1 Loan Default Prediction

Banks have a huge volume of applicants applying for loans. Some of the applicants do not have credit history or some might have very light credit score. It doesn't mean that lending money to them is highly risky so we should reject all of these applicants. This project uses data about personal loan. Our goal was to develop a model that could step by step explain the results of the model we built and what impact on the likelihood of the case falling into one of the binary categories (loans paid-off and charged). This model predict the 68 % of loan default and would be useful for the banks to make the best decision.

2 Use Resampling for data manipulation

Due to the fact that the existing dataset is not balanced, which means that there are many more customers with clear loan status than customers who default, we used the sampling method to address this issue. The sampling method is a special case of statistical inference where observations are selected from a population to answer a question about the whole population.

3 Obtaining the Data

In [1]:
```
# importing relevant libraries
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt



from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split, RandomizedSearchCV
from sklearn.preprocessing import MinMaxScaler


import statsmodels.api as sm
from statsmodels.tsa.stattools import adfuller
from statsmodels.graphics.tsaplots import plot_acf
from statsmodels.graphics.tsaplots import plot_pacf



from sklearn.metrics import mean_squared_error
import math
import warnings
warnings.filterwarnings('ignore')

import itertools
from collections import Counter


#from sklearn import preprocessing
from sklearn.preprocessing import StandardScaler, LabelEncoder
from sklearn.model_selection import train_test_split, GridSearchCV, cross_v

#resample the data
from imblearn.over_sampling import SMOTE,SMOTENC


from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import plot_confusion_matrix,classification_report,pre
from sklearn.pipeline import Pipeline
from xgboost import XGBClassifier

#Remove warnings
import warnings
warnings.filterwarnings('ignore')




%matplotlib inline
from matplotlib.pylab import rcParams
from matplotlib.ticker import FuncFormatter
```

```
from catboost import CatBoostClassifier
```

In [2]:
```
pip install plotly-express
```

```
Requirement already satisfied: plotly-express in /Users/claudiatsai/opt/a
naconda3/lib/python3.9/site-packages (0.4.1)
Requirement already satisfied: numpy>=1.11 in /Users/claudiatsai/opt/anac
onda3/lib/python3.9/site-packages (from plotly-express) (1.22.4)
Requirement already satisfied: patsy>=0.5 in /Users/claudiatsai/opt/anaco
nda3/lib/python3.9/site-packages (from plotly-express) (0.5.2)
Requirement already satisfied: statsmodels>=0.9.0 in /Users/claudiatsai/o
pt/anaconda3/lib/python3.9/site-packages (from plotly-express) (0.13.2)
Requirement already satisfied: plotly>=4.1.0 in /Users/claudiatsai/opt/an
aconda3/lib/python3.9/site-packages (from plotly-express) (5.11.0)
Requirement already satisfied: pandas>=0.20.0 in /Users/claudiatsai/opt/a
naconda3/lib/python3.9/site-packages (from plotly-express) (1.3.4)
Requirement already satisfied: scipy>=0.18 in /Users/claudiatsai/opt/anac
onda3/lib/python3.9/site-packages (from plotly-express) (1.7.1)
Requirement already satisfied: python-dateutil>=2.7.3 in /Users/claudiats
ai/opt/anaconda3/lib/python3.9/site-packages (from pandas>=0.20.0->plotly
-express) (2.8.2)
Requirement already satisfied: pytz>=2017.3 in /Users/claudiatsai/opt/ana
conda3/lib/python3.9/site-packages (from pandas>=0.20.0->plotly-express)
(2021.3)
Requirement already satisfied: six in /Users/claudiatsai/opt/anaconda3/li
b/python3.9/site-packages (from patsy>=0.5->plotly-express) (1.16.0)
Requirement already satisfied: tenacity>=6.2.0 in /Users/claudiatsai/opt/
anaconda3/lib/python3.9/site-packages (from plotly>=4.1.0->plotly-expres
s) (8.1.0)
Requirement already satisfied: packaging>=21.3 in /Users/claudiatsai/opt/
anaconda3/lib/python3.9/site-packages (from statsmodels>=0.9.0->plotly-ex
press) (21.3)
Requirement already satisfied: pyparsing!=3.0.5,>=2.0.2 in /Users/claudia
tsai/opt/anaconda3/lib/python3.9/site-packages (from packaging>=21.3->sta
tsmodels>=0.9.0->plotly-express) (3.0.4)
Note: you may need to restart the kernel to use updated packages.
```

In [3]:
```
pd.set_option('display.float_format', lambda x: '%.3f' % x)
```

In [4]:
```
def thousands(tick_val,pos):
    """adapted from https://dfrieds.com/data-visualizations/how-format-larg
    val = round(tick_val/1000, 1)
    new_tick_format = '{:.0f}K'.format(val)
    return new_tick_format
form = FuncFormatter(thousands)
```

Due to imbalance dataset, the models in previous notebook have very high accuracy scores and recall scores. In this note book, I will resample the dataset and run the models again.

In [5]:
```
loan=pd.read_csv('/Users/claudiatsai/Documents/Flatiron/Phase_5/data_loan_d
```

In [6]:
```
loan.head()
```

Out[6]:

	loan_amnt	term	int_rate	sub_grade	emp_title	emp_length	home_ownership	annual_inc	v
0	3600.000	36 months	13.990	C4	leadman	10+ years	MORTGAGE	55000.000	
1	24700.000	36 months	11.990	C1	Engineer	10+ years	MORTGAGE	65000.000	
2	20000.000	60 months	10.780	B4	truck driver	10+ years	MORTGAGE	63000.000	
3	35000.000	60 months	14.850	C5	Information Systems Officer	10+ years	MORTGAGE	110000.000	
4	10400.000	60 months	22.450	F1	Contract Specialist	3 years	MORTGAGE	104433.000	

5 rows × 25 columns

4 Scrubbing and Cleaning Data

In [7]:
```
loan.dtypes
```

Out[7]:
```
loan_amnt                float64
term                      object
int_rate                 float64
sub_grade                 object
emp_title                 object
emp_length                object
home_ownership            object
annual_inc               float64
verification_status       object
loan_status               object
purpose                   object
addr_state                object
fico_range_low           float64
fico_range_high          float64
open_acc                 float64
pub_rec                  float64
revol_bal                float64
revol_util               float64
total_acc                float64
initial_list_status       object
application_type          object
tot_cur_bal              float64
mort_acc                 float64
num_actv_bc_tl           float64
pub_rec_bankruptcies     float64
dtype: object
```

4.0.1 loan_status

Loan_status is the dependent variable in the dataset.

In [8]:
```
loan.loan_status.value_counts(normalize=True)
```

Out[8]:
```
Fully Paid                                             0.476
Current                                                0.389
Charged Off                                            0.119
Late (31-120 days)                                     0.009
In Grace Period                                        0.004
Late (16-30 days)                                      0.002
Does not meet the credit policy. Status:Fully Paid    0.001
Does not meet the credit policy. Status:Charged Off   0.000
Default                                                0.000
Name: loan_status, dtype: float64
```

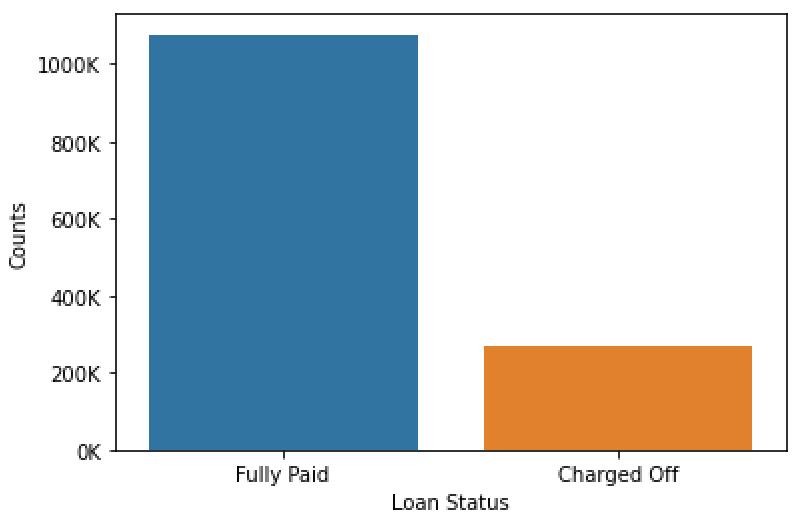
Focus on "Fully Paid" and "Charged Off" in loan_status.

In [10]:
```
loan_list=['Charged Off', 'Fully Paid']
loan= loan.loc[loan['loan_status'].isin(loan_list)]
```

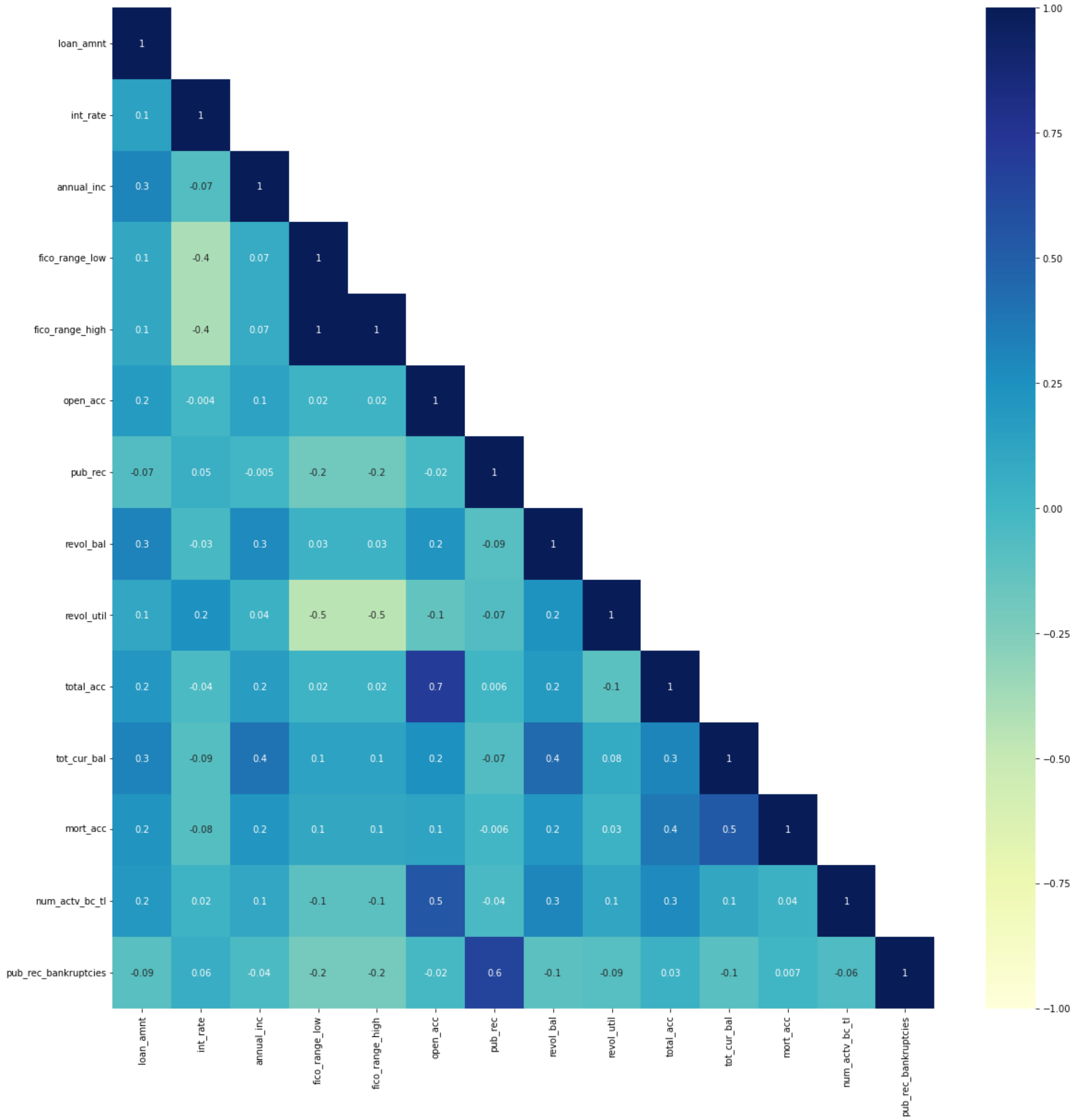
In [11]:
```
loan.loan_status.value_counts()
```

Out[11]:
```
Fully Paid     1076751
Charged Off     268559
Name: loan_status, dtype: int64
```

In [12]:
```
loan_status = loan['loan_status'].value_counts()
ax = sns.barplot(x = loan_status.index, y = loan_status.values)
ax.set_ylabel('Counts')
ax.set_xlabel('Loan Status')
ax.yaxis.set_major_formatter(form)
```



In [13]:
```
'''showed the lower triangular heatmap
https://datavizpyr.com/how-to-make-lower-triangular-heatmap-with-python/
'''
corr = loan.corr()
corr_tri = corr.where(np.tril(np.ones(corr.shape)).astype(np.bool))
fig, ax = plt.subplots(figsize = (20,20))
sns.heatmap(data = corr_tri, center = 0, cmap = "YlGnBu", annot = True, fmt
```



Check the null values in each variable

In [14]:
```
loan.isna().sum()
```

Out[14]:
```
loan_amnt                   0
term                        0
int_rate                    0
sub_grade                   0
emp_title               85785
emp_length              78511
home_ownership              0
annual_inc                  0
verification_status         0
loan_status                 0
purpose                     0
addr_state                  0
fico_range_low              0
fico_range_high             0
open_acc                    0
pub_rec                     0
revol_bal                   0
revol_util                857
total_acc                   0
initial_list_status         0
application_type            0
tot_cur_bal             67527
mort_acc                47281
num_actv_bc_tl          67527
pub_rec_bankruptcies      697
dtype: int64
```

In [15]:
```
null_data = ((loan.isna().sum()/len(loan))*100)[((loan.isna().sum()/len(loa
null_data
```

Out[15]:
```
emp_title               6.377
emp_length              5.836
revol_util              0.064
tot_cur_bal             5.019
mort_acc                3.515
num_actv_bc_tl          5.019
pub_rec_bankruptcies    0.052
dtype: float64
```

4.0.2 emp_title

In [16]:
```
loan.emp_title.describe()
```

Out[16]:
```
count      1259525
unique      378353
top        Teacher
freq         21268
Name: emp_title, dtype: object
```

The unique values of emp_titles are 378353 which is way more too large to put into categories. Drop this column.

In [17]:
```
loan = loan.drop('emp_title', axis=1)
```

4.0.3 emp_length

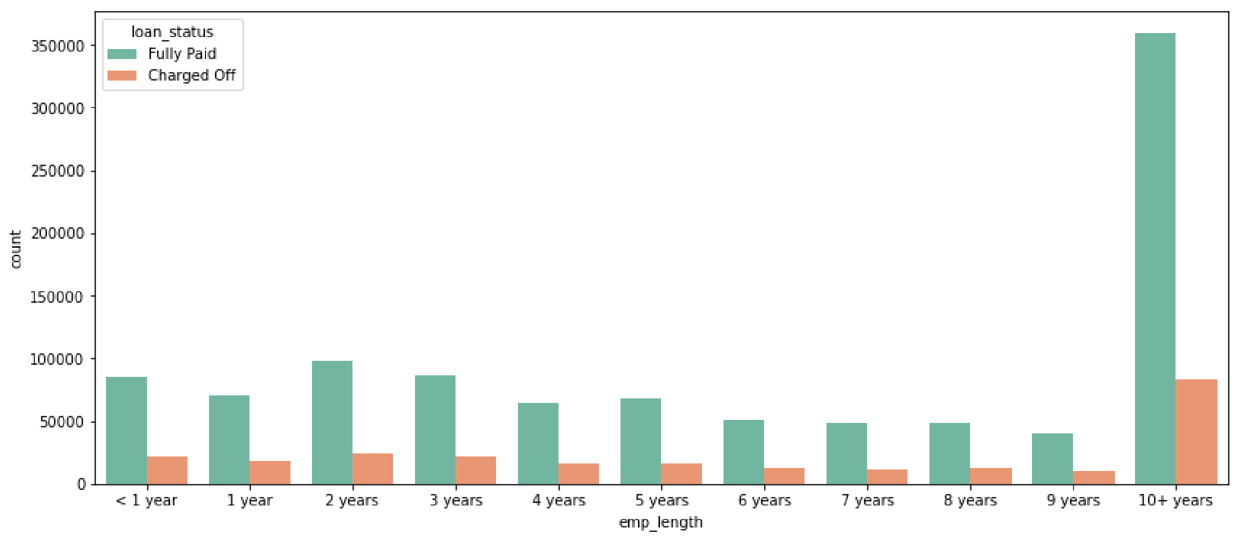
In [18]:
```
loan.emp_length.value_counts(normalize=True)
```

Out[18]:
```
10+ years    0.349
2 years      0.096
< 1 year     0.085
3 years      0.085
1 year       0.070
5 years      0.066
4 years      0.064
6 years      0.050
8 years      0.048
7 years      0.047
9 years      0.040
Name: emp_length, dtype: float64
```

In [19]:
```
emp_length_order = [ '< 1 year', '1 year', '2 years', '3 years', '4 years',
                     '5 years', '6 years', '7 years', '8 years', '9 years',
```

In [20]:
```
plt.figure(figsize=(14,6))
sns.countplot(x='emp_length',data=loan,order=emp_length_order,hue='loan_sta
```

Out[20]:
```
<AxesSubplot:xlabel='emp_length', ylabel='count'>
```



In [21]:
```
for order in emp_length_order:
    print(f"{order}:")
    print(f"{loan[loan.emp_length == order].loan_status.value_counts(normal
```

```
< 1 year:
Fully Paid     0.795
Charged Off    0.205
Name: loan_status, dtype: float64
1 year:
Fully Paid     0.794
Charged Off    0.206
Name: loan_status, dtype: float64
2 years:
Fully Paid     0.802
Charged Off    0.198
Name: loan_status, dtype: float64
3 years:
Fully Paid     0.800
Charged Off    0.200
Name: loan_status, dtype: float64
4 years:
Fully Paid     0.803
Charged Off    0.197
Name: loan_status, dtype: float64
5 years:
Fully Paid     0.804
Charged Off    0.196
Name: loan_status, dtype: float64
6 years:
Fully Paid     0.806
Charged Off    0.194
Name: loan_status, dtype: float64
7 years:
Fully Paid     0.805
Charged Off    0.195
Name: loan_status, dtype: float64
8 years:
Fully Paid     0.801
Charged Off    0.199
Name: loan_status, dtype: float64
9 years:
Fully Paid     0.801
Charged Off    0.199
Name: loan_status, dtype: float64
10+ years:
Fully Paid     0.812
Charged Off    0.188
Name: loan_status, dtype: float64
```

From above data, charged off rate is 19%-20% in each employee lengths. So emp_length will be dropped as well.

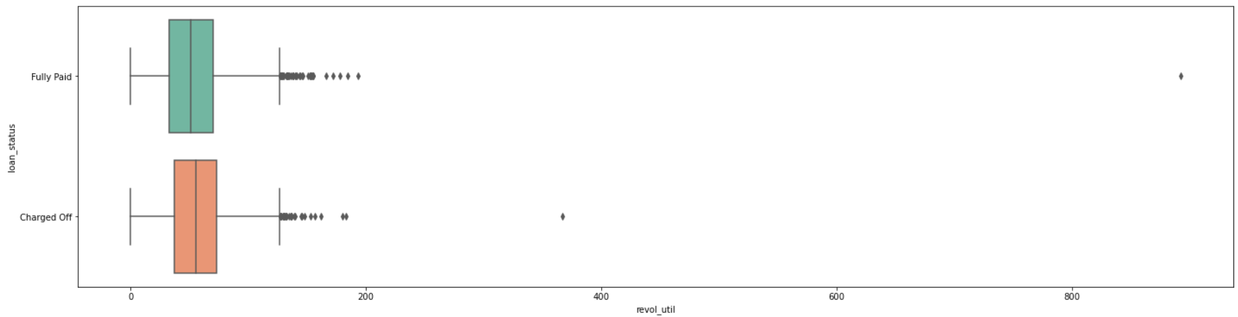
In [22]:
```
loan = loan.drop('emp_length',axis=1)
```

4.0.4 revol_util

revol_util: Revolving line utilization rate, or the amount of credit the borrower is using relative to all available revolving credit.

Feature "revol_util" has 0.06% null values in the dataset. Use the mean value to fill the null value.

In [23]:
```
plt.figure(figsize=(24,6))
sns.boxplot(data=loan, x='revol_util', y='loan_status', palette='Set2');
```



In [24]:
```
loan.revol_util = loan.revol_util.fillna(loan.revol_util.mean())
```

In [25]:
```
loan.revol_util.isna().sum()
```

Out[25]: 0

In [26]:
```
loan.groupby('loan_status')['revol_util'].describe()
```

Out[26]:

loan_status	count	mean	std	min	25%	50%	75%	max
Charged Off	268559.000	54.756	23.858	0.000	37.400	55.500	73.100	366.600
Fully Paid	1076751.000	51.075	24.619	0.000	32.500	51.300	70.000	892.300

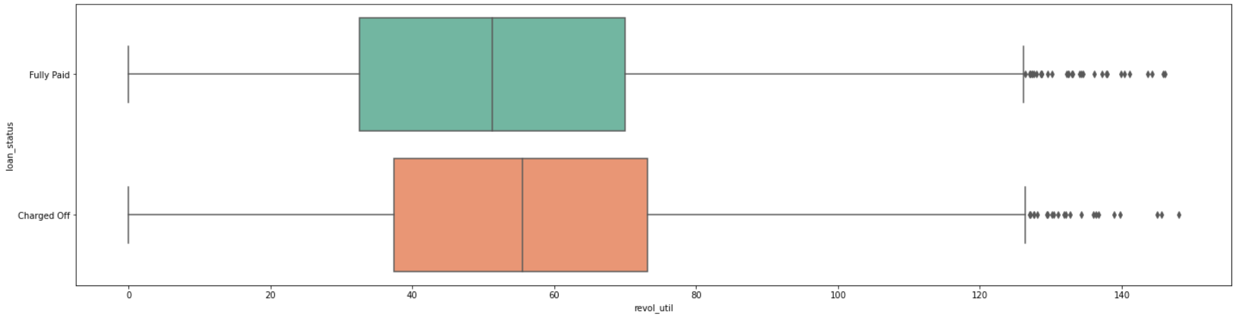
In [27]:
```
loan.shape
```

Out[27]:
```
(1345310, 23)
```

From above boxplot, outliers are observed.

In [28]:
```
loan = loan[loan['revol_util'] < 150]
```

In [29]:
```
plt.figure(figsize=(24,6))
sns.boxplot(data=loan, x='revol_util', y='loan_status', palette='Set2');
```



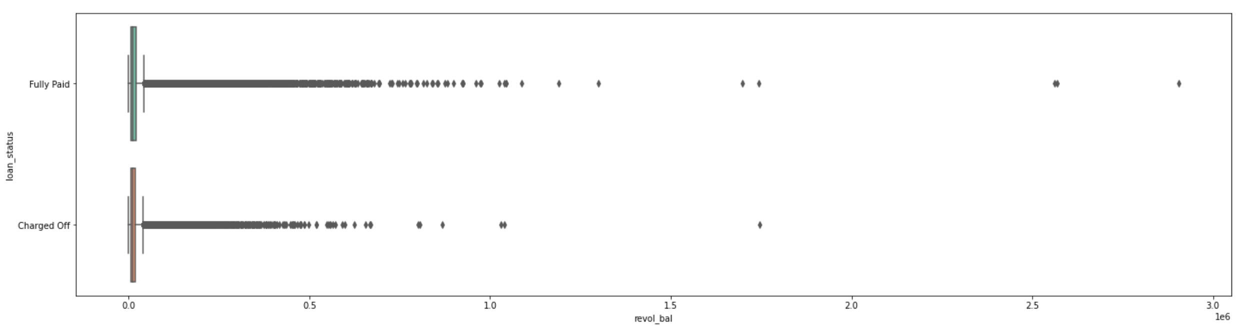
4.0.5 revol_bal

In [30]:
```
loan.groupby('loan_status')['revol_bal'].describe()
```

Out[30]:

loan_status	count	mean	std	min	25%	50%	75%	max
Charged Off	268553.000	15353.432	18954.234	0.000	5990.000	11072.000	19101.000	1746716.000
Fully Paid	1076737.000	16471.013	23086.415	0.000	5931.000	11150.000	19925.000	2904836.000

In [31]:
```
plt.figure(figsize=(24,6))
sns.boxplot(data=loan, x='revol_bal', y='loan_status', palette='Set2');
```



From above boxplot, outliers are observed. Keep the revolving balance less than $100,000.

In [32]:
```
loan = loan[loan['revol_bal'] < 100000]
```

In [33]:
```
loan.groupby('loan_status')['revol_bal'].describe()
```

Out[33]:

loan_status	count	mean	std	min	25%	50%	75%	max
Charged Off	266943.000	14427.093	12618.010	0.000	5962.000	11001.000	18890.500	99991.000
Fully Paid	1066241.000	14919.490	13529.348	0.000	5887.000	11028.000	19544.000	99992.000

4.0.6 mort_acc

#Feature "mort_acc" has 3.51% null values in the dataset.

In [34]:
```
loan.mort_acc.isna().sum()
```

Out[34]: 47037

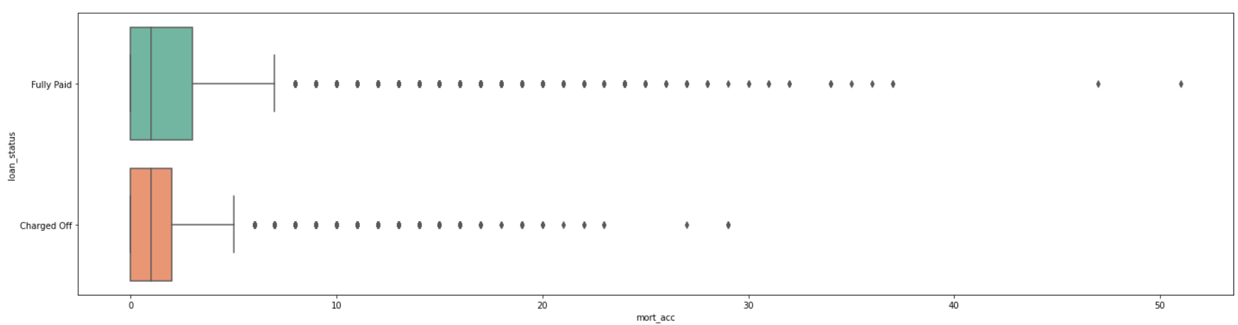
In [35]:
```
loan.groupby('loan_status')['mort_acc'].describe()
```

Out[35]:

loan_status	count	mean	std	min	25%	50%	75%	max
Charged Off	260082.000	1.360	1.815	0.000	0.000	1.000	2.000	29.000
Fully Paid	1026065.000	1.728	2.021	0.000	0.000	1.000	3.000	51.000

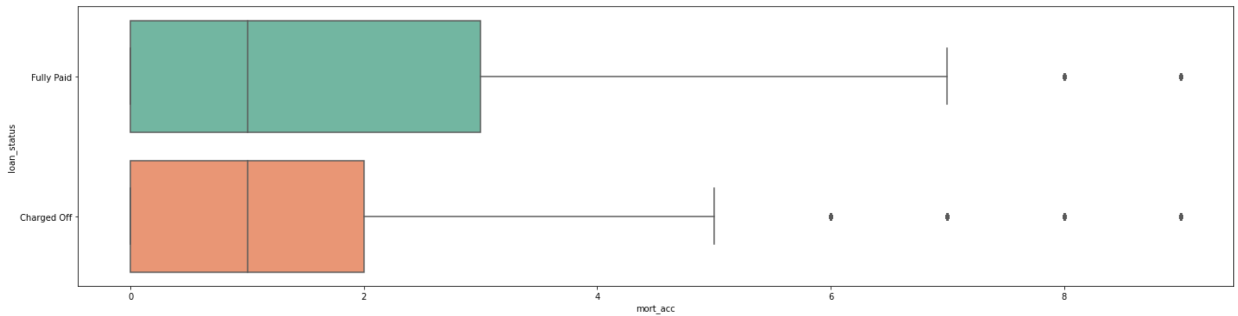
It looks like there are some outliers in the "mort_acc".

In [36]:
```
plt.figure(figsize=(24,6))
sns.boxplot(data=loan, x='mort_acc', y='loan_status', palette='Set2');
```



In [37]:
```
loan = loan[loan['mort_acc'] < 10]
```

In [38]:
```
plt.figure(figsize=(24,6))
sns.boxplot(data=loan, x='mort_acc', y='loan_status', palette='Set2');
```



In [39]:
```
loan.mort_acc.value_counts()
```

Out[39]:
```
0.000    523154
1.000    224572
2.000    186529
3.000    137029
4.000     93239
5.000     56405
6.000     31791
7.000     16394
8.000      8097
9.000      4131
Name: mort_acc, dtype: int64
```

In [40]:
```
loan.mort_acc.isna().sum()
```

Out[40]:
```
0
```

In [41]:
```
loan.shape
```

Out[41]:
```
(1281341, 23)
```

4.0.7 num_actv_bc_tl

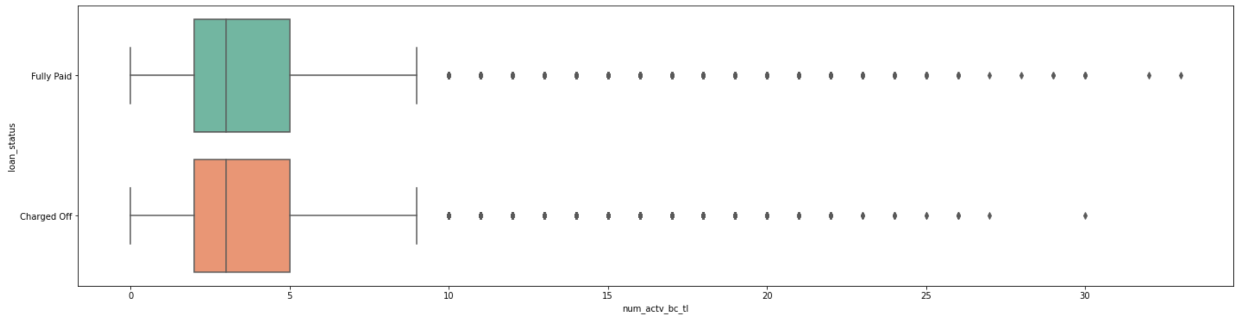
#Feature "num_actv_ba_tl" has 5.01% null values in the dataset.

In [42]:
```
loan.groupby('loan_status')['num_actv_bc_tl'].describe()
```

Out[42]:

loan_status	count	mean	std	min	25%	50%	75%	max
Charged Off	256082.000	3.816	2.352	0.000	2.000	3.000	5.000	30.000
Fully Paid	1005182.000	3.578	2.194	0.000	2.000	3.000	5.000	33.000

In [43]:
```
plt.figure(figsize=(24,6))
sns.boxplot(data=loan, x='num_actv_bc_tl', y='loan_status', palette='Set2')
```

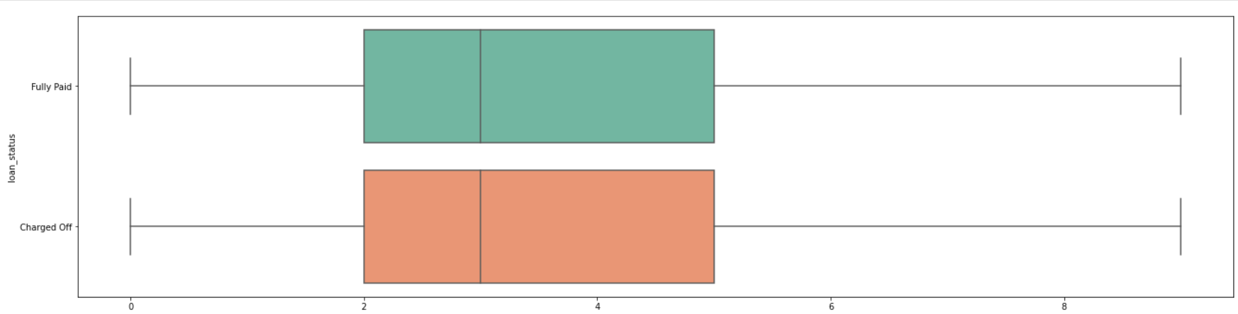


In [44]:
```
loan.num_actv_bc_tl.value_counts()
```

Out[44]:
```
3.000     271162
2.000     258563
4.000     209855
1.000     145277
5.000     139720
6.000      86523
7.000      50711
8.000      29670
0.000      27100
9.000      17418
10.000     10210
11.000      6043
12.000      3565
13.000      2120
14.000      1194
15.000       793
16.000       452
17.000       337
18.000       191
19.000       133
20.000        69
21.000        45
22.000        35
23.000        21
24.000        21
25.000        13
26.000        11
30.000         5
27.000         2
29.000         2
32.000         1
33.000         1
28.000         1
Name: num_actv_bc_tl, dtype: int64
```

In [45]:
```
loan = loan[loan['num_actv_bc_tl'] < 10]
```

In [46]:
```
plt.figure(figsize=(24,6))
sns.boxplot(data=loan, x='num_actv_bc_tl', y='loan_status', palette='Set2')
```



In [47]:
```
loan.corr()['num_actv_bc_tl'].sort_values()[:-1]
```

Out[47]:
```
fico_range_high         -0.115
fico_range_low          -0.115
pub_rec_bankruptcies    -0.053
pub_rec                 -0.030
int_rate                 0.023
mort_acc                 0.028
tot_cur_bal              0.081
annual_inc               0.087
revol_util               0.123
loan_amnt                0.185
total_acc                0.237
revol_bal                0.407
open_acc                 0.473
Name: num_actv_bc_tl, dtype: float64
```

In [48]:
```
loan.shape
```

Out[48]:
```
(1235999, 23)
```

4.0.8 pub_rec_bankruptcies

Number of public record bankruptcies.

In [49]:
```
loan.pub_rec_bankruptcies.isna().sum()
```

Out[49]:
```
0
```

In [50]:
```
loan.groupby('loan_status')['pub_rec_bankruptcies'].describe()
```

Out[50]:

loan_status	count	mean	std	min	25%	50%	75%	max
Charged Off	249420.000	0.160	0.412	0.000	0.000	0.000	0.000	11.000
Fully Paid	986579.000	0.138	0.381	0.000	0.000	0.000	0.000	12.000

In [51]:
```
loan.pub_rec_bankruptcies.value_counts()
```

Out[51]:
```
0.000     1072993
1.000      153183
2.000        7661
3.000        1560
4.000         393
5.000         137
6.000          44
7.000          14
8.000           9
9.000           3
11.000          1
12.000          1
Name: pub_rec_bankruptcies, dtype: int64
```

In [52]:
```
loan['pub_rec_bankruptcies']= loan['pub_rec_bankruptcies'].apply(lambda x:0

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

Out[52]:
```
0    1072993
1     163006
Name: pub_rec_bankruptcies, dtype: int64
```

4.0.9 pub_rec

Number of derogatory public records.

In [53]:
```
loan.groupby('loan_status')['pub_rec'].describe()
```

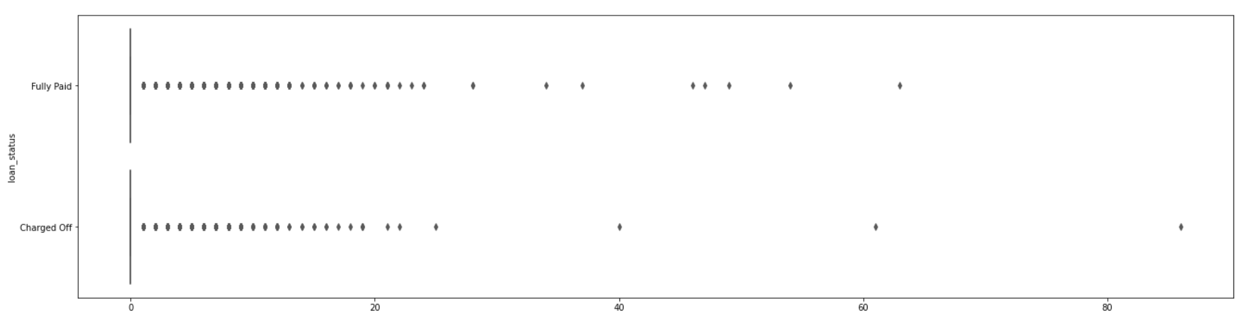
Out[53]:

	count	mean	std	min	25%	50%	75%	max
loan_status								
Charged Off	249420.000	0.257	0.671	0.000	0.000	0.000	0.000	86.000
Fully Paid	986579.000	0.219	0.599	0.000	0.000	0.000	0.000	63.000

In [54]:
```
loan.pub_rec.value_counts()
```

Out[54]:
```
0.000     1015437
1.000      184481
2.000       23788
3.000        7191
4.000        2555
5.000        1232
6.000         613
7.000         270
8.000         156
9.000          79
10.000         56
11.000         40
12.000         27
13.000         17
15.000          9
21.000          6
19.000          5
16.000          5
18.000          5
14.000          4
17.000          3
24.000          2
22.000          2
20.000          2
28.000          2
86.000          1
63.000          1
25.000          1
54.000          1
34.000          1
37.000          1
40.000          1
46.000          1
47.000          1
49.000          1
23.000          1
61.000          1
Name: pub_rec, dtype: int64
```

In [55]:
```
plt.figure(figsize=(24,6))
sns.boxplot(data=loan, x='pub_rec', y='loan_status', palette='Set2');
```



In [56]:
```
loan['pub_rec']= loan['pub_rec'].apply(lambda x:0 if x==0 else 1 )

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

Out[56]:
```
0    1015437
1     220562
Name: pub_rec, dtype: int64
```

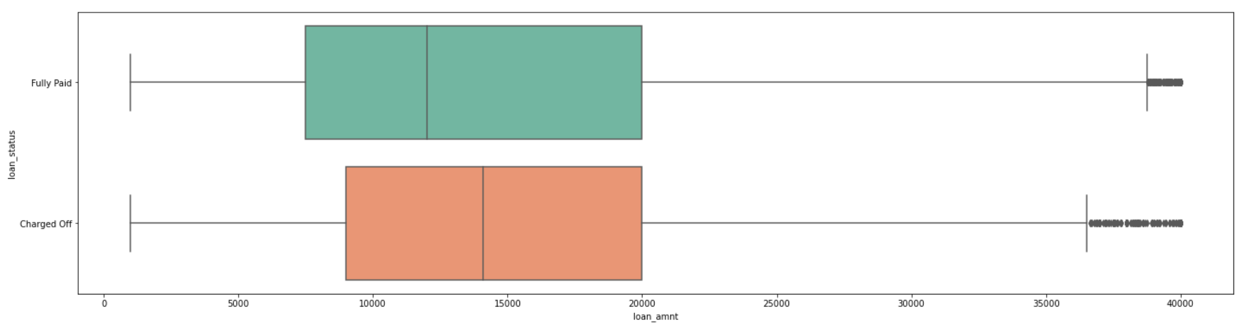
4.0.10 loan_amnt

In [57]:
```
loan.groupby('loan_status')['loan_amnt'].describe()
```

Out[57]:

loan_status	count	mean	std	min	25%	50%	75%	max
Charged Off	249420.000	15493.915	8744.101	1000.000	9000.000	14075.000	20000.000	40000.000
Fully Paid	986579.000	14069.840	8594.166	1000.000	7500.000	12000.000	20000.000	40000.000

In [58]:
```
plt.figure(figsize=(24,6))
sns.boxplot(data=loan, x='loan_amnt', y='loan_status', palette='Set2');
```



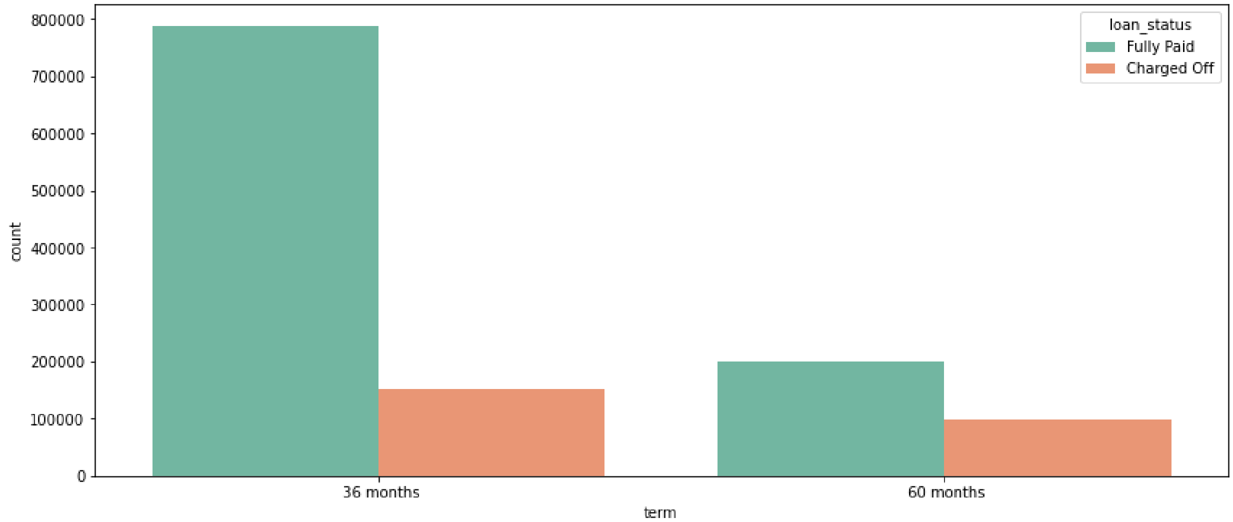
In [59]:
```
loan_amt_state = pd.DataFrame(loan.groupby('addr_state')['loan_amnt'].mean(
```

In [60]:
```
import plotly.express as px
fig = px.choropleth(loan_amt_state,
                    locations='addr_state',
                    locationmode="USA-states",
                    scope="usa",
                    color='loan_amnt',
                    color_continuous_scale="Viridis_r",


                    )
fig.show()
```

4.0.11 term

In [61]:
```
plt.figure(figsize=(14,6))
sns.countplot(x='term',data=loan,hue='loan_status', palette='Set2')
```

Out[61]: <AxesSubplot:xlabel='term', ylabel='count'>

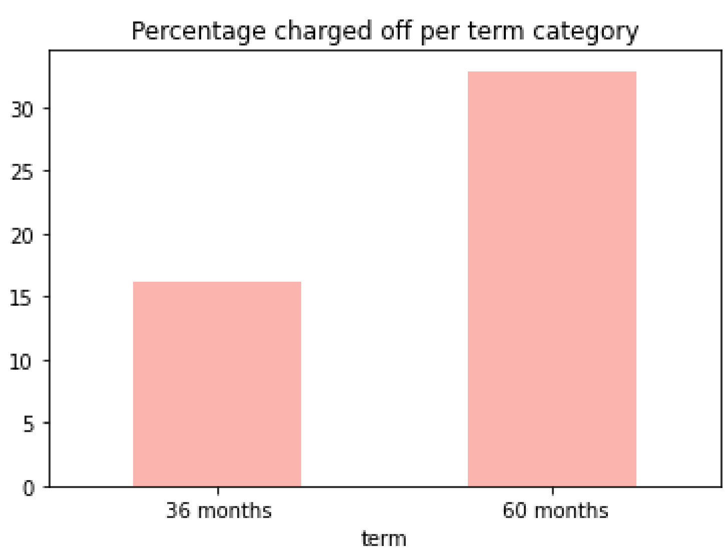


In [62]:
```
loan_term= pd.DataFrame(loan.groupby('term')['loan_status'].count()).reset_
loan_term
```

Out[62]:

	term	loan_status
0	36 months	939145
1	60 months	296854

In [63]:
```
charged_off = loan[loan['loan_status']=="Charged Off"].groupby("term").coun
fully_paid = loan[loan['loan_status']=="Fully Paid"].groupby("term").count(
percent_charged_off = (charged_off * 100)/(charged_off + fully_paid)
percent_charged_off.plot(kind='bar', cmap='Pastel1')
plt.title("Percentage charged off per term category")
plt.xticks(rotation=0);
```



Loan term with 60 month has higher rate of charged off.

In [64]:
```
dummies_term = pd.get_dummies(loan['term'], prefix='term',drop_first=True)
loan= pd.concat([loan.drop('term', axis=1), dummies_term], axis=1)
```

4.0.12 int_rate

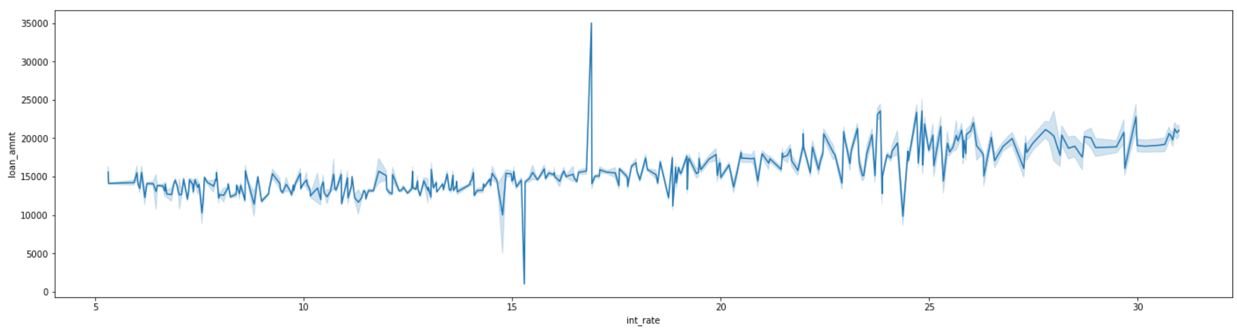
In [65]:
```
loan.groupby('loan_status')['int_rate'].describe()
```

Out[65]:

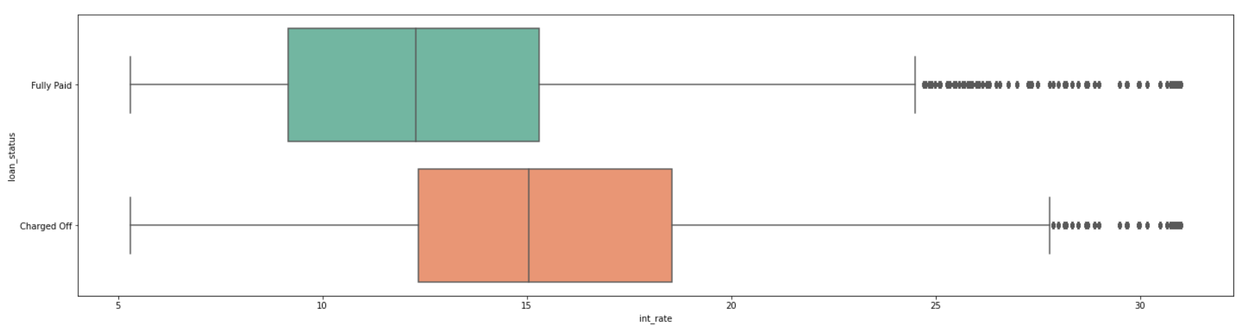
loan_status	count	mean	std	min	25%	50%	75%	max
Charged Off	249420.000	15.767	4.925	5.310	12.350	15.050	18.550	30.990
Fully Paid	986579.000	12.655	4.547	5.310	9.170	12.290	15.310	30.990

In [66]:
```
plt.figure(figsize=(24,6))
sns.lineplot(data=loan, x="int_rate", y="loan_amnt")
```

Out[66]: <AxesSubplot:xlabel='int_rate', ylabel='loan_amnt'>



In [67]:
```
plt.figure(figsize=(24,6))
sns.boxplot(data=loan, x='int_rate', y='loan_status', palette='Set2');
```

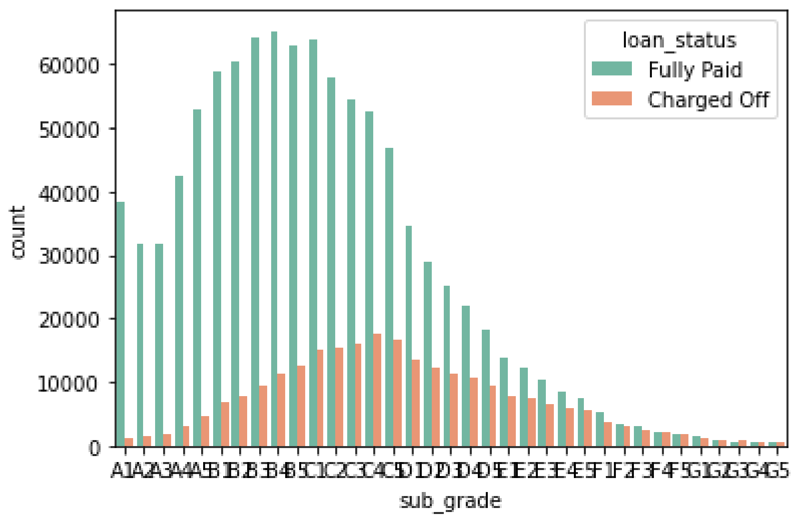


In [68]:
```
'''
plt.plot(x, y, label = "line 1")
plt.plot(y, x, label = "line 2")
plt.plot(x, np.sin(x), label = "curve 1")
plt.plot(x, np.cos(x), label = "curve 2")
plt.legend()
plt.show()
'''
```

Out[68]:
```
'\nplt.plot(x, y, label = "line 1")\nplt.plot(y, x, label = "line 2")\npl
t.plot(x, np.sin(x), label = "curve 1")\nplt.plot(x, np.cos(x), label =
"curve 2")\nplt.legend()\nplt.show()\n'
```

4.0.13 sub_grade

In [69]:
```
subgrade_order = sorted(loan['sub_grade'].unique().tolist())
sns.countplot(x='sub_grade',data=loan,order = subgrade_order, palette='Set2
```



In [70]:
```
dummies_subgrade = pd.get_dummies(loan['sub_grade'], prefix='sub_grade',dro
loan= pd.concat([loan.drop('sub_grade', axis=1), dummies_subgrade], axis=1)
```

4.0.14 home_ownership

In [71]:
```
loan['home_ownership'].value_counts()
```

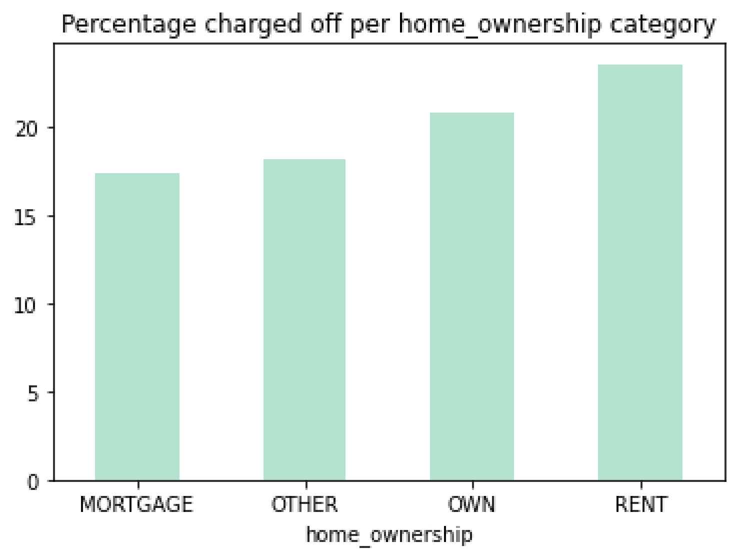
Out[71]:
```
MORTGAGE    608692
RENT        492585
OWN         134353
ANY            280
NONE            45
OTHER           44
Name: home_ownership, dtype: int64
```

In [72]:
```
owndership_list=['MORTGAGE', 'RENT','OTHER','OWN']
loan= loan.loc[loan['home_ownership'].isin(owndership_list)]
```

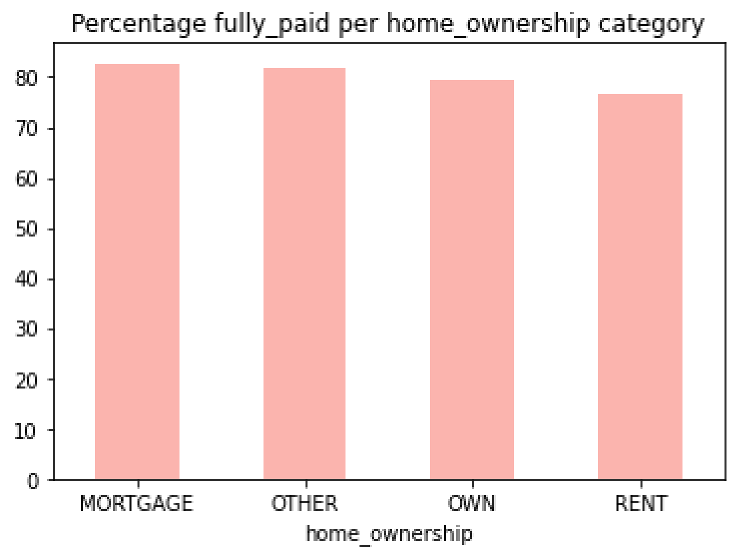
In [73]:
```
loan.home_ownership.value_counts()
```

Out[73]:
```
MORTGAGE    608692
RENT        492585
OWN         134353
OTHER           44
Name: home_ownership, dtype: int64
```

In [74]:
```
charged_off = loan[loan['loan_status']=="Charged Off"].groupby("home_owners
fully_paid = loan[loan['loan_status']=="Fully Paid"].groupby("home_ownershi
percentage_charged_off = (charged_off * 100)/(charged_off + fully_paid)
percentage_charged_off.plot(kind='bar', cmap='Pastel2')
plt.title("Percentage charged off per home_ownership category")
plt.xticks(rotation=0);
```



In [75]:
```
charged_off = loan[loan['loan_status']=="Charged Off"].groupby("home_owners
fully_paid = loan[loan['loan_status']=="Fully Paid"].groupby("home_ownershi
percentage_fully_paid = (fully_paid * 100)/(charged_off + fully_paid)
percentage_fully_paid.plot(kind='bar', cmap='Pastel1')
plt.title("Percentage fully_paid per home_ownership category")
plt.xticks(rotation=0);
```



In [76]:
```
#dummies_subgrade = pd.get_dummies(loan['sub_grade'], prefix='term',drop_fi
#loan= pd.concat([loan.drop('sub_grade', axis=1), dummies_subgrade], axis=1
```

In [77]:
```
dummies_ownership = pd.get_dummies(loan['home_ownership'], prefix='home_own
loan= pd.concat([loan.drop('home_ownership', axis=1), dummies_ownership], a
```

4.0.15 annual_inc

In [78]:
```
loan.groupby('loan_status')['annual_inc'].describe()
```

Out[78]:

loan_status	count	mean	std	min	25%	50%	75%	max
Charged Off	249360.000	69467.381	65356.198	0.000	43000.000	60000.000	84000.000	9500000.000
Fully Paid	986314.000	76264.558	67181.191	0.000	46900.000	65000.000	91000.000	10999200.000

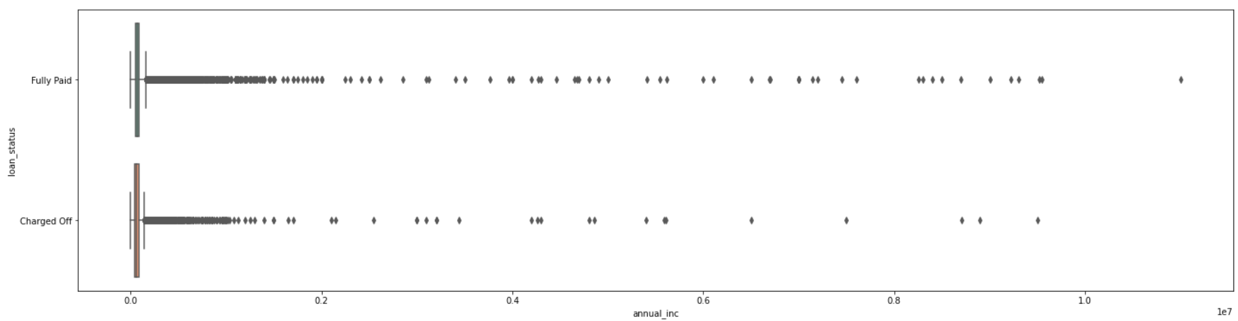
In [79]:
```
loan_state = pd.DataFrame(loan.groupby('addr_state')['annual_inc'].mean().s
```

In [80]:
```
import plotly.express as px
fig = px.choropleth(loan_state,
                    locations='addr_state',
                    locationmode="USA-states",
                    scope="usa",
                    color='annual_inc',
                    color_continuous_scale="Viridis_r",


                    )
fig.show()
```

In [81]:
```
loan.shape
```

Out[81]:
```
(1235674, 58)
```

In [82]:
```
plt.figure(figsize=(24,6))
sns.boxplot(data=loan, x='annual_inc', y='loan_status', palette='Set2');
```



From above, outliers are observed.

In [83]:
```
print(len(loan[loan['annual_inc']>250000])/loan.shape[0])
```

```
0.008131594579152754
```

Less than 1% customers have annual income greater than 250k. Keep annual income less than 250k.

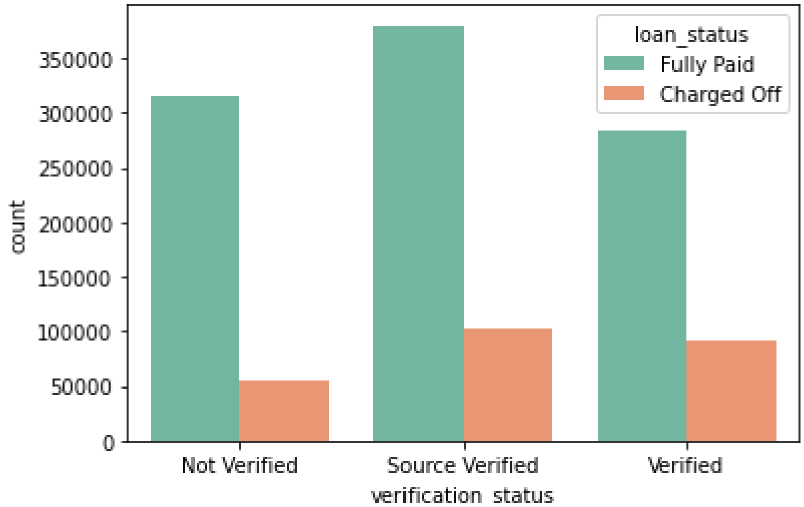
In [84]:
```
loan = loan[loan['annual_inc'] <= 250000]
```

4.0.16 verification_status

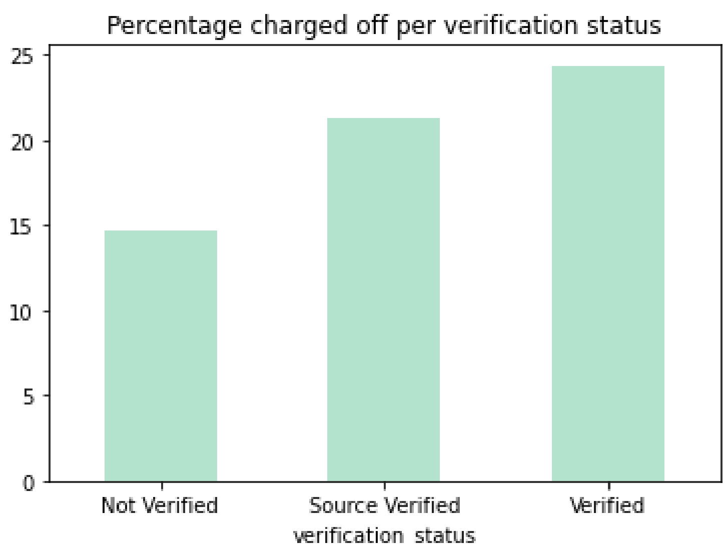
In [85]:
```
loan.verification_status.value_counts()
```

Out[85]:
```
Source Verified    482194
Verified           374769
Not Verified       368663
Name: verification_status, dtype: int64
```

In [86]:
```
sns.countplot(data=loan, x='verification_status', hue='loan_status', palett
```



In [87]:
```
charged_off = loan[loan['loan_status']=="Charged Off"].groupby("verificatio
fully_paid = loan[loan['loan_status']=="Fully Paid"].groupby("verification_
percentage_charged_off = (charged_off * 100)/(charged_off + fully_paid)
percentage_charged_off.plot(kind='bar', cmap='Pastel2')
plt.title("Percentage charged off per verification status")
plt.xticks(rotation=0);
```



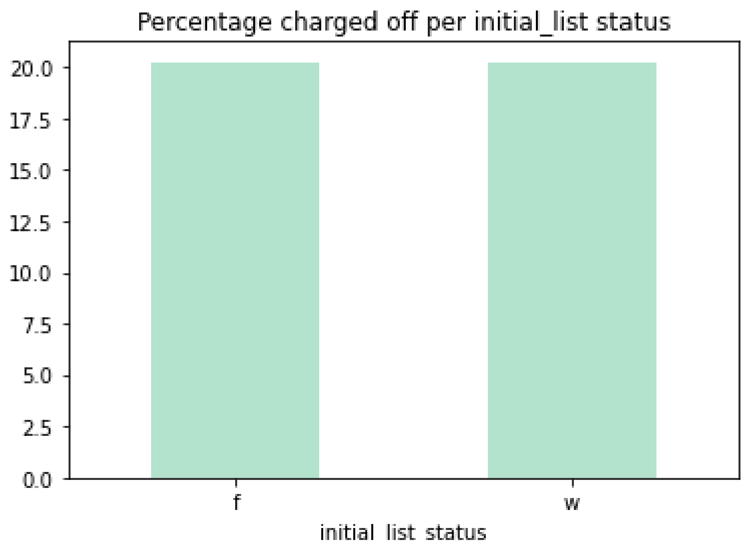
In [88]:
```
dummies_verification_status = pd.get_dummies(loan['verification_status'], d
loan= pd.concat([loan.drop('verification_status', axis=1), dummies_verifica
```

4.0.17 initial_list_status

In [89]:
```
loan.initial_list_status.value_counts()
```

Out[89]:
```
w    750443
f    475183
Name: initial_list_status, dtype: int64
```

In [90]:
```
charged_off = loan[loan['loan_status']=="Charged Off"].groupby("initial_lis
fully_paid = loan[loan['loan_status']=="Fully Paid"].groupby("initial_list_
percentage_charged_off = (charged_off * 100)/(charged_off + fully_paid)
percentage_charged_off.plot(kind='bar', cmap='Pastel2')
plt.title("Percentage charged off per initial_list status")
plt.xticks(rotation=0);
```



The percentage charged off in initial_list_status has no large difference. Drop this column.

In [91]:
```
loan=loan.drop('initial_list_status',axis=1)
```

4.0.18 purpose

In [92]:
```
loan.purpose.value_counts()
```

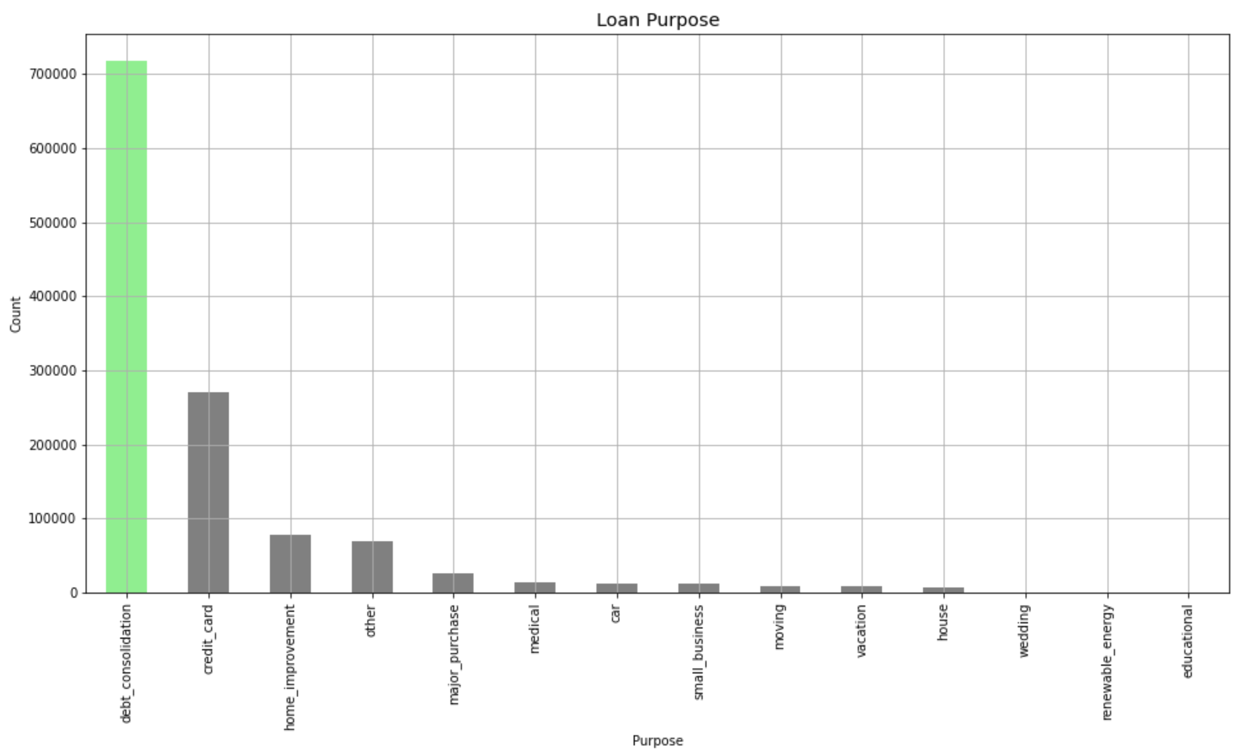
Out[92]:
```
debt_consolidation    718127
credit_card           271256
home_improvement       78179
other                  69809
major_purchase         25522
medical                14055
car                    12091
small_business         11923
moving                  8464
vacation                8244
house                   6325
wedding                  860
renewable_energy         770
educational                1
Name: purpose, dtype: int64
```

In [93]:
```
purpose_df= loan.purpose.value_counts()
```

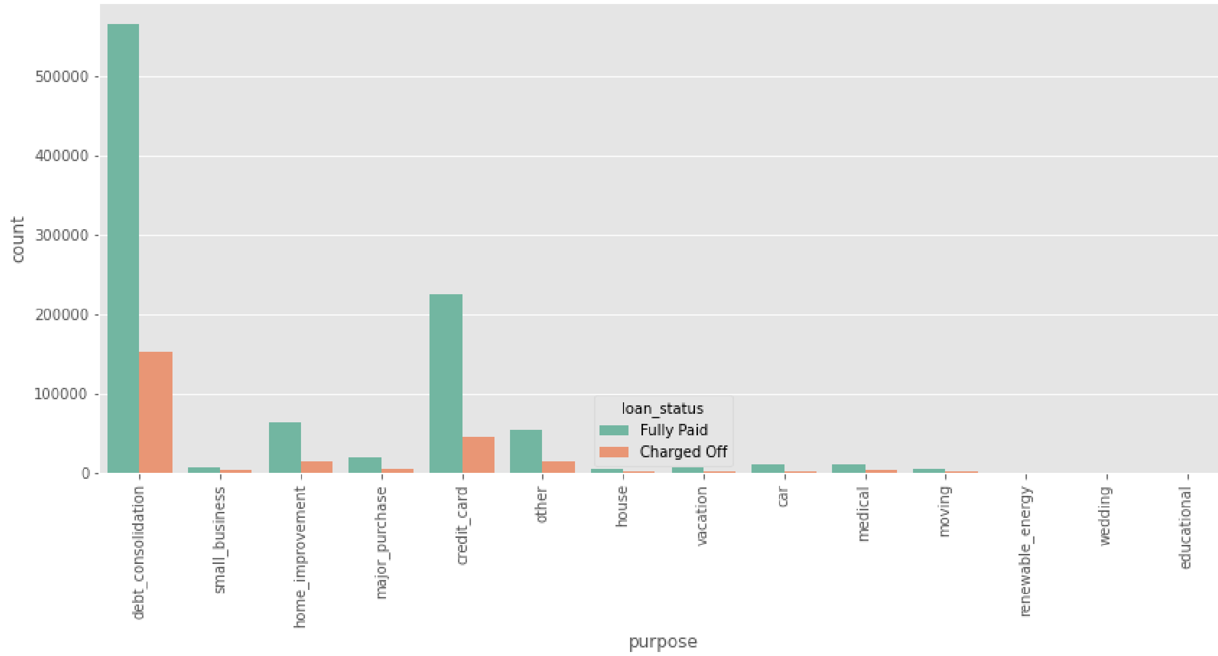
In [94]:
```
purpose_df.head()
```

Out[94]:
```
debt_consolidation    718127
credit_card           271256
home_improvement       78179
other                  69809
major_purchase         25522
Name: purpose, dtype: int64
```

In [95]:
```
fig,ax=plt.subplots(figsize=(16,8))
plt.style.use('ggplot')
clrs=['grey' if (value < max(purpose_df.values)) else 'lightgreen' for valu
purpose_df.plot(kind='bar',color=clrs)
ax.set_ylabel('Count')
ax.set_xlabel('Purpose')
ax.set_title('Loan Purpose')
ax.set_xticklabels(ax.get_xticklabels(),rotation=90)
plt.show()
```



In [96]:
```
plt.figure(figsize=(14,6))
purpose_order = sorted(loan['purpose'].unique().tolist())
sns.countplot(x='purpose',data=loan,hue='loan_status', palette='Set2')
plt.xticks(rotation=90);
```



In [97]:
```
dummies_purpose = pd.get_dummies(loan['purpose'], prefix='purpose',drop_fir
loan= pd.concat([loan.drop('purpose', axis=1), dummies_purpose], axis=1)
```

4.0.19 addr_state

In [98]:
```
loan.addr_state.value_counts()
```

Out[98]:
```
CA    175798
TX    101375
NY     97960
FL     86886
IL     46720
NJ     42617
PA     41346
OH     40604
GA     39484
NC     34871
VA     34158
MI     32813
AZ     29954
MD     28137
MA     27428
CO     27252
WA     26725
MN     22168
IN     21124
TN     19741
MO     19530
NV     18737
CT     17326
WI     16432
AL     15462
OR     15181
SC     14758
LA     14267
KY     11915
OK     11459
KS     10435
AR      9278
UT      9235
NM      6842
MS      6383
HI      6235
NH      5889
RI      5313
WV      4476
MT      3559
NE      3489
DE      3443
DC      2986
AK      2933
WY      2705
SD      2571
VT      2469
ME      1955
ID      1641
ND      1559
IA         2
Name: addr_state, dtype: int64
```

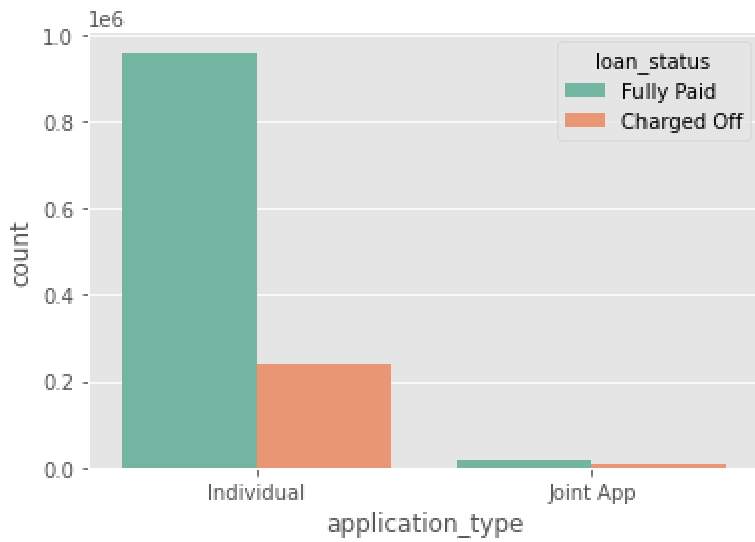
In [99]:
```
dummies_state = pd.get_dummies(loan['addr_state'], drop_first=True)
loan= pd.concat([loan.drop('addr_state', axis=1), dummies_state], axis=1)
```

4.0.20 application type

In [100]:
```
loan.application_type.value_counts()
```

Out[100]:
```
Individual    1200478
Joint App       25148
Name: application_type, dtype: int64
```

In [101]:
```
sns.countplot(data=loan, x='application_type', hue='loan_status', palette='
```



In [102]:
```
dummies_apptype = pd.get_dummies(loan['application_type'], drop_first=True)
loan= pd.concat([loan.drop('application_type', axis=1), dummies_apptype], a
```

4.0.21 fico_range_low & fico_range_high

In [103]:
```
loan.groupby('loan_status')['fico_range_high'].describe()
```

Out[103]:

	count	mean	std	min	25%	50%	75%	max
loan_status								
Charged Off	247991.000	691.361	25.649	664.000	674.000	684.000	704.000	850.000
Fully Paid	977635.000	701.302	32.465	664.000	674.000	694.000	719.000	850.000

In [104]:
```
loan.groupby('loan_status')['fico_range_low'].describe()
```

Out[104]:

loan_status	count	mean	std	min	25%	50%	75%	max
Charged Off	247991.000	687.361	25.649	660.000	670.000	680.000	700.000	845.000
Fully Paid	977635.000	697.302	32.464	660.000	670.000	690.000	715.000	845.000

There is no significant difference between fico_range_high and fico_range_low.

Keep fico_range_high in the dataset

In [105]:
```
loan = loan.drop('fico_range_low',axis=1)
```

4.0.22 Convert "Loan status" into binary feature

In [107]:
```
# One hot encoding for Y
class_mapping = {"Fully Paid":0, "Charged Off":1}
loan['loan_status']=loan['loan_status'].map(class_mapping)
```

In [ ]:
```
# Convert columns with yes or no to binary
#label_encoder = LabelEncoder()
#loan['loan_status'] = label_encoder.fit_transform(loan['loan_status'])
```

In [108]:
```
loan.head()
```

Out[108]:

	loan_amnt	int_rate	annual_inc	loan_status	fico_range_high	open_acc	pub_rec	revol_bal	rev
0	3600.000	13.990	55000.000	0	679.000	7.000	0	2765.000	
1	24700.000	11.990	65000.000	0	719.000	22.000	0	21470.000	
2	20000.000	10.780	63000.000	0	699.000	6.000	0	7869.000	
4	10400.000	22.450	104433.000	0	699.000	12.000	0	21929.000	
5	11950.000	13.440	34000.000	0	694.000	5.000	0	8822.000	

5 rows × 118 columns

4.1 Resample the Dataset

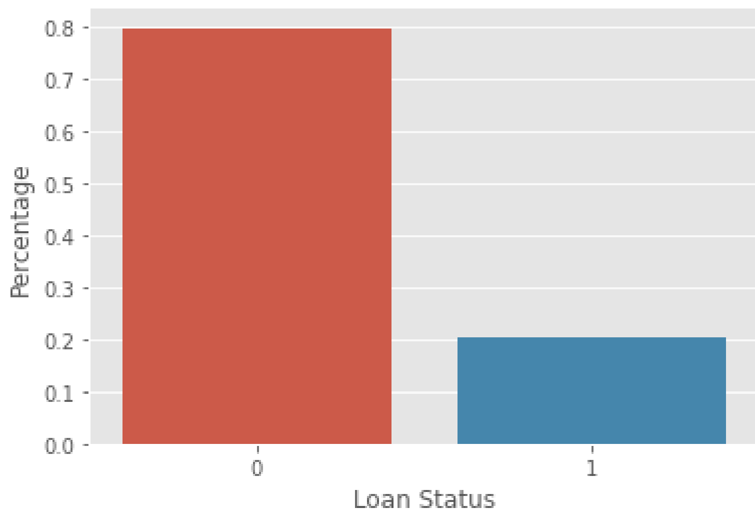
Current class for loan status

In [109]:
```
loan.loan_status.value_counts()
```

Out[109]:
```
0    977635
1    247991
Name: loan_status, dtype: int64
```

In [123]:
```
loan_status = loan['loan_status'].value_counts(normalize=True)
ax = sns.barplot(x = loan_status.index, y = loan_status.values)
ax.set_ylabel('Percentage')
ax.set_xlabel('Loan Status')
```

Out[123]:
```
Text(0.5, 0, 'Loan Status')
```



From above bar chart, imbalanced class was observed. Due to the large dataset, under-sampling the majority class.

In [127]:
```
# Class count
count_class_0, count_class_1 = loan.loan_status.value_counts()

# Divide by class
df_class_0 = loan[loan['loan_status'] == 0]
df_class_1 = loan[loan['loan_status'] == 1]
```

In this case, paid-off is the majority class in loan status . After under-sampling paid-off class, concatenating the under-sampling paid-off class and Charged class.

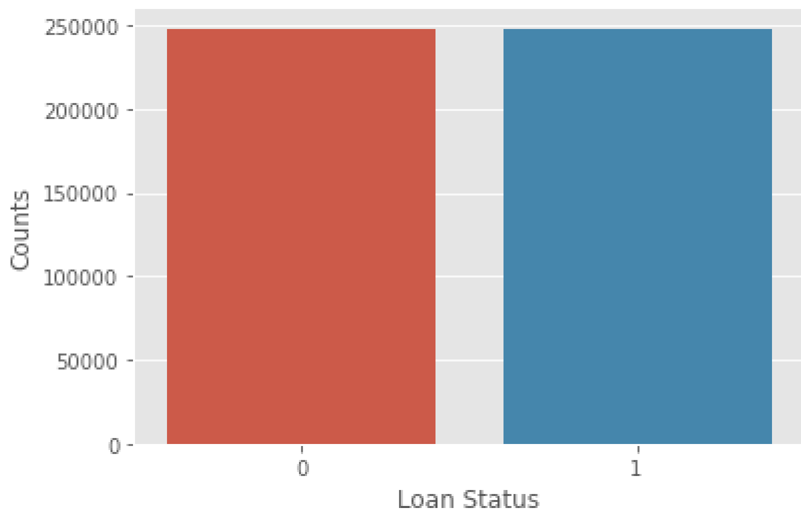
In [128]:
```
df_class_0_under = df_class_0.sample(count_class_1)
loan_under = pd.concat([df_class_0_under, df_class_1], axis=0)
```

Plot the loan_status again to show the balanced class.

In [130]:
```
loan_status_plot= loan_under['loan_status'].value_counts()
ax = sns.barplot(x = loan_status_plot.index, y = loan_status_plot.values)
print('Random under-sampling:')
print(loan_under.loan_status.value_counts())
ax.set_ylabel('Counts')
ax.set_xlabel('Loan Status')
```

```
Random under-sampling:
0    247991
1    247991
Name: loan_status, dtype: int64
```

Out[130]:
```
Text(0.5, 0, 'Loan Status')
```



4.2 Define X and Y

In [131]:
```
X = loan_under.drop(['loan_status'],axis=1)
y = loan_under['loan_status']
```

4.3 Train Test Split

Split the data into train and test set by test size 25%

In [132]:
```
X_train,X_test,y_train,y_test = train_test_split(X,y,test_size=0.25,random_
```

4.4 Standardize the Data

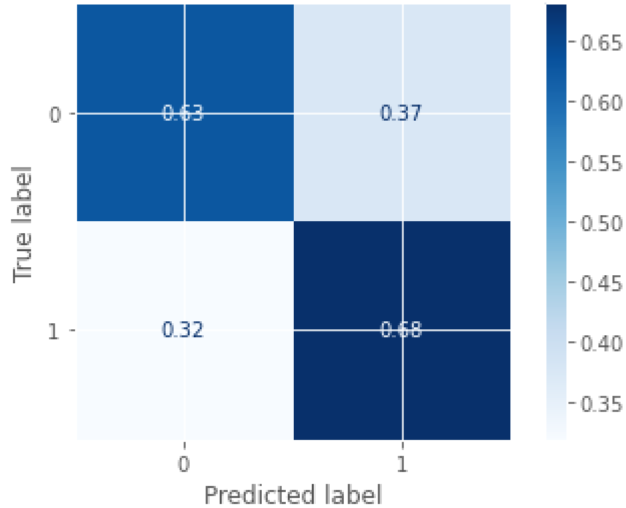
Standardize the data since the features in the data set have different ranges.

In [133]:
```
#Instantiate StandardScaler
scaler = StandardScaler()

#Transform X_train to scaled data set and fit the model with scaled X train
scaled_X_train = scaler.fit_transform(X_train)

#Transform X_test to scaled data set
scaled_X_test= scaler.transform(X_test)

#Convert scaled data into a DataFrame
scaled_X_train = pd.DataFrame(scaled_X_train,columns=X_train.columns)
scaled_X_test = pd.DataFrame(scaled_X_test,columns=X_test.columns)
```

4.5 Logistic Regression Model

In [134]:
```
lr= LogisticRegression(random_state = 123)
lr.fit(scaled_X_train,y_train)

y_train_pred = lr.predict(scaled_X_train)
y_test_pred = lr.predict(scaled_X_test)


plot_confusion_matrix(lr,scaled_X_test,y_test,
                                normalize='true',
                                cmap='Blues')


rs = recall_score(y_train,y_train_pred)
print(f"test:\n{classification_report(y_test,y_test_pred)}")
print(f"train:\n{classification_report(y_train,y_train_pred)}")

#print Test recall score
rs = recall_score(y_test,y_test_pred)
print(f"Test Recall_score {rs}")

# Print the accuracy on test set

print(f"Test accuracy score {lr.score(scaled_X_test,y_test)}")
```

```
test:
              precision    recall  f1-score   support

           0       0.66      0.63      0.65     62208
           1       0.64      0.68      0.66     61788

    accuracy                           0.65    123996
   macro avg       0.65      0.65      0.65    123996
weighted avg       0.65      0.65      0.65    123996

train:
              precision    recall  f1-score   support

           0       0.66      0.63      0.64    185783
           1       0.65      0.68      0.66    186203

    accuracy                           0.65    371986
   macro avg       0.65      0.65      0.65    371986
weighted avg       0.65      0.65      0.65    371986

Test Recall_score 0.6816533954813232
Test accuracy score 0.6541743282041356
```



Create a function to print scores and confusion matrix for the models

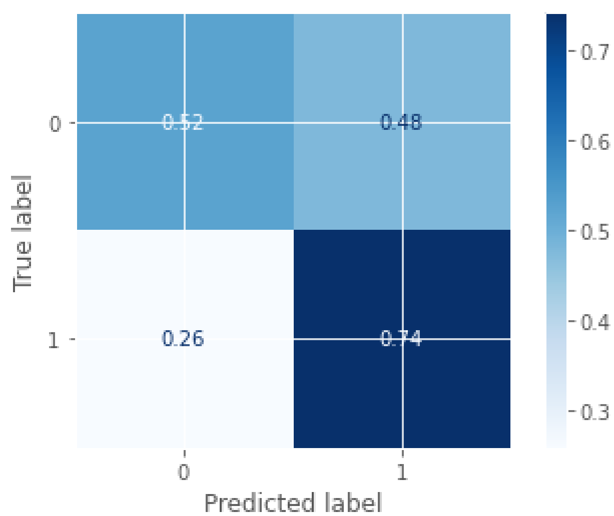
In [135]:
```
def eval_model(model,X_train,y_train,X_test,y_test):

    #fit the model
    model.fit(X_train,y_train)

    #predict the target variable
    y_train_pred = model.predict(X_train)
    y_test_pred = model.predict(X_test)

    #plot the confusion matrix with test set
    plot_confusion_matrix(model,X_test,y_test,normalize='true',cmap='Blues'

    #print recall score and classification report for train set and test se
    rs_train = recall_score(y_train,y_train_pred)
    rs_test = recall_score(y_test, y_test_pred)
    print(f"test:\n{classification_report(y_test,y_test_pred)}")
    print(f"train:\n{classification_report(y_train,y_train_pred)}")
    print(f"Train Recall_score {rs_train}")
    print(f"Test Recall_score {rs_test}")

    # Print the accuracy of a model
    acc_score = model.score(X_test,y_test)
    acc_score_train = model.score(X_train,y_train)
    print(f"Train accuracy score {acc_score_train}")
    print(f"Test accuracy score {acc_score}")
```

4.6 Decision Tree Model

In [136]:
```
# Instantiate a DecisionTreeClassifier()
dt= DecisionTreeClassifier(max_depth=3,random_state=123)
```

In [137]:
```
eval_model(dt,scaled_X_train,y_train,scaled_X_test,y_test)
```

```
test:
              precision    recall  f1-score   support

           0       0.67      0.52      0.59     62208
           1       0.61      0.74      0.67     61788

    accuracy                           0.63    123996
   macro avg       0.64      0.63      0.63    123996
weighted avg       0.64      0.63      0.63    123996

train:
              precision    recall  f1-score   support

           0       0.67      0.52      0.59    185783
           1       0.61      0.74      0.67    186203

    accuracy                           0.63    371986
   macro avg       0.64      0.63      0.63    371986
weighted avg       0.64      0.63      0.63    371986

Train Recall_score 0.74222219835341
Test Recall_score 0.7421991325176409
Train accuracy score 0.6324028323646589
Test accuracy score 0.6323994322397497
```

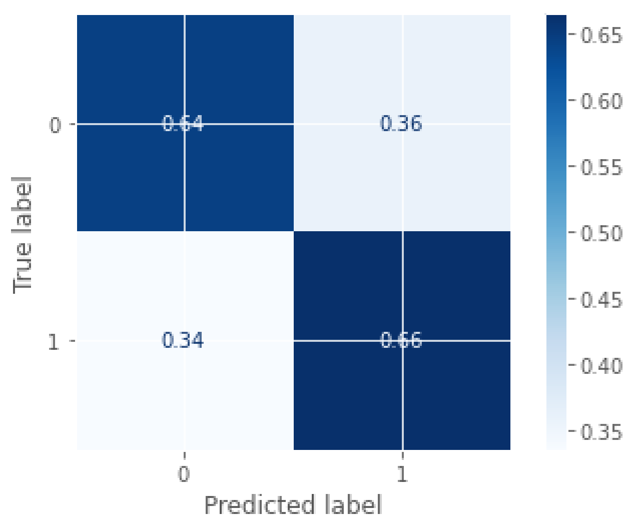


4.7 Random Forest Model (Baseline Model)

In [138]:
```
rf = RandomForestClassifier(random_state =123)
```

In [139]:
```
eval_model(rf,scaled_X_train,y_train,scaled_X_test,y_test)
```

```
test:
              precision    recall  f1-score   support

           0       0.66      0.64      0.65     62208
           1       0.65      0.66      0.66     61788

    accuracy                           0.65    123996
   macro avg       0.65      0.65      0.65    123996
weighted avg       0.65      0.65      0.65    123996

train:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00    185783
           1       1.00      1.00      1.00    186203

    accuracy                           1.00    371986
   macro avg       1.00      1.00      1.00    371986
weighted avg       1.00      1.00      1.00    371986

Train Recall_score 0.9999946295172473
Test Recall_score 0.664352301417751
Train accuracy score 0.9999973117267854
Test accuracy score 0.6536097938643182
```

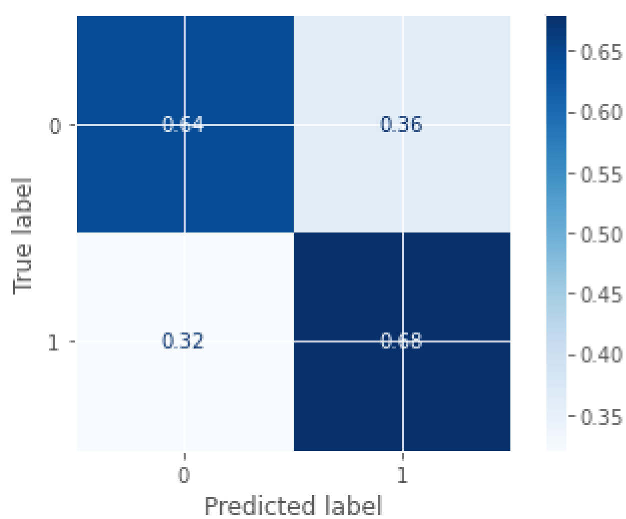


4.8 XG Boost Model

In [140]:
```
xg = XGBClassifier(random_state =123)
```

In [141]:
```
eval_model(xg,scaled_X_train,y_train,scaled_X_test,y_test)
```

```
[22:33:02] WARNING: ../src/learner.cc:1115: Starting in XGBoost 1.3.0, th
e default evaluation metric used with the objective 'binary:logistic' was
changed from 'error' to 'logloss'. Explicitly set eval_metric if you'd li
ke to restore the old behavior.
test:
              precision    recall  f1-score   support

           0       0.67      0.64      0.65     62208
           1       0.65      0.68      0.67     61788

    accuracy                           0.66    123996
   macro avg       0.66      0.66      0.66    123996
weighted avg       0.66      0.66      0.66    123996

train:
              precision    recall  f1-score   support

           0       0.69      0.66      0.68    185783
           1       0.68      0.70      0.69    186203

    accuracy                           0.68    371986
   macro avg       0.68      0.68      0.68    371986
weighted avg       0.68      0.68      0.68    371986

Train Recall_score 0.7013689360536619
Test Recall_score 0.6796303489350684
Train accuracy score 0.6820659917308716
Test accuracy score 0.6593519145778897
```



4.9 Tuning XG Boost Model

XGBoost model has the highest accuracy score 66% and recall score 68%. Tuning XGBoost model to improve model performance.

Use gridsearch to fnd the best parameters for the model

In [142]:
```
param_grid = {
    'learning_rate': [0.1, 0.2],
    'max_depth': [1,2,5,10],
    'min_child_weight': [1, 2],
    'subsample': [0.5, 0.7],
    'n_estimators': [100],
}
```

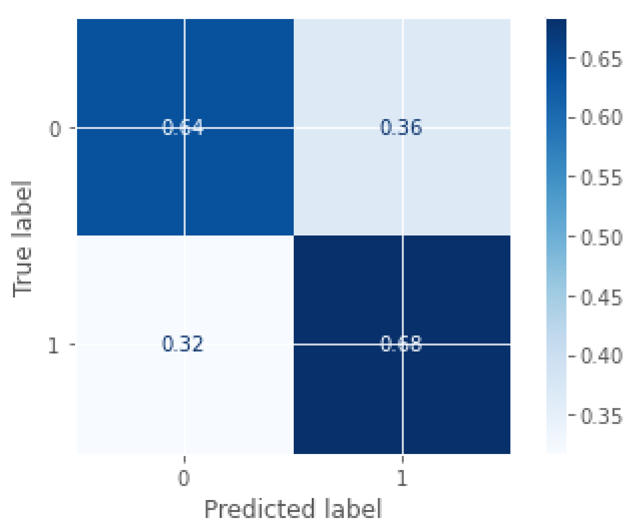
In [153]:
```
grid_clf = GridSearchCV(xg,param_grid,cv=3,scoring='recall',n_jobs=1)
grid_clf.fit(scaled_X_train,y_train)

best_parameters = grid_clf.best_params_

print('Grid Search found the following optimal parameters: ')
for param_name in sorted(best_parameters.keys()):
    print('%s: %r' % (param_name, best_parameters[param_name]))

training_preds = grid_clf.predict(scaled_X_train)
test_preds = grid_clf.predict(scaled_X_test)
training_accuracy = accuracy_score(y_train,training_preds)
test_accuracy = accuracy_score(y_test,test_preds)

print('')
print('Training Accuracy: {:.4}%'.format(training_accuracy * 100))
print('Validation accuracy: {:.4}%'.format(test_accuracy * 100))
```

```
[02:55:15] WARNING: ../src/learner.cc:1115: Starting in XGBoost 1.3.0, th
e default evaluation metric used with the objective 'binary:logistic' was
changed from 'error' to 'logloss'. Explicitly set eval_metric if you'd li
ke to restore the old behavior.
[02:55:21] WARNING: ../src/learner.cc:1115: Starting in XGBoost 1.3.0, th
e default evaluation metric used with the objective 'binary:logistic' was
changed from 'error' to 'logloss'. Explicitly set eval_metric if you'd li
ke to restore the old behavior.
[02:55:27] WARNING: ../src/learner.cc:1115: Starting in XGBoost 1.3.0, th
e default evaluation metric used with the objective 'binary:logistic' was
changed from 'error' to 'logloss'. Explicitly set eval_metric if you'd li
ke to restore the old behavior.
[02:55:33] WARNING: ../src/learner.cc:1115: Starting in XGBoost 1.3.0, th
e default evaluation metric used with the objective 'binary:logistic' was
changed from 'error' to 'logloss'. Explicitly set eval_metric if you'd li
ke to restore the old behavior.
[02:55:39] WARNING: ../src/learner.cc:1115: Starting in XGBoost 1.3.0, th
e default evaluation metric used with the objective 'binary:logistic' was
changed from 'error' to 'logloss'. Explicitly set eval_metric if you'd li
```

In [155]:
```
xg_grid=XGBClassifier(learning_rate=0.1,max_depth=10, min_child_weight=2,n_
```

In [156]:
```
eval_model(xg_grid,scaled_X_train,y_train,scaled_X_test,y_test)
```

```
[09:51:18] WARNING: ../src/learner.cc:1115: Starting in XGBoost 1.3.0, th
e default evaluation metric used with the objective 'binary:logistic' was
changed from 'error' to 'logloss'. Explicitly set eval_metric if you'd li
ke to restore the old behavior.
test:
              precision    recall  f1-score   support

           0       0.67      0.64      0.65     62208
           1       0.65      0.68      0.67     61788

    accuracy                           0.66    123996
   macro avg       0.66      0.66      0.66    123996
weighted avg       0.66      0.66      0.66    123996

train:
              precision    recall  f1-score   support

           0       0.72      0.69      0.70    185783
           1       0.70      0.73      0.72    186203

    accuracy                           0.71    371986
   macro avg       0.71      0.71      0.71    371986
weighted avg       0.71      0.71      0.71    371986

Train Recall_score 0.7344618507757662
Test Recall_score 0.682786301547226
Train accuracy score 0.7112014968305259
Test accuracy score 0.6592793315913417
```



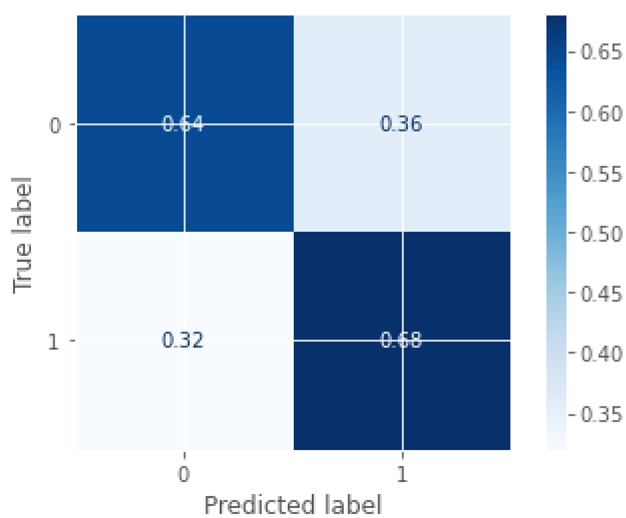
In [154]:
```
'''
grid_clf = GridSearchCV(xg,param_grid,cv=5,scoring='recall',n_jobs=1)
grid_clf.fit(scaled_X_train,y_train)

best_parameters = grid_clf.best_params_

print('Grid Search found the following optimal parameters: ')
for param_name in sorted(best_parameters.keys()):
    print('%s: %r' % (param_name, best_parameters[param_name]))

training_preds = grid_clf.predict(scaled_X_train)
test_preds = grid_clf.predict(scaled_X_test)
training_accuracy = accuracy_score(y_train,training_preds)
test_accuracy = accuracy_score(y_test,test_preds)

print('')
print('Training Accuracy: {:.4}%'.format(training_accuracy * 100))
print('Validation accuracy: {:.4}%'.format(test_accuracy * 100))
'''
```

```
[08:25:03] WARNING: ../src/learner.cc:1115: Starting in XGBoost 1.3.0, th
e default evaluation metric used with the objective 'binary:logistic' was
changed from 'error' to 'logloss'. Explicitly set eval_metric if you'd li
ke to restore the old behavior.
[08:25:10] WARNING: ../src/learner.cc:1115: Starting in XGBoost 1.3.0, th
e default evaluation metric used with the objective 'binary:logistic' was
changed from 'error' to 'logloss'. Explicitly set eval_metric if you'd li
ke to restore the old behavior.
[08:25:17] WARNING: ../src/learner.cc:1115: Starting in XGBoost 1.3.0, th
e default evaluation metric used with the objective 'binary:logistic' was
changed from 'error' to 'logloss'. Explicitly set eval_metric if you'd li
ke to restore the old behavior.
[08:25:24] WARNING: ../src/learner.cc:1115: Starting in XGBoost 1.3.0, th
e default evaluation metric used with the objective 'binary:logistic' was
changed from 'error' to 'logloss'. Explicitly set eval_metric if you'd li
ke to restore the old behavior.
[08:25:31] WARNING: ../src/learner.cc:1115: Starting in XGBoost 1.3.0, th
e default evaluation metric used with the objective 'binary:logistic' was
changed from 'error' to 'logloss'. Explicitly set eval_metric if you'd li
```

In [157]:
```
#xg_grid_1=XGBClassifier(learning_rate=0.2,max_depth=5, min_child_weight=2,
```

In [158]:
```
#eval_model(xg_grid_1,scaled_X_train,y_train,scaled_X_test,y_test)
```

```
[09:54:42] WARNING: ../src/learner.cc:1115: Starting in XGBoost 1.3.0, th
e default evaluation metric used with the objective 'binary:logistic' was
changed from 'error' to 'logloss'. Explicitly set eval_metric if you'd li
ke to restore the old behavior.
test:
              precision    recall  f1-score   support

           0       0.67      0.64      0.65     62208
           1       0.65      0.68      0.67     61788

    accuracy                           0.66    123996
   macro avg       0.66      0.66      0.66    123996
weighted avg       0.66      0.66      0.66    123996

train:
              precision    recall  f1-score   support

           0       0.67      0.65      0.66    185783
           1       0.66      0.69      0.67    186203

    accuracy                           0.67    371986
   macro avg       0.67      0.67      0.67    371986
weighted avg       0.67      0.67      0.67    371986

Train Recall_score 0.6871264157935156
Test Recall_score 0.6801482488509095
Train accuracy score 0.6686434435704569
Test accuracy score 0.6606100196780541
```



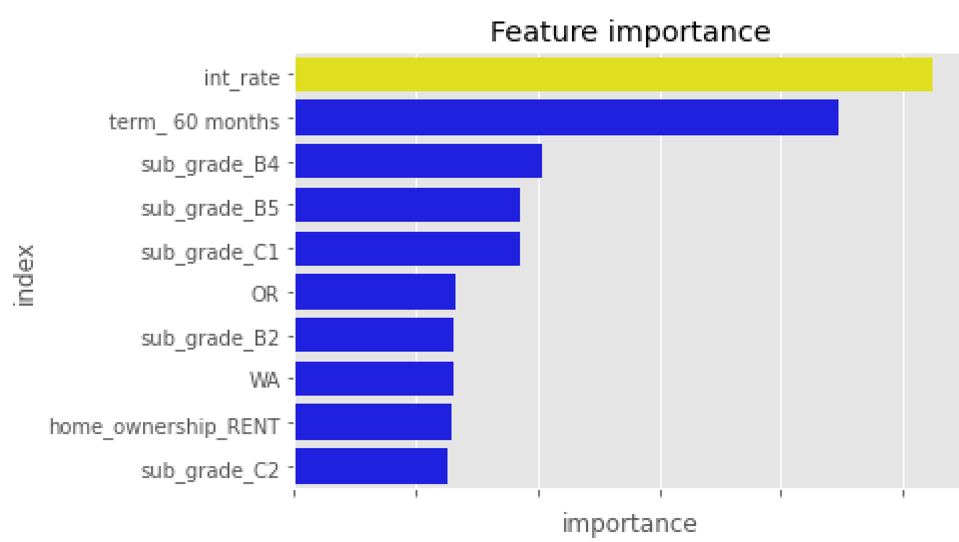
4.10 Find Feature Importances in XGBoost Model

Calculating feature importances and plot the feature by sorted values

In [161]:
```
# Calculate feature importances
feature_importances = xg_grid.feature_importances_

# Create a list of features: done
feature_list = list(scaled_X_train.columns)

# Save the results inside a DataFrame using feature_list as an index
relative_importances = pd.DataFrame(index=feature_list, data=feature_import

# Sort values to learn most important features
relative_importances.sort_values(by="importance", ascending=False)

# Show top 10 features
result = relative_importances.reset_index().sort_values('importance',ascend
```

Plot the top 10 feature importances

In [162]:
```
# plot feature imporances with sorted values
clrs=['blue' if (value < max(result.importance)) else 'yellow' for value in
ax=sns.barplot(data=result,x='importance',y='index',palette=clrs,ci= None)
ax.set_xlabel('importance')
ax.set_ylabel('index')
ax.set_title('Feature importance')

ax.set_xticklabels(ax.get_xticklabels(),rotation=90);
```



5 Conclusion

Interest Rate, term, subgrade, and home ownership affect the model prediction most.

Our model achieved achieve 68% prediciton on the test set.

From the confusion matrix, we can see our classifier has high recall. This means the proportion of borrowers predicted to default the loan is high.

6 Furthermore

- Try out more classification models
- Analyze the data by region or state to help banks to assess credit risk, provide accurate credit scores and make decisions on their loans in minutes after receiving each new incoming loan application
- Set up different threshold to improve recall score by business goal. It's because the binary classification models usually give the prediction of probability first and then assign the probabilities to 1 or 0 based on the default threshold of 0.5

In [ ]:

```

```