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0.1 Lending Club Case Study Analysis

Importing the required python modules for our analysis

[885]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
```

Reading the Data

[887]:
```
df = pd.read_csv("loan.csv",header=0)
```

Loading the Dataframe and checking basic info about the dataframe

[889]:
```
df.head()
```

[889]:
```
        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]
```

[890]:
```
df.shape
```

[890]:
```
(39717, 111)
```

[891]:
```
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
```

0.1.1 Data Cleaning and Manipulation

[893]:
```
(df.isnull().sum()*100)/len(df)
```

[893]:
```
id                              0.000000
member_id                       0.000000
loan_amnt                       0.000000
funded_amnt                     0.000000
funded_amnt_inv                 0.000000
                                  …
tax_liens                       0.098195
tot_hi_cred_lim               100.000000
total_bal_ex_mort             100.000000
total_bc_limit                100.000000
total_il_high_credit_limit    100.000000
Length: 111, dtype: float64
```

It is observed that there are many columns that are having all the values as null. Dropping these columns as they don't have significance in our analysis

[895]:
```
df = df.dropna(axis=1,how='all')
df.shape
```

[895]: (39717, 57)

[896]:
```
df = df.dropna(axis=0,how='all')
```

[897]:
```
df.shape
```

[897]: (39717, 57)

Checking for Duplicate rows in the dataframe

[899]:
```
duplicate_mask = df.duplicated(keep=False)
duplicate_rows = df[duplicate_mask]
print(duplicate_rows)
```

```
Empty DataFrame
Columns: [id, member_id, loan_amnt, funded_amnt, funded_amnt_inv, term,
int_rate, installment, grade, sub_grade, emp_title, emp_length, home_ownership,
annual_inc, verification_status, issue_d, loan_status, pymnt_plan, url, desc,
purpose, title, zip_code, addr_state, dti, delinq_2yrs, earliest_cr_line,
inq_last_6mths, mths_since_last_delinq, mths_since_last_record, open_acc,
pub_rec, revol_bal, revol_util, total_acc, initial_list_status, out_prncp,
out_prncp_inv, total_pymnt, total_pymnt_inv, total_rec_prncp, total_rec_int,
total_rec_late_fee, recoveries, collection_recovery_fee, last_pymnt_d,
last_pymnt_amnt, next_pymnt_d, last_credit_pull_d, collections_12_mths_ex_med,
policy_code, application_type, acc_now_delinq, chargeoff_within_12_mths,
delinq_amnt, pub_rec_bankruptcies, tax_liens]
Index: []

[0 rows x 57 columns]
```

[900]:
```
df = df.drop_duplicates()
```

[901]:
```
df.shape
```

[901]: (39717, 57)

Checking for Columns that are single valued as they won't contribute to our analysis

[903]:
```
unique_counts = df.nunique()
single_value_columns = unique_counts[unique_counts == 1].index.tolist()
print(single_value_columns)
```

```
['pymnt_plan', 'initial_list_status', 'collections_12_mths_ex_med',
'policy_code', 'application_type', 'acc_now_delinq', 'chargeoff_within_12_mths',
'delinq_amnt', 'tax_liens']
```

Dropping single valued columns

[905]:
```
df = df.drop(single_value_columns,axis=1)
df.shape
```

[905]:
```
(39717, 48)
```

Now we have 48 columns out of which some correspond to the post approval of loan

- We are analysing the user details and the driving factors of loan defaulting before approving loan.
- So we can safely remove the columns or 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 doesn't contribute to the loan defaulting in any way due to irrelevant information. So removing them.
- "desc" has description(text data) and does not contribute to the EDA analysis.
- "out_prncp_inv", "total_pymnt_inv", are useful for investors but not contribute 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 columns

- 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
- next_pymnt_d
- chargeoff_within_12_mths
- mths_since_last_delinq
- mths_since_last_record

[908]:

```
df.drop(["id", "member_id", "url", "title", "emp_title", ␣
↪"last_credit_pull_d","desc","out_prncp_inv","total_pymnt_inv","funded_amnt",␣
↪"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", "next_pymnt_d"␣
↪, "mths_since_last_delinq", "mths_since_last_record"], axis = 1, inplace =␣
↪True)
df.shape
```

[908]:

```
(39717, 24)
```

Columns with missing values

[910]:

```
(df.isna().sum()/len(df.index))*100
```

[910]:

```
loan_amnt                 0.000000
funded_amnt_inv           0.000000
term                      0.000000
int_rate                  0.000000
installment               0.000000
grade                     0.000000
sub_grade                 0.000000
emp_length                2.706650
home_ownership            0.000000
annual_inc                0.000000
verification_status       0.000000
issue_d                   0.000000
loan_status               0.000000
purpose                   0.000000
zip_code                  0.000000
addr_state                0.000000
dti                       0.000000
earliest_cr_line          0.000000
inq_last_6mths            0.000000
open_acc                  0.000000
pub_rec                   0.000000
revol_util                0.125891
total_acc                 0.000000
pub_rec_bankruptcies      1.754916
dtype: float64
```

Handling the missing value

[912]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 39717 entries, 0 to 39716
Data columns (total 24 columns):
```

```
 #   Column                Non-Null Count  Dtype
---  ------                --------------  -----
 0   loan_amnt             39717 non-null  int64
 1   funded_amnt_inv       39717 non-null  float64
 2   term                  39717 non-null  object
 3   int_rate              39717 non-null  object
 4   installment           39717 non-null  float64
 5   grade                 39717 non-null  object
 6   sub_grade             39717 non-null  object
 7   emp_length            38642 non-null  object
 8   home_ownership        39717 non-null  object
 9   annual_inc            39717 non-null  float64
 10  verification_status   39717 non-null  object
 11  issue_d               39717 non-null  object
 12  loan_status           39717 non-null  object
 13  purpose               39717 non-null  object
 14  zip_code              39717 non-null  object
 15  addr_state            39717 non-null  object
 16  dti                   39717 non-null  float64
 17  earliest_cr_line      39717 non-null  object
 18  inq_last_6mths        39717 non-null  int64
 19  open_acc              39717 non-null  int64
 20  pub_rec               39717 non-null  int64
 21  revol_util            39667 non-null  object
 22  total_acc             39717 non-null  int64
 23  pub_rec_bankruptcies  39020 non-null  float64
dtypes: float64(5), int64(5), object(14)
memory usage: 7.6+ MB
```

Standardizing the data

[914]:
```
df['int_rate']=df['int_rate'].str.rstrip('%')
print(df['int_rate'])
```

```
0        10.65
1        15.27
2        15.96
3        13.49
4        12.69
         …
39712     8.07
39713    10.28
39714     8.07
39715     7.43
39716    13.75
Name: int_rate, Length: 39717, dtype: object
```

[915]:
```
df['revol_util']=df['revol_util'].str.rstrip('%')
```

[916]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 39717 entries, 0 to 39716
Data columns (total 24 columns):
 #   Column                Non-Null Count  Dtype
---  ------                --------------  -----
 0   loan_amnt             39717 non-null  int64
 1   funded_amnt_inv       39717 non-null  float64
 2   term                  39717 non-null  object
 3   int_rate              39717 non-null  object
 4   installment           39717 non-null  float64
 5   grade                 39717 non-null  object
 6   sub_grade             39717 non-null  object
 7   emp_length            38642 non-null  object
 8   home_ownership        39717 non-null  object
 9   annual_inc            39717 non-null  float64
 10  verification_status   39717 non-null  object
 11  issue_d               39717 non-null  object
 12  loan_status           39717 non-null  object
 13  purpose               39717 non-null  object
 14  zip_code              39717 non-null  object
 15  addr_state            39717 non-null  object
 16  dti                   39717 non-null  float64
 17  earliest_cr_line      39717 non-null  object
 18  inq_last_6mths        39717 non-null  int64
 19  open_acc              39717 non-null  int64
 20  pub_rec               39717 non-null  int64
 21  revol_util            39667 non-null  object
 22  total_acc             39717 non-null  int64
 23  pub_rec_bankruptcies  39020 non-null  float64
dtypes: float64(5), int64(5), object(14)
memory usage: 7.6+ MB
```

Imputing Mode value for missing value for the column emp_length

[918]:
```
# df.emp_length.fillna('0',inplace=True) #dont replace na values with 0 instead␣
 ↪fill it with mode value as shown in the below line
print("Mode : " + df.emp_length.mode()[0])
df.emp_length.value_counts()
df['emp_length']=df.emp_length.str.extract('(\d+)')
df.head()
```

```
Mode : 10+ years
```

[918]:
```
   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  … zip_code addr_state  \
0        B2         10           RENT     24000.0  …    860xx         AZ
1        C4          1           RENT     30000.0  …    309xx         GA
2        C5         10           RENT     12252.0  …    606xx         IL
3        C1         10           RENT     49200.0  …    917xx         CA
4        B5          1           RENT     80000.0  …    972xx         OR

     dti earliest_cr_line inq_last_6mths open_acc  pub_rec revol_util  \
0  27.65           Jan-85              1        3        0      83.70
1   1.00           Apr-99              5        3        0       9.40
2   8.72           Nov-01              2        2        0      98.50
3  20.00           Feb-96              1       10        0         21
4  17.94           Jan-96              0       15        0      53.90

   total_acc  pub_rec_bankruptcies
0          9                   0.0
1          4                   0.0
2         10                   0.0
3         37                   0.0
4         38                   0.0

[5 rows x 24 columns]
```

Changing the Datatype of columns to integer type

[920]:
```
columns1=['loan_amnt','int_rate','funded_amnt_inv','installment','annual_inc','dti']
df[columns1]=df[columns1].apply(pd.to_numeric)
```

[921]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 39717 entries, 0 to 39716
Data columns (total 24 columns):
 #   Column                Non-Null Count  Dtype
---  ------                --------------  -----
 0   loan_amnt             39717 non-null  int64
 1   funded_amnt_inv       39717 non-null  float64
 2   term                  39717 non-null  object
 3   int_rate              39717 non-null  float64
 4   installment           39717 non-null  float64
 5   grade                 39717 non-null  object
 6   sub_grade             39717 non-null  object
 7   emp_length            38642 non-null  object
 8   home_ownership        39717 non-null  object
```

```
 9   annual_inc            39717 non-null  float64
 10  verification_status   39717 non-null  object
 11  issue_d               39717 non-null  object
 12  loan_status           39717 non-null  object
 13  purpose               39717 non-null  object
 14  zip_code              39717 non-null  object
 15  addr_state            39717 non-null  object
 16  dti                   39717 non-null  float64
 17  earliest_cr_line      39717 non-null  object
 18  inq_last_6mths        39717 non-null  int64
 19  open_acc              39717 non-null  int64
 20  pub_rec               39717 non-null  int64
 21  revol_util            39667 non-null  object
 22  total_acc             39717 non-null  int64
 23  pub_rec_bankruptcies  39020 non-null  float64
dtypes: float64(6), int64(5), object(13)
memory usage: 7.6+ MB
```

Percentage of missing values for revol_util is very low so we can drop those rows

[923]:
```python
df.dropna(axis = 0, subset = ['revol_util'] , inplace = True)
df.revol_util.isna().sum()
```

[923]:
```
0
```

Data Clean on pub_rec_bankruptcies column as it will be used in analysis

[925]:
```python
print('Before cleaning pub_rec_bankruptcies')
print(df.pub_rec_bankruptcies.isnull().sum())

# Replacing the 'Not Known' with NA values
df.pub_rec_bankruptcies.fillna('Not Known',inplace=True)

print('After cleaning pub_rec_bankruptcies')
print(df.pub_rec_bankruptcies.isnull().sum())
```

```
Before cleaning pub_rec_bankruptcies
697
After cleaning pub_rec_bankruptcies
0
```

Dropping the rows for loan_status==‘Current’ as the loan currently in progress and cannot contribute to conclusive evidence

[927]:
```python
df = df[df.loan_status != "Current"]
df.shape
```

[927]:
```
(38527, 24)
```

converting issue_d'to date type

[929]:
```
df['issue_d'] = pd.to_datetime(df.issue_d, format='%b-%y')
df['issue_d']
```

[929]:
```
0        2011-12-01
1        2011-12-01
2        2011-12-01
3        2011-12-01
5        2011-12-01
            …
39712    2007-07-01
39713    2007-07-01
39714    2007-07-01
39715    2007-07-01
39716    2007-06-01
Name: issue_d, Length: 38527, dtype: datetime64[ns]
```

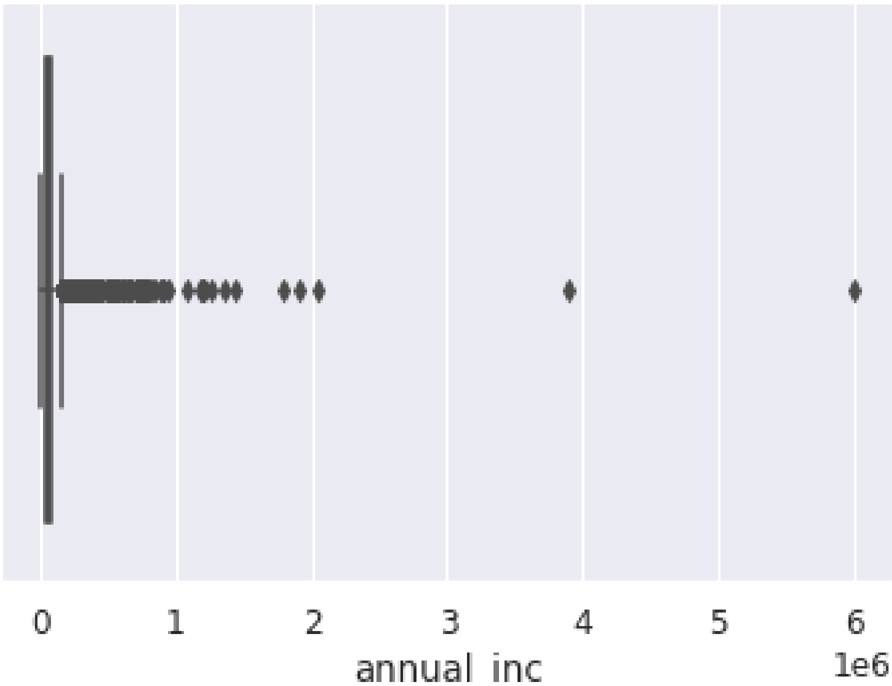
Creating two more columns issue_year and issue_month from issue_d(issue date) column

[931]:
```
df['issue_year']=pd.DatetimeIndex(df['issue_d']).year
df['issue_month']=pd.DatetimeIndex(df['issue_d']).month
```

Outlier Detection

[933]:
```
sns.boxplot(df['annual_inc'])
```

[933]:
```
<AxesSubplot:xlabel='annual_inc'>
```



The above graph clearly shows the presence of outliers

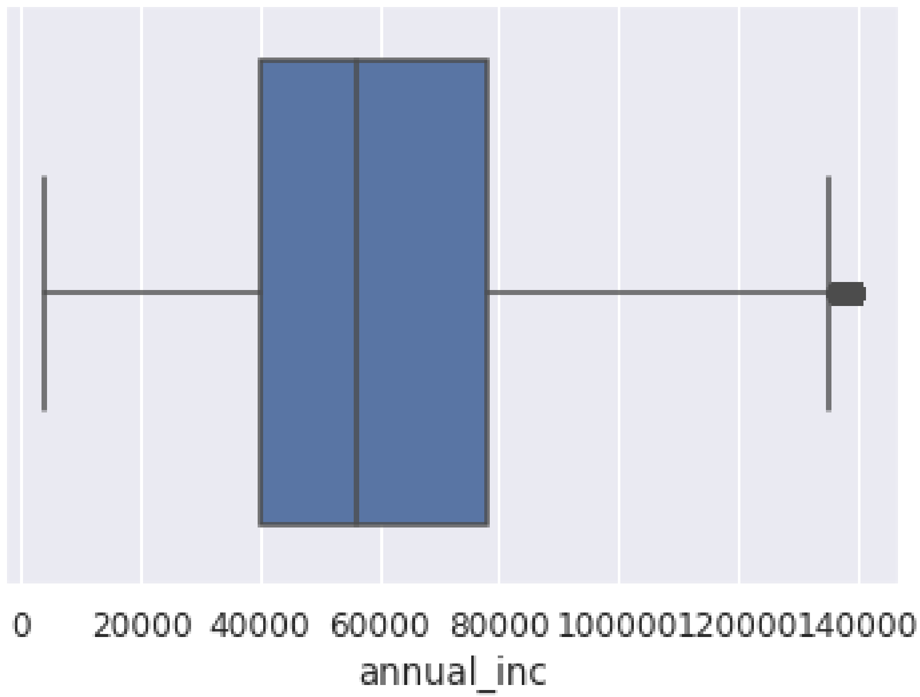
- The values after 95 percentile seems to be disconected from the general distribution and also there is huge increase in the value for small quantile variation.
- So, considering threshold for removing outliers as 0.95
- So, Removing them.

[935]:
```
quantile_info = df.annual_inc.quantile([0.5, 0.75,0.90, 0.95, 0.97,0.98, 0.99])
quantile_info
```

[935]:
```
0.50     59000.0
0.75     82000.0
0.90    115000.0
0.95    140004.0
0.97    165000.0
0.98    187000.0
0.99    234000.0
Name: annual_inc, dtype: float64
```

[936]:
```
per_95_annual_inc = df['annual_inc'].quantile(0.95)
df = df[df.annual_inc <= per_95_annual_inc]
sns.boxplot(df.annual_inc)
```

[936]:
```
<AxesSubplot:xlabel='annual_inc'>
```



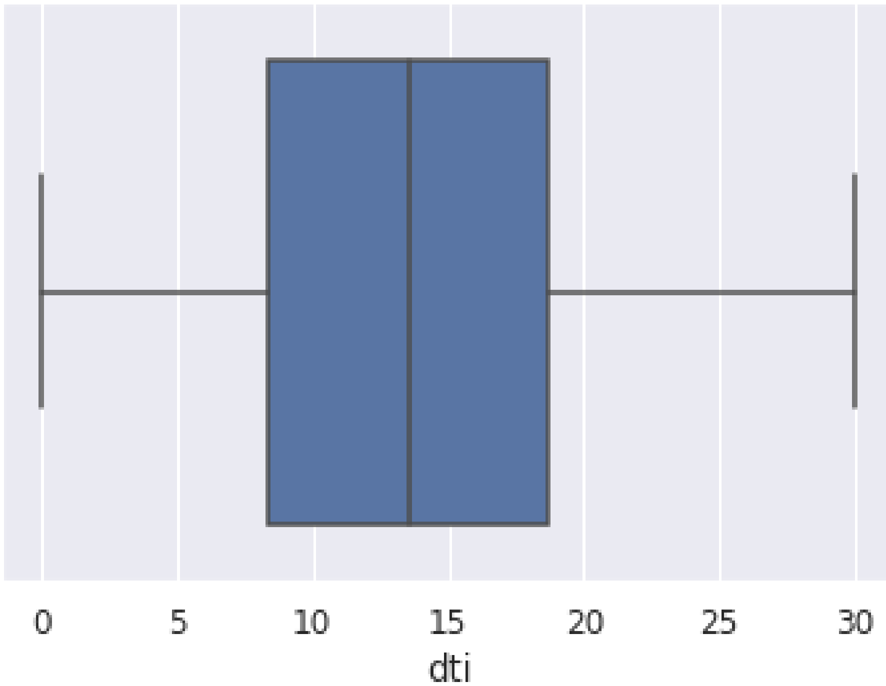
[937]:
```
# describe the annual income details
df['annual_inc'].describe()
```

[937]:
```
count     36606.000000
mean      60890.563839
std       27741.337421
min        4000.000000
25%       40000.000000
50%       56000.000000
75%       78000.000000
max      140004.000000
Name: annual_inc, dtype: float64
```

Observation The Annual income of most if applicants lies between 40k-75k.

[939]:
```
sns.boxplot(df.dti)
```

[939]: <AxesSubplot:xlabel='dti'>

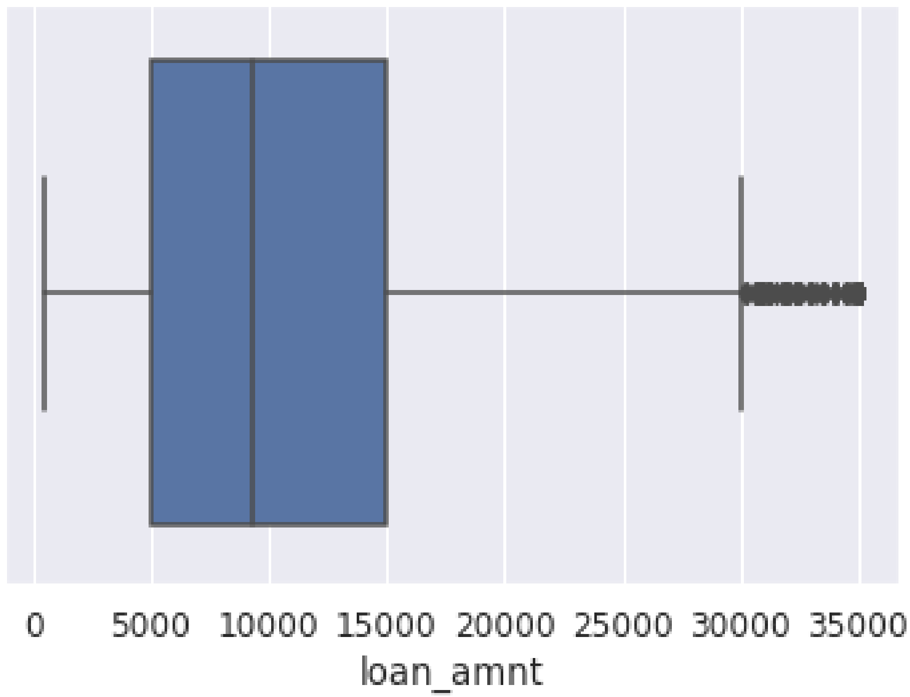


[940]:
```
# describe the Loan Amount
df['dti'].describe()
```

[940]:
```
count    36606.000000
mean        13.450146
std          6.660418
min          0.000000
25%          8.350000
50%         13.580000
75%         18.720000
max         29.990000
Name: dti, dtype: float64
```

[941]:
```
sns.boxplot(df.loan_amnt)
```

[941]: <AxesSubplot:xlabel='loan_amnt'>



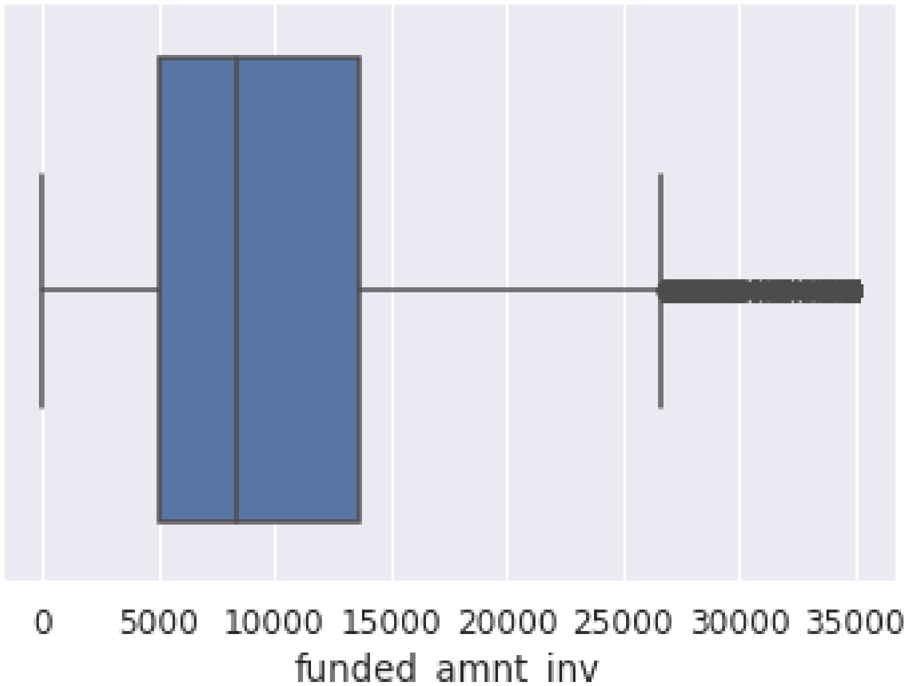
[942]:
```
# describe the Loan Amount
df['loan_amnt'].describe()
```

[942]:
```
count    36606.000000
mean     10690.058324
std       7048.412687
min        500.000000
25%       5000.000000
50%       9250.000000
75%      15000.000000
max      35000.000000
Name: loan_amnt, dtype: float64
```

Observation - Most of the loan amount applied was in the range of 5k-14k. Max Loan amount applied was ~27k.

[944]:
```
sns.boxplot(df.funded_amnt_inv)
```

[944]: <AxesSubplot:xlabel='funded_amnt_inv'>

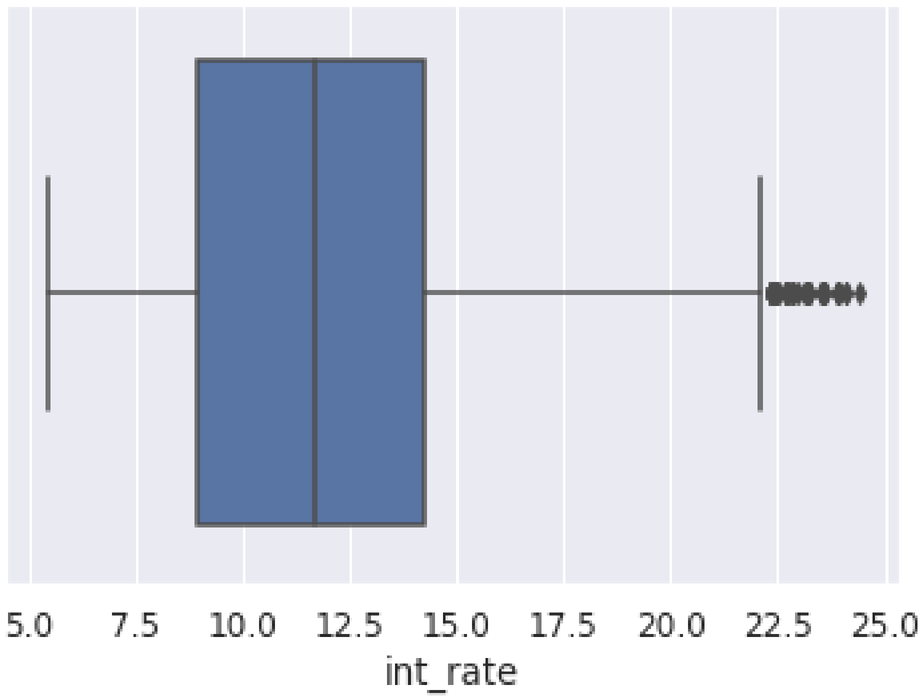


[945]:
```
# describe the funded amount
df['funded_amnt_inv'].describe()
```

[945]:
```
count    36606.000000
mean      9902.311039
std       6730.696329
min          0.000000
25%       4988.276705
50%       8396.342174
75%      13649.999283
max      35000.000000
Name: funded_amnt_inv, dtype: float64
```

[946]:
```
sns.boxplot(df.int_rate)
```

[946]:
```
<AxesSubplot:xlabel='int_rate'>
```



[947]:
```
# describe the interest rate
df['int_rate'].describe()
```

[947]:
```
count    36606.000000
mean        11.883216
std          3.666065
min          5.420000
25%          8.940000
50%         11.710000
75%         14.270000
max         24.400000
Name: int_rate, dtype: float64
```

Observation Most of the applicant's rate of interesrt is between in the range of 8%-14%.Average Rate of interest of rate is 11.7 %

Though there are some values far from distribution, the distribution is pretty continuous and there is no need to remove outliers / extreme values for these above columns.

Bucketing different variables for better analysis

[951]:
```
# Bucketting Loan Amount
def bucket_loan_amnt(column):
    if column <= 5000:
        return '0 - 5K'  # 25% quartile
```

```
    elif (column >5000) and (column <= 10000):
        return '5K - 10K'
    elif (column >10000) and (column <= 15000):
        return '10K - 15K'
    else:
        return '15K - above' # 75% quartile

df['loan_amnt_b'] = df.apply(lambda x : bucket_loan_amnt(x['loan_amnt']), axis␣
 ↪= 1)
```

[952]:
```
#Bucketing Annual Income
def bucket_annual_inc(column):
    if column <= 40000:
        return '0 - 40k' # 25% quartile
    elif (column >40000) and (column <= 50000):
        return '40k - 50k'
    elif (column >50000) and (column <= 60000):
        return '50k to 60k'
    elif (column >60000) and (column <= 70000):
        return '60k to 70k'
    elif (column >70000) and (column <= 80000):
        return '70k to 80k'
    else:
        return '80k - above' # 75% quartile

df['annual_inc_b'] = df.apply(lambda x: bucket_annual_inc(x['annual_inc']),␣
 ↪axis = 1)
```

[953]:
```
# Bucketing interest rate
def bucket_int_rate(column):
    if column <= 9:
        return 'Very Low' # 25% quartile
    elif (column >9) and (column <= 11):
        return 'Low'
    elif (column >11) and (column <= 13):
        return 'Moderate'
    elif (column >13) and (column <= 15):
        return 'High'
    else:
        return 'Very High' # 75% quartile

df['int_rate_b'] = df.apply(lambda x : bucket_int_rate(x.int_rate), axis = 1)
```

[954]:
```
def bucket_dti(column):
    if column <= 8:
        return 'Very Low' # 25% quartile
    elif (column >8) and (column <= 12):
```

```
        return 'Low'
    elif (column >12) and (column <= 16):
        return 'Moderate'
    elif (column >16) and (column <= 20):
        return 'High'
    else:
        return 'Very High' # 75% quartile

df['dti_b'] = df.apply(lambda x : bucket_dti(x.dti), axis = 1)
```

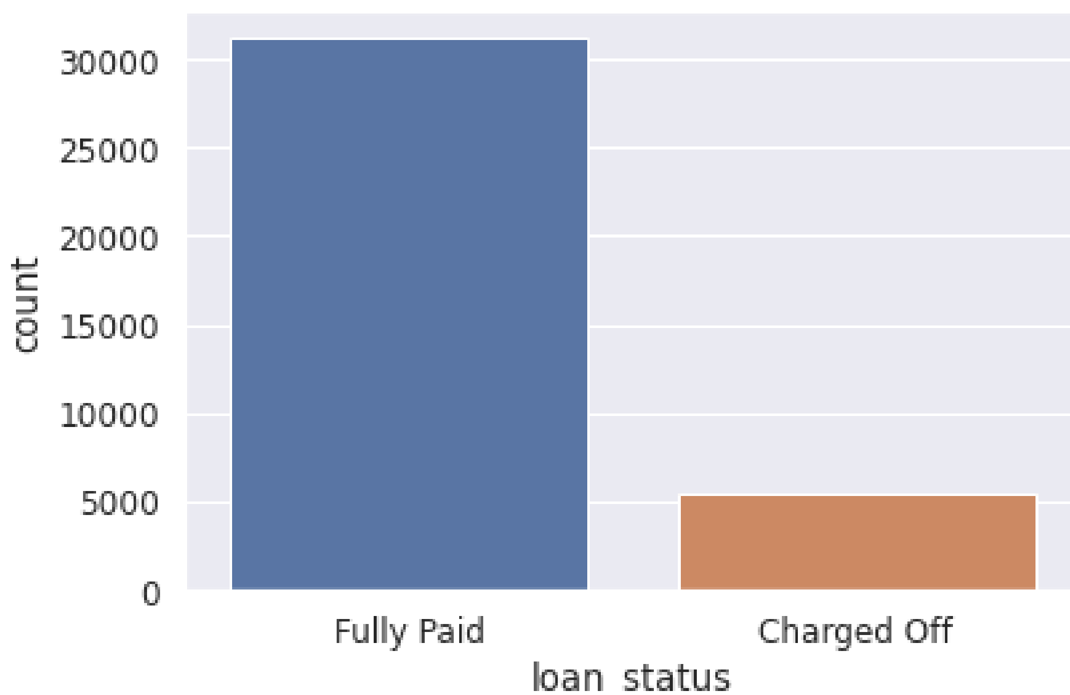
Univariate Analysis

[956]:
```
counts = df['loan_status'].value_counts()
percentages = counts.apply(lambda x: (x / df['loan_status'].count()) * 100)
print(percentages)
```

```
Fully Paid     85.242856
Charged Off    14.757144
Name: loan_status, dtype: float64
```

[957]:
```
sns.countplot(x = 'loan_status', data = df)
```

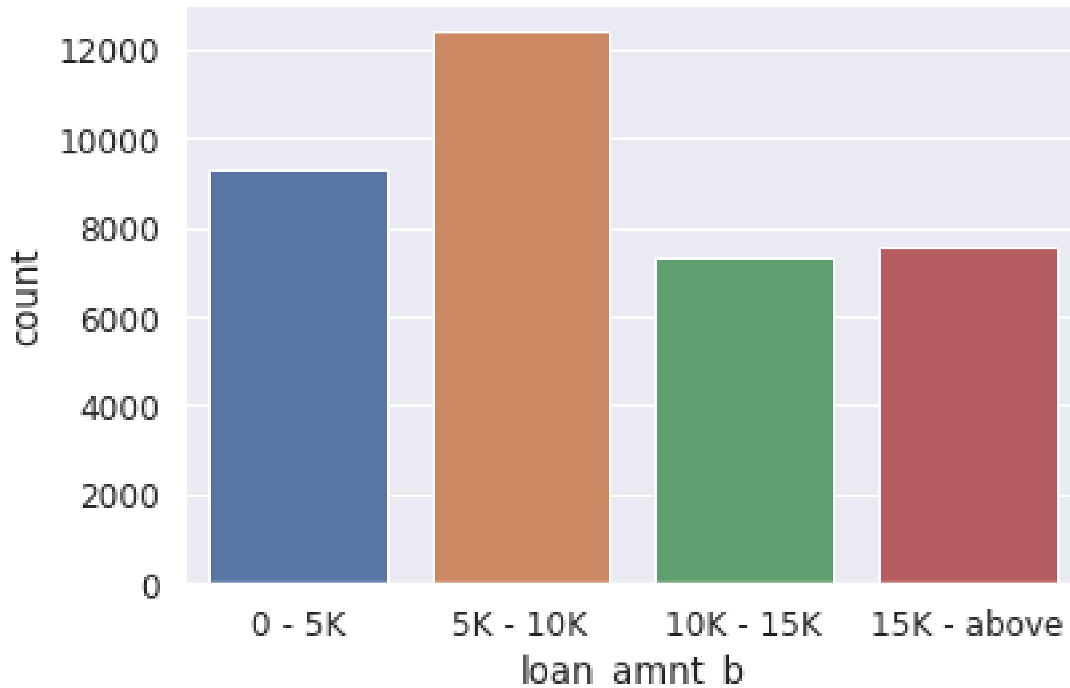
[957]: <AxesSubplot:xlabel='loan_status', ylabel='count'>



Observations - The following plot shows that around 14% loans were charged off out of the total loans issued

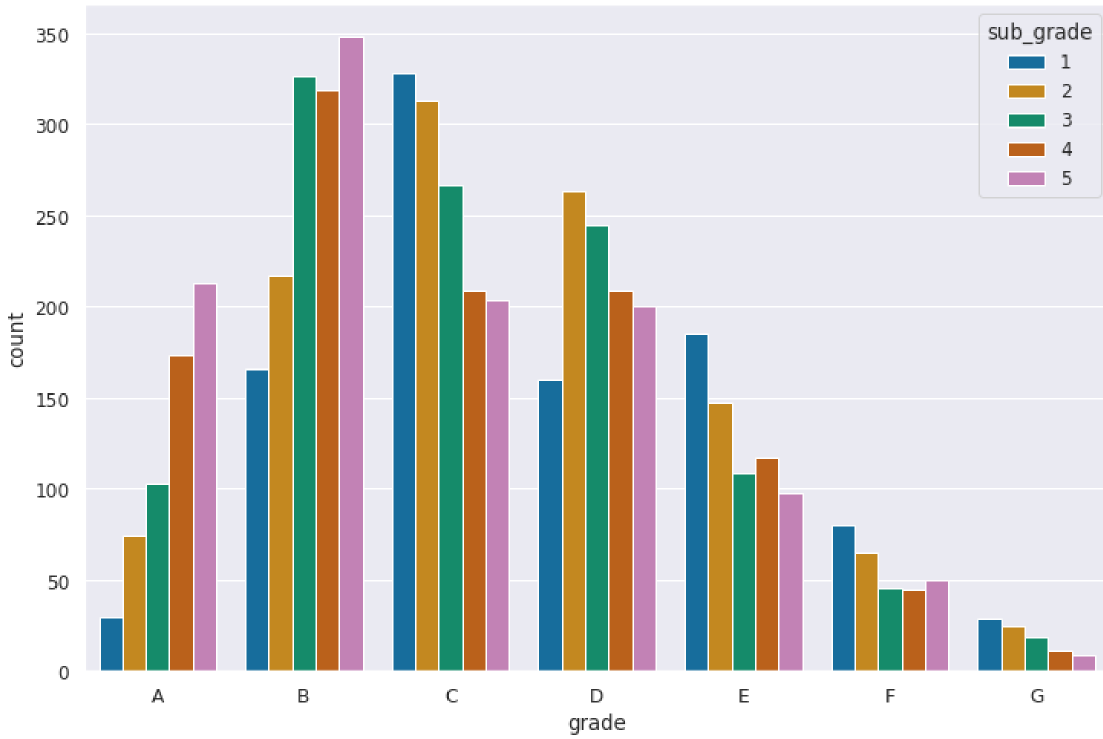
[959]:
```
sns.countplot(x = 'loan_amnt_b', data = df)
```

[959]: <AxesSubplot:xlabel='loan_amnt_b', ylabel='count'>



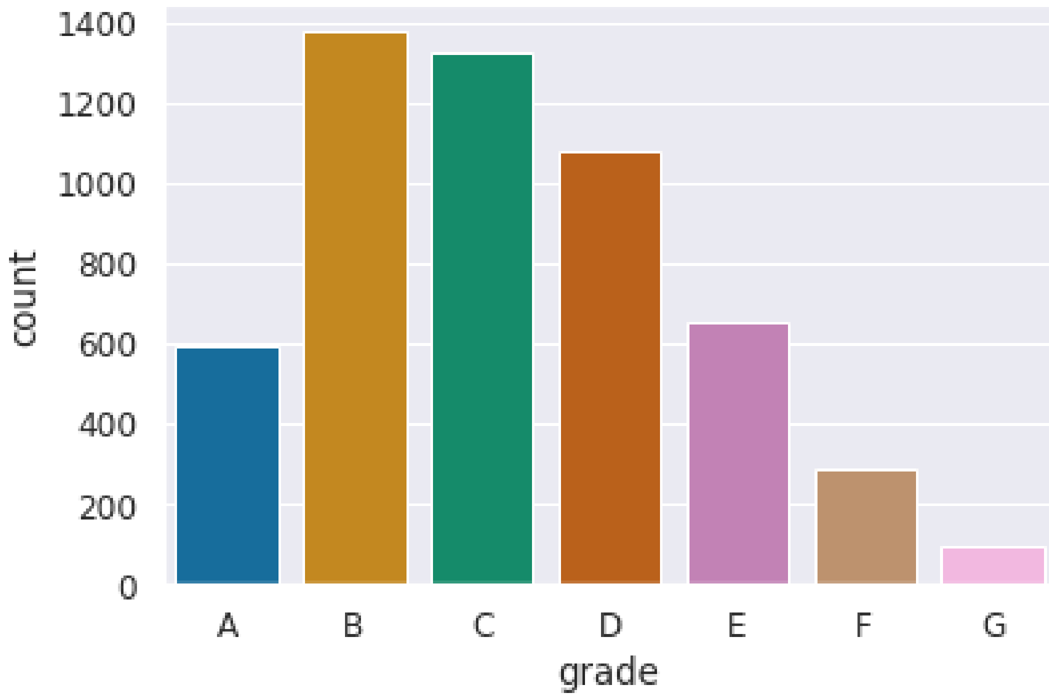
[960]:
```
df.sub_grade = pd.to_numeric(df.sub_grade.apply(lambda x : x[-1]))
df.sub_grade.head()
fig, ax = plt.subplots(figsize=(12,8))
sns.set_palette('colorblind')
sns.countplot(x = 'grade', order = ['A', 'B', 'C', 'D', 'E', 'F', 'G'] , hue =
↪'sub_grade',data = df[df.loan_status == 'Charged Off'])
```

[960]: <AxesSubplot:xlabel='grade', ylabel='count'>




```
[961]: sns.countplot(x = 'grade', data = df[df.loan_status == 'Charged Off'], order =␣
       ↪['A', 'B', 'C', 'D', 'E', 'F', 'G'])
```

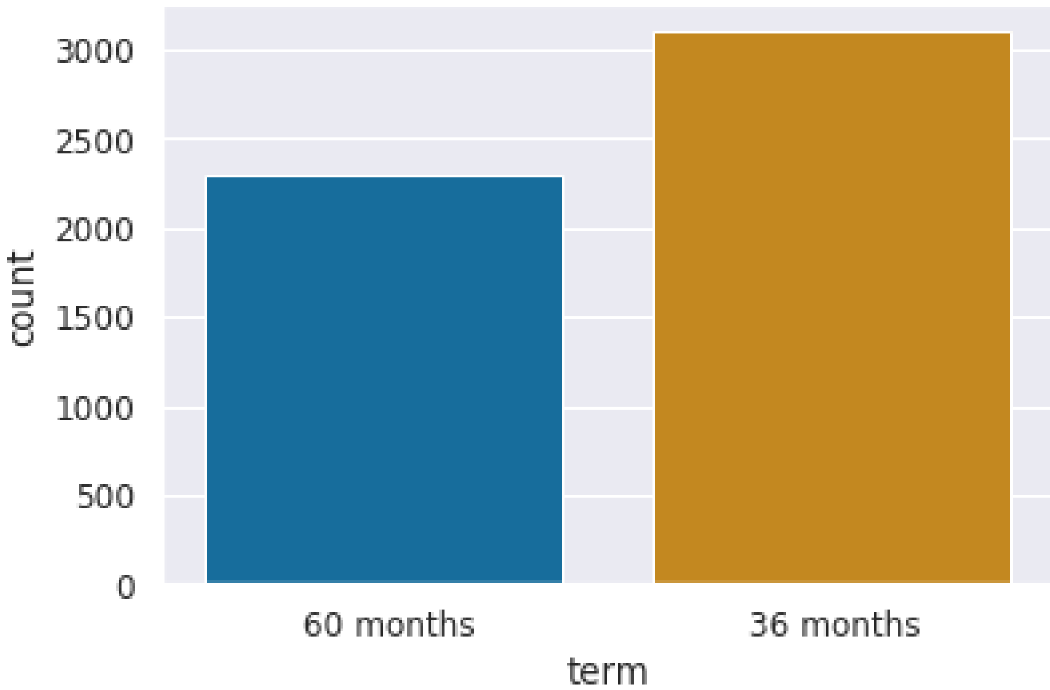
```
[961]: <AxesSubplot:xlabel='grade', ylabel='count'>
```



Observation - Most of the defaulters are people who are in grade B, C followed by D,E and A. Lowest defaulters are from grade G followed by F

[963]:
```
sns.countplot(x='term',data=df[df.loan_status=="Charged Off"])
```

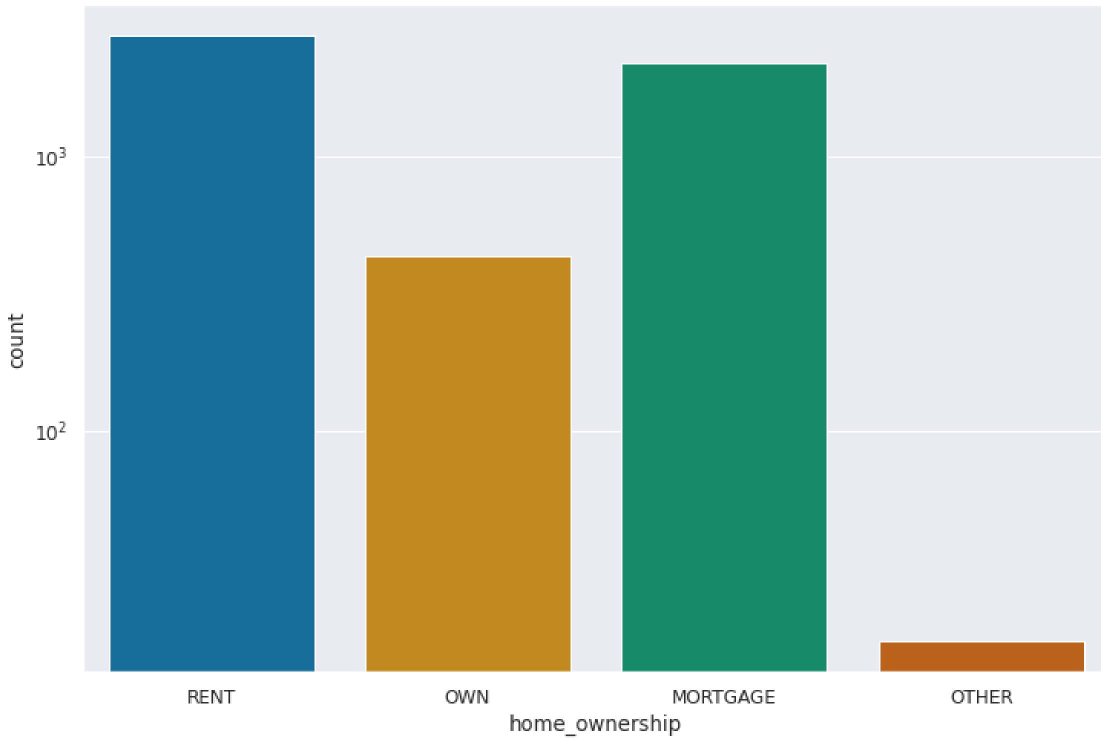
[963]: <AxesSubplot:xlabel='term', ylabel='count'>



[964]:
```
df['home_ownership'].replace(to_replace = ['NONE'],value='OTHER',inplace = True)
print(df['home_ownership'].unique())
fig, ax = plt.subplots(figsize = (12,8))
ax.set(yscale = 'log')
sns.countplot(x='home_ownership',data=df[df.loan_status=="Charged Off"])
```

```
['RENT' 'OWN' 'MORTGAGE' 'OTHER']
```

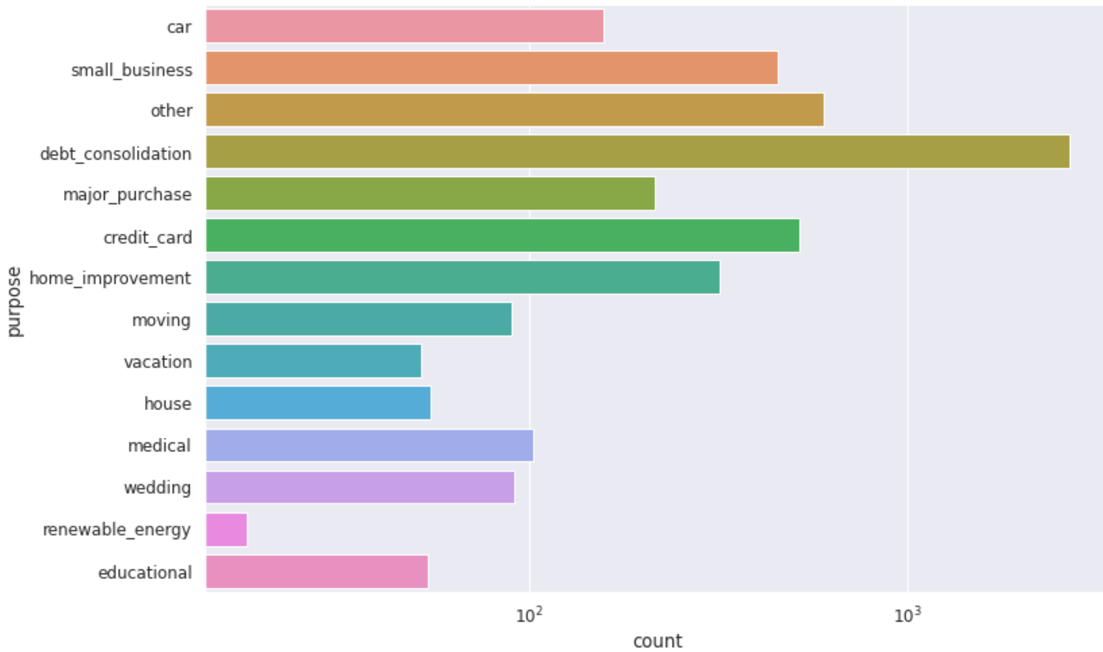
[964]:
```
<AxesSubplot:xlabel='home_ownership', ylabel='count'>
```



Observation - The Count plot shows that most of them living in rented home or mortgazed their home.

[966]:
```
fig, ax = plt.subplots(figsize = (12,8))
ax.set(xscale = 'log')
sns.countplot(y ='purpose', data=df[df.loan_status == 'Charged Off'])
```

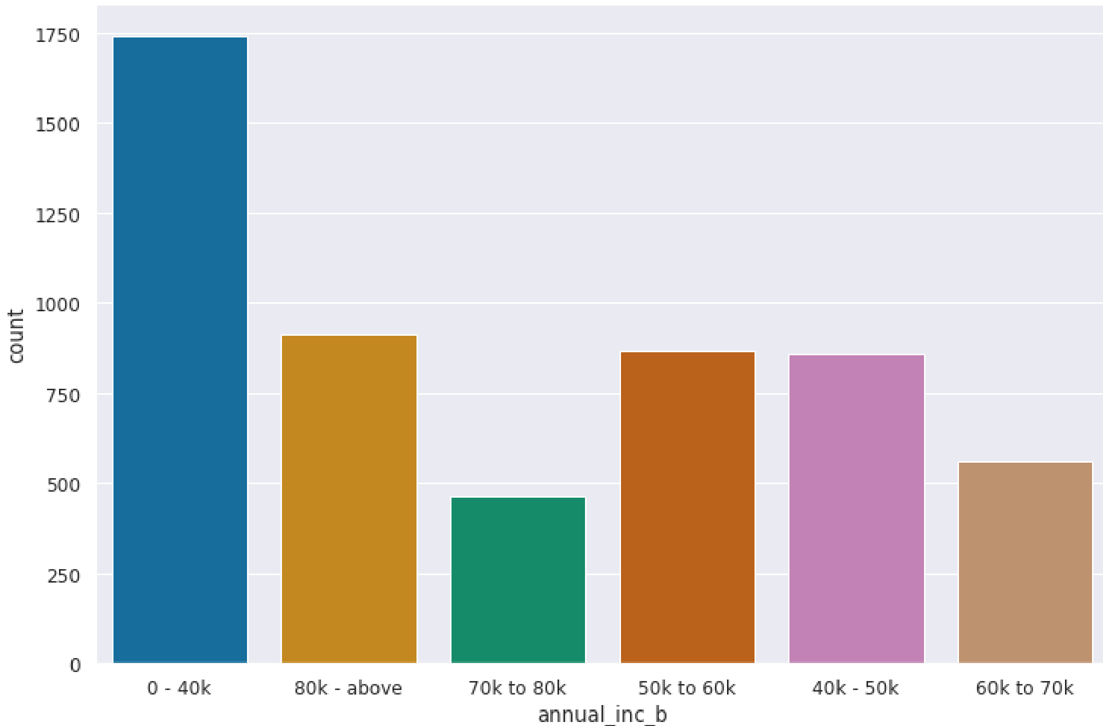
[966]: <AxesSubplot:xlabel='count', ylabel='purpose'>



Observation - The Count Plot shows that most of the loans were taken for the purpose of debt consolidation & paying credit card bill.. Number of charged off count also high too for these loans.

[968]:
```
plt.figure(figsize=(12, 8))
sns.countplot(x='annual_inc_b',data=df[df.loan_status=="Charged Off"])
```

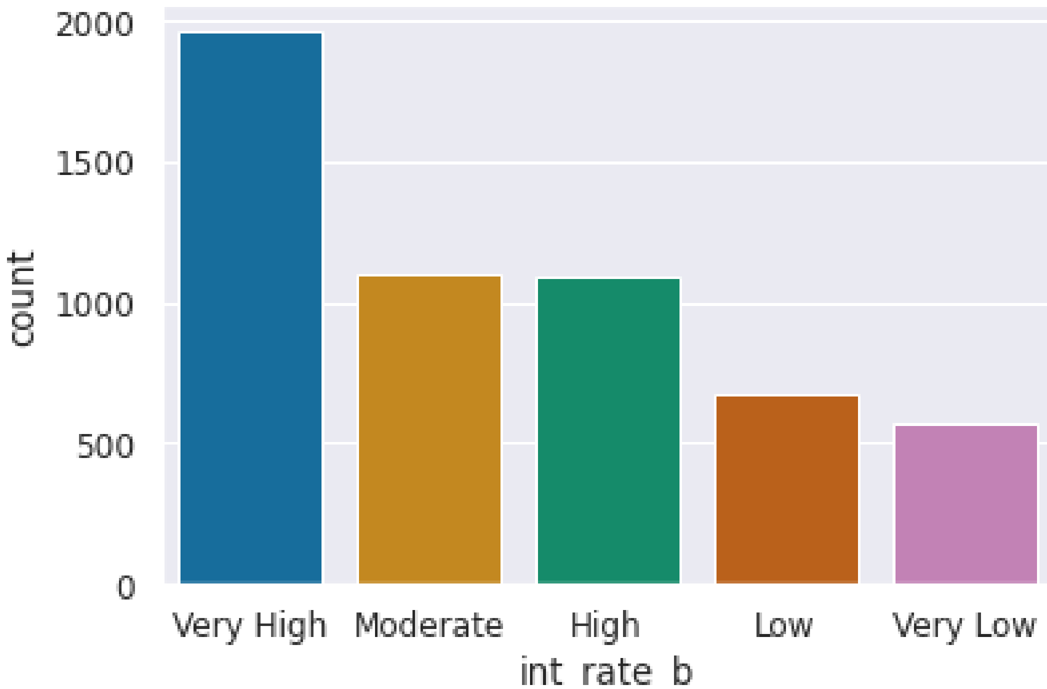
[968]: <AxesSubplot:xlabel='annual_inc_b', ylabel='count'>



Observation - We observe that most of the charged-off loans are from the people with annual income between 0-40K.

[970]:
```
sns.countplot(x='int_rate_b',data=df[df.loan_status=="Charged Off"])
```

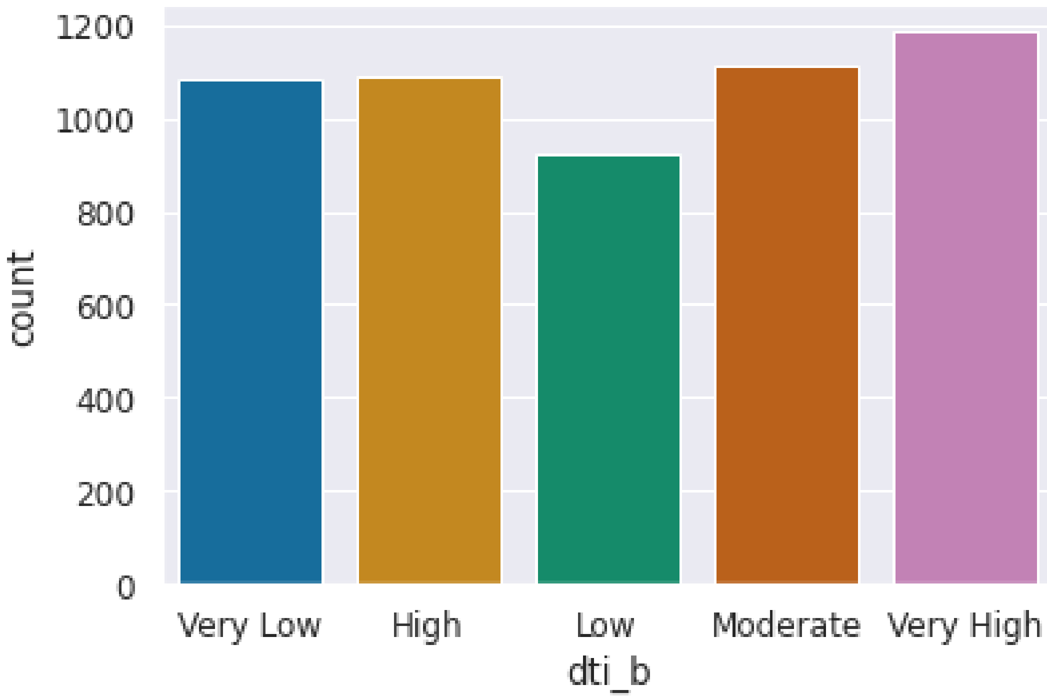
[970]: <AxesSubplot:xlabel='int_rate_b', ylabel='count'>



Observation - We see that people who have interest rate categorized as "Very High" that is interest rate > 13 are more likely to default on their loans.

[971]:
```
sns.countplot(x='dti_b',data=df[df.loan_status=="Charged Off"])
```

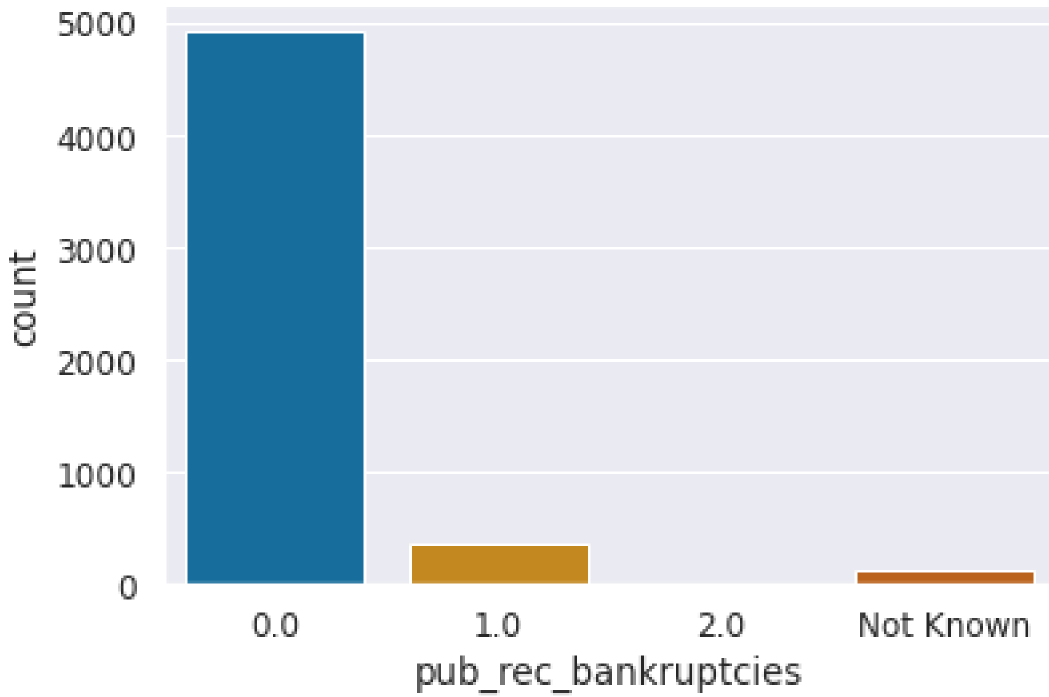
[971]: <AxesSubplot:xlabel='dti_b', ylabel='count'>



Observation - We can observe that the charged-of ratio is more or less is the same acros all dti groups.

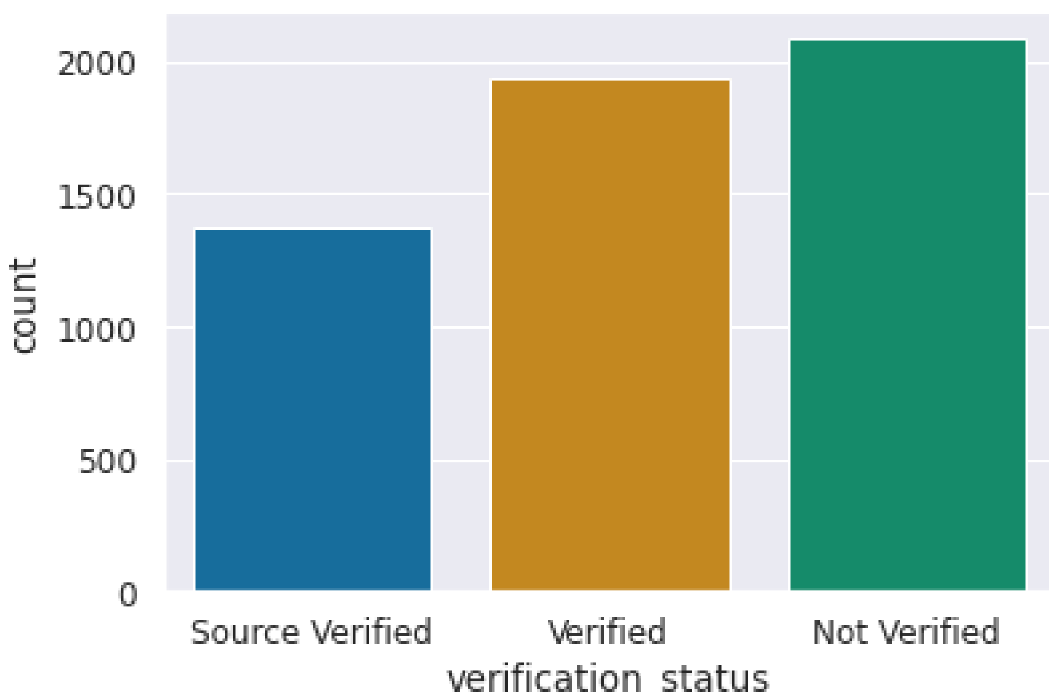
[972]:
```
sns.countplot(x='pub_rec_bankruptcies',data=df[df.loan_status=="Charged Off"])
```

[972]: <AxesSubplot:xlabel='pub_rec_bankruptcies', ylabel='count'>



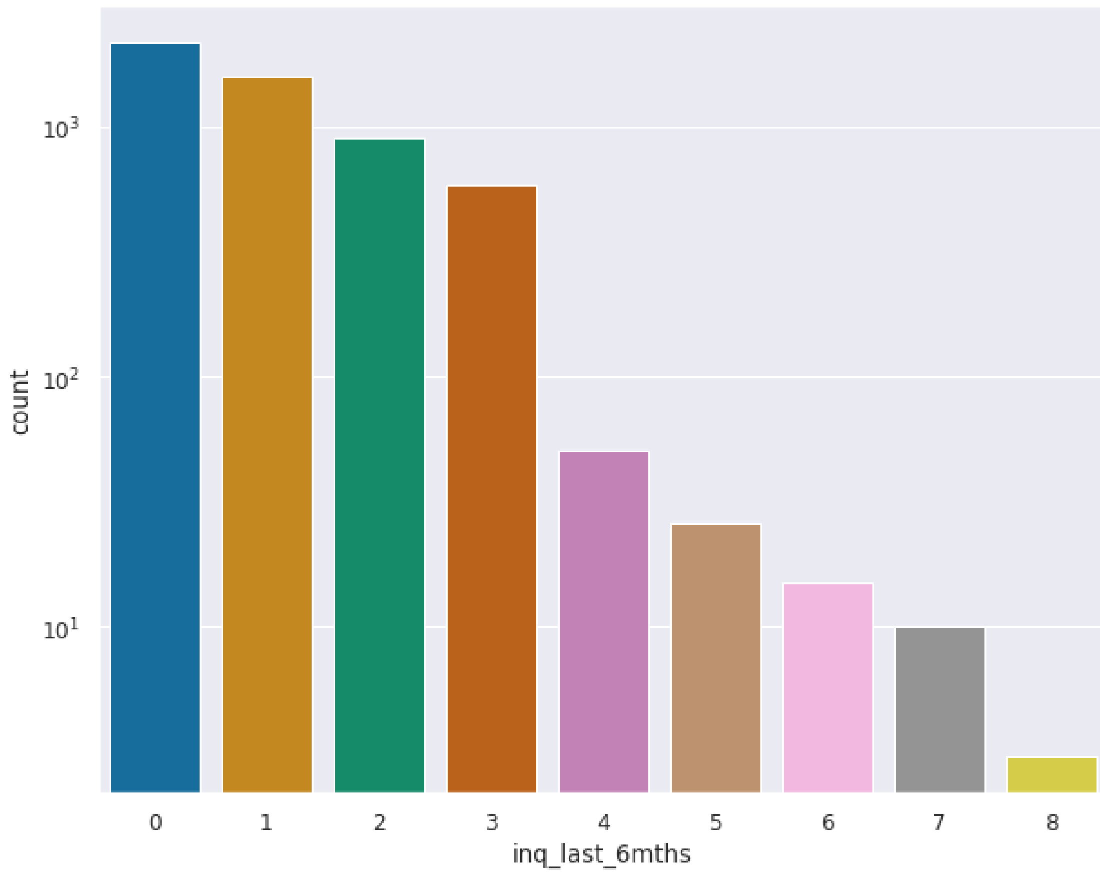
[973]:
```
sns.countplot(x='verification_status',data=df[df.loan_status=="Charged Off"])
```

[973]: <AxesSubplot:xlabel='verification_status', ylabel='count'>



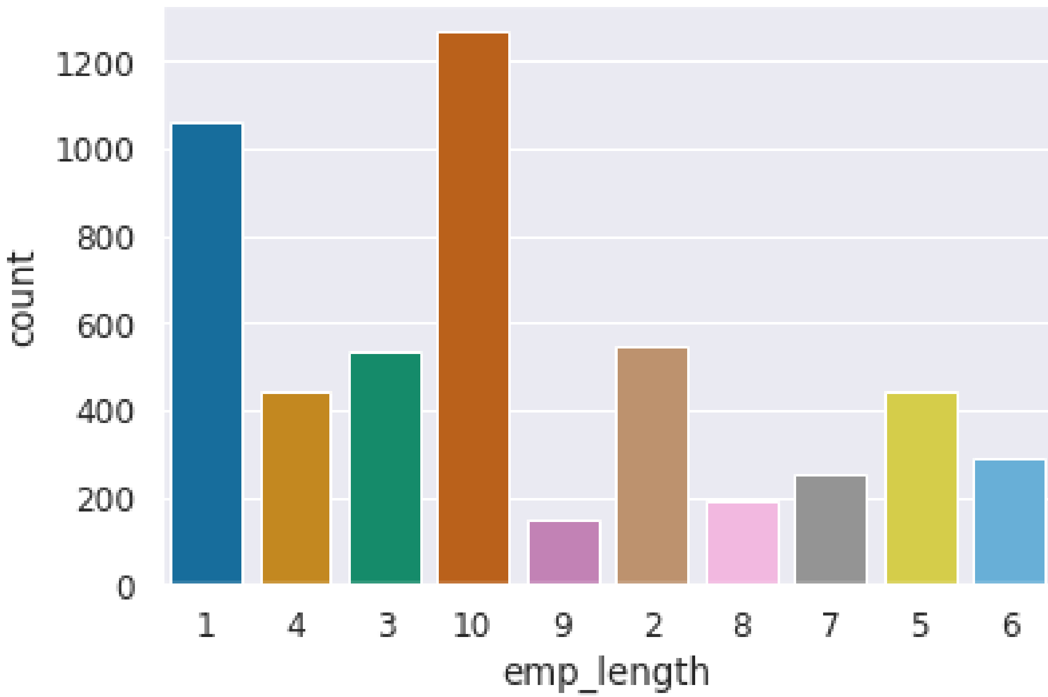
[974]:
```
fig,ax = plt.subplots(figsize = (10,8))
ax.set_yscale('log')
sns.countplot(x="inq_last_6mths",data=df[df.loan_status=="Charged Off"])
```

[974]: <AxesSubplot:xlabel='inq_last_6mths', ylabel='count'>



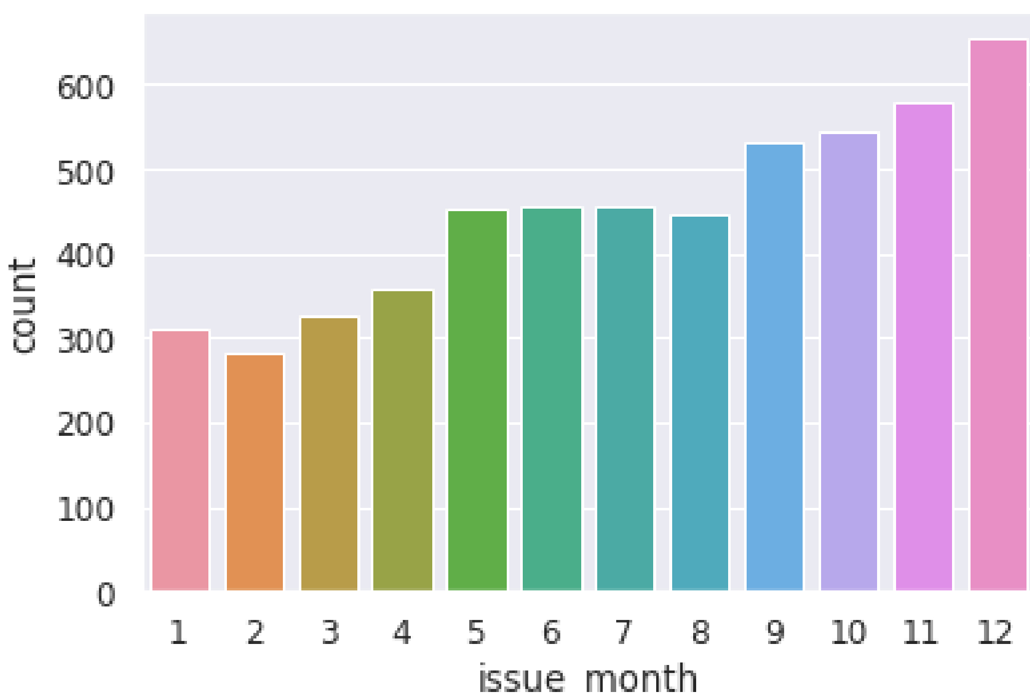
[975]:
```
sns.countplot(x='emp_length',data=df[df.loan_status=="Charged Off"])
```

[975]: <AxesSubplot:xlabel='emp_length', ylabel='count'>



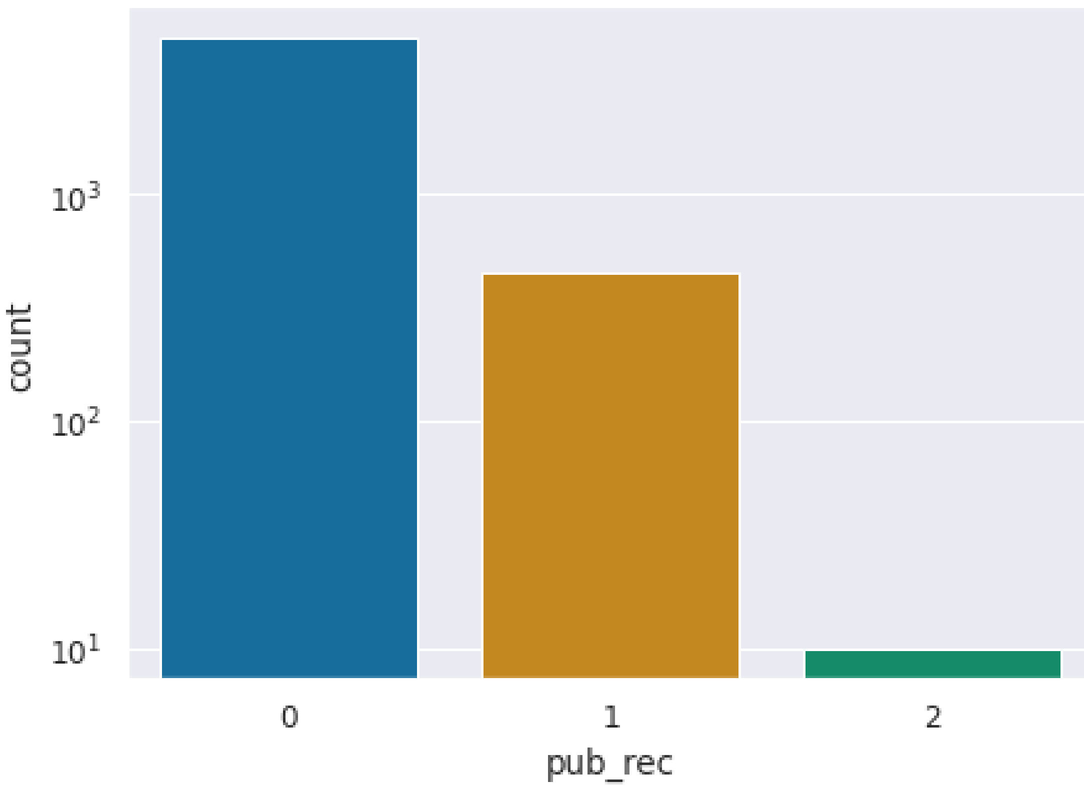
[978]:
```
sns.countplot(x="issue_month",data=df[df.loan_status=="Charged Off"])
```

[978]: <AxesSubplot:xlabel='issue_month', ylabel='count'>



[980]:
```
fig,ax = plt.subplots(figsize = (7,5))
ax.set_yscale('log')
sns.countplot(x='pub_rec',data=df[df.loan_status=="Charged Off"])
```

[980]: <AxesSubplot:xlabel='pub_rec', ylabel='count'>

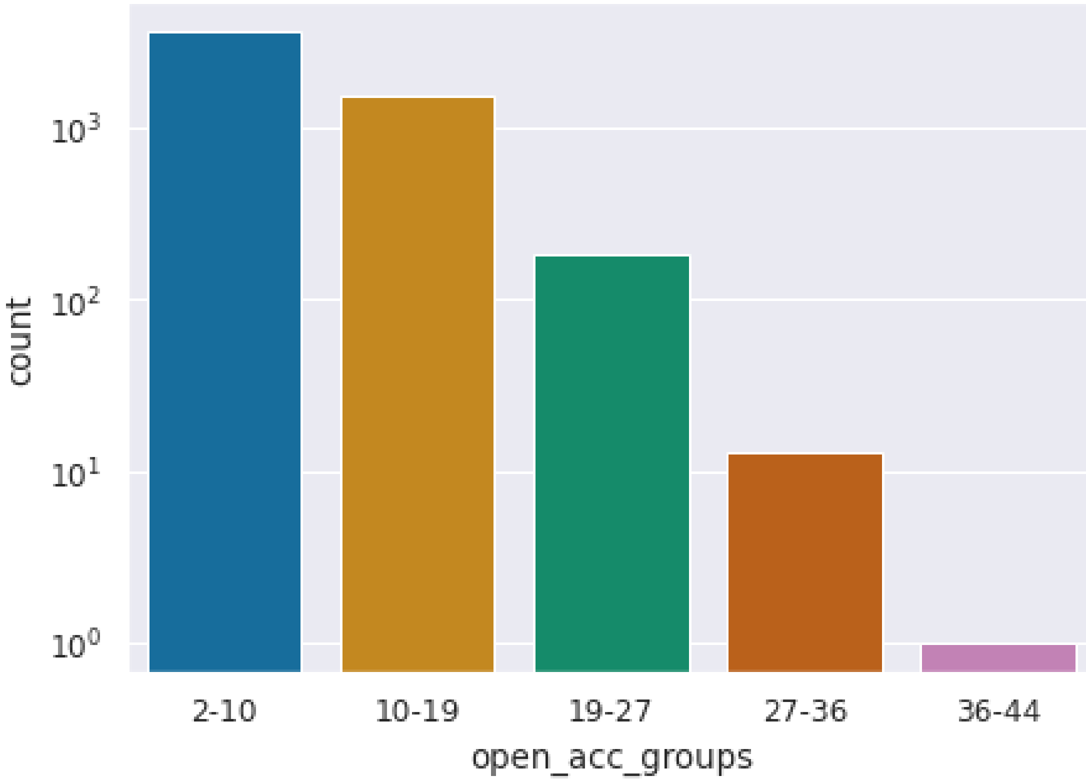


Observation - Creating Buckets for open_acc, revol_util and total_acc columns for our analysis

[983]:
```
df['open_acc_groups'] = pd.cut(df['open_acc'],bins = 5,precision␣
↪=0,labels=['2-10','10-19','19-27','27-36','36-44'])
df['revol_util_groups'] = pd.cut(df['revol_util'], bins=5,precision␣
↪=0,labels=['0-20','20-40','40-60','60-80','80-100'])
df['total_acc_groups'] = pd.cut(df['total_acc'], bins=5,precision␣
↪=0,labels=['2-20','20-37','37-55','55-74','74-90'])
```

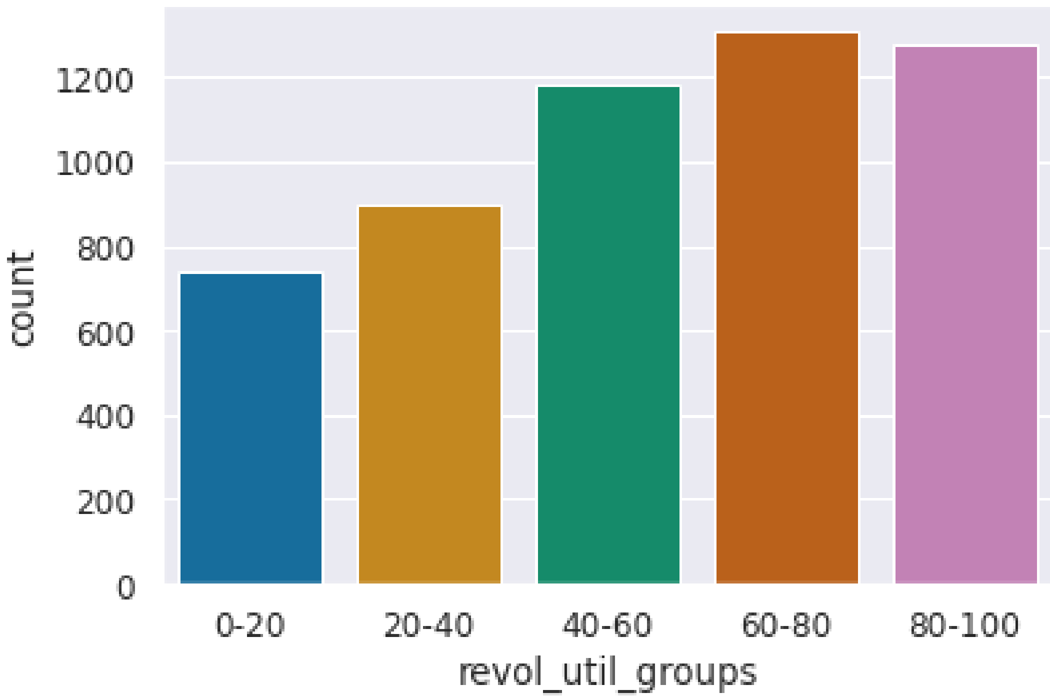
[984]:
```
fig, ax = plt.subplots(figsize = (7,5))
ax.set_yscale('log')
sns.countplot(x='open_acc_groups', data=df[df.loan_status == 'Charged Off'])
```

[984]: <AxesSubplot:xlabel='open_acc_groups', ylabel='count'>



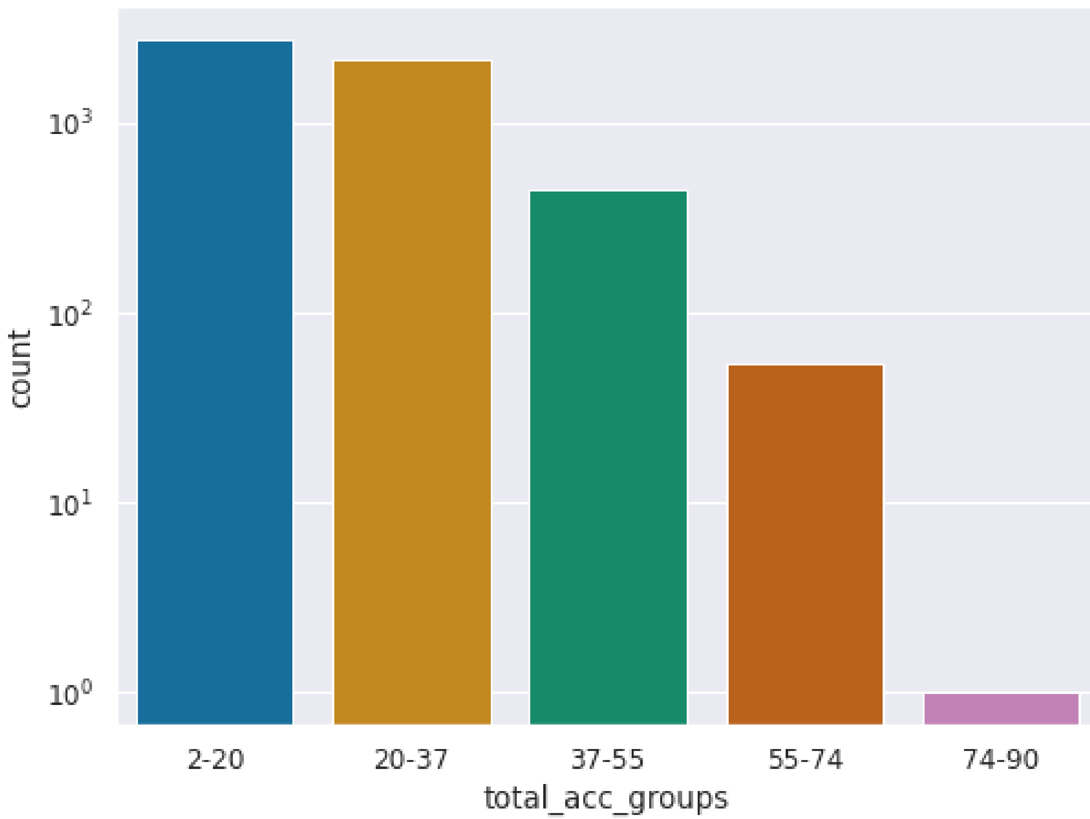
[985]:
```
sns.countplot(x='revol_util_groups', data=df[df.loan_status == 'Charged Off'])
```

[985]: <AxesSubplot:xlabel='revol_util_groups', ylabel='count'>



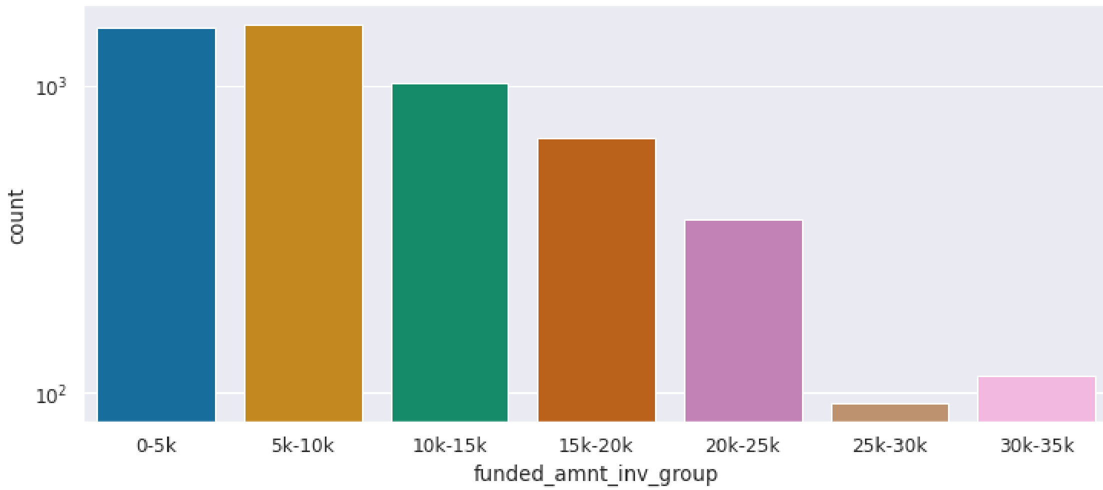
[986]:
```
fig, ax = plt.subplots(figsize = (8,6))
ax.set_yscale('log')
sns.countplot(x='total_acc_groups', data=df[df.loan_status == 'Charged Off'])
```

[986]: <AxesSubplot:xlabel='total_acc_groups', ylabel='count'>



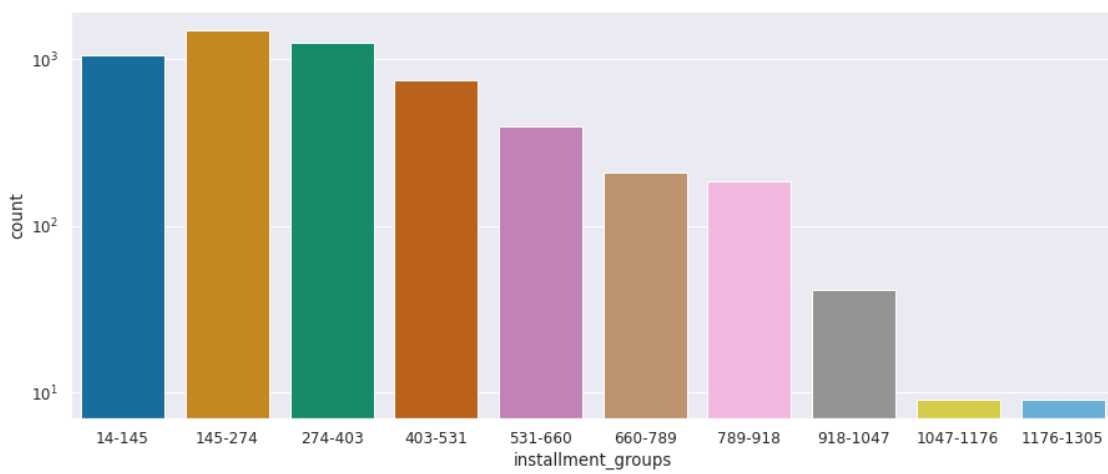

```
[987]: df['funded_amnt_inv_group'] = pd.cut(df['funded_amnt_inv'],␣
        ↪bins=7,labels=['0-5k','5k-10k','10k-15k','15k-20k','20k-25k','25k-30k','30k-35k'])␣
        ↪## bin is starting from -35?
       fig,ax = plt.subplots(figsize = (12,5))
       ax.set_yscale('log')
       sns.countplot(x='funded_amnt_inv_group', data=df[df['loan_status']=='Charged␣
        ↪Off'])
```

```
[987]: <AxesSubplot:xlabel='funded_amnt_inv_group', ylabel='count'>
```



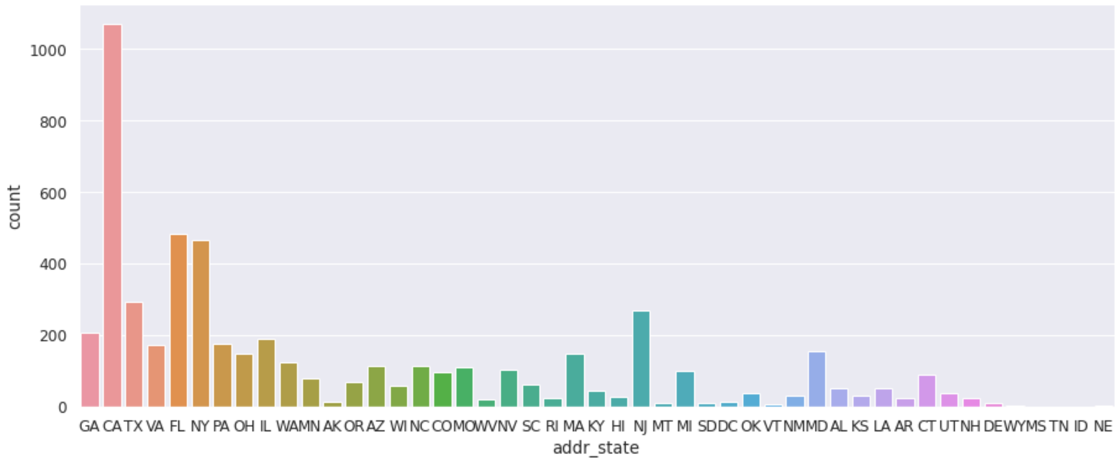
[988]:
```
df['installment_groups'] = pd.cut(df['installment'], bins=10,precision␣
↪=0,labels=['14-145','145-274','274-403','403-531','531-660','660-789','789-918','918-1047',
fig,ax = plt.subplots(figsize = (15,6))
ax.set_yscale('log')
sns.countplot(x='installment_groups', data=df[df['loan_status']=='Charged Off'])
```

[988]: <AxesSubplot:xlabel='installment_groups', ylabel='count'>



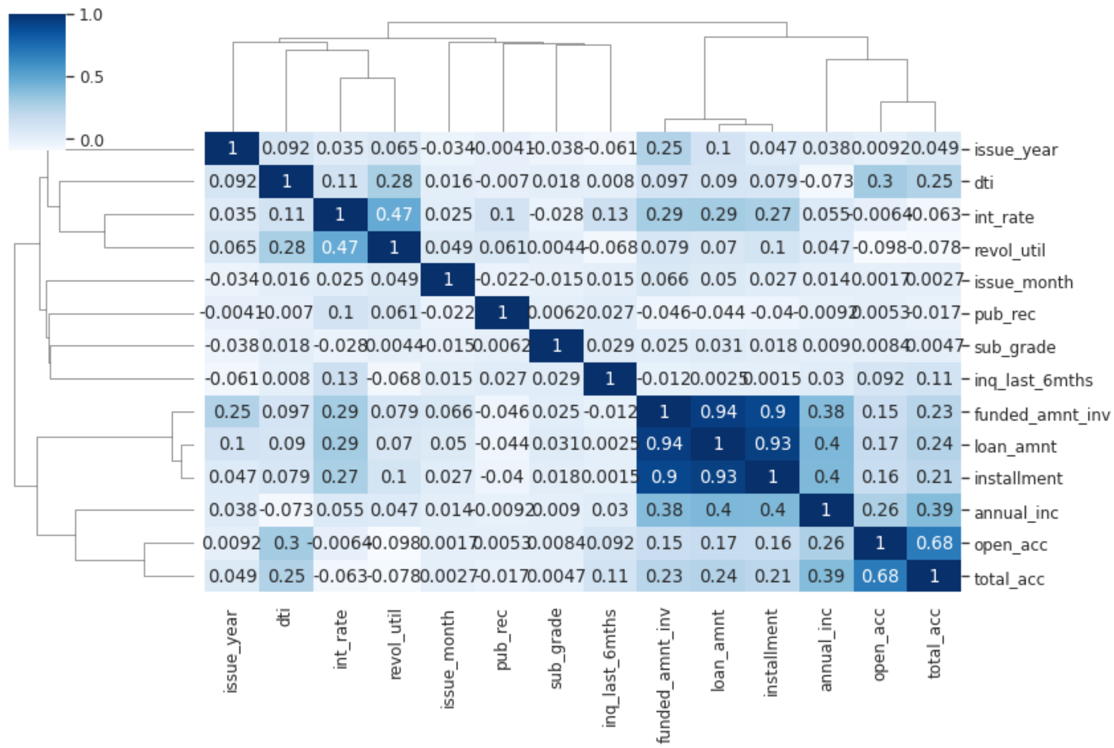
[989]:
```
fig,ax = plt.subplots(figsize = (15,6))
sns.countplot(x="addr_state",data=df[df.loan_status=="Charged Off"])
```

[989]: <AxesSubplot:xlabel='addr_state', ylabel='count'>



0.1.2 Correlation Analysis

[991]:
```
corr_loan = df
corr = corr_loan.corr()
sns.set(font_scale=1.1)
sns.clustermap(corr, annot=True, figsize=(12, 8), cmap="Blues")
plt.show()
```



Observation -

- Annual Income to Debt To Income Ratio i.e. dti are negatively correlated
- Loan_amnt has negative correlation with pub_rec_bankrupticies
- Loan Amount,Investor Amount and Funding Amount are strongly correlated
- Positive correlation between Annual Income and employment years
- Positive correlation between annual income and funded amount that means people with high income gets high funded amount
- Positive correlation between annual income and total payment
- Term has a strong correlation with loan amount
- Term has a strong correlation with interest rate

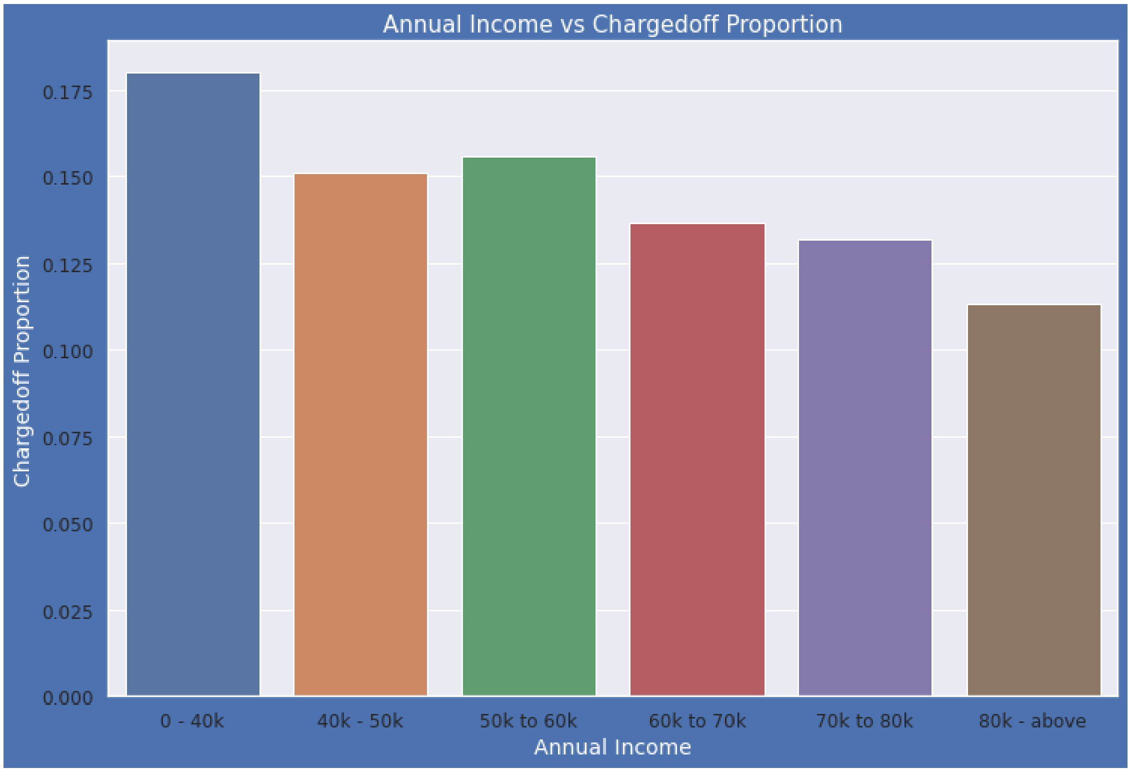
0.1.3 Bivariate Analysis

[992]:
```
inc_range_vs_loan = df.groupby(['annual_inc_b', 'loan_status']).loan_status.
 ↪count().unstack().fillna(0).reset_index()
inc_range_vs_loan['Total'] = inc_range_vs_loan['Charged Off']+␣
 ↪inc_range_vs_loan['Fully Paid']
inc_range_vs_loan['Chargedoff_Proportion'] = inc_range_vs_loan['Charged Off'] /␣
 ↪inc_range_vs_loan['Total']
inc_range_vs_loan.sort_values('Chargedoff_Proportion', ascending=False)
```

[992]:
```
loan_status annual_inc_b  Charged Off  Fully Paid  Total  \
0                 0 - 40k         1740        7924   9664
2               50k to 60k         867        4703   5570
1                40k - 50k         858        4825   5683
3               60k to 70k         559        3537   4096
4               70k to 80k         464        3059   3523
5              80k - above         914        7156   8070

loan_status  Chargedoff_Proportion
0                         0.180050
2                         0.155655
1                         0.150977
3                         0.136475
4                         0.131706
5                         0.113259
```

[993]:
```
fig, ax1 = plt.subplots(figsize=(12, 8),facecolor='b')
ax1.set_title('Annual Income vs Chargedoff Proportion',fontsize=15,color = 'w')
ax1=sns.barplot(x='annual_inc_b', y='Chargedoff_Proportion',␣
 ↪data=inc_range_vs_loan)
ax1.set_ylabel('Chargedoff Proportion',fontsize=14,color = 'w')
ax1.set_xlabel('Annual Income',fontsize=14,color='w')
plt.show()
```



Observation -

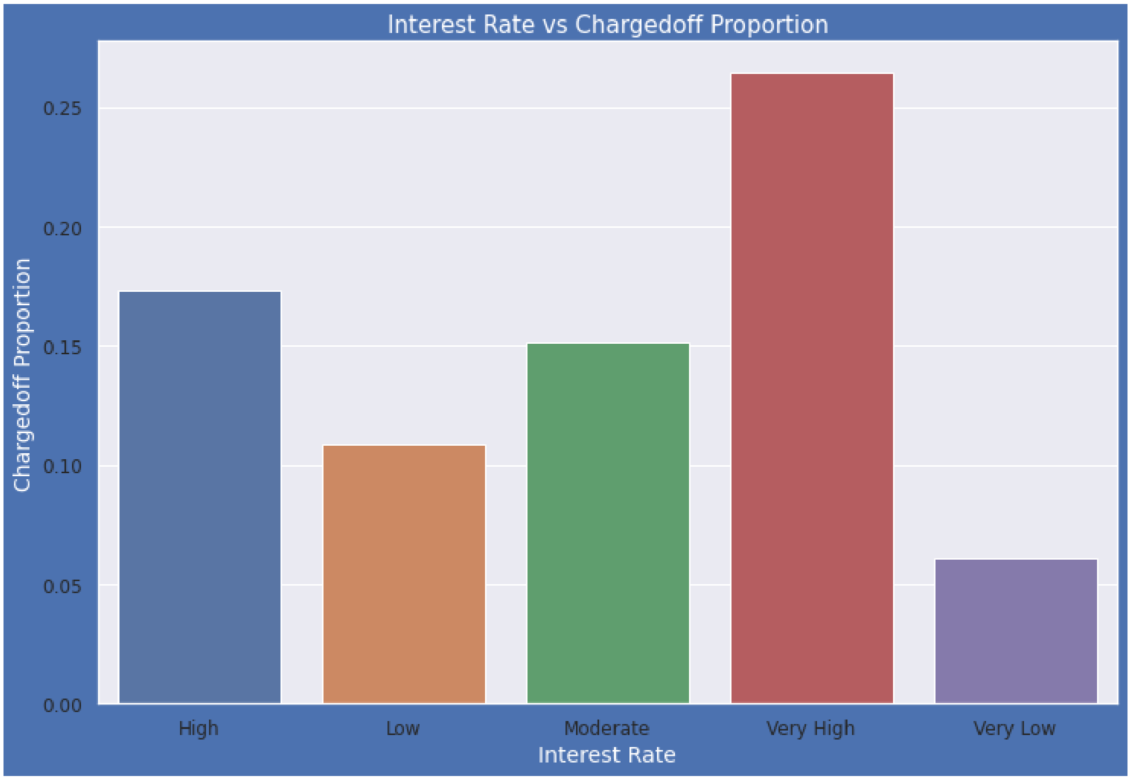
- Income range of 80000+ has less chance of getting charged off.
- Income range of -20000 has high chances of charged off.
- With increase in annual income charged off proportion got decreased. So, they are inversely proportional

[994]:
```
interest_vs_loan = df.groupby(['int_rate_b', 'loan_status']).loan_status.
    ↪count().unstack().fillna(0).reset_index()
interest_vs_loan['Total'] = interest_vs_loan['Charged Off']+␣
    ↪interest_vs_loan['Fully Paid']
interest_vs_loan['Chargedoff_Proportion'] = interest_vs_loan['Charged Off'] /␣
    ↪interest_vs_loan['Total']
interest_vs_loan.sort_values('Chargedoff_Proportion', ascending=False)
```

[994]:

loan_status	int_rate_b	Charged Off	Fully Paid	Total	Chargedoff_Proportion
3	Very High	1963	5462	7425	0.264377
0	High	1087	5184	6271	0.173338
2	Moderate	1100	6171	7271	0.151286
1	Low	677	5548	6225	0.108755
4	Very Low	575	8839	9414	0.061079

[995]:
```
fig, ax1 = plt.subplots(figsize=(12, 8),facecolor='b')
ax1.set_title('Interest Rate vs Chargedoff Proportion',fontsize=15,color='w')
ax1=sns.barplot(x='int_rate_b', y='Chargedoff_Proportion',␣
↪data=interest_vs_loan)
ax1.set_xlabel('Interest Rate',fontsize=14,color='w')
ax1.set_ylabel('Chargedoff Proportion',fontsize=14,color = 'w')
plt.show()
```



Observation -

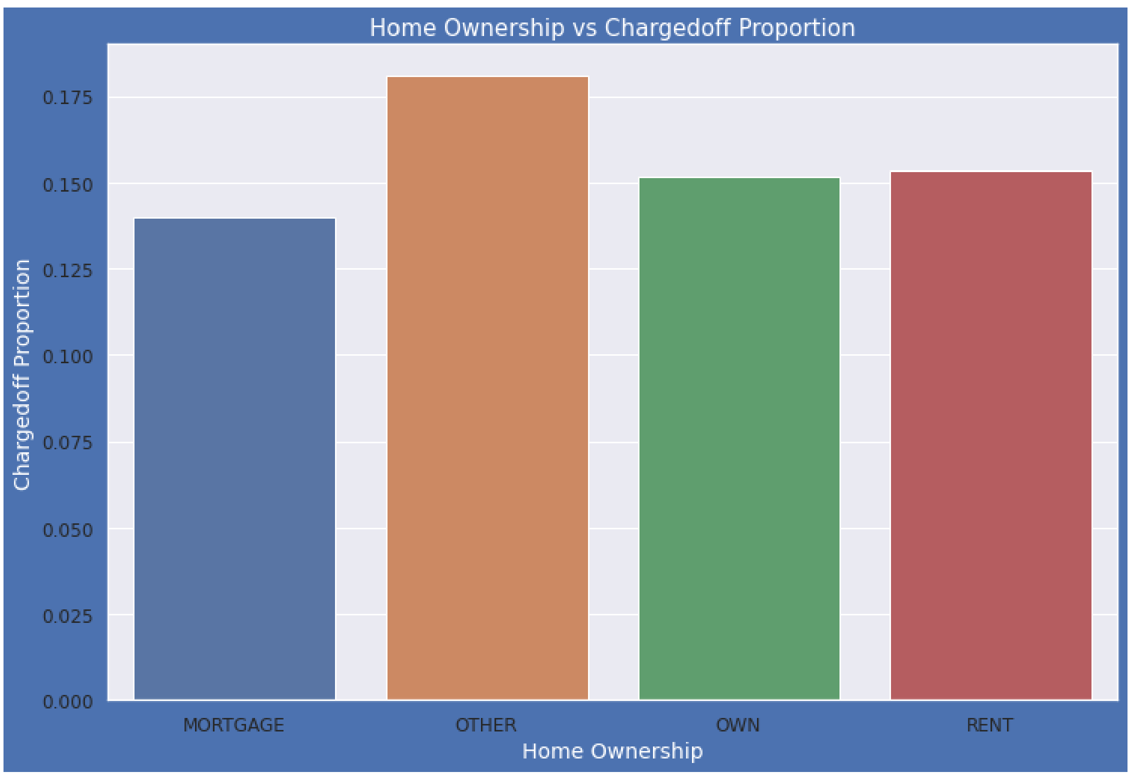
- Interest Rates which is less than 10% have very less chances of defaulting on their loan
- Charged off proportion increases with higher interest rates

[996]:
```
home_ownership_vs_loan = df.groupby(['home_ownership', 'loan_status']).
↪loan_status.count().unstack().fillna(0).reset_index()
home_ownership_vs_loan['Total'] = home_ownership_vs_loan['Charged Off']+␣
↪home_ownership_vs_loan['Fully Paid']
home_ownership_vs_loan['Chargedoff_Proportion'] =␣
↪home_ownership_vs_loan['Charged Off'] / home_ownership_vs_loan['Total']
home_ownership_vs_loan.sort_values('Chargedoff_Proportion', ascending=False)
```

[996]:
```
loan_status home_ownership  Charged Off  Fully Paid  Total  \
1                    OTHER           17          77     94
3                     RENT         2763       15237  18000
2                      OWN          432        2415   2847
0                 MORTGAGE         2190       13475  15665

loan_status  Chargedoff_Proportion
1                         0.180851
3                         0.153500
2                         0.151739
0                         0.139802
```

[997]:
```
fig, ax1 = plt.subplots(figsize=(12, 8),facecolor='b')
ax1.set_title('Home Ownership vs Chargedoff Proportion',fontsize=15,color='w')
ax1=sns.barplot(x='home_ownership', y='Chargedoff_Proportion',␣
 ↪data=home_ownership_vs_loan)
ax1.set_xlabel('Home Ownership',fontsize=14,color='w')
ax1.set_ylabel('Chargedoff Proportion',fontsize=14,color = 'w')
plt.show()
```



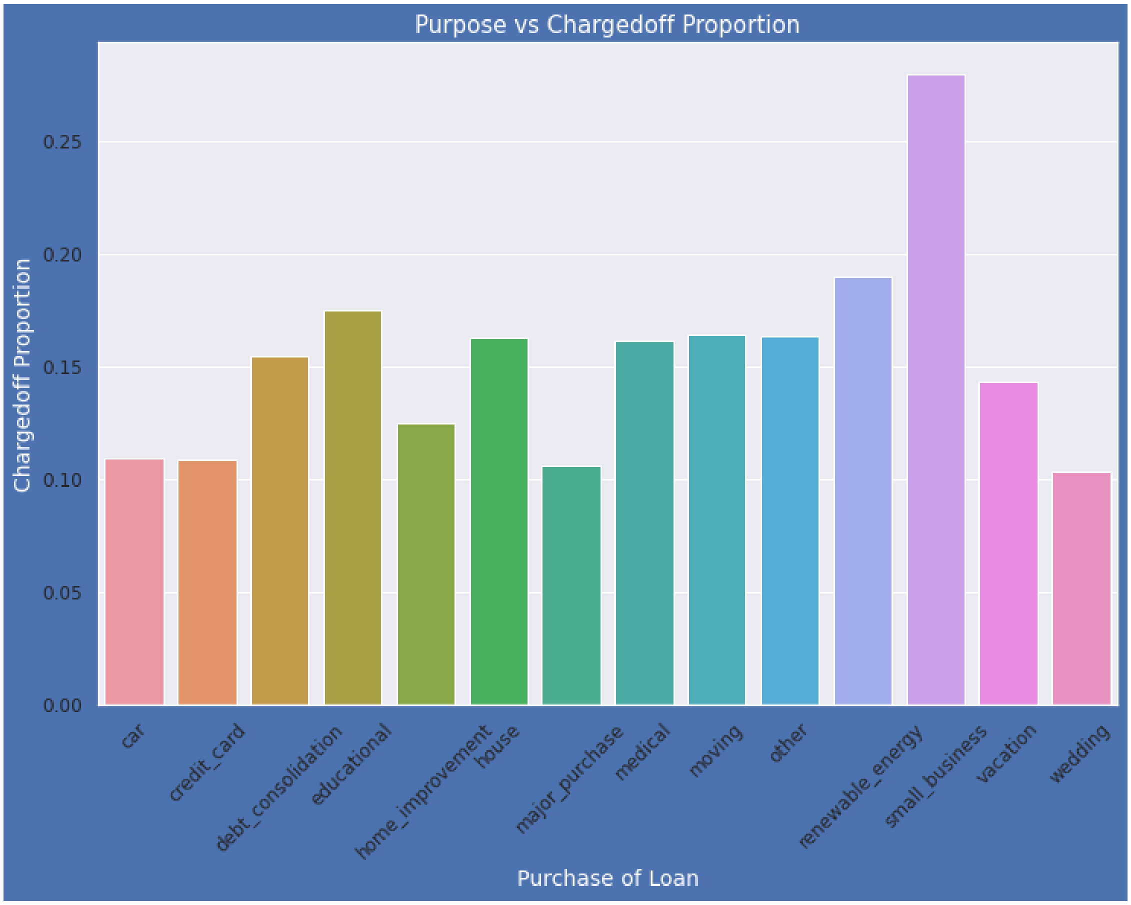
Observation No strong evidence or correlation observed

[998]:
```
purpose_vs_loan = df.groupby(['purpose', 'loan_status']).loan_status.count().
    ↪unstack().fillna(0).reset_index()
purpose_vs_loan['Total'] = purpose_vs_loan['Charged Off']+␣
    ↪purpose_vs_loan['Fully Paid']
purpose_vs_loan['Chargedoff_Proportion'] = purpose_vs_loan['Charged Off'] /␣
    ↪purpose_vs_loan['Total']
purpose_vs_loan.sort_values('Chargedoff_Proportion', ascending=False)
```

[998]:
```
loan_status              purpose  Charged Off  Fully Paid  Total  \
11                small_business          454        1168   1622
10              renewable_energy           18          77     95
3                    educational           54         255    309
8                         moving           90         458    548
9                          other          601        3085   3686
5                          house           55         283    338
7                        medical          103         536    639
2             debt_consolidation         2672       14621  17293
12                      vacation           52         312    364
4               home_improvement          319        2232   2551
0                            car          158        1288   1446
1                    credit_card          518        4264   4782
6                 major_purchase          216        1825   2041
13                       wedding           92         800    892

loan_status  Chargedoff_Proportion
11                        0.279901
10                        0.189474
3                         0.174757
8                         0.164234
9                         0.163049
5                         0.162722
7                         0.161189
2                         0.154513
12                        0.142857
4                         0.125049
0                         0.109267
1                         0.108323
6                         0.105830
13                        0.103139
```

[999]:
```
fig, ax1 = plt.subplots(figsize=(12, 8),facecolor='b')
ax1.set_title('Purpose vs Chargedoff Proportion',fontsize=15,color='w')
ax1=sns.barplot(x='purpose', y='Chargedoff_Proportion', data=purpose_vs_loan)
ax1.set_xlabel('Purchase of Loan',fontsize=14,color='w')
ax1.set_ylabel('Chargedoff Proportion',fontsize=14,color = 'w')
plt.xticks(rotation=45)
plt.show()
```



Observation - Small business have the highest chances of defaulting of loans followed by debt consolidation, renewable energy

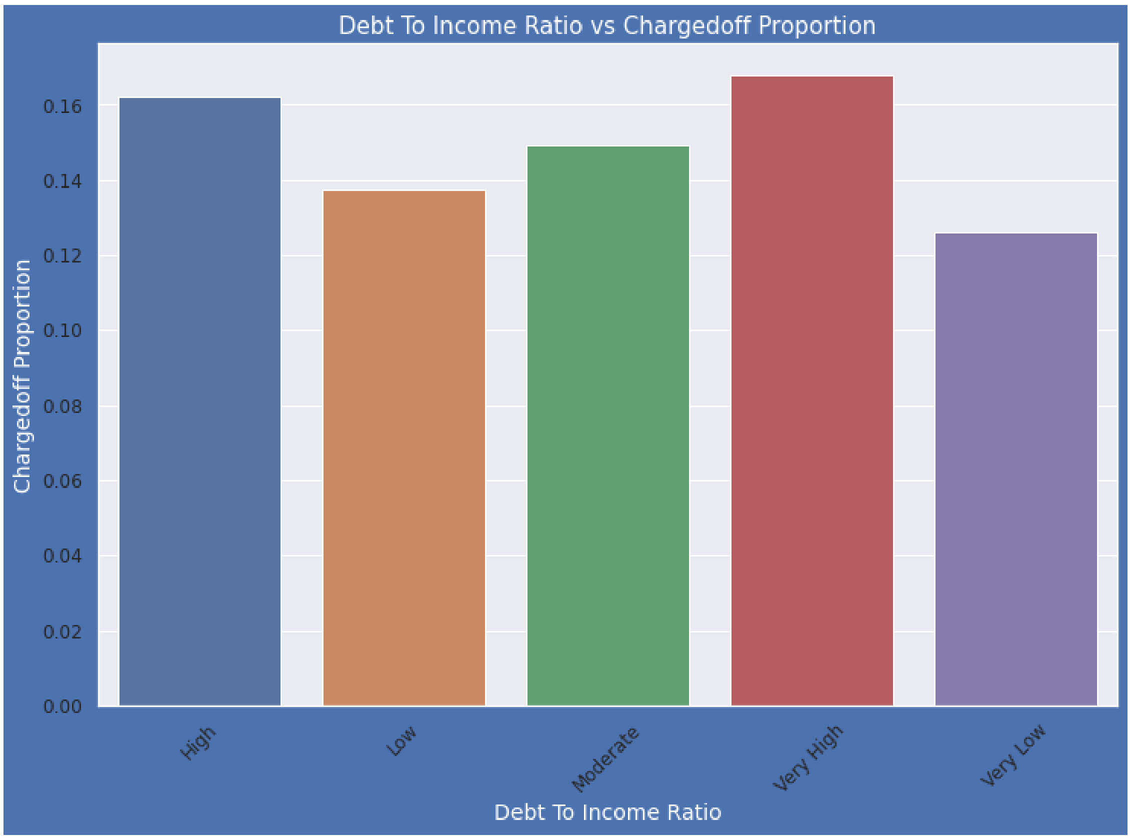
[1000]:
```
dti_vs_loan = df.groupby(['dti_b', 'loan_status']).loan_status.count().
    ↪unstack().fillna(0).reset_index()
dti_vs_loan['Total'] = dti_vs_loan['Charged Off']+ dti_vs_loan['Fully Paid']
dti_vs_loan['Chargedoff_Proportion'] = dti_vs_loan['Charged Off'] /␣
    ↪dti_vs_loan['Total']
dti_vs_loan.sort_values('Chargedoff_Proportion', ascending=False)
```

[1000]:

loan_status	dti_b	Charged Off	Fully Paid	Total	Chargedoff_Proportion
3	Very High	1187	5880	7067	0.167964
0	High	1089	5619	6708	0.162343
2	Moderate	1114	6348	7462	0.149290
1	Low	926	5818	6744	0.137307
4	Very Low	1086	7539	8625	0.125913

[1001]:

```
fig, ax1 = plt.subplots(figsize=(12, 8),facecolor='b')
ax1.set_title('Debt To Income Ratio vs Chargedoff␣
↪Proportion',fontsize=15,color='w')
ax1=sns.barplot(x='dti_b', y='Chargedoff_Proportion', data=dti_vs_loan)
ax1.set_xlabel('Debt To Income Ratio',fontsize=14,color='w')
ax1.set_ylabel('Chargedoff Proportion',fontsize=14,color = 'w')
plt.xticks(rotation=45)
plt.show()
```



Observation -

- High dti value have high risk of defaults

[1002]:
```
pub_rec_bankruptcies_vs_loan = df.groupby(['pub_rec_bankruptcies',␣
↪'loan_status']).loan_status.count().unstack().fillna(0).reset_index()
pub_rec_bankruptcies_vs_loan['Total'] = pub_rec_bankruptcies_vs_loan['Charged␣
↪Off']+ pub_rec_bankruptcies_vs_loan['Fully Paid']
pub_rec_bankruptcies_vs_loan['Chargedoff_Proportion'] =␣
↪pub_rec_bankruptcies_vs_loan['Charged Off'] /␣
↪pub_rec_bankruptcies_vs_loan['Total']
```

```
pub_rec_bankruptcies_vs_loan.sort_values('Chargedoff_Proportion',␣
↪ascending=False)
```

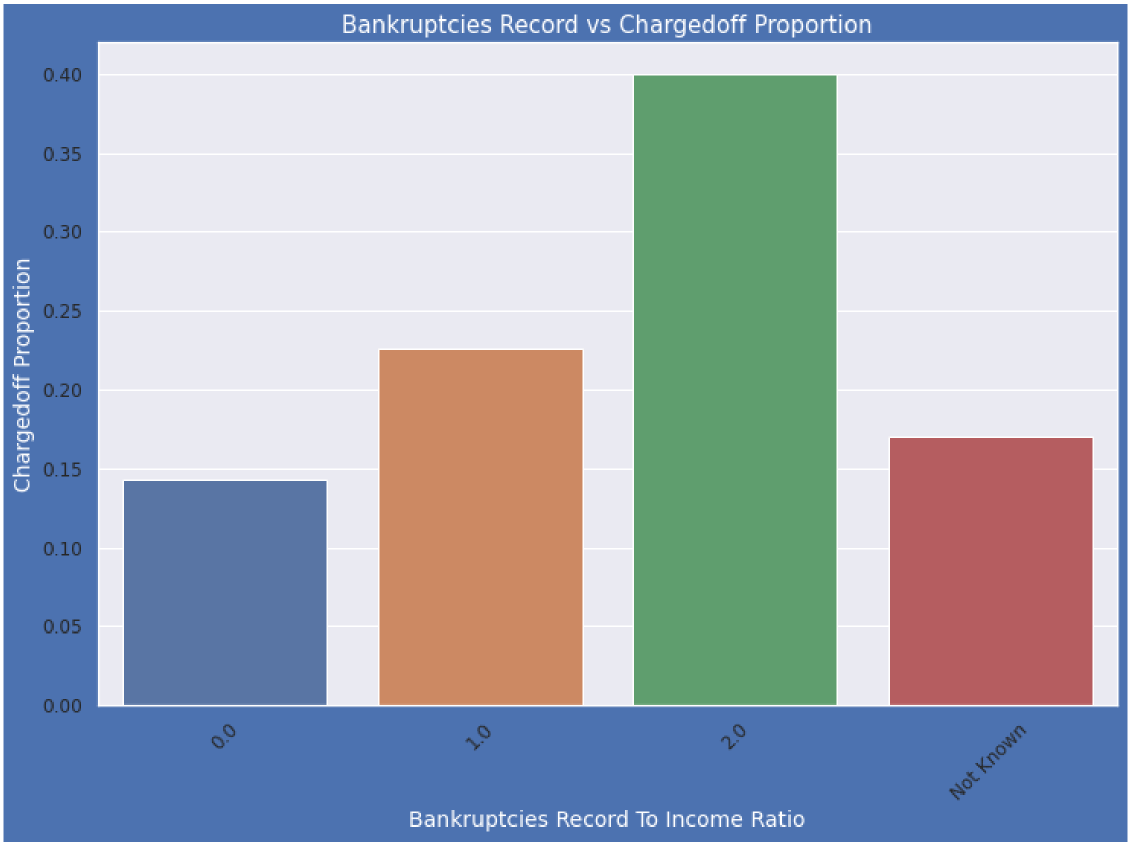
[1002]:

```
loan_status pub_rec_bankruptcies  Charged Off  Fully Paid  Total  \
2                            2.0            2           3      5
1                            1.0          361        1237   1598
3                      Not Known          112         546    658
0                            0.0         4927       29418  34345

loan_status  Chargedoff_Proportion
2                         0.400000
1                         0.225907
3                         0.170213
0                         0.143456
```

[1003]:

```
fig, ax1 = plt.subplots(figsize=(12, 8),facecolor='b')
ax1.set_title('Bankruptcies Record vs Chargedoff␣
↪Proportion',fontsize=15,color='w')
ax1=sns.barplot(x='pub_rec_bankruptcies', y='Chargedoff_Proportion',␣
↪data=pub_rec_bankruptcies_vs_loan)
ax1.set_xlabel('Bankruptcies Record To Income Ratio',fontsize=14,color='w')
ax1.set_ylabel('Chargedoff Proportion',fontsize=14,color = 'w')
plt.xticks(rotation=45)
plt.show()
```



Observation -

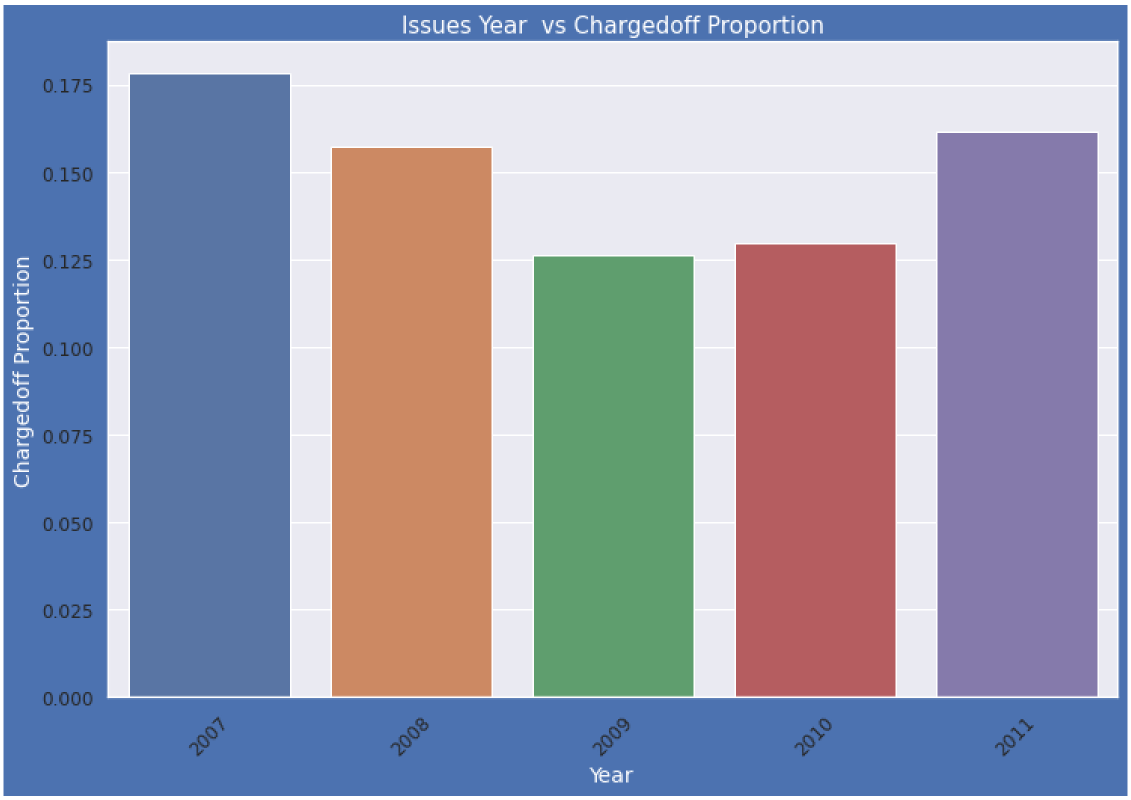
- Bankruptcies record with 2 is having high impact on loan defaults
- Lower the Bankruptcies lower the risk.

[1004]:
```
issue_year_vs_loan = df.groupby(['issue_year', 'loan_status']).loan_status.
    ↪count().unstack().fillna(0).reset_index()
issue_year_vs_loan['Total'] = issue_year_vs_loan['Charged Off']+␣
    ↪issue_year_vs_loan['Fully Paid']
issue_year_vs_loan['Chargedoff_Proportion'] = issue_year_vs_loan['Charged Off']␣
    ↪/ issue_year_vs_loan['Total']
issue_year_vs_loan.sort_values('Chargedoff_Proportion', ascending=False)
```

[1004]:

loan_status	issue_year	Charged Off	Fully Paid	Total	Chargedoff_Proportion
0	2007	41	189	230	0.178261
4	2011	3139	16298	19437	0.161496
1	2008	233	1248	1481	0.157326
3	2010	1425	9569	10994	0.129616
2	2009	564	3900	4464	0.126344

[1005]:
```
fig, ax1 = plt.subplots(figsize=(12, 8),facecolor='b')
ax1.set_title('Issues Year  vs Chargedoff Proportion',fontsize=15,color='w')
ax1=sns.barplot(x='issue_year', y='Chargedoff_Proportion',␣
 ↪data=issue_year_vs_loan)
ax1.set_xlabel('Year',fontsize=14,color='w')
ax1.set_ylabel('Chargedoff Proportion',fontsize=14,color = 'w')
plt.xticks(rotation=45)
plt.show()
```



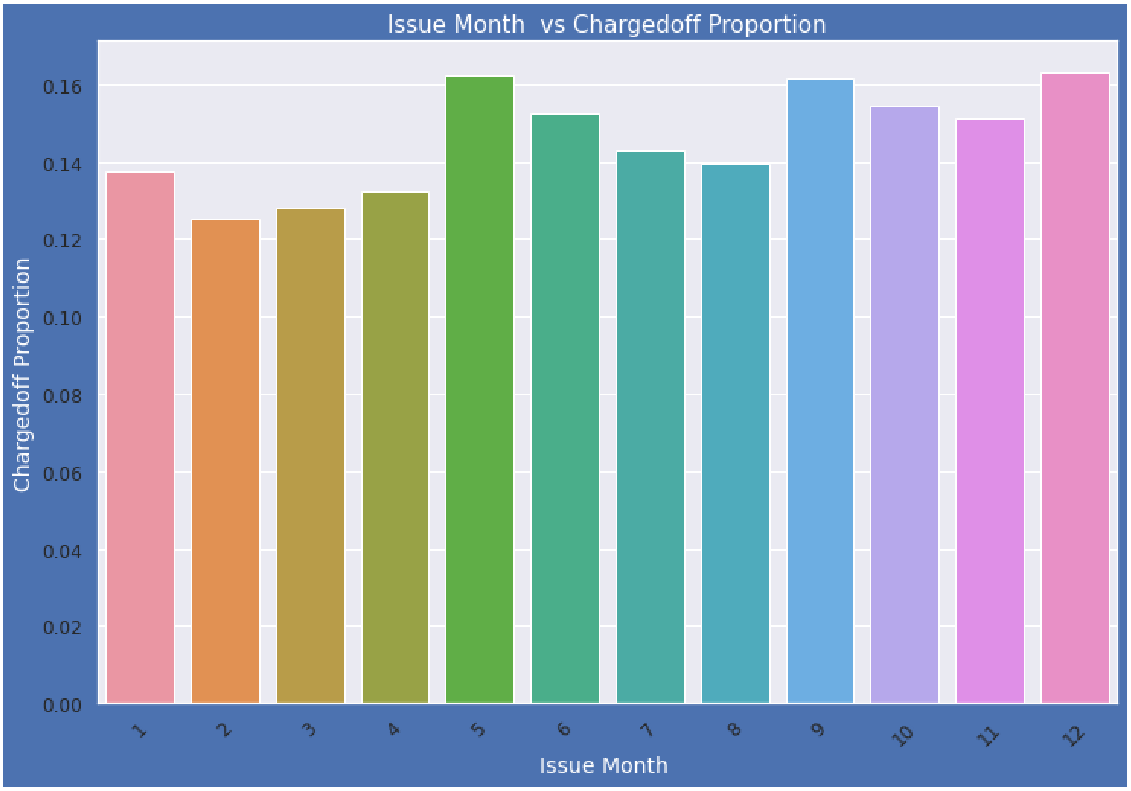
Observation - Most number of defaults where in the year 2011 which can be attributed to 2011 Debt ceiling crisis.

[1006]:
```
issue_month_vs_loan = df.groupby(['issue_month', 'loan_status']).loan_status.
 ↪count().unstack().fillna(0).reset_index()
issue_month_vs_loan['Total'] = issue_month_vs_loan['Charged Off']+␣
 ↪issue_month_vs_loan['Fully Paid']
issue_month_vs_loan['Chargedoff_Proportion'] = issue_month_vs_loan['Charged␣
 ↪Off'] / issue_month_vs_loan['Total']
issue_month_vs_loan.sort_values('Chargedoff_Proportion', ascending=False)
```

[1006]:
```
loan_status  issue_month  Charged Off  Fully Paid  Total  \
11                    12          655        3361   4016
4                      5          453        2335   2788
8                      9          532        2758   3290
9                     10          545        2983   3528
5                      6          457        2543   3000
10                    11          578        3238   3816
6                      7          456        2734   3190
7                      8          448        2763   3211
0                      1          311        1952   2263
3                      4          359        2352   2711
2                      3          326        2218   2544
1                      2          282        1967   2249

loan_status  Chargedoff_Proportion
11                        0.163098
4                         0.162482
8                         0.161702
9                         0.154478
5                         0.152333
10                        0.151468
6                         0.142947
7                         0.139520
0                         0.137428
3                         0.132423
2                         0.128145
1                         0.125389
```

[1007]:
```
fig, ax1 = plt.subplots(figsize=(12, 8),facecolor='b')
ax1.set_title('Issue Month  vs Chargedoff Proportion',fontsize=15,color='w')
ax1=sns.barplot(x='issue_month', y='Chargedoff_Proportion',␣
 ↪data=issue_month_vs_loan)
ax1.set_xlabel('Issue Month ',fontsize=14,color='w')
ax1.set_ylabel('Chargedoff Proportion',fontsize=14,color = 'w')
plt.xticks(rotation=45)
plt.show()
```



Observation -

- Maximum number of defaults occured when the loan was sanctioned/issued in Dec.
- We can see that loans taken during the second half of the year have more chances of getting charged off than first half of the year.

[1008]:
```
addr_state_vs_loan = df.groupby(['addr_state', 'loan_status']).loan_status.
 ↪count().unstack().fillna(0).reset_index()
addr_state_vs_loan['Total'] = addr_state_vs_loan['Charged Off']+␣
 ↪addr_state_vs_loan['Fully Paid']
addr_state_vs_loan['Chargedoff_Proportion'] = addr_state_vs_loan['Charged Off']␣
 ↪/ addr_state_vs_loan['Total']
addr_state_vs_loan.sort_values('Chargedoff_Proportion', ascending=False)
```

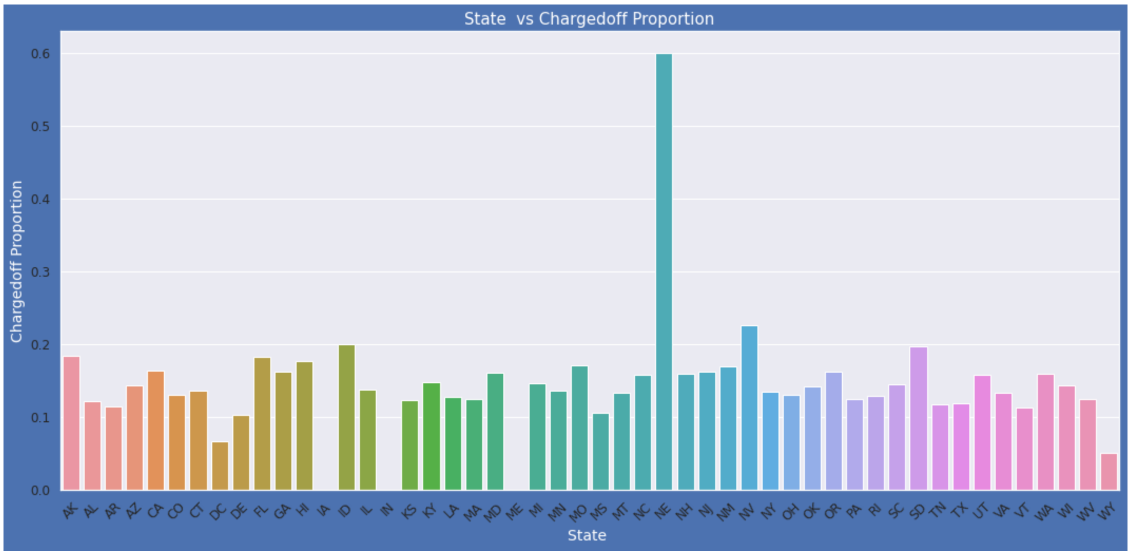
[1008]:

loan_status	addr_state	Charged Off	Fully Paid	Total	Chargedoff_Proportion
28	NE	3.0	2.0	5.0	0.600000
32	NV	103.0	353.0	456.0	0.225877
13	ID	1.0	4.0	5.0	0.200000
40	SD	12.0	49.0	61.0	0.196721
0	AK	13.0	58.0	71.0	0.183099
9	FL	484.0	2167.0	2651.0	0.182573
11	HI	28.0	131.0	159.0	0.176101

24	MO	110.0	536.0	646.0	0.170279
31	NM	30.0	147.0	177.0	0.169492
4	CA	1072.0	5482.0	6554.0	0.163564
36	OR	69.0	358.0	427.0	0.161593
10	GA	208.0	1080.0	1288.0	0.161491
30	NJ	269.0	1398.0	1667.0	0.161368
20	MD	155.0	809.0	964.0	0.160788
29	NH	25.0	132.0	157.0	0.159236
46	WA	124.0	659.0	783.0	0.158365
27	NC	113.0	605.0	718.0	0.157382
43	UT	38.0	204.0	242.0	0.157025
17	KY	45.0	259.0	304.0	0.148026
22	MI	100.0	582.0	682.0	0.146628
39	SC	64.0	377.0	441.0	0.145125
3	AZ	116.0	692.0	808.0	0.143564
47	WI	60.0	361.0	421.0	0.142518
35	OK	40.0	241.0	281.0	0.142349
14	IL	192.0	1213.0	1405.0	0.136655
23	MN	80.0	506.0	586.0	0.136519
6	CT	91.0	581.0	672.0	0.135417
33	NY	468.0	2996.0	3464.0	0.135104
26	MT	11.0	72.0	83.0	0.132530
44	VA	173.0	1135.0	1308.0	0.132263
34	OH	149.0	994.0	1143.0	0.130359
5	CO	96.0	645.0	741.0	0.129555
38	RI	24.0	162.0	186.0	0.129032
18	LA	51.0	350.0	401.0	0.127182
48	WV	21.0	148.0	169.0	0.124260
19	MA	150.0	1058.0	1208.0	0.124172
37	PA	176.0	1242.0	1418.0	0.124118
16	KS	30.0	214.0	244.0	0.122951
1	AL	51.0	371.0	422.0	0.120853
42	TX	293.0	2179.0	2472.0	0.118528
41	TN	2.0	15.0	17.0	0.117647
2	AR	26.0	202.0	228.0	0.114035
45	VT	6.0	47.0	53.0	0.113208
25	MS	2.0	17.0	19.0	0.105263
8	DE	11.0	97.0	108.0	0.101852
7	DC	13.0	181.0	194.0	0.067010
49	WY	4.0	76.0	80.0	0.050000
12	IA	0.0	5.0	5.0	0.000000
15	IN	0.0	9.0	9.0	0.000000
21	ME	0.0	3.0	3.0	0.000000

[1009]:
```
fig, ax1 = plt.subplots(figsize=(18, 8),facecolor='b')
ax1.set_title('State  vs Chargedoff Proportion',fontsize=15,color='w')
```

```
ax1=sns.barplot(x='addr_state', y='Chargedoff_Proportion',␣
↪data=addr_state_vs_loan)
ax1.set_xlabel('State ',fontsize=14,color='w')
ax1.set_ylabel('Chargedoff Proportion',fontsize=14,color = 'w')
plt.xticks(rotation=45)
plt.show()
```



Observation -

- State of NE has a very high chances of getting defaulted on loans
- State of NV,CA and FL shows good number of charge offs

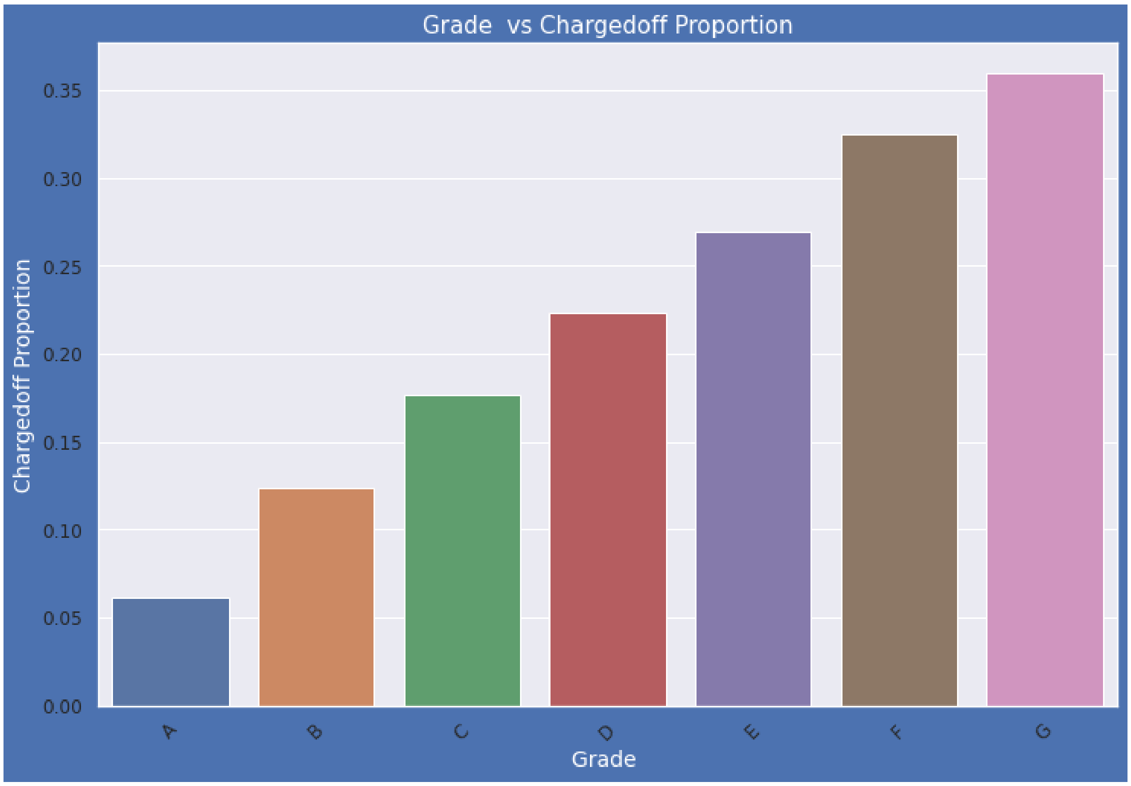
[1010]:
```
grade_vs_loan = df.groupby(['grade', 'loan_status']).loan_status.count().
↪unstack().fillna(0).reset_index()
grade_vs_loan['Total'] = grade_vs_loan['Charged Off']+ grade_vs_loan['Fully␣
↪Paid']
grade_vs_loan['Chargedoff_Proportion'] = grade_vs_loan['Charged Off'] /␣
↪grade_vs_loan['Total']
grade_vs_loan.sort_values('Chargedoff_Proportion', ascending=False)
```

[1010]:

loan_status	grade	Charged Off	Fully Paid	Total	Chargedoff_Proportion
6	G	93	166	259	0.359073
5	F	286	595	881	0.324631
4	E	656	1781	2437	0.269183
3	D	1077	3743	4820	0.223444
2	C	1321	6146	7467	0.176912
1	B	1376	9720	11096	0.124009
0	A	593	9053	9646	0.061476

[1011]:

```
fig, ax1 = plt.subplots(figsize=(12, 8),facecolor='b')
ax1.set_title('Grade  vs Chargedoff Proportion',fontsize=15,color='w')
ax1=sns.barplot(x='grade', y='Chargedoff_Proportion', data=grade_vs_loan)
ax1.set_xlabel('Grade ',fontsize=14,color='w')
ax1.set_ylabel('Chargedoff Proportion',fontsize=14,color = 'w')
plt.xticks(rotation=45)
plt.show()
```



Observation

- Grade A has the least proportion of people defaulting on their loans.
- Grade F and G have high charged off proportion
- Chances of getting charged off is increasing with grades moving from A to G

[1012]:

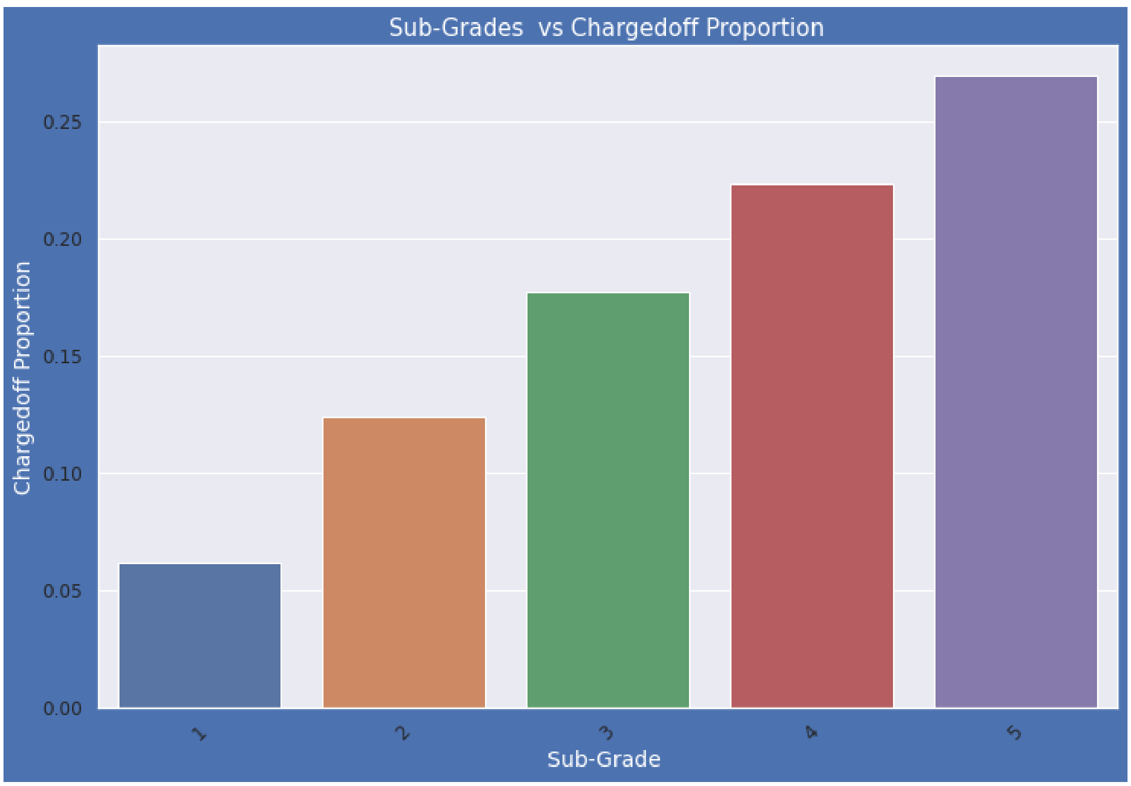
```
subgrade_vs_loan=df.groupby(['sub_grade','loan_status']).loan_status.count().
 ↪unstack().fillna(0).reset_index()
subgrade_vs_loan['Total']=grade_vs_loan['Charged Off'] + grade_vs_loan['Fully␣
 ↪Paid']
subgrade_vs_loan['ChargedOff_Proportion']=grade_vs_loan['Charged Off']/
 ↪grade_vs_loan['Total']
subgrade_vs_loan.sort_values('ChargedOff_Proportion',ascending=False)
```

[1012]:

loan_status	sub_grade	Charged Off	Fully Paid	Total	ChargedOff_Proportion
4	5	1122	6308	2437	0.269183
3	4	1083	6596	4820	0.223444
2	3	1115	6430	7467	0.176912
1	2	1104	6150	11096	0.124009
0	1	978	5720	9646	0.061476

[1013]:

```
fig, ax1 = plt.subplots(figsize=(12, 8),facecolor='b')
ax1.set_title('Sub-Grades  vs Chargedoff Proportion',fontsize=15,color='w')
ax1=sns.barplot(x='sub_grade', y='ChargedOff_Proportion', data=subgrade_vs_loan)
ax1.set_xlabel('Sub-Grade ',fontsize=14,color='w')
ax1.set_ylabel('Chargedoff Proportion',fontsize=14,color = 'w')
plt.xticks(rotation=45)
plt.show()
```



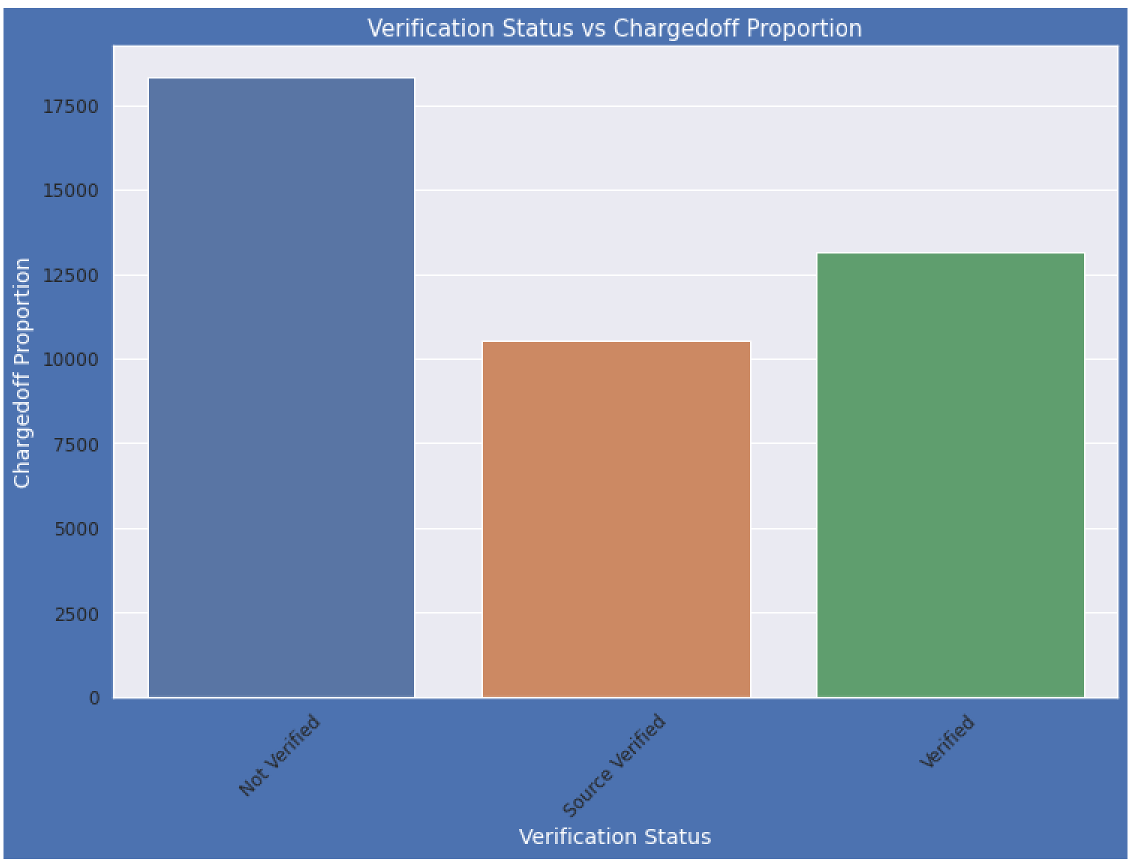
[1014]:

```
verify_vs_loan = df.groupby(['verification_status','loan_status']).loan_status.
 ↪count().unstack().fillna(0).reset_index()
verify_vs_loan['Total'] = verify_vs_loan['Charged Off']+verify_vs_loan['Fully␣
 ↪Paid']
verify_vs_loan['ChargedOff_Proportion'] = verify_vs_loan['Charged␣
 ↪Off']+verify_vs_loan['Total']
verify_vs_loan.sort_values('ChargedOff_Proportion',ascending=False)
```

[1014]:
```
loan_status verification_status  Charged Off  Fully Paid  Total  \
0                  Not Verified         2089       14164  16253
2                      Verified         1943        9266  11209
1               Source Verified         1370        7774   9144

loan_status  ChargedOff_Proportion
0                            18342
2                            13152
1                            10514
```

[1016]:
```
fig, ax1 = plt.subplots(figsize=(12, 8),facecolor='b')
ax1.set_title('Verification Status vs Chargedoff␣
↪Proportion',fontsize=15,color='w')
ax1=sns.barplot(x='verification_status', y='ChargedOff_Proportion',␣
↪data=verify_vs_loan)
ax1.set_xlabel('Verification Status',fontsize=14,color='w')
ax1.set_ylabel('Chargedoff Proportion',fontsize=14,color = 'w')
plt.xticks(rotation=45)
plt.show()
```



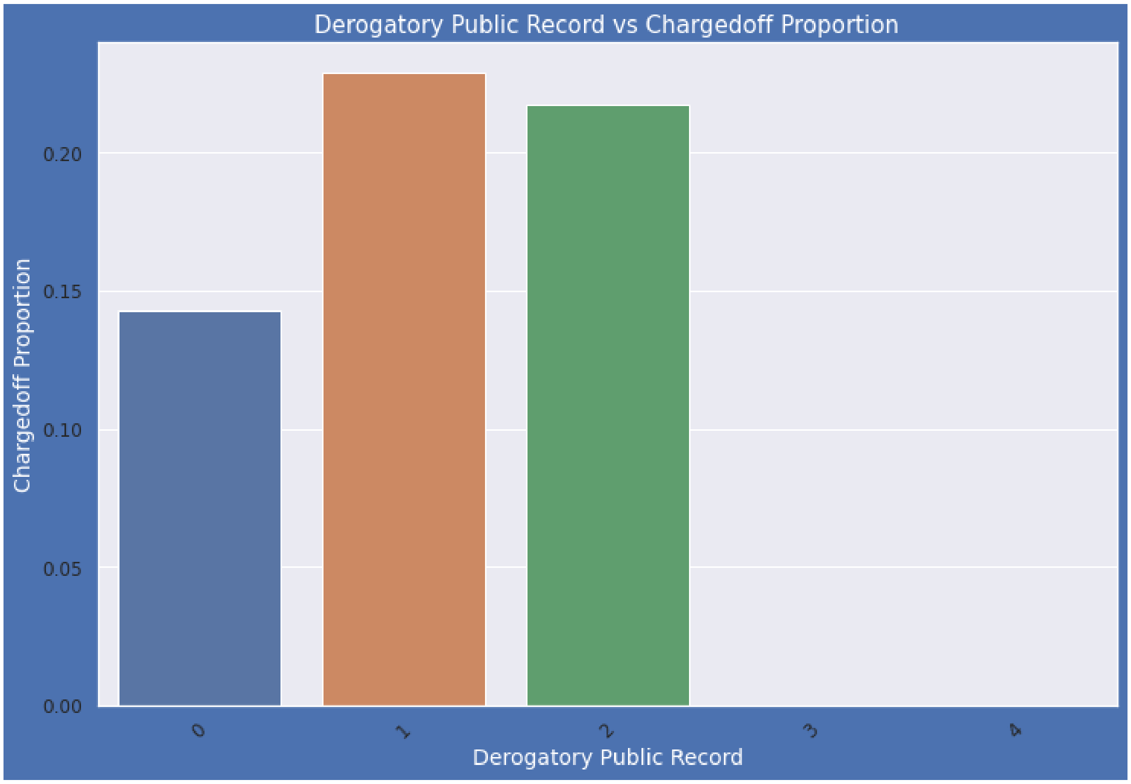
Observation - As there is not much difference in Charged off proportions, the variable doesn't provide any insight on Charged Off Proportion

[1017]:
```
bankruptcies_vs_loan = df.groupby(['pub_rec','loan_status']).loan_status.
    ↪count().unstack().fillna(0).reset_index()
bankruptcies_vs_loan['Total'] = bankruptcies_vs_loan['Charged Off'] +␣
    ↪bankruptcies_vs_loan['Fully Paid']
bankruptcies_vs_loan['Chargedoff_Proportion'] = bankruptcies_vs_loan['Charged␣
    ↪Off'] / bankruptcies_vs_loan['Total']
bankruptcies_vs_loan.sort_values('Chargedoff_Proportion', ascending=False)
```

[1017]:

loan_status	pub_rec	Charged Off	Fully Paid	Total	Chargedoff_Proportion
1	1	449.0	1514.0	1963.0	0.228732
2	2	10.0	36.0	46.0	0.217391
0	0	4943.0	29646.0	34589.0	0.142907
3	3	0.0	6.0	6.0	0.000000
4	4	0.0	2.0	2.0	0.000000

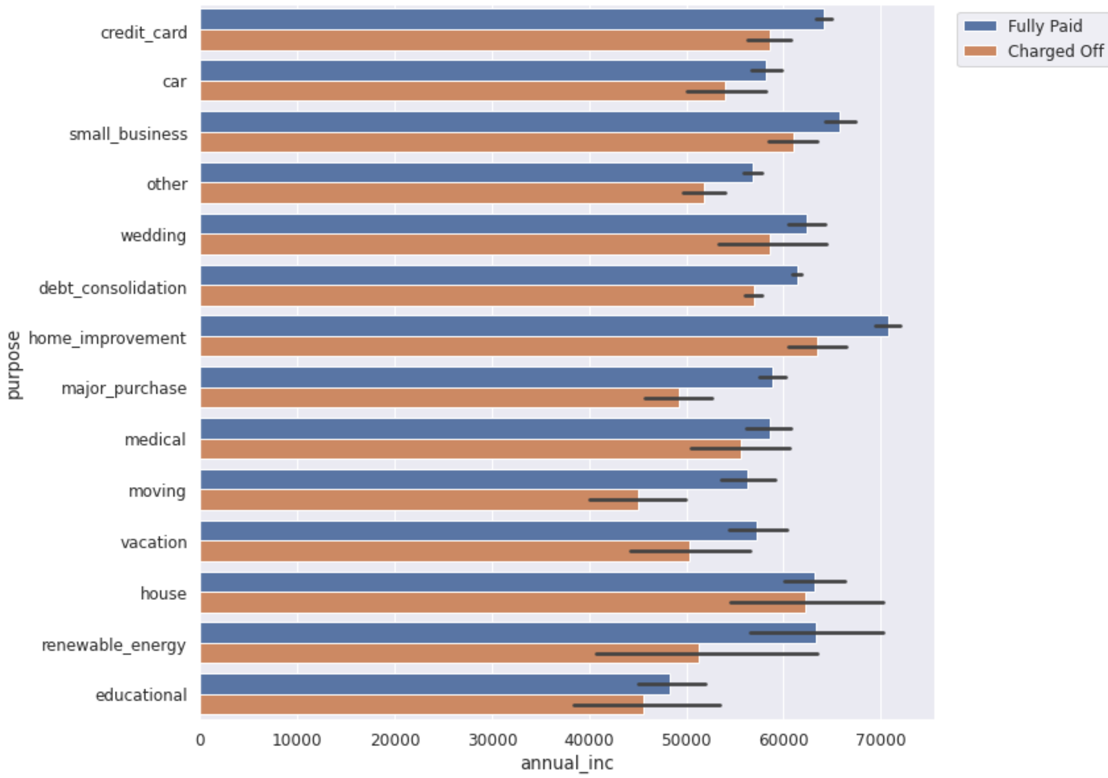
[1018]:
```
fig, ax1 = plt.subplots(figsize=(12, 8),facecolor='b')
ax1.set_title('Derogatory Public Record vs Chargedoff␣
    ↪Proportion',fontsize=15,color='w')
ax1=sns.barplot(x='pub_rec', y='Chargedoff_Proportion',␣
    ↪data=bankruptcies_vs_loan)
ax1.set_xlabel('Derogatory Public Record',fontsize=14,color='w')
ax1.set_ylabel('Chargedoff Proportion',fontsize=14,color = 'w')
plt.xticks(rotation=45)
plt.show()
```



Observation -

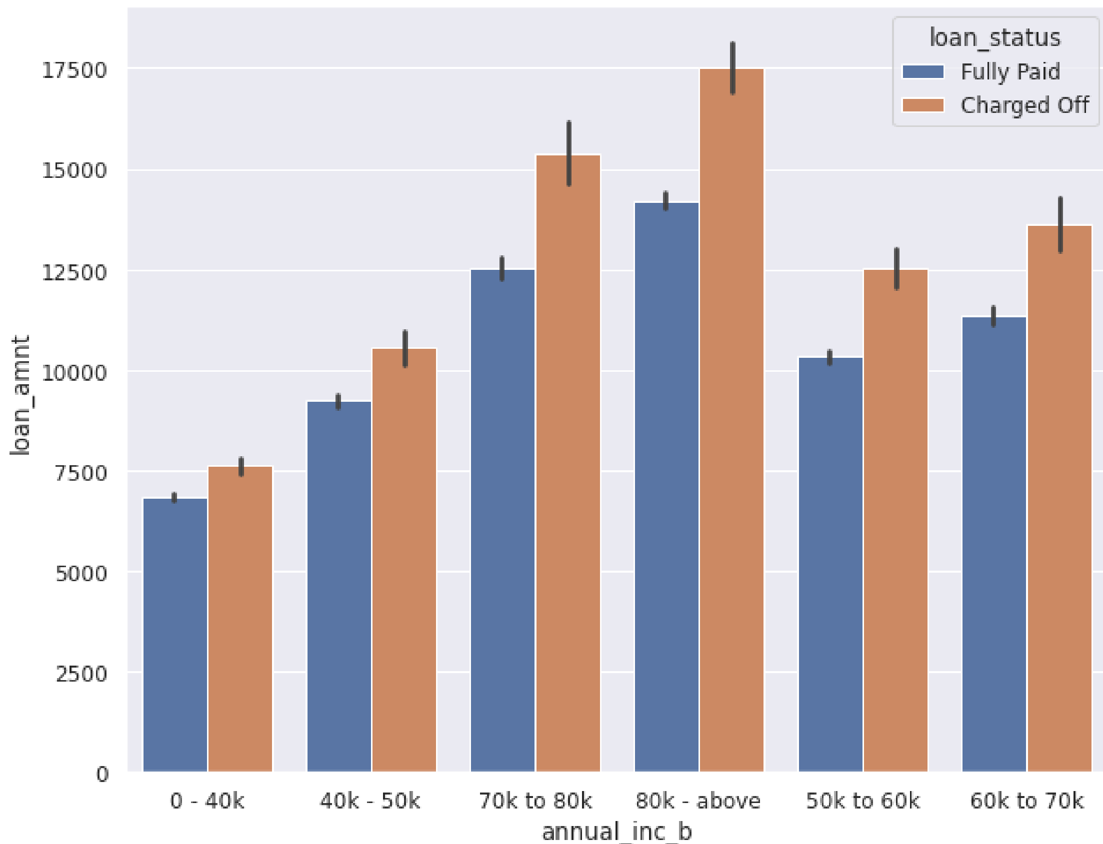
- Those who already have pub_rec value 1 or 2 have charged off chances higher than who have no Derogatory Public Record.
- pub_rec count 3-4 has less numbers so cannot reach on any conclusions.

[1019]:
```
plt.figure(figsize=(10,10))
sns.barplot(data =df,x='annual_inc', y='purpose', hue
↪='loan_status',palette="deep")
plt.legend(loc='upper right', bbox_to_anchor=(1.25, 1))
plt.show()
```



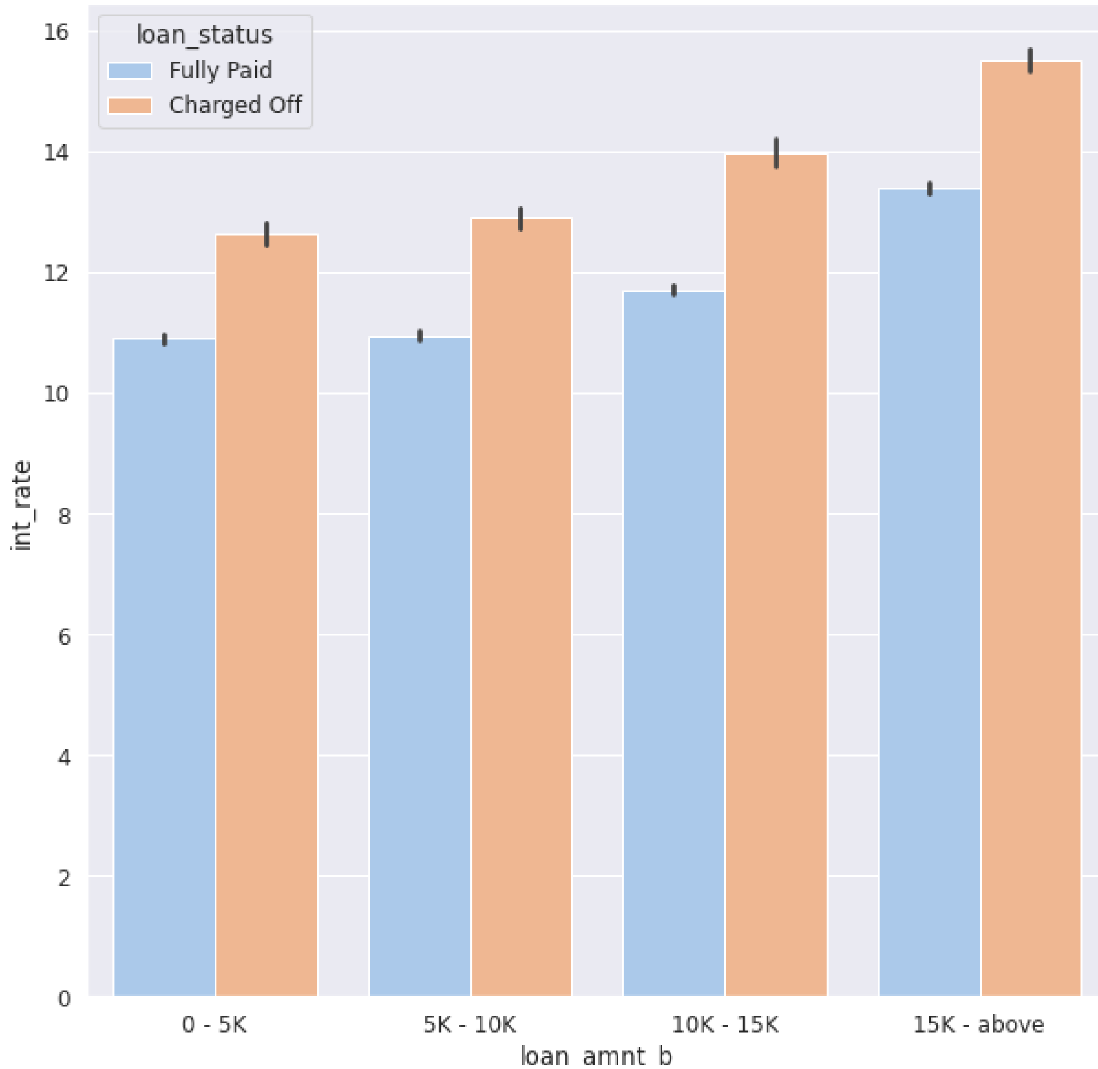
[1236]:
```
plt.figure(figsize=(10,8))
sns.barplot(x = "annual_inc_b", y = "loan_amnt", hue = 'loan_status', data = df)
```

[1236]: <AxesSubplot:xlabel='annual_inc_b', ylabel='loan_amnt'>



Observation Across all the income groups, the loan_amount is higher for people who defaulted.

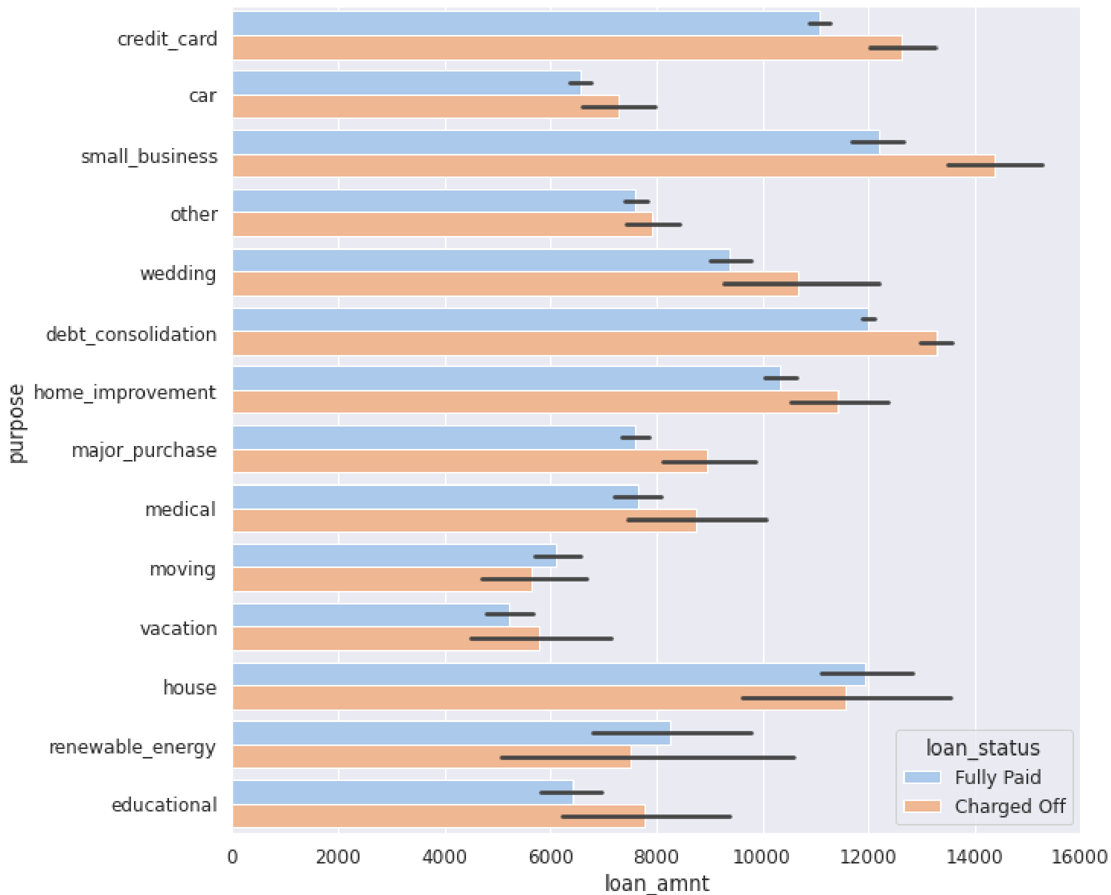
[1024]:
```
plt.figure(figsize=(10,10))
sns.barplot(data =df,x='loan_amnt_b', y='int_rate', hue␣
↪='loan_status',palette="pastel")
plt.show()
#same as above. select which one to use
```



Observation The interest rate for charged off loans is pretty high than that of fully paid loans in all the loan_amount groups. This can be a pretty strong driving factor for loan defaulting.

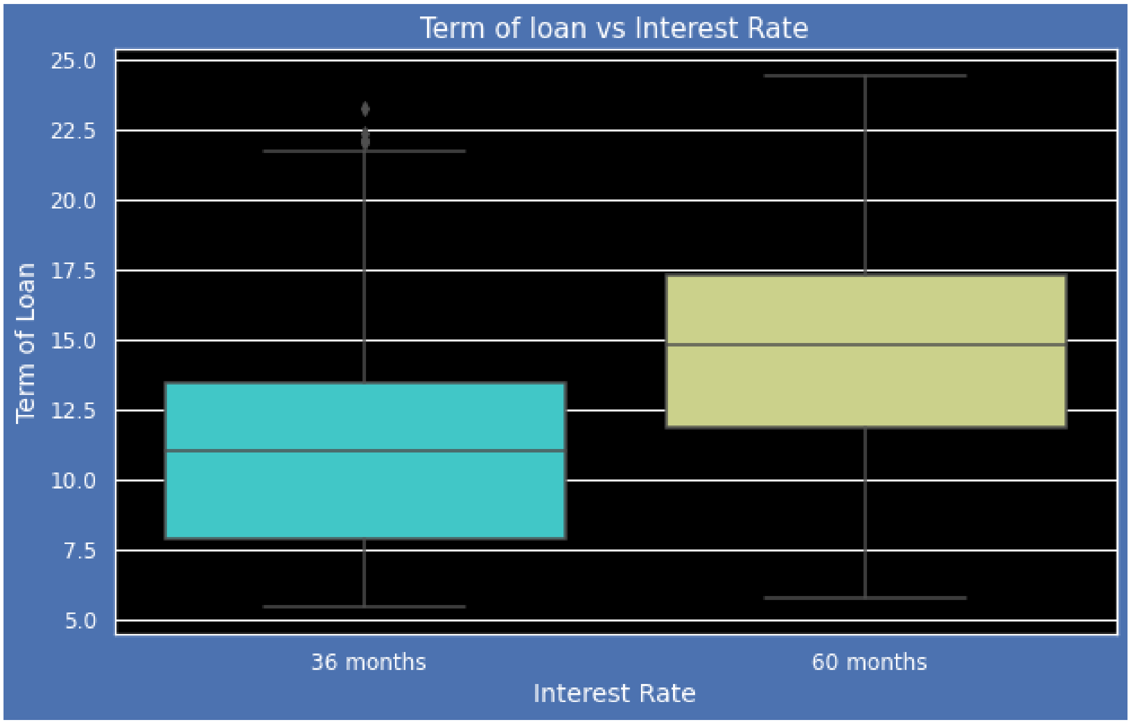
[1026]:

```
plt.figure(figsize=(10,10))
sns.barplot(data =df,x='loan_amnt', y='purpose', hue␣
↪='loan_status',palette="pastel")
plt.show()
```

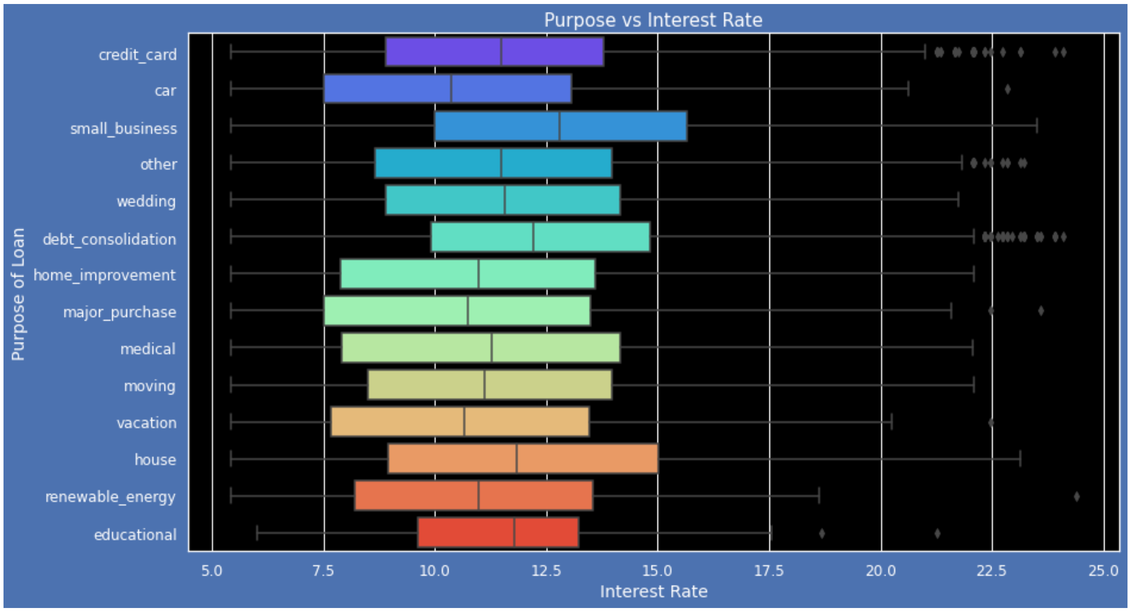


[1027]:

```
with plt.style.context('dark_background'):
  plt.figure(figsize=(10,6),facecolor='b')
  ax=sns.boxplot(y='int_rate',x='term',data=df,palette='rainbow')
  ax.set_title('Term of loan vs Interest Rate',fontsize=15,color='w')
  ax.set_xlabel('Interest Rate',fontsize=14,color='w')
  ax.set_ylabel('Term of Loan',fontsize=14,color='w')
  plt.show()
```




```
[1028]: with plt.style.context('dark_background'):
  plt.figure(figsize=(14,8),facecolor='b')
  ax = sns.boxplot(x='int_rate', y='purpose', data =df,palette='rainbow')
  ax.set_title('Purpose vs Interest Rate',fontsize=15,color='w')
  ax.set_xlabel('Interest Rate',fontsize=14,color = 'w')
  ax.set_ylabel('Purpose of Loan',fontsize=14,color = 'w')
  plt.show()
```

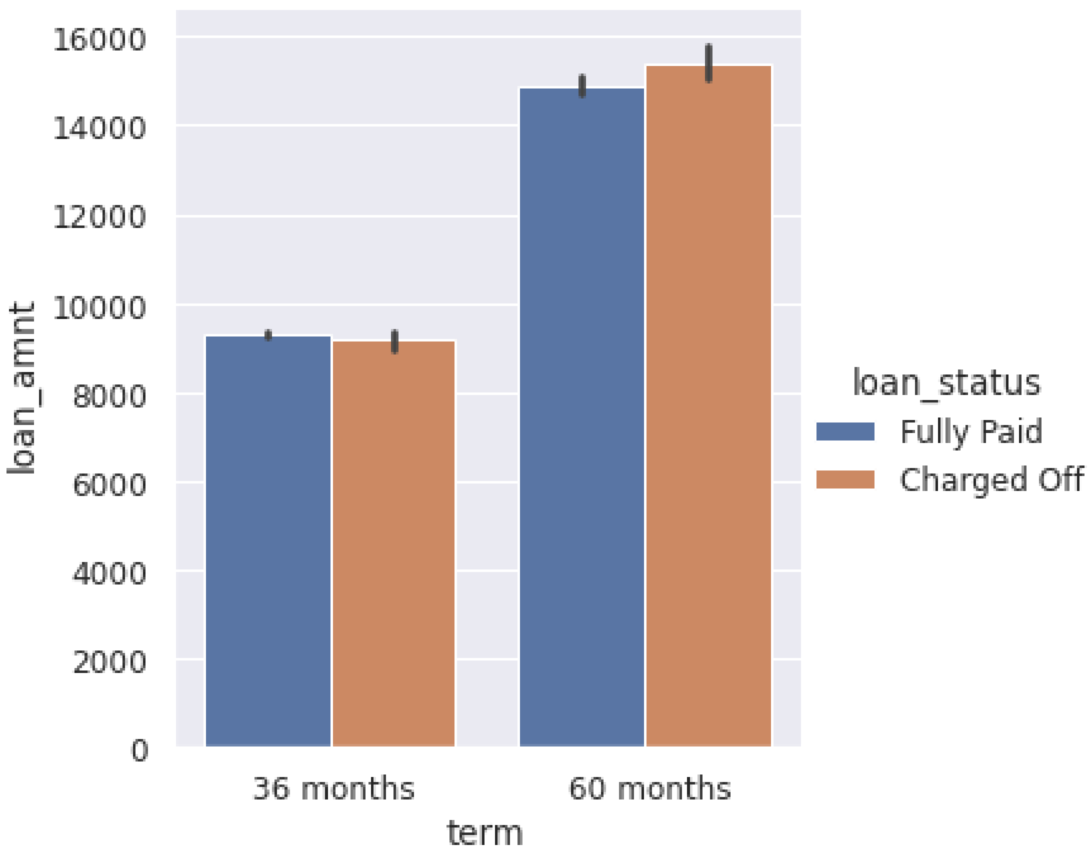


Observations -

- It is clear that avearge intrest rate is highest for small business purpose.
- Loans taken for small business purposes had to repay the loan with more intrest rate as compared to other.Debt consolidation is 2nd where borrowers had to pay more interest rate.

[1255]:
```
sns.catplot(x = 'term', y = 'loan_amnt', data = df,hue = 'loan_status', kind =␣
 ↪'bar')
```

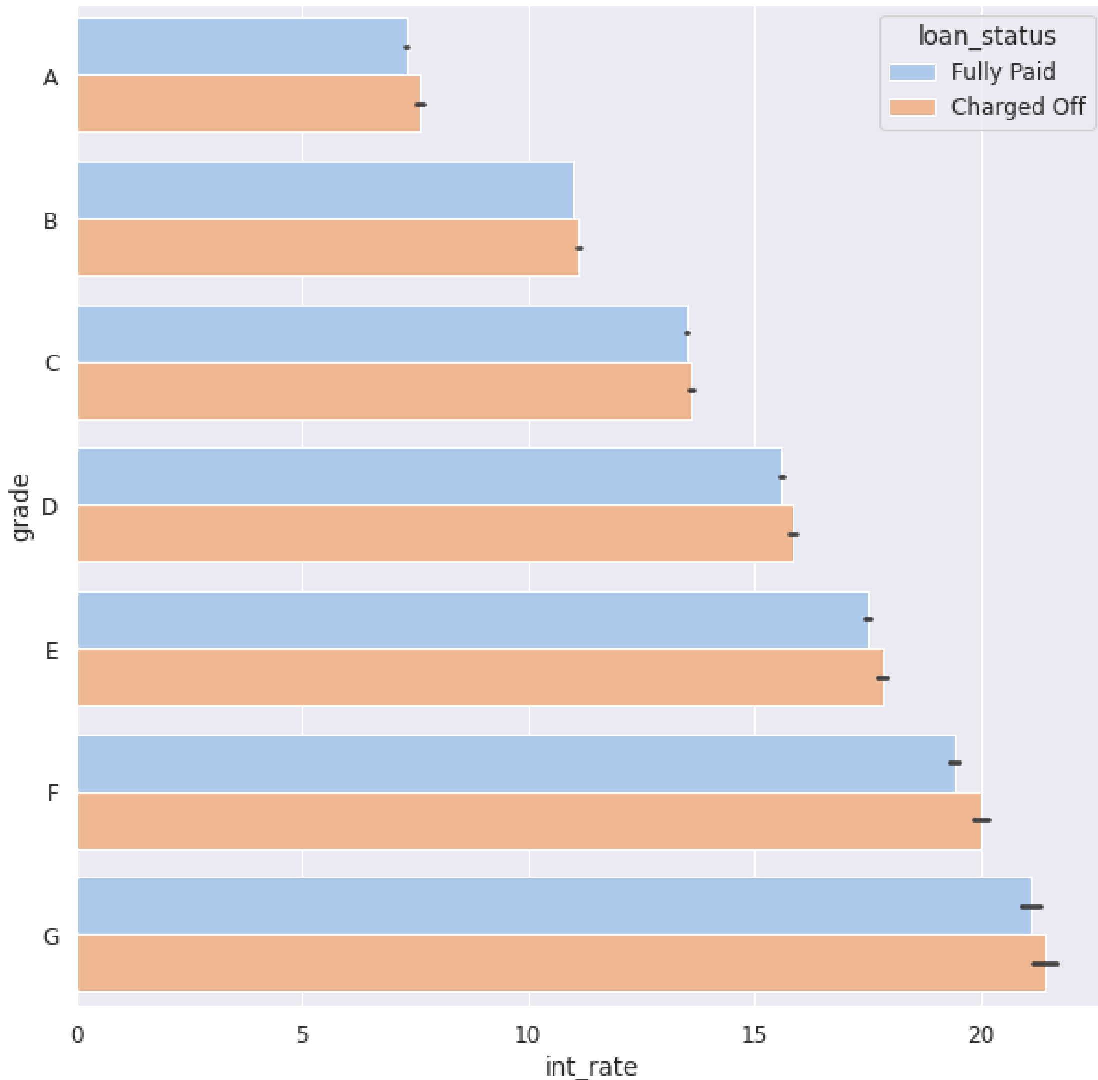
[1255]: `<seaborn.axisgrid.FacetGrid at 0x7f45821c04c0>`



Observations - It is clear that intrest rate is increasing with loan amount increase.probably when loan amount is more it is taken for longer loan term, we saw earlier that longer the loan term more the interest rates.

[1035]:
```
plt.figure(figsize=(10,10))
sns.barplot(data =df,x='int_rate', y='grade', hue␣
 ↪='loan_status',palette="pastel", order=['A','B','C','D','E','F','G'])
```

```
plt.show()
```



Observations - A-grade is a top letter grade for a lender to assign to a borrower. The higher the borrower's credit grade,the lower the interest rate offered to that borrower on a loan. It is clear that intrest rate is increasing with grades moving from A to F.

0.2 Observations from Analysis

0.2.1 The above analysis with respect to the charged off loans. There is a more probability of defaulting when :

- Applicants taking loan for 'home improvement' and have income of 60k -70k
- Applicants whose home ownership is 'MORTGAGE and have income of 60-70k

- Applicants who receive interest at the rate of 21-24% and have an income of 70k-80k
-

[ ]:
```

```