Lending Club Case Study- Exploratory Data Analysis

Project Brief

This assignment will give an idea about how real business problems are solved using EDA. In this case study it will develop a basic understanding of risk analytics in banking and financial services and understand how data is used to minimise the risk of losing money while lending to customers.

Business Objectives

This company is the largest online loan marketplace, facilitating personal loans, business loans, and financing of medical procedures. Borrowers can easily access lower interest rate loans through a fast online interface.

Like most other lending companies, lending loans to 'risky' applicants is the largest source of financial loss (called credit loss). The credit loss is the amount of money lost by the lender when the borrower refuses to pay or runs away with the money owed.

In other words, borrowers who default cause the largest amount of loss to the lenders. In this case, the customers labelled as 'charged-off' are the 'defaulters'.

If one is able to identify these risky loan applicants, then such loans can be reduced thereby cutting down the amount of credit loss. Identification of such applicants using EDA is the aim of this case study.

In other words, the company wants to understand the driving factors (or driver variables) behind loan default, i.e. the variables which are strong indicators of default.The company can utilise this knowledge for its portfolio and risk assessment.

In [1]:
```
# Importing the necessary modules
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')

# supress scientific notation of values
pd.options.display.float_format = '{:.2f}'.format

# increasing max number of columns and rows  displayed with pandas.
pd.set_option('display.max_columns', 150)
pd.set_option('display.max_rows', 100)
```

Dataset

It contains the complete loan data for all loans issued through the time period 2007 t0 2011.

In [2]:
```
# Loading data set file in to data frame.
data = pd.read_csv('loan.csv')
data.head(3)
```

Out[2]:

	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
0	1077501	1296599	5000	5000	4975.00	36 months	10.65%	162.87	B	B2	NaN	10+ years	RENT	24000.00	Verified	Dec-11	Fully Paid	n
1	1077430	1314167	2500	2500	2500.00	60 months	15.27%	59.83	C	C4	Ryder	< 1 year	RENT	30000.00	Source Verified	Dec-11	Charged Off	n
2	1077175	1313524	2400	2400	2400.00	36 months	15.96%	84.33	C	C5	NaN	10+ years	RENT	12252.00	Not Verified	Dec-11	Fully Paid	n

	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
0	https://lendingclub.com/browse/loanDetail.acti...	Borrower added on 12/22/11 > I need to upgra...	credit_card	Computer	860xx	AZ	27.65	0	Jan-85	1	NaN	NaN	3	0	13648	83.70%	9
1	https://lendingclub.com/browse/loanDetail.acti...	Borrower added on 12/22/11 > I plan to use t...	car	bike	309xx	GA	1.00	0	Apr-99	5	NaN	NaN	3	0	1687	9.40%	4
2	https://lendingclub.com/browse/loanDetail.acti...	NaN	small_business	real estate business	606xx	IL	8.72	0	Nov-01	2	NaN	NaN	2	0	2956	98.50%	10

In [3]:
```
# Lower rows of data frame
data.tail(3)
```

Out[3]:

	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
39714	90395	90390	5000	5000	1325.00	36 months	8.07%	156.84	A	A4	NaN	< 1 year	MORTGAGE	100000.00	Not Verified	Jul-07	Fully Paid	n
39715	90376	89243	5000	5000	650.00	36 months	7.43%	155.38	A	A2	NaN	< 1 year	MORTGAGE	200000.00	Not Verified	Jul-07	Fully Paid	n
39716	87023	86999	7500	7500	800.00	36 months	13.75%	255.43	E	E2	Evergreen Center	< 1 year	OWN	22000.00	Not Verified	Jun-07	Fully Paid	n

	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
39714	https://lendingclub.com/browse/loanDetail.acti...	NaN	debt_consolidation	MBA Loan Consolidation	017xx	MA	2.30	0	Oct-98	0	0.00	0.00	11	0	9698	19.40%
39715	https://lendingclub.com/browse/loanDetail.acti...	NaN	other	JAL Loan	208xx	MD	3.72	0	Nov-88	0	0.00	0.00	17	0	85607	0.70%
39716	https://lendingclub.com/browse/loanDetail.acti...	I plan to consolidate over $7,000 of debt: a c...	debt_consolidation	Consolidation Loan	027xx	MA	14.29	1	Oct-03	0	11.00	0.00	7	0	4175	51.50%

Understanding the Dataset

In [4]:
```
# shape of data frame
print(data.shape)

# stats of the given dataset
data.describe()
```

```
(39717, 111)
```

Out[4]:

	id	member_id	loan_amnt	funded_amnt	funded_amnt_inv	installment	annual_inc	dti	delinq_2yrs	inq_last_6mths	mths_since_last_delinq	mths_since_last_record	open_acc	pub_rec	revol_bal	total_acc
count	39717.00	39717.00	39717.00	39717.00	39717.00	39717.00	39717.00	39717.00	39717.00	39717.00	14035.00	2786.00	39717.00	39717.00	39717.00	39717.00
mean	683131.91	850463.56	11219.44	10947.71	10397.45	324.56	68968.93	13.32	0.15	0.87	35.90	69.70	9.29	0.06	13382.53	22.09
std	210694.13	265678.31	7456.67	7187.24	7128.45	208.87	63793.77	6.68	0.49	1.07	22.02	43.82	4.40	0.24	15885.02	11.40
min	54734.00	70699.00	500.00	500.00	0.00	15.69	4000.00	0.00	0.00	0.00	0.00	0.00	2.00	0.00	0.00	2.00
25%	516221.00	666780.00	5500.00	5400.00	5000.00	167.02	40404.00	8.17	0.00	0.00	18.00	22.00	6.00	0.00	3703.00	13.00
50%	665665.00	850812.00	10000.00	9600.00	8975.00	280.22	59000.00	13.40	0.00	1.00	34.00	90.00	9.00	0.00	8850.00	20.00
75%	837755.00	1047339.00	15000.00	15000.00	14400.00	430.78	82300.00	18.60	0.00	1.00	52.00	104.00	12.00	0.00	17058.00	29.00
max	1077501.00	1314167.00	35000.00	35000.00	35000.00	1305.19	6000000.00	29.99	11.00	8.00	120.00	129.00	44.00	4.00	149588.00	90.00

	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_amnt	collections_12_mths_ex_med	mths_since_last_major_derog	policy_code	annual_inc_joint
count	39717.00	39717.00	39717.00	39717.00	39717.00	39717.00	39717.00	39717.00	39717.00	39717.00	39661.00	0.00	39717.00	0.00
mean	51.23	50.99	12153.60	11567.15	9793.35	2263.66	1.36	95.22	12.41	2678.83	0.00	NaN	1.00	NaN
std	375.17	373.82	9042.04	8942.67	7065.52	2608.11	7.29	688.74	148.67	4447.14	0.00	NaN	0.00	NaN
min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	NaN	1.00	NaN
25%	0.00	0.00	5576.93	5112.31	4600.00	662.18	0.00	0.00	0.00	218.68	0.00	NaN	1.00	NaN
50%	0.00	0.00	9899.64	9287.15	8000.00	1348.91	0.00	0.00	0.00	546.14	0.00	NaN	1.00	NaN
75%	0.00	0.00	16534.43	15798.81	13653.26	2833.40	0.00	0.00	0.00	3293.16	0.00	NaN	1.00	NaN
max	6311.47	6307.37	58563.68	58563.68	35000.02	23563.68	180.20	29623.35	7002.19	36115.20	0.00	NaN	1.00	NaN

Data Cleaning

In [5]:
```
# Finding percentage of null or missing values
null_perc = round(100*(data.isnull().sum()/len(data.index)), 2)

# Printing columns which have more than 0% missing values
null_perc[ null_perc > 0 ]
```

Out[5]:
```
emp_title                        6.19
emp_length                       2.71
desc                            32.58
title                            0.03
mths_since_last_delinq          64.66
mths_since_last_record          92.99
revol_util                       0.13
last_pymnt_d                     0.18
next_pymnt_d                    97.13
last_credit_pull_d               0.01
collections_12_mths_ex_med       0.14
mths_since_last_major_derog    100.00
annual_inc_joint               100.00
dti_joint                      100.00
verification_status_joint      100.00
tot_coll_amt                   100.00
tot_cur_bal                    100.00
open_acc_6m                    100.00
open_il_6m                     100.00
open_il_12m                    100.00
open_il_24m                    100.00
mths_since_rcnt_il             100.00
total_bal_il                   100.00
il_util                        100.00
open_rv_12m                    100.00
open_rv_24m                    100.00
max_bal_bc                     100.00
all_util                       100.00
total_rev_hi_lim               100.00
inq_fi                         100.00
total_cu_tl                    100.00
inq_last_12m                   100.00
acc_open_past_24mths           100.00
avg_cur_bal                    100.00
bc_open_to_buy                 100.00
bc_util                        100.00
chargeoff_within_12_mths         0.14
mo_sin_old_il_acct             100.00
mo_sin_old_rev_tl_op           100.00
mo_sin_rcnt_rev_tl_op          100.00
mo_sin_rcnt_tl                 100.00
mort_acc                       100.00
mths_since_recent_bc           100.00
mths_since_recent_bc_dlq       100.00
mths_since_recent_inq          100.00
mths_since_recent_revol_delinq 100.00
num_accts_ever_120_pd          100.00
num_actv_bc_tl                 100.00
num_actv_rev_tl                100.00
num_bc_sats                    100.00
num_bc_tl                      100.00
num_il_tl                      100.00
num_op_rev_tl                  100.00
num_rev_accts                  100.00
num_rev_tl_bal_gt_0            100.00
num_sats                       100.00
num_tl_120dpd_2m               100.00
num_tl_30dpd                   100.00
num_tl_90g_dpd_24m             100.00
num_tl_op_past_12m             100.00
pct_tl_nvr_dlq                 100.00
percent_bc_gt_75               100.00
pub_rec_bankruptcies             1.75
tax_liens                        0.10
tot_hi_cred_lim                100.00
total_bal_ex_mort              100.00
total_bc_limit                 100.00
total_il_high_credit_limit     100.00
dtype: float64
```

In [6]:
```
# Removing columns which has more than 30% null values in it
print(data.shape)
data.drop(null_perc[ null_perc > 30 ].index, axis=1, inplace=True)
print(data.shape)
```

```
(39717, 111)
(39717, 53)
```

In [7]:
```
# Finding number of unique values in each column
data.nunique().sort_values().head(20)
```

Out[7]:
```
tax_liens                      1
delinq_amnt                    1
chargeoff_within_12_mths       1
acc_now_delinq                 1
application_type               1
policy_code                    1
collections_12_mths_ex_med     1
initial_list_status            1
pymnt_plan                     1
term                           2
pub_rec_bankruptcies           3
verification_status            3
loan_status                    3
pub_rec                        5
home_ownership                 5
grade                          7
inq_last_6mths                 9
delinq_2yrs                   11
emp_length                    11
purpose                       14
dtype: int64
```

We have to remove these columns, as these columns have only one unique value in all the rows, which will not give any usefull outcome.

'tax_liens', 'delinq_amnt', 'chargeoff_within_12_mths', 'acc_now_delinq', 'application_type', 'policy_code', 'collections_12_mths_ex_med', 'initial_list_status', 'pymnt_plan'

In [8]:
```
#Dropping Columns with only one values.
print(data.shape)
data = data.drop(['tax_liens', 'delinq_amnt', 'chargeoff_within_12_mths', 'acc_now_delinq', 'application_type', 'policy_code', 'collections_12_mths_ex_med', 'initial_list_status', 'pymnt_plan'],axis=1)
print(data.shape)
```

```
(39717, 53)
(39717, 44)
```

In [9]:
```
#Finding number of unique values, printing high unique valued columns
data.nunique().sort_values(ascending=False).head(20)
```

Out[9]:
```
id                         39717
url                        39717
member_id                  39717
total_pymnt                37850
total_pymnt_inv            37518
total_rec_int              35148
last_pymnt_amnt            34930
emp_title                  28820
revol_bal                  21711
title                      19615
installment                15383
funded_amnt_inv             8205
total_rec_prncp             7976
annual_inc                  5318
recoveries                  4040
dti                         2868
collection_recovery_fee     2616
total_rec_late_fee          1356
out_prncp_inv               1138
out_prncp                   1137
dtype: int64
```

emp_title, and title columns have more unique values

In [10]:
```
data.drop(['emp_title', 'title'], axis=1, inplace=True)
```

id, url, and member_id having all unique values. any one of these can be used as primary key. Let's use id as a primary key. so remove url and member id columns.

In [11]:
```
data.drop(['member_id', 'url'], axis=1, inplace=True)
```

total_rec_prncp,total_rec_int, total_rec_late_fee, ,collection_recovery_fee,recoveries, last_credit_pull_d, last_pymnt_d, out_prncp, out_prncp_inv variables are valid for barrowers who already took loan. As we are only interested only in loan application details these columns can be removed. recoveries, collection_recovery_fee columns are only valid for charged off loans. W ill removed these colomns.

In [12]:
```
data.drop(['total_rec_int', 'total_rec_prncp', 'total_rec_late_fee', 'last_credit_pull_d', 'recoveries', 'collection_recovery_fee', 'last_pymnt_d'], axis=1, inplace=True)
data.drop(['out_prncp', 'out_prncp_inv'], axis=1, inplace=True)
```

In [13]:
```
# Finding percentage of null or missing values
null_perc = round(100*(data.isnull().sum()/len(data.index)), 2)
null_perc[ null_perc > 0 ]
```

Out[13]:
```
emp_length             2.71
revol_util             0.13
pub_rec_bankruptcies   1.75
dtype: float64
```

In [14]:
```
print(data.shape)
data.dropna(subset=['emp_length', 'revol_util', 'pub_rec_bankruptcies'], inplace=True)
print(data.shape)
# Finding percentage of null or missing values
null_perc = round(100*(data.isnull().sum()/len(data.index)), 2)
null_perc[ null_perc > 0 ]
```

```
(39717, 31)
(37898, 31)
```

Out[14]:
```
Series([], dtype: float64)
```

Loan Status Column has 3 different values. we need only Fully Paid and Charged Off. So, we have to remove the rows with Current values in loan status.

In [15]:
```
# Removing current loan status rows
print(data.shape)
data = data[data.loan_status != 'Current']
print(data.shape)
```

```
(37898, 31)
(36800, 31)
```

In [16]:
```
# Checking unique values for term column
data.term.unique()
```

Out[16]:
```
array([' 36 months', ' 60 months'], dtype=object)
```

In [17]:
```
# Stripping empty space in values in term
data['term'] = data.term.str.strip()
data.term.unique()
```

Out[17]:
```
array(['36 months', '60 months'], dtype=object)
```

Data type conversions

In [18]:
```
# Finding datatype in all coulmns
data.dtypes
```

Out[18]:
```
id                        int64
loan_amnt                 int64
funded_amnt               int64
funded_amnt_inv         float64
term                     object
int_rate                 object
installment             float64
grade                    object
sub_grade                object
emp_length               object
home_ownership           object
annual_inc              float64
verification_status      object
issue_d                  object
loan_status              object
purpose                  object
zip_code                 object
addr_state               object
dti                     float64
delinq_2yrs               int64
earliest_cr_line         object
inq_last_6mths            int64
open_acc                  int64
pub_rec                   int64
revol_bal                 int64
revol_util               object
total_acc                 int64
total_pymnt             float64
total_pymnt_inv         float64
last_pymnt_amnt         float64
pub_rec_bankruptcies    float64
dtype: object
```

Int_rate and revol_util are having '%' symbol values and having data type of object. removing % at the end and convert to float

In [19]:
```
# stripping '%' value
data['int_rate'] = data.int_rate.str.strip('%').astype(float)
data['revol_util'] = data.revol_util.str.strip('%').astype(float)
```

issue_d, earliest_cr_line are having date values, lets convert column data type to date.

In [20]:
```
# converting to date type
data['issue_d'] = pd.to_datetime(data.issue_d, format='%b-%y')
data['issue_d'] = data['issue_d'].apply(lambda x: x-pd.DateOffset(years=100) if x.year > 2020 else x)
data['earliest_cr_line'] = pd.to_datetime(data.earliest_cr_line, format='%b-%y')
data['earliest_cr_line'] = data['earliest_cr_line'].apply(lambda x: x-pd.DateOffset(years=100) if x.year > 2020 else x)
# Converted to proper datatypes for analysis
data.dtypes
```

Out[20]:
```
id                               int64
loan_amnt                        int64
funded_amnt                      int64
funded_amnt_inv                float64
term                            object
int_rate                       float64
installment                    float64
grade                           object
sub_grade                       object
emp_length                      object
home_ownership                  object
annual_inc                     float64
verification_status             object
issue_d                 datetime64[ns]
loan_status                     object
purpose                         object
zip_code                        object
addr_state                      object
dti                            float64
delinq_2yrs                      int64
earliest_cr_line        datetime64[ns]
inq_last_6mths                   int64
open_acc                         int64
pub_rec                          int64
revol_bal                        int64
revol_util                     float64
total_acc                        int64
total_pymnt                    float64
total_pymnt_inv                float64
last_pymnt_amnt                float64
pub_rec_bankruptcies           float64
dtype: object
```

Derived Variables

create new columns from date type columns

- **we are deriving new columns of weekday, month & year from the existing "issue_d" column.**
- **Creating Approved Loan amount ratio which is a ratio of Funded Amount by investor to Requested Loan amount.**

In [21]:
```
# issue_d column
data['issue_d_year'] = data.issue_d.dt.year
data['issue_d_month'] = data.issue_d.dt.strftime('%b')
data['issue_d_weekday'] = data.issue_d.dt.weekday

# data type conversion of year and weekday
data['issue_d_year'] = data['issue_d_year'].astype(object)
data['issue_d_weekday'] = data['issue_d_weekday'].astype(object)

# earliest_cr_line
data['earliest_cr_line_year'] = data.earliest_cr_line.dt.year
data['earliest_cr_line_month'] = data.earliest_cr_line.dt.strftime('%b')

# data type conversion of year and weekday
data['earliest_cr_line_year'] = data['earliest_cr_line_year'].astype(object)

# approved_loan_amnt_ratio
data['approved_loan_amnt_ratio'] = round(data.funded_amnt_inv*100/data.loan_amnt,2)
```

In [22]:
```
# Converted date formats for analysis
print(data.shape)
data.head(3)
data.dtypes
```

```
(36800, 37)
```

Out[22]:
```
id                                   int64
loan_amnt                            int64
funded_amnt                          int64
funded_amnt_inv                    float64
term                                object
int_rate                           float64
installment                        float64
grade                               object
sub_grade                           object
emp_length                          object
home_ownership                      object
annual_inc                         float64
verification_status                 object
issue_d                     datetime64[ns]
loan_status                         object
purpose                             object
zip_code                            object
addr_state                          object
dti                                float64
delinq_2yrs                          int64
earliest_cr_line            datetime64[ns]
inq_last_6mths                       int64
open_acc                             int64
pub_rec                              int64
revol_bal                            int64
revol_util                         float64
total_acc                            int64
total_pymnt                        float64
total_pymnt_inv                    float64
last_pymnt_amnt                    float64
pub_rec_bankruptcies               float64
issue_d_year                        object
issue_d_month                       object
issue_d_weekday                     object
earliest_cr_line_year               object
earliest_cr_line_month              object
approved_loan_amnt_ratio           float64
dtype: object
```

Univariate Analysis

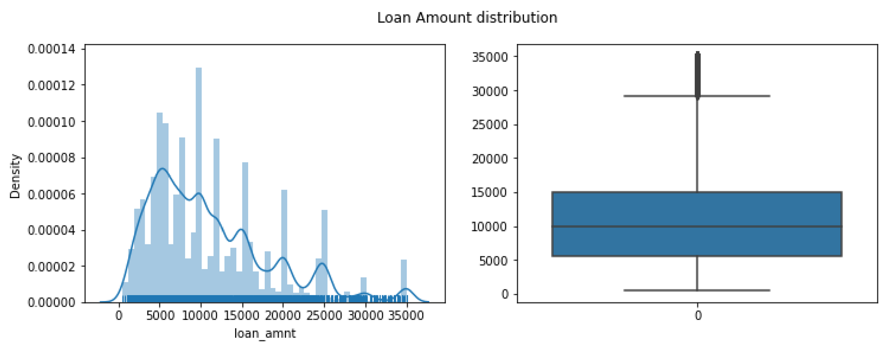
Univariate analysis explores each variable in a data set separately. These are the possible driver variables.

loan_amnt
funded_amnt
funded_amnt_inv
term
int_rate
installment
grade
sub_grade
emp_length
home_ownership
annual_inc
verification_status
loan_status
purpose
addr_state
dti
earliest_cr_line
pub_rec
pub_rec_bankruptcies
issue_d_year
issue_d_month
issue_d_weekday
earliest_cr_line_year
earliest_cr_line_month
approved_loan_amnt_ratio

Loan Amount

The listed amount of the loan applied for by the borrower. If at some point in time, the credit department reduces the loan amount, then it will be reflected in this value.

In [23]:
```
#Increasing the figure size of plot
plt.figure(figsize=(12,4))
#Setting subplot index
plt.subplot(1,2,1)
#Histogram plot
sns.distplot(a=data.loan_amnt, rug=True)
plt.subplot(1,2,2)
#Box plot
sns.boxplot(data=data.loan_amnt)
#Single title for both subplots.
plt.suptitle('Loan Amount distribution')
plt.show()
```



In [24]:
```
# Stats of Laon amount
data.loan_amnt.describe(percentiles=[0.05,0.1,0.25,0.5,0.75,0.9,0.95,0.99])
```

Out[24]:
```
count   36800.00
mean    11149.54
std      7369.86
min       500.00
5%       2400.00
10%      3200.00
25%      5500.00
50%     10000.00
75%     15000.00
90%     22000.00
95%     25000.00
99%     35000.00
max     35000.00
Name: loan_amnt, dtype: float64
```

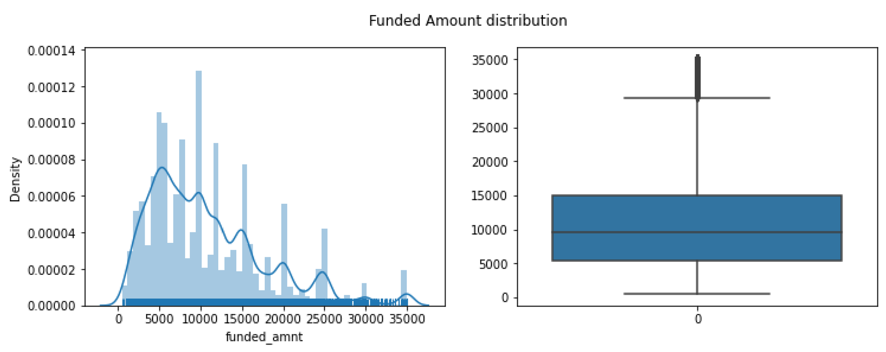
Observations:

More number of people took loan amount of 10000, and also meadian of distribution is 10000. very less people took more than 30000 loan amount.

funded_amnt

The total amount committed to that loan at that point in time.

In [25]:
```
plt.figure(figsize=(12,4))
plt.subplot(1,2,1)
sns.distplot(a=data.funded_amnt, rug=True)
plt.subplot(1,2,2)
sns.boxplot(data=data.funded_amnt)
plt.suptitle('Funded Amount distribution')
plt.show()
```



In [26]:
```
# Stats of funded amount
data.funded_amnt.describe(percentiles=[0.05,0.1,0.25,0.5,0.75,0.9,0.95,0.99])
```

Out[26]:
```
count   36800.00
mean    10880.79
std      7109.16
min       500.00
5%       2400.00
10%      3200.00
25%      5400.00
50%      9600.00
75%     15000.00
90%     20375.00
95%     25000.00
99%     35000.00
max     35000.00
Name: funded_amnt, dtype: float64
```

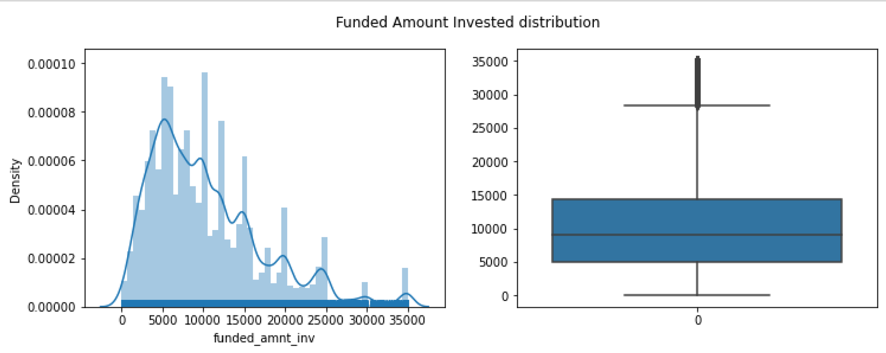
Observations:

Funded amount data behaves similar to loan Amount, that means Lender approved most of Applied loan amount.

funded_amnt_inv

The total amount committed by investors for that loan at that point in time.

In [27]:
```
plt.figure(figsize=(12,4))
plt.subplot(1,2,1)
sns.distplot(a=data.funded_amnt_inv, rug=True)
plt.subplot(1,2,2)
sns.boxplot(data=data.funded_amnt_inv)
plt.suptitle('Funded Amount Invested distribution')
plt.show()
```



In [28]:
```
#Stats of funded_amnt_inv
data.funded_amnt_inv.describe(percentiles=[0.05,0.1,0.25,0.5,0.75,0.9,0.95,0.99])
```

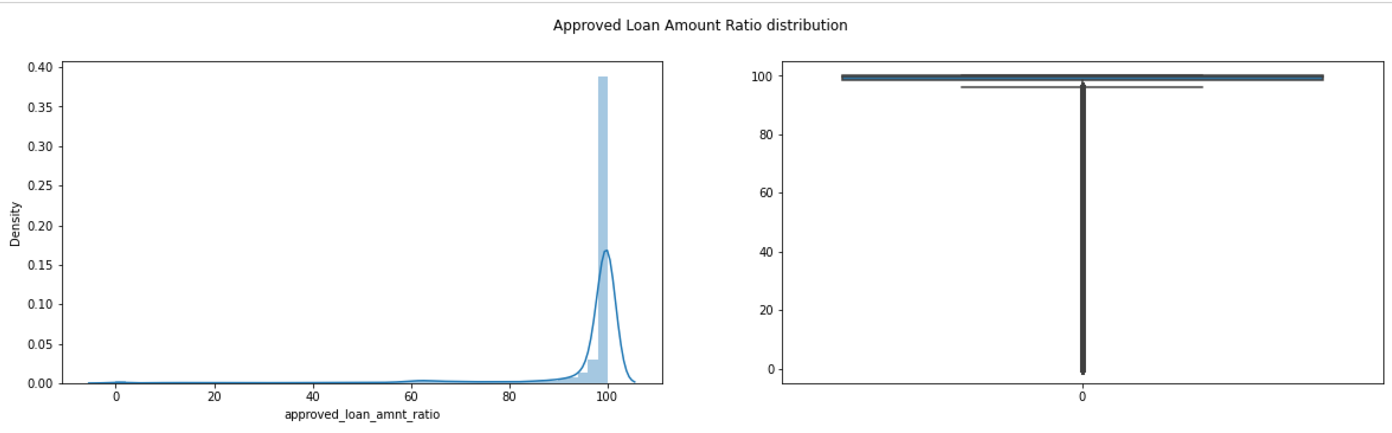
Out[28]:
```
count   36800.00
mean    10439.06
std      7008.52
min         0.00
5%       2000.00
10%      3000.00
25%      5000.00
50%      9000.00
75%     14350.00
90%     20000.00
95%     24655.82
99%     34725.00
max     35000.00
Name: funded_amnt_inv, dtype: float64
```

Observations:

Funded amount investment data behaves similar to loan Amount, that means Lender approved most of the Applied loan amount.

Approved Loan Amount Ratio

In [29]:
```
plt.figure(figsize=(20,5))
plt.subplot(1,2,1)
sns.distplot(a=data.approved_loan_amnt_ratio)
plt.subplot(1,2,2)
sns.boxplot(data=data.approved_loan_amnt_ratio)
plt.suptitle('Approved Loan Amount Ratio distribution')
plt.show()
```

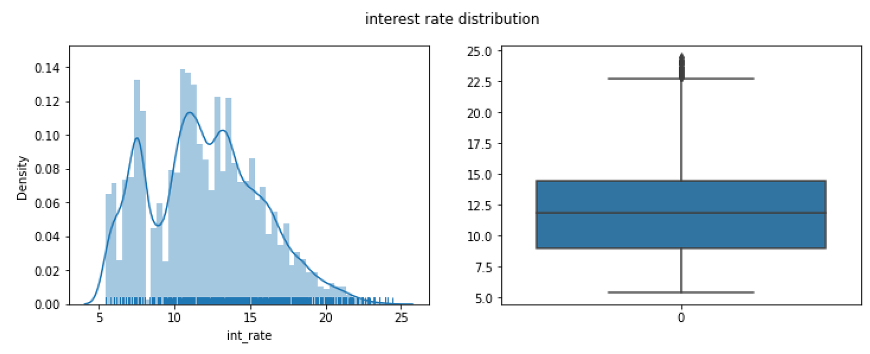


Observations:

70% of Borrowers got 100% loan amount from investors.

Interest Rate

In [30]:
```
plt.figure(figsize=(12,4))
plt.subplot(1,2,1)
sns.distplot(a=data.int_rate, rug=True)
plt.subplot(1,2,2)
sns.boxplot(data=data.int_rate)
plt.suptitle('interest rate distribution')
plt.show()
```



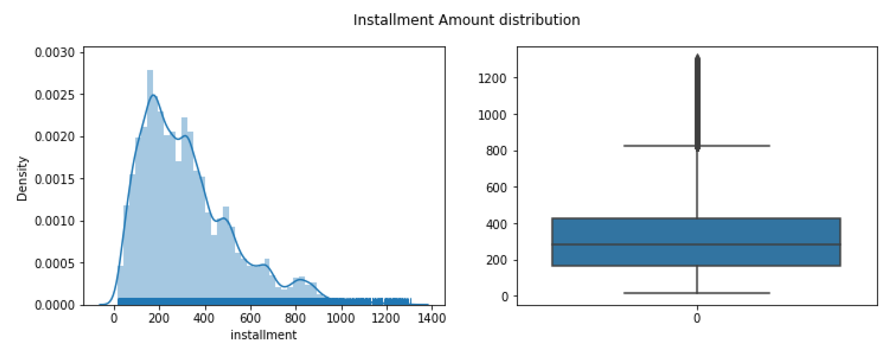
Observations:

From the above plots and statistics of interest rates we can conclude that most of the interest rates lies between 9% to 14.5%. Some borrowers took loan at higher rates of interest i.e., 22.5%

Installment

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

In [31]:
```
installment = data.installment
plt.figure(figsize=(12,4))
plt.subplot(1,2,1)
sns.distplot(a=installment, rug=True)
plt.subplot(1,2,2)
sns.boxplot(data=installment)
plt.suptitle('Installment Amount distribution')
plt.show()
```



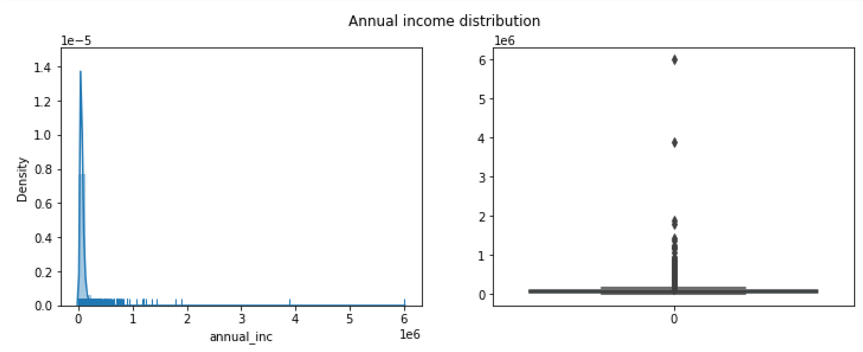
Observations:

Most representative value of Installment amount is around 250 to 300.

annual_inc

The self-reported annual income provided by the borrower during registration.

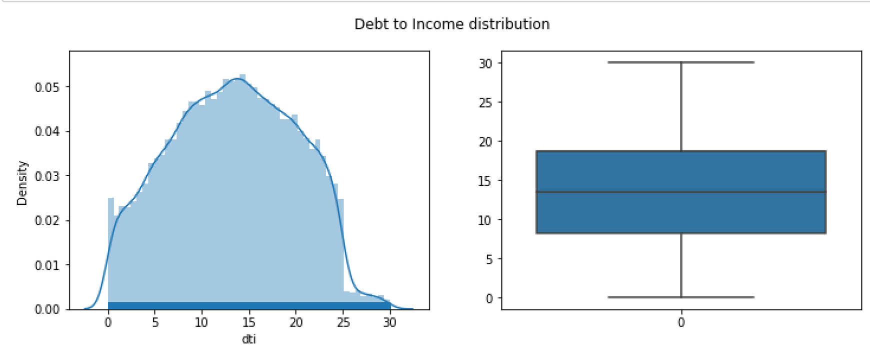
In [32]:
```
var1 = data.annual_inc
plt.figure(figsize=(12,4))
plt.subplot(1,2,1)
sns.distplot(a=var1, rug=True)
plt.subplot(1,2,2)
sns.boxplot(data=var1)
plt.suptitle('Annual income distribution')
plt.show()
```



DTI

A ratio calculated using the borrower's total monthly debt payments on the total debt obligations, excluding mortgage and the requested LC loan, divided by the borrower's self-reported monthly income.

In [33]:
```
var1 = data.dti
plt.figure(figsize=(12,4))
plt.subplot(1,2,1)
sns.distplot(a=var1, rug=True)
plt.subplot(1,2,2)
sns.boxplot(data=var1)
plt.suptitle('Debt to Income distribution')
plt.show()
```



Observations:

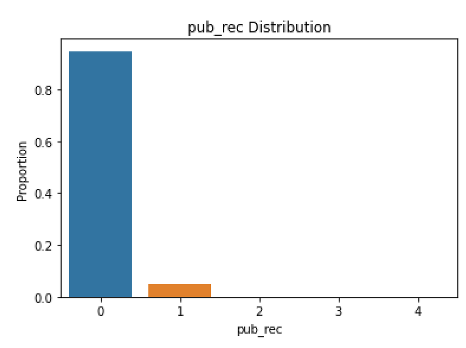
There are no outliers and the distribution is much similar to normal distribution.
All the loans are given to barrower's who have Debt to Income ration less than 30.

Pub rec

Number of Public derogatory records

In [34]:
```
var = 'pub_rec'
#Probability / Percentage of each values
prob_df = data[var].value_counts(normalize=True).reset_index()
sns.barplot(x='index', y=var, data=prob_df)
plt.xlabel(var)
plt.ylabel('Proportion')
plt.title(var+' Distribution')
```

Out[34]: `Text(0.5, 1.0, 'pub_rec Distribution')`



Observations:

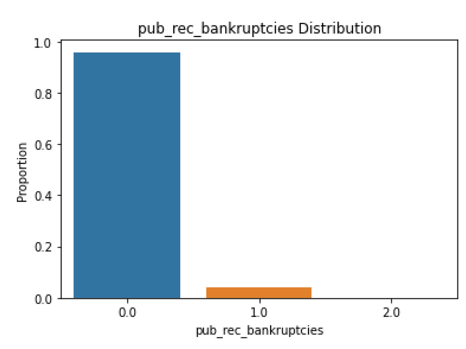
Near about 90% borrower's having no public derogatory records.

pub_rec_bankruptcies

Number of public record bankruptcies

In [35]:
```
var = 'pub_rec_bankruptcies'
#Probability / Percentage of each values
prob_df = data[var].value_counts(normalize=True).reset_index()
sns.barplot(x='index', y=var, data=prob_df)
plt.xlabel(var)
plt.ylabel('Proportion')
plt.title(var+' Distribution')
```

Out[35]: `Text(0.5, 1.0, 'pub_rec_bankruptcies Distribution')`



Observations:

99% borrowers have not went bankrupt.

Loan issue date (issue_d)

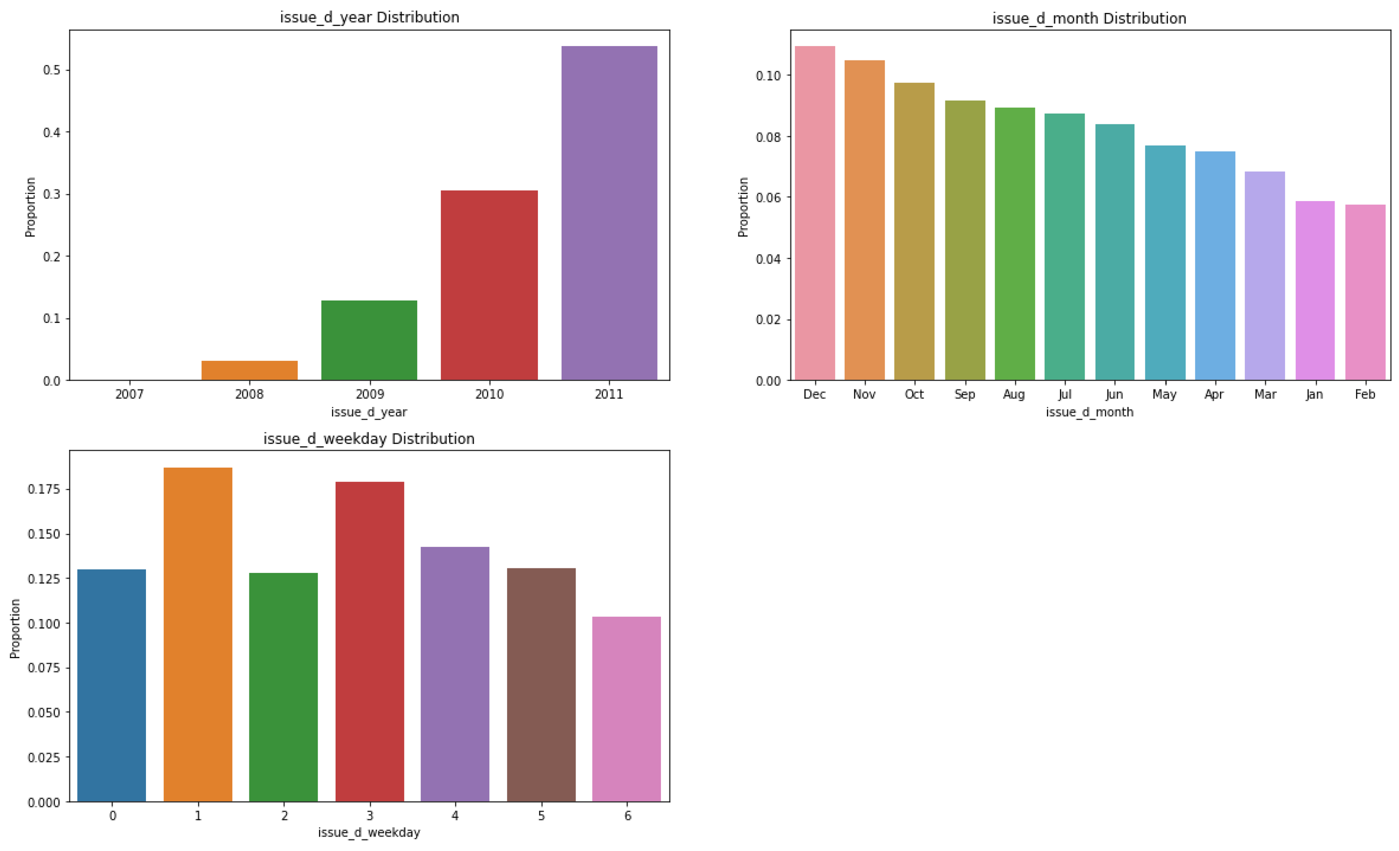
The month which the loan was funded

In [36]:
```
var = 'issue_d_year'
#Probability / Percentage of each values
prob_df = data[var].value_counts(normalize=True).reset_index()
plt.figure(figsize=(20,12))
plt.subplot(2,2,1)
sns.barplot(x='index', y=var, data=prob_df)
plt.xlabel(var)
plt.ylabel('Proportion')
plt.title(var+' Distribution')

var = 'issue_d_month'
#Probability / Percentage of each values
prob_df = data[var].value_counts(normalize=True).reset_index()
plt.subplot(2,2,2)
sns.barplot(x='index', y=var, data=prob_df)
plt.xlabel(var)
plt.ylabel('Proportion')
plt.title(var+' Distribution')

var = 'issue_d_weekday'
#Probability / Percentage of each values
prob_df = data[var].value_counts(normalize=True).reset_index()
plt.subplot(2,2,3)
sns.barplot(x='index', y=var, data=prob_df)
plt.xlabel(var)
plt.ylabel('Proportion')
plt.title(var+' Distribution')

plt.show()
```



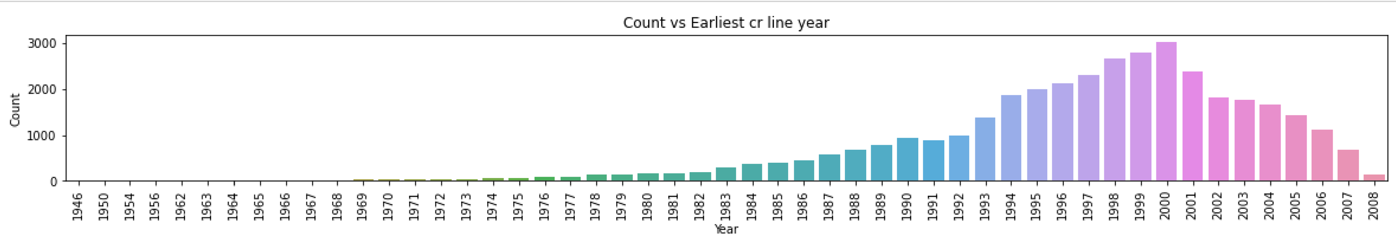
Observations:

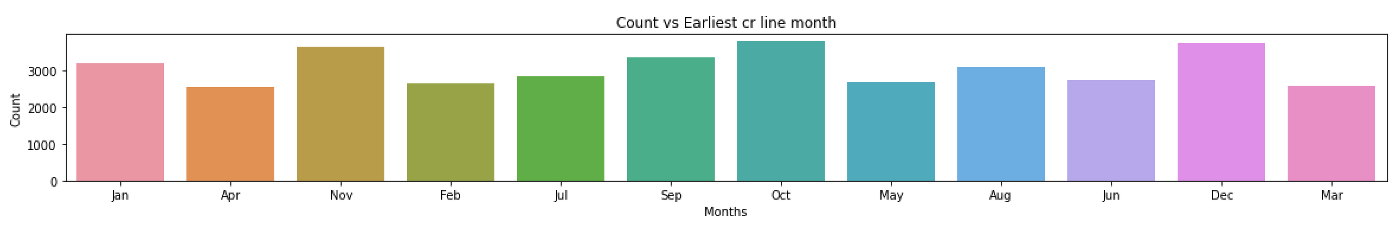
The lending club has doubling loan issues every year. There are more issues of loan in last 3 months every end of the ear i.e., Oct, Nov and Dec. Lending club has issued more loans on tuesday and thursday than other week days.

Erliest Credit line (earliest_cr_line)

The month the borrower's earliest reported credit line was opened

In [37]:
```
plt.figure(figsize=(20,5))
plt.subplot(2,1,1)
sns.countplot(data.earliest_cr_line_year)
plt.title('Count vs Earliest cr line year')
plt.xticks(rotation=90)
plt.xlabel('Year')
plt.ylabel('Count')
plt.figure(figsize=(20,5))
plt.subplot(2,1,2)
sns.countplot(data.earliest_cr_line_month)
plt.title('Count vs Earliest cr line month')
plt.xlabel('Months')
plt.ylabel('Count')
plt.show()
```





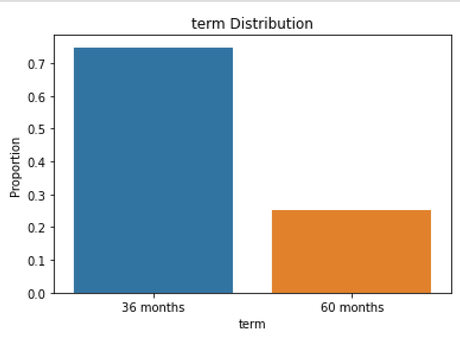
Observations:

Many of Loan borrowers of Lender have got earlier credit line in 2000 year, and also most have got earlier credit line on end of the year i.e., Oct, Nov, Dec

Term

The number of payments on the loan. Values are in months and can be either 36 or 60.

In [38]:
```
var = 'term'
#Probability / Percentage of each values
prob_df = data[var].value_counts(normalize=True).reset_index()
sns.barplot(x='index', y=var, data=prob_df)
plt.xlabel(var)
plt.ylabel('Proportion')
plt.title(var+' Distribution')
plt.show()
```



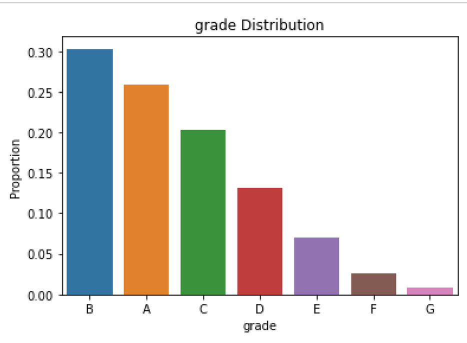
Observations:

Borrowers have taken 36 months tenure more than 60 months.

Grade

LC assigned loan grade

In [39]:
```
var = 'grade'
#Probability / Percentage of each values
prob_df = data[var].value_counts(normalize=True).reset_index()
sns.barplot(x='index', y=var, data=prob_df)
plt.xlabel(var)
plt.ylabel('Proportion')
plt.title(var+' Distribution')
plt.show()
```



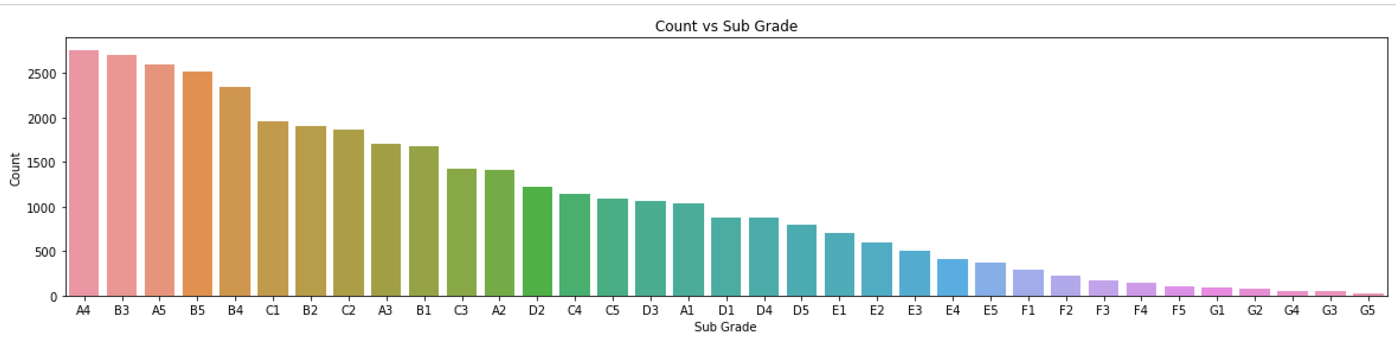
Observations:

Most borrowers fall under A and B grades then other grades

Sub Grade

LC assigned loan subgrade

In [40]:
```
plt.figure(figsize=(20,4))
sns.countplot(data.sub_grade, order=data.sub_grade.value_counts().index)
plt.title('Count vs Sub Grade')
plt.xlabel('Sub Grade')
plt.ylabel('Count')
plt.show()
```



Observations:

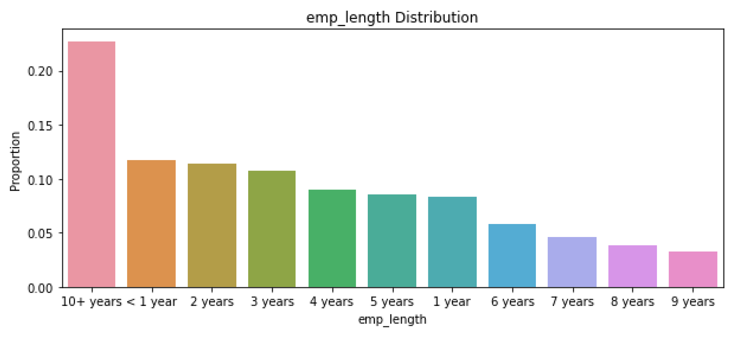
All sub grades are gradually decrEses from A TO G.

Employment length

Employment length in years. Possible values are between 0 and 10 where 0 means less than one year and 10 means ten or more years.

In [41]:
```
plt.figure(figsize=(10,4))
var = 'emp_length'
#Probability / Percentage of each values
prob_df = data[var].value_counts(normalize=True).reset_index()

sns.barplot(x='index', y=var, data=prob_df)
plt.xlabel(var)
plt.ylabel('Proportion')
plt.title(var+' Distribution')
plt.show()
```



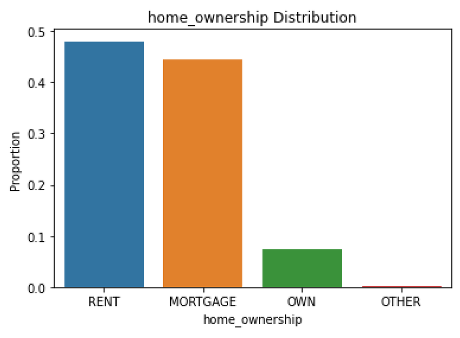
Observations:

Borrowers are mostly 10+ years emploment length.

Home Ownership

The home ownership status provided by the borrower during registration. Our values are: RENT, OWN, MORTGAGE, OTHER.

In [42]:
```
var = 'home_ownership'
#Probability / Percentage of each values
prob_df = data[var].value_counts(normalize=True).reset_index()
#Plotting percentage proporation vs home ownership
sns.barplot(x='index', y=var, data=prob_df)
plt.xlabel(var)
plt.ylabel('Proportion')
plt.title(var+' Distribution')
plt.show()
```



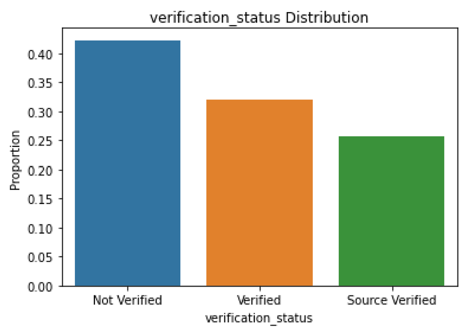
Observations:

The loan borrowers are mostly having rented and mortgage houses.

Verification Status

Indicates if income was verified by LC, not verified, or if the income source was verified

In [43]:
```
var = 'verification_status'
#Probability / Percentage of each values
prob_df = data[var].value_counts(normalize=True).reset_index()
sns.barplot(x='index', y=var, data=prob_df)
plt.xlabel(var)
plt.ylabel('Proportion')
plt.title(var+' Distribution')
plt.show()
```



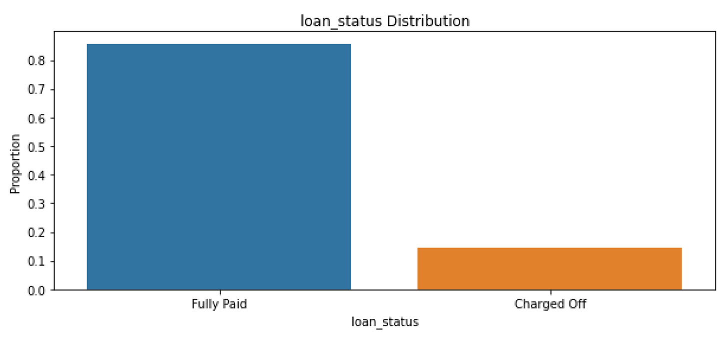
Observations:

Majority of loans were given without verification of applicants income.

Loan Status

Current status of the loan

In [44]:
```
plt.figure(figsize=(10,4))
var = 'loan_status'
#Probability / Percentage of each values
prob_df = data[var].value_counts(normalize=True).reset_index()
sns.barplot(x='index', y=var, data=prob_df)
plt.xlabel(var)
plt.ylabel('Proportion')
plt.title(var+' Distribution')
plt.show()
```



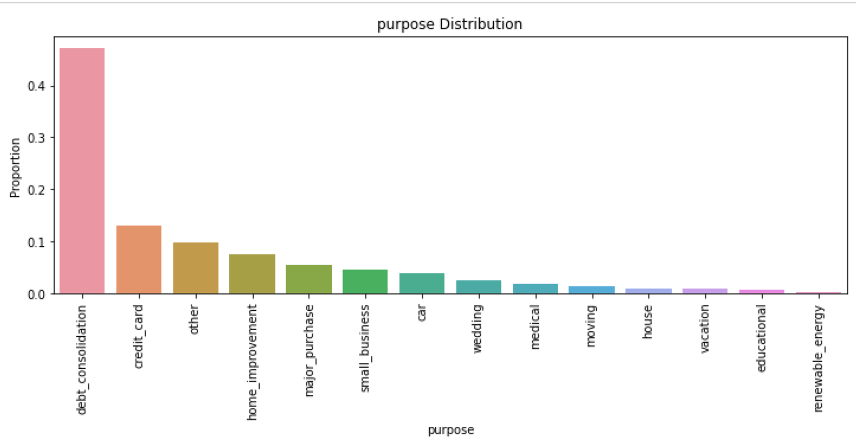
Observations:

85% of borrowers has paid the loan fully. where are 14% are defaulted the loan.

Purpose

A category provided by the borrower for the loan request.

In [45]:
```
plt.figure(figsize=(12,4))
var = 'purpose'
#Probability / Percentage of each values
prob_df = data[var].value_counts(normalize=True).reset_index()
sns.barplot(x='index', y=var, data=prob_df)
plt.xlabel(var)
plt.xticks(rotation=90)
plt.ylabel('Proportion')
plt.title(var+' Distribution')
plt.show()
```



Observations:

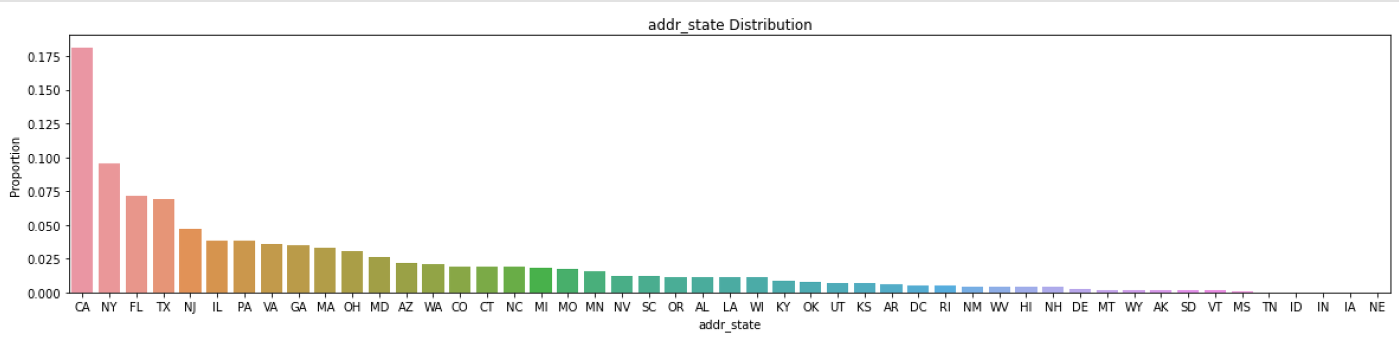
More number of people took loan for debt consolidation and a very few people took for renewable energy

Borrower's State

The state provided by the borrower in the loan application

In [46]:
```
plt.figure(figsize=(20,4))
var = 'addr_state'

#Probability / Percentage of each values
prob_df = data[var].value_counts(normalize=True).reset_index()
sns.barplot(x='index', y=var, data=prob_df)
plt.xlabel(var)
plt.ylabel('Proportion')
plt.title(var+' Distribution')
plt.show()
```



Observations:

Most of the borrowers are from CA and NY

Segmented Univariate Analysis

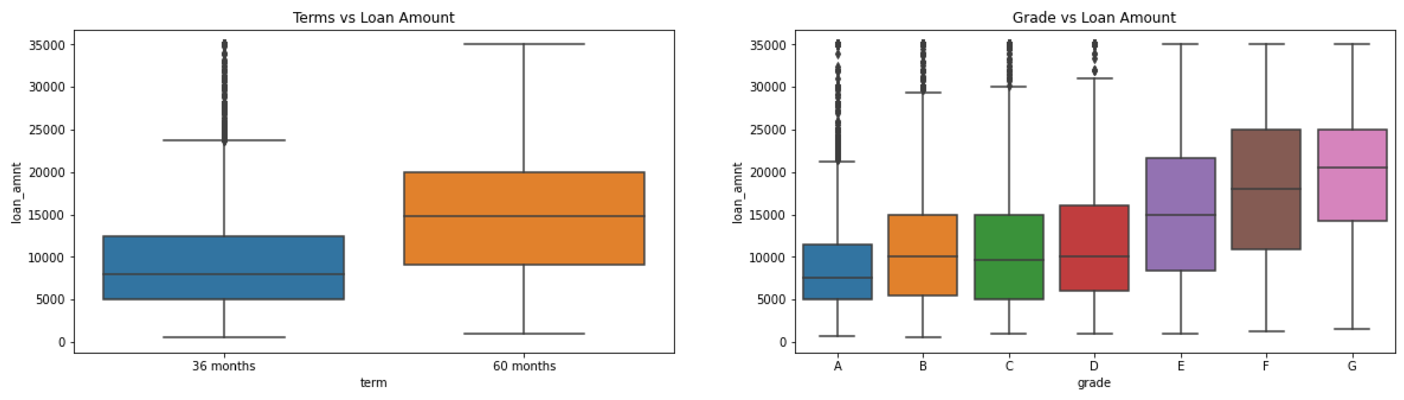
Segmented univariate analysis can show the change metric in pattern across the different segments of the same variable. following are the variables on which we are applying ssegmented analysis.

Loan Amount
Funded Amount
Intrest Rate
Anual Income
DTI
Public record
Public Record Bankcurapcy
inq_last_6mths
Approval loan amount ratio

Loan Amount

In [47]:
```
plt.figure(figsize=(20,5))
plt.subplot(121)
sns.boxplot(x='term', y=data.loan_amnt, data=data)
plt.title('Terms vs Loan Amount')
plt.subplot(122)
plt.title('Grade vs Loan Amount')
#Finding grades with sorted alphabetical order
grade_ord = data.grade.unique()
grade_ord.sort()
sns.boxplot(x='grade', y=data.loan_amnt, order = grade_ord, data=data)
```

Out[47]: <AxesSubplot:title={'center':'Grade vs Loan Amount'}, xlabel='grade', ylabel='loan_amnt'>

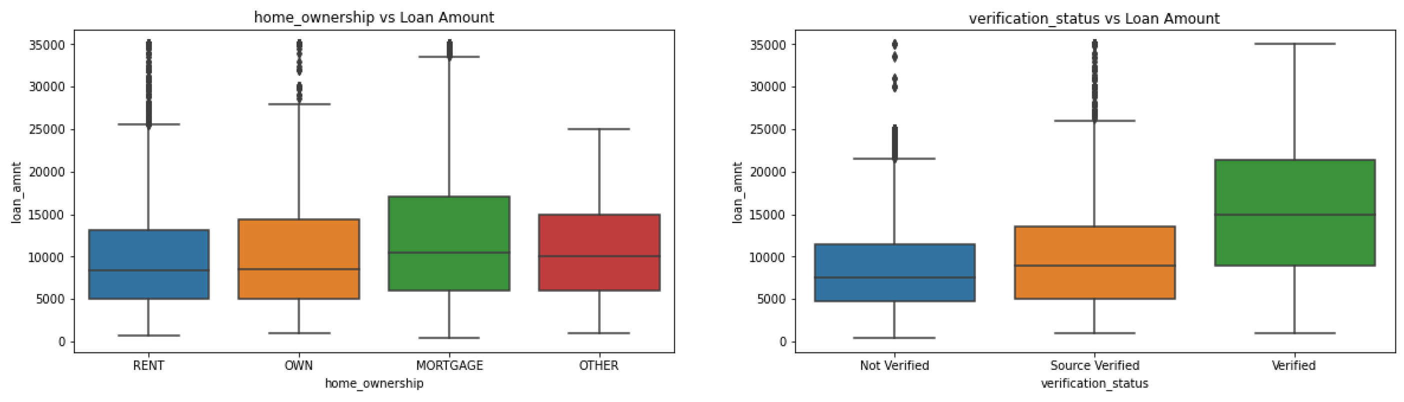


Observations:

Higher amount loans have high tenure i.e, 60 months. Grade 'F' and 'G' have taken max loan amount. As Grades are decreasing the loan amount is increasing.

In [48]:
```
plt.figure(figsize=(20,5))
plt.subplot(121)
sns.boxplot(x='home_ownership', y=data.loan_amnt, data=data)
plt.title('home_ownership vs Loan Amount')
plt.subplot(122)
plt.title('verification_status vs Loan Amount')
verification_status_ord = data.verification_status.unique()
verification_status_ord.sort()
sns.boxplot(x='verification_status', y=data.loan_amnt, order = verification_status_ord, data=data)
```

Out[48]: <AxesSubplot:title={'center':'verification_status vs Loan Amount'}, xlabel='verification_status', ylabel='loan_amnt'>

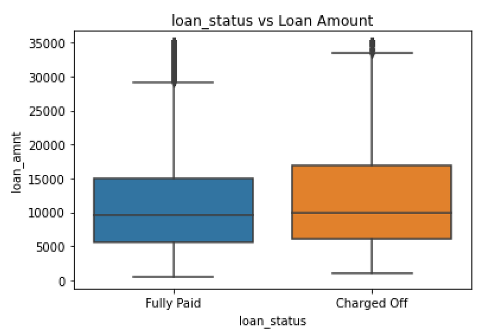


Observations:

More borrowers are from MORTAGE and also the median loan amount also high for MORTAGE owned borrowers. And most of borrowers are verified for borrowing loan >9k

In [49]:
```
sns.boxplot(x='loan_status', y=data.loan_amnt, data=data)
plt.title('loan_status vs Loan Amount')
```

Out[49]: Text(0.5, 1.0, 'loan_status vs Loan Amount')

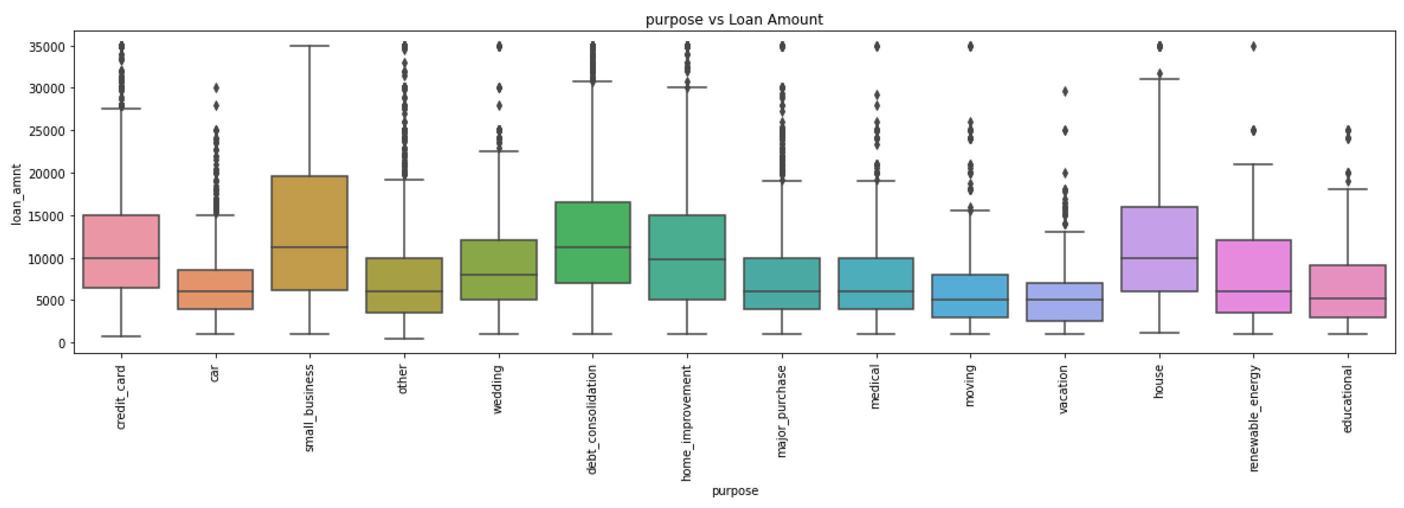


Observations:

Charged Off loans have higher amounts than Fully Paid ones.

In [50]:
```
plt.figure(figsize=(20,5))
sns.boxplot(x='purpose', y=data.loan_amnt, data=data)
#Rotating x values 90 for better visibility
plt.xticks(rotation=90)
plt.title('purpose vs Loan Amount')
```

Out[50]: Text(0.5, 1.0, 'purpose vs Loan Amount')

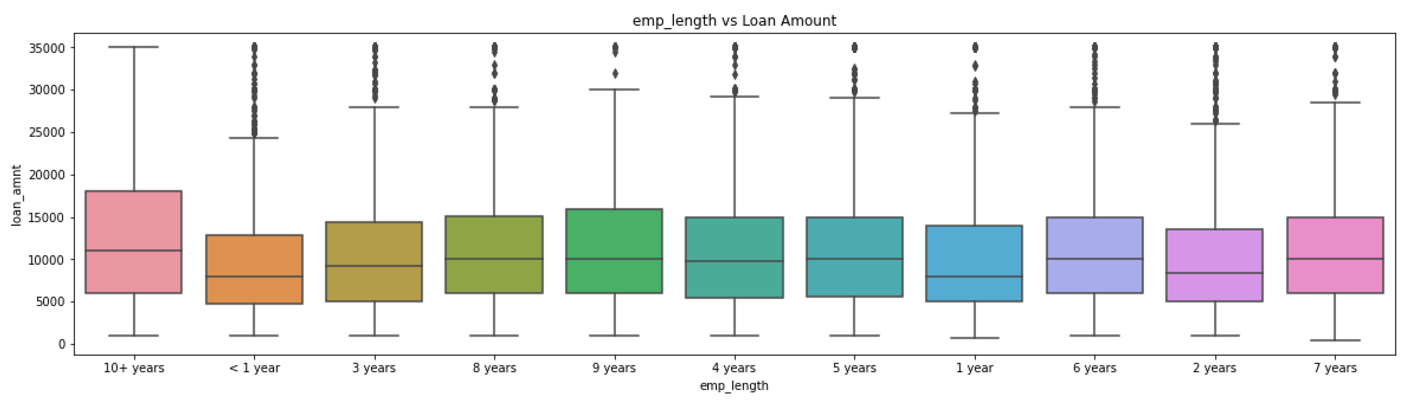


Observations:

More loan amount is from the Small bussiness.

In [51]:
```
plt.figure(figsize=(20,5))
sns.boxplot(x='emp_length', y=data.loan_amnt, data=data)
plt.title('emp_length vs Loan Amount')
```

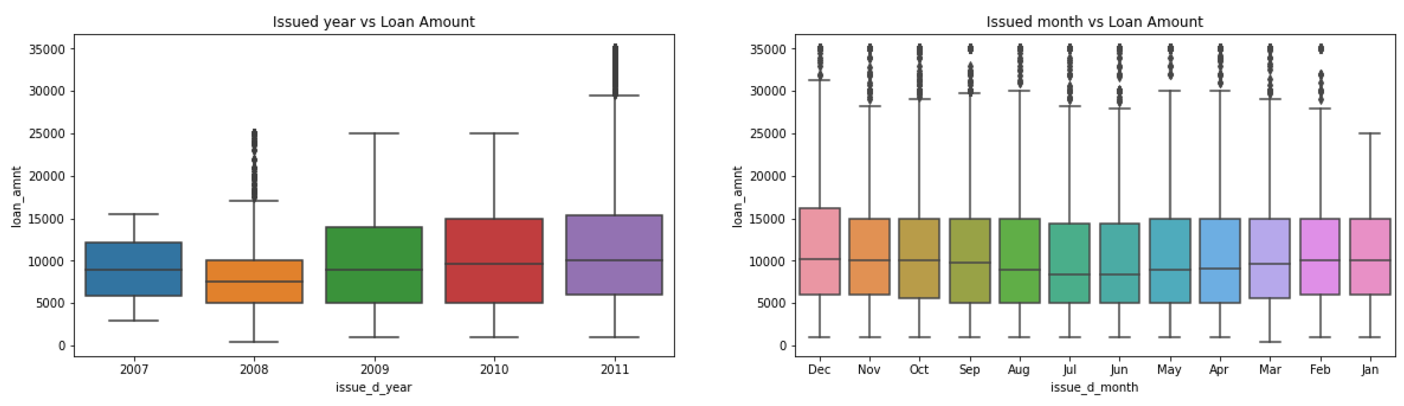
Out[51]: Text(0.5, 1.0, 'emp_length vs Loan Amount')



Observations:

More borrowers are from 10+ years and least is <1 year

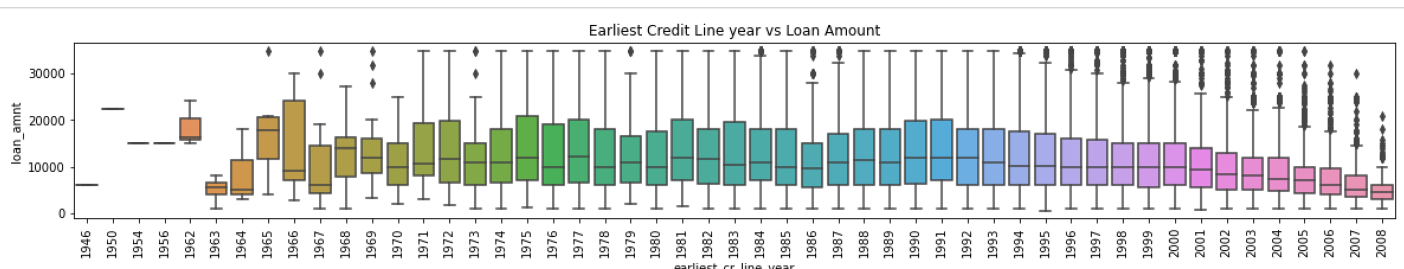
In [52]:
```
#Issue_d
plt.figure(figsize=(20,5))
plt.subplot(121)
sns.boxplot(x=data.issue_d_year, y=data.loan_amnt, data=data)
plt.title('Issued year vs Loan Amount')
plt.subplot(122)
sns.boxplot(x=data.issue_d_month, y=data.loan_amnt, data=data)
plt.title('Issued month vs Loan Amount')
plt.show()
```

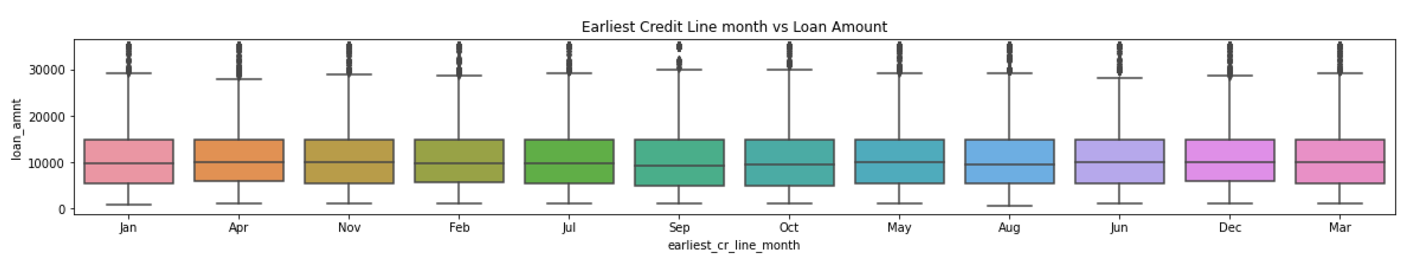


Observations:

The median loan amount in each year did not change much but the distribution is more spread as the years increase, which means people have taken different loan amounts in each year.
In December, people have taken heigher amounts as distribution goes high above median.

In [53]:
```
#earliest_cr_line
plt.figure(figsize=(20,6))
plt.subplot(211)
sns.boxplot(x=data.earliest_cr_line_year, y=data.loan_amnt, data=data)
plt.xticks(rotation=90)
plt.title('Earliest Credit Line year vs Loan Amount')
plt.figure(figsize=(20,6))
plt.subplot(212)
sns.boxplot(x=data.earliest_cr_line_month, y=data.loan_amnt, data=data)
plt.title('Earliest Credit Line month vs Loan Amount')
plt.show()
```





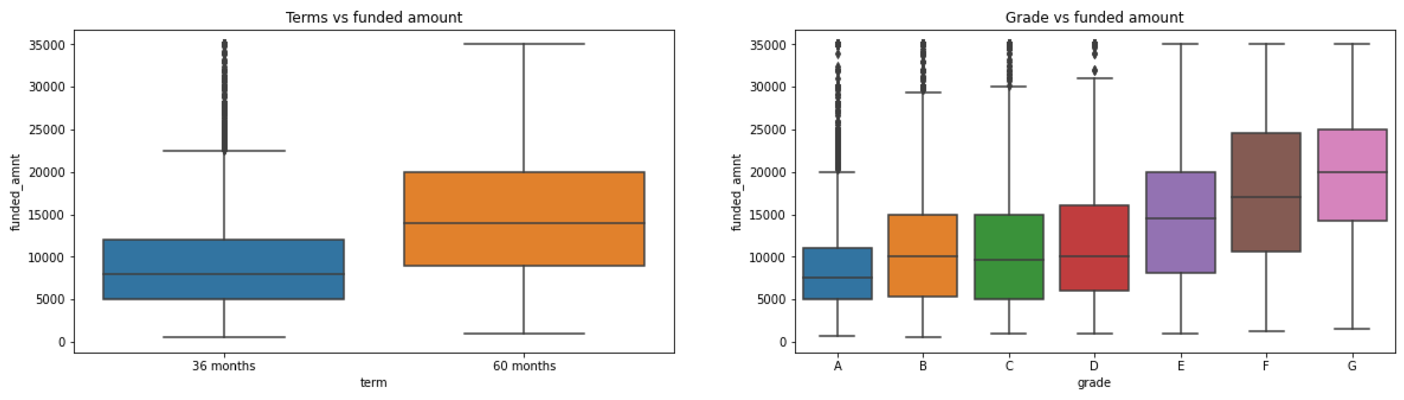
Observations:

Borrowers who go earliest credit line in 1966 got wide spreaded amount of loans than others.

funded_amnt

In [54]:
```
plt.figure(figsize=(20,5))
plt.subplot(121)
sns.boxplot(x='term', y=data.funded_amnt, data=data)
plt.title('Terms vs funded amount')
plt.subplot(122)
plt.title('Grade vs funded amount')
grade_ord = data.grade.unique()
grade_ord.sort()
sns.boxplot(x='grade', y=data.funded_amnt, order = grade_ord, data=data)
```

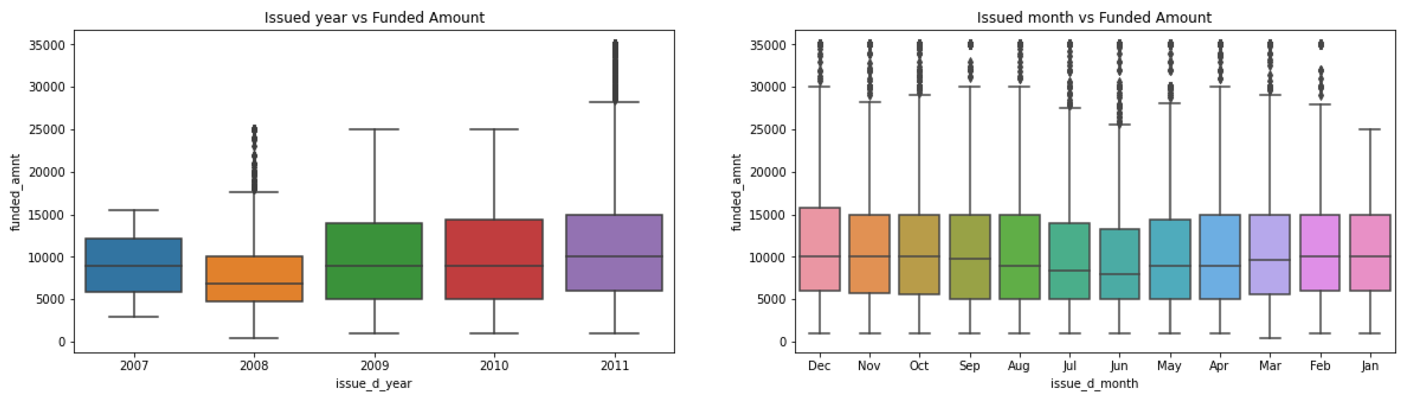
Out[54]:
```
<AxesSubplot:title={'center':'Grade vs funded amount'}, xlabel='grade', ylabel='funded_amnt'>
```



Observations:

More borrowers lies between 60 months tenure.Grades F & G lies in more funded amount.

In [55]:
```
#Issue_d
plt.figure(figsize=(20,5))
plt.subplot(121)
sns.boxplot(x=data.issue_d_year, y=data.funded_amnt, data=data)
plt.title('Issued year vs Funded Amount')
plt.subplot(122)
sns.boxplot(x=data.issue_d_month, y=data.funded_amnt, data=data)
plt.title('Issued month vs Funded Amount')
plt.show()
```

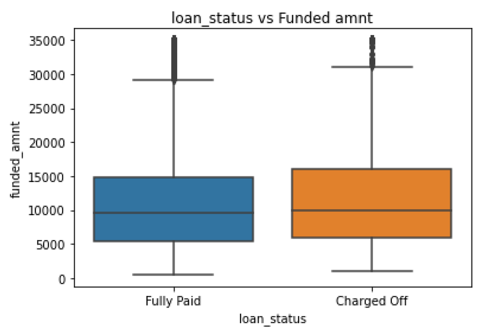


Observations:

Year 2009,2010,2011 have pritty much same funded amount.

In [56]:
```
sns.boxplot(x='loan_status', y=data.funded_amnt, data=data)
plt.title('loan_status vs Funded amnt')
```

Out[56]:
```
Text(0.5, 1.0, 'loan_status vs Funded amnt')
```

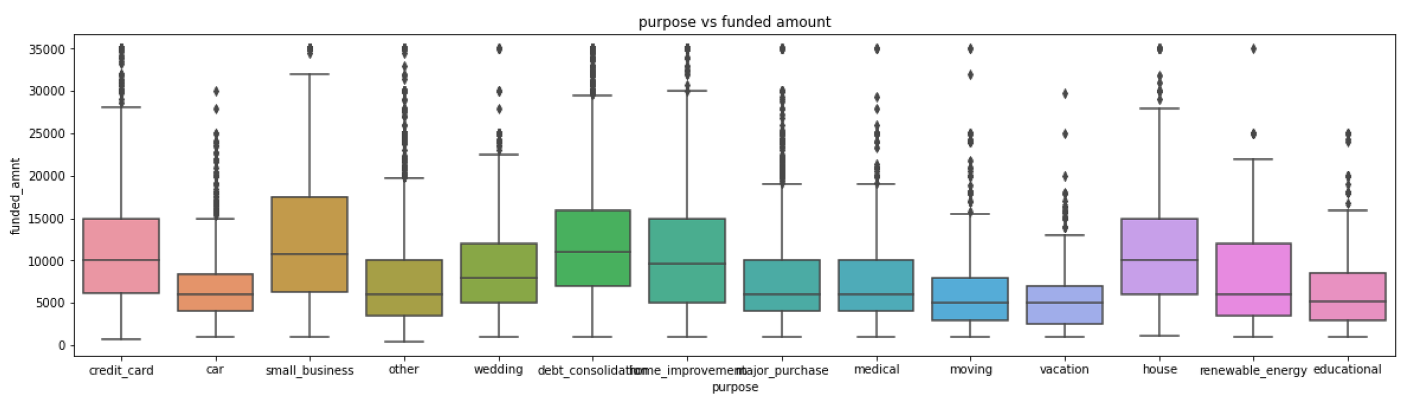


Observations:

Funded amount for charged off is slightly more than fully paid.

In [57]:
```
plt.figure(figsize=(20,5))
sns.boxplot(x='purpose', y=data.funded_amnt, data=data)
plt.title('purpose vs funded amount')
```

Out[57]:
```
Text(0.5, 1.0, 'purpose vs funded amount')
```

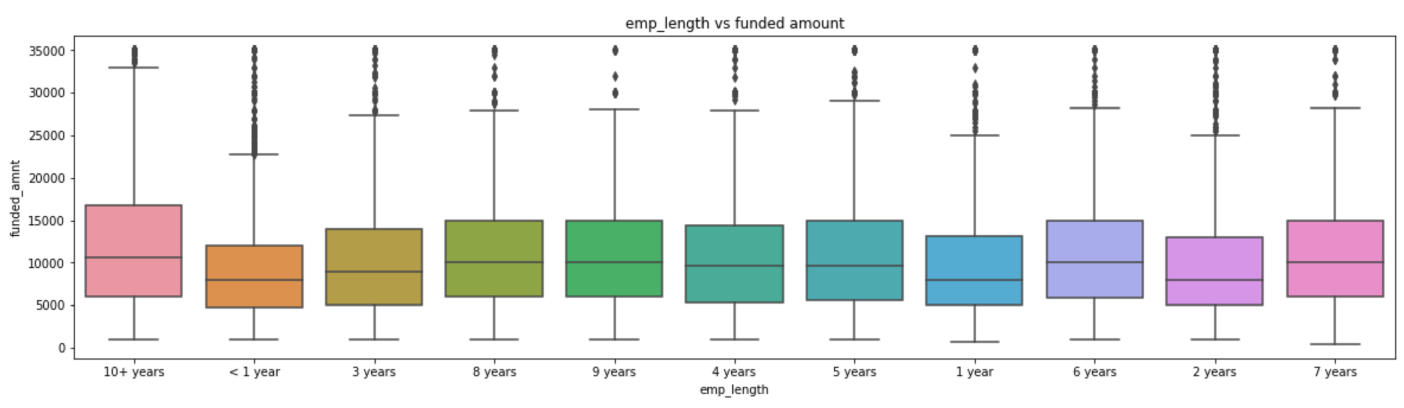


Observations:

Funded amount is more for small buisness purpose than other purposes.

In [58]:
```
plt.figure(figsize=(20,5))
sns.boxplot(x='emp_length', y=data.funded_amnt, data=data)
plt.title('emp_length vs funded amount')
```

Out[58]:
```
Text(0.5, 1.0, 'emp_length vs funded amount')
```



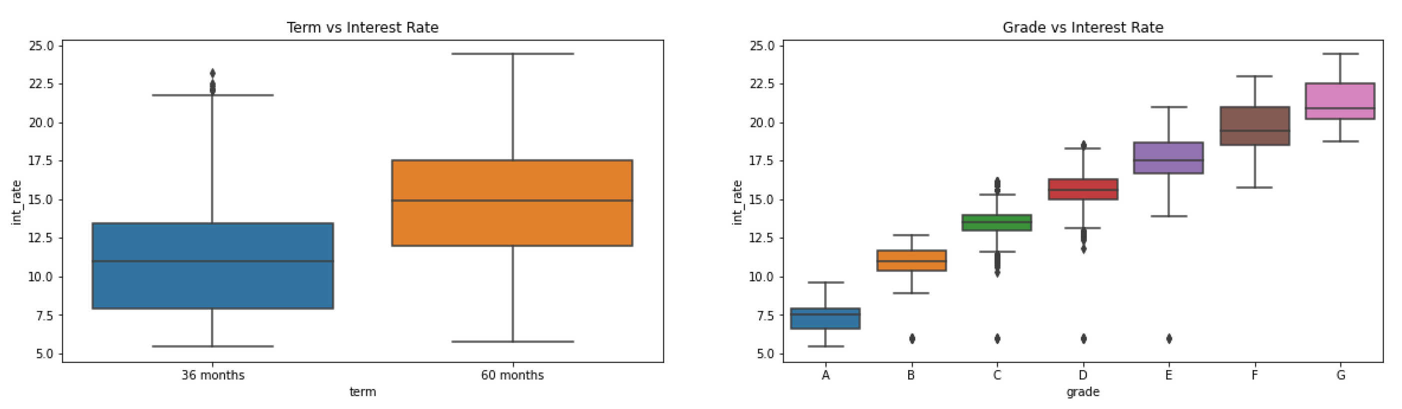
Observations:

Funded amount is higher for 10+ years emp length.

int_rate

In [59]:
```
plt.figure(figsize=(20,5))
plt.subplot(121)
sns.boxplot(x='term', y=data.int_rate, data=data)
plt.title('Term vs Interest Rate')
plt.subplot(122)
plt.title('Grade vs Interest Rate')
grade_ord = data.grade.unique()
grade_ord.sort()
sns.boxplot(x='grade', y=data.int_rate, order = grade_ord, data=data)
```

Out[59]:
```
<AxesSubplot:title={'center':'Grade vs Interest Rate'}, xlabel='grade', ylabel='int_rate'>
```

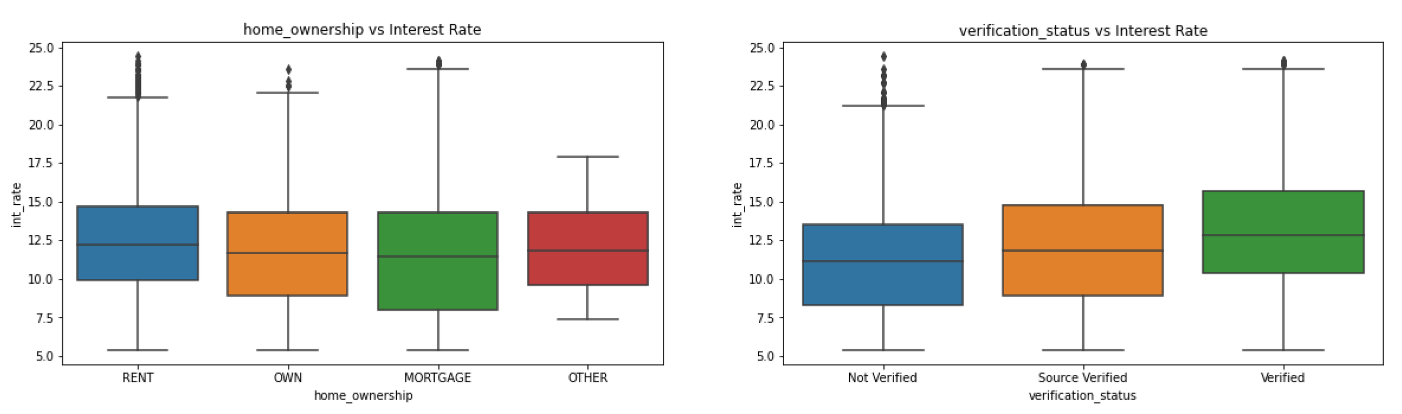


Observations:

The interest rates are higher for Higher tenure loans. And Also Interest Rates are Higher as Grades are Lowering from A TO G.

In [60]:
```
plt.figure(figsize=(20,5))
plt.subplot(121)
sns.boxplot(x='home_ownership', y=data.int_rate, data=data)
plt.title('home_ownership vs Interest Rate')
plt.subplot(122)
plt.title('verification_status vs Interest Rate')
verification_status_ord = data.verification_status.unique()
verification_status_ord.sort()
sns.boxplot(x='verification_status', y=data.int_rate, order = verification_status_ord, data=data)
```

Out[60]:
```
<AxesSubplot:title={'center':'verification_status vs Interest Rate'}, xlabel='verification_status', ylabel='int_rate'>
```

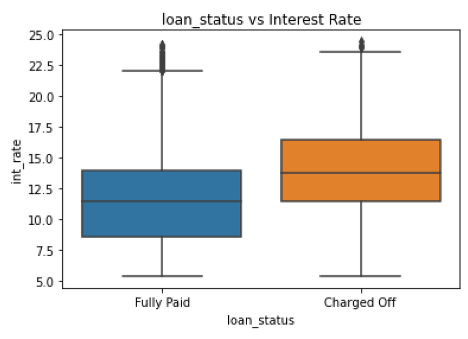


Observations:

Barrowers with Own and Mortgage got loans with less interest rates. And the non verified Barrowers got less interest rates compared to Verified and Source Verified barrowers.

In [61]:
```
sns.boxplot(x='loan_status', y=data.int_rate, data=data)
plt.title('loan_status vs Interest Rate')
```

Out[61]: Text(0.5, 1.0, 'loan_status vs Interest Rate')

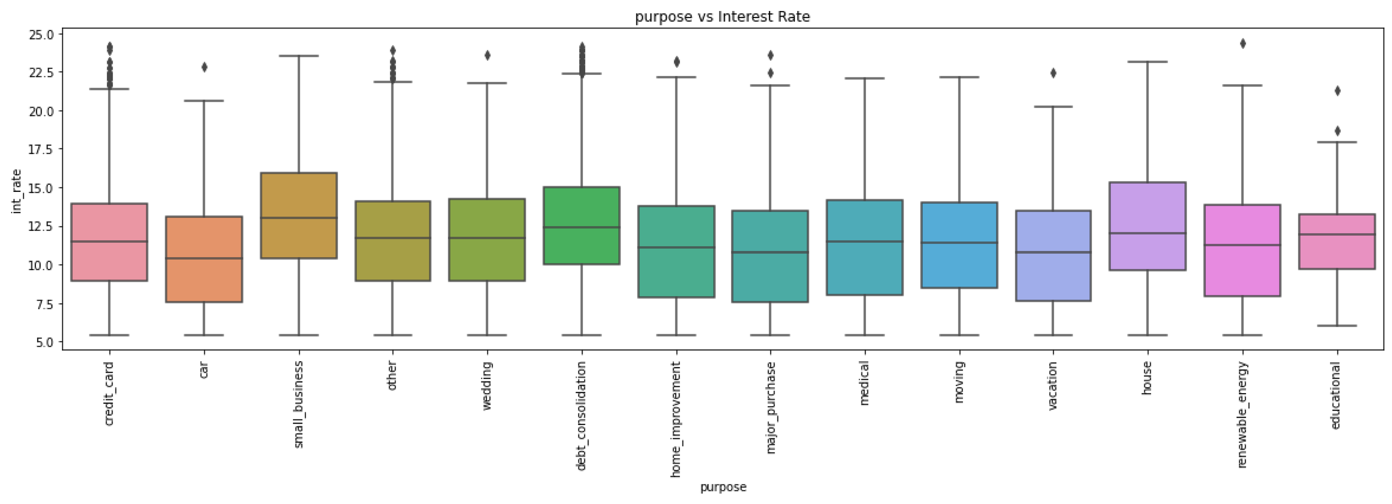


Observations:

Higher the interest rate more the chance of Defaulting the loan.

In [62]:
```
plt.figure(figsize=(20,5))
sns.boxplot(x='purpose', y=data.int_rate, data=data)
plt.xticks(rotation=90)
plt.title('purpose vs Interest Rate')
```

Out[62]: Text(0.5, 1.0, 'purpose vs Interest Rate')

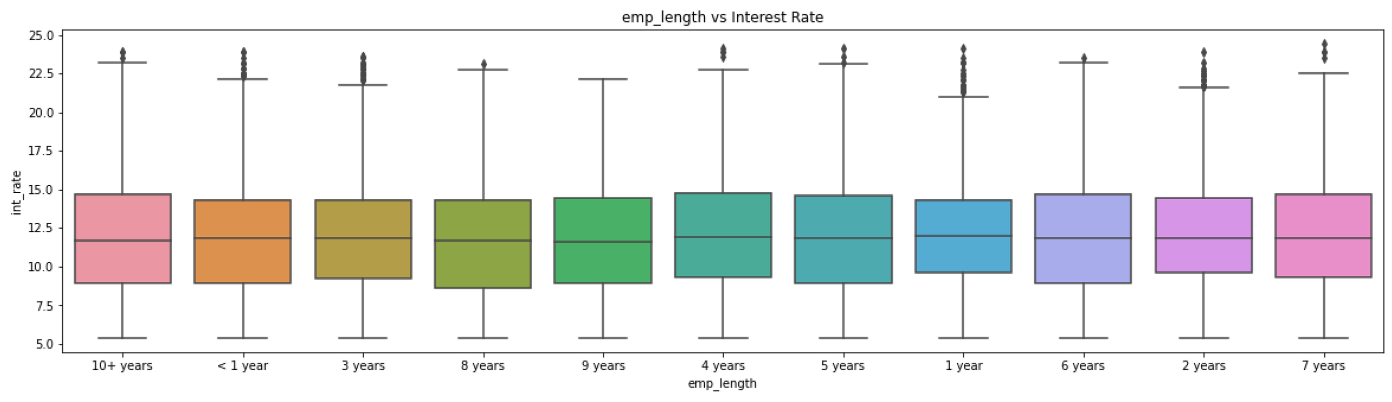


Observations:

Small Business, Debt Consolidation and House loans are given with more interest rates compare to others.

In [63]:
```
plt.figure(figsize=(20,5))
sns.boxplot(x='emp_length', y=data.int_rate, data=data)
plt.title('emp_length vs Interest Rate')
```

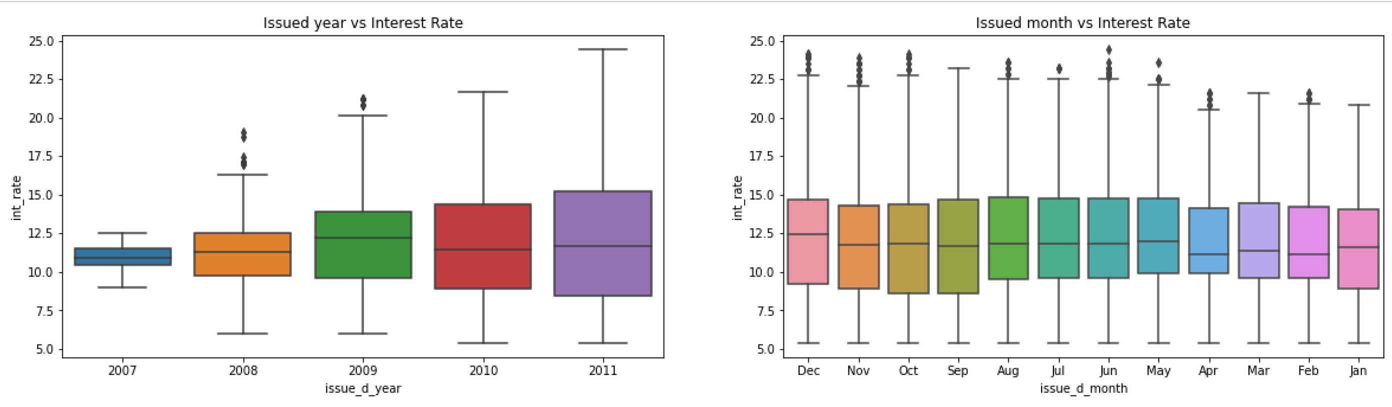
Out[63]: Text(0.5, 1.0, 'emp_length vs Interest Rate')



Observations:

There is not such relation found between Employment length and interest rate.

In [64]:
```
#Issue_d
plt.figure(figsize=(20,5))
plt.subplot(121)
sns.boxplot(x=data.issue_d_year, y=data.int_rate, data=data)
plt.title('Issued year vs Interest Rate')
plt.subplot(122)
sns.boxplot(x=data.issue_d_month, y=data.int_rate, data=data)
plt.title('Issued month vs Interest Rate')
plt.show()
```

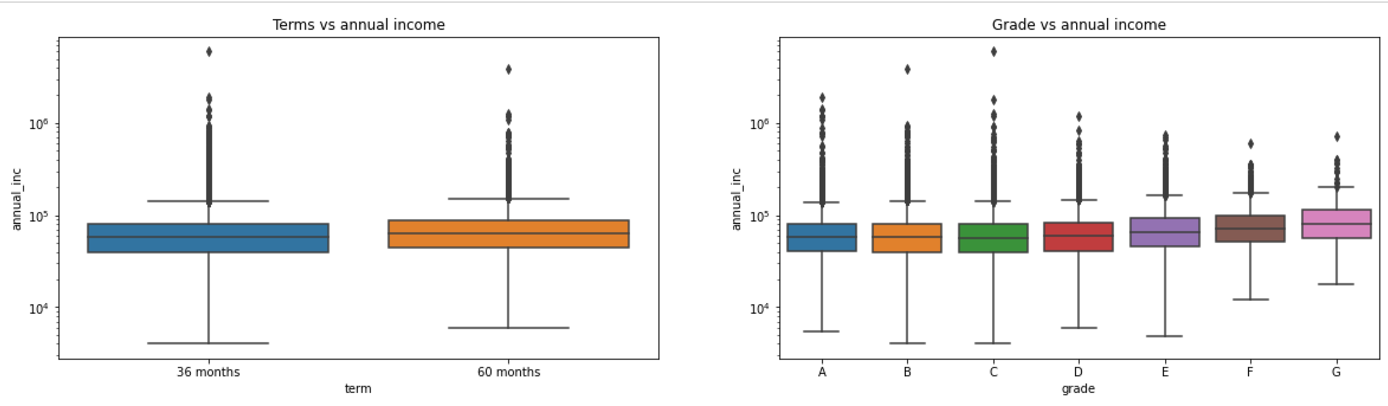


Observations:

As the years of business increase the interest rates are getting more different,median of of interest rate is bit same in all the years

annual_inc

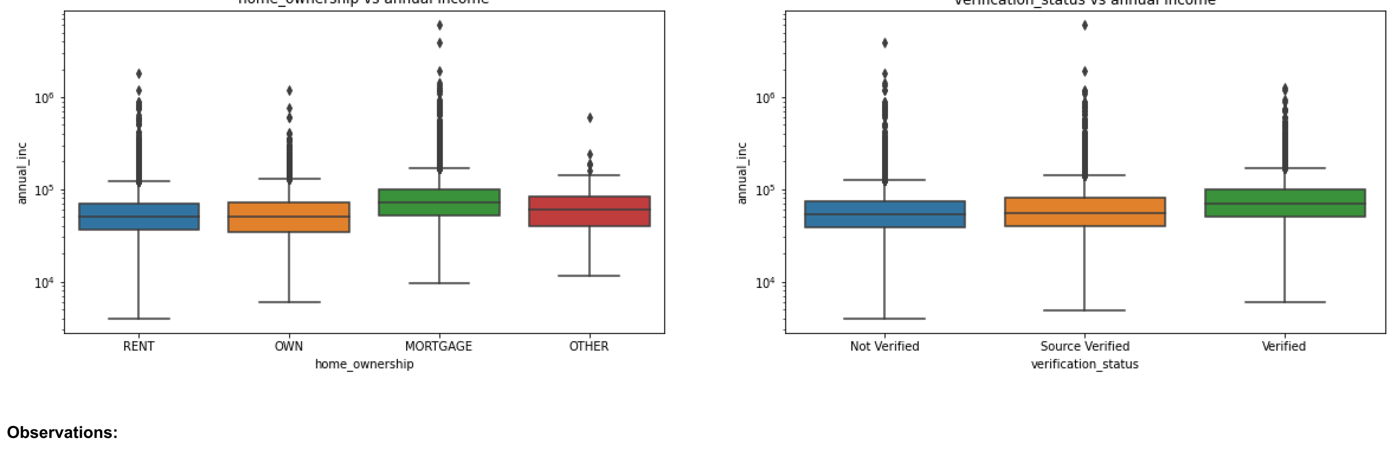
In [65]:
```
plt.figure(figsize=(20,5))
plt.subplot(121)
sns.boxplot(x='term', y=data.annual_inc, data=data)
plt.title('Terms vs annual income')
plt.yscale('log')
plt.subplot(122)
plt.title('Grade vs annual income')
grade_ord = data.grade.unique()
grade_ord.sort()
sns.boxplot(x='grade', y=data.annual_inc, order = grade_ord, data=data)
plt.yscale('log')
```



Observations:

Annual income is higher for lower grades(F & G).

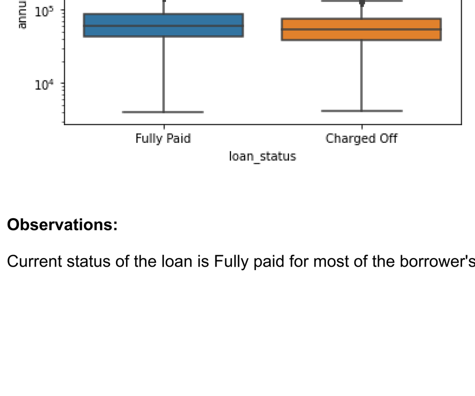
In [66]:
```
plt.figure(figsize=(20,5))
plt.subplot(121)
sns.boxplot(x='home_ownership', y=data.annual_inc, data=data)
plt.title('home_ownership vs annual income')
plt.yscale('log')
plt.subplot(122)
plt.title('verification_status vs annual income')
verification_status_ord = data.verification_status.unique()
verification_status_ord.sort()
sns.boxplot(x='verification_status', y=data.annual_inc, order = verification_status_ord, data=data)
plt.yscale('log')
```



Observations:

The home ownership status for mortage has higher income. The income source was verfied for most of the borrowers who had higher annual incomes.

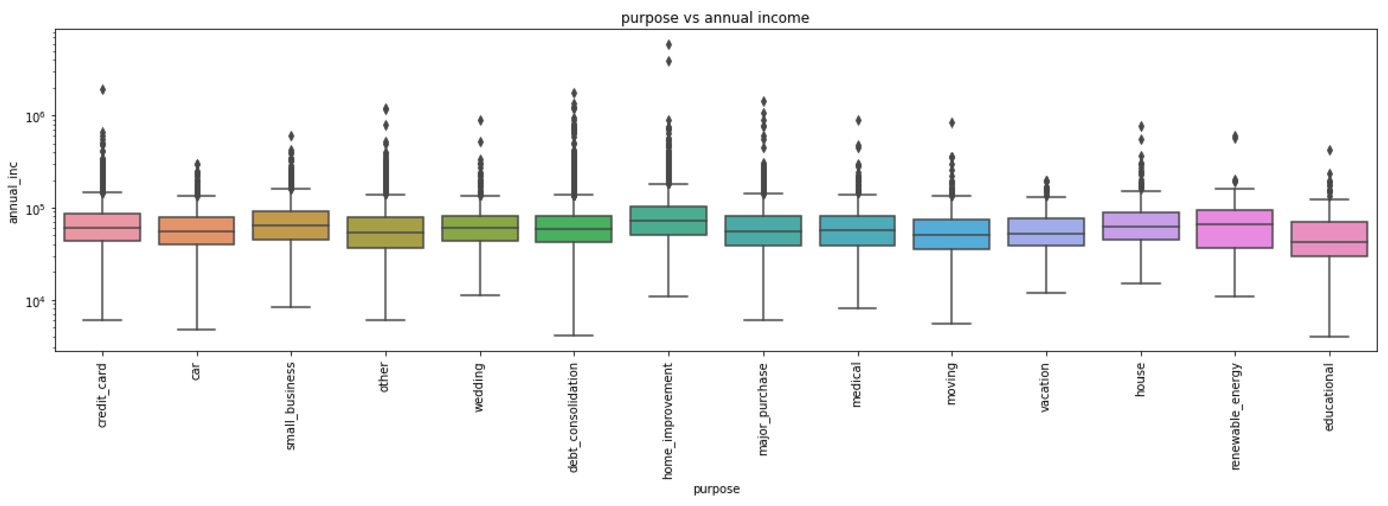
In [67]:
```
sns.boxplot(x='loan_status', y=data.annual_inc, data=data)
plt.title('loan_status vs annual income')
plt.yscale('log')
```



Observations:

Current status of the loan is Fully paid for most of the borrower's who had higher annual incomes.

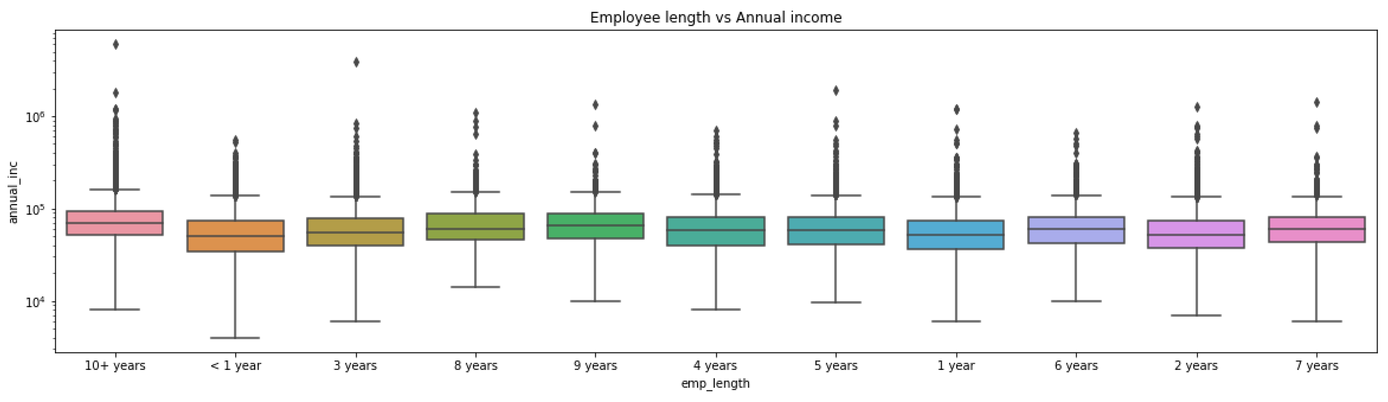
In [68]:
```
plt.figure(figsize=(20,5))
sns.boxplot(x='purpose', y=data.annual_inc, data=data)
plt.xticks(rotation=90)
plt.title('purpose vs annual income')
plt.yscale('log')
```



Observations:

A category belonging to Renewable energy, small business and home improvements have higher annual income provided by the borrower for the loan request.

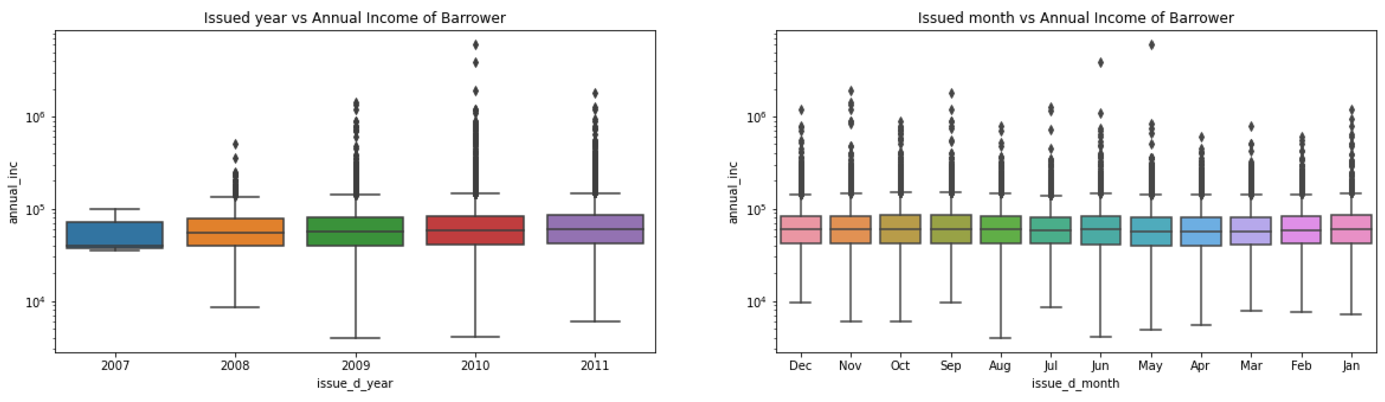
In [69]:
```
plt.figure(figsize=(20,5))
sns.boxplot(x='emp_length', y=data.annual_inc, data=data)
plt.title('Employee length vs Annual income')
plt.yscale('log')
```



Observations:

The borrowers who has higer income have taken loans for 10+ years of duration.

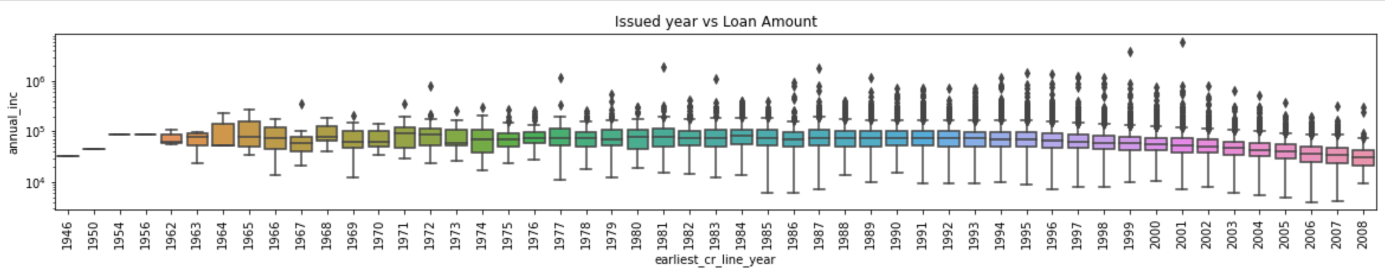
In [70]:
```
#Issue_d
plt.figure(figsize=(20,5))
plt.subplot(121)
sns.boxplot(x=data.issue_d_year, y=data.annual_inc, data=data)
plt.title('Issued year vs Annual Income of Barrower')
plt.yscale('log')
plt.subplot(122)
sns.boxplot(x=data.issue_d_month, y=data.annual_inc, data=data)
plt.title('Issued month vs Annual Income of Barrower')
plt.yscale('log')
plt.show()
```

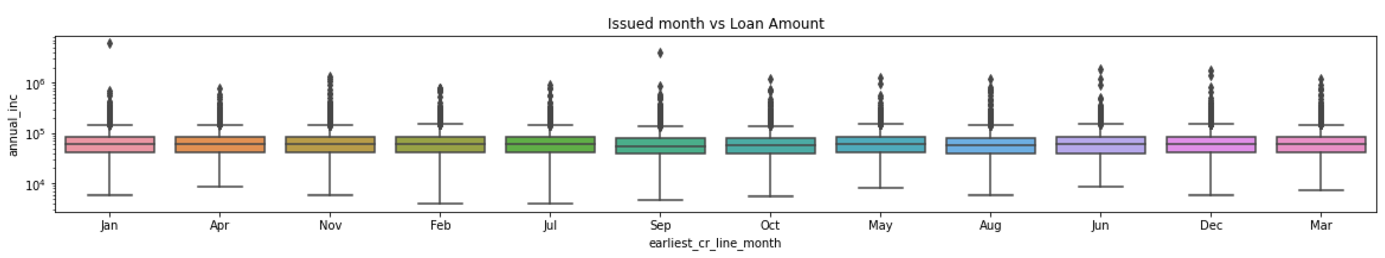


Observations:

Annual income has no impact with the month.

In [71]:
```
#earliest_cr_line
plt.figure(figsize=(20,6))
plt.subplot(211)
sns.boxplot(x=data.earliest_cr_line_year, y=data.annual_inc, data=data)
plt.xticks(rotation=90)
#for better analysis plotting on log scale of y values
plt.yscale('log')
plt.title('Issued year vs Loan Amount')
plt.figure(figsize=(20,6))
plt.subplot(212)
sns.boxplot(x=data.earliest_cr_line_month, y=data.annual_inc, data=data)
plt.title('Issued month vs Loan Amount')
plt.yscale('log')
plt.show()
```





Observations:

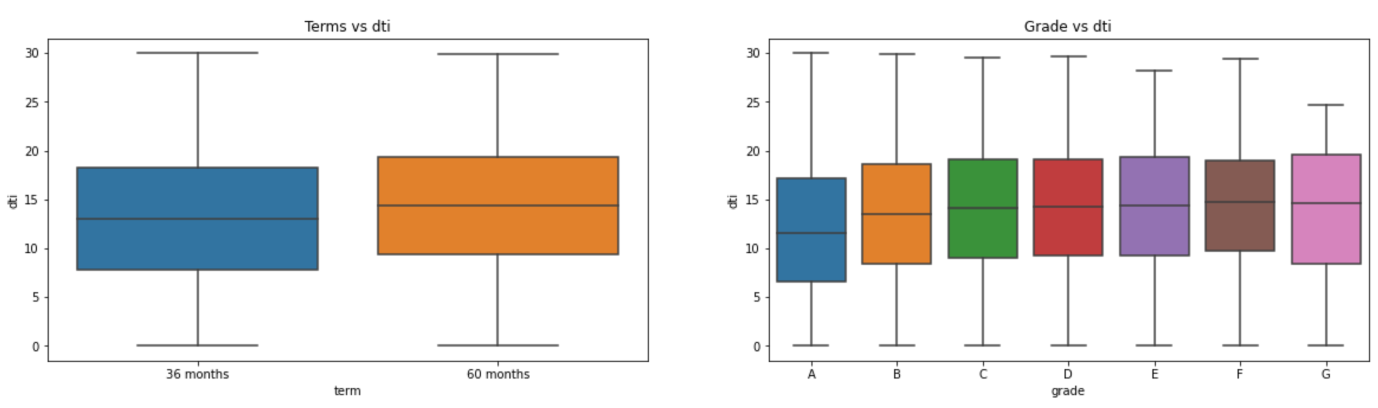
There is not particular pattern in the annual income and earliest Credit line year and month.

DTI

Debt to Income Ratio

In [72]:
```
plt.figure(figsize=(20,5))
plt.subplot(121)
sns.boxplot(x='term', y=data.dti, data=data)
plt.title('Terms vs dti')
plt.subplot(122)
plt.title('Grade vs dti')
grade_ord = data.grade.unique()
grade_ord.sort()
sns.boxplot(x='grade', y=data.dti, order = grade_ord, data=data)
```

Out[72]:
```
<AxesSubplot:title={'center':'Grade vs dti'}, xlabel='grade', ylabel='dti'>
```

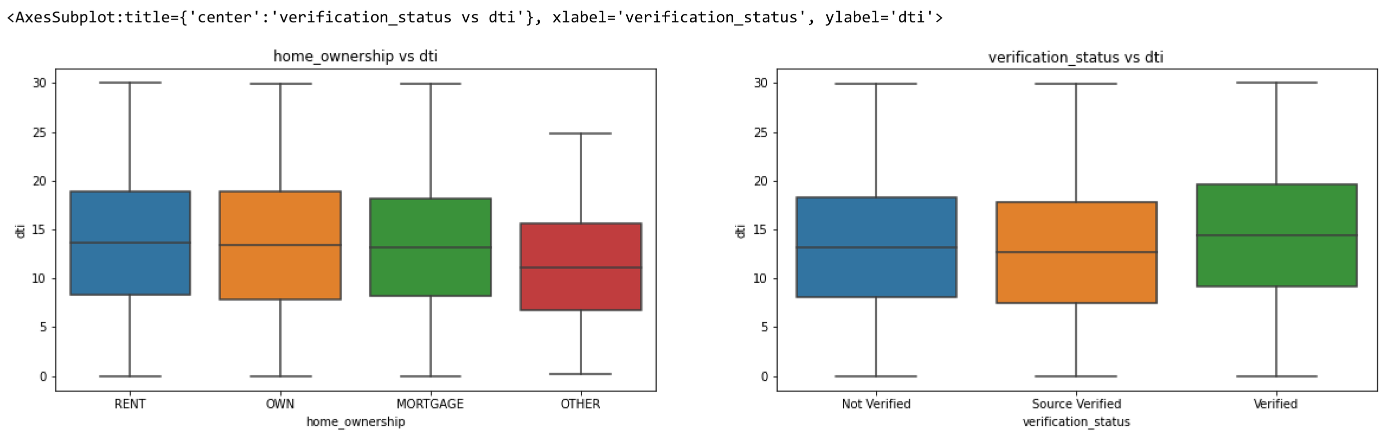


Observations:

DTI is bit high for people who got tenure of 60 months. A Grade barrowers are having low DTI than Other grades. DTI should be low for having high repayment percentage.

In [73]:
```
plt.figure(figsize=(20,5))
plt.subplot(121)
sns.boxplot(x='home_ownership', y=data.dti, data=data)
plt.title('home_ownership vs dti')
plt.subplot(122)
plt.title('verification_status vs dti')
verification_status_ord = data.verification_status.unique()
verification_status_ord.sort()
sns.boxplot(x='verification_status', y=data.dti, order = verification_status_ord, data=data)
```

Out[73]:
```
<AxesSubplot:title={'center':'verification_status vs dti'}, xlabel='verification_status', ylabel='dti'>
```

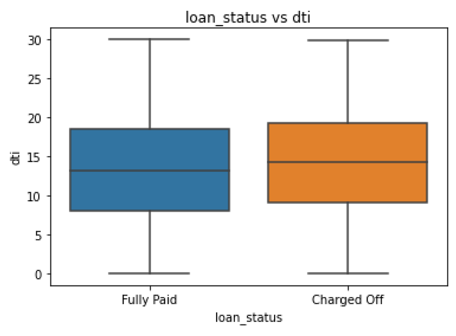


Observations:

People in Other home ownership has less DTI than others. This is may be bacause other people have mortgage and home loans.

In [74]:
```
sns.boxplot(x='loan_status', y=data.dti, data=data)
plt.title('loan_status vs dti')
```

Out[74]: Text(0.5, 1.0, 'loan_status vs dti')

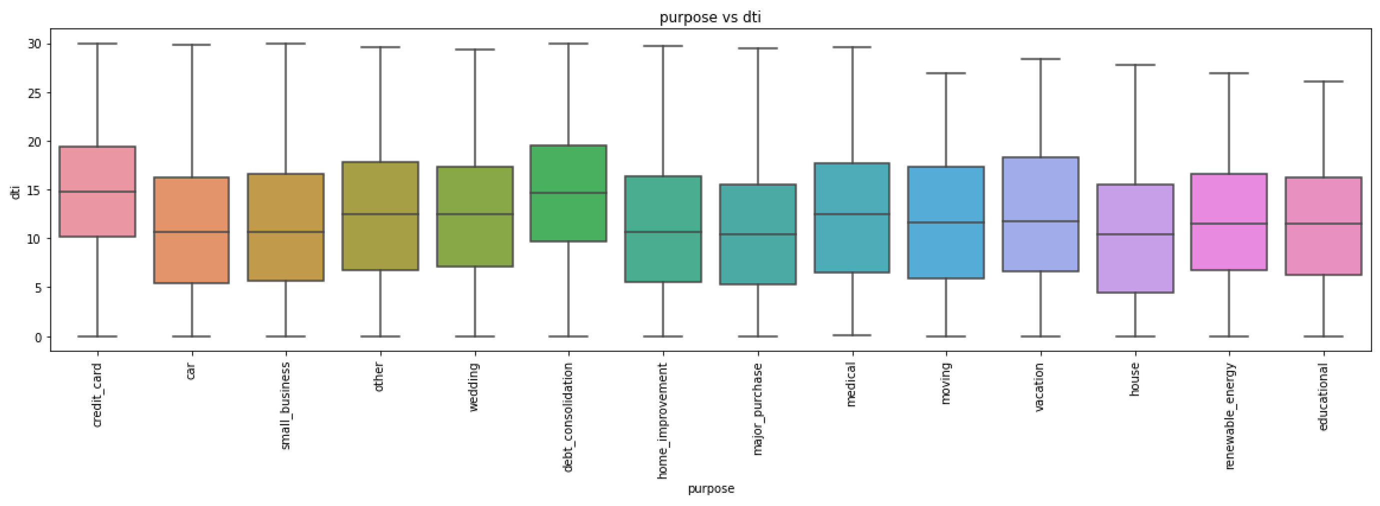


Observations:

Borrowers with high DTI has bit more probability to default

In [75]:
```
plt.figure(figsize=(20,5))
sns.boxplot(x='purpose', y=data.dti, data=data)
plt.xticks(rotation=90)
plt.title('purpose vs dti')
```

Out[75]: Text(0.5, 1.0, 'purpose vs dti')

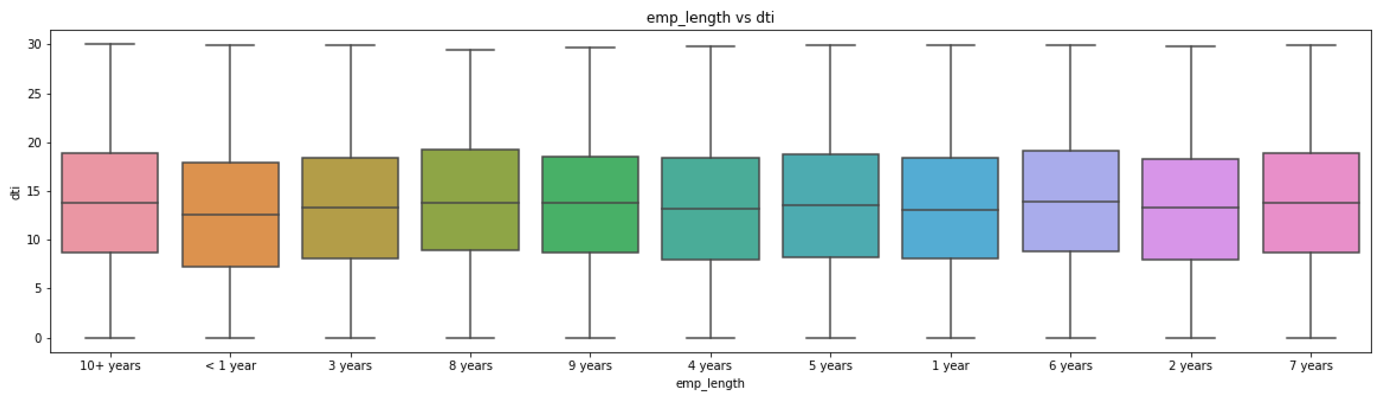


Observations:

Borrowers who took loan for credit card and debt consolidation purpose has more DTI than other purposes.

In [76]:
```
plt.figure(figsize=(20,5))
sns.boxplot(x='emp_length', y=data.dti, data=data)
plt.title('emp_length vs dti')
```

Out[76]: Text(0.5, 1.0, 'emp_length vs dti')



Observations:

The dti is much similar for borrowers with all the employment length.

pub_rec

Number of derogatory public records

In [77]:
```
#Finding proportion of values in each value of category
df = data.groupby(['pub_rec', 'term'], as_index=False)['id'].count()
df['proportion'] = df.groupby('pub_rec').transform(lambda x: x/x.sum())
df.head(3)
```

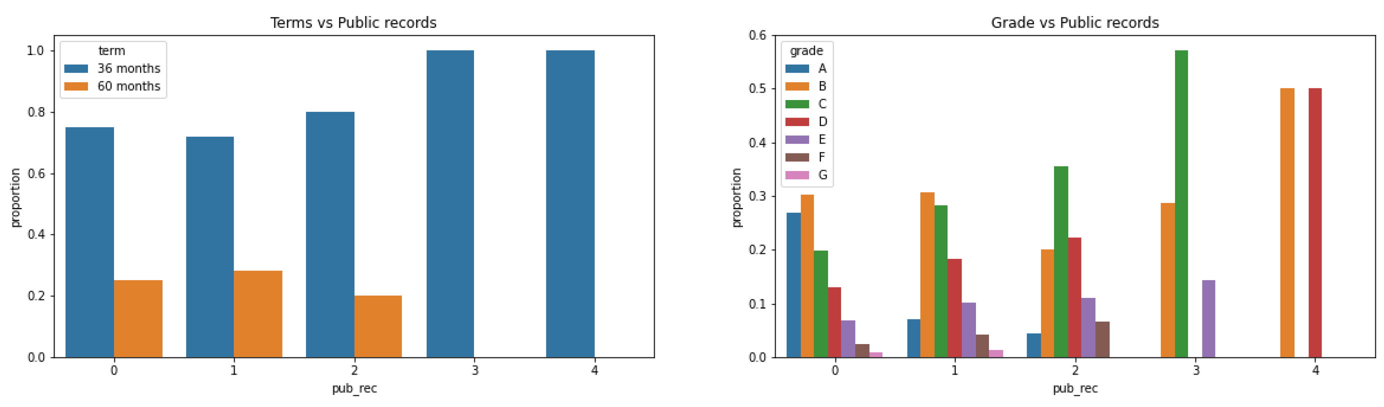
Out[77]:

	pub_rec	term	id	proportion
0	0	36 months	26152	0.75
1	0	60 months	8719	0.25
2	1	36 months	1349	0.72

In [78]:
```
plt.figure(figsize=(20,5))
plt.subplot(121)
sns.barplot(x='pub_rec', y='proportion', hue='term', data=df)
plt.title('Terms vs Public records')

df = data.groupby(['pub_rec', 'grade'], as_index=False)['id'].count()
df['proportion'] = df.groupby('pub_rec').transform(lambda x: x/x.sum())
plt.subplot(122)
plt.title('Grade vs Public records')
grade_ord = data.grade.unique()
grade_ord.sort()
sns.barplot(x='pub_rec', y='proportion', hue='grade', data=df)
```

Out[78]: <AxesSubplot:title={'center':'Grade vs Public records'}, xlabel='pub_rec', ylabel='proportion'>



Observations:

Borrowers higher public derogatory records took loan for 36 months tenure.
A grade people are having less derogatory records than the other grades. B,C,D, graded people are having high pub_recs.

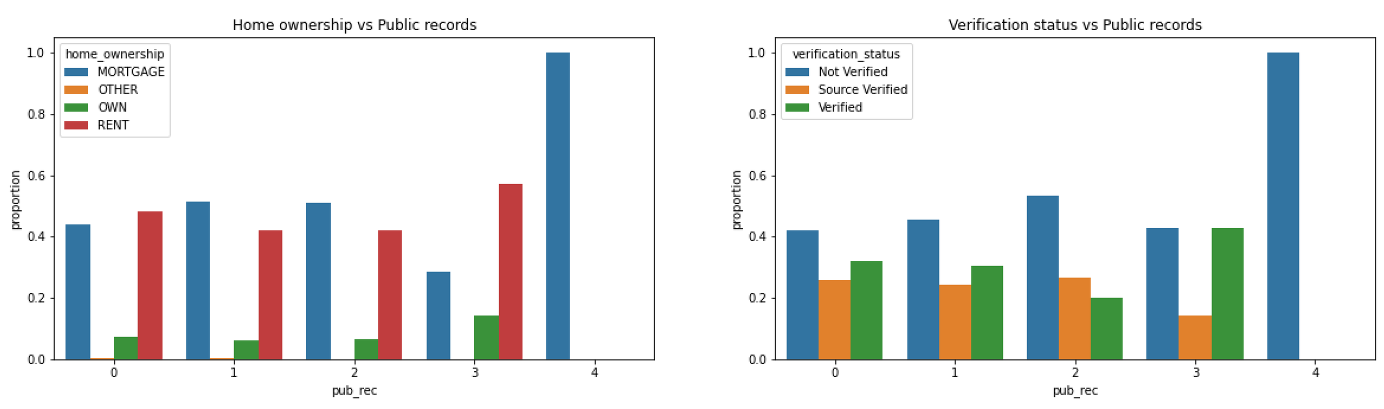
In [79]:
```
plt.figure(figsize=(20,5))
plt.subplot(121)

df = data.groupby(['pub_rec', 'home_ownership'], as_index=False)['id'].count()
df['proportion'] = df.groupby('pub_rec').transform(lambda x: x/x.sum())
sns.barplot(x='pub_rec', y='proportion', hue='home_ownership', data=df)
plt.title('Home ownership vs Public records')

df = data.groupby(['pub_rec', 'verification_status'], as_index=False)['id'].count()
df['proportion'] = df.groupby('pub_rec').transform(lambda x: x/x.sum())
plt.subplot(122)
sns.barplot(x='pub_rec', y='proportion', hue='verification_status', data=df)

plt.title('Verification status vs Public records')
```

Out[79]: Text(0.5, 1.0, 'Verification status vs Public records')



Observations:

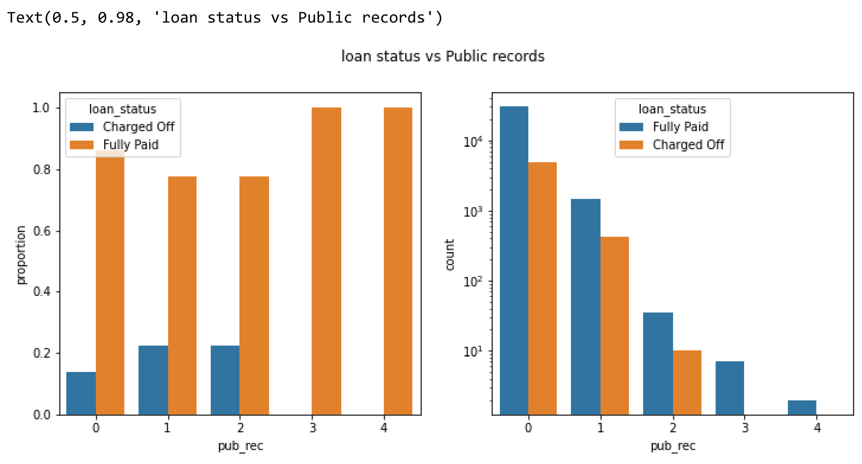
Borrowers with 4 public Derogatory records are high in mortgage owned house category and also Not verified Catogry.

In [80]:
```
#Proportion of values for each category
df = data.groupby(['pub_rec', 'loan_status'], as_index=False)['id'].count()
df['proportion'] = df.groupby('pub_rec').transform(lambda x: x/x.sum())

plt.figure(figsize=(12,5))
plt.subplot(121)
sns.barplot(x='pub_rec', y='proportion', hue='loan_status', data=df)

plt.subplot(122)
sns.countplot(data.pub_rec, hue='loan_status', data=data)
plt.yscale('log')
plt.suptitle('loan status vs Public records')
```

Out[80]: Text(0.5, 0.98, 'loan status vs Public records')

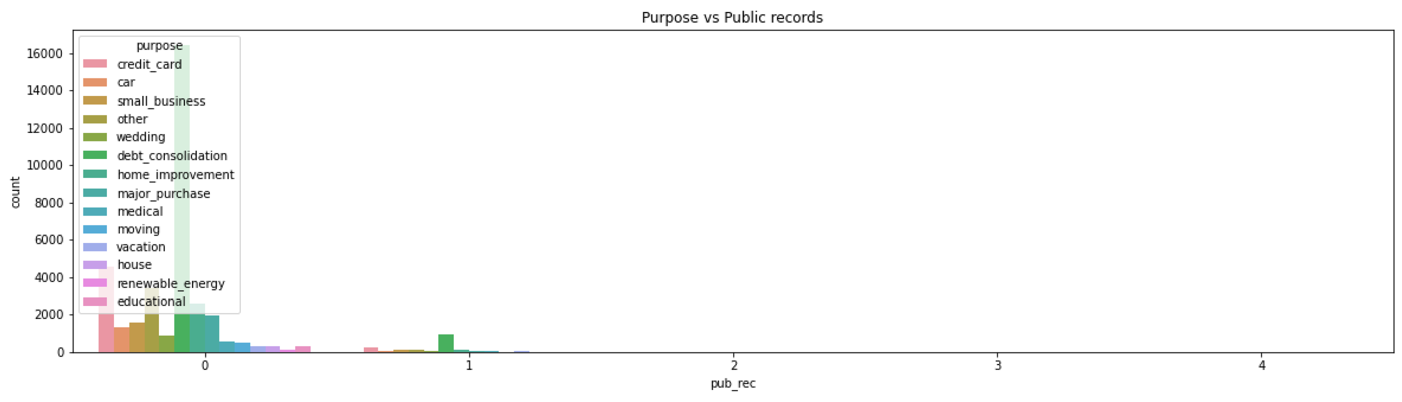


Observations:

There is increase in deafulted loans for borrowers with derogatory records from 0 to 2. Most borrowers are in 0 pub_rec category.

In [81]:
```
plt.figure(figsize=(20,5))
sns.countplot(data.pub_rec, hue='purpose', data=data)
plt.title('Purpose vs Public records')
```

Out[81]: `Text(0.5, 1.0, 'Purpose vs Public records')`



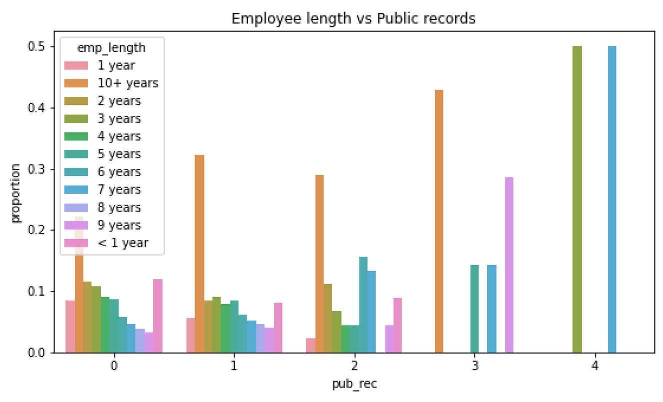
Observations:

There is high amount of debt cansolidation borrowers.

In [82]:
```
plt.figure(figsize=(20,5))
#Proportion of values for each category
df = data.groupby(['pub_rec', 'emp_length'], as_index=False)['id'].count()
df['proportion'] = df.groupby('pub_rec').transform(lambda x: x/x.sum())

plt.subplot(121)
sns.barplot(x='pub_rec', y='proportion', hue='emp_length', data=df)
plt.title('Employee length vs Public records')
```

Out[82]: `Text(0.5, 1.0, 'Employee length vs Public records')`



Observations:

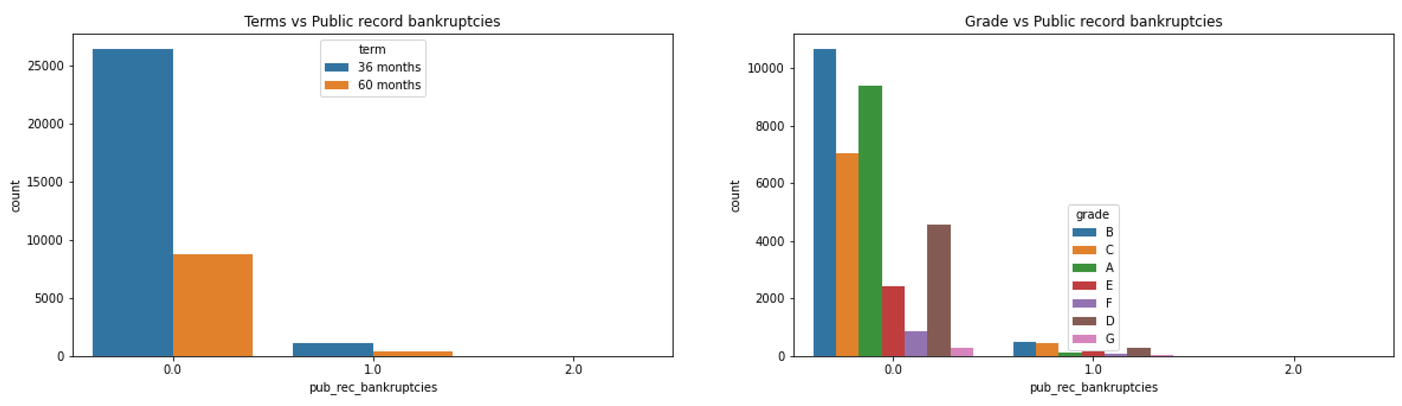
There is more number of 3 year & 7 year emp lenth borrowers.

pub_rec_bankruptcies

Number of public record bankruptcies

In [83]:
```
plt.figure(figsize=(20,5))
plt.subplot(121)
sns.countplot(data.pub_rec_bankruptcies, hue='term', data=data)
plt.title('Terms vs Public record bankruptcies')
plt.subplot(122)
plt.title('Grade vs Public record bankruptcies')
grade_ord = data.grade.unique()
grade_ord.sort()
sns.countplot(data.pub_rec_bankruptcies, hue='grade', data=data)
```

Out[83]: `<AxesSubplot:title={'center':'Grade vs Public record bankruptcies'}, xlabel='pub_rec_bankruptcies', ylabel='count'>`

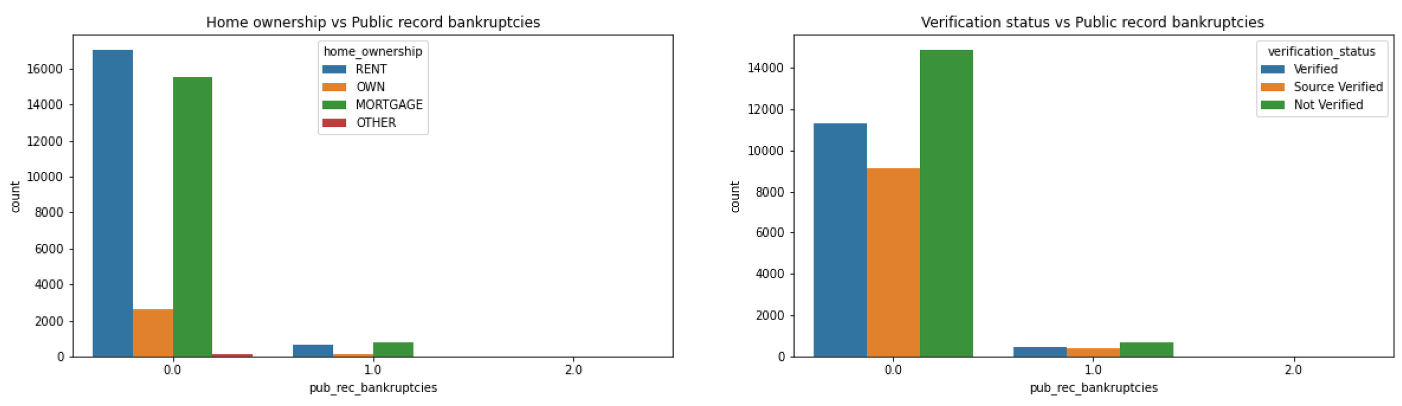


Observations:

36 months tenure borrowers are in large amount than 60 months tenure. Grades B,C,A are higher than other grades when compared with pub rec bankcruptcies.

In [84]:
```
plt.figure(figsize=(20,5))
plt.subplot(121)
sns.countplot(data.pub_rec_bankruptcies, hue='home_ownership', data=data)
plt.title('Home ownership vs Public record bankruptcies')
plt.subplot(122)
plt.title('Verification status vs Public record bankruptcies')
verification_status_ord = data.verification_status.unique()
verification_status_ord.sort()
sns.countplot(data.pub_rec_bankruptcies, hue='verification_status', data=data)
```

Out[84]: `<AxesSubplot:title={'center':'Verification status vs Public record bankruptcies'}, xlabel='pub_rec_bankruptcies', ylabel='count'>`

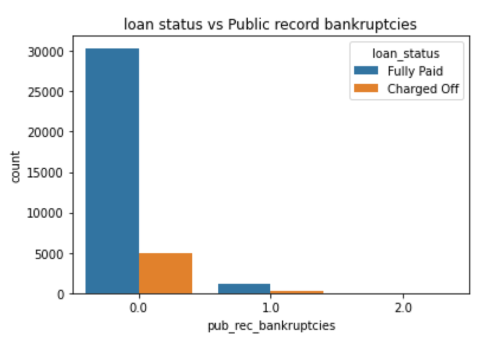


Observations:

Mortage & rent type of borrowers are in large scale. Most of are not verified one as per the plot.

In [85]:
```
sns.countplot(data.pub_rec_bankruptcies, hue='loan_status', data=data)
plt.title('loan status vs Public record bankruptcies')
```

Out[85]: `Text(0.5, 1.0, 'loan status vs Public record bankruptcies')`

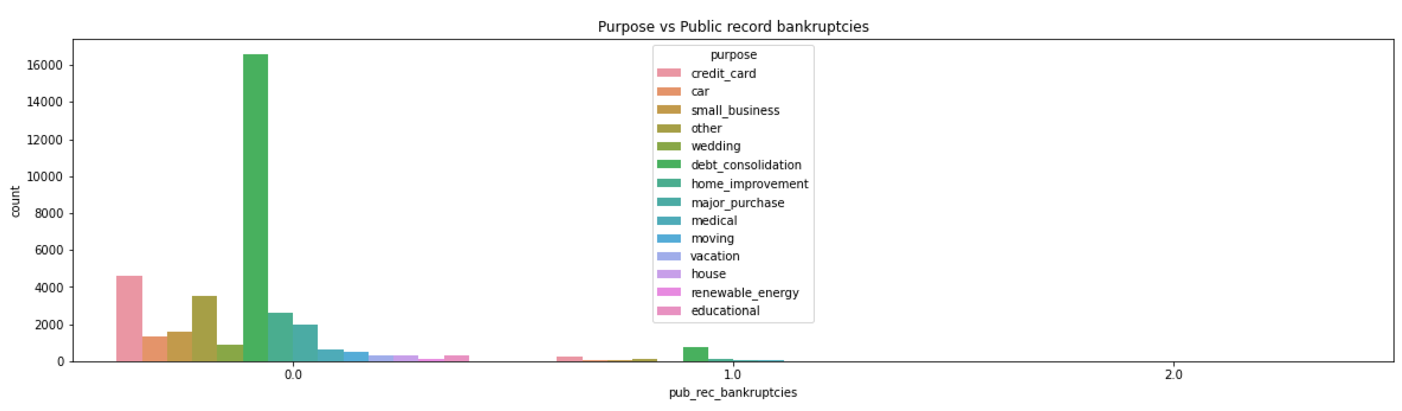


Observations:

Most borrower are of fully paid status.

In [86]:
```
plt.figure(figsize=(20,5))
sns.countplot(data.pub_rec_bankruptcies, hue='purpose', data=data)
plt.title('Purpose vs Public record bankruptcies')
```

Out[86]: `Text(0.5, 1.0, 'Purpose vs Public record bankruptcies')`

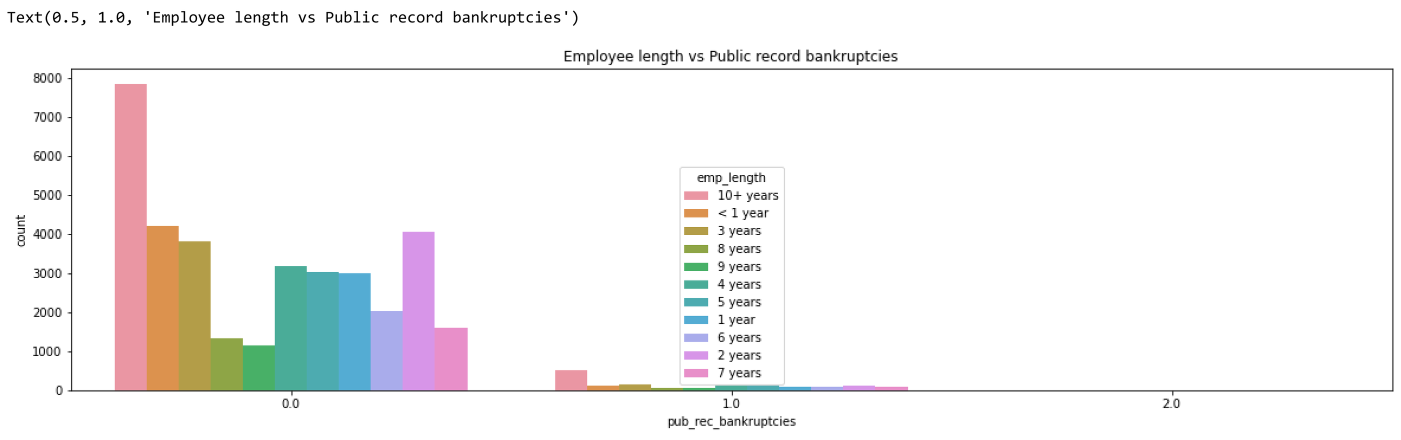


Observations:

ther is large amount of borrower belongs to debt consolidation category.

In [87]:
```
plt.figure(figsize=(20,5))
sns.countplot(data.pub_rec_bankruptcies, hue='emp_length', data=data)
plt.title('Employee length vs Public record bankruptcies')
```

Out[87]: `Text(0.5, 1.0, 'Employee length vs Public record bankruptcies')`

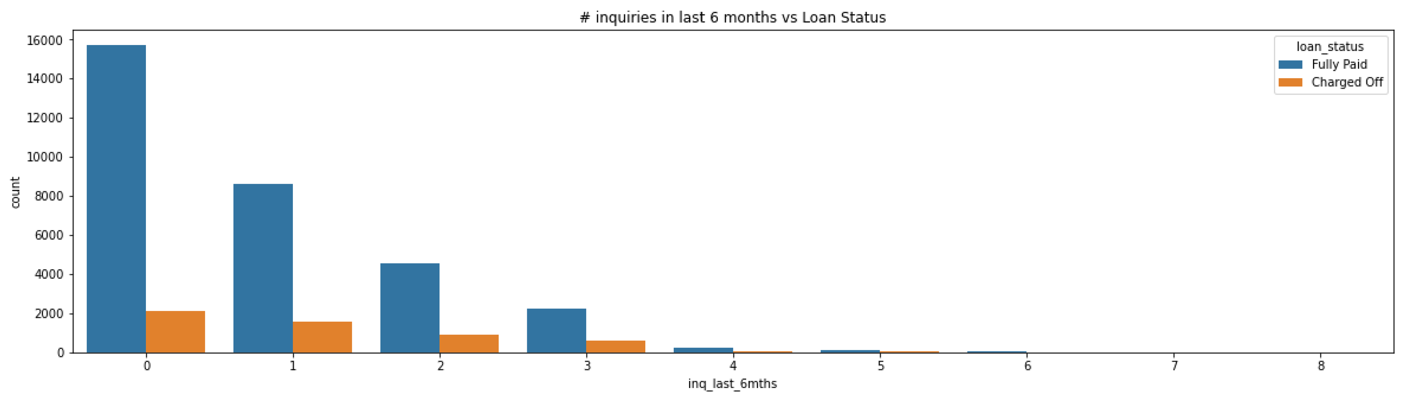


Observations:

There is largeamount of borrowers belong to 10 + year category of emp length.

inq_last_6mths

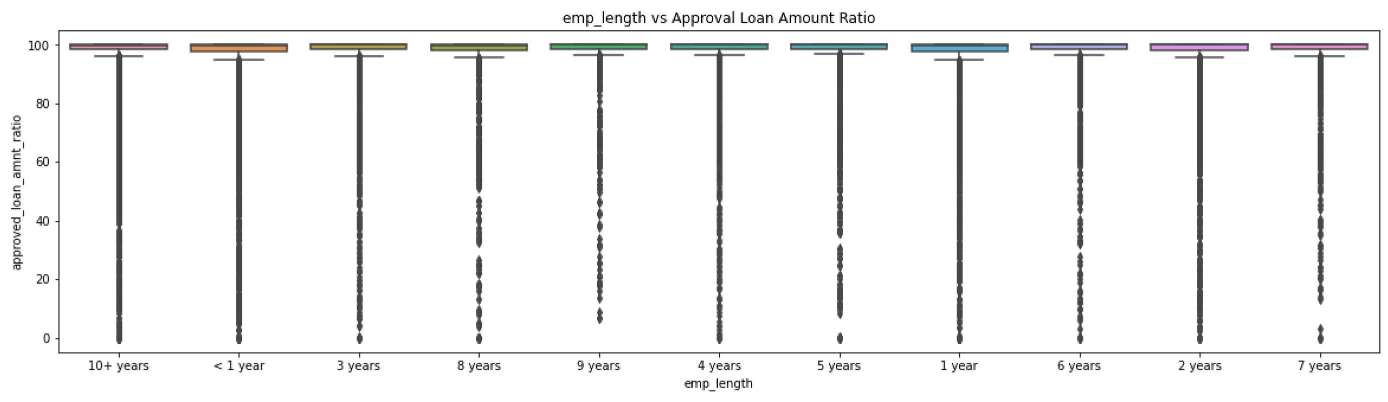
In [88]:
```
plt.figure(figsize=(20,5))
sns.countplot(data.inq_last_6mths, hue='loan_status', data=data)
plt.title('# inquiries in last 6 months vs Loan Status')
plt.show()
```



Approval Loan Amount Ratio

In [89]:
```
plt.figure(figsize=(20,5))
sns.boxplot(x='emp_length', y=data.approved_loan_amnt_ratio, data=data)
plt.title('emp_length vs Approval Loan Amount Ratio')
```

Out[89]: `Text(0.5, 1.0, 'emp_length vs Approval Loan Amount Ratio')`

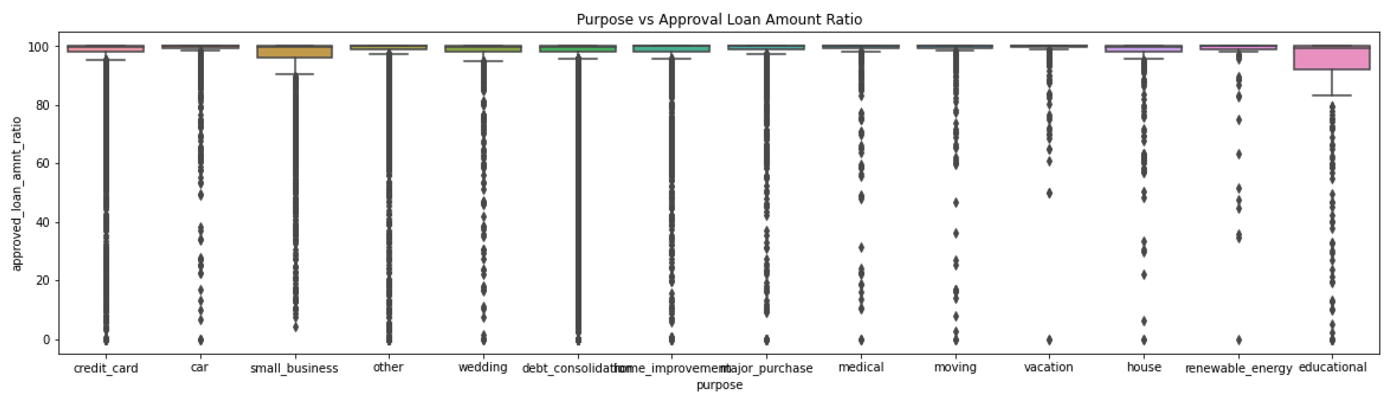


Observations:

There is not much relation between approval of loan amount ratio and employment length

In [90]:
```
plt.figure(figsize=(20,5))
sns.boxplot(x='purpose', y=data.approved_loan_amnt_ratio, data=data)
plt.title('Purpose vs Approval Loan Amount Ratio')
```

Out[90]: `Text(0.5, 1.0, 'Purpose vs Approval Loan Amount Ratio')`

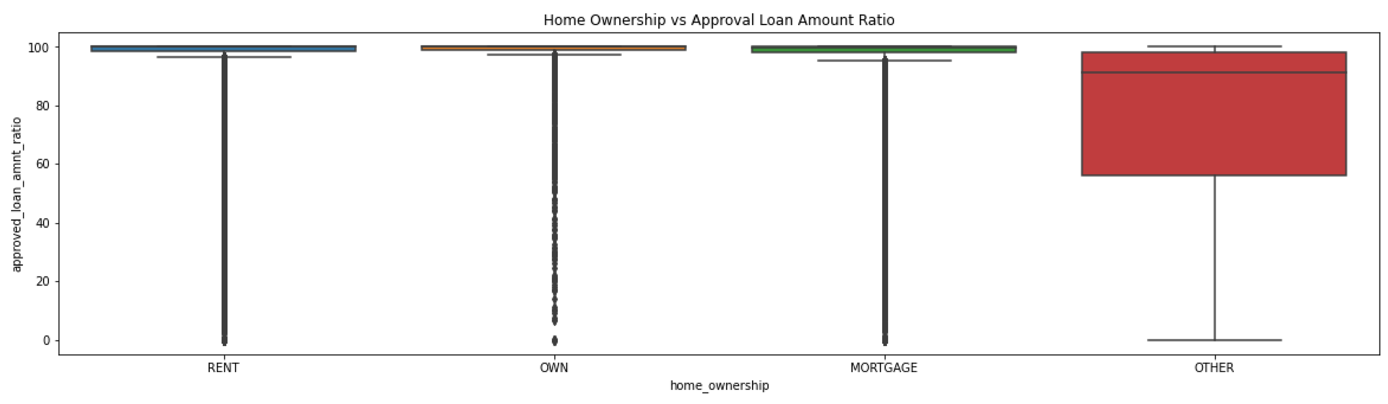


Observations:

The Funded amount by investors is lower than requested loan amount in education and small business purposes.

In [91]:
```
plt.figure(figsize=(20,5))
sns.boxplot(x='home_ownership', y=data.approved_loan_amnt_ratio, data=data)
plt.title('Home Ownership vs Approval Loan Amount Ratio')
```

Out[91]: `Text(0.5, 1.0, 'Home Ownership vs Approval Loan Amount Ratio')`



Observations:

Borrowers with Other home ownership are having less approved ratio which mean they got less amount than request amount.

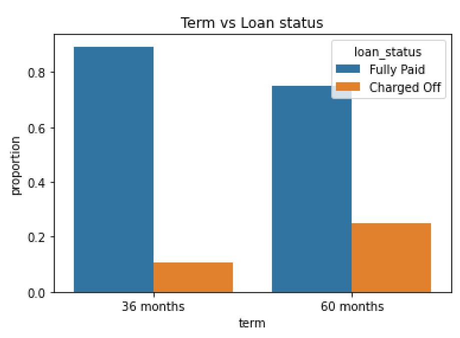
Bivariate Analysis

Bivariate analysis is one of the simplest forms of quantitative analysis. It involves the analysis of two variables, for the purpose of determining the empirical relationship between them.

Term vs Loan Status

In [92]:
```
#Proportion of values for each category
df = data.groupby(['term', 'loan_status'], as_index=False)['id'].count()
df['proportion'] = df.groupby('term').transform(lambda x: x/x.sum())
sns.barplot(x='term', y='proportion', hue='loan_status', data=df, hue_order = ['Fully Paid', 'Charged Off'])
plt.title('Term vs Loan status')
```

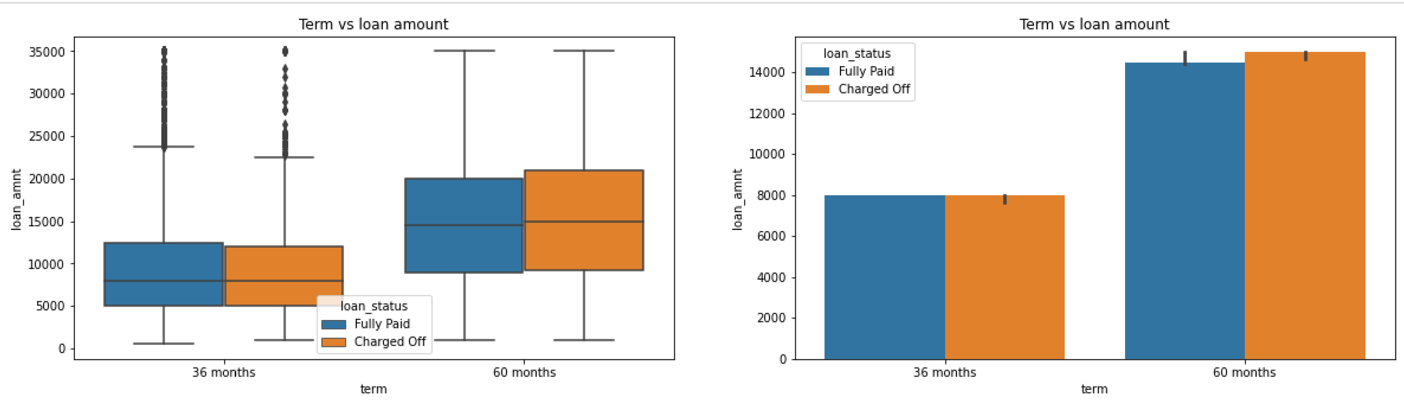
Out[92]: `Text(0.5, 1.0, 'Term vs Loan status')`



Observations:

There are more proportion of borrowers defaulted loan in 60 months term then 36 months. Also the Fully Paid rate is higher in 36 months tenure.

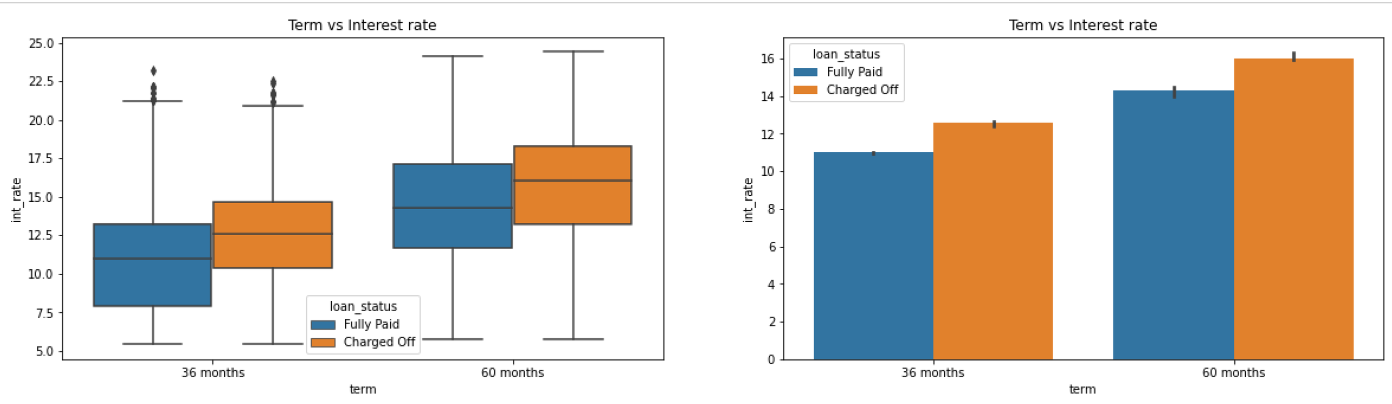
In [93]:
```
plt.figure(figsize=(20,5))
plt.subplot(121)
sns.boxplot(x='term', y='loan_amnt', hue='loan_status', data=data)
plt.title('Term vs loan amount')
plt.subplot(122)
sns.barplot(x='term', y='loan_amnt', hue='loan_status', data=data, estimator=np.median)
plt.title('Term vs loan amount')
plt.show()
```



Observations:

Loan amount is not a decider for defaults in both 36 adn 60 months. Borrowers have equal distribtion is both default and non default for 36 and 60 months tenures.

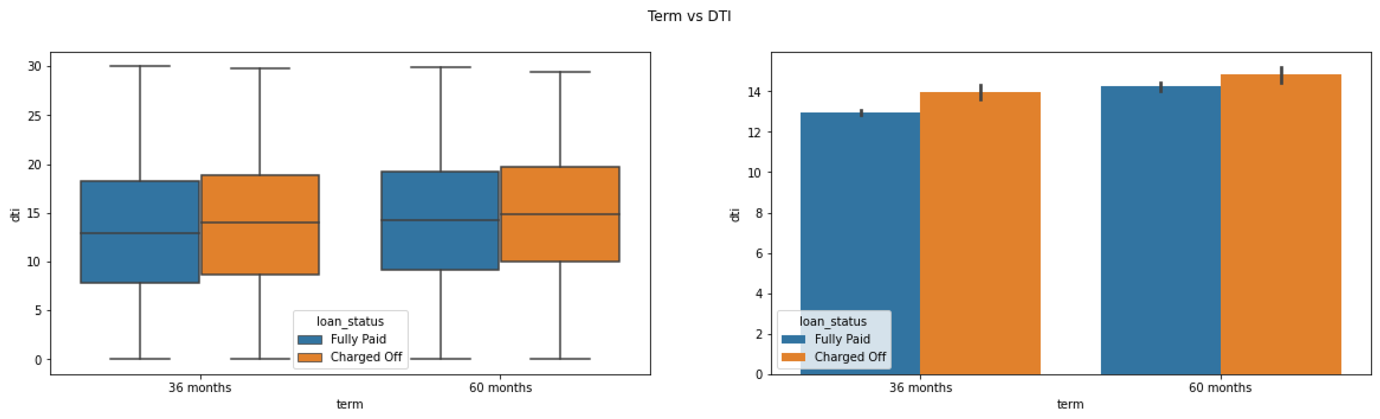
In [94]:
```
plt.figure(figsize=(20,5))
plt.subplot(121)
sns.boxplot(x='term', y='int_rate', hue='loan_status', data=data)
plt.title('Term vs Interest rate')
plt.subplot(122)
sns.barplot(x='term', y='int_rate', hue='loan_status', data=data, estimator=np.median)
plt.title('Term vs Interest rate')
plt.show()
```



Observations:

For higher interest rates the default rate is higher in both 36 and 60 months tenure.

In [95]:
```
plt.figure(figsize=(20,5))
plt.subplot(121)
sns.boxplot(x='term', y='dti', hue='loan_status', data=data)
plt.subplot(122)
sns.barplot(x='term', y='dti', hue='loan_status', data=data, estimator=np.median)
plt.suptitle('Term vs DTI')
plt.show()
```



Observations:

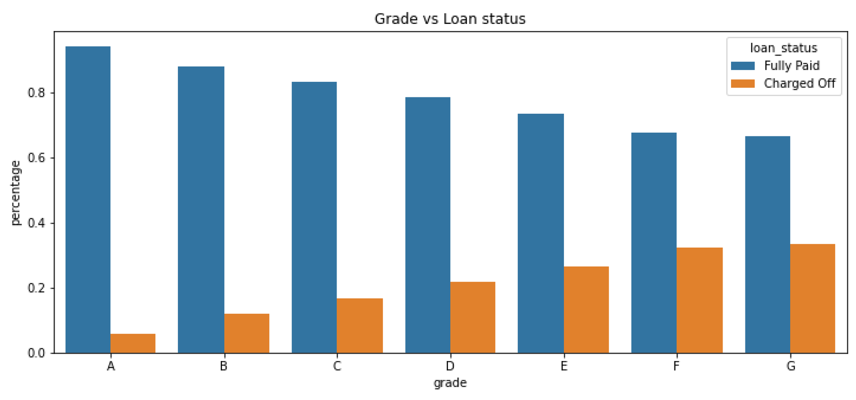
Comparitively charge-off are higher when compared with fully-paid for the Debit to income ratio.

Grade

In [96]:
```
#Sorting Grades from A to G
grade_ord = data.grade.unique()
grade_ord.sort()

df = data.groupby(['grade', 'loan_status'], as_index=False)['id'].count()
df['percentage'] = df.groupby('grade').transform(lambda x: x/x.sum())
plt.figure(figsize=(12,5))
sns.barplot(x='grade', y='percentage', hue='loan_status', data=df, hue_order = ['Fully Paid', 'Charged Off'])
plt.title('Grade vs Loan status')
```

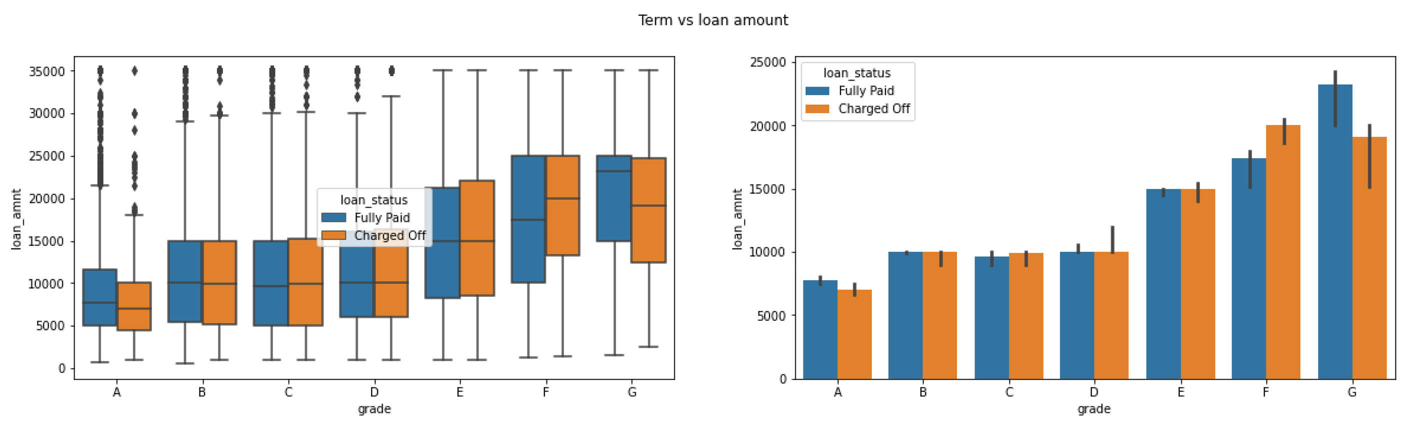
Out[96]: `Text(0.5, 1.0, 'Grade vs Loan status')`



Observations:

The above graph clearly says the Charged off increases as grades decreases.

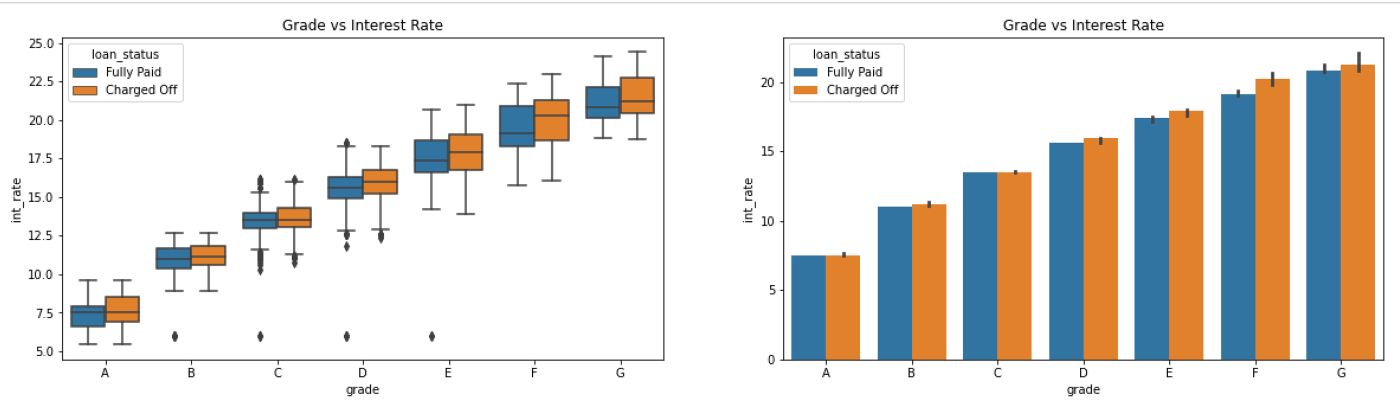
In [97]:
```
plt.figure(figsize=(20,5))
plt.subplot(121)
sns.boxplot(x='grade', y='loan_amnt', hue='loan_status', data=data, order = grade_ord)
plt.subplot(122)
sns.barplot(x='grade', y='loan_amnt', hue='loan_status', data=data, estimator=np.median, order = grade_ord)
plt.suptitle('Term vs loan amount')
plt.show()
```



Observations:

For lower grades 'F' and 'G' there are more difference between charged-off and fully paid. The lower grade people has taken higher amount of loans and also they are more prone to default the loan.

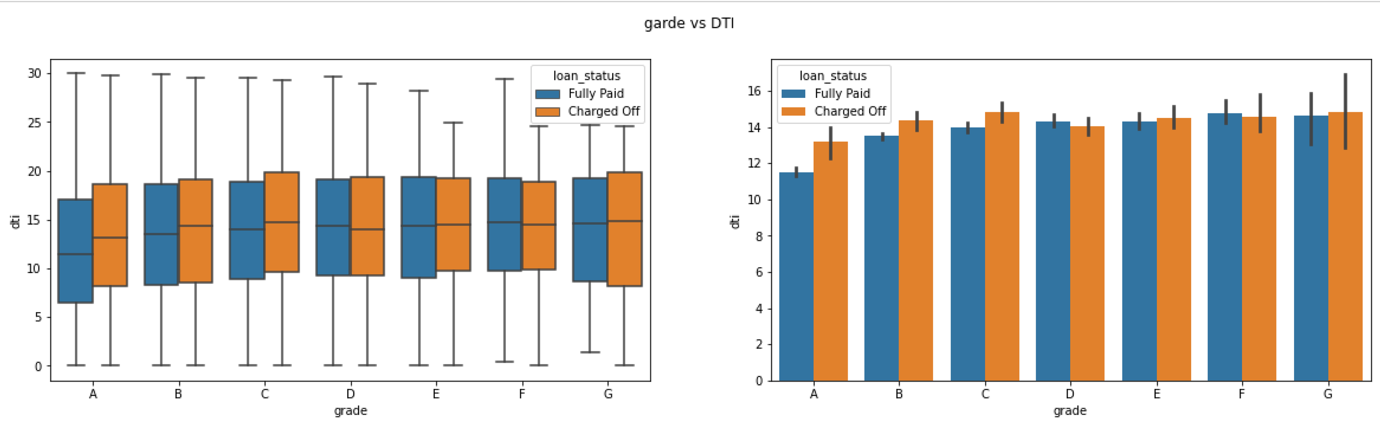
In [98]:
```
plt.figure(figsize=(20,5))
plt.subplot(121)
sns.boxplot(x='grade', y='int_rate', hue='loan_status', data=data, order = grade_ord)
plt.title('Grade vs Interest Rate')
plt.subplot(122)
sns.barplot(x='grade', y='int_rate', hue='loan_status', data=data, order = grade_ord, estimator=np.median)
plt.title('Grade vs Interest Rate')
plt.show()
```



Observations:

As grade decreases the interest rate gradually increases. and they are more and more prone to default the loan.

In [99]:
```
plt.figure(figsize=(20,5))
plt.subplot(121)
sns.boxplot(x='grade', y='dti', hue='loan_status', data=data, order=grade_ord)
plt.subplot(122)
sns.barplot(x='grade', y='dti', hue='loan_status', data=data, estimator=np.median, order = grade_ord)
plt.suptitle('garde vs DTI')
plt.show()
```



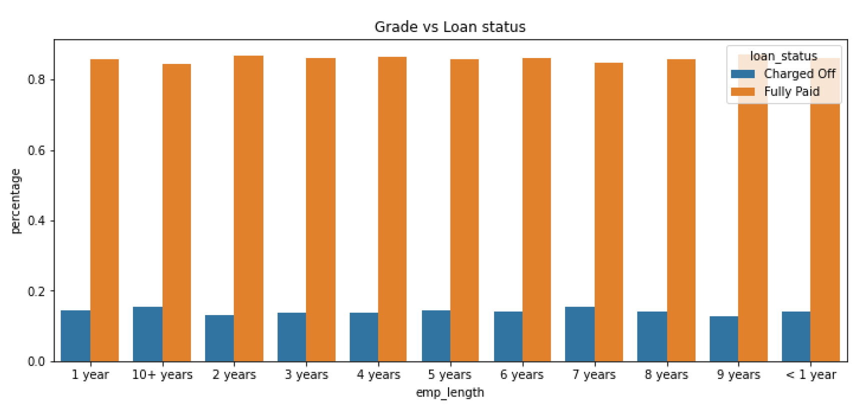
Observations:

There is not much change in dti in each grade and loan status.

Employment Length

In [100]:
```
df = data.groupby(['emp_length', 'loan_status'], as_index=False)['id'].count()
df['percentage'] = df.groupby('emp_length').transform(lambda x: x/x.sum())
plt.figure(figsize=(12,5))
sns.barplot(x='emp_length', y='percentage', hue='loan_status', data=df)
plt.title('Grade vs Loan status')
```

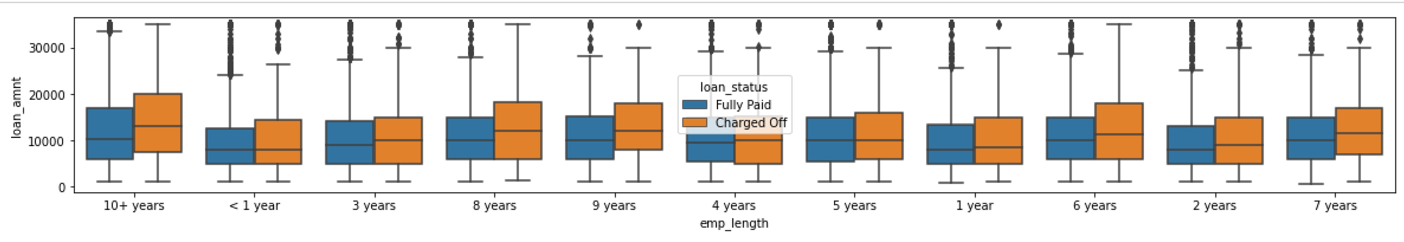
Out[100]: `Text(0.5, 1.0, 'Grade vs Loan status')`

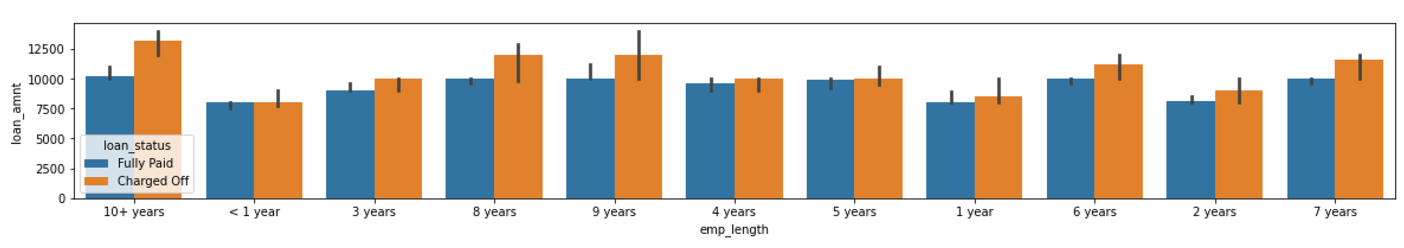


Observations:

There is not big changes or pattern observed defaulters across employment lengths.

In [101]:
```
plt.figure(figsize=(20,6))
plt.subplot(211)
sns.boxplot(x='emp_length', y='loan_amnt', hue='loan_status', data=data)
plt.figure(figsize=(20,6))
plt.subplot(212)
sns.barplot(x='emp_length', y='loan_amnt', hue='loan_status', data=data, estimator=np.median)
plt.show()
```

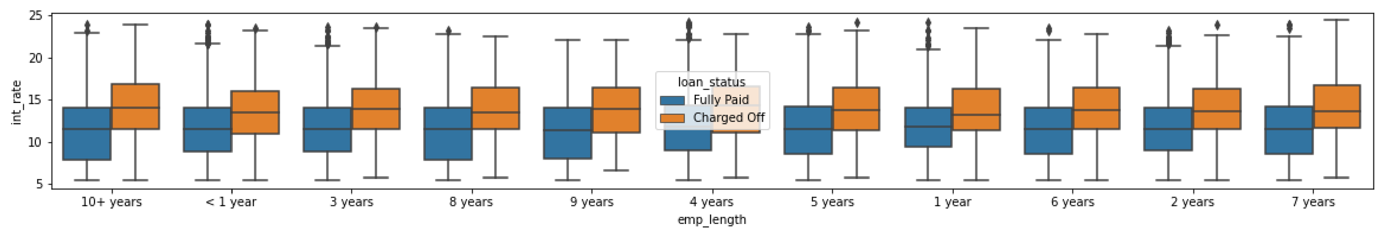


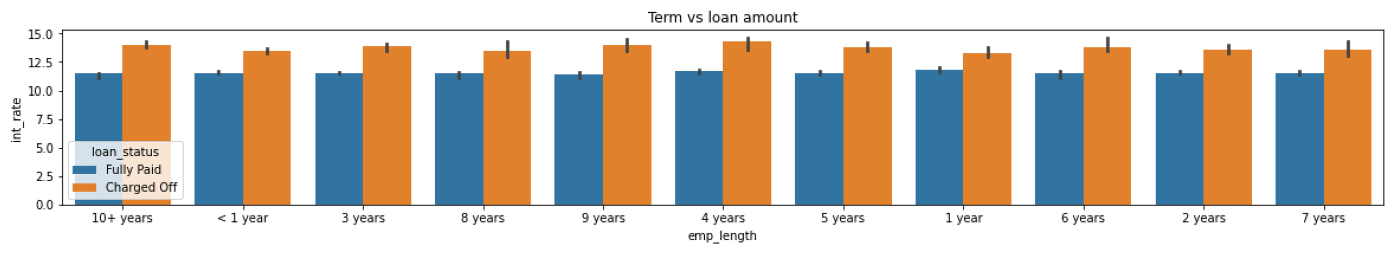


Observations:

Borrowers with higher employment lengths and took more loan amounts got more default rate.

In [102]:
```
plt.figure(figsize=(20,6))
plt.subplot(211)
sns.boxplot(x='emp_length', y='int_rate', hue='loan_status', data=data)
plt.figure(figsize=(20,6))
plt.subplot(212)
sns.barplot(x='emp_length', y='int_rate', hue='loan_status', data=data, estimator=np.median)
plt.title('Term vs loan amount')
plt.show()
```

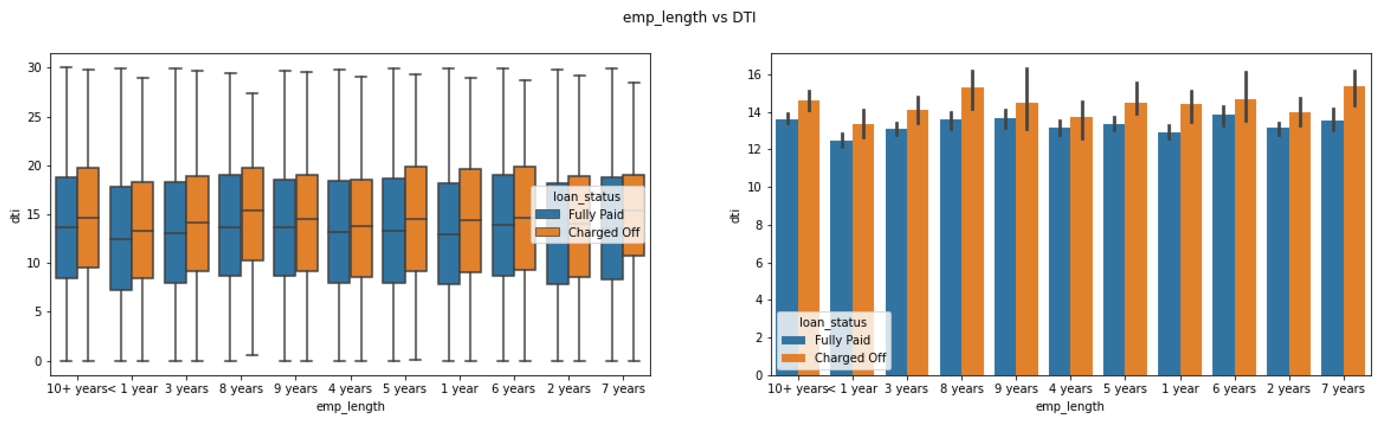




Observations:

Irrespective of employment length loans with more interest rates got defaulted more.

In [103]:
```
plt.figure(figsize=(20,5))
plt.subplot(121)
sns.boxplot(x='emp_length', y='dti', hue='loan_status', data=data)
plt.subplot(122)
sns.barplot(x='emp_length', y='dti', hue='loan_status', data=data, estimator=np.median)
plt.suptitle('emp_length vs DTI')
plt.show()
```



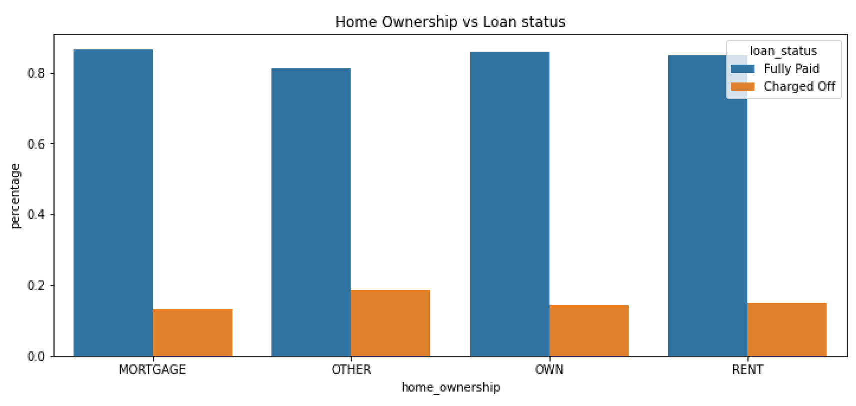
Observations:

Employment Length and DTI are not showing any patterns towards defaults.

Home Ownership

In [104]:
```
df = data.groupby(['home_ownership', 'loan_status'], as_index=False)['id'].count()
df['percentage'] = df.groupby('home_ownership').transform(lambda x: x/x.sum())
plt.figure(figsize=(12,5))
sns.barplot(x='home_ownership', y='percentage', hue='loan_status', data=df, hue_order = ['Fully Paid', 'Charged Off'])
plt.title('Home Ownership vs Loan status')
```

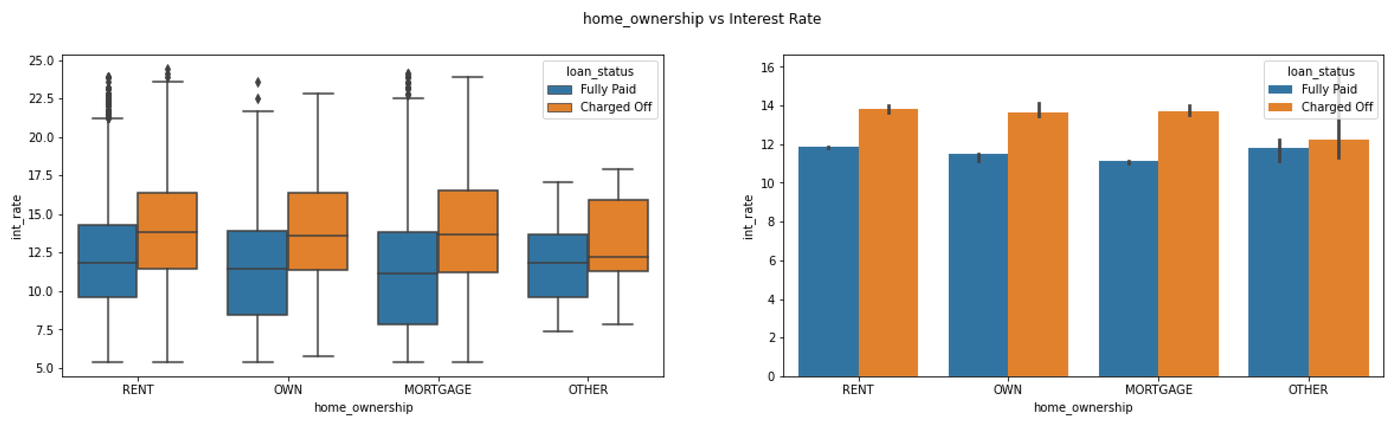
Out[104]: Text(0.5, 1.0, 'Home Ownership vs Loan status')



Observations:

There are bit high percentage of defaults are recorded in other home ownership category.

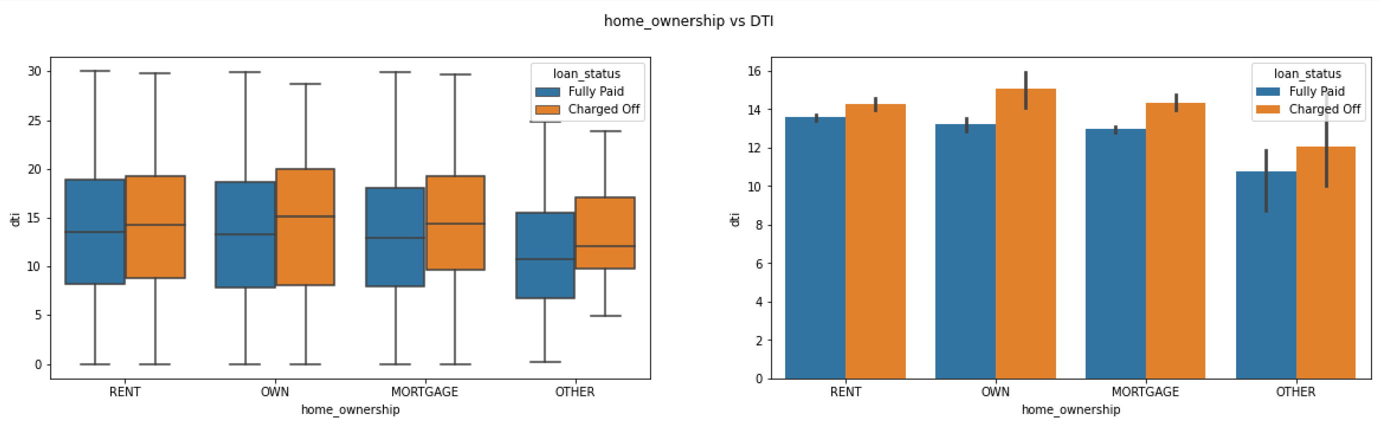
In [105]:
```
plt.figure(figsize=(20,5))
plt.subplot(121)
sns.boxplot(x='home_ownership', y='int_rate', hue='loan_status', data=data)
plt.subplot(122)
sns.barplot(x='home_ownership', y='int_rate', hue='loan_status', data=data, estimator=np.median)
plt.suptitle('home_ownership vs Interest Rate')
plt.show()
```



Observations:

Irrespective of Home owner ship, when the interest rate is high the dafault rate also high.

In [106]:
```
plt.figure(figsize=(20,5))
plt.subplot(121)
sns.boxplot(x='home_ownership', y='dti', hue='loan_status', data=data)
plt.subplot(122)
sns.barplot(x='home_ownership', y='dti', hue='loan_status', data=data, estimator=np.median)
plt.suptitle('home_ownership vs DTI')
plt.show()
```



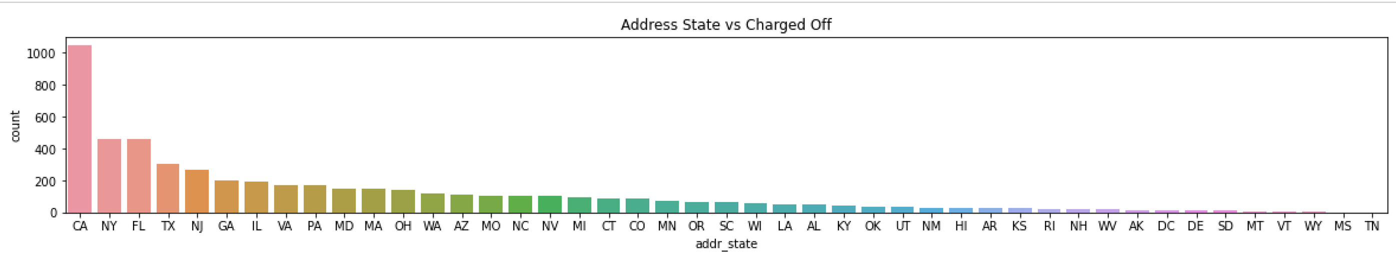
Observations:

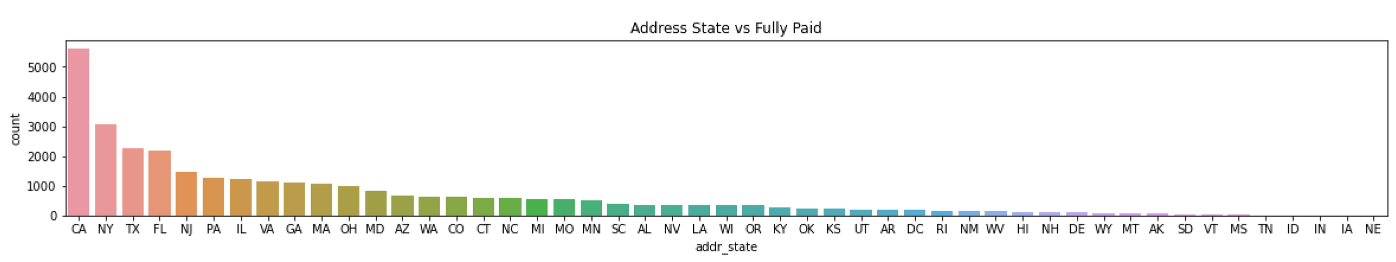
Borrowers in other home ownership category has less dti than other categories. There is equal posibility of home owners defaulting for all the home ownerships.

Address State

In [107]:
```
charged_off_df = data[data.loan_status.values == 'Charged Off']
plt.figure(figsize=(20,6))
plt.subplot(211)
sns.countplot(x='addr_state', data=charged_off_df, order=charged_off_df.addr_state.value_counts().index)
plt.title('Address State vs Charged Off')

fp_df = data[data.loan_status.values == 'Fully Paid']
plt.figure(figsize=(20,6))
plt.subplot(212)
sns.countplot(x='addr_state', data=fp_df, order=fp_df.addr_state.value_counts().index)
plt.title('Address State vs Fully Paid')
plt.show()
```





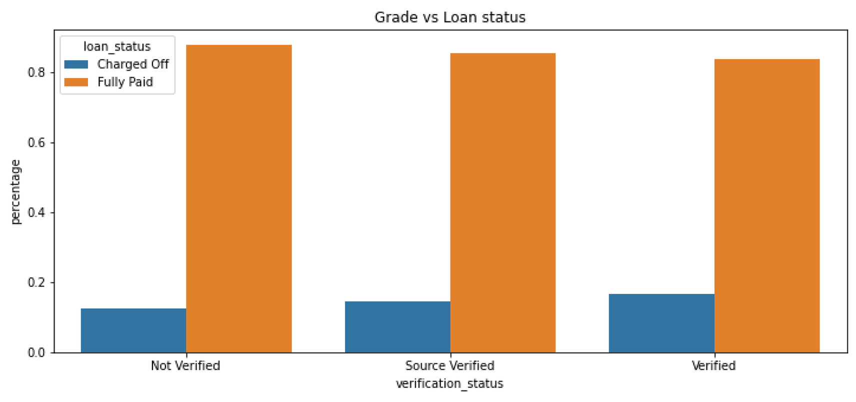
Observations:

More number of borrowers defaulted in CA , FL and NY states

Verfication Status

In [108]:
```
df = data.groupby(['verification_status', 'loan_status'], as_index=False)['id'].count()
df['percentage'] = df.groupby('verification_status').transform(lambda x: x/x.sum())
plt.figure(figsize=(12,5))
sns.barplot(x='verification_status', y='percentage', hue='loan_status', data=df)
plt.title('Grade vs Loan status')
```

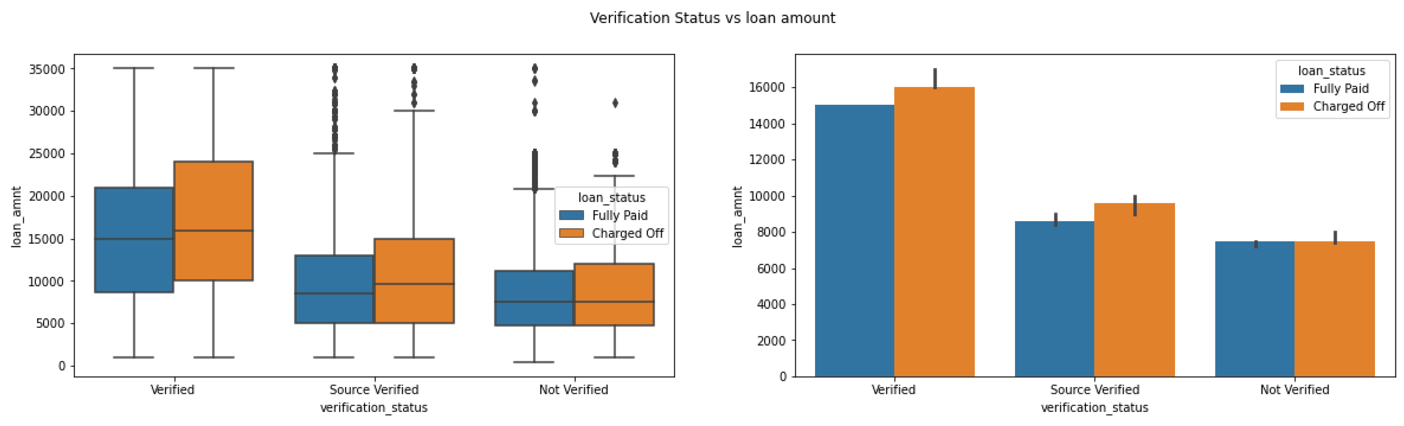
Out[108]: Text(0.5, 1.0, 'Grade vs Loan status')



Observations:

There is not a large change in charged of loans for all varification status.

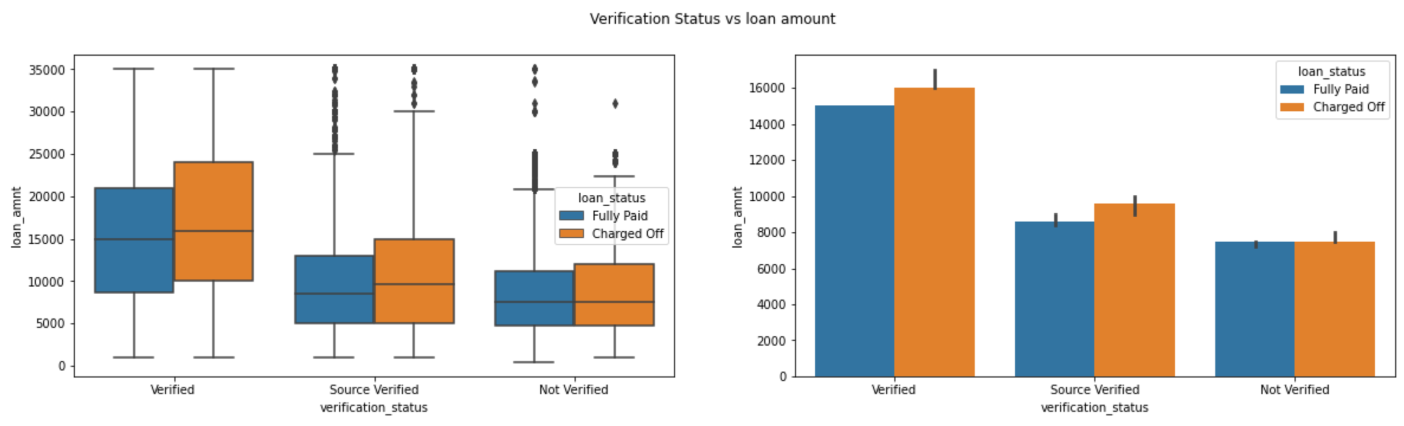
In [109]:
```
plt.figure(figsize=(20,5))
plt.subplot(121)
sns.boxplot(x='verification_status', y='loan_amnt', hue='loan_status', data=data)
plt.subplot(122)
sns.barplot(x='verification_status', y='loan_amnt', hue='loan_status', data=data, estimator=np.median)
plt.suptitle('Verification Status vs loan amount')
plt.show()
```



Observations:

There is difference between the verified & source verified borrowers in there loan amount when they are charged off

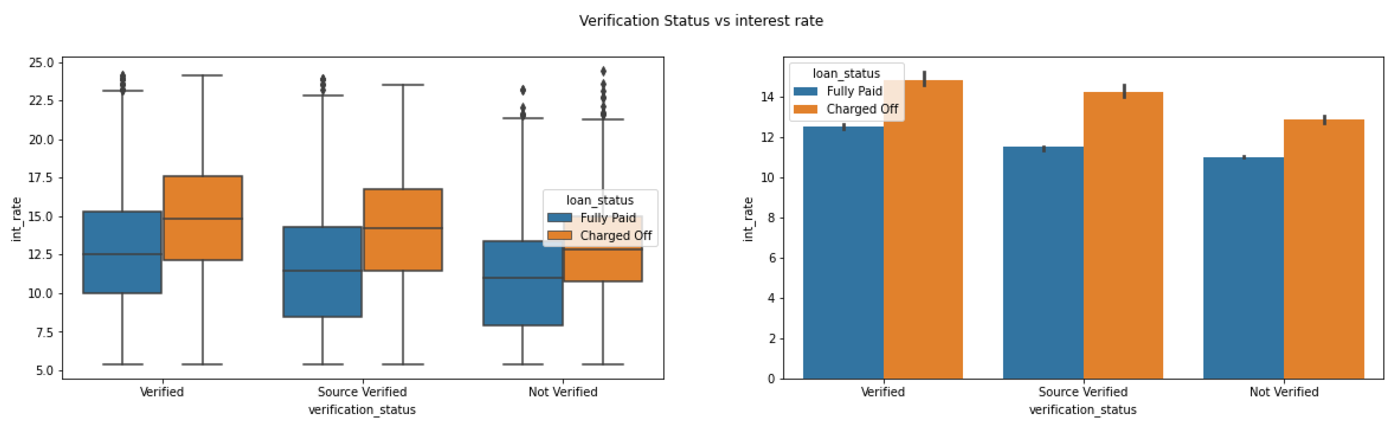
In [110]:
```
plt.figure(figsize=(20,5))
plt.subplot(121)
sns.boxplot(x='verification_status', y='loan_amnt', hue='loan_status', data=data)
plt.subplot(122)
sns.barplot(x='verification_status', y='loan_amnt', hue='loan_status', data=data, estimator=np.median)
plt.suptitle('Verification Status vs loan amount')
plt.show()
```



Observations:

Verified loans are given more loan amounts compared to others.

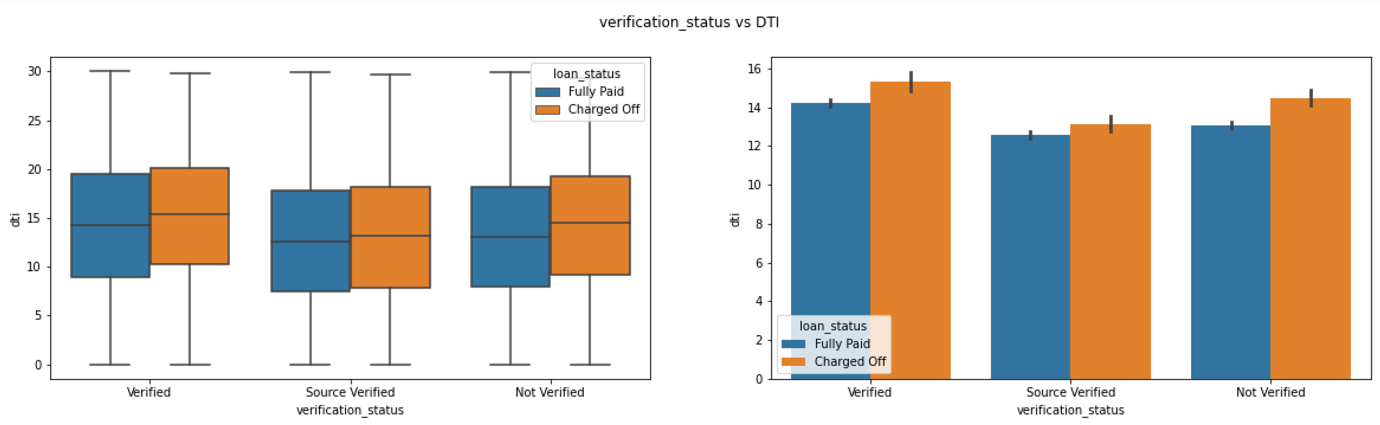
In [111]:
```
plt.figure(figsize=(20,5))
plt.subplot(121)
sns.boxplot(x='verification_status', y='int_rate', hue='loan_status', data=data)
plt.subplot(122)
sns.barplot(x='verification_status', y='int_rate', hue='loan_status', data=data, estimator=np.median)
plt.suptitle('Verification Status vs interest rate')
plt.show()
```



Observations:

Irrespective of verification status higher interest rates are incurring default of loan.

In [112]:
```
plt.figure(figsize=(20,5))
plt.subplot(121)
sns.boxplot(x='verification_status', y='dti', hue='loan_status', data=data)
plt.subplot(122)
sns.barplot(x='verification_status', y='dti', hue='loan_status', data=data, estimator=np.median)
plt.suptitle('verification_status vs DTI')
plt.show()
```



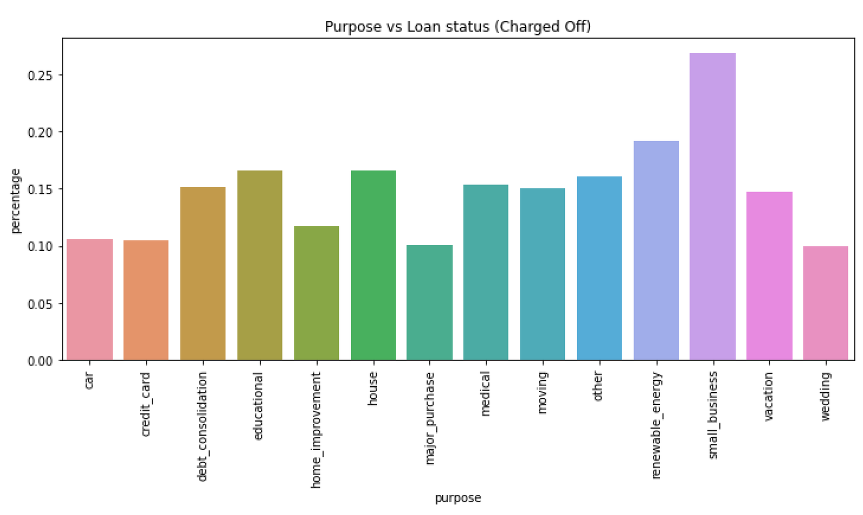
Observations:

There is slight increase in the dti mean for defaulted loans for all the verification status categories.

Purpose

In [113]:
```
df = data.groupby(['purpose', 'loan_status'], as_index=False)['id'].count()
df['percentage'] = df.groupby('purpose').transform(lambda x: x/x.sum())
df = df[df.loan_status == 'Charged Off']
plt.figure(figsize=(12,5))
sns.barplot(x='purpose', y='percentage', data=df)
plt.xticks(rotation=90)
plt.title('Purpose vs Loan status (Charged Off)')
```

Out[113]: Text(0.5, 1.0, 'Purpose vs Loan status (Charged Off)')



Observations:

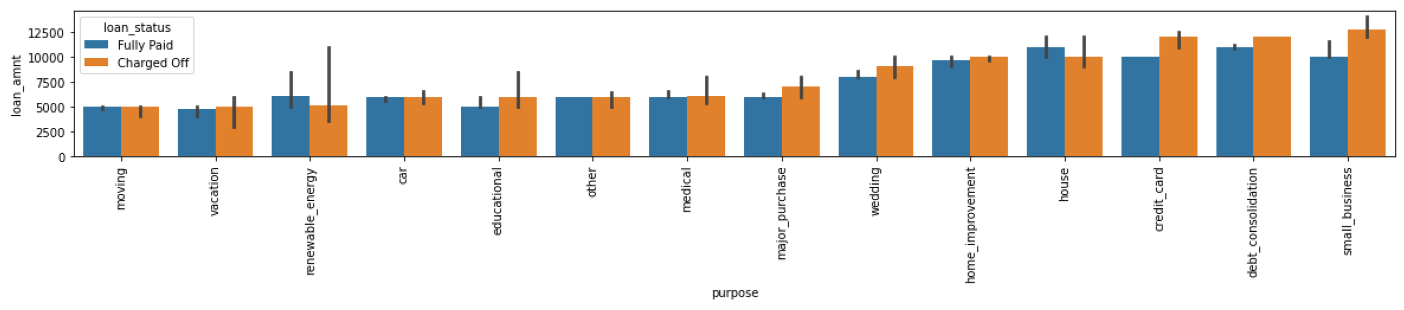
Charged-off are higher for small_business comparitively.

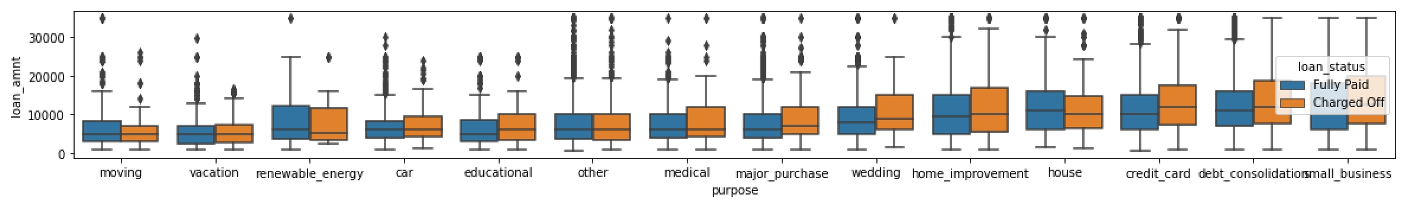
In [114]:
```
df = data.groupby(['purpose', 'loan_status'], as_index=False)['loan_amnt'].median()

plt.suptitle('Purpose vs loan amount')
plt.figure(figsize=(20,5))
plt.subplot(211)
sns.barplot(x='purpose', y='loan_amnt', hue='loan_status', data= data, order=df[df.loan_status == 'Charged Off'].sort_values(by='loan_amnt').purpose, estimator=np.median)
plt.xticks(rotation=90)

plt.figure(figsize=(20,5))
plt.subplot(212)
sns.boxplot(x='purpose', y='loan_amnt', hue='loan_status', data= data, order=df[df.loan_status == 'Charged Off'].sort_values(by='loan_amnt').purpose)
plt.show()
```

<Figure size 432x288 with 0 Axes>





Observations:

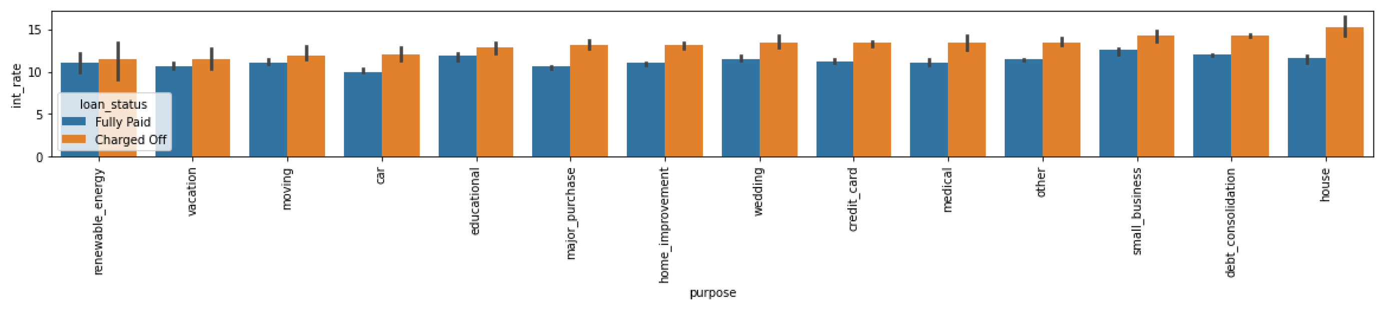
Small Business has more defaults when the loan amount is also high.

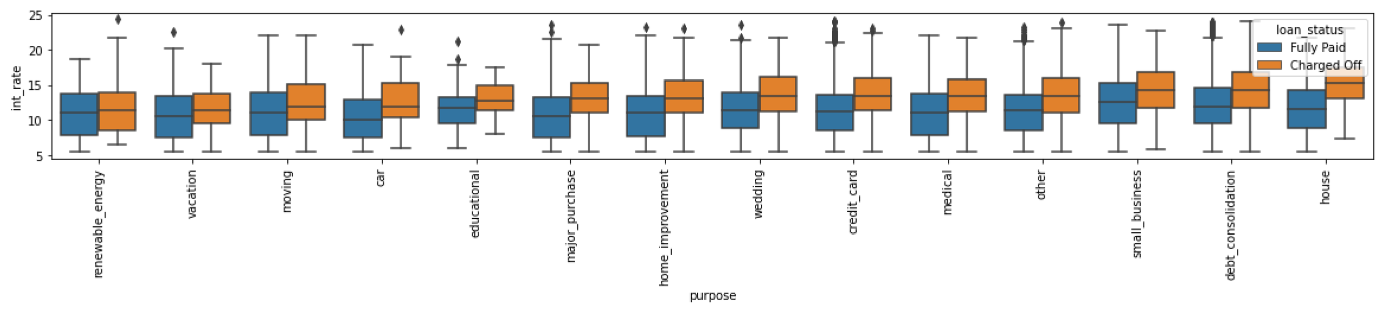
In [115]:
```
df = data.groupby(['purpose', 'loan_status'], as_index=False)['int_rate'].median()
purpose_ord = df[df.loan_status == 'Charged Off'].sort_values(by='int_rate').purpose

plt.suptitle('Purpose vs interest rate')
plt.figure(figsize=(20,5))
plt.subplot(211)
sns.barplot(x='purpose', y='int_rate', hue='loan_status', data= data, estimator=np.median, order = purpose_ord)
plt.xticks(rotation=90)

plt.figure(figsize=(20,5))
plt.subplot(212)
sns.boxplot(x='purpose', y='int_rate', hue='loan_status', data= data, order = purpose_ord)
plt.xticks(rotation=90)
plt.show()
```

<Figure size 432x288 with 0 Axes>



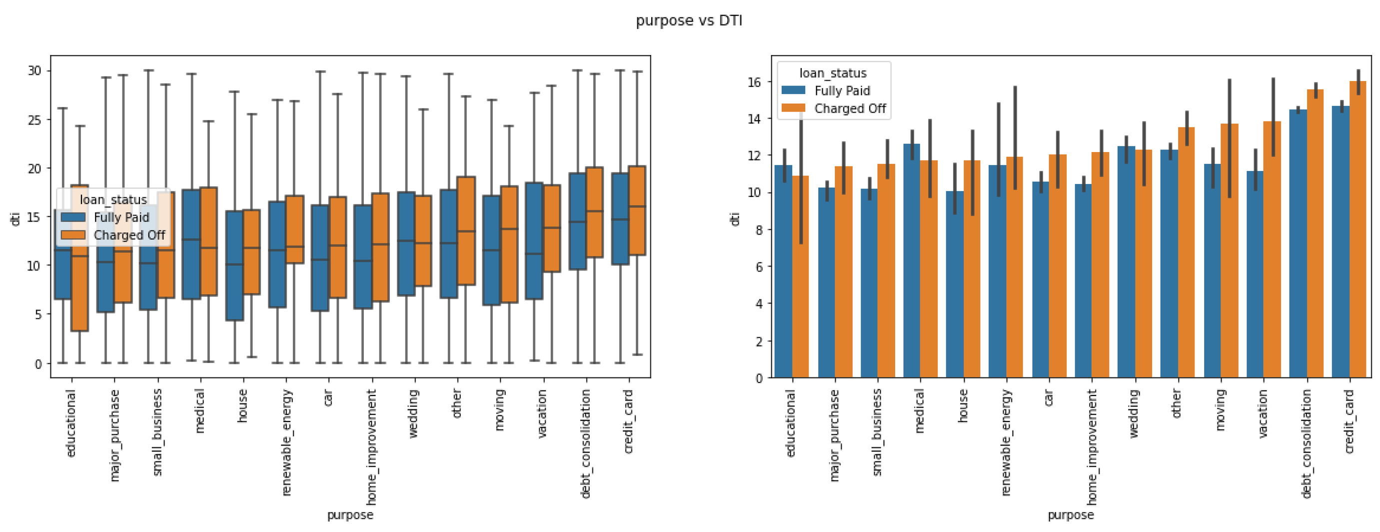


Observations:

Home loans with high interest rates are mostly defaulted. Even small business and debt consolidation has similar observation.

In [116]:
```
df = data.groupby(['purpose', 'loan_status'], as_index=False)['dti'].median()
purpose_ord = df[df.loan_status == 'Charged Off'].sort_values(by='dti').purpose

plt.figure(figsize=(20,5))
plt.suptitle('purpose vs DTI')
plt.subplot(121)
sns.boxplot(x='purpose', y='dti', hue='loan_status', data=data, order=purpose_ord)
plt.xticks(rotation=90)
plt.subplot(122)
sns.barplot(x='purpose', y='dti', hue='loan_status', data=data, estimator=np.median, order = purpose_ord)
plt.xticks(rotation=90)
plt.show()
```

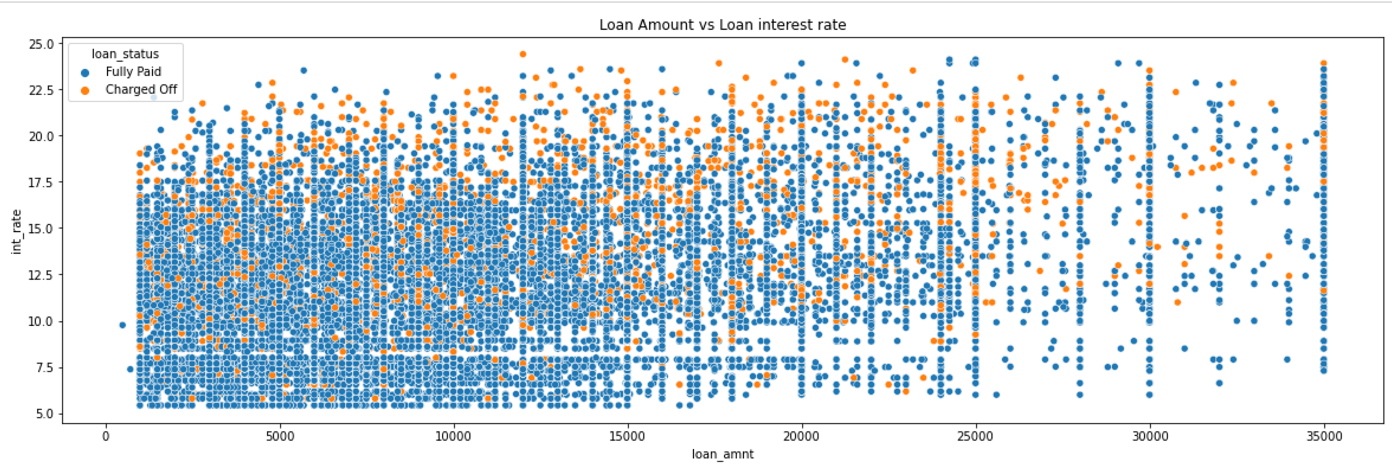


Observations:

Could not find any pattern from this plot.

Loan Amount vs Interest Rate

In [117]:
```
plt.figure(figsize=(20,6))
#scatter plot for analysing distribution
sns.scatterplot(x='loan_amnt', y='int_rate', data=data, hue='loan_status')
plt.title('Loan Amount vs Loan interest rate')
plt.show()
```

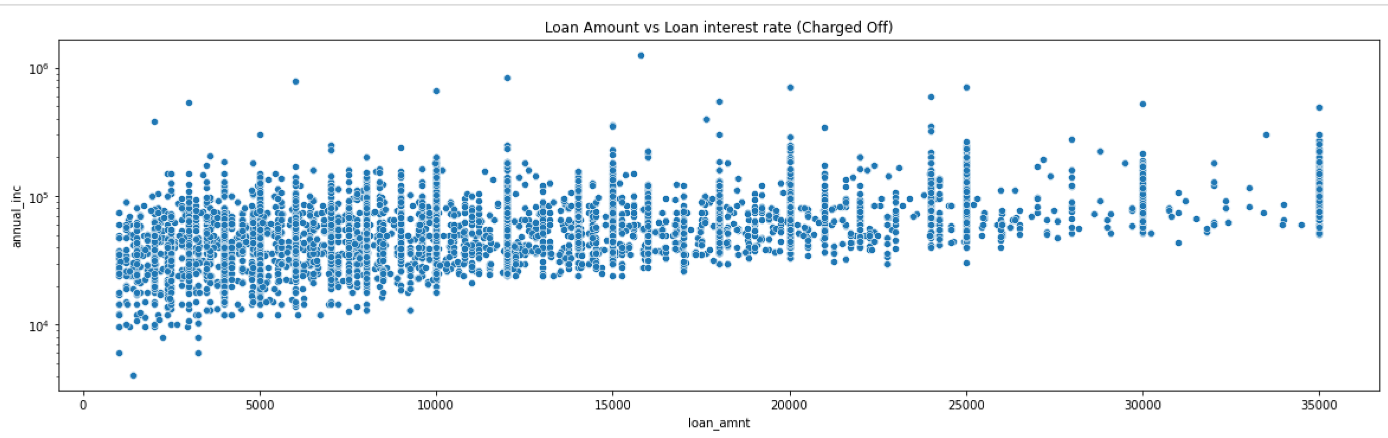


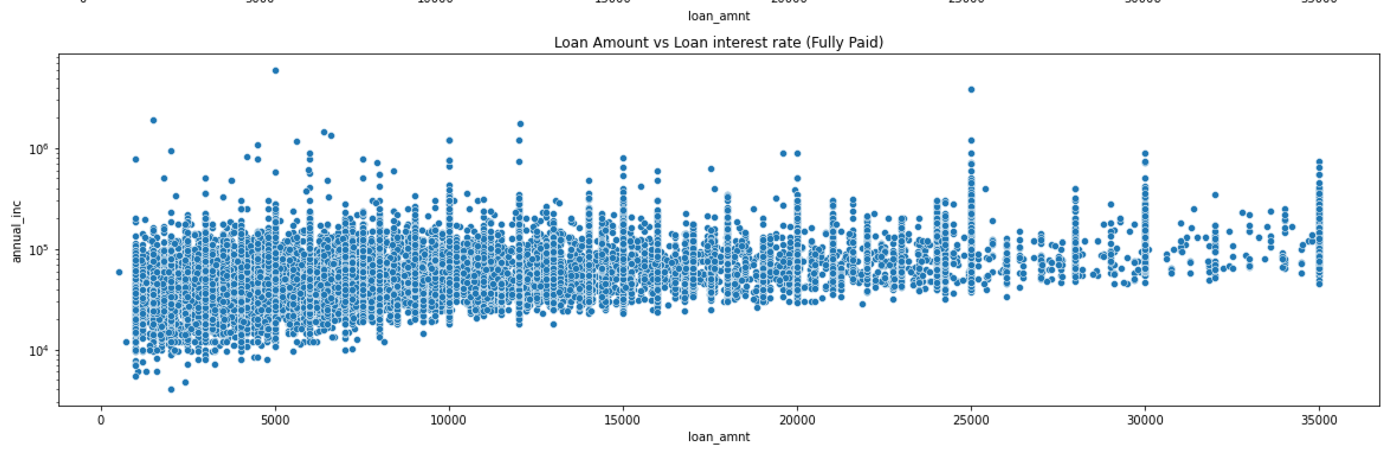
Observations:

Values are pretty much spread accross all the space. There is not specific pattern found in the spread.

Loan Amount vs Annual income

In [118]:
```
plt.figure(figsize=(20,12))
plt.subplot(211)
sns.scatterplot(x='loan_amnt', y='annual_inc', data=data[data.loan_status == 'Charged Off'])
plt.yscale('log')
plt.title('Loan Amount vs Loan interest rate (Charged Off)')
plt.subplot(212)
sns.scatterplot(x='loan_amnt', y='annual_inc', data=data[data.loan_status == 'Fully Paid'])
plt.yscale('log')
plt.title('Loan Amount vs Loan interest rate (Fully Paid)')
plt.show()
```



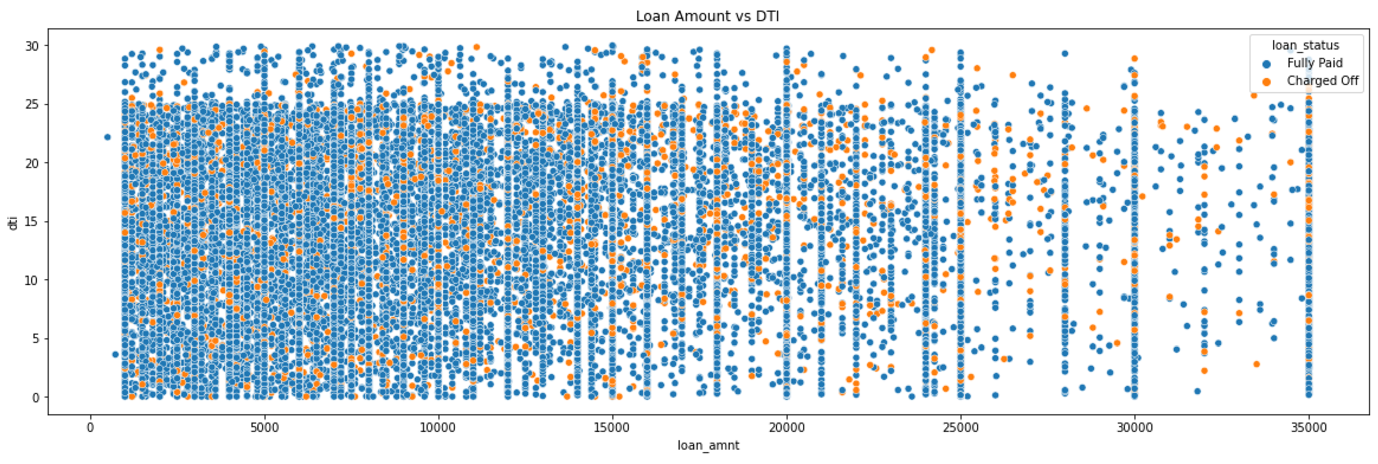


Observations:

Both Fully paid and Charged Off loans are having similar pattern versus Annual income. We can fit a linear pattern with a line which has very much less slope.

Loan Amount vs DTI

In [119]:
```
plt.figure(figsize=(20,6))
sns.scatterplot(x='loan_amnt', y='dti', data=data, hue='loan_status')
plt.title('Loan Amount vs DTI')
plt.show()
```



Observations:

Values are pretty much spread accross all the space. There is not specific pattern found in the spread.

Interest Rate vs DTI

In [120]:
```
plt.figure(figsize=(20,6))
sns.scatterplot(x='int_rate', y='dti', data=data, hue='loan_status')
plt.title('Interest rate vs DTI')
plt.show()
```

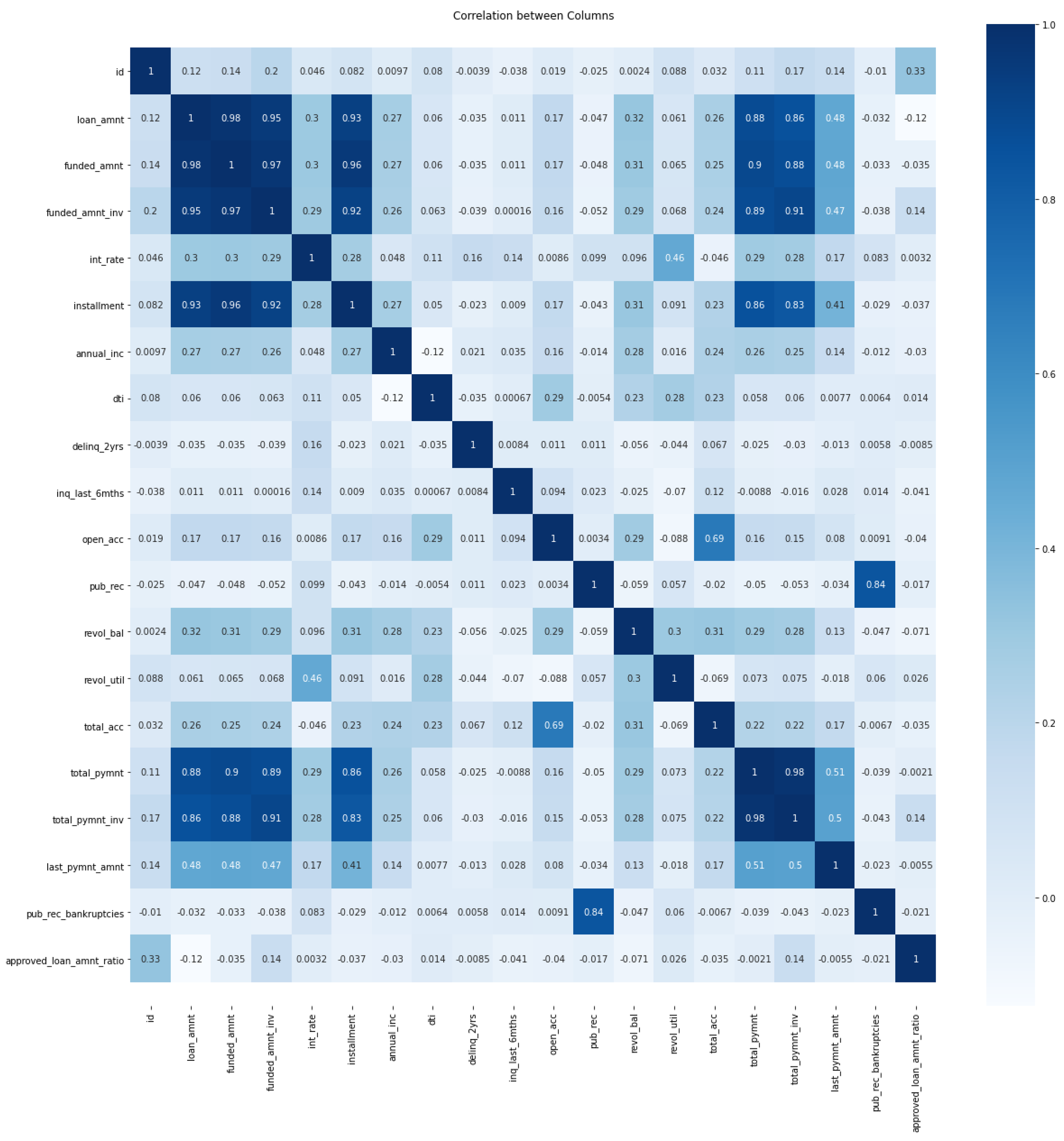
Observations:

Values are spread all accross, but we can see one thing here irrespective of DTI when interest rates are high charged off loans are high.

Correlation Matrix

finding the correlation between the variables of dataset

In [121]:
```
#Finding correlation matric
corr_matrix = data.corr()
plt.figure(figsize=(20,20))
#plotting correlatioon matric on a heat map
ax = sns.heatmap(corr_matrix, annot = True, cmap='Blues')
top, bottom = ax.get_ylim()
ax.set_ylim(top+0.5, bottom-0.5)
plt.title("Correlation between Columns")
plt.show()
```



Observations:

The no. of derogatory public records column is highly correlated with public bankruptcies records.
Interest rates are high for people with high revol utilisation.

Conclusion

1. irrespective of DTI when interest rates are high charged off loans are high.
2. Home loans with high interest rates are mostly defaulted.
3. Small Business has more defaults when the loan amount is also high.
4. Charged-off loan status are higher for small_business comparitively.
5. Irrespective of verification status higher interest rates are incurring default of loan.
6. More number of borrowers defaulted in CA , FL and NY states.
7. Irrespictive of Home owner ship, when the interest rate is high the dafault rate also high.
8. Irrespictive of employment length loans with more interest rates got defaulted more.
9. As grade decreases the interest rate gradually increases. and they are more and more prone to default the loan.
10. The lower grade people has taken higher amount of loans and also they are more prone to default the loan.
11. Interest rates are high for people with high revol utilisation.

In [ ]: