Lending Club Default Analysis

Background

Lending club is the largest peer-to-peer marketplace connecting borrowers with lenders. Borrowers apply through an online platform where they are assigned an internal score. Lenders decide 1) Whether to lend and 2) The terms of loan such as interest rate, monthly instalment, tenure etc.

Background Objective

The aim is to identify patterns which indicate if a person is likely to default, which may be used for taking actions such as denying the loan, reducing the amount of loan, lending (to risky applicants) at a higher interest rate, etc.

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

In [2]:
```
df=pd.read_csv('loan.csv')
df
```

Out[2]:

	id	member_id	loan_amnt	funded_amnt	funded_amnt_inv	term	int_rate	installme
0	1077501	1296599	5000	5000	4975.0	36 months	10.65%	162.
1	1077430	1314167	2500	2500	2500.0	60 months	15.27%	59.
2	1077175	1313524	2400	2400	2400.0	36 months	15.96%	84.
3	1076863	1277178	10000	10000	10000.0	36 months	13.49%	339.
4	1075358	1311748	3000	3000	3000.0	60 months	12.69%	67.
...	...	...	...	...	...	...	...	
39712	92187	92174	2500	2500	1075.0	36 months	8.07%	78.
39713	90665	90607	8500	8500	875.0	36 months	10.28%	275.
39714	90395	90390	5000	5000	1325.0	36 months	8.07%	156.
39715	90376	89243	5000	5000	650.0	36 months	7.43%	155.
39716	87023	86999	7500	7500	800.0	36 months	13.75%	255.

39717 rows × 111 columns

In [3]:
```
df.shape
```

Out[3]:
```
(39717, 111)
```

In [4]:
```
df.columns
```

Out[4]:
```
Index(['id', 'member_id', 'loan_amnt', 'funded_amnt', 'funded_amnt_inv',
       'term', 'int_rate', 'installment', 'grade', 'sub_grade',
       ...
       'num_tl_90g_dpd_24m', 'num_tl_op_past_12m', 'pct_tl_nvr_dlq',
       'percent_bc_gt_75', 'pub_rec_bankruptcies', 'tax_liens',
       'tot_hi_cred_lim', 'total_bal_ex_mort', 'total_bc_limit',
       'total_il_high_credit_limit'],
      dtype='object', length=111)
```

In [5]:
```
pd.set_option('display.max_columns',None)
#pd.set_option('display.max_rows',None)
```

In [6]:
```
df.head(4)
```

Out[6]:

	id	member_id	loan_amnt	funded_amnt	funded_amnt_inv	term	int_rate	installment
0	1077501	1296599	5000	5000	4975.0	36 months	10.65%	162.87
1	1077430	1314167	2500	2500	2500.0	60 months	15.27%	59.83
2	1077175	1313524	2400	2400	2400.0	36 months	15.96%	84.33
3	1076863	1277178	10000	10000	10000.0	36 months	13.49%	339.31

In [7]:
```
# Checking for null values
df.isnull().sum()
```

Out[7]:
```
id                             0
member_id                      0
loan_amnt                      0
funded_amnt                    0
funded_amnt_inv                0
                           ...
tax_liens                     39
tot_hi_cred_lim            39717
total_bal_ex_mort          39717
total_bc_limit             39717
total_il_high_credit_limit 39717
Length: 111, dtype: int64
```

In [8]:
```
# percentage of missing values in each column
round(df.isnull().sum()/len(df.index), 2)*100
```

Out[8]:
```
id                              0.0
member_id                       0.0
loan_amnt                       0.0
funded_amnt                     0.0
funded_amnt_inv                 0.0
                              ...
tax_liens                       0.0
tot_hi_cred_lim               100.0
total_bal_ex_mort             100.0
total_bc_limit                100.0
total_il_high_credit_limit    100.0
Length: 111, dtype: float64
```

In [9]:
```
# removing the columns having more than 100% missing values
missing_columns = df.columns[100*(df.isnull().sum()/len(df.index))==100]
print(missing_columns)
```

```
Index(['mths_since_last_major_derog', 'annual_inc_joint', 'dti_joint',
       'verification_status_joint', 'tot_coll_amt', 'tot_cur_bal',
       'open_acc_6m', 'open_il_6m', 'open_il_12m', 'open_il_24m',
       'mths_since_rcnt_il', 'total_bal_il', 'il_util', 'open_rv_12m',
       'open_rv_24m', 'max_bal_bc', 'all_util', 'total_rev_hi_lim', 'inq_fi',
       'total_cu_tl', 'inq_last_12m', 'acc_open_past_24mths', 'avg_cur_bal',
       'bc_open_to_buy', 'bc_util', 'mo_sin_old_il_acct',
       'mo_sin_old_rev_tl_op', 'mo_sin_rcnt_rev_tl_op', 'mo_sin_rcnt_tl',
       'mort_acc', 'mths_since_recent_bc', 'mths_since_recent_bc_dlq',
       'mths_since_recent_inq', 'mths_since_recent_revol_delinq',
       'num_accts_ever_120_pd', 'num_actv_bc_tl', 'num_actv_rev_tl',
       'num_bc_sats', 'num_bc_tl', 'num_il_tl', 'num_op_rev_tl',
       'num_rev_accts', 'num_rev_tl_bal_gt_0', 'num_sats', 'num_tl_120dpd_2m',
       'num_tl_30dpd', 'num_tl_90g_dpd_24m', 'num_tl_op_past_12m',
       'pct_tl_nvr_dlq', 'percent_bc_gt_75', 'tot_hi_cred_lim',
       'total_bal_ex_mort', 'total_bc_limit', 'total_il_high_credit_limit'],
      dtype='object')
```

In [10]:
```
df=df.drop(missing_columns,axis=1)
df.shape
```

Out[10]:
```
(39717, 57)
```

In [11]:
```
# Checking for null value percentage
100*(df.isnull().sum()/len(df.index))
```

Out[11]:
```
id                             0.000000
member_id                      0.000000
loan_amnt                      0.000000
funded_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_title                      6.191303
emp_length                     2.706650
home_ownership                 0.000000
annual_inc                     0.000000
verification_status            0.000000
issue_d                        0.000000
loan_status                    0.000000
pymnt_plan                     0.000000
url                            0.000000
desc                          32.580507
purpose                        0.000000
title                          0.027696
zip_code                       0.000000
addr_state                     0.000000
dti                            0.000000
delinq_2yrs                    0.000000
earliest_cr_line               0.000000
inq_last_6mths                 0.000000
mths_since_last_delinq        64.662487
mths_since_last_record        92.985372
open_acc                       0.000000
pub_rec                        0.000000
revol_bal                      0.000000
revol_util                     0.125891
total_acc                      0.000000
initial_list_status            0.000000
out_prncp                      0.000000
out_prncp_inv                  0.000000
total_pymnt                    0.000000
total_pymnt_inv                0.000000
total_rec_prncp                0.000000
total_rec_int                  0.000000
total_rec_late_fee             0.000000
recoveries                     0.000000
collection_recovery_fee        0.000000
last_pymnt_d                   0.178765
last_pymnt_amnt                0.000000
next_pymnt_d                  97.129693
last_credit_pull_d             0.005036
collections_12_mths_ex_med     0.140998
policy_code                    0.000000
application_type               0.000000
acc_now_delinq                 0.000000
```

```
chargeoff_within_12_mths      0.140998
delinq_amnt                   0.000000
pub_rec_bankruptcies          1.754916
tax_liens                     0.098195
dtype: float64
```

In [12]:
```
# Dropping columns with >90% missing values
df=df.drop(df.columns[100*(df.isnull().sum()/len(df.index))>=90],axis=1)
df.shape
```

Out[12]: (39717, 55)

In [13]:
```
# There are now 2 columns having approx 32 and 64% missing values -
# description and months since last delinquent
# let's have a look at a few entries in the columns
df[['desc', 'mths_since_last_delinq']].head()
```

Out[13]:

	desc	mths_since_last_delinq
0	Borrower added on 12/22/11 > I need to upgra...	NaN
1	Borrower added on 12/22/11 > I plan to use t...	NaN
2	NaN	NaN
3	Borrower added on 12/21/11 > to pay for prop...	35.0
4	Borrower added on 12/21/11 > I plan on combi...	38.0

The column description contains the comments the applicant had written while applying for the loan. This column is not in use in this analysis.

Secondly, months since last delinquent represents the number months passed since the person last fell into the 90 DPD group. Since at the time of loan application, we will not have this data (it gets generated months after the loan has been approved), it cannot be used as a predictor of default at the time of loan approval.

Thus let's drop the two columns.

In [14]:
```
df=df.drop(['desc', 'mths_since_last_delinq'],axis=1)
df.shape
```

Out[14]: (39717, 53)

In [15]:
```
100*(df.isnull().sum()/len(df.index))
```

Out[15]:
```
id                            0.000000
member_id                     0.000000
loan_amnt                     0.000000
funded_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_title                     6.191303
emp_length                    2.706650
home_ownership                0.000000
annual_inc                    0.000000
verification_status           0.000000
issue_d                       0.000000
loan_status                   0.000000
pymnt_plan                    0.000000
url                           0.000000
purpose                       0.000000
title                         0.027696
zip_code                      0.000000
addr_state                    0.000000
dti                           0.000000
delinq_2yrs                   0.000000
earliest_cr_line              0.000000
inq_last_6mths                0.000000
open_acc                      0.000000
pub_rec                       0.000000
revol_bal                     0.000000
revol_util                    0.125891
total_acc                     0.000000
initial_list_status           0.000000
out_prncp                     0.000000
out_prncp_inv                 0.000000
total_pymnt                   0.000000
total_pymnt_inv               0.000000
total_rec_prncp               0.000000
total_rec_int                 0.000000
total_rec_late_fee            0.000000
recoveries                    0.000000
collection_recovery_fee       0.000000
last_pymnt_d                  0.178765
last_pymnt_amnt               0.000000
last_credit_pull_d            0.005036
collections_12_mths_ex_med    0.140998
policy_code                   0.000000
application_type              0.000000
acc_now_delinq                0.000000
chargeoff_within_12_mths      0.140998
delinq_amnt                   0.000000
pub_rec_bankruptcies          1.754916
tax_liens                     0.098195
dtype: float64
```

There are some more columns with missing values,but we will ignore them as of now due to less percentage of missing values.

Now checking for rows with missing values.

In [16]:
```
(df.isnull().sum(axis=1))
```

Out[16]:
```
0        1
1        0
2        1
3        0
4        0
        ..
39712    4
39713    4
39714    5
39715    5
39716    4
Length: 39717, dtype: int64
```

In [17]:
```
(df.isnull().sum(axis=1)>5).sum()
```

Out[17]:
```
0
```

Since there are no missing values >5 in rows, lets ignore effect of NaNs.

In [18]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 39717 entries, 0 to 39716
Data columns (total 53 columns):
 #   Column                      Non-Null Count  Dtype  
---  ------                      --------------  -----  
 0   id                          39717 non-null  int64  
 1   member_id                   39717 non-null  int64  
 2   loan_amnt                   39717 non-null  int64  
 3   funded_amnt                 39717 non-null  int64  
 4   funded_amnt_inv             39717 non-null  float64
 5   term                        39717 non-null  object 
 6   int_rate                    39717 non-null  object 
 7   installment                 39717 non-null  float64
 8   grade                       39717 non-null  object 
 9   sub_grade                   39717 non-null  object 
 10  emp_title                   37258 non-null  object 
 11  emp_length                  38642 non-null  object 
 12  home_ownership              39717 non-null  object 
 13  annual_inc                  39717 non-null  float64
 14  verification_status         39717 non-null  object 
 15  issue_d                     39717 non-null  object 
 16  loan_status                 39717 non-null  object 
 17  pymnt_plan                  39717 non-null  object 
 18  url                         39717 non-null  object 
 19  purpose                     39717 non-null  object 
 20  title                       39706 non-null  object 
 21  zip_code                    39717 non-null  object 
 22  addr_state                  39717 non-null  object 
 23  dti                         39717 non-null  float64
 24  delinq_2yrs                 39717 non-null  int64  
 25  earliest_cr_line            39717 non-null  object 
 26  inq_last_6mths              39717 non-null  int64  
 27  open_acc                    39717 non-null  int64  
 28  pub_rec                     39717 non-null  int64  
 29  revol_bal                   39717 non-null  int64  
 30  revol_util                  39667 non-null  object 
 31  total_acc                   39717 non-null  int64  
 32  initial_list_status         39717 non-null  object 
 33  out_prncp                   39717 non-null  float64
 34  out_prncp_inv               39717 non-null  float64
 35  total_pymnt                 39717 non-null  float64
 36  total_pymnt_inv             39717 non-null  float64
 37  total_rec_prncp             39717 non-null  float64
 38  total_rec_int               39717 non-null  float64
 39  total_rec_late_fee          39717 non-null  float64
 40  recoveries                  39717 non-null  float64
 41  collection_recovery_fee     39717 non-null  float64
 42  last_pymnt_d                39646 non-null  object 
 43  last_pymnt_amnt             39717 non-null  float64
 44  last_credit_pull_d          39715 non-null  object 
 45  collections_12_mths_ex_med  39661 non-null  float64
 46  policy_code                 39717 non-null  int64  
 47  application_type            39717 non-null  object 
 48  acc_now_delinq              39717 non-null  int64  
```

```
 49  chargeoff_within_12_mths    39661 non-null  float64
 50  delinq_amnt                 39717 non-null  int64
 51  pub_rec_bankruptcies        39020 non-null  float64
 52  tax_liens                   39678 non-null  float64
dtypes: float64(18), int64(13), object(22)
memory usage: 16.1+ MB
```

In [19]:
```
# The column int_rate is character type, let's convert it to float
df['int_rate'] = df['int_rate'].apply(lambda x: float(x.split("%")[0]))
df['int_rate']
```

Out[19]:
```
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: float64
```

In [20]:
```
df.emp_length.head(2)
```

Out[20]:
```
0    10+ years
1     < 1 year
Name: emp_length, dtype: object
```

In [21]:
```
df.emp_length.shape
```

Out[21]:
```
(39717,)
```

In [22]:
```
df.emp_length=df.emp_length[~df.emp_length.isnull()].apply(lambda x: x.replace('+
df.emp_length
```

Out[22]:
```
0        10.0
1         1.0
2        10.0
3        10.0
4         1.0
         ...
39712     4.0
39713     3.0
39714     1.0
39715     1.0
39716     1.0
Name: emp_length, Length: 39717, dtype: float64
```

In [23]:
```
df.emp_length.shape
```

Out[23]:
```
(39717,)
```

In [24]:
```
df.emp_length.dtype
```

Out[24]:
```
dtype('float64')
```

Data Analysis

The variables related to customer behaviour are not available at the time of loan application, and thus they cannot be used as predictors for credit approval.

Thus we are going to drop the variables related to customer behavior.

In [25]:
```
behaviour_var =  [
  "delinq_2yrs",
  "earliest_cr_line",
  "inq_last_6mths",
  "open_acc",
  "pub_rec",
  "revol_bal",
  "revol_util",
  "total_acc",
  "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",
  "last_credit_pull_d",
  "application_type"]
behaviour_var
```

Out[25]:
```
['delinq_2yrs',
 'earliest_cr_line',
 'inq_last_6mths',
 'open_acc',
 'pub_rec',
 'revol_bal',
 'revol_util',
 'total_acc',
 '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',
 'last_credit_pull_d',
 'application_type']
```

In [26]:
```
# let's now remove the behaviour variables from analysis
df = df.drop(behaviour_var, axis=1)
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 39717 entries, 0 to 39716
Data columns (total 32 columns):
 #   Column                      Non-Null Count  Dtype  
---  ------                      --------------  -----  
 0   id                          39717 non-null  int64  
 1   member_id                   39717 non-null  int64  
 2   loan_amnt                   39717 non-null  int64  
 3   funded_amnt                 39717 non-null  int64  
 4   funded_amnt_inv             39717 non-null  float64
 5   term                        39717 non-null  object 
 6   int_rate                    39717 non-null  float64
 7   installment                 39717 non-null  float64
 8   grade                       39717 non-null  object 
 9   sub_grade                   39717 non-null  object 
 10  emp_title                   37258 non-null  object 
 11  emp_length                  38642 non-null  float64
 12  home_ownership              39717 non-null  object 
 13  annual_inc                  39717 non-null  float64
 14  verification_status         39717 non-null  object 
 15  issue_d                     39717 non-null  object 
 16  loan_status                 39717 non-null  object 
 17  pymnt_plan                  39717 non-null  object 
 18  url                         39717 non-null  object 
 19  purpose                     39717 non-null  object 
 20  title                       39706 non-null  object 
 21  zip_code                    39717 non-null  object 
 22  addr_state                  39717 non-null  object 
 23  dti                         39717 non-null  float64
 24  initial_list_status         39717 non-null  object 
 25  collections_12_mths_ex_med  39661 non-null  float64
 26  policy_code                 39717 non-null  int64  
 27  acc_now_delinq              39717 non-null  int64  
 28  chargeoff_within_12_mths    39661 non-null  float64
 29  delinq_amnt                 39717 non-null  int64  
 30  pub_rec_bankruptcies        39020 non-null  float64
 31  tax_liens                   39678 non-null  float64
dtypes: float64(10), int64(7), object(15)
memory usage: 9.7+ MB
```

In [27]:
```
# Also, we will not be able to use the variables zip code, address, state etc.
# The variable 'title' is derived from the variable 'purpose' ,thus let get rid o

df = df.drop(['title', 'url', 'zip_code', 'addr_state'], axis=1)
df.head()
```

Out[27]:

	id	member_id	loan_amnt	funded_amnt	funded_amnt_inv	term	int_rate	installment
0	1077501	1296599	5000	5000	4975.0	36 months	10.65	162.87
1	1077430	1314167	2500	2500	2500.0	60 months	15.27	59.83
2	1077175	1313524	2400	2400	2400.0	36 months	15.96	84.33
3	1076863	1277178	10000	10000	10000.0	36 months	13.49	339.31
4	1075358	1311748	3000	3000	3000.0	60 months	12.69	67.79

Here the target variable is loan_status. We need to relabel the values to a binary form - 0 or 1, 1 indicating that the person has defaulted and 0 otherwise.

In [28]:
```
#df['loan_status'] = df['loan_status'].astype('category')
df['loan_status'].value_counts()
```

Out[28]:
```
Fully Paid     32950
Charged Off     5627
Current         1140
Name: loan_status, dtype: int64
```

We can see that fully paid comprises most of the loans. The ones marked 'current' are neither fully paid not defaulted, so we get rid of the current loans. Also, let's tag the other two values as 0 or 1.

In [29]:
```
df=df[~(df['loan_status'] == 'Current')]
df
```

Out[29]:

	id	member_id	loan_amnt	funded_amnt	funded_amnt_inv	term	int_rate	installme
0	1077501	1296599	5000	5000	4975.0	36 months	10.65	162.
1	1077430	1314167	2500	2500	2500.0	60 months	15.27	59.
2	1077175	1313524	2400	2400	2400.0	36 months	15.96	84.
3	1076863	1277178	10000	10000	10000.0	36 months	13.49	339.
5	1075269	1311441	5000	5000	5000.0	36 months	7.90	156.
...	...	...	...	...	...	...	...	
39712	92187	92174	2500	2500	1075.0	36 months	8.07	78.
39713	90665	90607	8500	8500	875.0	36 months	10.28	275.
39714	90395	90390	5000	5000	1325.0	36 months	8.07	156.
39715	90376	89243	5000	5000	650.0	36 months	7.43	155.
39716	87023	86999	7500	7500	800.0	36 months	13.75	255.

38577 rows × 28 columns

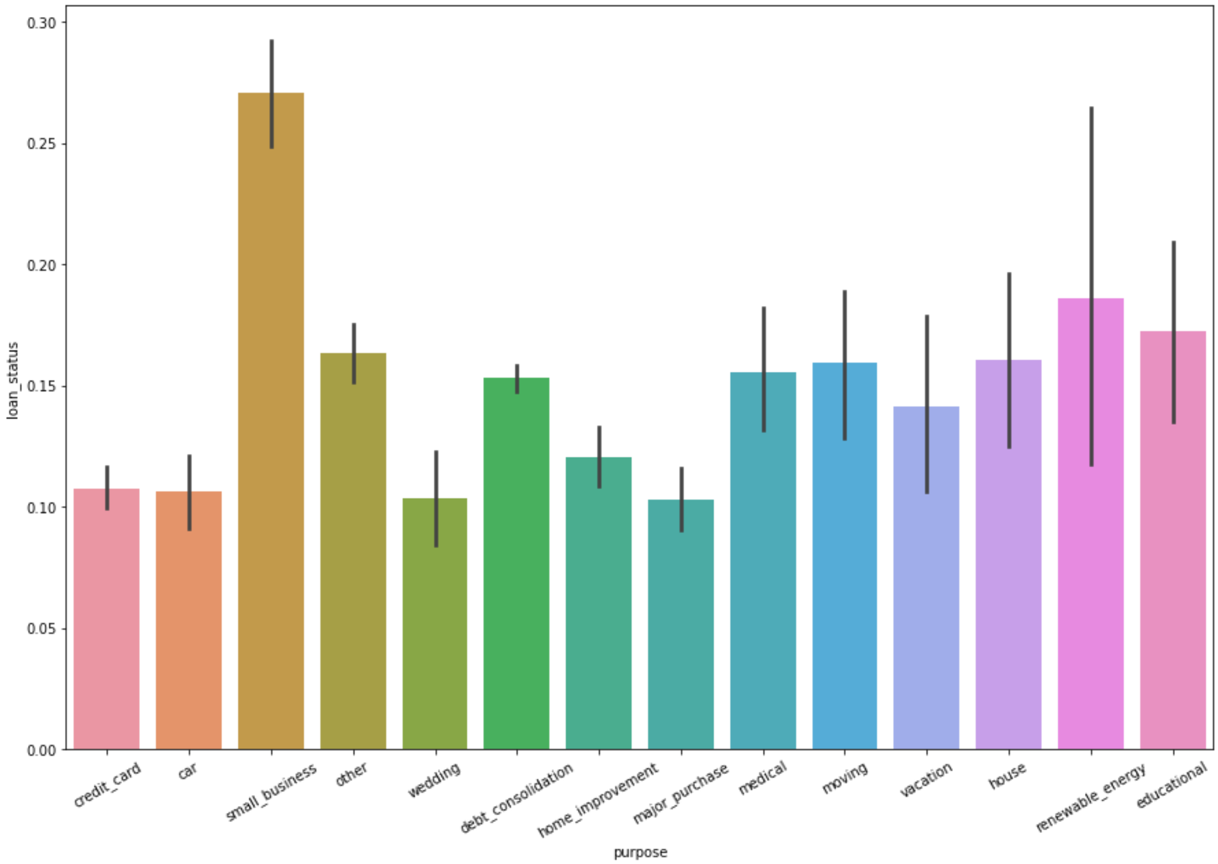
In [30]:
```
df['loan_status']=df['loan_status'].apply(lambda x:0 if x=='Fully Paid' else 1)
df['loan_status'].value_counts()
```

Out[30]:
```
0    32950
1     5627
Name: loan_status, dtype: int64
```

In [31]:
```
# Over all default rate.
100*((df['loan_status']==1).sum())/len(df.index)
```

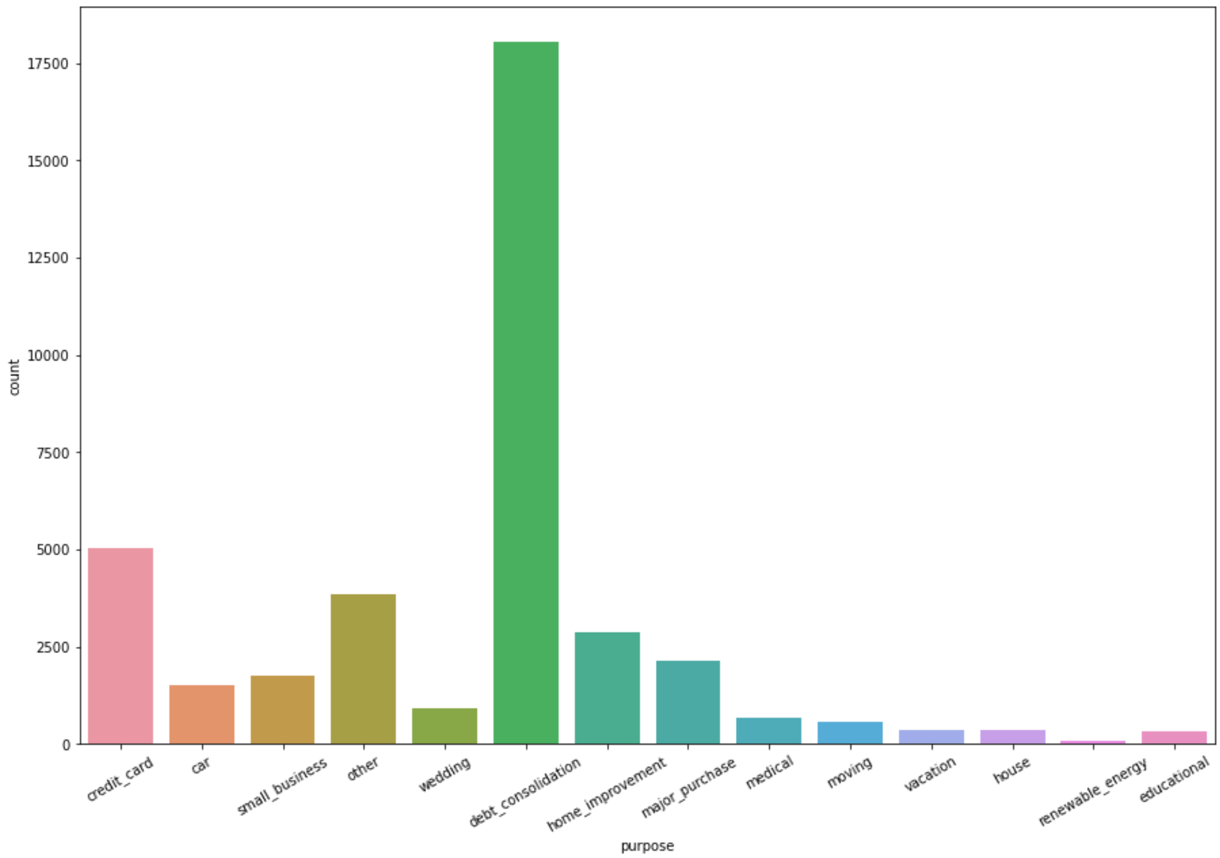
Out[31]:
```
14.586411592399616
```

In [32]:
```
# plotting for loans of different purpose against default rate.
plt.figure(figsize=[15,10])
q=sns.barplot(x='purpose',y='loan_status',data=df)
q.set_xticklabels(q.get_xticklabels(),rotation=30)
plt.show()
```



From the above plot it can be infered that the loan application for small_business purpose is most likely to default, follwed by renewable_energy and education.

In [33]:
```
plt.figure(figsize=[15,10])
q=sns.countplot(x='purpose',data=df)
q.set_xticklabels(q.get_xticklabels(),rotation=30)
plt.show()
```



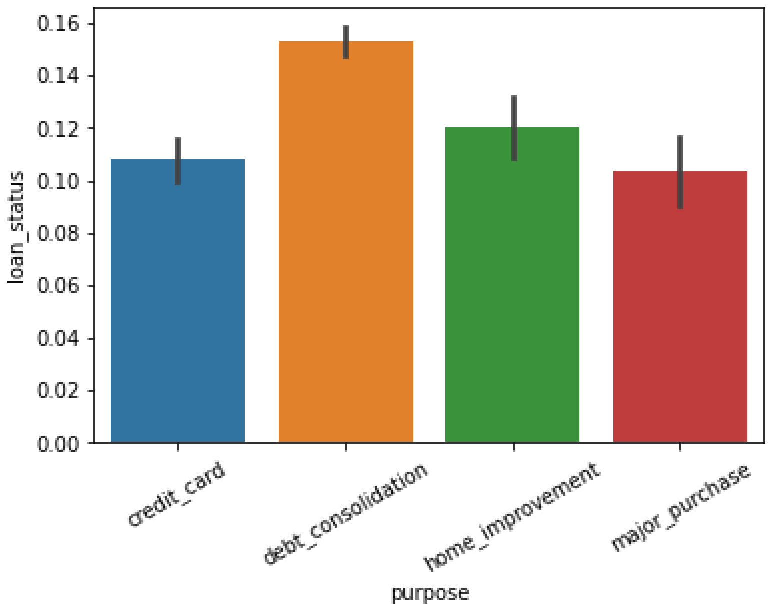
From the above plot it can be infered that most of the applicants are applying loan for the purpose of debt_consolidtion followed by credit_card, home_improvement and major_purchase.

Hence filtering the data only for these major categories and checking for the defaulties.

In [34]:
```
# Dropping all the categories which are irrelavent
df_maxpur=df[(df['purpose']=='credit_card')| (df['purpose']=='debt_consolidation'
              (df['purpose']=='home_improvement') | (df['purpose']=='major_purcha
df_maxpur.purpose.value_counts()
```

Out[34]:
```
debt_consolidation    18055
credit_card            5027
home_improvement       2875
major_purchase         2150
Name: purpose, dtype: int64
```

In [35]:
```
# bar plot for top 4 categories in purpose.
q=sns.barplot(x='purpose',y='loan_status',data=df_maxpur)
q.set_xticklabels(q.get_xticklabels(),rotation=30)
plt.show()
```

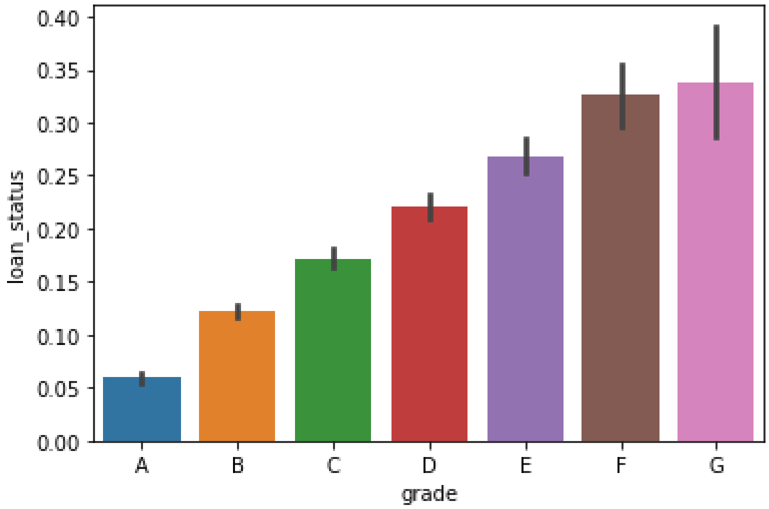


From the above plot it can be infered that among the top 4 purpose applicants applying for the debt_consolidation are more likely to default followed by home_impromen and credit_card.

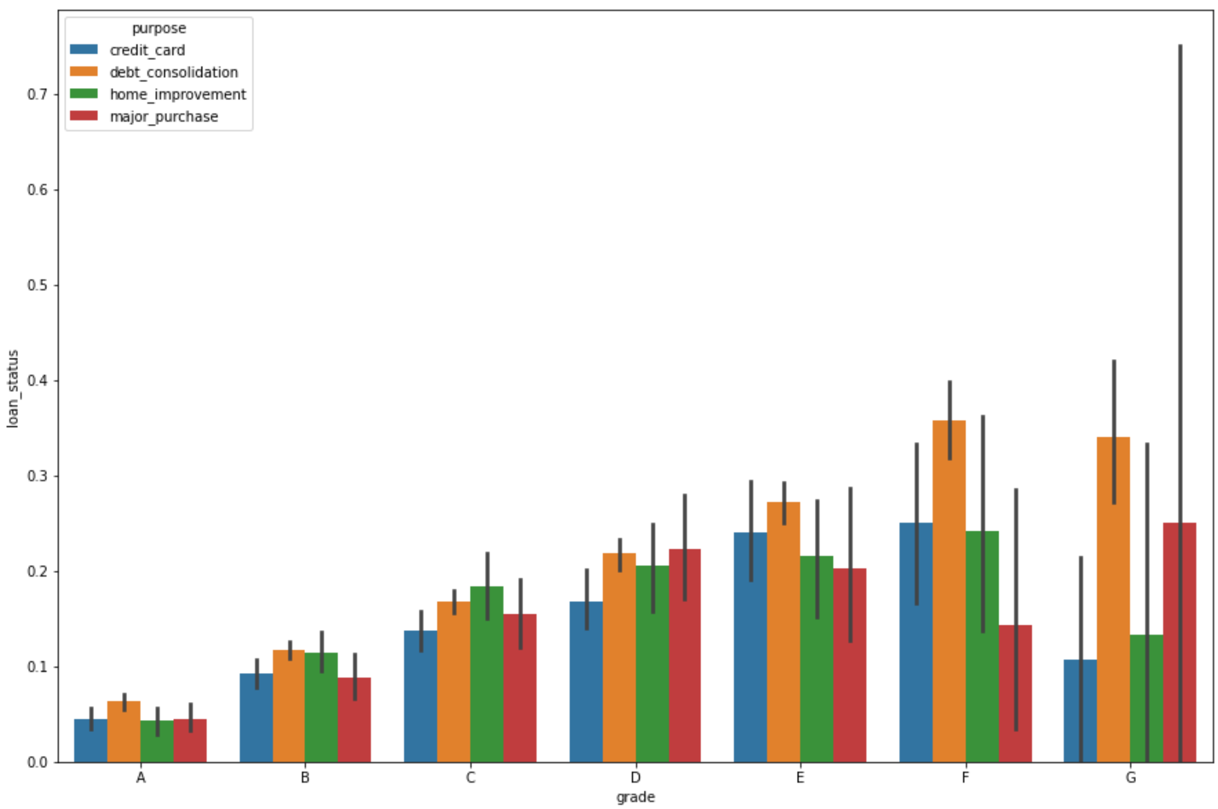
In [36]:
```
#Defining the function to plot categorical variable for 4 major purposes
def plot_catmaxpur(prv):
    sns.barplot(x=prv,y='loan_status',hue='purpose',data=df_maxpur)
    plt.show()
```

In [37]:
```
#Defining the function to plot categorical variable
def plot_cat(prv):
    sns.barplot(x=prv,y='loan_status',data=df)
    plt.show()
```

In [38]:
```
# plotting default rate across grade of loan
plot_cat(df.grade.sort_values())
```

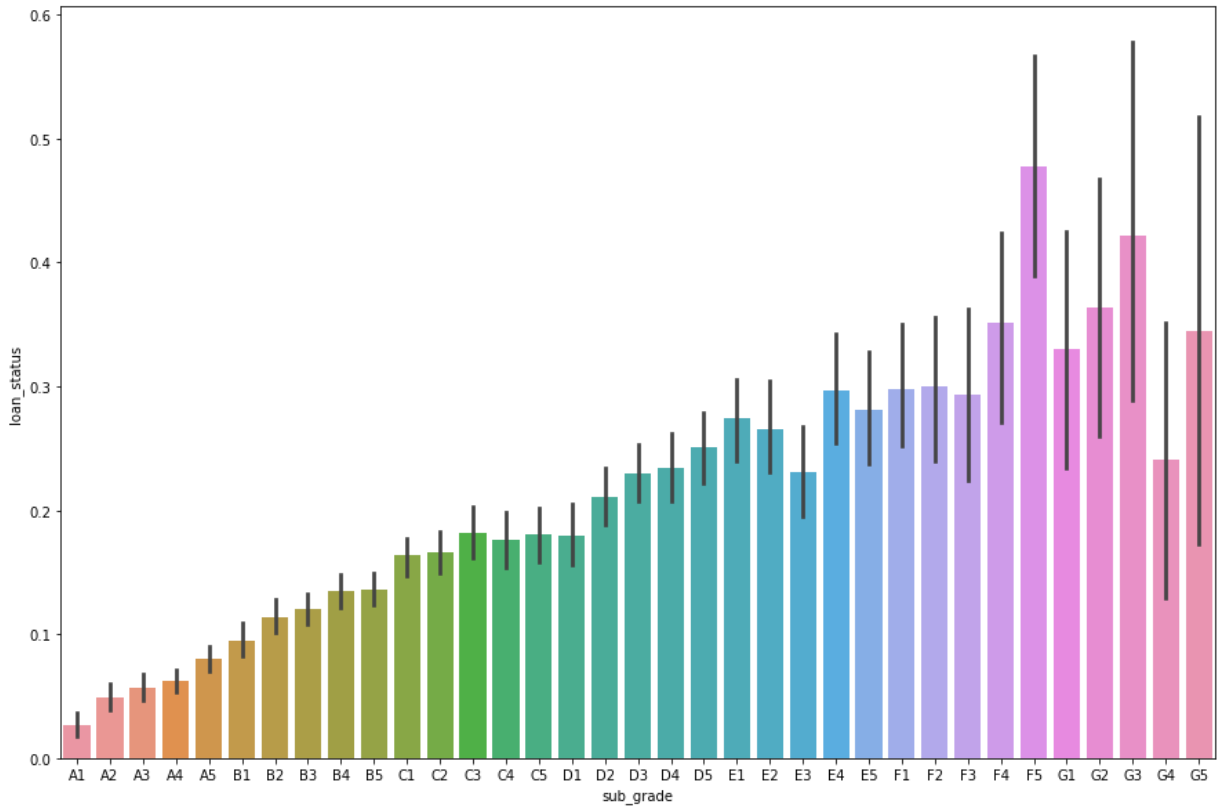


In [39]:
```
# plotting default rate across grade of loan for 4 major purposes.
plt.figure(figsize=[15,10])
plot_catmaxpur(df.grade.sort_values())
```



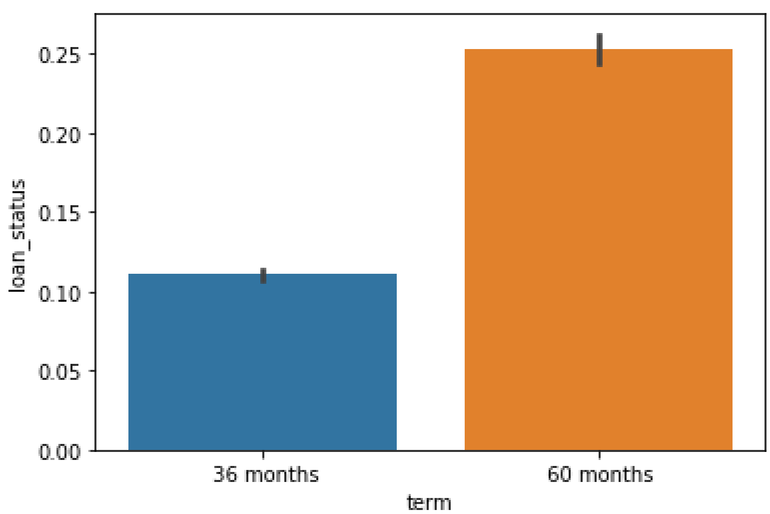
From the above plot it can be infered that as the aplicant with good grade is not likely too fall in defaults.This is expected because the grade is decided by Lending Club based on the riskiness of the loan. Among all the grade categories the debt_consolidation loans are more likely to defult.

In [40]:
```
# plotting for the sub grades
plt.figure(figsize=[15,10])
plot_cat(df.sub_grade.sort_values())
```

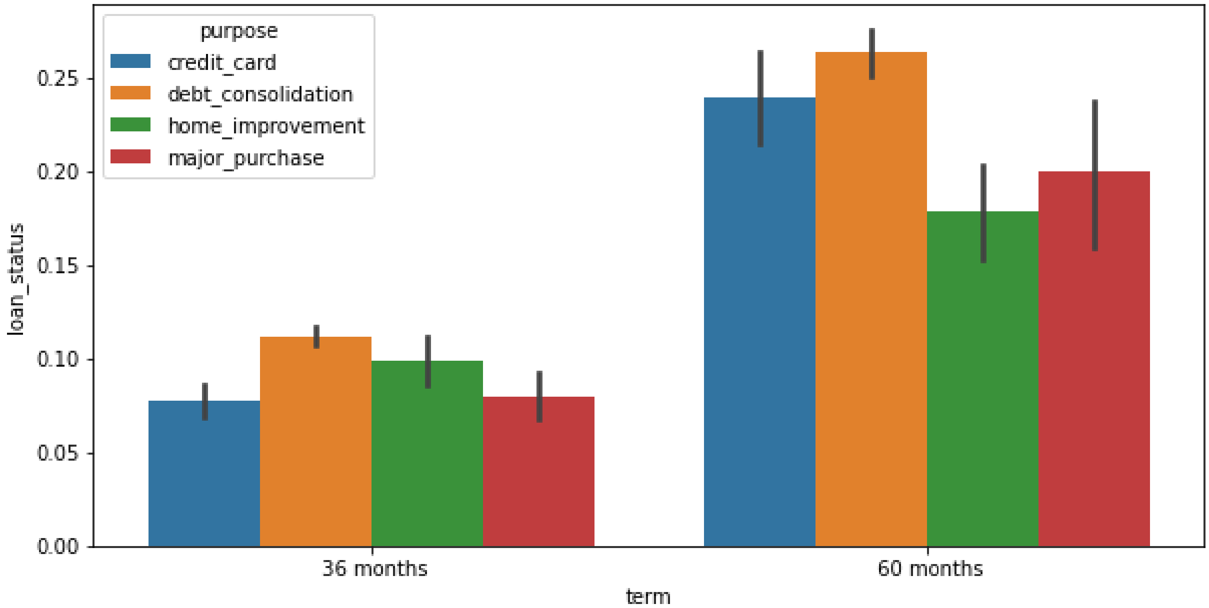


From the above plot it can be inferred that sub-grades also follows the same pattern as grades.

In [41]:
```
# plotting for term
plot_cat('term')
```

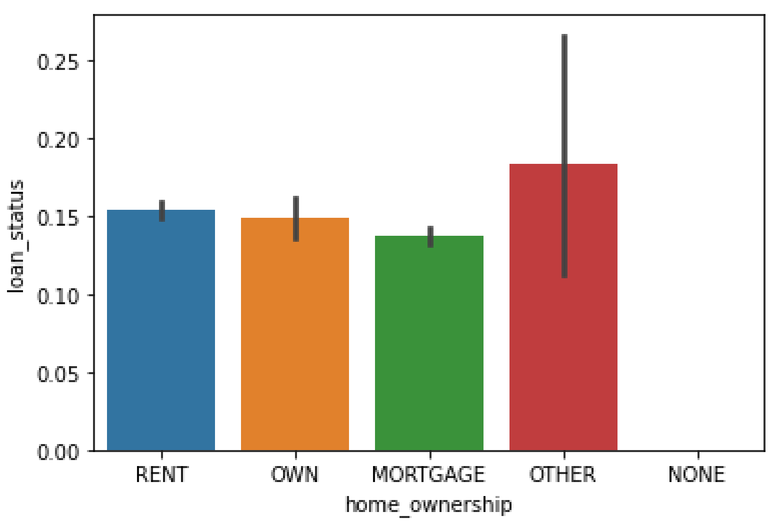


In [42]:
```
# plotting for term for 4 major purposes
plt.figure(figsize=[10,5])
plot_catmaxpur('term')
```

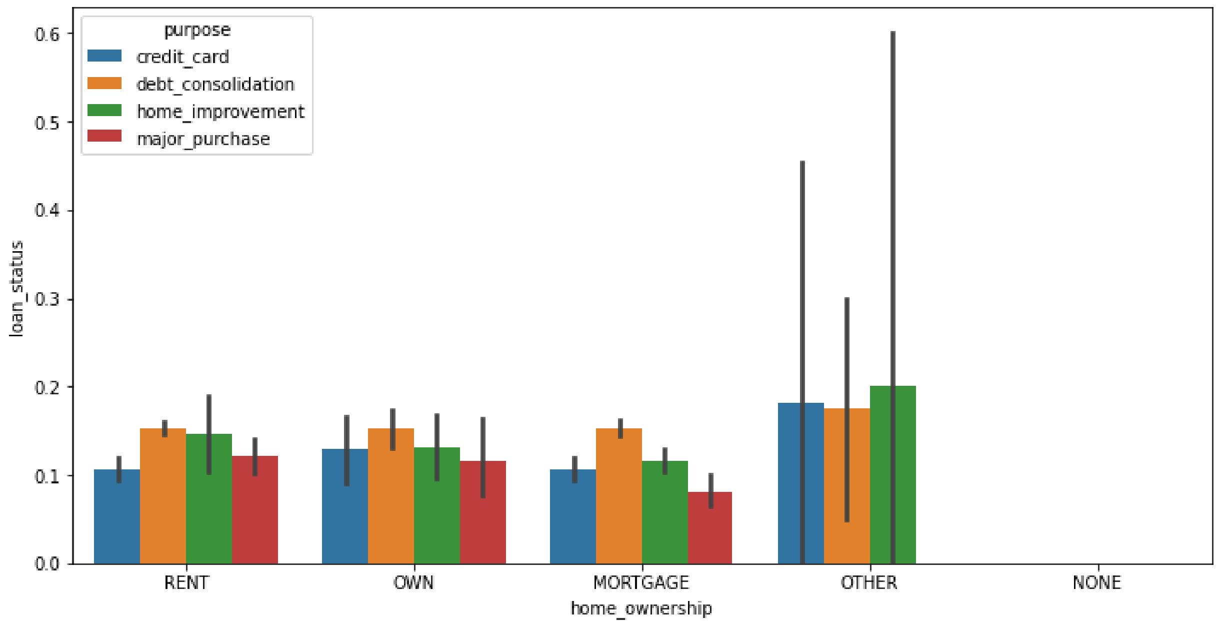


From the above plot it is infered that as the longterm loans are more likely to default.Among all the term categories the debt_consolidation loans are more likely to defult.

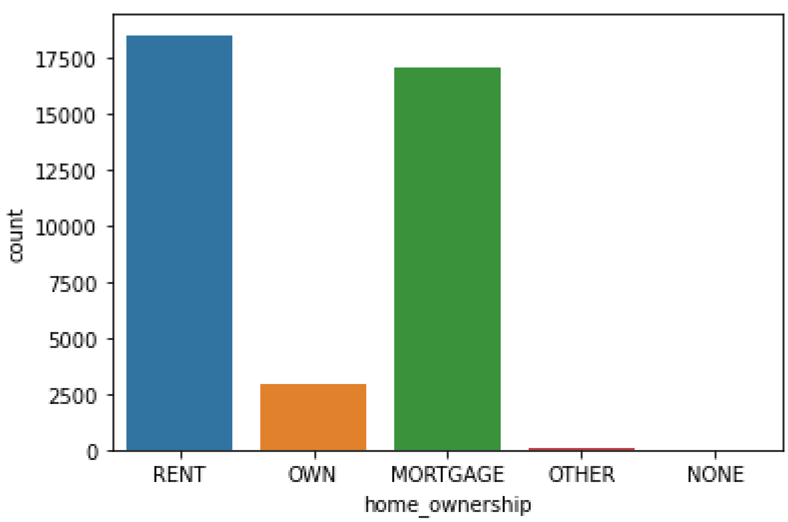
In [43]:
```
# plotting for home variables
plot_cat('home_ownership')
```



In [44]:
```
# plotting for term for 4 major purposes
plt.figure(figsize=[12,6])
plot_catmaxpur('home_ownership')
```



In [45]:
```
#plotting for frequency of home ownership
sns.countplot(x=df['home_ownership'])
plt.show()
```



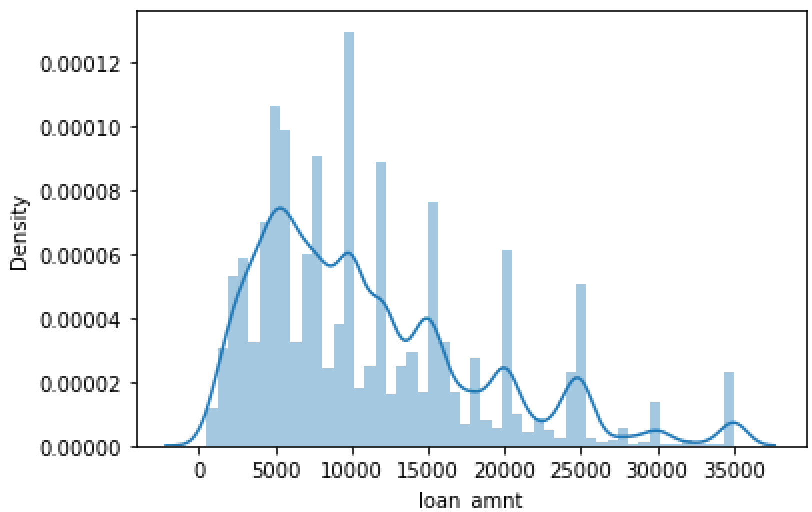
From the above home ownership plots it can be seen that even tough there are significant difference in number of loan applicants for Rent and Own house, the chances of defaulting the count is same for both the categories.Among most of the home_ownership categories the debt_consolidation loans are more likely to defult.

Now we will analyse how the default rate varies across continuous variables.

In [46]:
```
df.loan_amnt.describe()
```

Out[46]:
```
count    38577.000000
mean     11047.025430
std       7348.441646
min        500.000000
25%       5300.000000
50%       9600.000000
75%      15000.000000
max      35000.000000
Name: loan_amnt, dtype: float64
```

In [47]:
```
sns.distplot(df['loan_amnt'])
plt.show()
```



The easiest way to analyse how default rates vary across continous variables is to bin the variables into discrete categories.

Hence binning the loan amount variable into small, medium, high, very high.

In [48]:
```
def loan_amount(prv):
    if prv<5000:
        return 'low'
    elif prv >= 5000 and prv < 15000:
        return 'medium'
    elif prv >= 15000 and prv < 25000:
        return 'high'
    else:
        return 'very high'
```

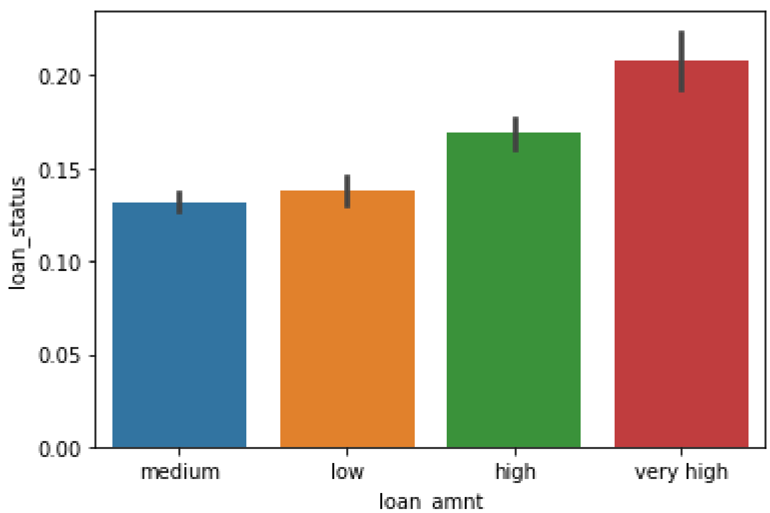
In [49]:
```
df['loan_amnt']=df.loan_amnt.apply(lambda x: loan_amount(x))
df.loan_amnt.value_counts()
```

Out[49]:
```
medium       20675
high          7696
low           7444
very high     2762
Name: loan_amnt, dtype: int64
```

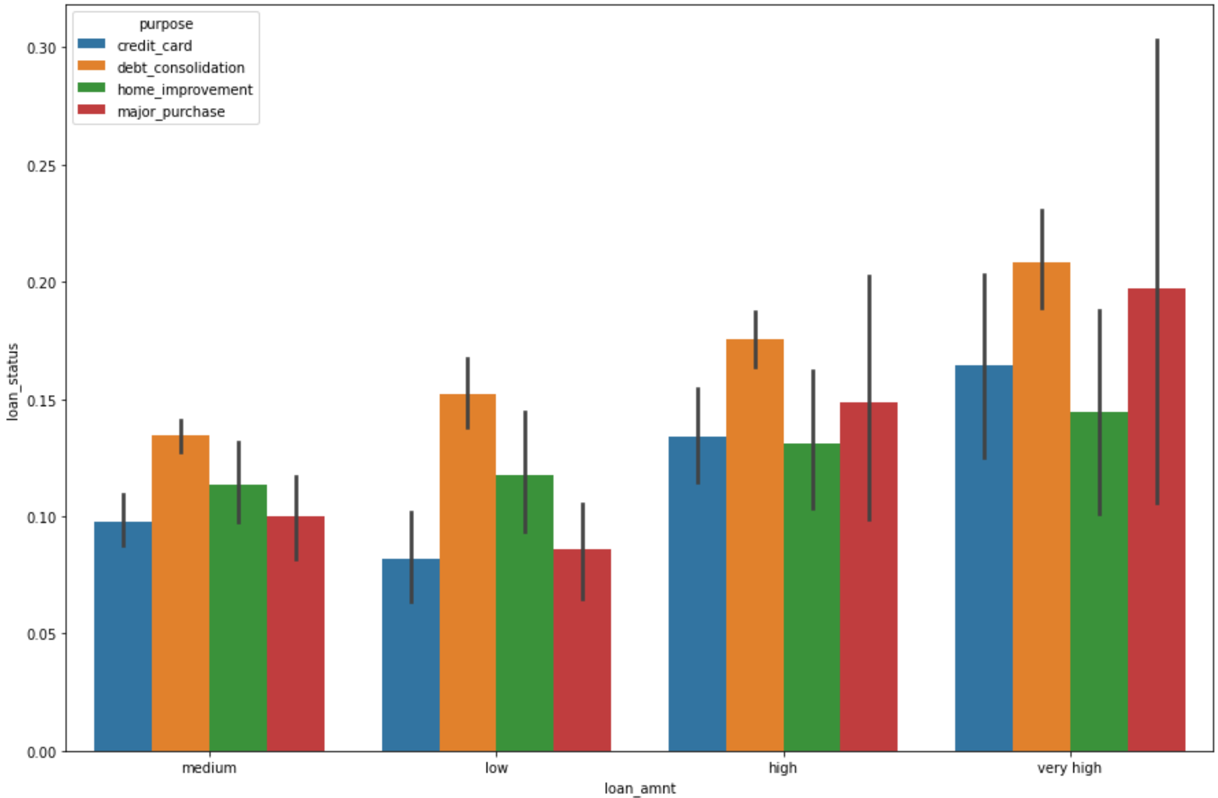
In [50]:
```
df_maxpur['loan_amnt']=df_maxpur.loan_amnt.apply(lambda x: loan_amount(x))
df_maxpur['loan_amnt'].value_counts()
```

Out[50]:
```
medium       15355
high          6376
low           4153
very high     2223
Name: loan_amnt, dtype: int64
```

In [51]:
```
plot_cat('loan_amnt')
```



In [52]:
```
plt.figure(figsize=[15,10])
plot_catmaxpur('loan_amnt')
```



From the above plot it can be infer that as the loan amount increaases the applicant is more likely to default.Among all the loan_amnt categories the debt_consolidation loans are more likely to defult.

In [53]:
```
df.int_rate.describe()
```

Out[53]:
```
count    38577.000000
mean        11.932219
std          3.691327
min          5.420000
25%          8.940000
50%         11.710000
75%         14.380000
max         24.400000
Name: int_rate, dtype: float64
```

In [54]:
```
# lets also convert interest rate to low, medium, high
# binning int_rate
def int_rat(prv):
    if prv < 8:
        return 'low'
    elif prv >=8 and prv < 13:
        return 'medium'
    else:
        return 'high'
```

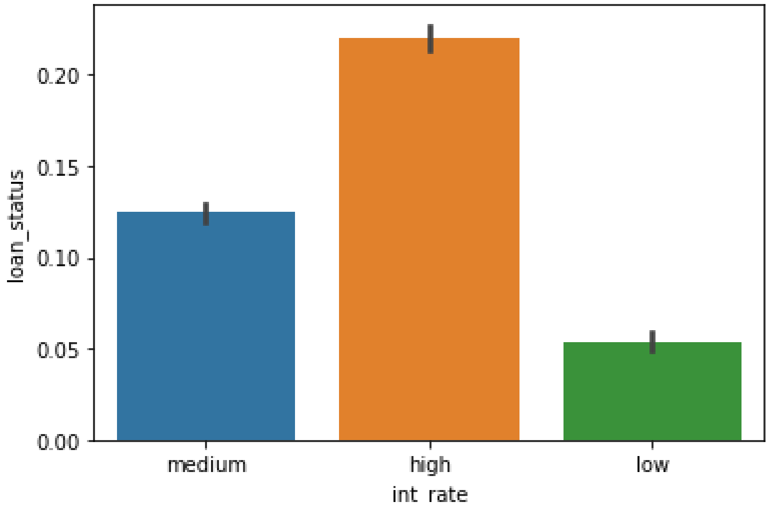
In [55]:
```
df['int_rate']=df.int_rate.apply(lambda x: int_rat(x))
df.int_rate.value_counts()
```

Out[55]:
```
medium    15971
high      14579
low        8027
Name: int_rate, dtype: int64
```

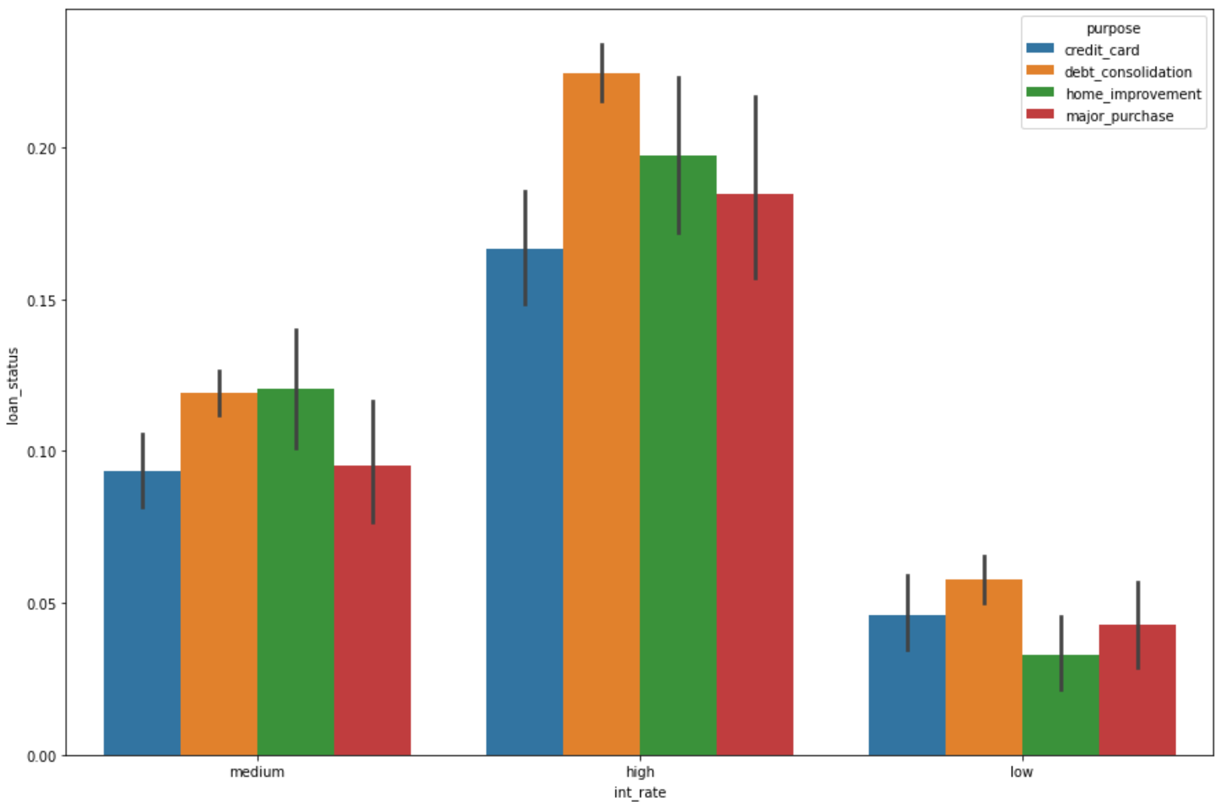
In [56]:
```
df_maxpur['int_rate']=df_maxpur.int_rate.apply(lambda x: int_rat(x))
df_maxpur['int_rate'].value_counts()
```

Out[56]:
```
medium    11543
high      10872
low        5692
Name: int_rate, dtype: int64
```

In [57]:
```
plot_cat('int_rate')
```



In [58]:
```
plt.figure(figsize=[15,10])
plot_catmaxpur('int_rate')
```



From the above plot it can be infered that higher the rate of interest, higher the default rate.Among most of the int_rate categories the debt_consolidation loans are more likely to defult.

In [59]:
```
df.dti.describe()
```

Out[59]:
```
count    38577.000000
mean        13.272727
std          6.673044
min          0.000000
25%          8.130000
50%         13.370000
75%         18.560000
max         29.990000
Name: dti, dtype: float64
```

In [60]:
```
# Binning the debt to income ratio
def dti(prv):
    if prv <= 10:
        return 'low'
    elif prv > 10 and prv <=20:
        return 'medium'
    else:
        return 'high'
```

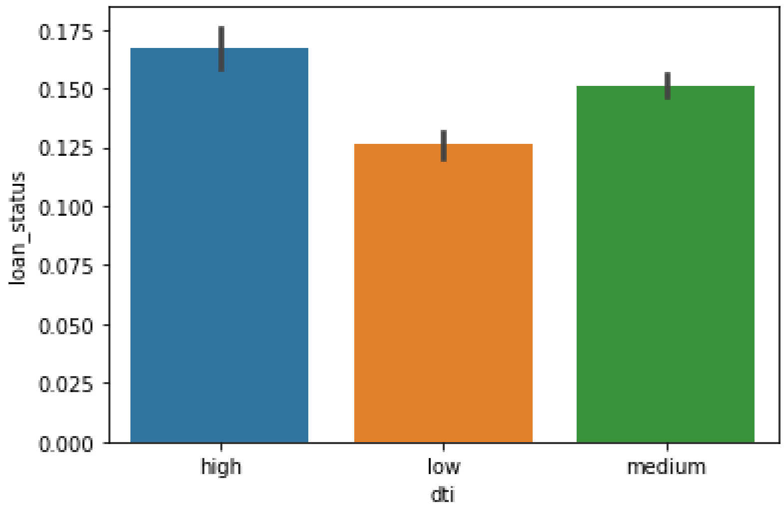
In [61]:
```
df['dti'] = df['dti'].apply(lambda x: dti(x))
df['dti'].value_counts()
```

Out[61]:
```
medium    18441
low       12935
high       7201
Name: dti, dtype: int64
```

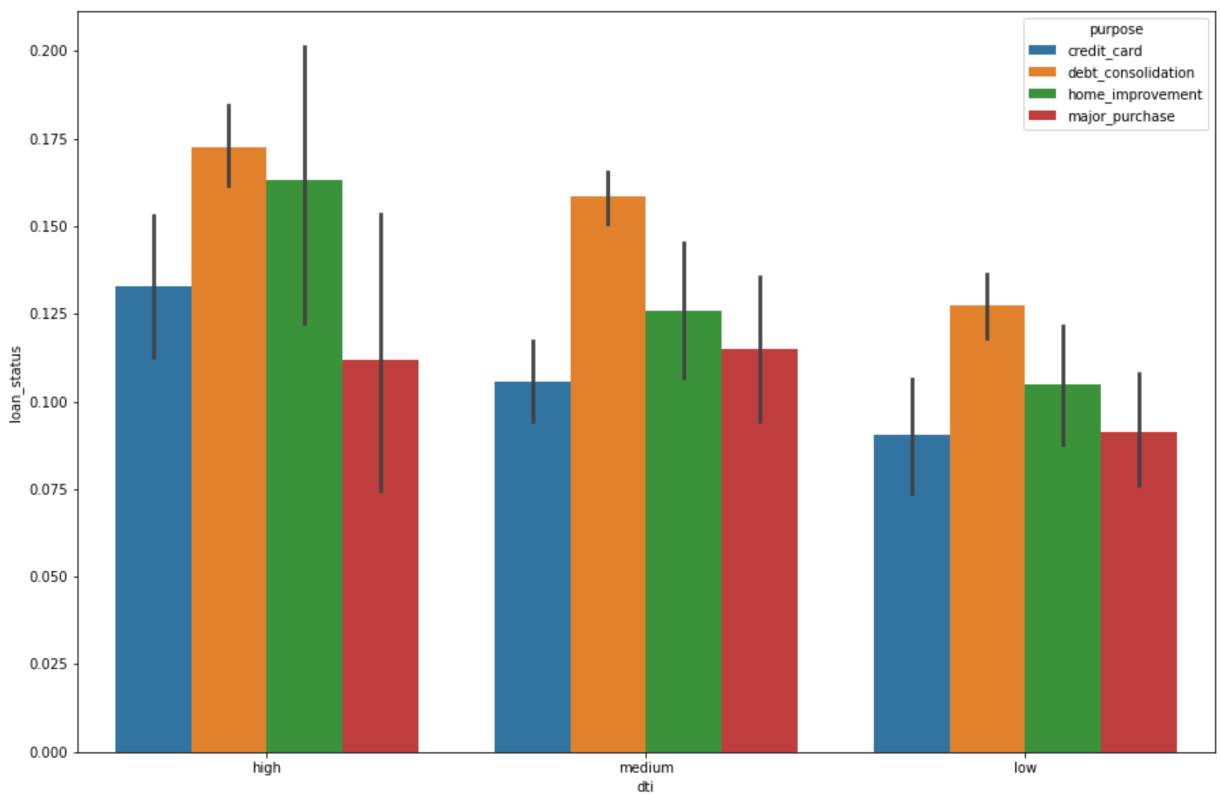
In [62]:
```
df_maxpur['dti'] = df_maxpur['dti'].apply(lambda x: dti(x))
df_maxpur['dti'].value_counts()
```

Out[62]:
```
medium    13991
low        8445
high       5671
Name: dti, dtype: int64
```

In [63]:
```
plot_cat('dti')
```



In [64]:
```
plt.figure(figsize=[15,10])
plot_catmaxpur('dti')
```



From the above plot it can be infered that higher the debt to income ratio, higher the default rate.Among all the dti categories the debt_consolidation loans are more likely to defult.

In [65]:
```
df.installment.describe()
```

Out[65]:
```
count    38577.000000
mean       322.466318
std        208.639215
min         15.690000
25%        165.740000
50%        277.860000
75%        425.550000
max       1305.190000
Name: installment, dtype: float64
```

In [66]:
```
# binnin for installment
def installment(prv):
    if prv <= 200:
        return 'low'
    elif prv > 200 and prv <=400:
        return 'medium'
    elif prv > 400 and prv <=600:
        return 'high'
    else:
        return 'very high'
```

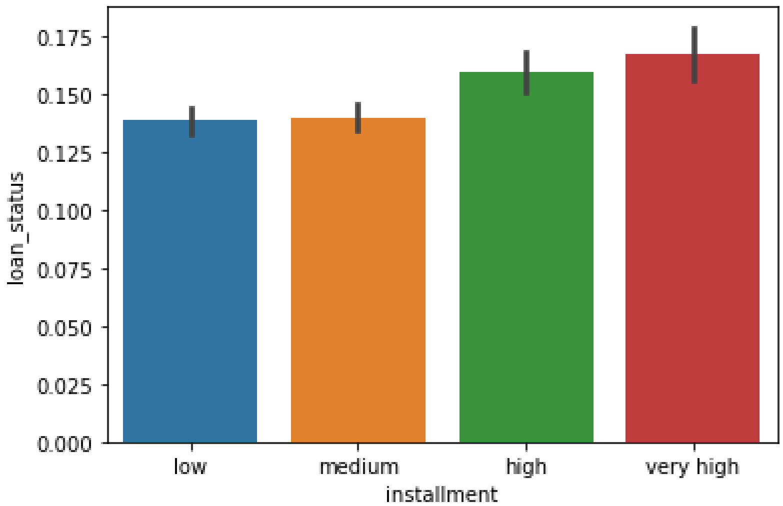
In [67]:
```
df['installment'] = df['installment'].apply(lambda x: installment(x))
df['installment'].value_counts()
```

Out[67]:
```
medium       14732
low          13074
high          6563
very high     4208
Name: installment, dtype: int64
```

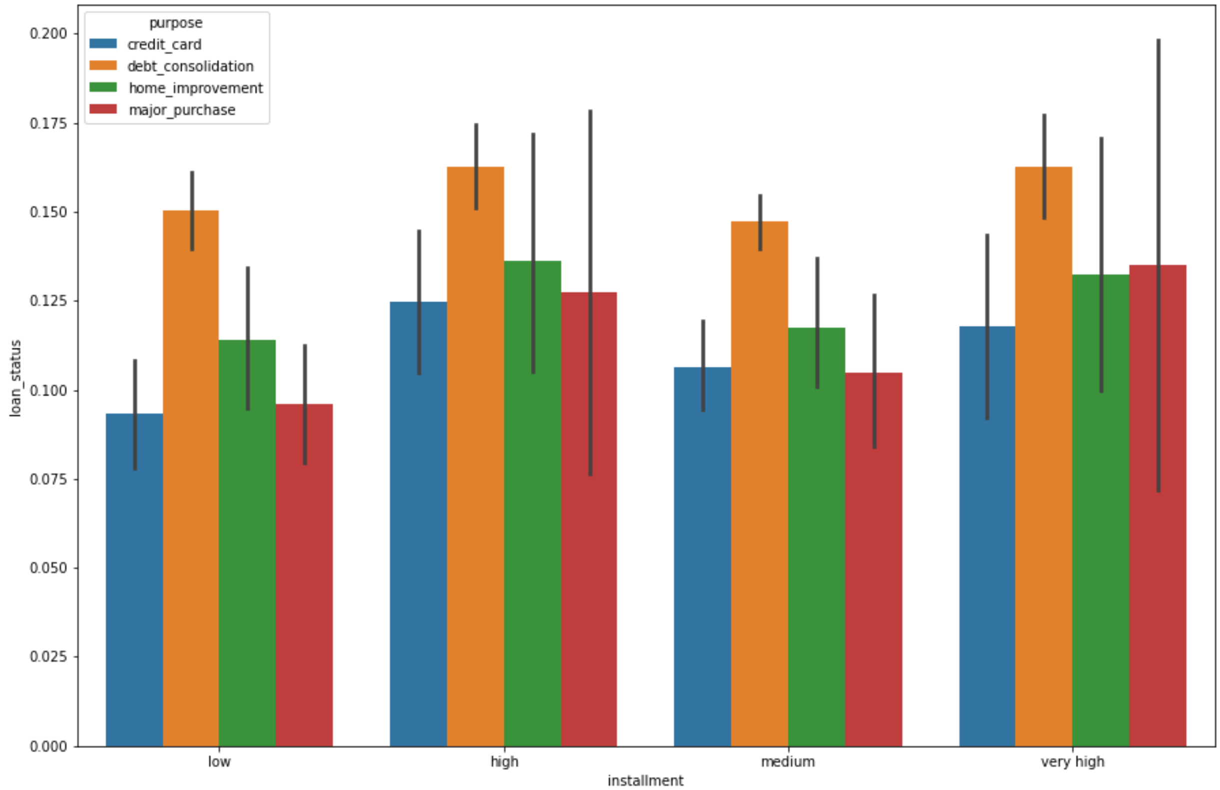
In [68]:
```
df_maxpur['installment'] = df_maxpur['installment'].apply(lambda x: installment(x
df_maxpur['installment'].value_counts()
```

Out[68]:
```
medium       11371
low           7796
high          5467
very high     3473
Name: installment, dtype: int64
```

In [69]:
```
plot_cat('installment')
```



In [70]:
```
plt.figure(figsize=[15,10])
plot_catmaxpur('installment')
```



From the above plot it can be infered that higher the installment amount, higher the default rate.Among all the installment categories the debt_consolidation loans are more likely to defult.

In [71]:
```
df.annual_inc.describe()
```

Out[71]:
```
count    3.857700e+04
mean     6.877797e+04
std      6.421868e+04
min      4.000000e+03
25%      4.000000e+04
50%      5.886800e+04
75%      8.200000e+04
max      6.000000e+06
Name: annual_inc, dtype: float64
```

In [72]:
```
# binning for annual income
def annual_income(prv):
    if prv <= 50000:
        return 'low'
    elif prv > 50000 and prv <=100000:
        return 'medium'
    elif prv > 100000 and prv <=150000:
        return 'high'
    else:
        return 'very high'
```

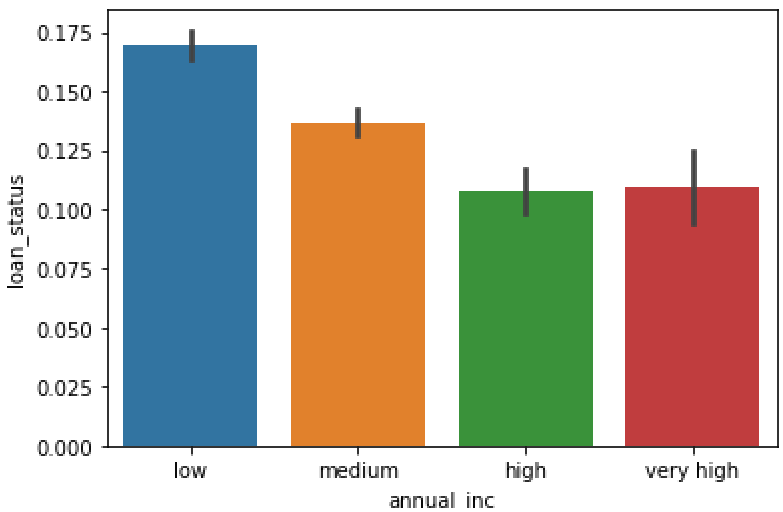
In [73]:
```
df['annual_inc'] = df['annual_inc'].apply(lambda x: annual_income(x))
df['annual_inc'].value_counts()
```

Out[73]:
```
medium       17707
low          15389
high          3995
very high     1486
Name: annual_inc, dtype: int64
```

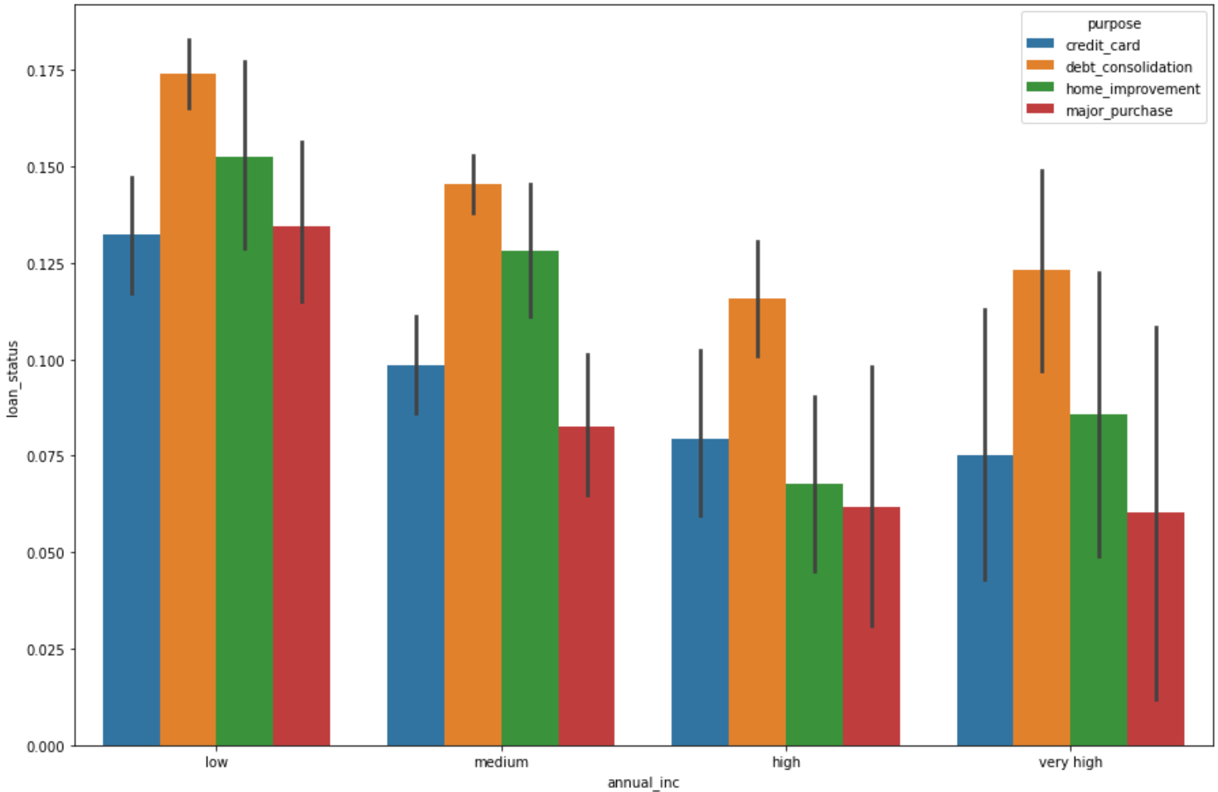
In [74]:
```
df_maxpur['annual_inc'] = df_maxpur['annual_inc'].apply(lambda x: annual_income(x
df_maxpur['annual_inc'].value_counts()
```

Out[74]:
```
medium       13241
low          10776
high          2999
very high     1091
Name: annual_inc, dtype: int64
```

In [75]:
```
plot_cat('annual_inc')
```



In [76]:
```
plt.figure(figsize=[15,10])
plot_catmaxpur('annual_inc')
```



From the above plot it can be infered that lower the annual income, higher the default rate.Among all the annual income categories the debt_consolidation loans are more likely to defult.

SUMMARY

- Most of the applicants are applying loan for the purpose of debt_consolidtion followed by credit_card, home_improvement and major_purchase.
- Among the top 4 purpose applicants applying for the debt_consolidation are more likely to default followed by home_impromentt and credit_card.
- The aplicant with good grade is not likely too fall in defaults.This is expected because the grade is decided by Lending Club based on the riskiness of the loan, same pattern is followed by sub_grade category.
- Even tough there are significant difference in number of loan applicants for Rent and Own house, the chances of defaulting the count is same for both the categories.

The following traits indicate that the applicant is more likely to default:

- Lower grade :[*High impact.*]
- sub_grade :[*Medium impact.*]
- Higher debt to income ratio :[*High impact.*]
- Higher loan amount :[*Medium impact.*]
- Long term loans :[*High impact.*]
- Lower the annual income :[*High impact.*]
- Higher the number of instalements :[*Medium impact.*]
- Higher rate of interest :[*High impact.*]

```
In [ ]:
```