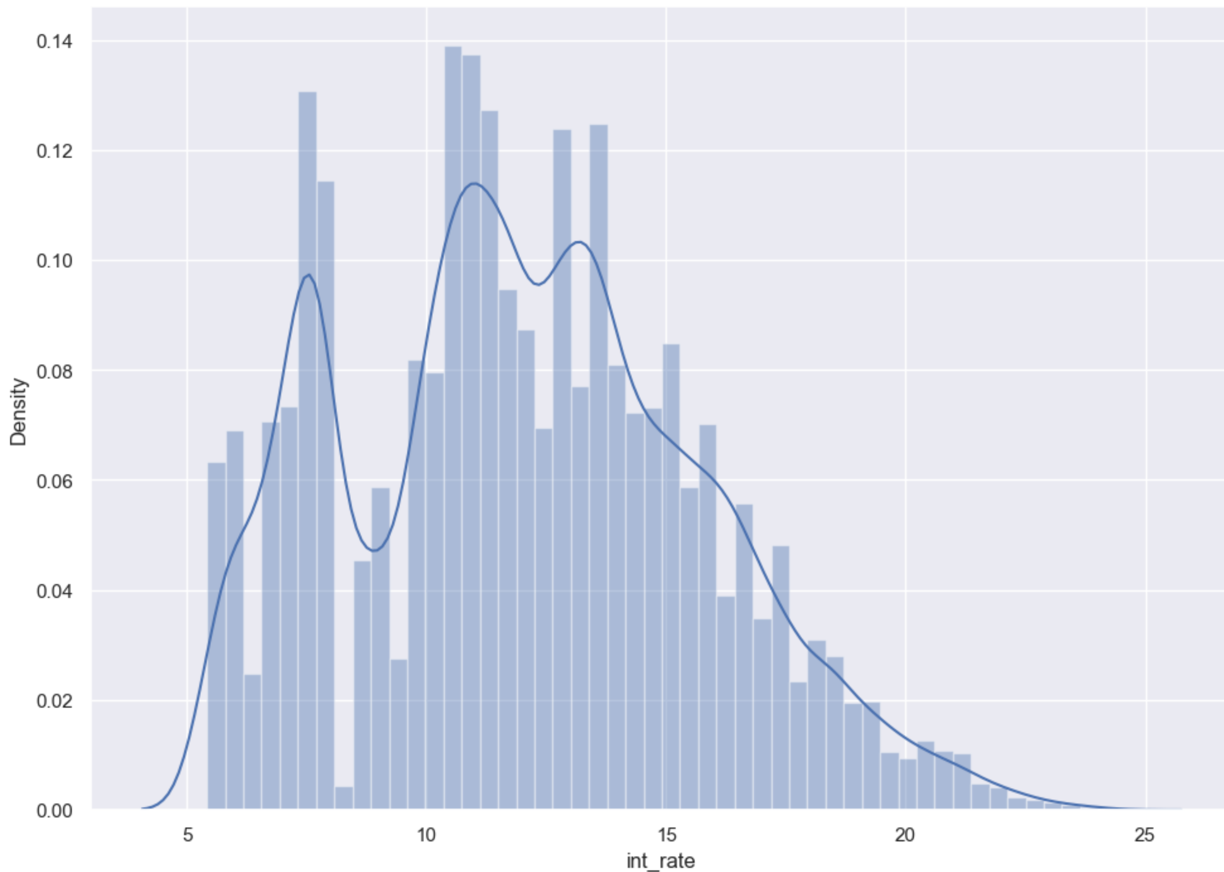
```
sns.distplot(loan_df["loan_amnt"])
```

```
<Axes: xlabel='loan_amnt', ylabel='Density'>
```



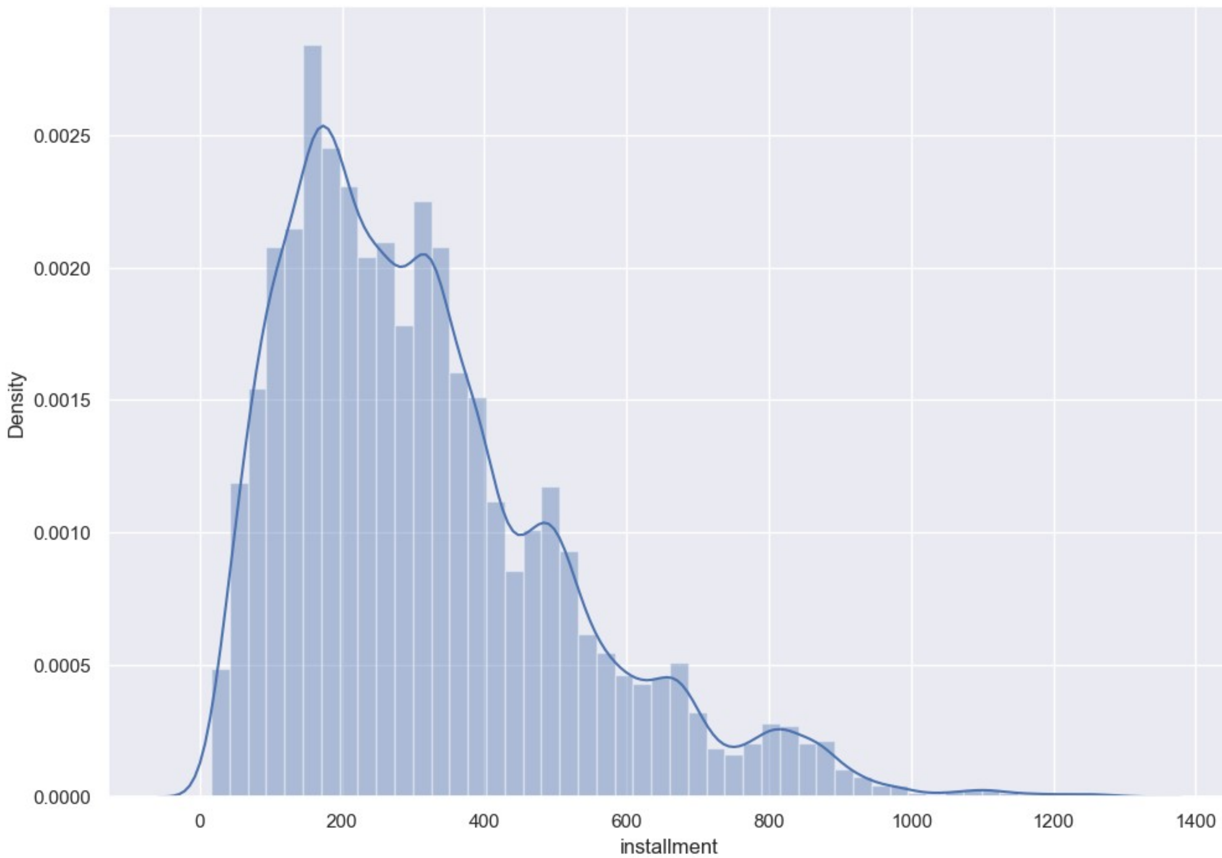

```
sns.distplot(loan_df["int_rate"] )
```

```
<Axes: xlabel='int_rate', ylabel='Density'>
```




```
sns.distplot(loan_df["installment"] )
```

```
<Axes: xlabel='installment', ylabel='Density'>
```



Findings

- Most of the people were given a loan in the month of december
- Most of the people were given a loan for year 2011
- The number of loans gien increases as the months are incresing

Conclusions From Univariate Analysis

- There are a very large number of loans that are fully paid as compared to charged off
- Most of the loans were given in the grade category B
- Most of the people who were given a loan live on rent
- Most of loans were given to people for the debt consolidation purpose
- Most of the people were given a loan in the month of december
- Most of the people were given a loan for year 2011
- The number of loans given increases as the months are incresing
- Most of the people were given a loan for a period of 36 months

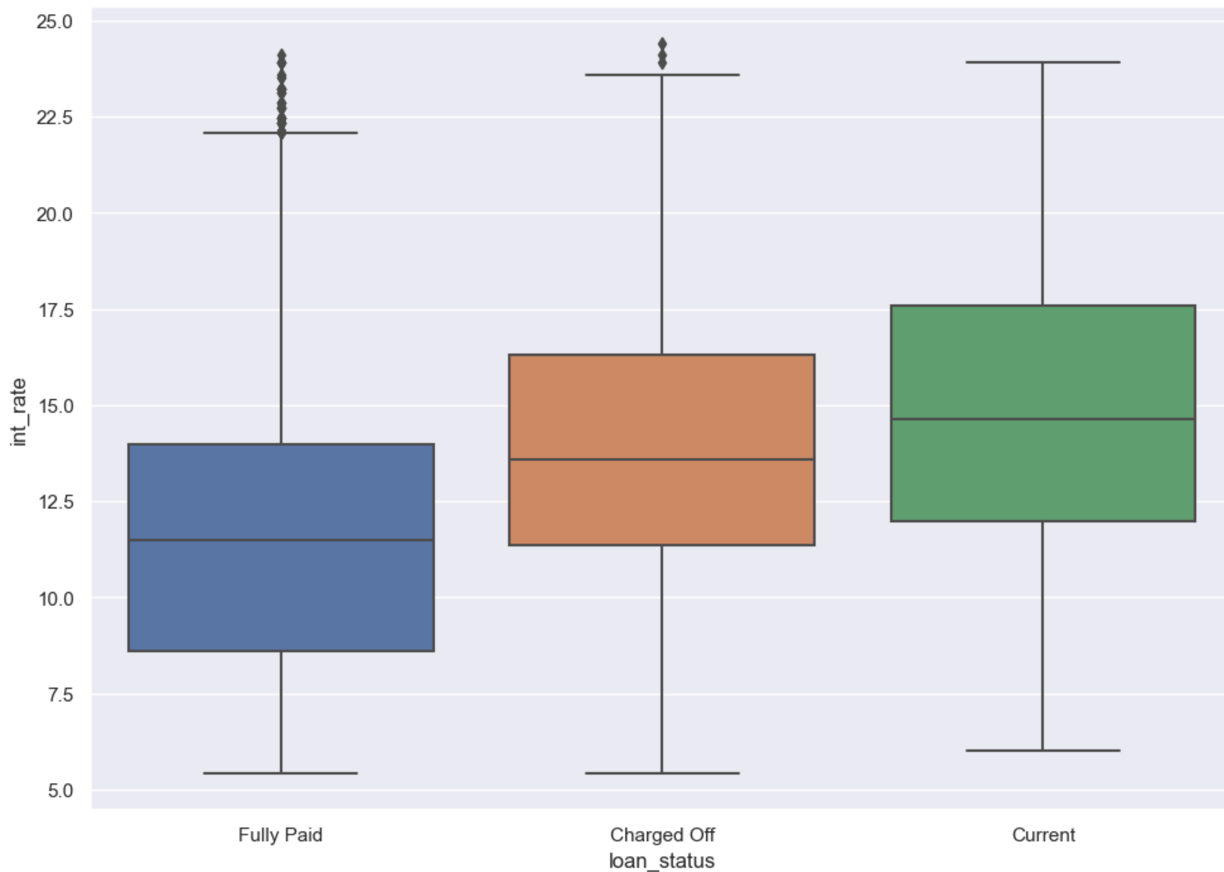
Bivariate Analysis

Comparing Categorical VS Numerical Data using boxplots

Plotting graphs for loan status VS intrest Rate as loan status seems to be the target variable

```
sns.boxplot(x = 'loan_status', y = 'int_rate' ,data=loan_df)
```

```
<Axes: xlabel='loan_status', ylabel='int_rate'>
```



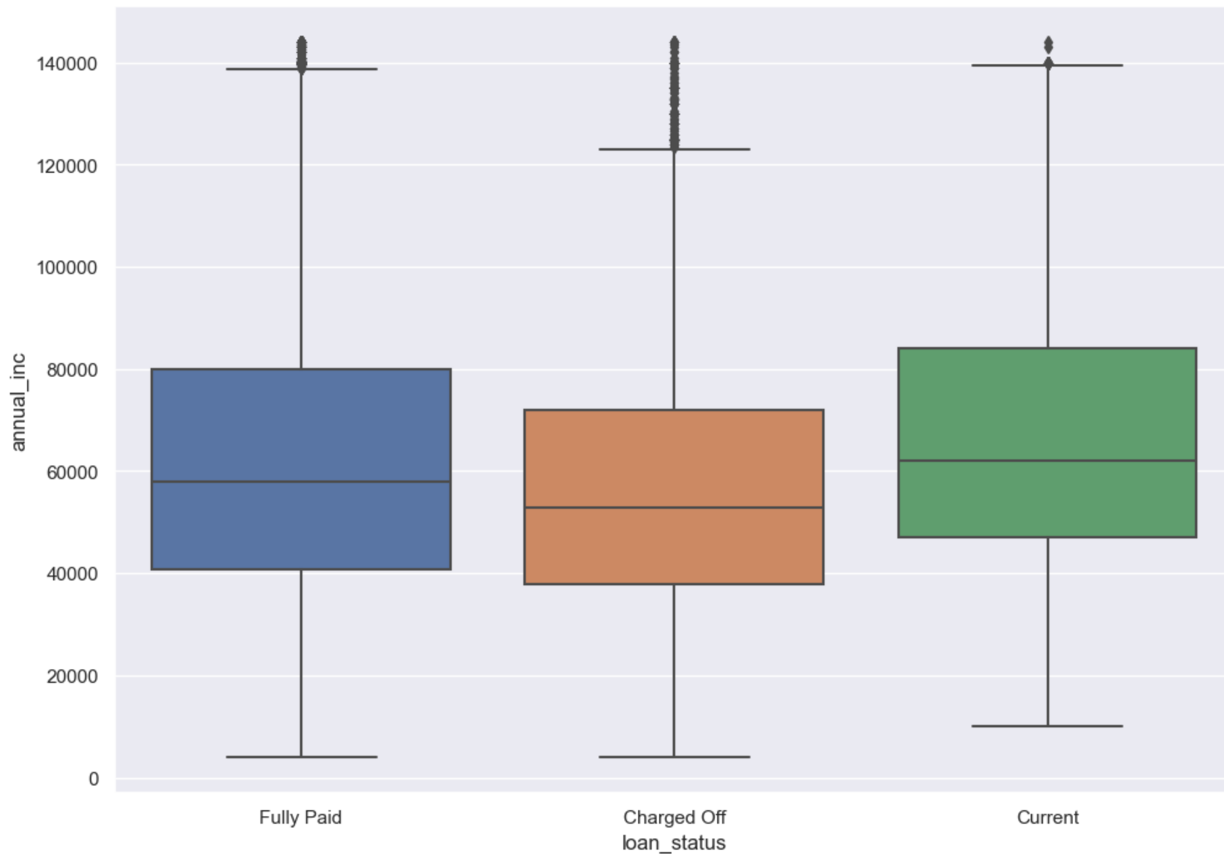
Findings

- Most of the people who default loan have been charged a higher intrest rate

Plotting graphs for loan status VS annual income

```
sns.boxplot(x = 'loan_status', y = 'annual_inc' ,data=loan_df)
```

```
<Axes: xlabel='loan_status', ylabel='annual_inc'>
```



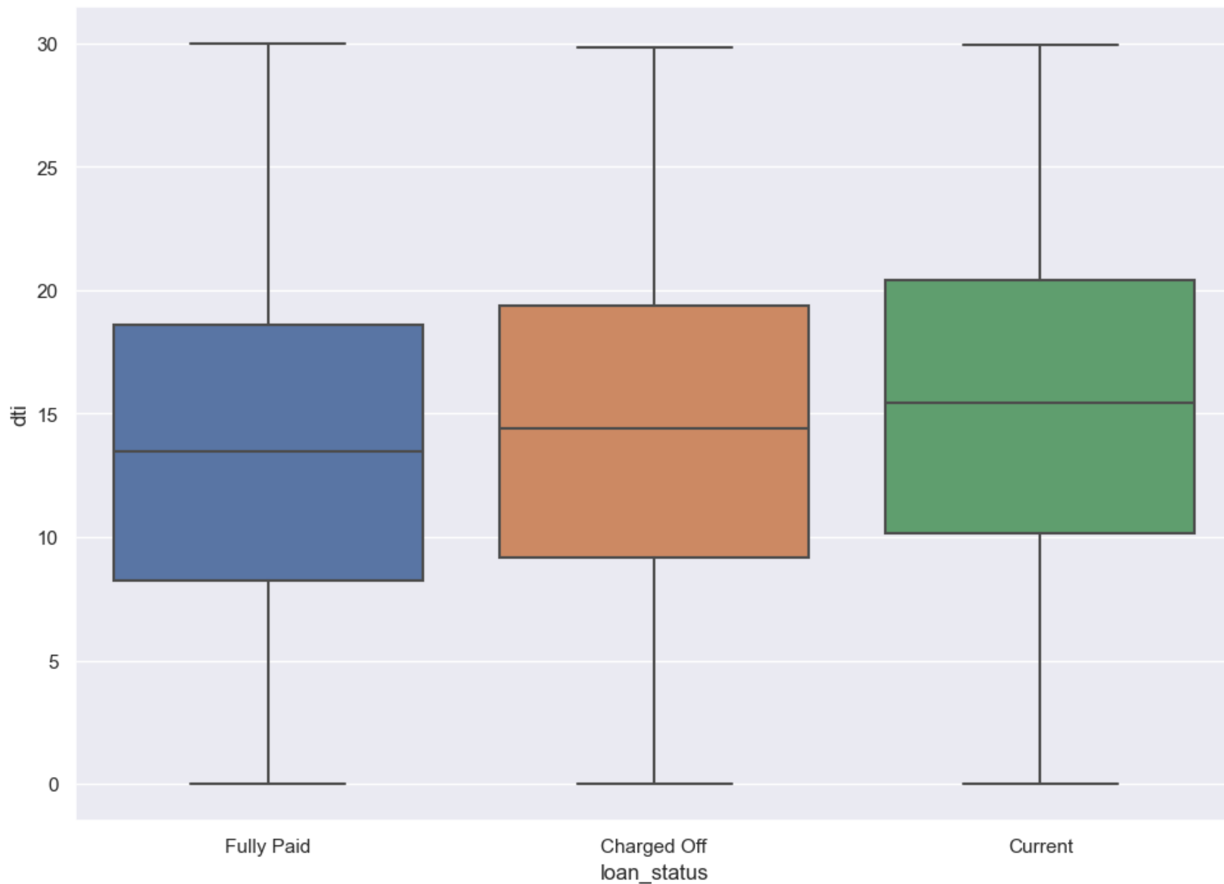
Findings

- Most of the people who default loan have a slightly lower annual income

Plotting graphs for loan status vs dti

```
sns.boxplot(x = 'loan_status', y = 'dti' ,data=loan_df)
```

```
<Axes: xlabel='loan_status', ylabel='dti'>
```



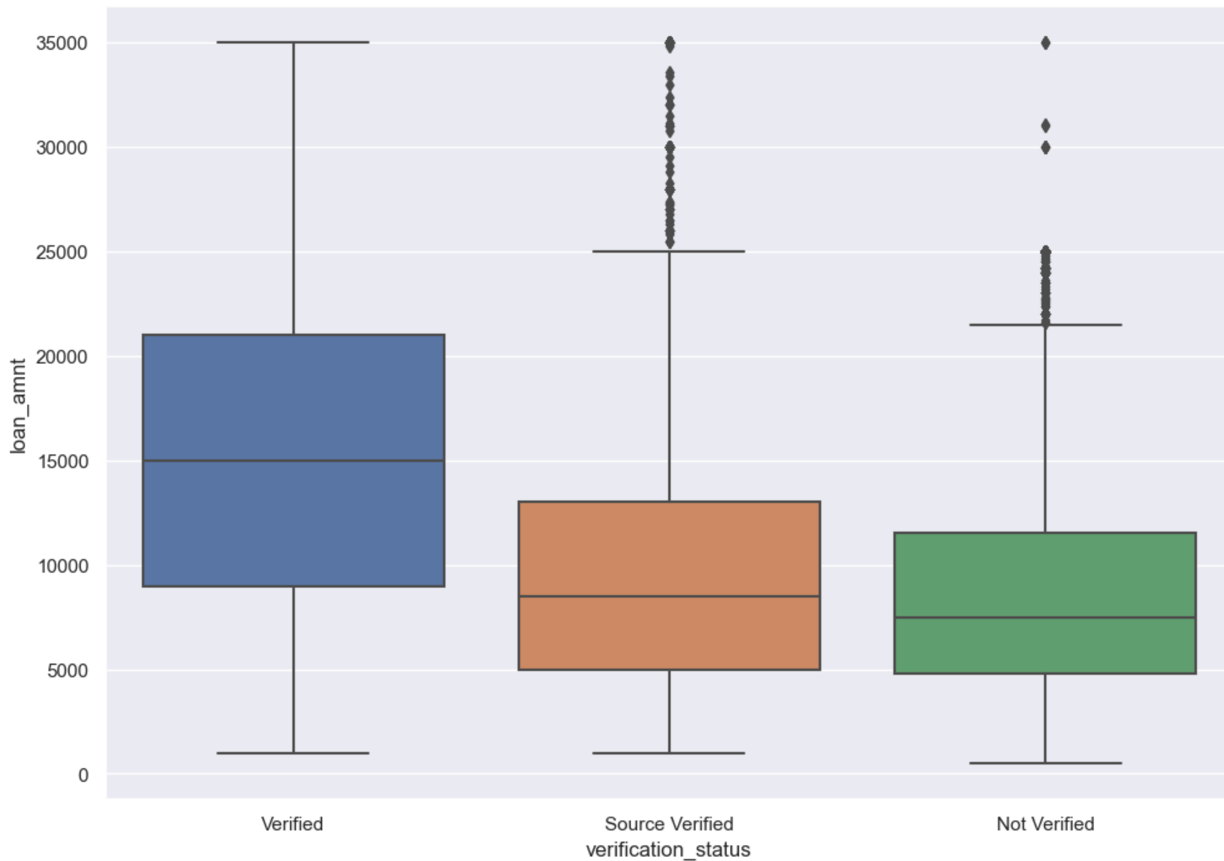
Findings

- Most of the people who default loan have a slightly higher dti (A ratio calculated using the borrower's total monthly debt payments on the total debt obligations)

Plotting graphs for loan status vs verification_status

```
sns.boxplot( x="verification_status",y="loan_amnt", data=loan_df)
```

```
<Axes: xlabel='verification_status', ylabel='loan_amnt'>
```



Findings

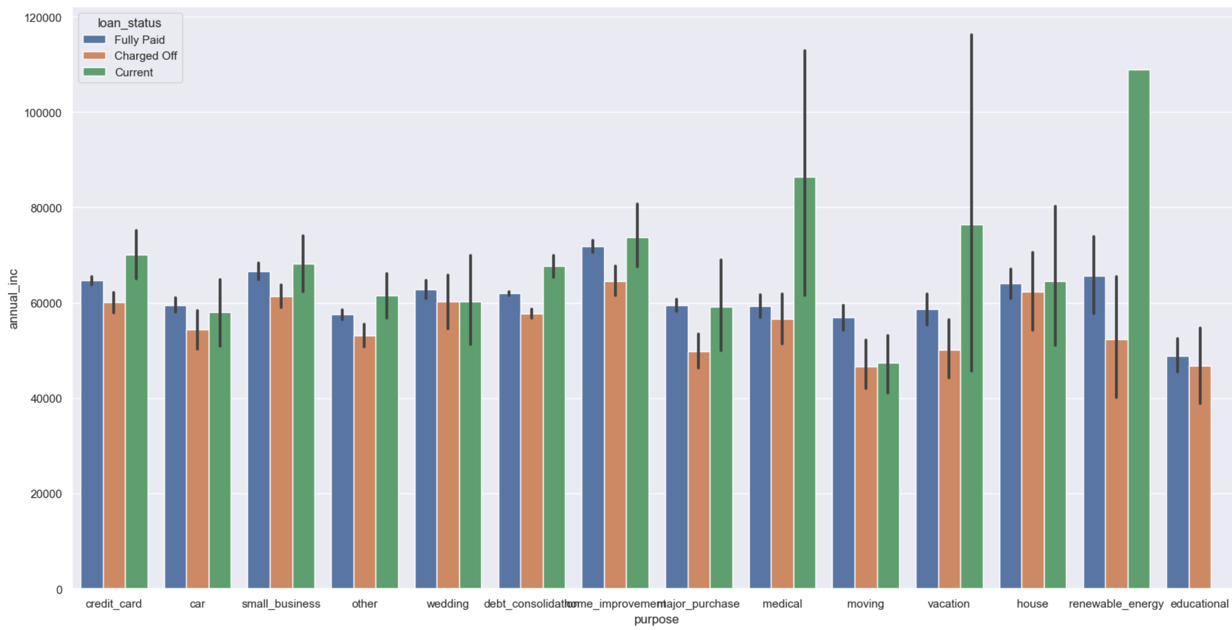
- People who were verified were given a higher loan amount

Comparing other values with loan status

comparing annual income vs loan purpose

```
fig, ax = plt.subplots(figsize = (20,10))
sns.barplot(data =loan_df,y='annual_inc', x='purpose', hue
='loan_status')

<Axes: xlabel='purpose', ylabel='annual_inc'>
```



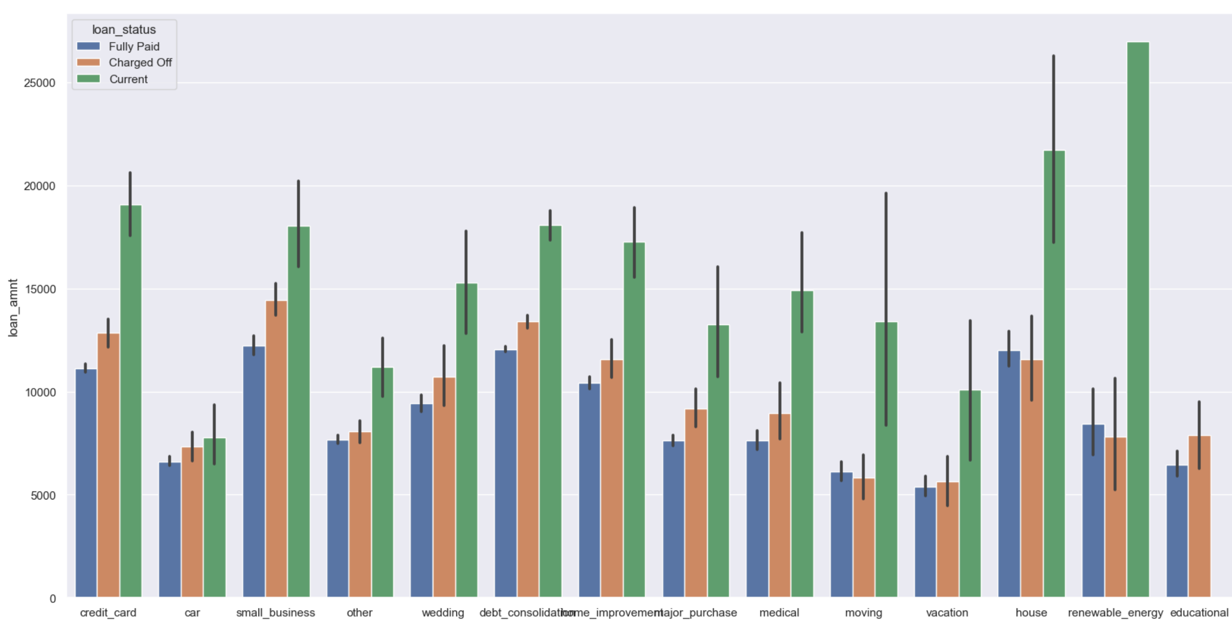
Findings

*The loan takers higher annual incomes are being spent onrenewable_energy, home_improvment,small_businesses and house

comparing loan amnt vs loan purpose

```
fig, ax = plt.subplots(figsize = (20,10))
sns.barplot(data =loan_df,y='loan_amnt', x='purpose', hue
='loan_status')
```

```
<Axes: xlabel='purpose', ylabel='loan_amnt'>
```



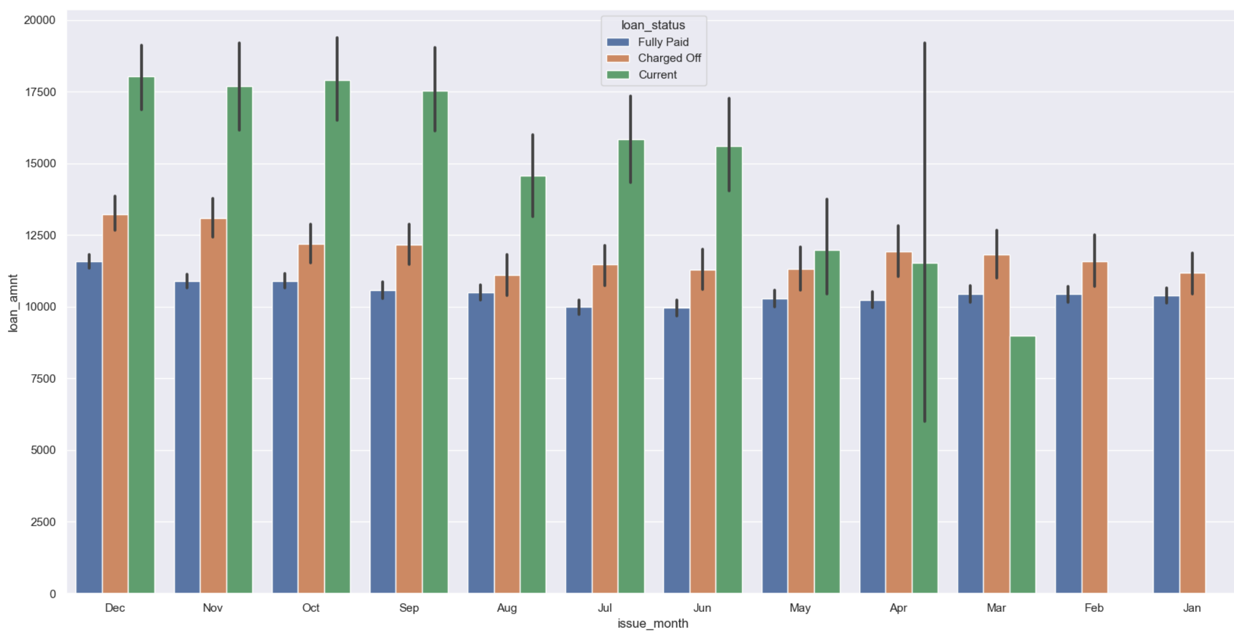
Findings

- From the above graph we can conclude that the maximum loan were charged off in the following categories credit card , small business, debt consolidation and house
- Credit card and debt consolidation being the major risky sectors for giving out the loan

Plotting a graph for year and month vs the loan status

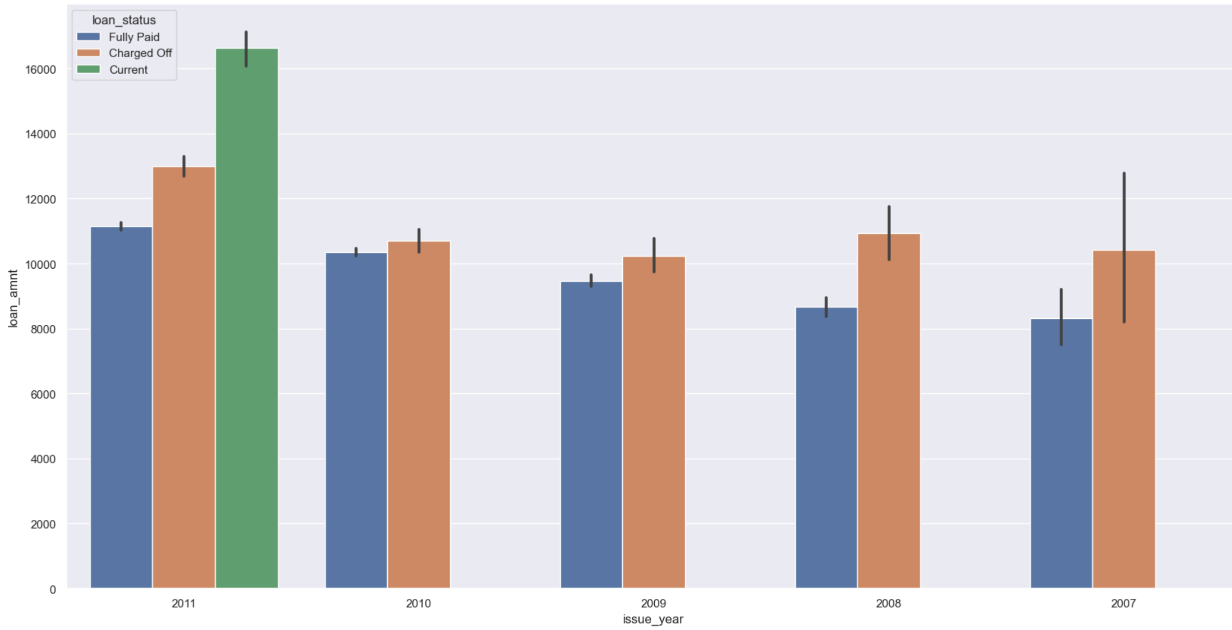
```
fig, ax = plt.subplots(figsize = (20,10))
sns.barplot(data =loan_df,y='loan_amnt', x='issue_month', hue
='loan_status')
```

```
<Axes: xlabel='issue_month', ylabel='loan_amnt'>
```




```
fig, ax = plt.subplots(figsize = (20,10))
sns.barplot(data =loan_df,y='loan_amnt', x='issue_year', hue
='loan_status')
```

```
<Axes: xlabel='issue_year', ylabel='loan_amnt'>
```



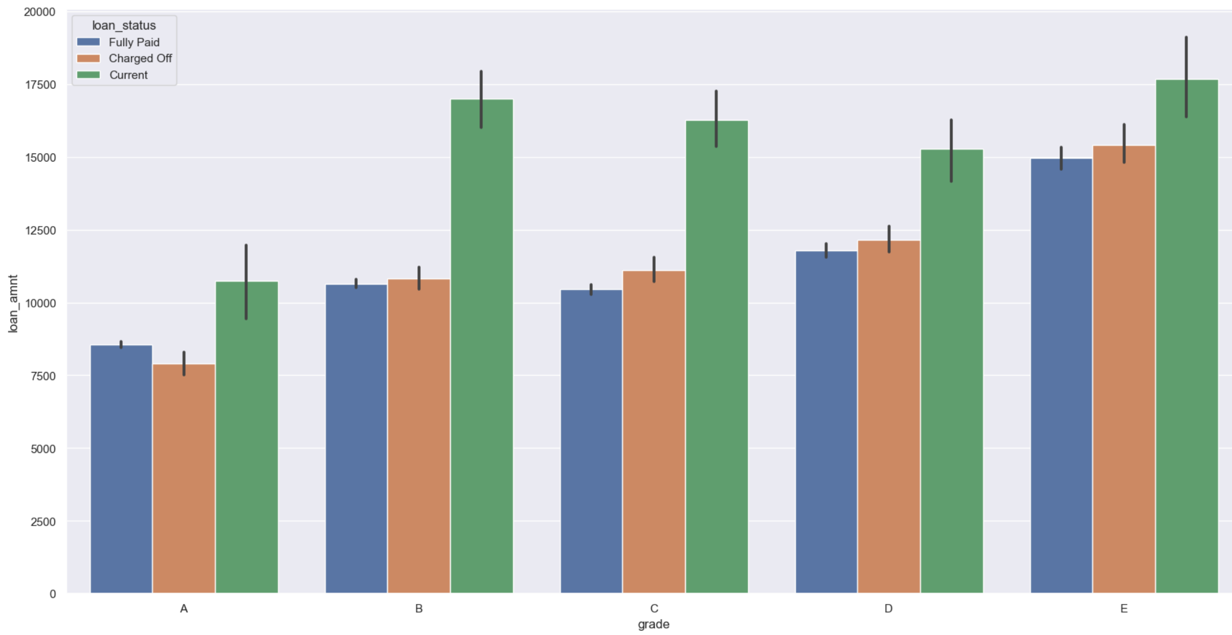
Findings

- From the above graphs we can conclude that most of the defaults happened in the later months of the year like sep, out, nov, dec
- From the year vs the loan status graph we can conclude that a high number of loans were charged off in the year 2011

Plotting a graph for loan amount vs grade

```
fig, ax = plt.subplots(figsize = (20,10))
sns.barplot(data =loan_df,y='loan_amnt', x='grade', hue
='loan_status', order=['A','B','C','D','E'])
```

```
<Axes: xlabel='grade', ylabel='loan_amnt'>
```



Findings

- From the above graphs we can conclude that people with grade E have a higher loan amount sanctioned

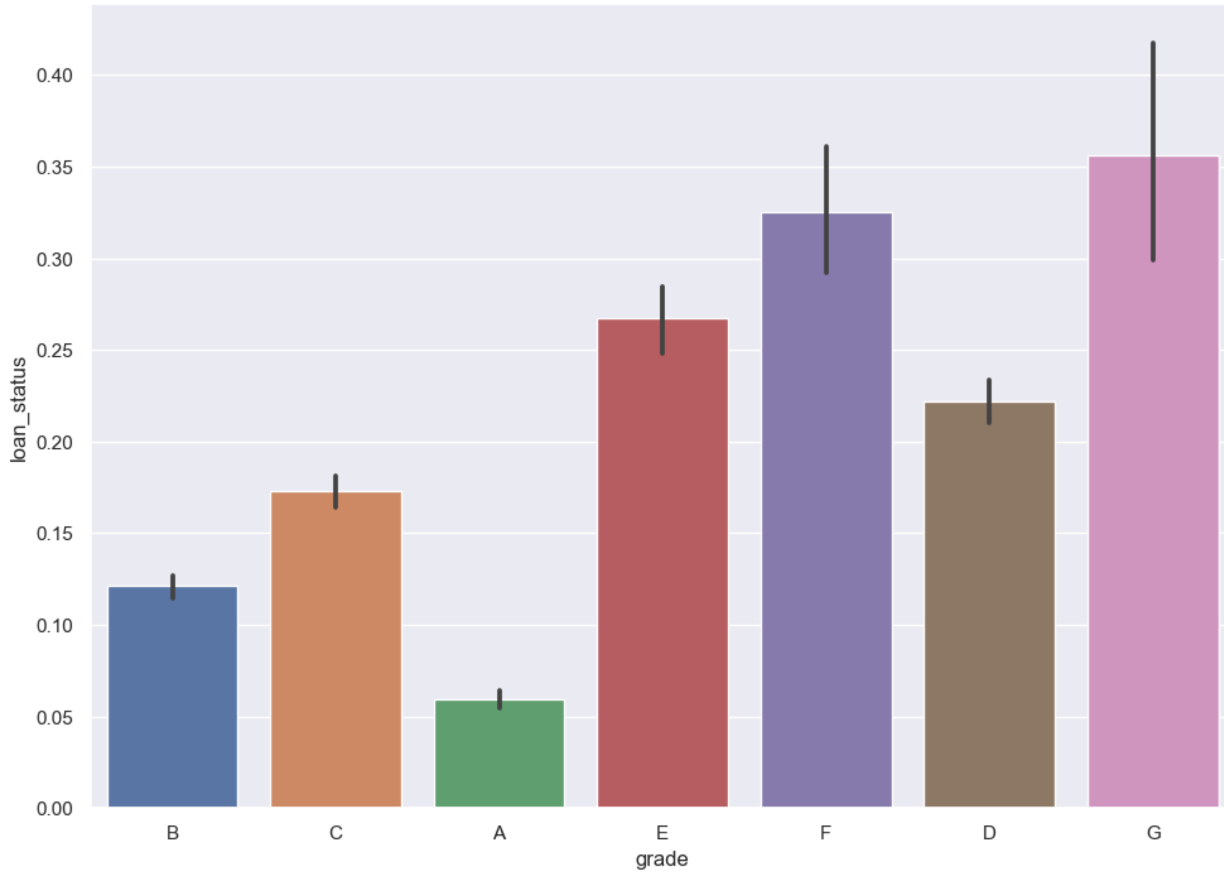
Converting the Loan Status our target variable to a int for the further risk comparisions

```
loan_df['loan_status'] = loan_df['loan_status'].astype('category')
loan_df = loan_df[loan_df.loan_status != 'Current']
loan_df.loan_status.value_counts()
loan_df['loan_status'] = loan_df['loan_status'].apply(lambda x: 0 if
x=='Fully Paid' else 1)
```

Plotting Grade vs the loan status distribution

```
sns.barplot(x='grade', y='loan_status', data=loan_df)
loan_df['loan_status'].value_counts()

0    30497
1     5187
Name: loan_status, dtype: int64
```



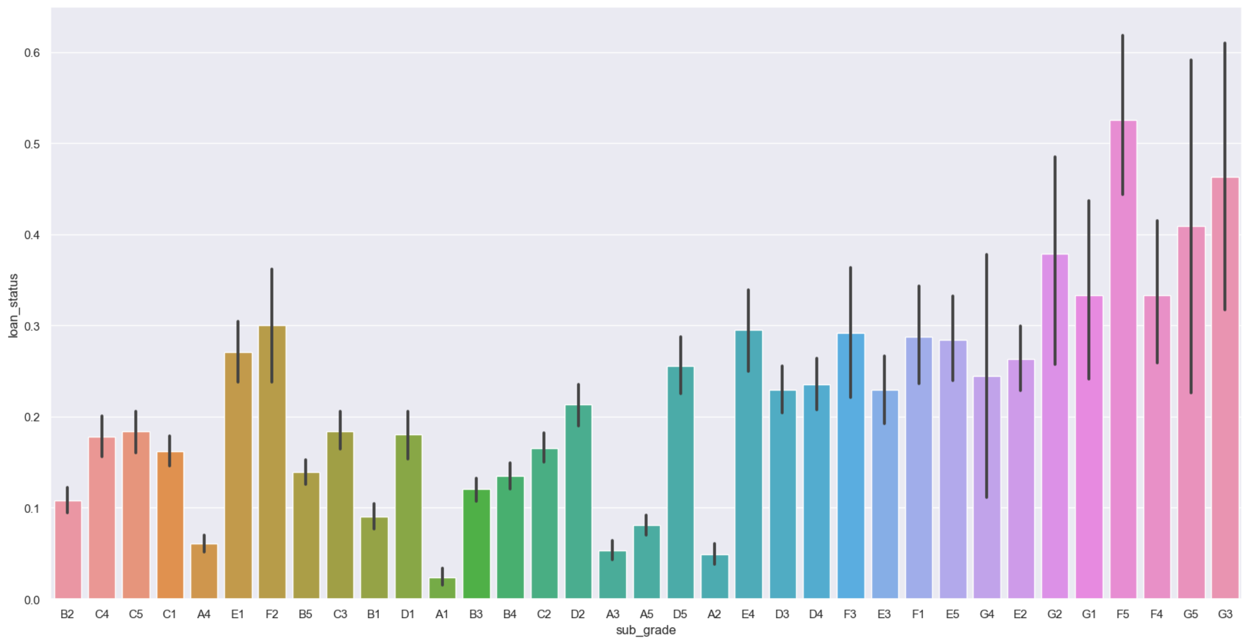
Findings

- From the above graphs we can conclude that grade G and F loans are the most risky loans to be given

Plotting Sub Grade vs the loan status distribution

```
fig, ax = plt.subplots(figsize = (20,10))
sns.barplot(x='sub_grade', y='loan_status', data=loan_df)

<Axes: xlabel='sub_grade', ylabel='loan_status'>
```



Findings

- From the above graph we can conclude that Risk increases as the sub grade of loan inccreases example A1 A2 A3 so on

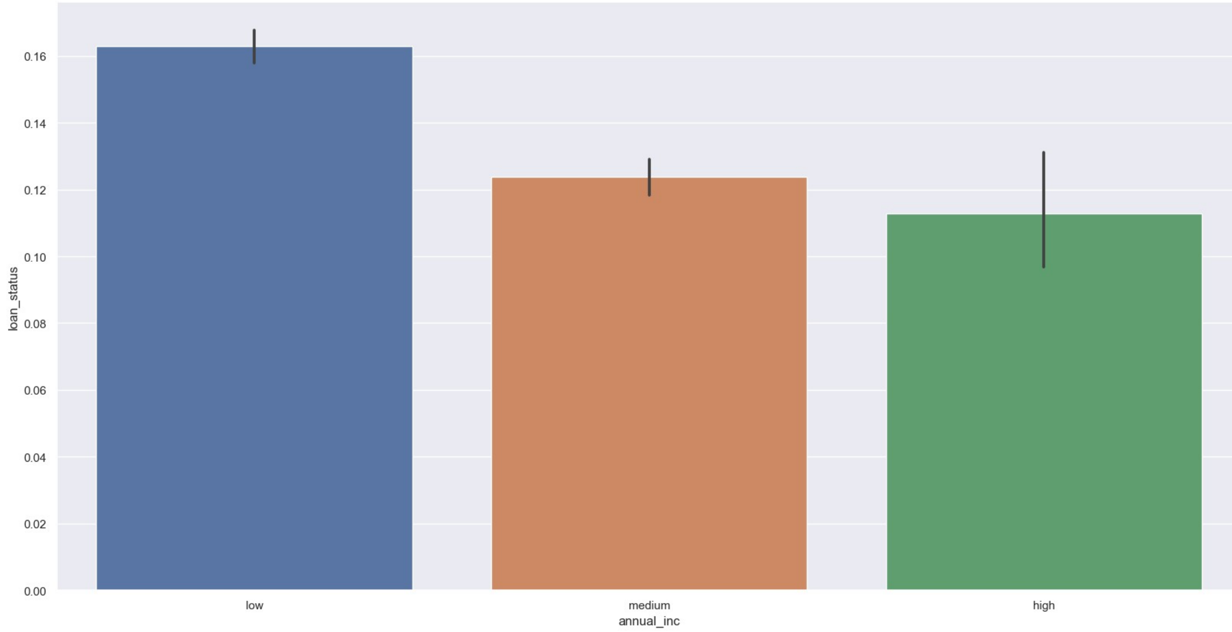
Lets do a segmented analysis for a relation between the annual income and the loan status

```
def cat_annual_income(n):
    if n <= 60000:
        return 'low'
    elif n > 60000 and n <=120000:
        return 'medium'
    elif n > 120000 and n <=175000:
        return 'high'
    else:
        return 'very high'

loan_df['annual_inc'] = loan_df['annual_inc'].apply(lambda x:
cat_annual_income(x))

fig, ax = plt.subplots(figsize = (20,10))
sns.barplot(x='annual_inc', y='loan_status', data=loan_df)

<Axes: xlabel='annual_inc', ylabel='loan_status'>
```



Findings

- Lower the annual income is higher is the risk for the loan defaults

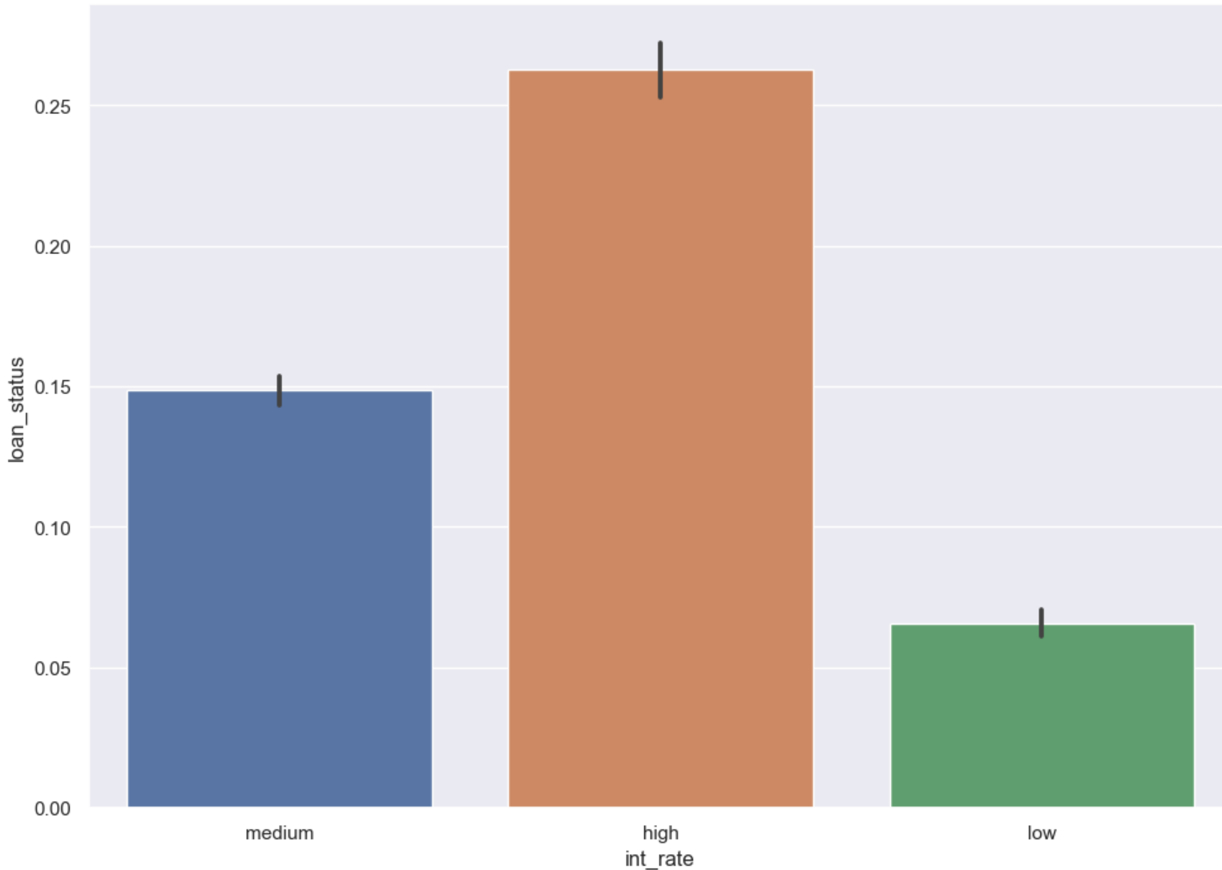
Lets do a segmented analysis for a relation between the interest rate and the loan status

```
def catagorical_int_rate(n):
    if n <= 15:
        return 'low'
    elif n > 15 and n <=20:
        return 'medium'
    else:
        return 'high'


loan_df['int_rate'] = loan_df['int_rate'].apply(lambda x: int_rate(x))

sns.barplot(x='int_rate', y='loan_status', data=loan_df)

<Axes: xlabel='int_rate', ylabel='loan_status'>
```



Findings

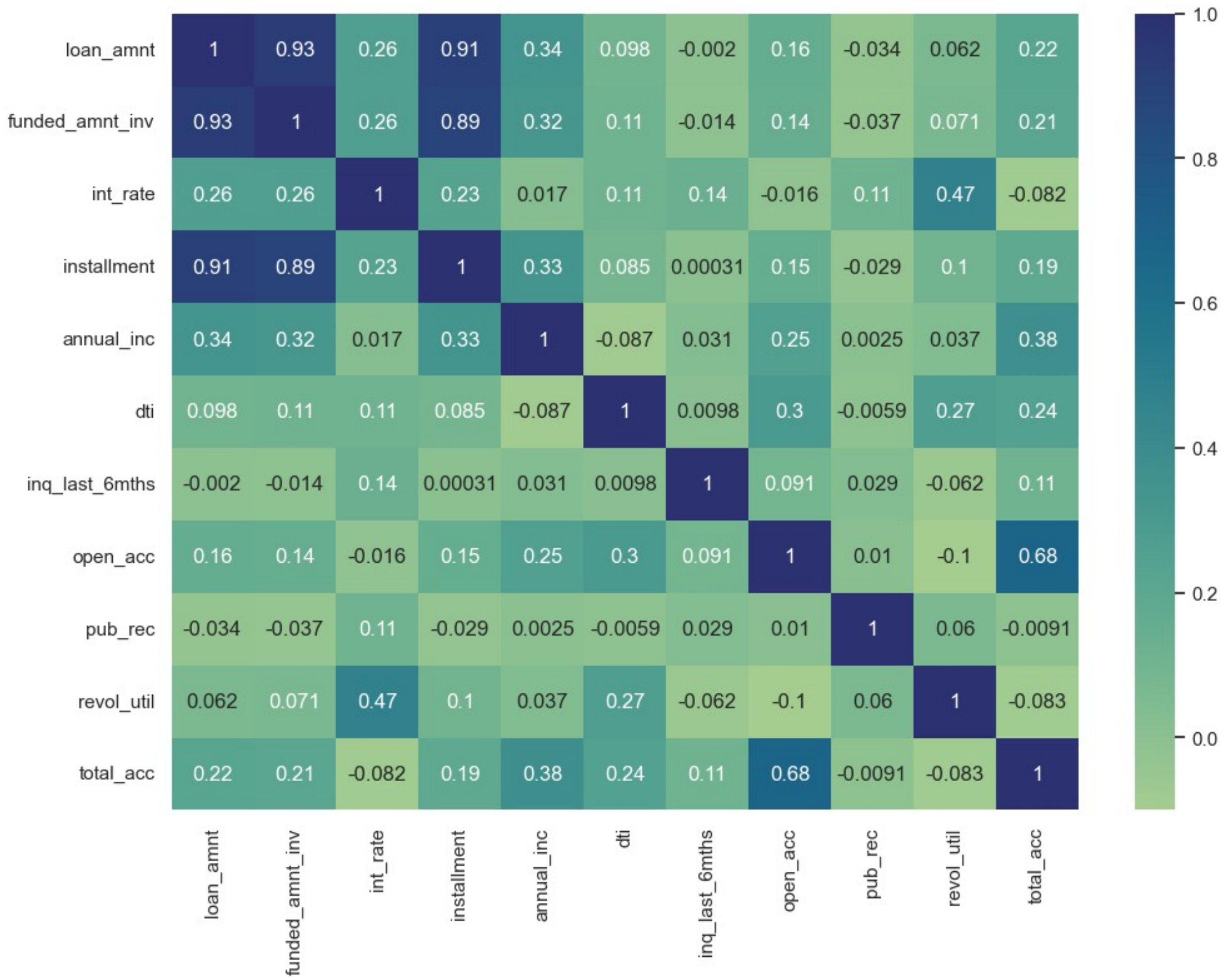
- High Interest Rates have a higher probablity of the defaults

Checking the co-relation between All the numerical values

```
loan_corelation= dt.corr()

sns.set(rc={'figure.figsize':(11.7,8.27)})
sns.heatmap(loan_corelation,annot=True, cmap="crest")
```

```
<Axes: >
```



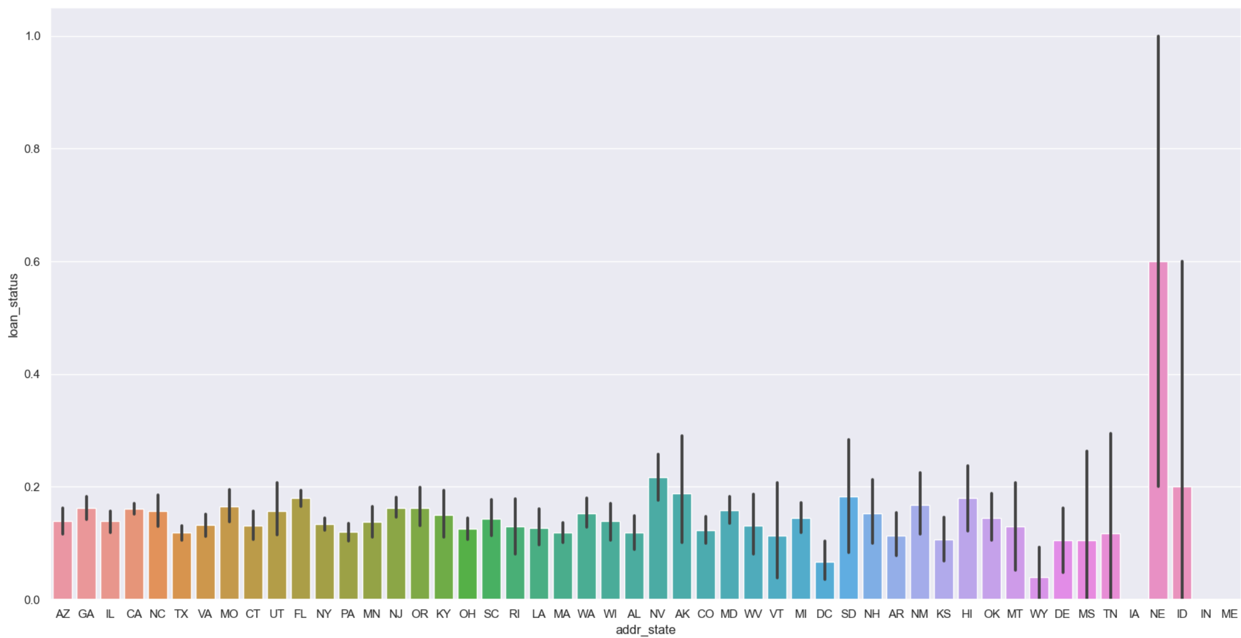
Findings

- Open accounts is positively corelated with the total accounts
- Installment is positively corelated with the loan_amnt and funded_amnt_inv

Experimental: Comparing address state data with the loan status

```
fig, ax = plt.subplots(figsize = (20,10))
sns.barplot(x='addr_state', y='loan_status', data=loan_df)

<Axes: xlabel='addr_state', ylabel='loan_status'>
```



Findings

- We see a High Number of defaults from states like NE,ID,and NV, Where NE being the extremely highest

Conclusions

Insights

Univariate Analysis

- There are a very large number of loans that are fully paid as compared to charged off
- Most of the loans were given in the grade category B
- Most of the people who were given a loan live on rent
- Most of loans were given to people for the debt consolidation purpose
- Most of the people were given a loan in the month of december
- Most of the people were given a loan for year 2011
- The number of loans given increases as the months are incresing
- Most of the people were given a loan for a period of 36 months

Segmented Univariate Analysis

- Lower the annual income is higher is the risk for the loan defaults
- High Interest Rates have a higher probablity of the defaults

Bivariate Analysis

- Most of the people who default loan have been charged a higher intrest rate
- Most of the people who default loan have a slightly lower annual income

- Most of the people who default loan have a slightly higher dti (A ratio calculated using the borrower's total monthly debt payments on the total debt obligations)
- People who were verified were given a higher loan amount
- The loan takers higher annual incomes are being spent on renewable_energy,home_improvment,small_businesses and house
- From the above graph we can conclude that the maximum loan were charged off in the following categories credit card , small business, debt consolidation and house
- Credit card and debt consolidation being the major risky sectors for giving out the loan
- Most of the defaults happened in the later months of the year like sep, out, nov, dec
- A high number of loans were charged off in the year 2011
- People with grade E have a higher loan amount sanctioned
- Grade G and F loans are the most risky loans to be given
- Risk increases as the sub grade of loan inccreases example A1 A2 A3 so on
- Open accounts is positively corelated with the total accounts
- Installment is positively corelated with the loan_amnt and funded_amnt_inv
- We see a High Number of defaults from states like NE,ID,and NV, Where NE being the extremely highest

Recommendations

The following factors highly determine the loan defauting outcomes

- Intrest Rate
- Annual Income
- DTI
- Verification Status

Other Factors affecting the loan outcomes

- Grade G and F loans are the most risky loans to be given
- Most of the defaults happened in the later months of the year like sep, out, nov, dec
- Credit card and debt consolidation being the major risky sectors for giving out the loan
- We see a High Number of defaults from states like NE,ID,and NV, Where NE being the extremely highest
- Risk increases as the sub grade of loan increases example A1 A2 A3 so on
- Most of the people who default loan have been charged a higher intrest rate
- Most of the people who default loan have a slightly lower annual income