

Banking Loan

Importing Libraries and warnings

```
In [2]: import warnings
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

Importing data

```
In [86]: warnings.filterwarnings("ignore")
loan = pd.read_csv(r"C:\Users\SURBDESA\Downloads\loan (1)\loan.csv")
```

```
In [87]: loan
```

Out[87]:

	id	member_id	loan_amnt	funded_amnt	funded_amnt_inv	term	int_rate	installment	grade	sub_grade	...	num_tl_90g_dpd_24m	nun
0	1077501	1296599	5000	5000	4975.0	36 months	10.65%	162.87	B	B2	...	NaN	
1	1077430	1314167	2500	2500	2500.0	60 months	15.27%	59.83	C	C4	...	NaN	
2	1077175	1313524	2400	2400	2400.0	36 months	15.96%	84.33	C	C5	...	NaN	
3	1076863	1277178	10000	10000	10000.0	36 months	13.49%	339.31	C	C1	...	NaN	
4	1075358	1311748	3000	3000	3000.0	60 months	12.69%	67.79	B	B5	...	NaN	
...
39712	92187	92174	2500	2500	1075.0	36 months	8.07%	78.42	A	A4	...	NaN	
39713	90665	90607	8500	8500	875.0	36 months	10.28%	275.38	C	C1	...	NaN	
39714	90395	90390	5000	5000	1325.0	36 months	8.07%	156.84	A	A4	...	NaN	
39715	90376	89243	5000	5000	650.0	36 months	7.43%	155.38	A	A2	...	NaN	
39716	87023	86999	7500	7500	800.0	36 months	13.75%	255.43	E	E2	...	NaN	

39717 rows × 111 columns



Dropping columns where data missing is greater than 90%

```
In [88]: missing_columns = loan.columns[100*(loan.isnull().sum()/len(loan.index)) > 90]
print(missing_columns)
```

```
Index(['mths_since_last_record', 'next_pymnt_d', '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 [89]: loan.drop(missing_columns , axis = 1, inplace = True)
```

```
In [90]: loan.isnull().sum()
```

```
Out[90]: id 0
member_id 0
loan_amnt 0
funded_amnt 0
funded_amnt_inv 0
term 0
int_rate 0
installment 0
grade 0
sub_grade 0
emp_title 2459
emp_length 1075
home_ownership 0
annual_inc 0
verification_status 0
issue_d 0
loan_status 0
pymnt_plan 0
url 0
desc 12940
purpose 0
title 11
zip_code 0
addr_state 0
dti 0
delinq_2yrs 0
earliest_cr_line 0
inq_last_6mths 0
mths_since_last_delinq 25682
open_acc 0
pub_rec 0
revol_bal 0
revol_util 50
total_acc 0
initial_list_status 0
out_prncp 0
out_prncp_inv 0
total_pymnt 0
total_pymnt_inv 0
total_rec_prncp 0
total_rec_int 0
total_rec_late_fee 0
recoveries 0
collection_recovery_fee 0
```

```
last_pymnt_d          71
last_pymnt_amnt       0
last_credit_pull_d    2
collections_12_mths_ex_med  56
policy_code           0
application_type       0
acc_now_delinq        0
chargeoff_within_12_mths  56
delinq_amnt           0
pub_rec_bankruptcies  697
tax_liens             39
dtype: int64
```

```
In [91]: # dropping the two columns
loan = loan.drop(['desc', 'mths_since_last_delinq'], axis=1)
```

```
In [92]: loan.isnull().sum()
```

```
Out[92]: id 0
member_id 0
loan_amnt 0
funded_amnt 0
funded_amnt_inv 0
term 0
int_rate 0
installment 0
grade 0
sub_grade 0
emp_title 2459
emp_length 1075
home_ownership 0
annual_inc 0
verification_status 0
issue_d 0
loan_status 0
pymnt_plan 0
url 0
purpose 0
title 11
zip_code 0
addr_state 0
dti 0
delinq_2yrs 0
earliest_cr_line 0
inq_last_6mths 0
open_acc 0
pub_rec 0
revol_bal 0
revol_util 50
total_acc 0
initial_list_status 0
out_prncp 0
out_prncp_inv 0
total_pymnt 0
total_pymnt_inv 0
total_rec_prncp 0
total_rec_int 0
total_rec_late_fee 0
recoveries 0
collection_recovery_fee 0
last_pymnt_d 71
last_pymnt_amnt 0
```

```
last_credit_pull_d      2
collections_12_mths_ex_med  56
policy_code             0
application_type        0
acc_now_delinq          0
chargeoff_within_12_mths  56
delinq_amnt             0
pub_rec_bankruptcies    697
tax_liens                39
dtype: int64
```

```
In [93]: loan.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

```

We can clearly see that employee length that is how many years employee has worked has object data type

We can convert data to integer variable for better data quality

```
In [94]: loan['emp_length'].value_counts()
```

```

Out[94]: 10+ years      8879
< 1 year    4583
2 years     4388
3 years     4095
4 years     3436
5 years     3282
1 year      3240
6 years     2229
7 years     1773
8 years     1479
9 years     1258
Name: emp_length, dtype: int64

```

```
In [95]: loan['months'] = loan.term.apply(lambda x : x.split()[0])
```

```
In [96]: loan.drop(['term'],axis = 1,inplace = True)
```

```
In [97]: loan = loan[~loan.emp_length.isnull()]
```

```
In [98]: loan.emp_length.isnull().sum()
```

```
Out[98]: 0
```

```
In [99]: loan.emp_length.value_counts()
```

```
Out[99]: 10+ years    8879
< 1 year      4583
2 years       4388
3 years       4095
4 years       3436
5 years       3282
1 year        3240
6 years       2229
7 years       1773
8 years       1479
9 years       1258
Name: emp_length, dtype: int64
```

```
In [100... loan['emp_length'] = loan.emp_length.str.extract('(\d+)')
```

```
In [101... loan.emp_length.value_counts()
```

```
Out[101]: 10    8879
1     7823
2     4388
3     4095
4     3436
5     3282
6     2229
7     1773
8     1479
9     1258
Name: emp_length, dtype: int64
```

```
In [102... loan['emp_length'] = loan['emp_length'].apply(lambda x: pd.to_numeric(x))
```

```
In [103... loan.info()
```

```
<class 'pandas.core.frame.DataFrame'>
```

```
Int64Index: 38642 entries, 0 to 39716
```

```
Data columns (total 53 columns):
```

#	Column	Non-Null Count	Dtype
0	id	38642 non-null	int64
1	member_id	38642 non-null	int64
2	loan_amnt	38642 non-null	int64
3	funded_amnt	38642 non-null	int64
4	funded_amnt_inv	38642 non-null	float64
5	int_rate	38642 non-null	object
6	installment	38642 non-null	float64
7	grade	38642 non-null	object
8	sub_grade	38642 non-null	object
9	emp_title	37202 non-null	object
10	emp_length	38642 non-null	int64
11	home_ownership	38642 non-null	object
12	annual_inc	38642 non-null	float64
13	verification_status	38642 non-null	object
14	issue_d	38642 non-null	object
15	loan_status	38642 non-null	object
16	pymnt_plan	38642 non-null	object
17	url	38642 non-null	object
18	purpose	38642 non-null	object
19	title	38632 non-null	object
20	zip_code	38642 non-null	object
21	addr_state	38642 non-null	object
22	dti	38642 non-null	float64
23	delinq_2yrs	38642 non-null	int64
24	earliest_cr_line	38642 non-null	object
25	inq_last_6mths	38642 non-null	int64
26	open_acc	38642 non-null	int64
27	pub_rec	38642 non-null	int64
28	revol_bal	38642 non-null	int64
29	revol_util	38595 non-null	object
30	total_acc	38642 non-null	int64
31	initial_list_status	38642 non-null	object
32	out_prncp	38642 non-null	float64
33	out_prncp_inv	38642 non-null	float64
34	total_pymnt	38642 non-null	float64
35	total_pymnt_inv	38642 non-null	float64
36	total_rec_prncp	38642 non-null	float64
37	total_rec_int	38642 non-null	float64
38	total_rec_late_fee	38642 non-null	float64

```

39 recoveries                38642 non-null float64
40 collection_recovery_fee    38642 non-null float64
41 last_pymnt_d               38576 non-null object
42 last_pymnt_amnt            38642 non-null float64
43 last_credit_pull_d         38640 non-null object
44 collections_12_mths_ex_med 38586 non-null float64
45 policy_code                38642 non-null int64
46 application_type           38642 non-null object
47 acc_now_delinq             38642 non-null int64
48 chargeoff_within_12_mths   38586 non-null float64
49 delinq_amnt                38642 non-null int64
50 pub_rec_bankruptcies       37945 non-null float64
51 tax_liens                  38603 non-null float64
52 months                     38642 non-null object

```

dtypes: float64(18), int64(14), object(21)

memory usage: 15.9+ MB

Data analysis

The objective is to identify predictors of default so that at the time of loan application, we can use those variables for approval/rejection of the loan

In [104...

```

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[104]: ['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 [105... loan.drop(behaviour_var, axis = 1 , inplace = True)
```

```
In [106... loan.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 38642 entries, 0 to 39716
Data columns (total 32 columns):
#   Column                                Non-Null Count  Dtype
---  -
0   id                                     38642 non-null  int64
1   member_id                             38642 non-null  int64
2   loan_amnt                             38642 non-null  int64
3   funded_amnt                           38642 non-null  int64
4   funded_amnt_inv                       38642 non-null  float64
5   int_rate                              38642 non-null  object
6   installment                           38642 non-null  float64
7   grade                                 38642 non-null  object
8   sub_grade                             38642 non-null  object
9   emp_title                             37202 non-null  object
10  emp_length                             38642 non-null  int64
11  home_ownership                         38642 non-null  object
12  annual_inc                             38642 non-null  float64
13  verification_status                   38642 non-null  object
14  issue_d                               38642 non-null  object
15  loan_status                           38642 non-null  object
16  pymnt_plan                             38642 non-null  object
17  url                                    38642 non-null  object
18  purpose                               38642 non-null  object
19  title                                 38632 non-null  object
20  zip_code                              38642 non-null  object
21  addr_state                            38642 non-null  object
22  dti                                    38642 non-null  float64
23  initial_list_status                   38642 non-null  object
24  collections_12_mths_ex_med            38586 non-null  float64
25  policy_code                           38642 non-null  int64
26  acc_now_delinq                         38642 non-null  int64
27  chargeoff_within_12_mths              38586 non-null  float64
28  delinq_amnt                           38642 non-null  int64
29  pub_rec_bankruptcies                  37945 non-null  float64
30  tax_liens                             38603 non-null  float64
31  months                                38642 non-null  object
dtypes: float64(8), int64(8), object(16)
memory usage: 9.7+ MB
```

```
In [107... loan.drop(['title', 'url', 'zip_code', 'addr_state'], axis=1, inplace = True)
```

```
In [108... loan.loan_status.value_counts()
```

```
Out[108]: Fully Paid      32145  
Charged Off      5399  
Current          1098  
Name: loan_status, dtype: int64
```

Loan status has 3 categories , there is no need of current category in data as we need to find defaulters based on historical loan application status.

```
In [109... loan = loan[loan['loan_status'] != 'Current']  
loan['loan_status'] = loan['loan_status'].apply(lambda x: 'Non-Default' if x=='Fully Paid' else 'Default')
```

```
In [110... loan['loan_status_categor'] = loan.loan_status
```

```
In [111... loan.loan_status_categor.value_counts()
```

```
Out[111]: Non-Default      32145  
Default          5399  
Name: loan_status_categor, dtype: int64
```

```
In [112... #Current loan status is not needed for analyzing  
loan = loan[loan['loan_status'] != 'Current']  
loan['loan_status'] = loan['loan_status'].apply(lambda x: 0 if x=='Non-Default' else 1)  
  
# converting loan_status to integer type  
loan['loan_status'] = loan['loan_status'].apply(lambda x: pd.to_numeric(x))  
  
# summarising the values  
loan['loan_status'].value_counts()
```

```
Out[112]: 0      32145  
1        5399  
Name: loan_status, dtype: int64
```

Default rate

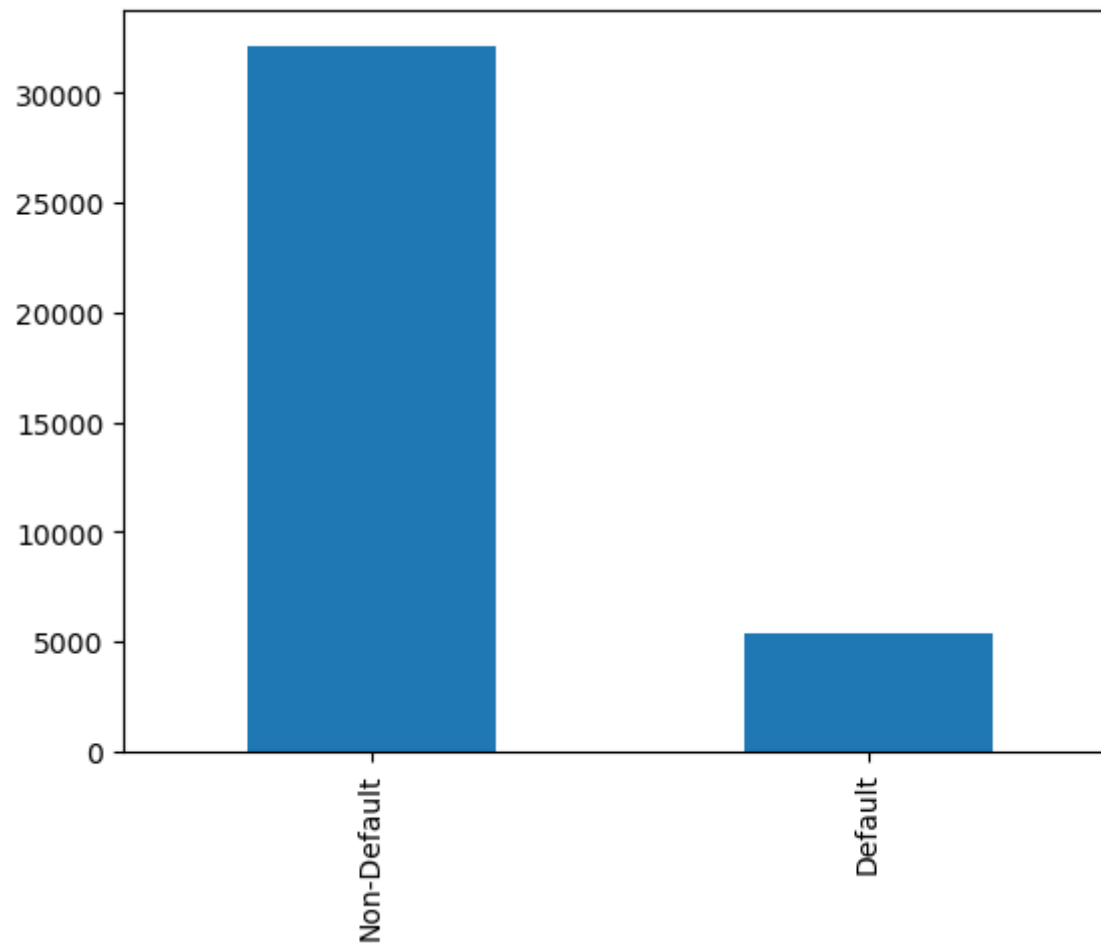
```
In [113... round(np.mean(loan['loan_status']==1), 2)
```

```
Out[113]: 0.14
```

Loan default rate is 14% .

```
In [114]: loan.loan_status_categor.value_counts().plot.bar()
```

```
Out[114]: <AxesSubplot:>
```



```
In [115]: loan
```

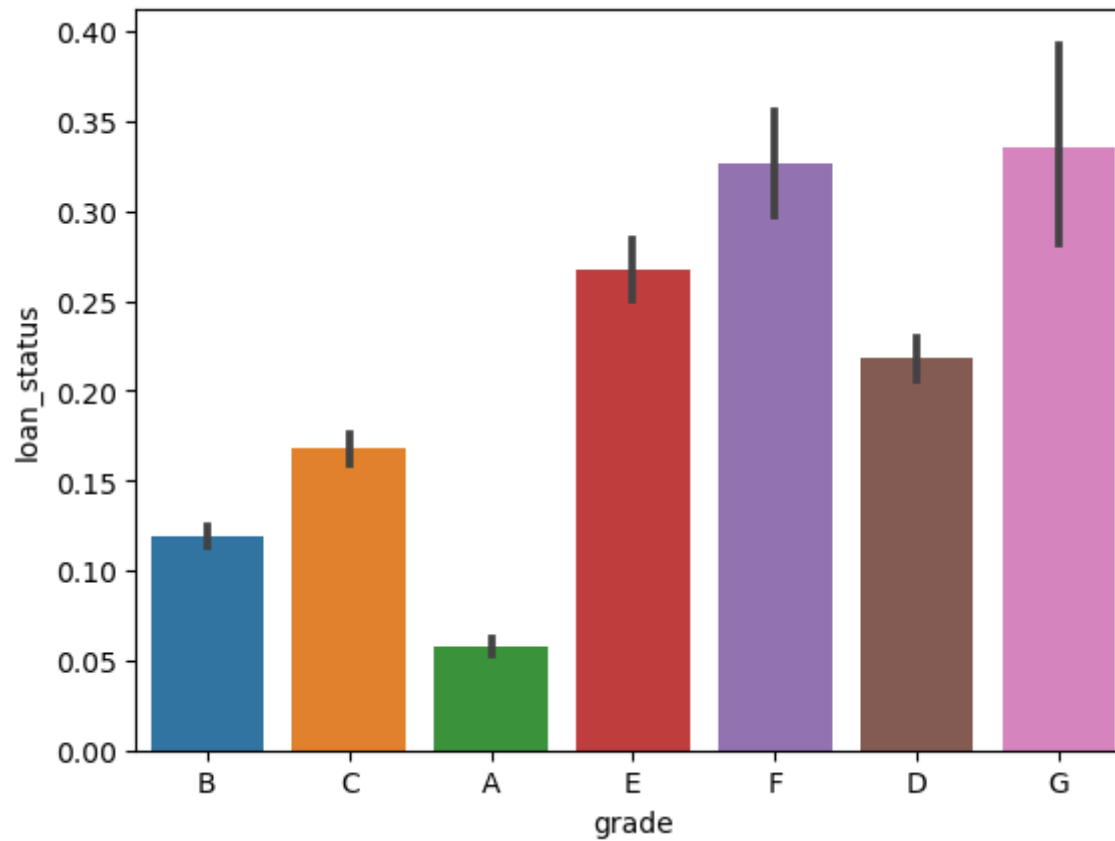

Out[115]:

	id	member_id	loan_amnt	funded_amnt	funded_amnt_inv	int_rate	installment	grade	sub_grade	emp_title	...	initial_list_status	col
0	1077501	1296599	5000	5000	4975.0	10.65%	162.87	B	B2	NaN	...	f	
1	1077430	1314167	2500	2500	2500.0	15.27%	59.83	C	C4	Ryder	...	f	
2	1077175	1313524	2400	2400	2400.0	15.96%	84.33	C	C5	NaN	...	f	
3	1076863	1277178	10000	10000	10000.0	13.49%	339.31	C	C1	AIR RESOURCES BOARD	...	f	
5	1075269	1311441	5000	5000	5000.0	7.90%	156.46	A	A4	Veolia Transportaton	...	f	
...	
39712	92187	92174	2500	2500	1075.0	8.07%	78.42	A	A4	FiSite Research	...	f	
39713	90665	90607	8500	8500	875.0	10.28%	275.38	C	C1	Squarewave Solutions, Ltd.	...	f	
39714	90395	90390	5000	5000	1325.0	8.07%	156.84	A	A4	NaN	...	f	
39715	90376	89243	5000	5000	650.0	7.43%	155.38	A	A2	NaN	...	f	
39716	87023	86999	7500	7500	800.0	13.75%	255.43	E	E2	Evergreen Center	...	f	

37544 rows × 29 columns



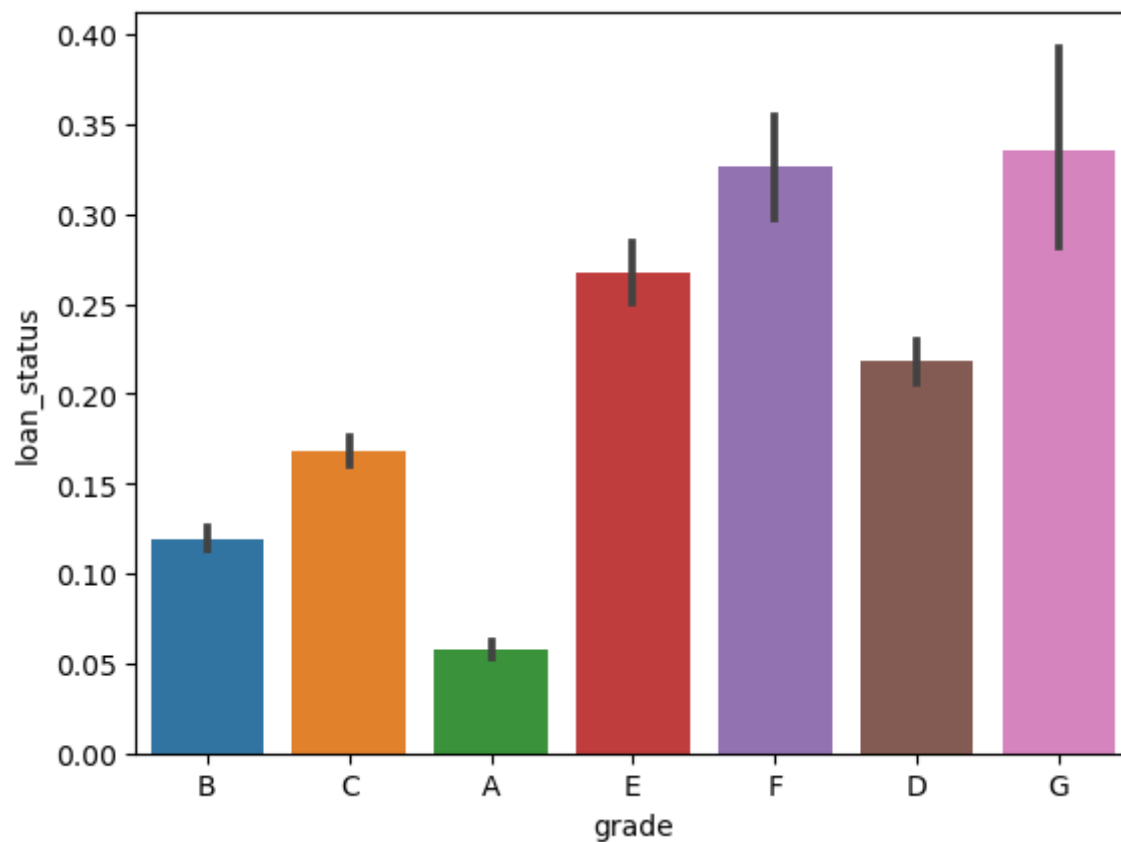
```
In [116... sns.barplot(x='grade', y='loan_status', data=loan)
plt.show()
```



Overall default rate is 14%

So let's plot against categorical variable to gain more insight

```
In [117... sns.barplot(x='grade', y='loan_status', data=loan)  
plt.show()
```

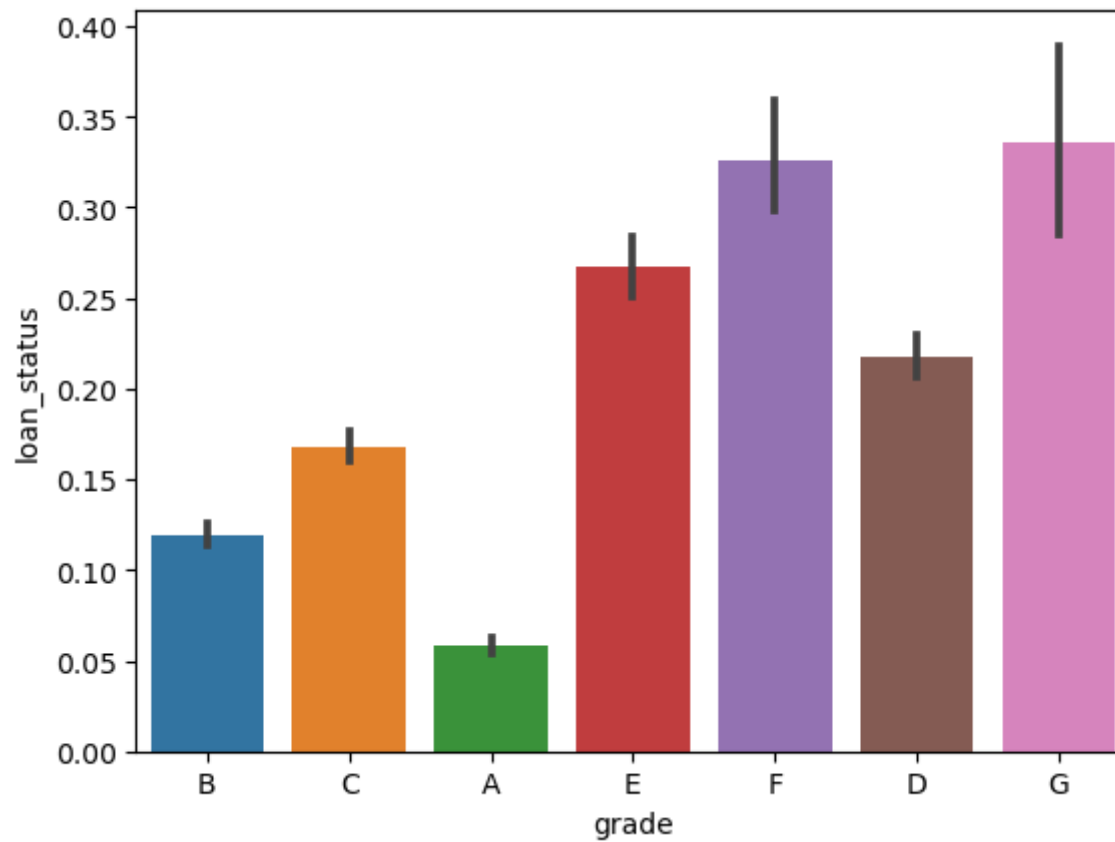


```
In [118... loan.grade.value_counts()
```

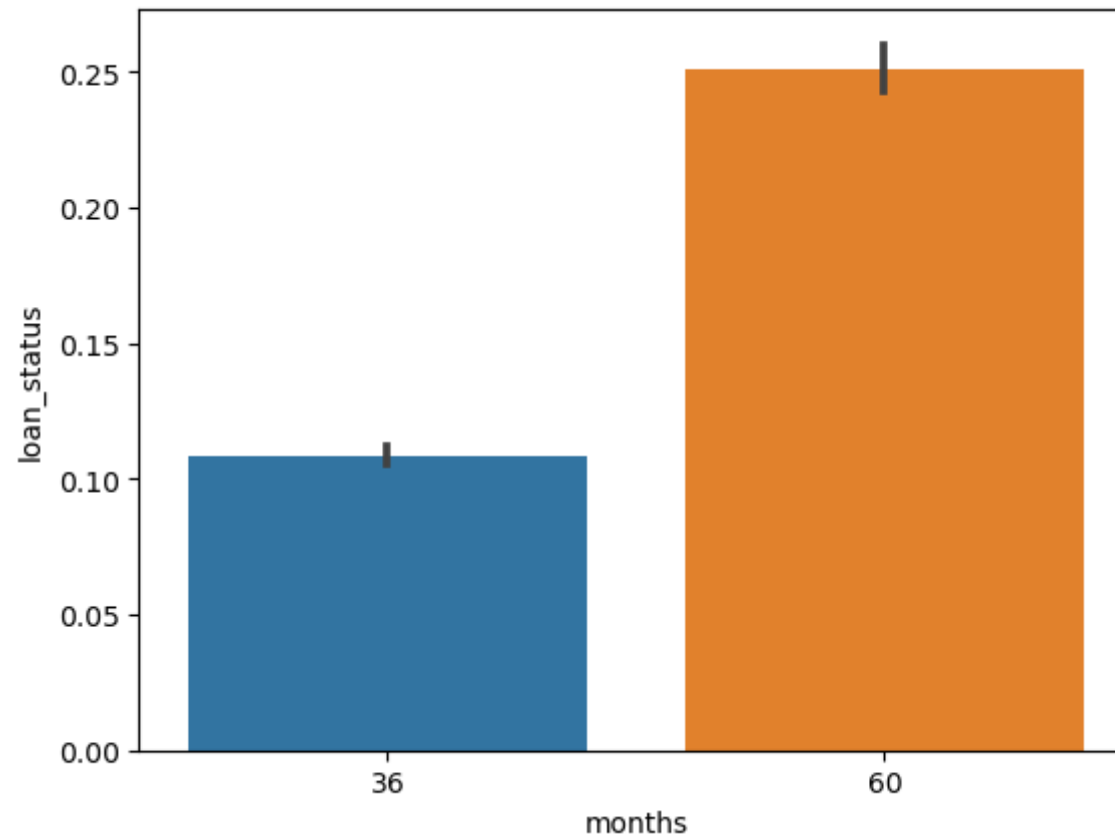
```
Out[118]: B    11359  
A     9660  
C     7669  
D     4979  
E     2620  
F       959  
G       298  
Name: grade, dtype: int64
```

```
In [119... def plot_data(categor_var):  
    sns.barplot(x=categor_var, y='loan_status', data=loan)  
    plt.show()
```

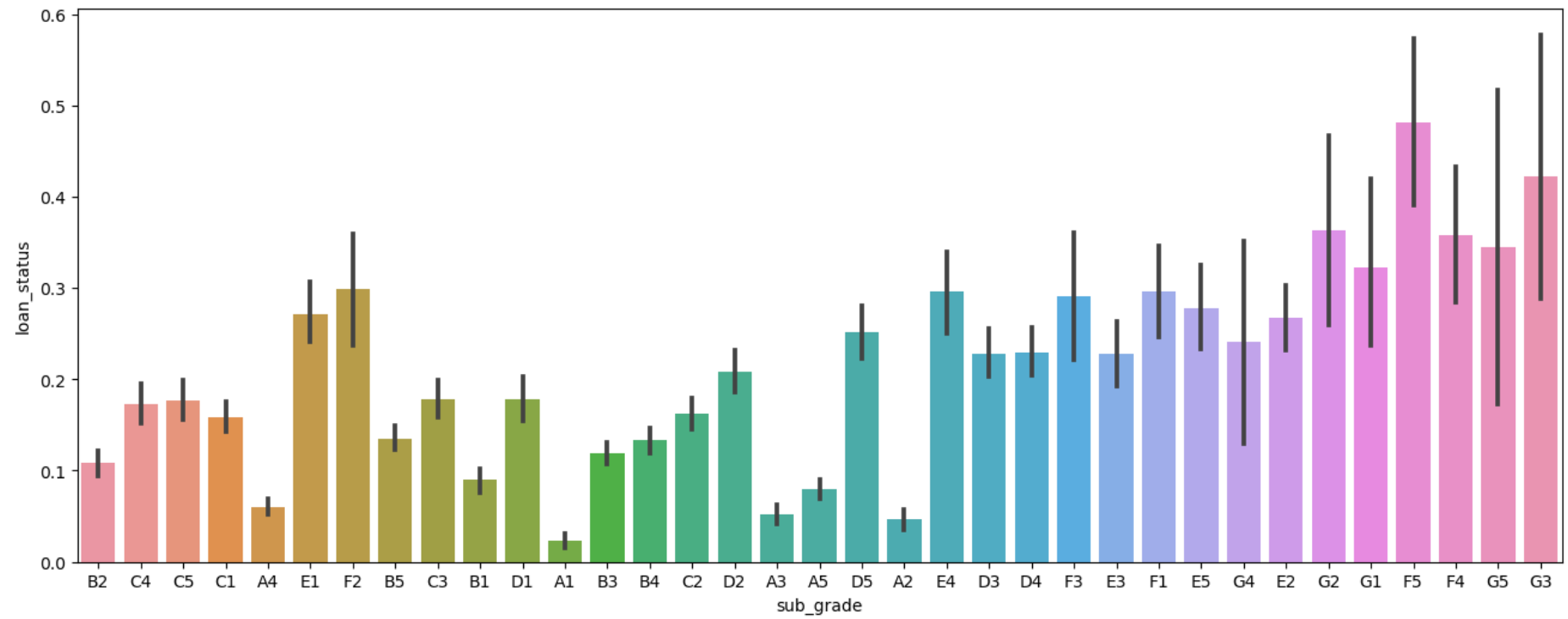
```
In [120... # We can clearly figure out that grade E,F,D,G has higher default rate.  
plot_data('grade')
```



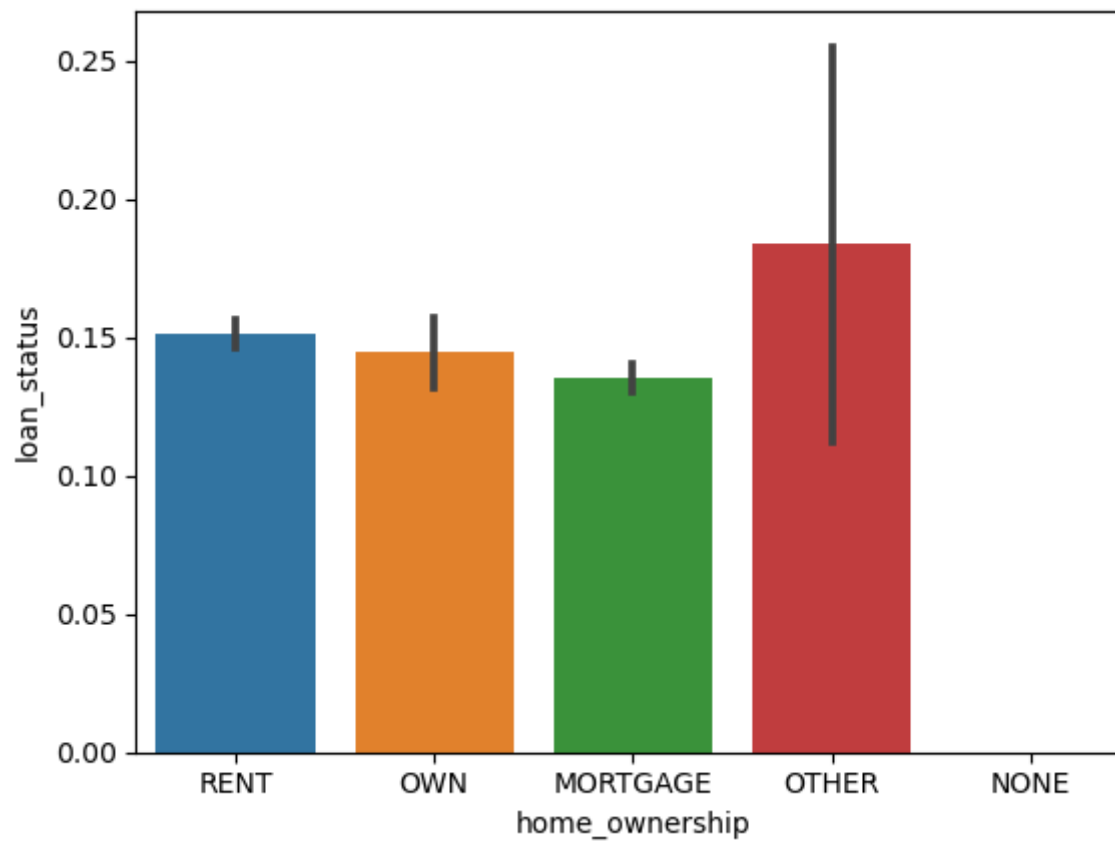
```
In [121... # we can clearly see that 60 months term has higher default rate than 36 months.  
plot_data('months')
```



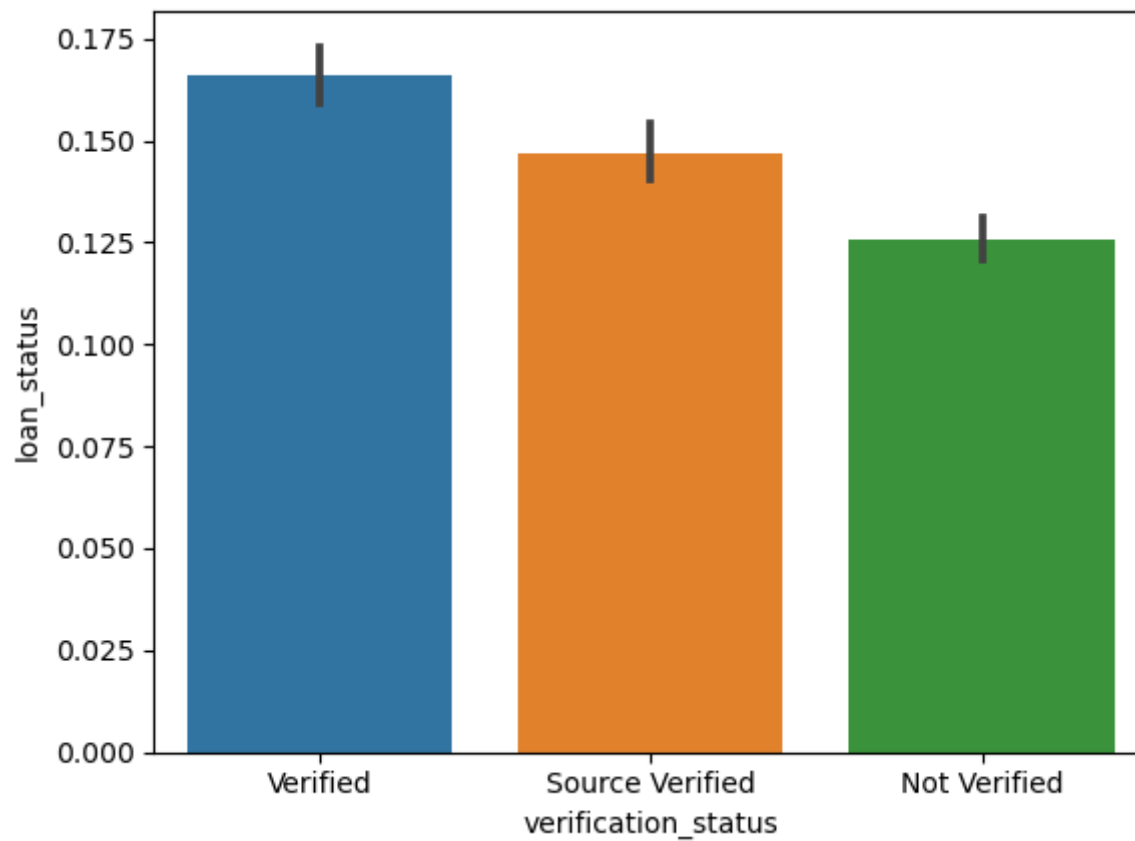
```
In [122... # sub-grade: A1 is better than A2 better than A3 and so on
plt.figure(figsize=(16, 6))
plot_data('sub_grade')
```



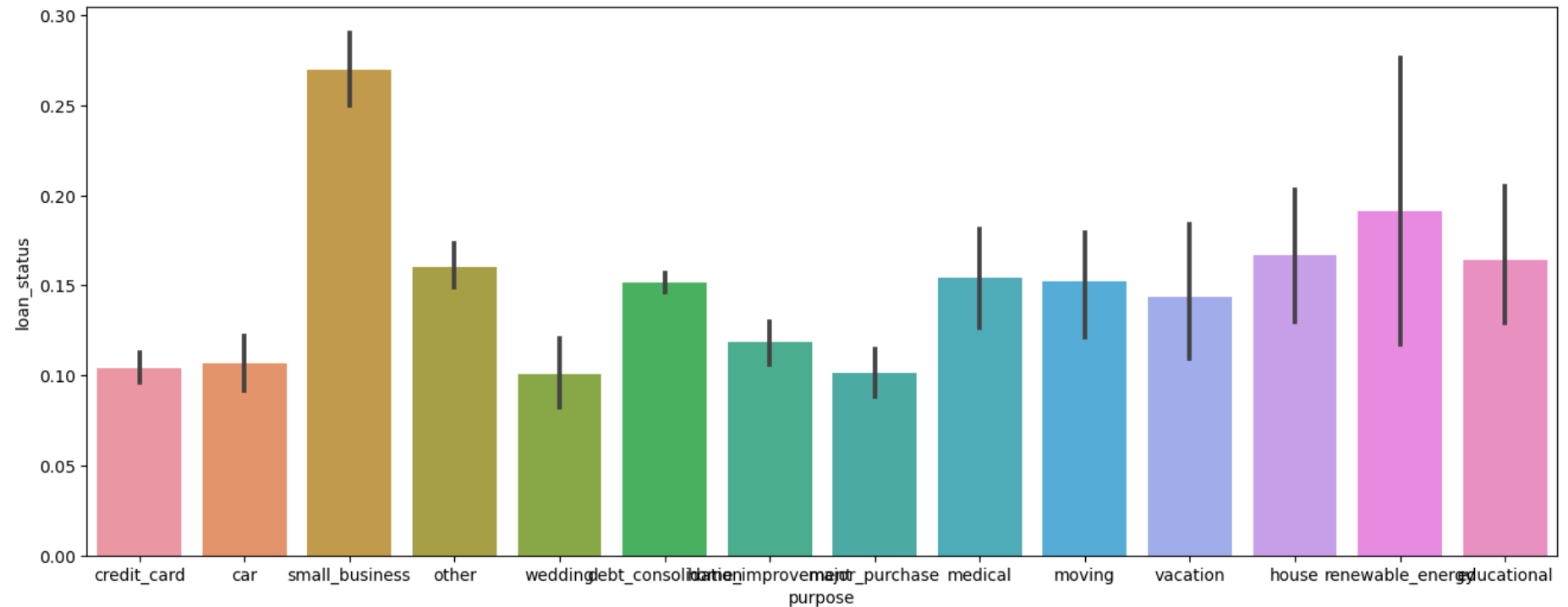
```
In [123... plot_data('home_ownership')
```



```
In [125... # verification_status: Verified loan has more default rate than not verified  
plot_data('verification_status')
```



```
In [126... # purpose: small business loans default rate is the largest than compared to others.  
plt.figure(figsize=(16, 6))  
plot_data('purpose')
```

```
In [127... loan['issue_d'].describe
```

```
Out[127]: <bound method NDFrame.describe of 0      Dec-11
1      Dec-11
2      Dec-11
3      Dec-11
5      Dec-11
...
39712   Jul-07
39713   Jul-07
39714   Jul-07
39715   Jul-07
39716   Jun-07
Name: issue_d, Length: 37544, dtype: object>
```

```
In [128... loan['Dates'] = pd.to_datetime(loan['issue_d'], format='%b-%y')
```

```
In [129... loan['month'] = loan['Dates'].apply(lambda x: x.month)
```

In [130... `loan['month'].describe`

Out[130]: `<bound method NDFrame.describe of 0` 12
 1 12
 2 12
 3 12
 5 12
 ..
 39712 7
 39713 7
 39714 7
 39715 7
 39716 6
 Name: month, Length: 37544, dtype: int64>

In [131... `loan['year'] = loan['Dates'].apply(lambda x: x.year)`

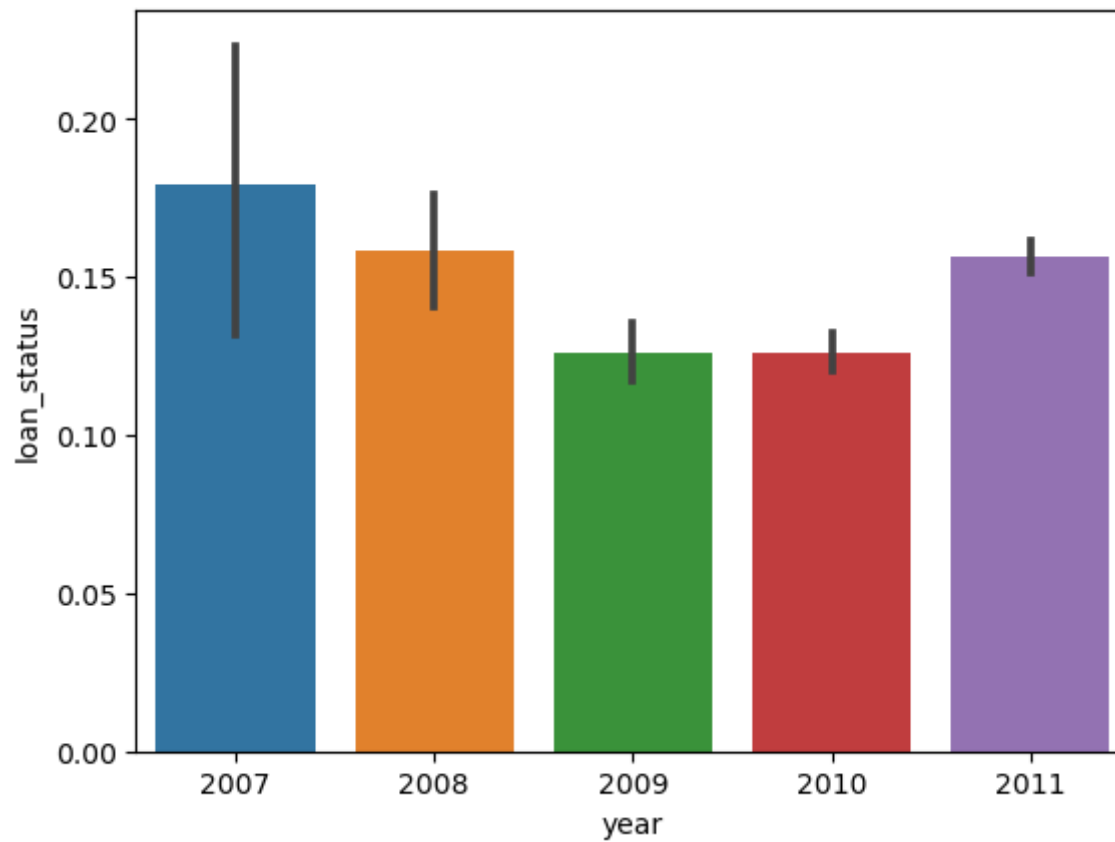
In [133... `loan['year'].value_counts()`

Out[133]:
 2011 19801
 2010 11214
 2009 4716
 2008 1562
 2007 251
 Name: year, dtype: int64

In [134... `loan.groupby('year').year.count()`

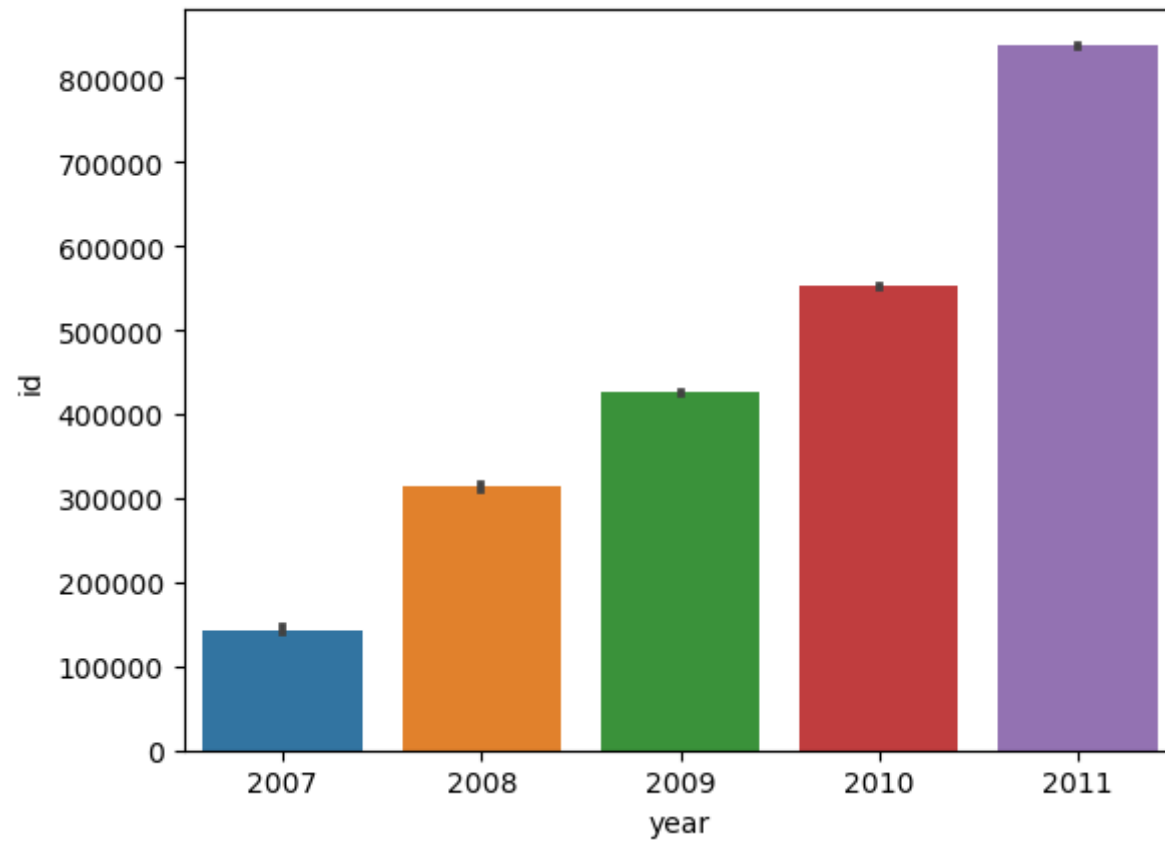
Out[134]:
 year
 2007 251
 2008 1562
 2009 4716
 2010 11214
 2011 19801
 Name: year, dtype: int64

In [135... *#the default rate was high in the year 2007 then gradually decreased but suddenly got increased in the year 2011*
`plot_data('year')`



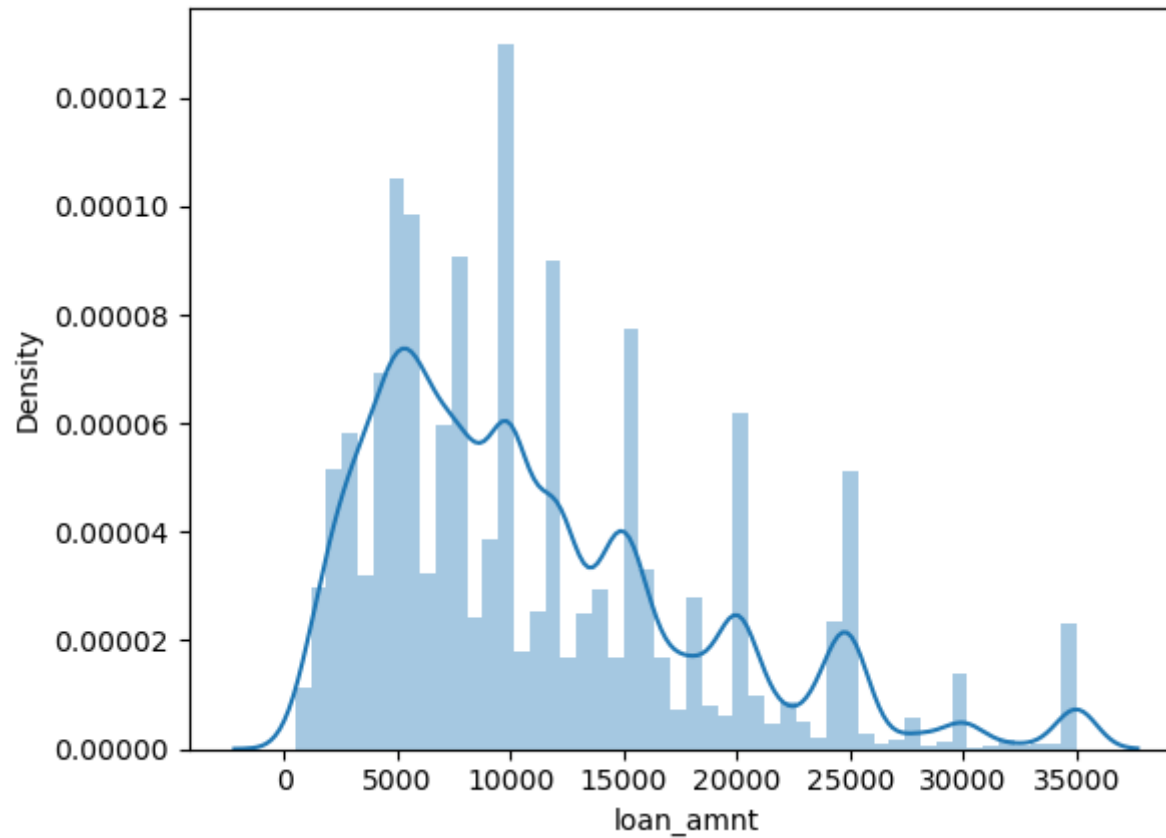
```
In [137... sns.barplot(x='year', y='id', data=loan)
```

```
Out[137]: <AxesSubplot:xlabel='year', ylabel='id'>
```



In [204...

```
sns.distplot(loan['loan_amnt'])  
plt.show()
```



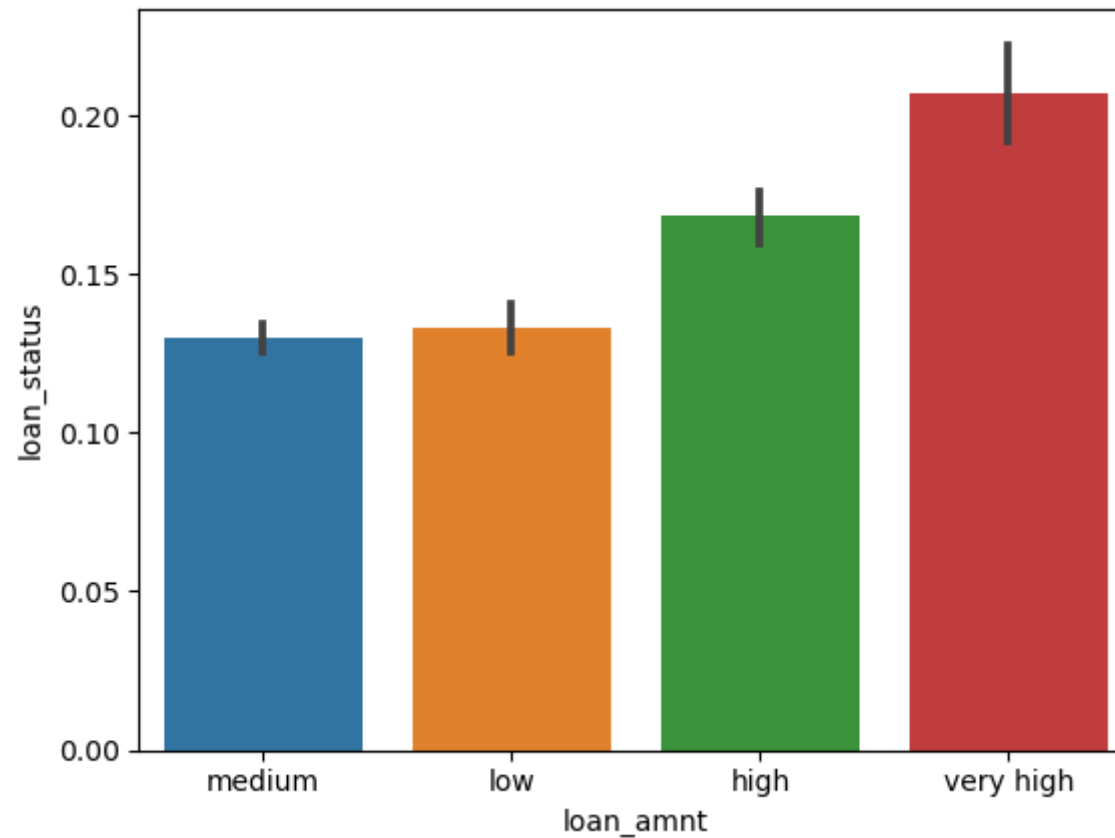
```
In [213... #Let's bin the loan amount variable into small, medium, high, very high.
def loan_amount(n):
    if n < 5000:
        return 'low'
    elif n >=5000 and n < 15000:
        return 'medium'
    elif n >= 15000 and n < 25000:
        return 'high'
    else:
        return 'very high'

loan['loan_amnt'] = loan['loan_amnt'].apply(lambda x: loan_amount(x))
```

```
In [214... loan['loan_amnt'].value_counts()
```

```
Out[214]: medium      20157  
         high        7572  
         low         7095  
         very high   2720  
         Name: loan_amnt, dtype: int64
```

```
In [216... # higher the loan amount, higher is the default rate  
plot_data('loan_amnt')
```



```
In [227... loan['int_rate'] = loan['int_rate'].apply(lambda x: pd.to_numeric(x.split("%")[0]))
```

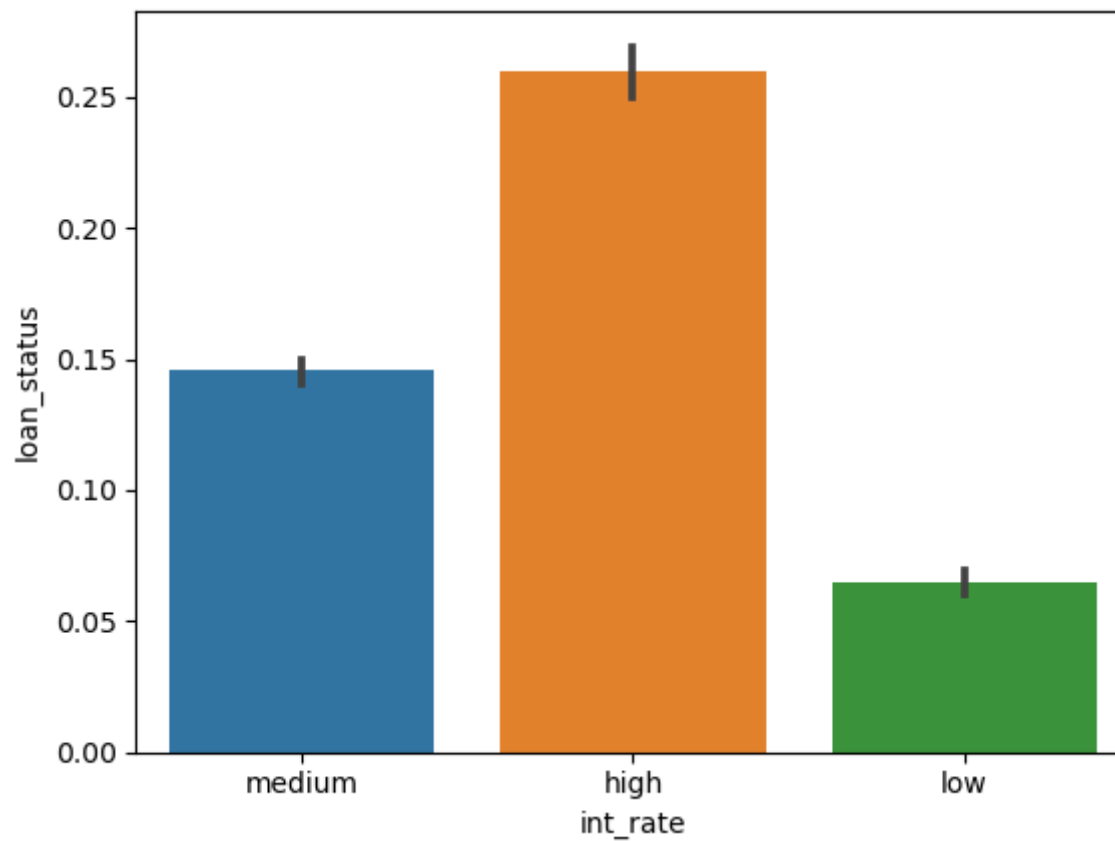
```
In [228... loan.int_rate.value_counts()
```

```
Out[228]: 10.99    891
          11.49    766
          7.51    756
          13.49    736
          7.88    701
          ...
          16.96     1
          18.36     1
          16.15     1
          16.01     1
          16.20     1
Name: int_rate, Length: 370, dtype: int64
```

```
In [229... def int_rate(n):
              if n <= 10:
                  return 'low'
              elif n > 10 and n <=15:
                  return 'medium'
              else:
                  return 'high'

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

```
In [230... #Higher the rate of interest higher is the default rate
plot_data('int_rate')
```



In [233...

```
def dti(n):  
    if n <= 10:  
        return 'low'  
    elif n > 10 and n <=20:  
        return 'medium'  
    else:  
        return 'high'  
  
loan['dti'] = loan['dti'].apply(lambda x: dti(x))
```

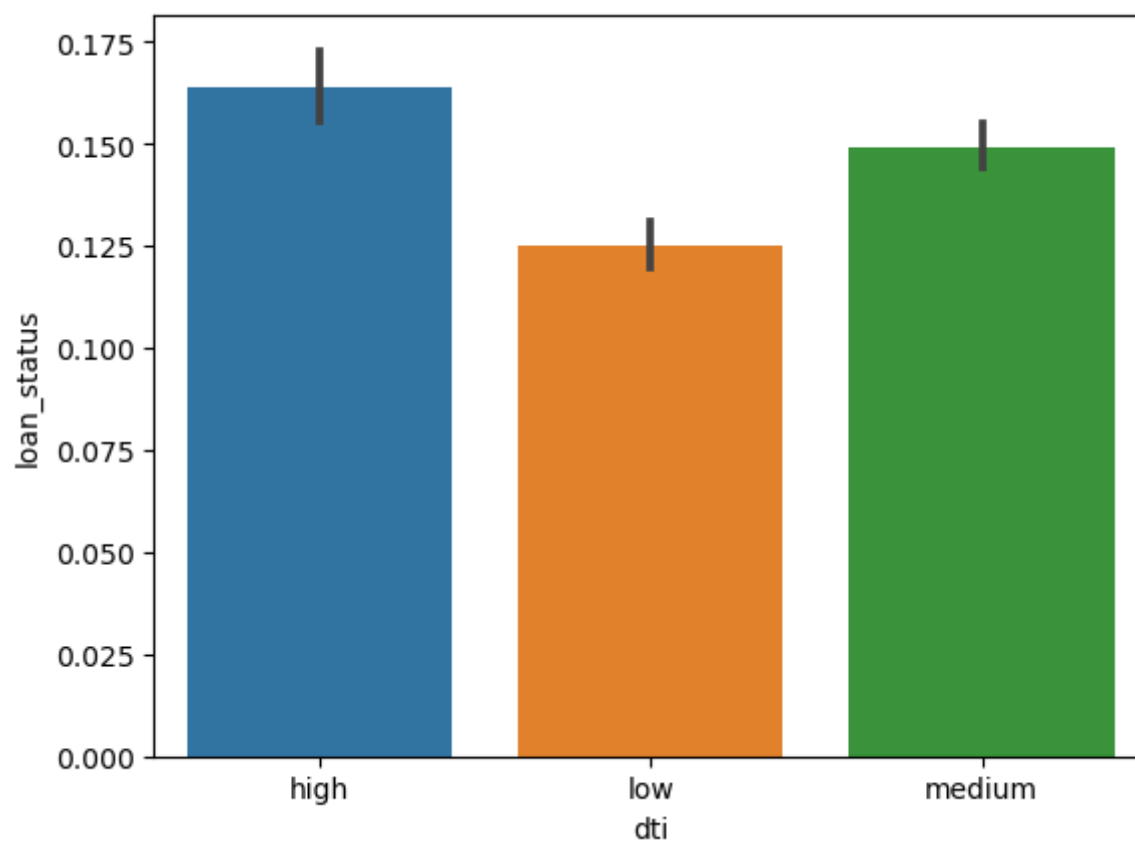
In [234...

```
loan['dti'].value_counts()
```



```
Out[234]: medium    18002  
low          12545  
high         6997  
Name: dti, dtype: int64
```

```
In [238... # comparing default rates across debt to income ratio  
# higher debt to income ratio has higher default rates  
plot_data('dti')
```



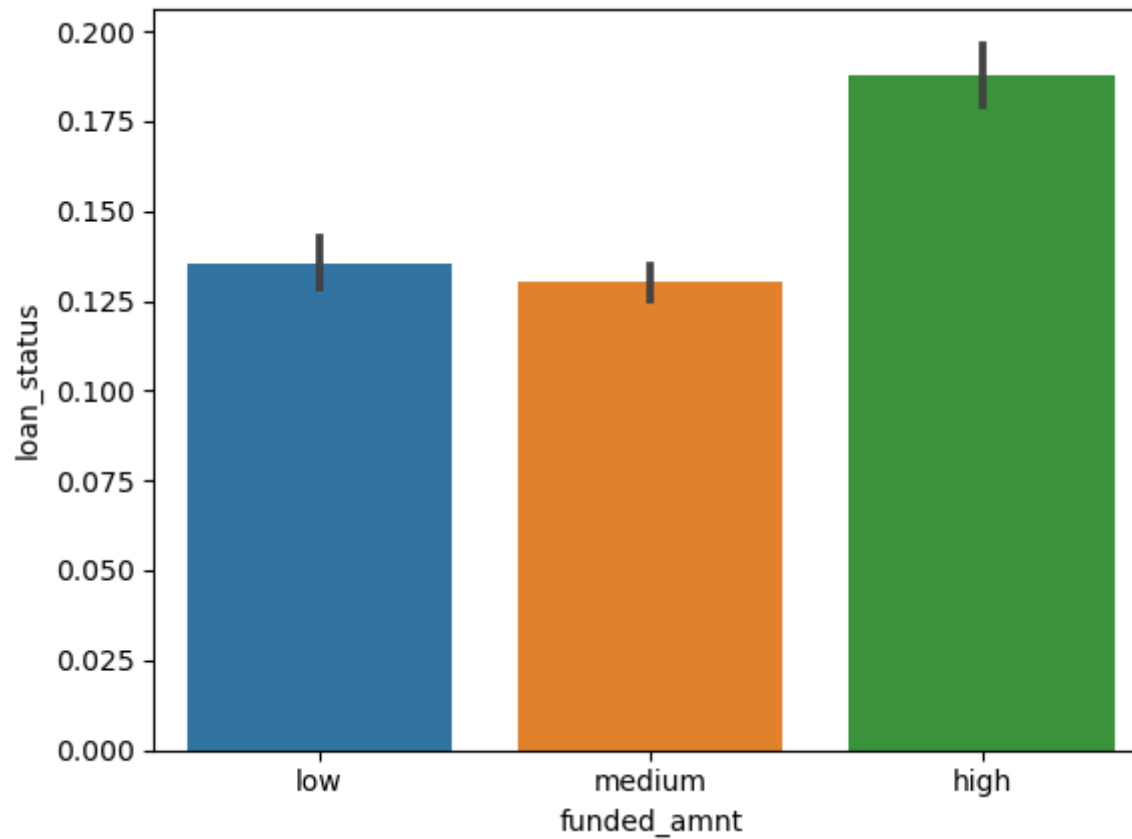
```
In [241... # funded amount  
def funded_amount(n):  
    if n <= 5000:  
        return 'low'  
    elif n > 5000 and n <=15000:  
        return 'medium'  
    else:
```

```
return 'high'
```

```
loan['funded_amnt'] = loan['funded_amnt'].apply(lambda x: funded_amount(x))
```

In [242...

```
#Higher funds are provided to customer higher is the default rate  
plot_data('funded_amnt')
```



In [243...

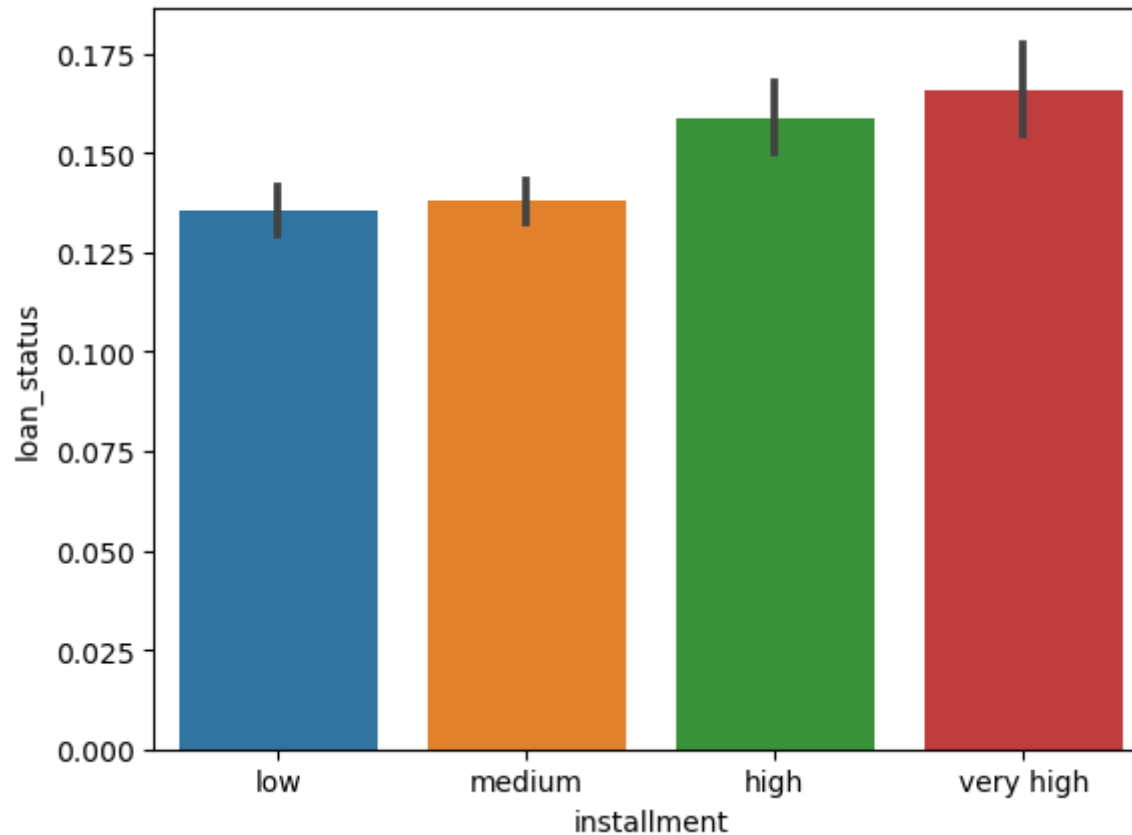
```
# installment  
def installment(n):  
    if n <= 200:  
        return 'low'  
    elif n > 200 and n <=400:  
        return 'medium'  
    elif n > 400 and n <=600:  
        return 'high'  
    else:
```

```
return 'very high'
```

```
loan['installment'] = loan['installment'].apply(lambda x: installment(x))
```

In [244...

```
# the higher the installment amount, the higher the default rate  
plot_data('installment')
```



In [245...

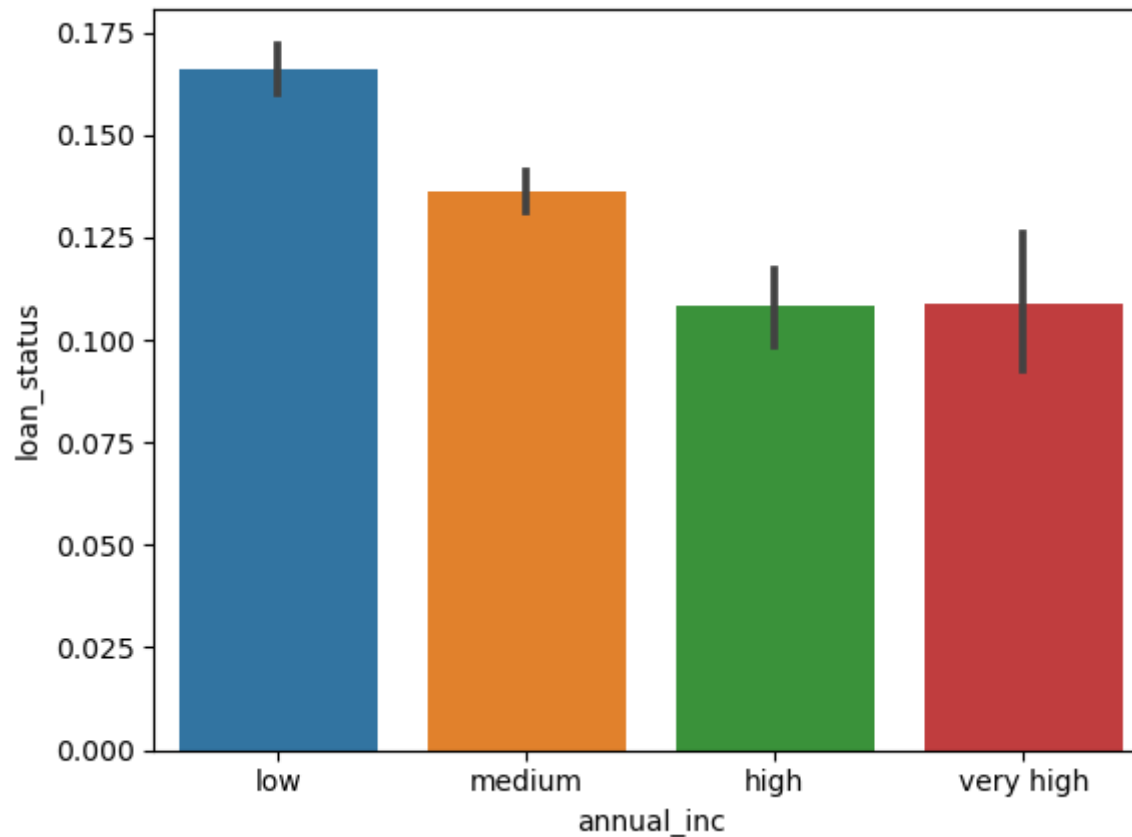
```
# annual income  
def annual_income(n):  
    if n <= 50000:  
        return 'low'  
    elif n > 50000 and n <=100000:  
        return 'medium'  
    elif n > 100000 and n <=150000:  
        return 'high'  
    else:
```

```
return 'very high'
```

```
loan['annual_inc'] = loan['annual_inc'].apply(lambda x: annual_income(x))
```

In [246...

```
#lower the income of customer higher is the default rate  
plot_data('annual_inc')
```



In [247...

```
# Emp_length  
loan.emp_length.isnull().sum()
```

Out[247]:

0

In [249...

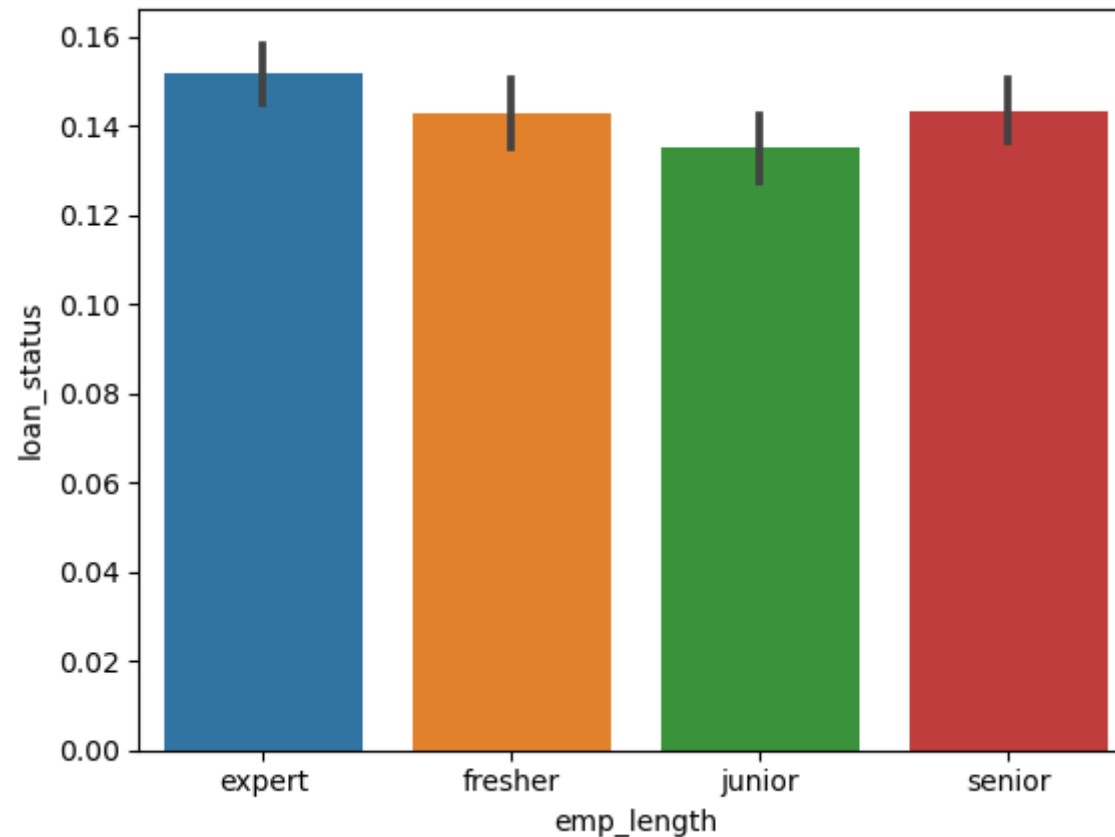
```
# binning the variable  
def emp_length(n):  
    if n <= 1:
```

```
    return 'fresher'
elif n > 1 and n <=3:
    return 'junior'
elif n > 3 and n <=7:
    return 'senior'
else:
    return 'expert'

loan['emp_length'] = loan['emp_length'].apply(lambda x: emp_length(x))
```

In [250...

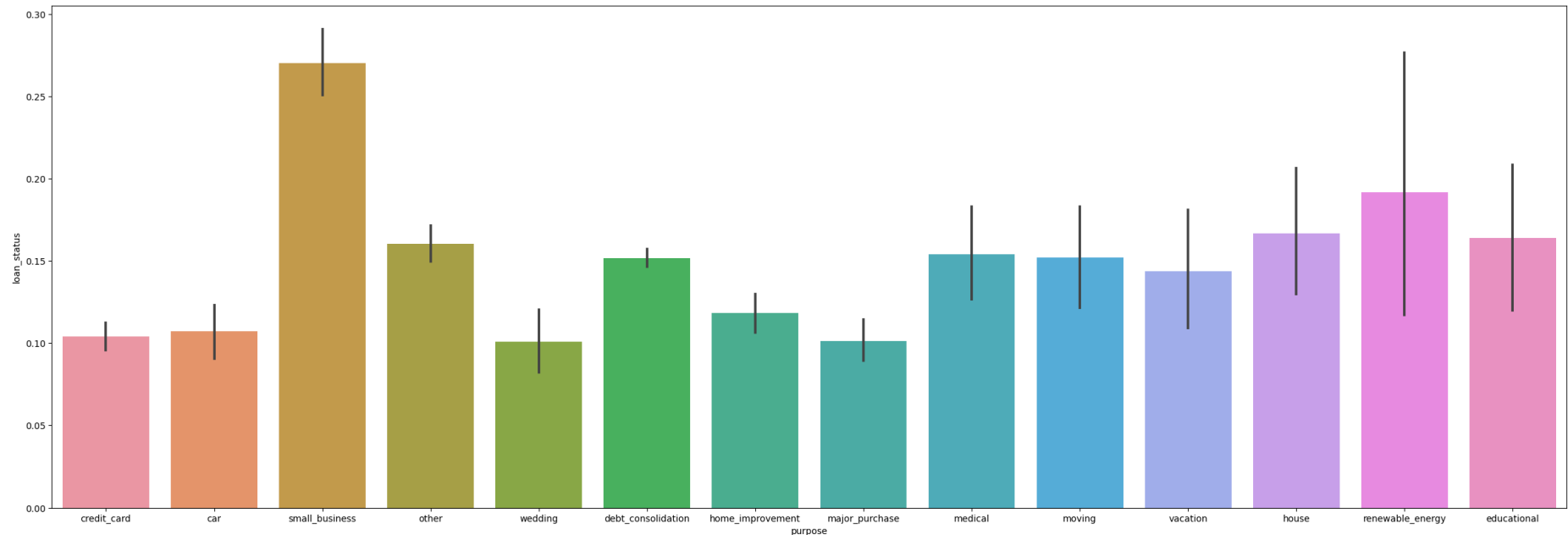
```
#Surprisingly customers with highest level experience has higher default rate
plot_data('emp_length')
```



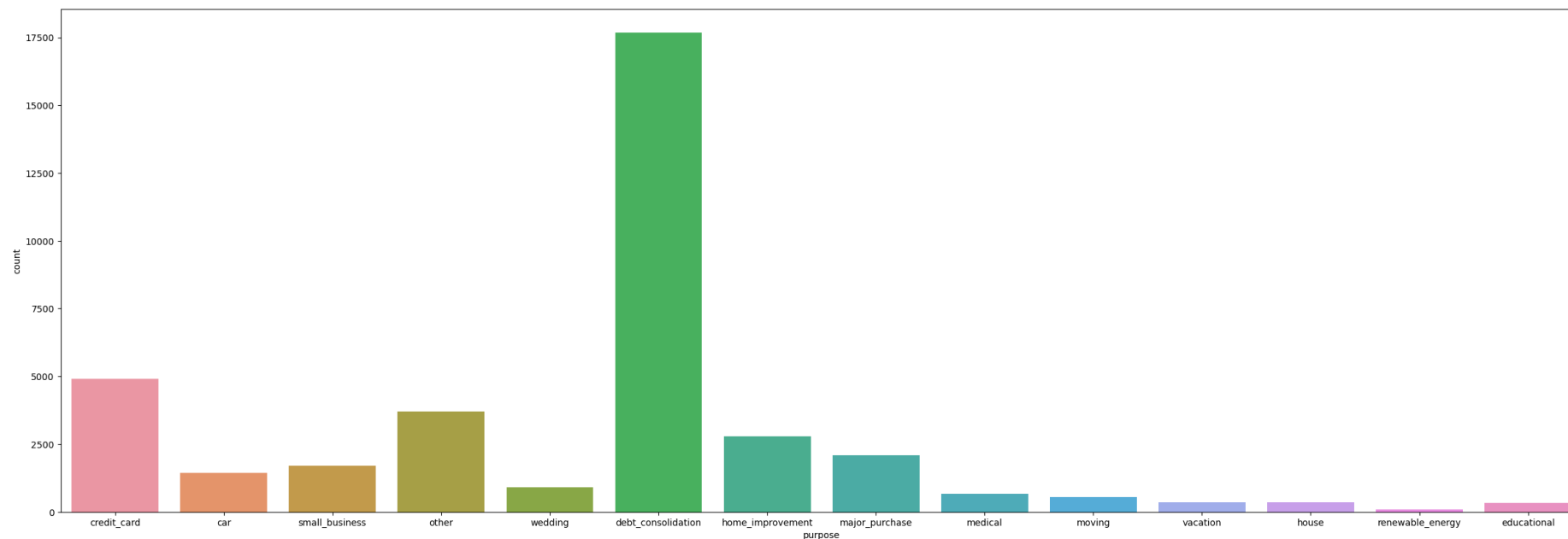
We have now compared the default rates across various variables, and some of the important predictors are purpose of the loan, interest rate, annual income, grade etc.

let's again have a look at the default rates across the purpose of the loan.

```
In [255... # purpose: small business loans default the most then others
plt.figure(figsize=(30, 10))
plot_data('purpose')
```



```
In [257... # Lets first look at the number of loans for each type (purpose) of the loan
# most loans are debt consolidation(to repay credit card bills or other loan payments), compared to others.
plt.figure(figsize=(30, 10))
sns.countplot(x='purpose', data=loan)
plt.show()
```

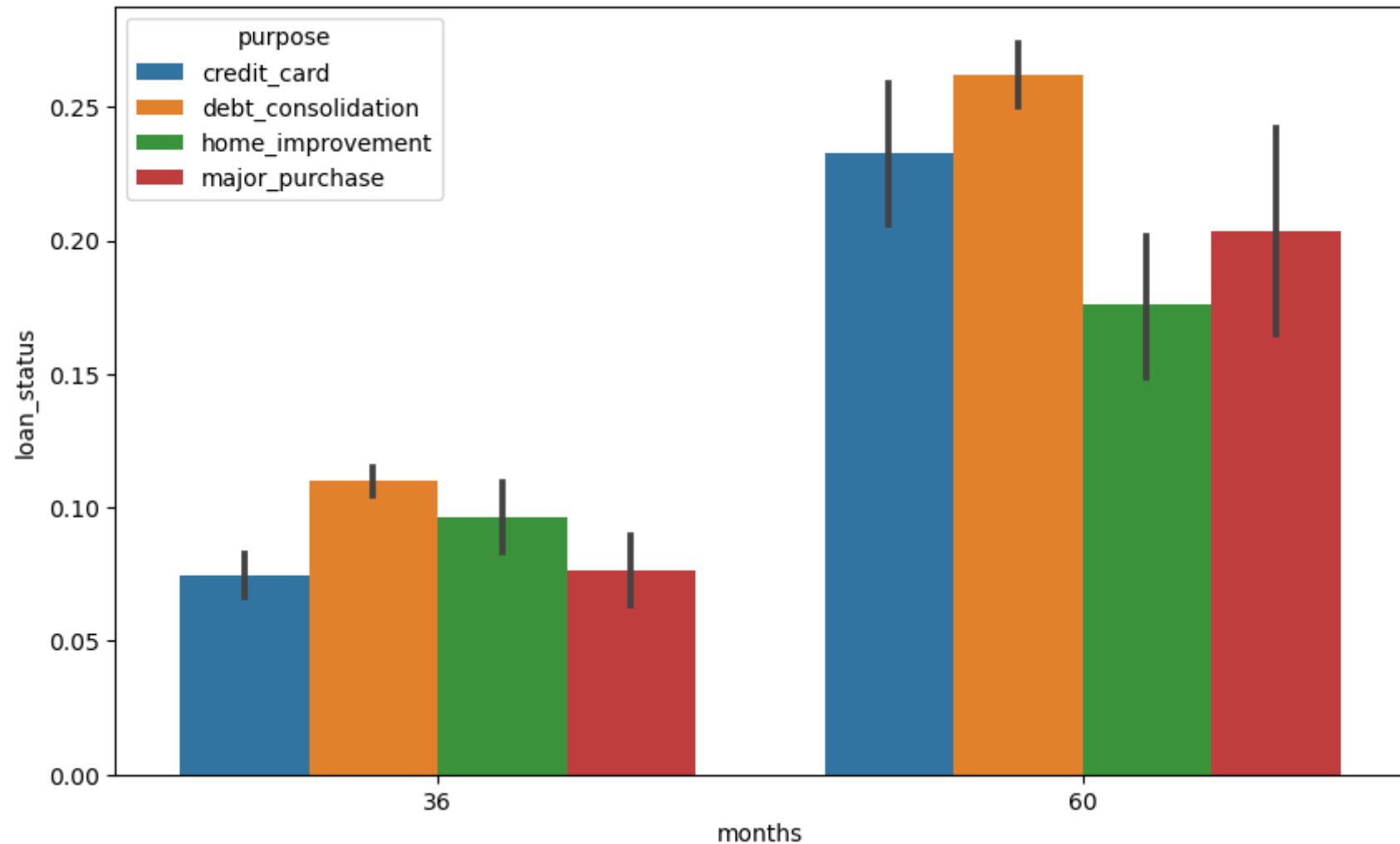


```
In [263... # filtering the loan for the 4 types of loans mentioned above
main_purposes = ["credit_card", "debt_consolidation", "home_improvement", "major_purchase"]
loan = loan[loan['purpose'].isin(main_purposes)]
loan['purpose'].value_counts()
```

```
Out[263]: debt_consolidation    17675
credit_card              4899
home_improvement         2785
major_purchase           2080
Name: purpose, dtype: int64
```

```
In [265... # Let's now compare the default rates across two types of categorical variables
# purpose of loan (constant) and another categorical variable (which changes)

plt.figure(figsize=[10, 6])
sns.barplot(x='months', y="loan_status", hue='purpose', data=loan)
plt.show()
```

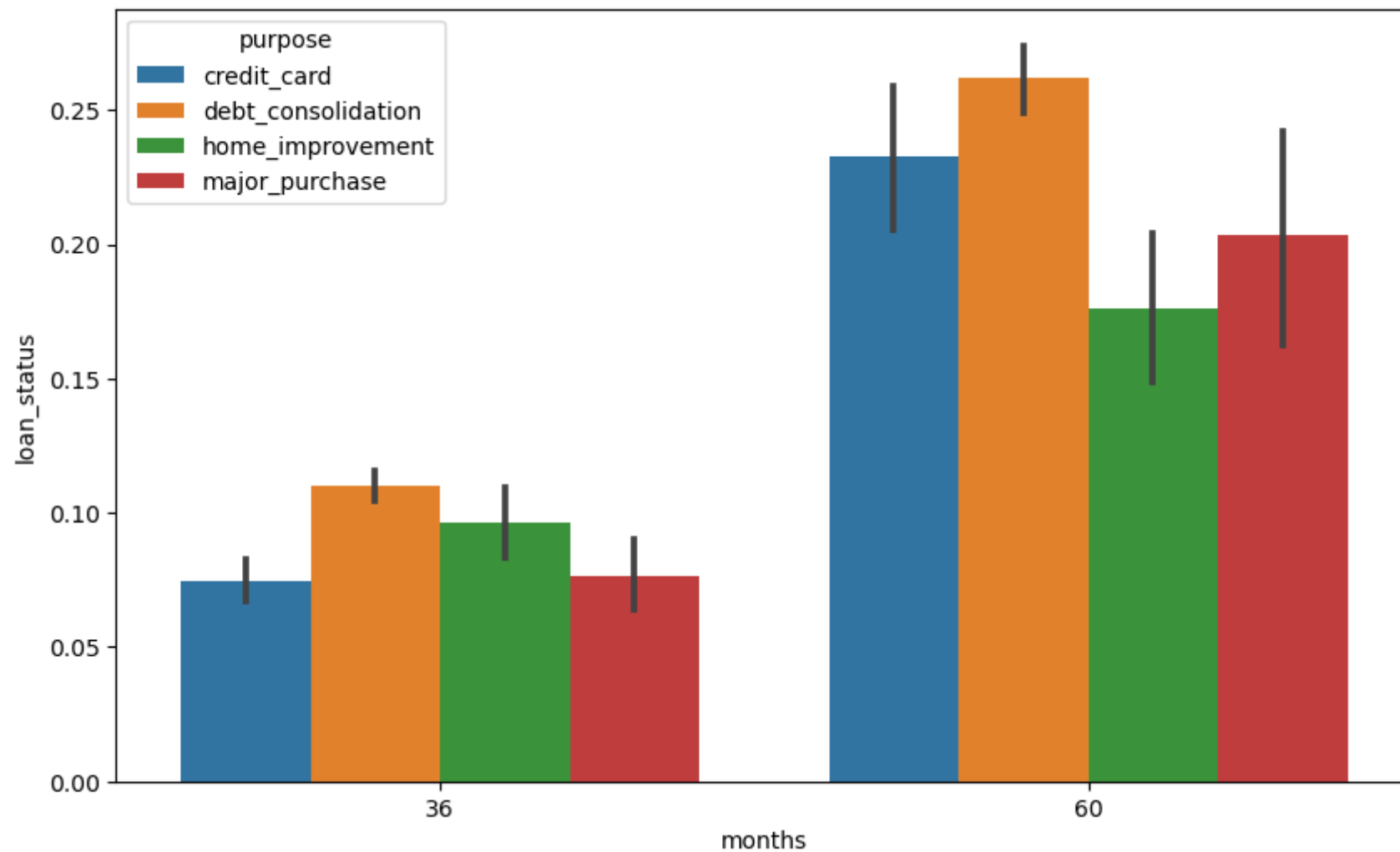


We can clearly see that whether it is 36 months term period or 60 months debt_consolidation has the highest default rate.

```
In [266... def plot_segmented(cat_var):  
    plt.figure(figsize=(10, 6))  
    sns.barplot(x=cat_var, y='loan_status', hue='purpose', data=loan)  
    plt.show()
```

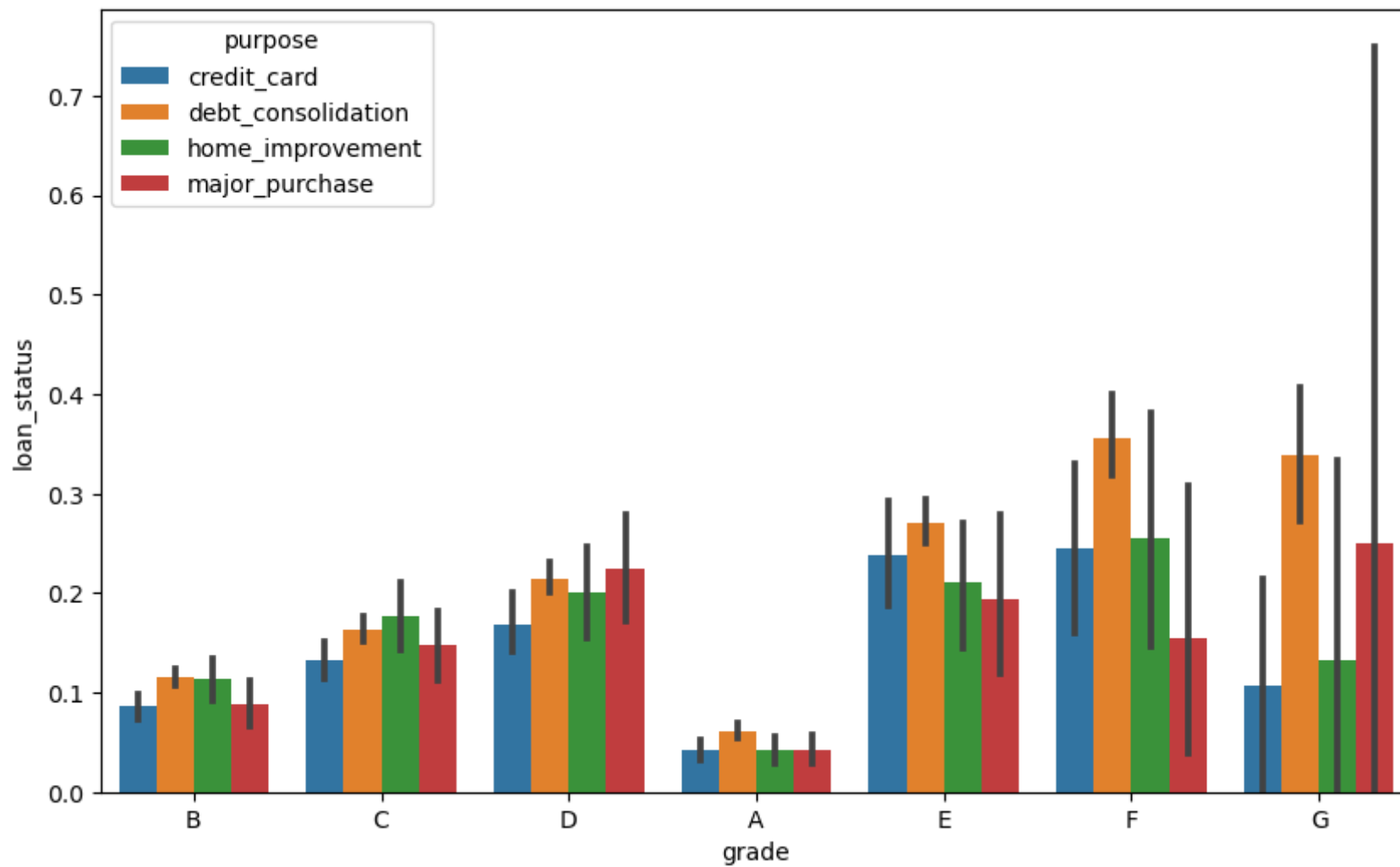


```
plot_segmented('months')
```



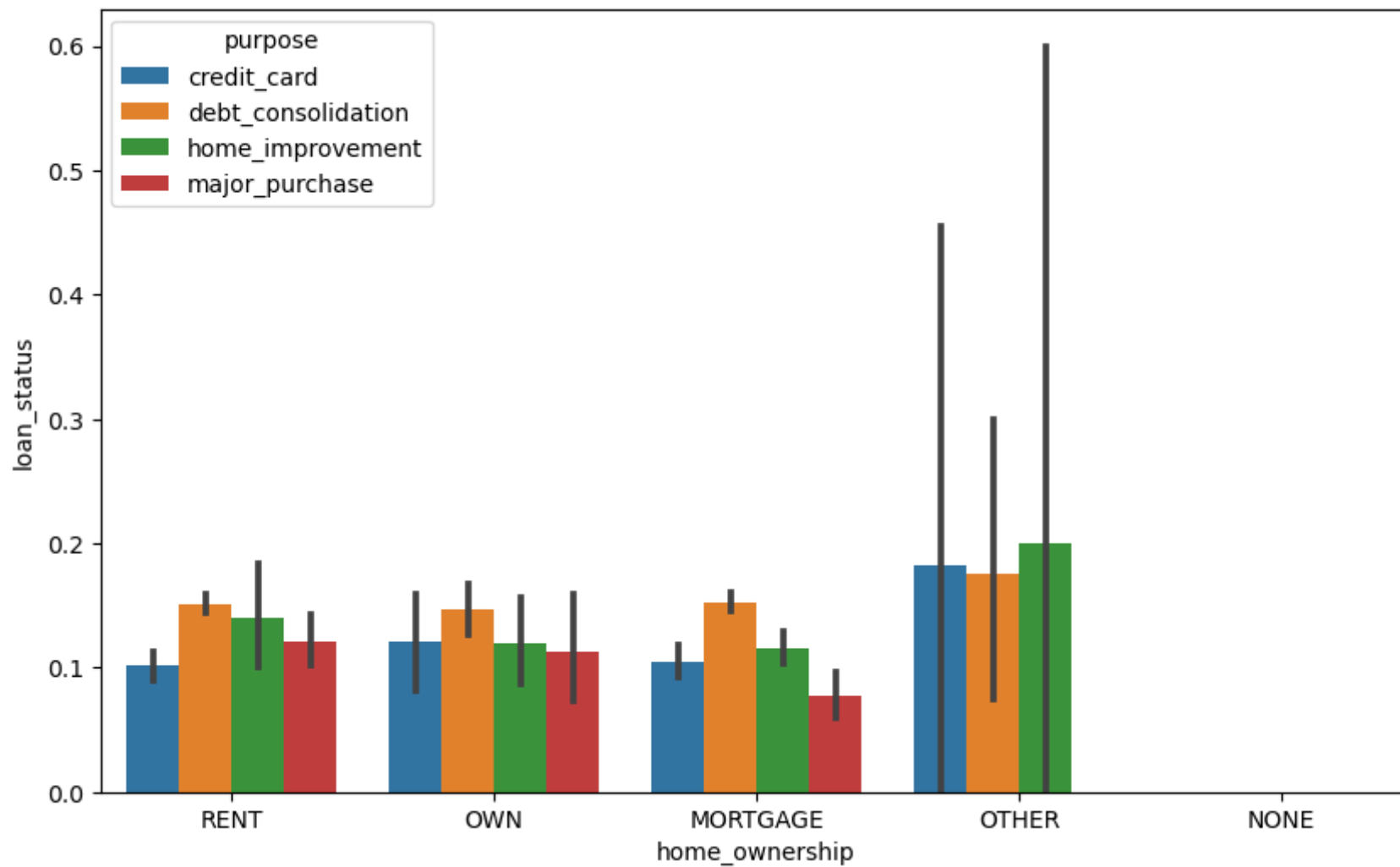
In [267...

```
# grade of loan  
plot_segmented('grade')
```



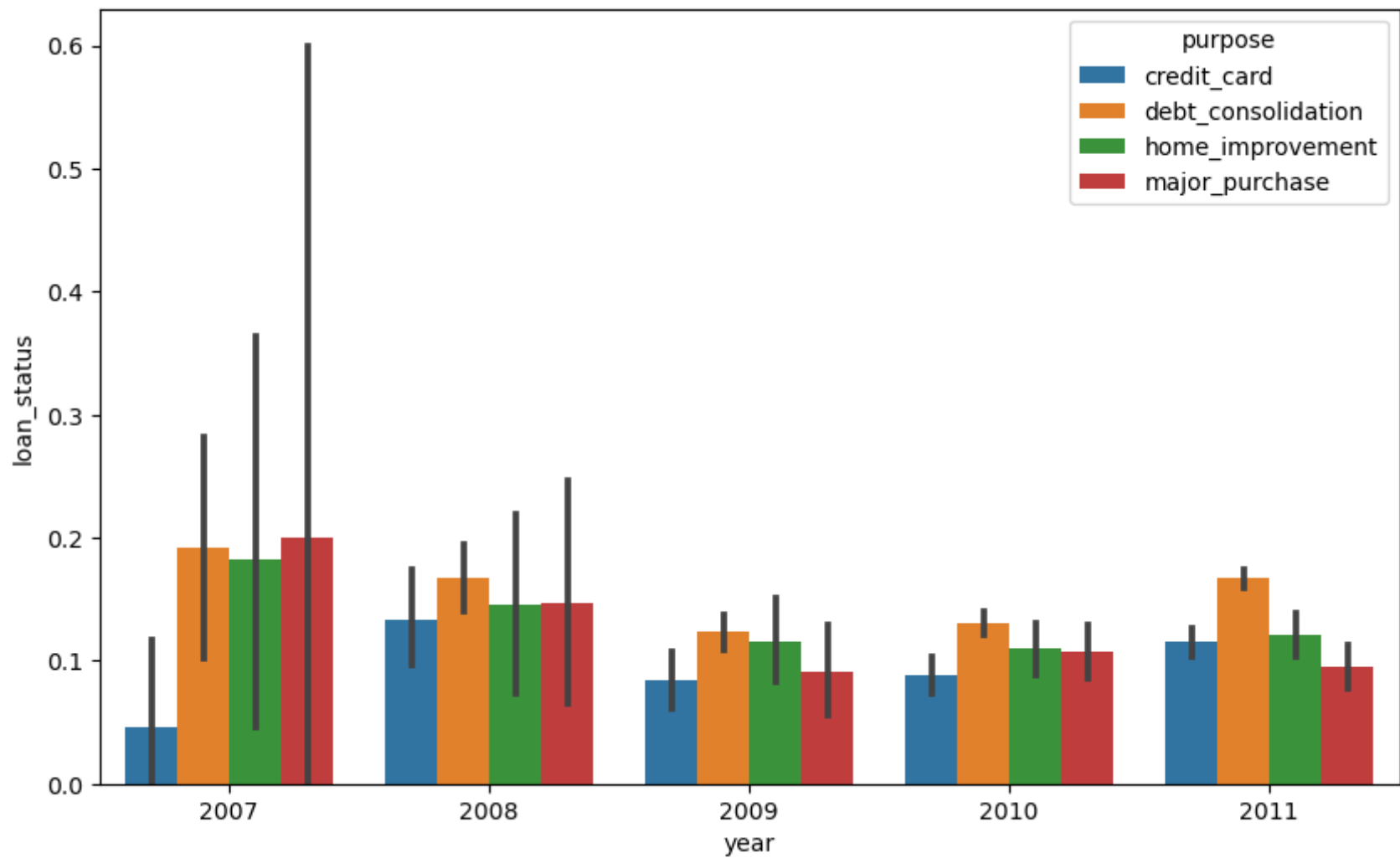
In [268...

```
# home ownership  
plot_segmented('home_ownership')
```



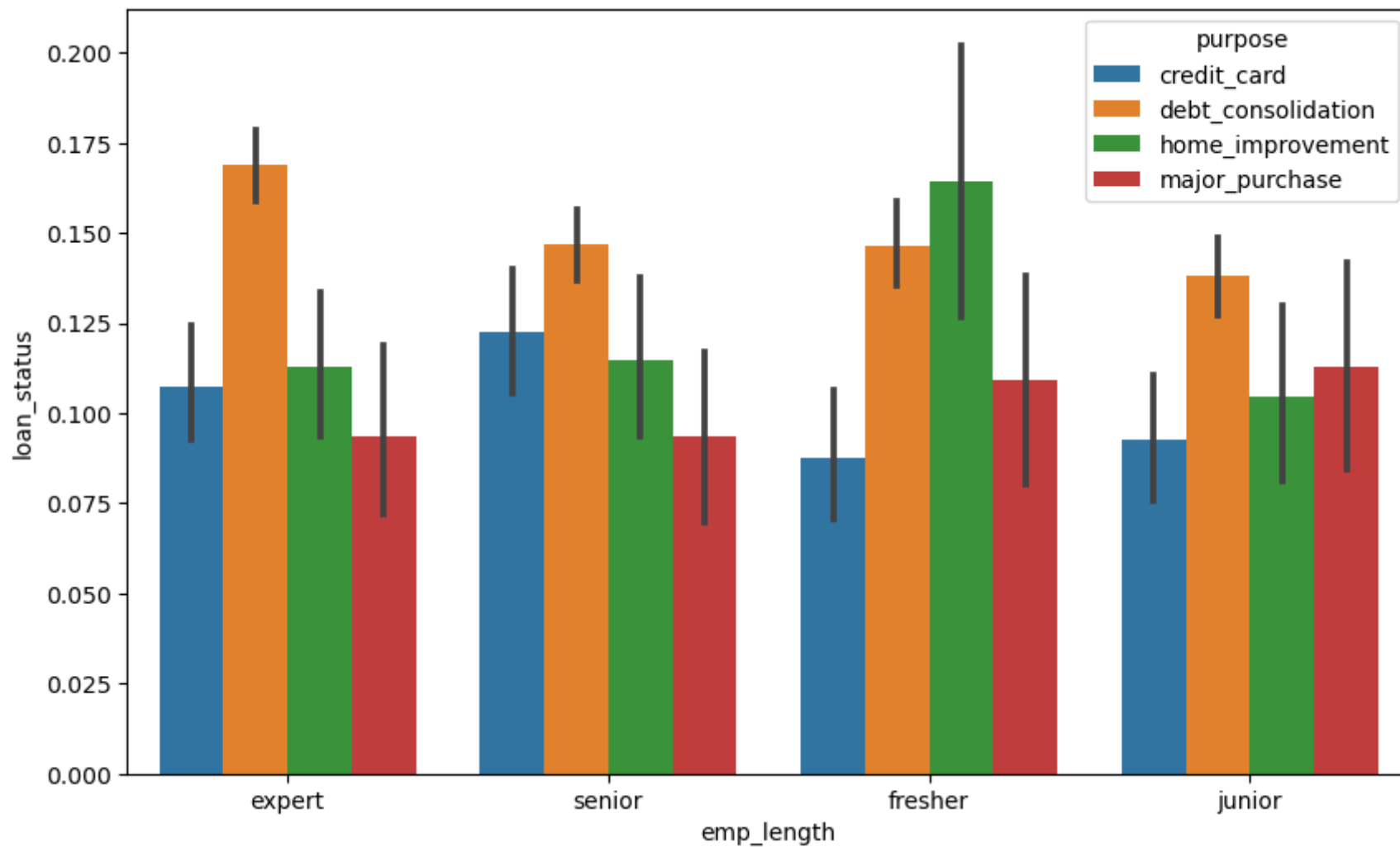
In [269...

```
# year  
plot_segmented('year')
```

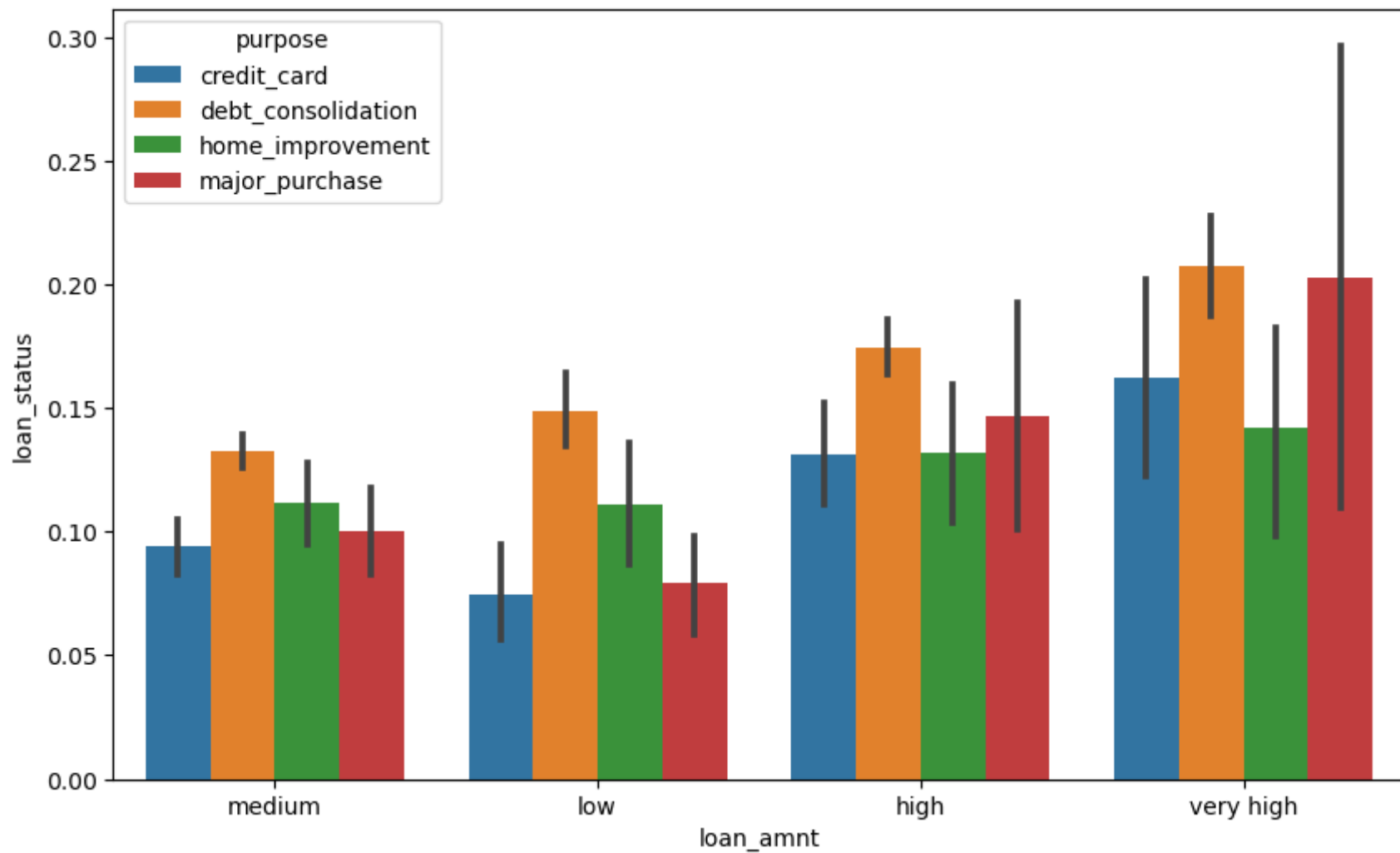


In [270...

```
# emp_length  
plot_segmented('emp_length')
```

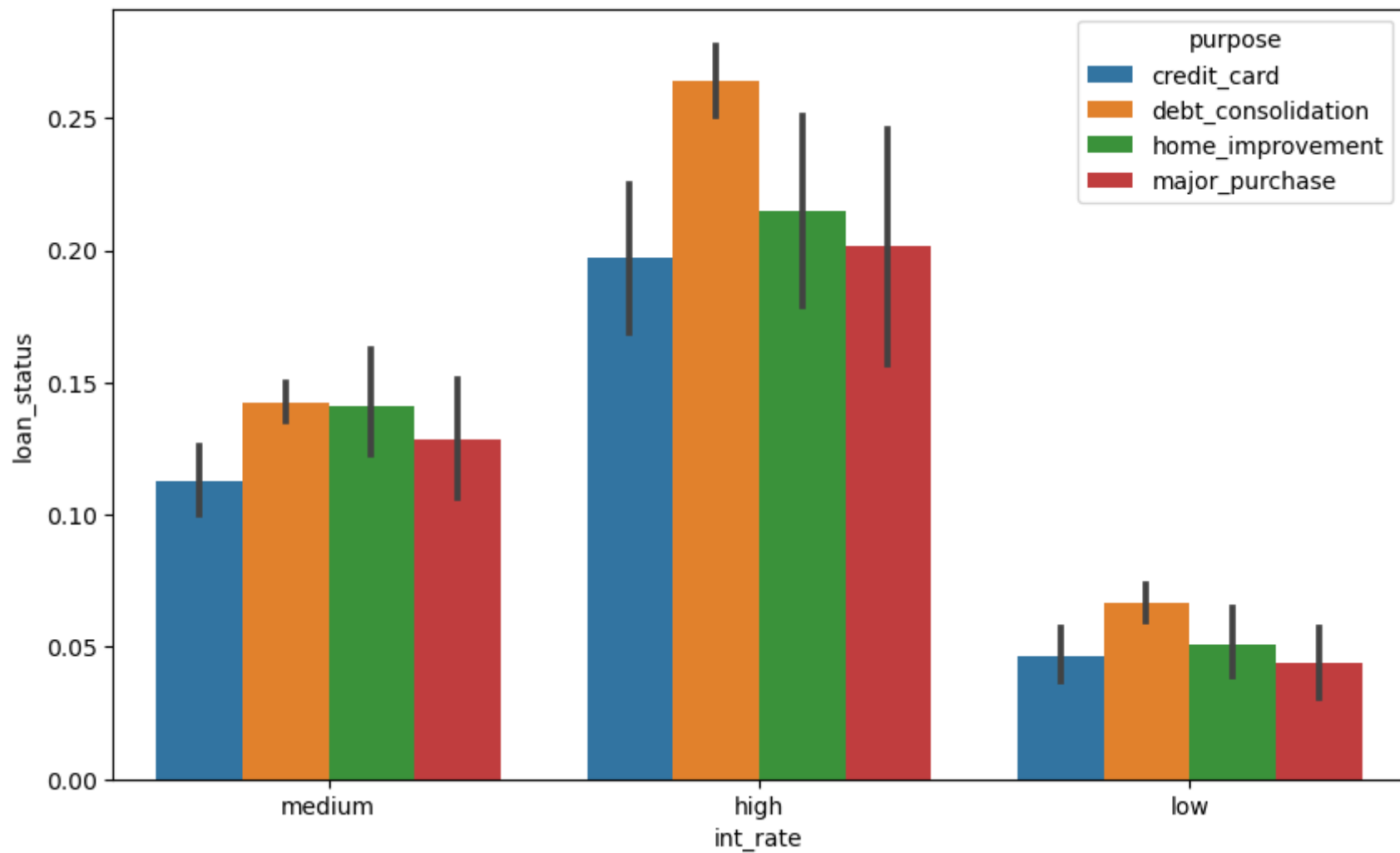


```
In [271... # loan_amnt: same trend across loan purposes  
plot_segmented('loan_amnt')
```



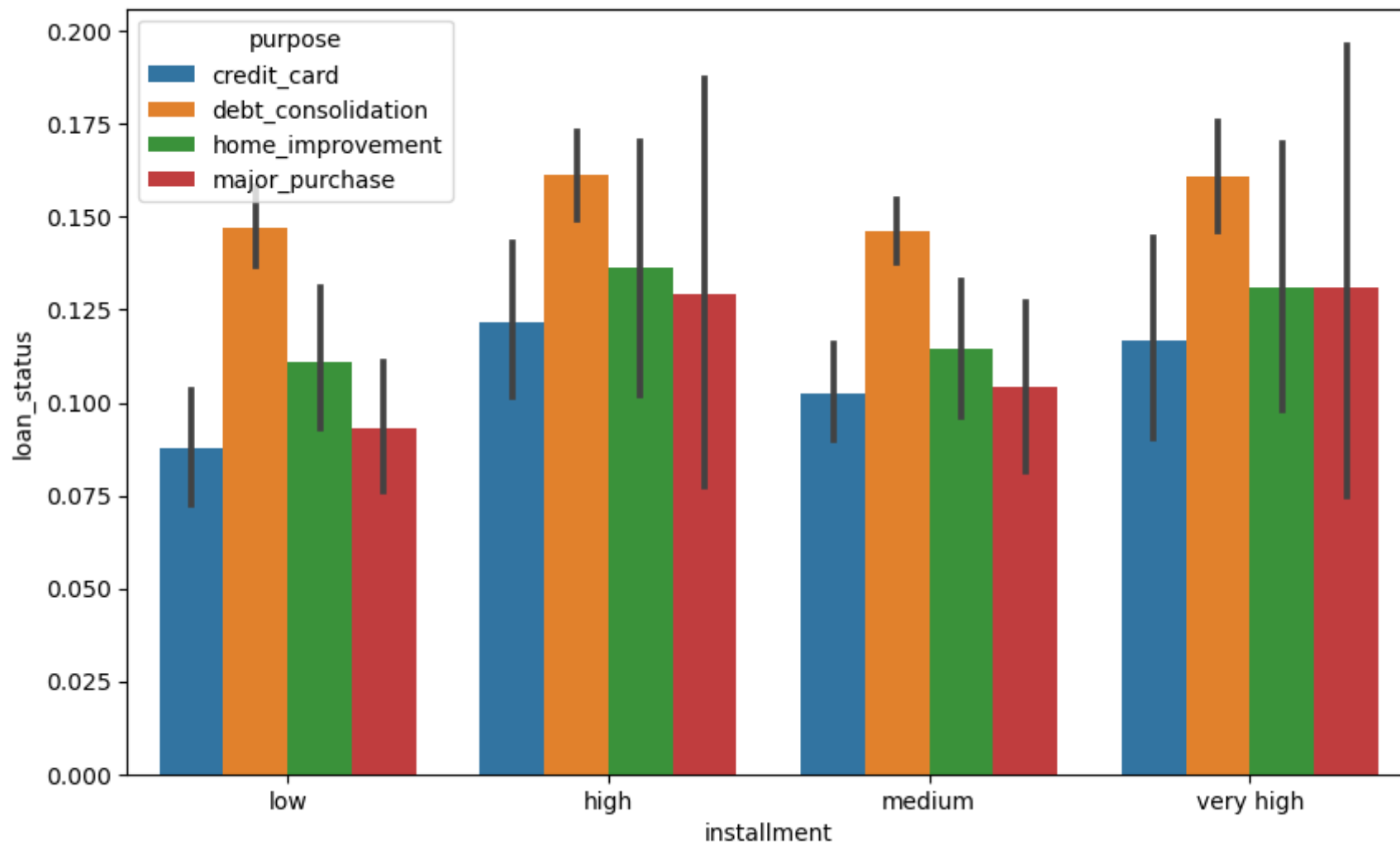
In [272...

```
# interest rate  
plot_segmented('int_rate')
```



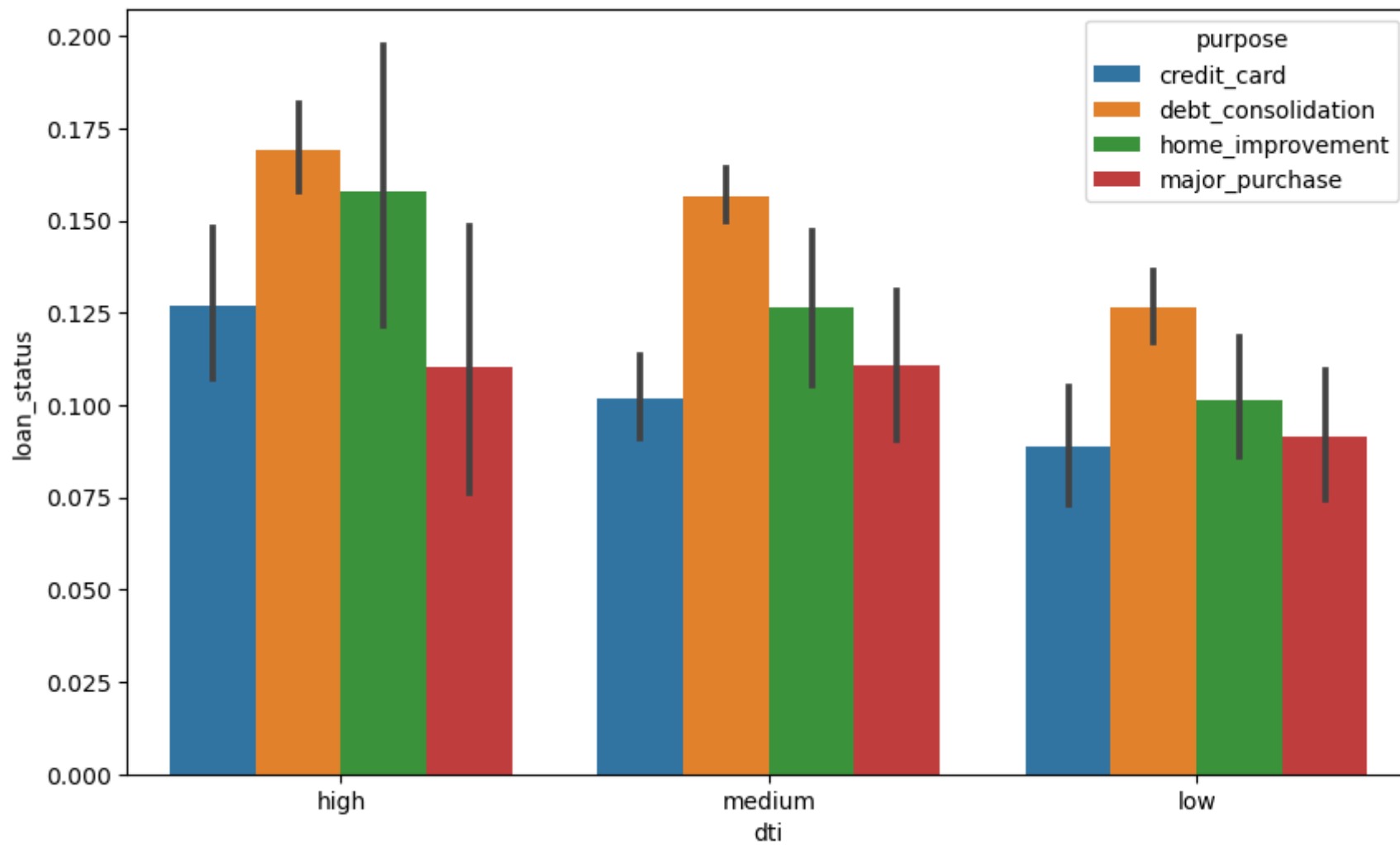
In [273...

```
# installment  
plot_segmented('installment')
```



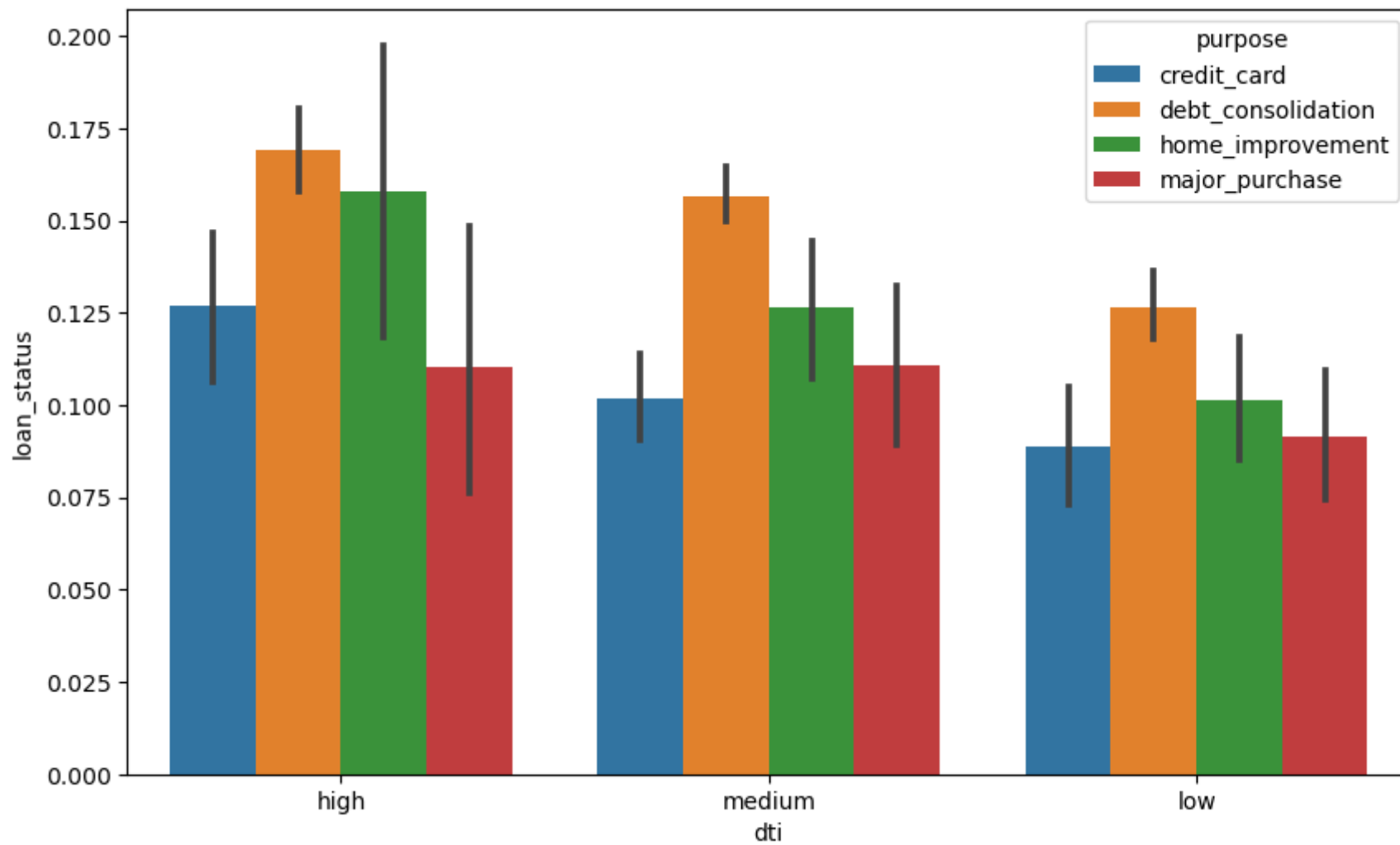
In [274...

```
# debt to income ratio  
plot_segmented('dti')
```

In [275...

```
# debt to income ratio  
plot_segmented('dti')
```



In []:

In []: