Lending Club Loan Default Prediction

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In [1]:
```
from IPython.display import display
from PIL import Image
path="C:/Users/puj83/OneDrive/Portfolio/Loan/Lending_Club_logo.png"
display(Image.open(path))
```

Link to Dataset:

https://www.kaggle.com/loknath2017/lending-loan-data?select=accepted_2007_to_2017Q3.csv.gz (https://www.kaggle.com/loknath2017/lending-loan-data?select=accepted_2007_to_2017Q3.csv.gz)

Abstract:

Year after year, there are millions of people who default on their loans which causes high risk to the lending partner. Many wonder, what makes a customer default on a loan? Is it their income, debt to income ratio, or it something more behaviorial that causes this trend? In this project, we will explore potential indicator variables that play a large role in terms of customers defaulting on their loans.

Industry:

Financial Services/Internet

Company Information:

LendingClub is a US peer-to-peer lending company, headquartered in San Francisco, California. It was the first peer-to-peer lender to register its offerings as securities with the Securities and Exchange Commission (SEC), and to offer loan trading on a secondary market. LendingClub is the world's largest peer-to-peer lending platform. The company claims that $15.98 billion in loans had been originated through its platform up to December 31, 2015.

LendingClub enables borrowers to create unsecured personal loans between 1,000 and 40,000. The standard loan period is three years. Investors can search and browse the loan listings on LendingClub website and select loans that they want to invest in based on the information supplied about the borrower, amount of loan, loan grade, and loan purpose. Investors make money from interest. LendingClub makes money by charging borrowers an origination fee and investors a service fee.

LendingClub also makes traditional direct to consumer loans, including automobile refinance transactions, through WebBank, an FDIC-insured, state-chartered industrial bank that is headquartered in Salt Lake City Utah. The loans are not funded by investors but are assigned to other financial institutions.

The company raised $1 billion in what became the largest technology IPO of 2014 in the United States. Though viewed as a pioneer in the fintech industry and one of the largest such firms, LendingClub experienced problems in early 2016, with difficulties in attracting investors, a scandal over some of the firm's loans and concerns by the board over CEO Renaud Laplanche's disclosures leading to a large drop in its share price and Laplanche's resignation.

https://www.lendingclub.com/ (https://www.lendingclub.com/)

https://en.wikipedia.org/wiki/LendingClub (https://en.wikipedia.org/wiki/LendingClub)

Use Case:

Build a model to predict which factors drives loan defaults

Initial Dataset:

Loan Dataset

Tool:

Python (Jupyter Notebook)

In [2]:
```
!pip install treeinterpreter
```

```
Requirement already satisfied: treeinterpreter in c:\users\puj83\anaconda3\li
b\site-packages (0.2.2)
```

In [3]:
```
# Import packages & libraries
import os
import pandas as pd
from pandas import Series, DataFrame
#import pandas_profiling

pd.set_option('display.max_rows', None,'display.max_columns', None)

import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
sns.set_style('whitegrid')
%matplotlib inline

from collections import Counter

from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC, LinearSVC
from sklearn.ensemble import RandomForestClassifier, AdaBoostClassifier, Gradi
entBoostingClassifier, ExtraTreesClassifier, VotingClassifier
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
from sklearn.neighbors import KNeighborsClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.tree import DecisionTreeClassifier
from sklearn.neural_network import MLPClassifier
from sklearn.model_selection import GridSearchCV, cross_val_score, StratifiedK
Fold, learning_curve, cross_validate
from sklearn.metrics import confusion_matrix, precision_score, recall_score, f
1_score, make_scorer, roc_auc_score,accuracy_score, roc_curve
from scipy.stats import ks_2samp
from treeinterpreter import treeinterpreter as ti

from sklearn.impute import SimpleImputer
imputer = SimpleImputer(missing_values=np.nan, strategy='mean')#from sklearn i
mport cross_validation
from sklearn import metrics

"""
from sklearn import metrics
from sklearn import linear_model

from sklearn import tree
from sklearn import svm
from sklearn import ensemble
from sklearn import neighbors
from sklearn import preprocessing
"""

# ignore Deprecation Warning
import warnings
#warnings.filterwarnings("ignore", category=DeprecationWarning,RuntimeWarning)
warnings.filterwarnings("ignore")

#plt.style.use('fivethirtyeight') # Good looking plots
pd.set_option('display.max_columns', None) # Display any number of columns
```

```
C:\Users\puj83\anaconda3\lib\site-packages\sklearn\utils\deprecation.py:144:
FutureWarning: The sklearn.ensemble.forest module is  deprecated in version
0.22 and will be removed in version 0.24. The corresponding classes / functio
ns should instead be imported from sklearn.ensemble. Anything that cannot be
imported from sklearn.ensemble is now part of the private API.
  warnings.warn(message, FutureWarning)
```

In [4]:
```
df = pd.read_csv("C:/Users/puj83/OneDrive/Portfolio/Loan/accepted_2007_to_2017
Q3.csv.gz",compression='gzip',low_memory=True)
```

In [5]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1646801 entries, 0 to 1646800
Columns: 150 entries, id to settlement_term
dtypes: float64(113), object(37)
memory usage: 1.8+ GB
```

In [6]:
```
df.sample(5)
```

Out[6]:

	id	member_id	loan_amnt	funded_amnt	funded_amnt_inv	term	int_rate	in
1190010	119426724	NaN	11000.0	11000.0	11000.0	36 months	9.93	
1067153	96850692	NaN	20000.0	20000.0	20000.0	60 months	28.69	
1115051	88793757	NaN	10000.0	10000.0	10000.0	36 months	12.79	
62767	29254130	NaN	8200.0	8200.0	8200.0	36 months	9.17	
1606820	70592712	NaN	9000.0	9000.0	9000.0	36 months	6.97	

In [7]:
```
df['loan_status'].value_counts()
```

Out[7]:
```
Current                                                788950
Fully Paid                                             646902
Charged Off                                            168084
Late (31-120 days)                                      23763
In Grace Period                                         10474
Late (16-30 days)                                        5786
Does not meet the credit policy. Status:Fully Paid      1988
Does not meet the credit policy. Status:Charged Off      761
Default                                                   70
Name: loan_status, dtype: int64
```

In [8]:
```
df = df.loc[df['loan_status'].isin(['Fully Paid','Charged Off'])]
```

In [9]:
```
df['loan_status'].value_counts(normalize=False, dropna=False)
```

Out[9]:
```
Fully Paid     646902
Charged Off    168084
Name: loan_status, dtype: int64
```

In [10]:
```
df['loan_status'].value_counts(normalize=True, dropna=False)
```

Out[10]:
```
Fully Paid     0.793758
Charged Off    0.206242
Name: loan_status, dtype: float64
```

In [11]:
```
# Define a function to visulize the features with missing values, and % of tot
al values, & datatype
def missing_values_table(df):
     # Total missing values
    mis_val = df.isnull().sum()
    # Percentage of missing values
    mis_val_percent = 100 * df.isnull().sum() / len(df)
    mis_val_type = df.dtypes
    # Make a table with the results
    mis_val_table = pd.concat([mis_val, mis_val_percent, mis_val_type], axis=1
)

     # Rename the columns
    mis_val_table_ren_columns = mis_val_table.rename(columns = {0 : 'Missing V
alues', 1 : '% of Total Values', 2: 'type'})

    # Sort the table by percentage of missing descending
    mis_val_table_ren_columns = mis_val_table_ren_columns[ mis_val_table_ren_c
olumns.iloc[:,1] != 0].sort_values('% of Total Values', ascending=False).round
(1)

    # Print some summary information
    print ("Your selected dataframe has " + str(df.shape[1]) + " columns.\n"
"There are " + str(mis_val_table_ren_columns.shape[0]) + " columns that have m
issing values.")

    # Return the dataframe with missing information
    return mis_val_table_ren_columns
```

In [12]:
```
missing_values_table(df)
```

```
Your selected dataframe has 150 columns.
There are 104 columns that have missing values.
```

Out[12]:

	Missing Values	% of Total Values	type
member_id	814986	100.0	float64
next_pymnt_d	814986	100.0	object
orig_projected_additional_accrued_interest	814885	100.0	float64
sec_app_mths_since_last_major_derog	814683	100.0	float64
hardship_length	814395	99.9	float64
hardship_type	814395	99.9	object
hardship_reason	814395	99.9	object
hardship_status	814395	99.9	object
deferral_term	814395	99.9	float64
hardship_amount	814395	99.9	float64
hardship_start_date	814395	99.9	object
payment_plan_start_date	814395	99.9	object
hardship_end_date	814395	99.9	object
hardship_dpd	814395	99.9	float64
hardship_payoff_balance_amount	814395	99.9	float64
hardship_last_payment_amount	814395	99.9	float64
hardship_loan_status	814395	99.9	object
sec_app_revol_util	814105	99.9	float64
sec_app_chargeoff_within_12_mths	814088	99.9	float64
sec_app_fico_range_high	814088	99.9	float64
sec_app_earliest_cr_line	814088	99.9	object
sec_app_inq_last_6mths	814088	99.9	float64
sec_app_mort_acc	814088	99.9	float64
sec_app_open_acc	814088	99.9	float64
sec_app_open_act_il	814088	99.9	float64
sec_app_num_rev_accts	814088	99.9	float64
sec_app_fico_range_low	814088	99.9	float64
sec_app_collections_12_mths_ex_med	814088	99.9	float64
revol_bal_joint	814088	99.9	float64
verification_status_joint	811207	99.5	object
dti_joint	811207	99.5	float64
annual_inc_joint	811207	99.5	float64
settlement_amount	802316	98.4	float64
settlement_date	802316	98.4	object
settlement_status	802316	98.4	object

	Missing Values	% of Total Values	type
debt_settlement_flag_date	802316	98.4	object
settlement_percentage	802316	98.4	float64
settlement_term	802316	98.4	float64
desc	695254	85.3	object
mths_since_last_record	680839	83.5	float64
il_util	660068	81.0	float64
mths_since_rcnt_il	641720	78.7	float64
all_util	637773	78.3	float64
inq_last_12m	637762	78.3	float64
total_cu_tl	637762	78.3	float64
open_acc_6m	637762	78.3	float64
max_bal_bc	637761	78.3	float64
open_il_12m	637761	78.3	float64
open_il_24m	637761	78.3	float64
inq_fi	637761	78.3	float64
total_bal_il	637761	78.3	float64
open_rv_24m	637761	78.3	float64
open_rv_12m	637761	78.3	float64
open_act_il	637761	78.3	float64
mths_since_recent_bc_dlq	625423	76.7	float64
mths_since_last_major_derog	609571	74.8	float64
mths_since_recent_revol_delinq	549325	67.4	float64
mths_since_last_delinq	417171	51.2	float64
mths_since_recent_inq	117711	14.4	float64
num_tl_120dpd_2m	93246	11.4	float64
mo_sin_old_il_acct	89559	11.0	float64
pct_tl_nvr_dlq	67664	8.3	float64
avg_cur_bal	67539	8.3	float64
num_rev_accts	67528	8.3	float64
mo_sin_rcnt_rev_tl_op	67528	8.3	float64
mo_sin_old_rev_tl_op	67528	8.3	float64
total_rev_hi_lim	67527	8.3	float64
total_il_high_credit_limit	67527	8.3	float64
num_tl_90g_dpd_24m	67527	8.3	float64
tot_hi_cred_lim	67527	8.3	float64
tot_cur_bal	67527	8.3	float64

	Missing Values	% of Total Values	type
tot_coll_amt	67527	8.3	float64
num_tl_op_past_12m	67527	8.3	float64
num_tl_30dpd	67527	8.3	float64
num_rev_tl_bal_gt_0	67527	8.3	float64
num_op_rev_tl	67527	8.3	float64
num_il_tl	67527	8.3	float64
num_bc_tl	67527	8.3	float64
num_actv_rev_tl	67527	8.3	float64
num_actv_bc_tl	67527	8.3	float64
num_accts_ever_120_pd	67527	8.3	float64
mo_sin_rcnt_tl	67527	8.3	float64
num_sats	55841	6.9	float64
num_bc_sats	55841	6.9	float64
bc_util	55665	6.8	float64
percent_bc_gt_75	55453	6.8	float64
bc_open_to_buy	55176	6.8	float64
mths_since_recent_bc	54578	6.7	float64
emp_title	48571	6.0	object
mort_acc	47281	5.8	float64
acc_open_past_24mths	47281	5.8	float64
total_bal_ex_mort	47281	5.8	float64
total_bc_limit	47281	5.8	float64
emp_length	42253	5.2	object
title	7918	1.0	object
last_pymnt_d	1469	0.2	object
pub_rec_bankruptcies	697	0.1	float64
revol_util	490	0.1	float64
collections_12_mths_ex_med	56	0.0	float64
chargeoff_within_12_mths	56	0.0	float64
last_credit_pull_d	39	0.0	object
tax_liens	39	0.0	float64
dti	36	0.0	float64
inq_last_6mths	1	0.0	float64

In [13]:
```
missing_frac = df.isnull().mean()
drop_list = sorted(missing_frac[missing_frac > 0.50].index)
```

In [14]:
```
print(drop_list)
```

```
['all_util', 'annual_inc_joint', 'debt_settlement_flag_date', 'deferral_ter
m', 'desc', 'dti_joint', 'hardship_amount', 'hardship_dpd', 'hardship_end_dat
e', 'hardship_last_payment_amount', 'hardship_length', 'hardship_loan_statu
s', 'hardship_payoff_balance_amount', 'hardship_reason', 'hardship_start_dat
e', 'hardship_status', 'hardship_type', 'il_util', 'inq_fi', 'inq_last_12m',
'max_bal_bc', 'member_id', 'mths_since_last_delinq', 'mths_since_last_major_d
erog', 'mths_since_last_record', 'mths_since_rcnt_il', 'mths_since_recent_bc_
dlq', 'mths_since_recent_revol_delinq', 'next_pymnt_d', 'open_acc_6m', 'open_
act_il', 'open_il_12m', 'open_il_24m', 'open_rv_12m', 'open_rv_24m', 'orig_pr
ojected_additional_accrued_interest', 'payment_plan_start_date', 'revol_bal_j
oint', 'sec_app_chargeoff_within_12_mths', 'sec_app_collections_12_mths_ex_me
d', 'sec_app_earliest_cr_line', 'sec_app_fico_range_high', 'sec_app_fico_rang
e_low', 'sec_app_inq_last_6mths', 'sec_app_mort_acc', 'sec_app_mths_since_las
t_major_derog', 'sec_app_num_rev_accts', 'sec_app_open_acc', 'sec_app_open_ac
t_il', 'sec_app_revol_util', 'settlement_amount', 'settlement_date', 'settlem
ent_percentage', 'settlement_status', 'settlement_term', 'total_bal_il', 'tot
al_cu_tl', 'verification_status_joint']
```

In [15]:
```
len(drop_list)
```

Out[15]:
```
58
```

In [16]:
```
def drop_cols(cols):
    df.drop(labels=cols, axis=1, inplace=True)
```

In [17]:
```
drop_cols(drop_list)
```

In [18]:
```
df.shape
```

Out[18]:
```
(814986, 92)
```

In [19]:
```
print(sorted(df.columns))
```

```
['acc_now_delinq', 'acc_open_past_24mths', 'addr_state', 'annual_inc', 'appli
cation_type', 'avg_cur_bal', 'bc_open_to_buy', 'bc_util', 'chargeoff_within_1
2_mths', 'collection_recovery_fee', 'collections_12_mths_ex_med', 'debt_settl
ement_flag', 'delinq_2yrs', 'delinq_amnt', 'disbursement_method', 'dti', 'ear
liest_cr_line', 'emp_length', 'emp_title', 'fico_range_high', 'fico_range_lo
w', 'funded_amnt', 'funded_amnt_inv', 'grade', 'hardship_flag', 'home_ownersh
ip', 'id', 'initial_list_status', 'inq_last_6mths', 'installment', 'int_rat
e', 'issue_d', 'last_credit_pull_d', 'last_fico_range_high', 'last_fico_range
_low', 'last_pymnt_amnt', 'last_pymnt_d', 'loan_amnt', 'loan_status', '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_inq', 'num_accts_
ever_120_pd', 'num_actv_bc_tl', 'num_actv_rev_tl', 'num_bc_sats', 'num_bc_t
l', 'num_il_tl', 'num_op_rev_tl', 'num_rev_accts', 'num_rev_tl_bal_gt_0', 'nu
m_sats', 'num_tl_120dpd_2m', 'num_tl_30dpd', 'num_tl_90g_dpd_24m', 'num_tl_op
_past_12m', 'open_acc', 'out_prncp', 'out_prncp_inv', 'pct_tl_nvr_dlq', 'perc
ent_bc_gt_75', 'policy_code', 'pub_rec', 'pub_rec_bankruptcies', 'purpose',
'pymnt_plan', 'recoveries', 'revol_bal', 'revol_util', 'sub_grade', 'tax_lien
s', 'term', 'title', 'tot_coll_amt', 'tot_cur_bal', 'tot_hi_cred_lim', 'total
_acc', 'total_bal_ex_mort', 'total_bc_limit', 'total_il_high_credit_limit',
'total_pymnt', 'total_pymnt_inv', 'total_rec_int', 'total_rec_late_fee', 'tot
al_rec_prncp', 'total_rev_hi_lim', 'verification_status', 'zip_code']
```

In [20]:
```
drop_list = ['acc_now_delinq', 'acc_open_past_24mths', 'avg_cur_bal', 'bc_open_to_buy', 'bc_util',
             'chargeoff_within_12_mths', 'collection_recovery_fee', 'collections_12_mths_ex_med',
             'debt_settlement_flag', 'delinq_2yrs', 'delinq_amnt', 'disbursement_method', 'funded_amnt',
             'funded_amnt_inv', 'hardship_flag', 'inq_last_6mths', 'last_credit_pull_d', 'last_fico_range_high',
             'last_fico_range_low', 'last_pymnt_amnt', 'last_pymnt_d', 'mo_sin_rcnt_rev_tl_op', 'mo_sin_rcnt_tl',
             'mths_since_recent_bc', 'mths_since_recent_inq', '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',  'out_prncp', 'out_prncp_inv', 'pct_tl_nvr_dlq', 'percent_bc_gt_75',
             'pymnt_plan', 'recoveries', 'tax_liens', 'tot_coll_amt', 'tot_cur_bal', 'tot_hi_cred_lim',
             'total_bal_ex_mort', 'total_bc_limit', 'total_il_high_credit_limit', 'total_pymnt', 'total_pymnt_inv',
             'total_rec_int', 'total_rec_late_fee', 'total_rec_prncp', 'total_rev_hi_lim']
```

In [21]:
```
drop_cols(drop_list)
```

In [22]:
```
print(sorted(df.columns))
```

```
['addr_state', 'annual_inc', 'application_type', 'dti', 'earliest_cr_line',
'emp_length', 'emp_title', 'fico_range_high', 'fico_range_low', 'grade', 'hom
e_ownership', 'id', 'initial_list_status', 'installment', 'int_rate', 'issue_
d', 'loan_amnt', 'loan_status', 'mo_sin_old_il_acct', 'mo_sin_old_rev_tl_op',
'mort_acc', 'open_acc', 'policy_code', 'pub_rec', 'pub_rec_bankruptcies', 'pu
rpose', 'revol_bal', 'revol_util', 'sub_grade', 'term', 'title', 'total_acc',
'verification_status', 'zip_code']
```

In [23]:
```
len(df.columns)
```

Out[23]:
```
34
```

In [24]:
```
# make general plots to examine each feature
def plot_var(col_name, full_name, continuous):
    """
    Visualize a variable with/without faceting on the loan status.
    - col_name is the variable name in the dataframe
    - full_name is the full variable name
    - continuous is True for continuous variables
    """
    fig, (ax1, ax2) = plt.subplots(1, 2, sharex=False, figsize=(15,3))
    # plot1: counts distribution of the variable

    if continuous:
        sns.distplot(df.loc[df[col_name].notnull(), col_name], kde=False, ax=a
x1)
    else:
        sns.countplot(df[col_name], order=sorted(df[col_name].unique()), color
='#5975A4', saturation=1, ax=ax1)
    ax1.set_xlabel(full_name)
    ax1.set_ylabel('Count')
    ax1.set_title(full_name)


    # plot2: bar plot of the variable grouped by loan_status
    if continuous:
        sns.boxplot(x=col_name, y='loan_status', data=df, ax=ax2)
        ax2.set_ylabel('')
        ax2.set_title(full_name + ' by Loan Status')
    else:
        Charged_Off_rates = df.groupby(col_name)['loan_status'].value_counts(n
ormalize=True)[:,'Charged Off']
        sns.barplot(x=Charged_Off_rates.index, y=Charged_Off_rates.values, col
or='#5975A4', saturation=1, ax=ax2)
        ax2.set_ylabel('Fraction of Loans Charged Off')
        ax2.set_title('Charged Off Rate by ' + full_name)
        ax2.set_xlabel(full_name)

    # plot3: kde plot of the variable gropued by loan_status
    if continuous:
        facet = sns.FacetGrid(df, hue = 'loan_status', size=3, aspect=4)
        facet.map(sns.kdeplot, col_name, shade=True)
        #facet.set(xlim=(df[col_name].min(), df[col_name].max()))
        facet.add_legend()
    else:
        fig = plt.figure(figsize=(12,3))
        sns.countplot(x=col_name, hue='loan_status', data=df, order=sorted(df[
col_name].unique()) )

    plt.tight_layout()
```

In [25]:
```
df['id'].sample(5)
```

Out[25]:
```
1133584    87953895
601070     45424504
587193     46843573
207968     12275087
191919     12957070
Name: id, dtype: object
```

In [26]:
```
len(df['id'].unique())
```

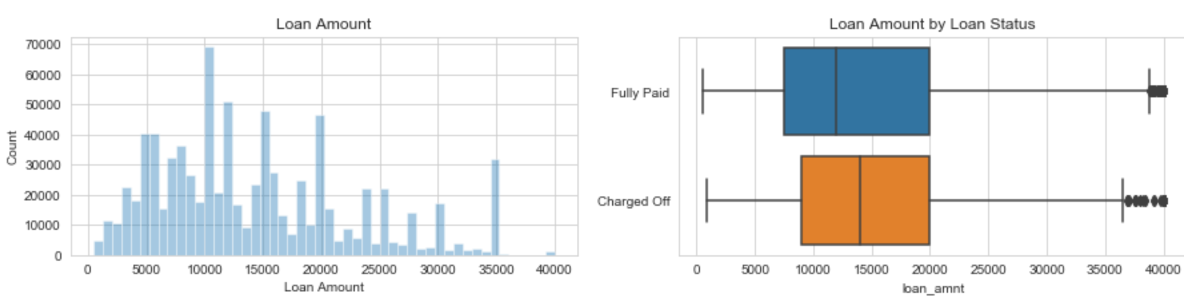
Out[26]:
```
814986
```

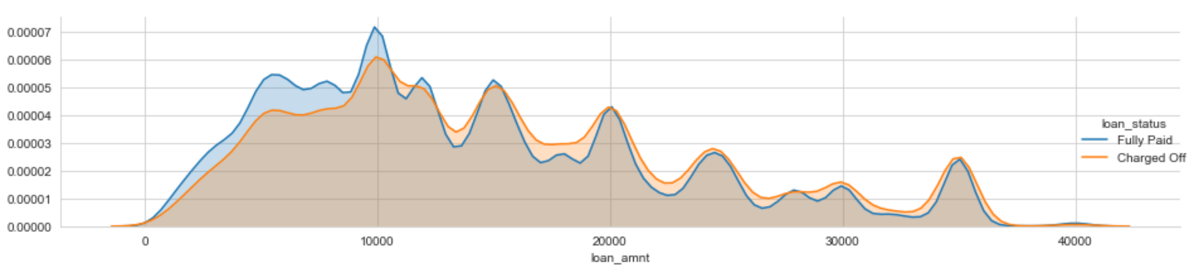
In [27]:
```
drop_cols('id')
```

In [28]:
```
df['loan_amnt'].describe()
```

Out[28]:
```
count    814986.000000
mean      14315.458210
std        8499.799241
min         500.000000
25%        8000.000000
50%       12000.000000
75%       20000.000000
max       40000.000000
Name: loan_amnt, dtype: float64
```

In [29]:
```
plot_var('loan_amnt', 'Loan Amount', continuous=True)
```





In [30]:
```
df['term'].sample(5)
```

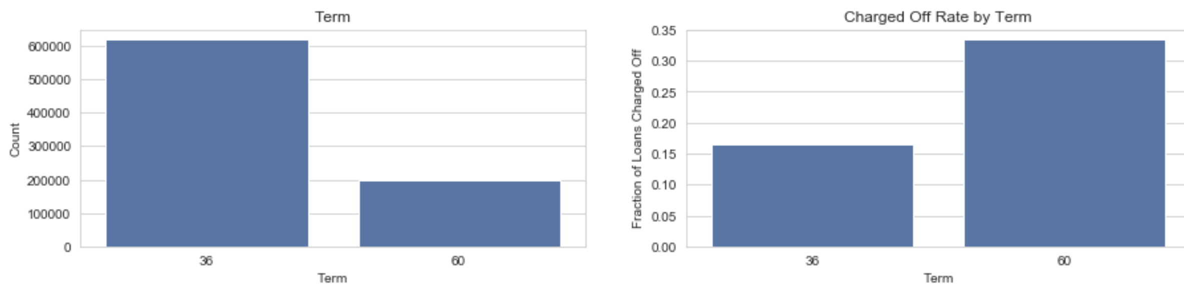
Out[30]:
```
262344      60 months
191707      36 months
26673       36 months
63522       36 months
1601321     36 months
Name: term, dtype: object
```

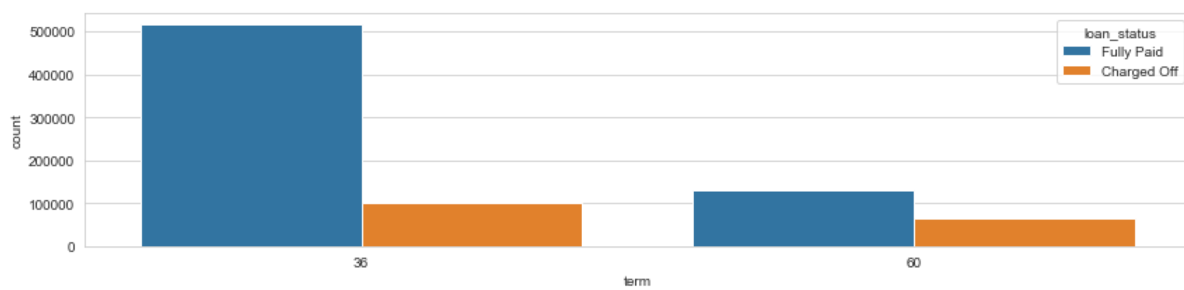
In [31]:
```
df['term'].value_counts(dropna=False)
```

Out[31]:
```
 36 months    618460
 60 months    196526
Name: term, dtype: int64
```

In [32]:
```
df['term'] = df['term'].apply(lambda s: np.int8(s.split()[0]))
```

In [33]:
```
plot_var('term', 'Term', continuous=False)
```





In [34]:
```
df['term'].value_counts(normalize=True)
```

Out[34]:
```
36    0.75886
60    0.24114
Name: term, dtype: float64
```

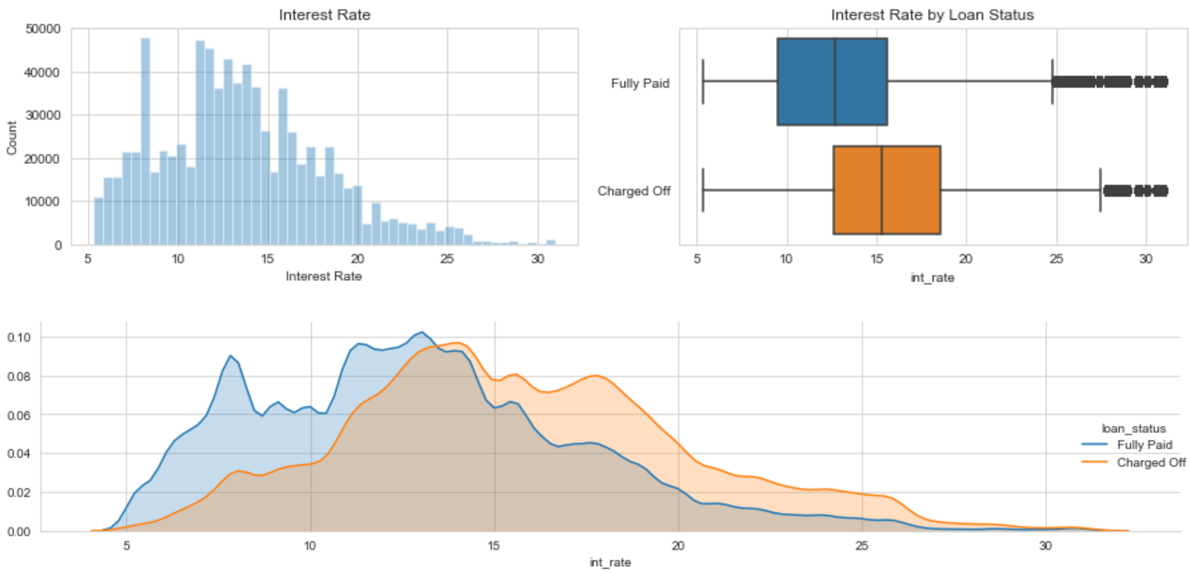
In [35]:
```
df.groupby('term')['loan_status'].value_counts(normalize=True).loc[:,'Charged
 Off']
```

Out[35]:
```
term
36    0.165710
60    0.333793
Name: loan_status, dtype: float64
```

In [36]:
```
df['int_rate'].describe()
```

Out[36]:
```
count    814986.000000
mean         13.490993
std           4.618486
min           5.320000
25%           9.990000
50%          13.110000
75%          16.290000
max          30.990000
Name: int_rate, dtype: float64
```

In [37]:
```python
plot_var('int_rate', 'Interest Rate', continuous=True)
```



In [38]:
```python
def outliers_modified_z_score(dataframe, n, features):
    """
    Takes a dataframe df of features and returns a list of the indices corresponding to the observations containing more than n outliers according to the modified z-score Method
    """
    threshold = 3.5
    outlier_indices = []
    for col in features:
        median_y = np.median(dataframe[col])
        median_absolute_deviation_y = np.median([np.abs(y - median_y) for y in dataframe[col]])
        modified_z_scores = [0.6745 * (y - median_y) / median_absolute_deviation_y for y in dataframe[col]]
        outlier_list_col = dataframe[np.abs(modified_z_scores) > threshold].index
       # append the found outlier indices for col to the list of outlier indices
        outlier_indices.extend(outlier_list_col)
        # select observations containing more than 2 outliers
    outlier_indices = Counter(outlier_indices)
    multiple_outliers = list( k for k, v in outlier_indices.items() if v > n )
    return multiple_outliers

#Outliers_to_drop_z_score = outliers_modified_z_score(df,2,['loan_amnt', 'term', 'int_rate', 'installment', 'annual_inc', 'dti','fico_range_high', 'pub_rec', 'mo_sin_old_il_acct', 'mo_sin_old_rev_tl_op', 'mort_acc','earliest_cr_line_'])
```

In [39]:
```
def outliers_iqr(dataframe, n, features):
    """
    Takes a dataframe df of features and returns a list of the indices
    corresponding to the observations containing more than n outliers accordin
g
    to the Tukey method.
    """
    outlier_indices = []
    for col in features:
        # 1st quartile (25%) & # 3rd quartile (75%)
        quartile_1, quartile_3 = np.percentile(dataframe[col], [25,75])
        #quartile_3 = np.percentile(dataframe[col], 75)

        iqr = quartile_3 - quartile_1
        lower_bound = quartile_1 - (iqr * 1.5)
        upper_bound = quartile_3 + (iqr * 1.5)
        # Determine a list of indices of outliers for feature col
        outlier_list_col = dataframe[(dataframe[col] < lower_bound) | (datafra
me[col] > upper_bound)].index
       # append the found outlier indices for col to the list of outlier indic
es
        outlier_indices.extend(outlier_list_col)
        # select observations containing more than 2 outliers
    outlier_indices = Counter(outlier_indices)
    multiple_outliers = list( k for k, v in outlier_indices.items() if v > n )
    return multiple_outliers
```

In [40]:
```
df.groupby('loan_status')['int_rate'].describe()
```

Out[40]:

loan_status	count	mean	std	min	25%	50%	75%	max
Charged Off	168084.0	15.736335	4.625755	5.32	12.59	15.31	18.55	30.99
Fully Paid	646902.0	12.907587	4.434262	5.32	9.49	12.68	15.61	30.99

In [41]:
```
df.loc[(df.int_rate > 15.61) & (df.loan_status == 'Fully Paid')].shape[0]
```

Out[41]: 150885

In [42]:
```
(df.loc[(df.int_rate > 15.61) & (df.loan_status == 'Fully Paid')].shape[0])/df
['loan_status'].value_counts(normalize=False, dropna=False)[0]
```

Out[42]: 0.2332424385764768

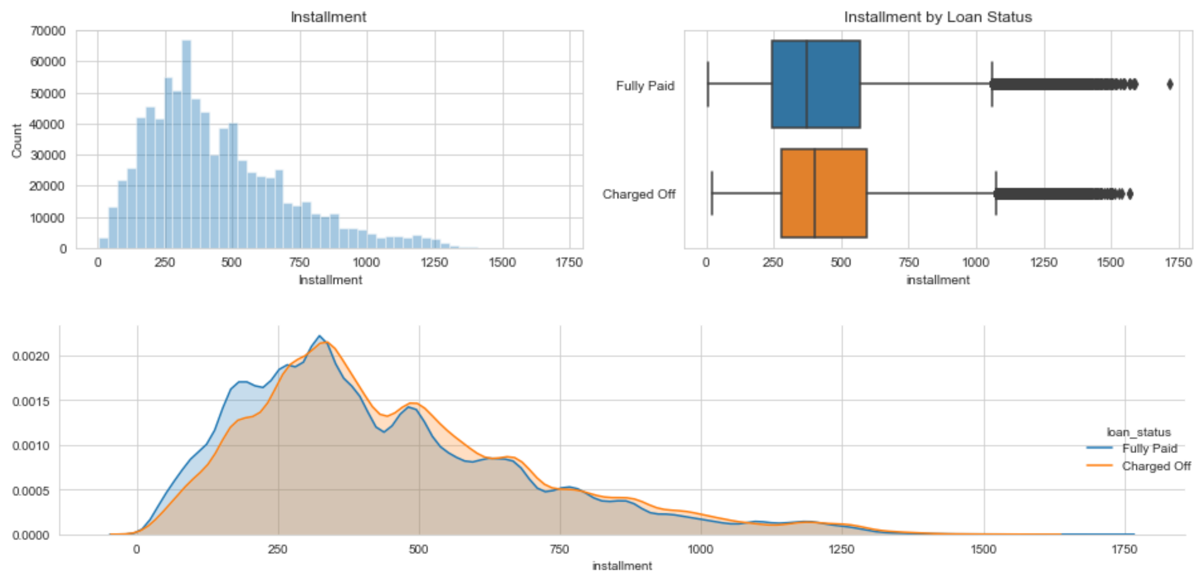
In [43]:
```
df.loc[(df.int_rate >18.55) & (df.loan_status == 'Charged Off')].shape[0]/df[
'loan_status'].value_counts(normalize=False, dropna=False)[1]
```

Out[43]: 0.24427072178196615

In [44]:
```
df['installment'].describe()
```

Out[44]:
```
count    814986.000000
mean        436.749624
std         255.732093
min           4.930000
25%         251.400000
50%         377.040000
75%         576.290000
max        1714.540000
Name: installment, dtype: float64
```

In [45]:
```
plot_var('installment', 'Installment', continuous=True)
```



In [46]:
```
df.groupby('loan_status')['installment'].describe()
```

Out[46]:

loan_status	count	mean	std	min	25%	50%	75%	max
Charged Off	168084.0	459.973673	255.309267	21.62	276.14	402.39	595.87	1569.11
Fully Paid	646902.0	430.715339	255.496761	4.93	244.76	370.92	569.72	1714.54

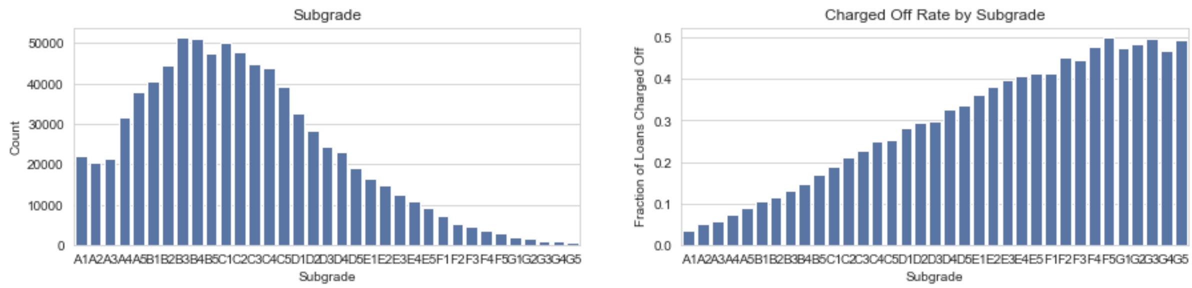
In [47]:
```
sorted(df['grade'].unique())
```

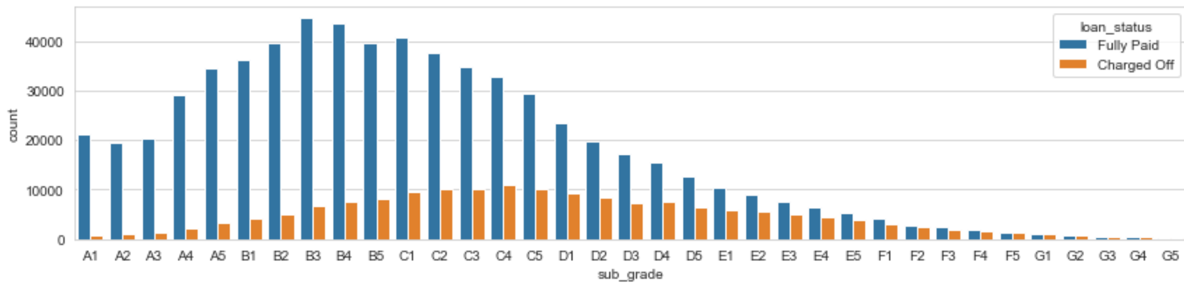
Out[47]:
```
['A', 'B', 'C', 'D', 'E', 'F', 'G']
```

In [48]:
```
print(sorted(df['sub_grade'].unique()))
```

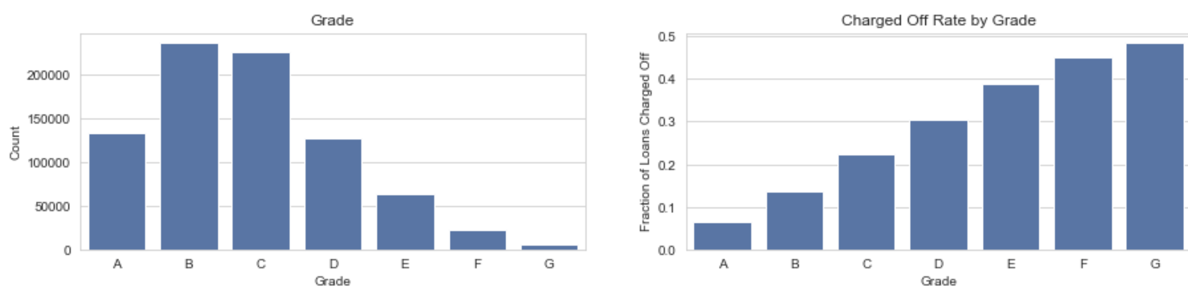
```
['A1', 'A2', 'A3', 'A4', 'A5', 'B1', 'B2', 'B3', 'B4', 'B5', 'C1', 'C2', 'C
3', 'C4', 'C5', 'D1', 'D2', 'D3', 'D4', 'D5', 'E1', 'E2', 'E3', 'E4', 'E5',
'F1', 'F2', 'F3', 'F4', 'F5', 'G1', 'G2', 'G3', 'G4', 'G5']
```

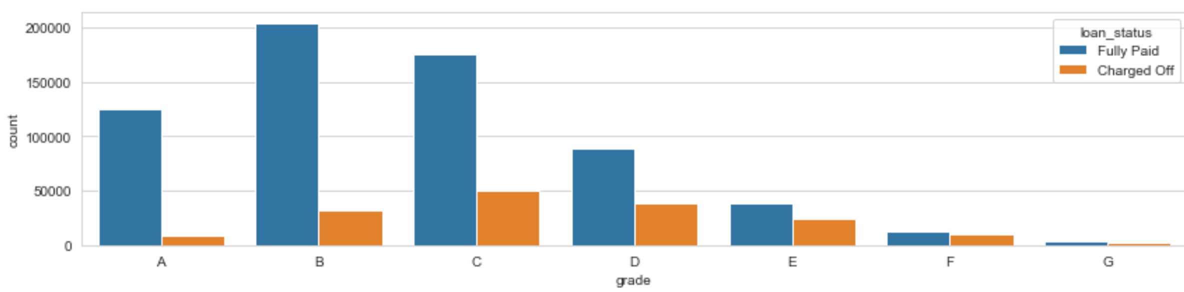
In [49]:
```
plot_var('sub_grade','Subgrade',continuous=False)
```





In [50]:
```
plot_var('grade','Grade',continuous=False)
```





In [51]:
```
#df.drop(labels='grade',axis=1,inplace=True)
drop_cols('grade')
```

In [52]:
```
df['emp_title'].describe()
```

Out[52]:
```
count      766415
unique     280473
top       Teacher
freq        11351
Name: emp_title, dtype: object
```

In [53]:
```
df['emp_title'].sample(5)
```

Out[53]:
```
693773          Executive Assistant
847658             Store Supervisor
222396                      Auditor
899590    Acme Construction Supply
836919                 Optometrist
Name: emp_title, dtype: object
```

In [54]:
```
drop_cols('emp_title')
```

In [55]:
```
df['emp_length'].value_counts(dropna=False).sort_index()
```

Out[55]:
```
1 year        53411
10+ years    264873
2 years       73493
3 years       64999
4 years       48752
5 years       52149
6 years       40290
7 years       39407
8 years       38887
9 years       31900
< 1 year      64572
NaN           42253
Name: emp_length, dtype: int64
```

In [56]:
```
df['emp_length'].replace('10+ years', '10 years', inplace=True)
```

In [57]:
```
df['emp_length'].replace('< 1 year', '0 years', inplace=True)
```

In [58]:
```
df['emp_length'].value_counts(dropna=False).sort_index()
```

Out[58]:
```
0 years      64572
1 year       53411
10 years    264873
2 years      73493
3 years      64999
4 years      48752
5 years      52149
6 years      40290
7 years      39407
8 years      38887
9 years      31900
NaN          42253
Name: emp_length, dtype: int64
```

In [59]:
```
df.emp_length.map( lambda x: str(x).split()[0]).value_counts(dropna=True).sort_index()
```

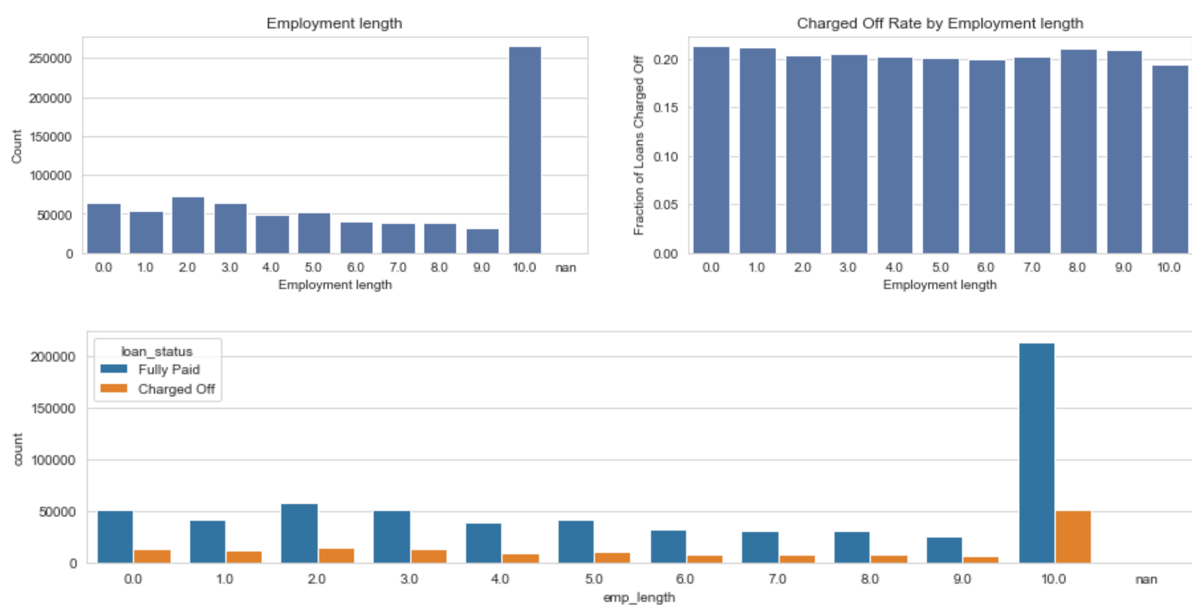
Out[59]:
```
0       64572
1       53411
10     264873
2       73493
3       64999
4       48752
5       52149
6       40290
7       39407
8       38887
9       31900
nan     42253
Name: emp_length, dtype: int64
```

In [60]:
```
df['emp_length'] = df.emp_length.map( lambda x: float(str(x).split()[0]))
```

In [61]:
```
df['emp_length'].sample(5)
```

Out[61]:
```
216040      1.0
282067      2.0
887187      2.0
1099976    10.0
467054     10.0
Name: emp_length, dtype: float64
```

In [62]:
```
plot_var('emp_length', 'Employment length', continuous=False)
```



In [63]:
```
df['home_ownership'].value_counts()
```

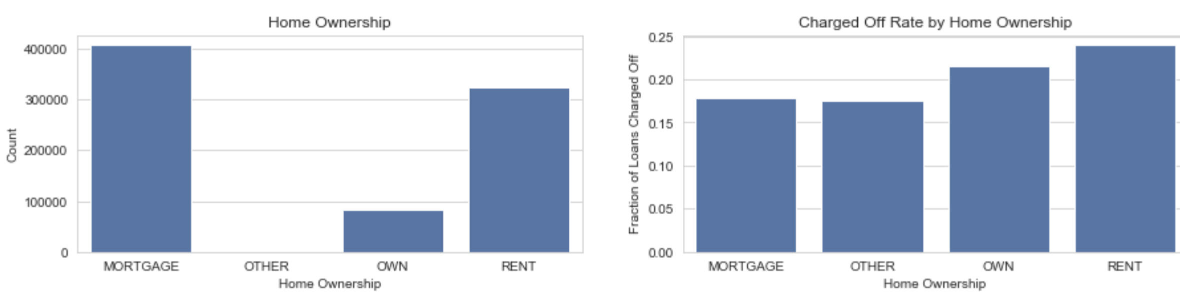
Out[63]:
```
MORTGAGE    406866
RENT        325071
OWN          82765
OTHER          144
ANY             94
NONE            46
Name: home_ownership, dtype: int64
```

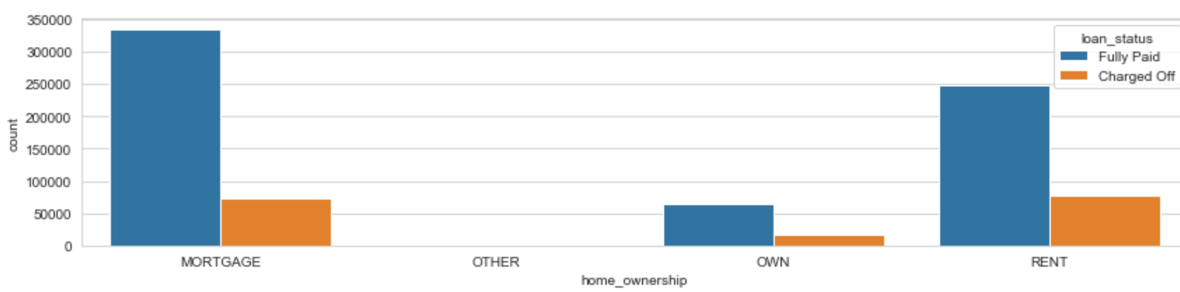
In [64]:
```
df['home_ownership'].replace(['NONE','ANY'],'OTHER', inplace=True)
```

In [65]:
```
df['home_ownership'].value_counts()
```

Out[65]:
```
MORTGAGE    406866
RENT        325071
OWN          82765
OTHER          284
Name: home_ownership, dtype: int64
```

In [66]:
```
plot_var('home_ownership', 'Home Ownership', continuous=False)
```





In [67]:
```
df.groupby('home_ownership')['loan_status'].value_counts(normalize=True).loc
[:,'Charged Off']
```

Out[67]:
```
home_ownership
MORTGAGE    0.177808
OTHER       0.176056
OWN         0.215804
RENT        0.239422
Name: loan_status, dtype: float64
```

In [68]:
```
df['annual_inc'].describe()
```

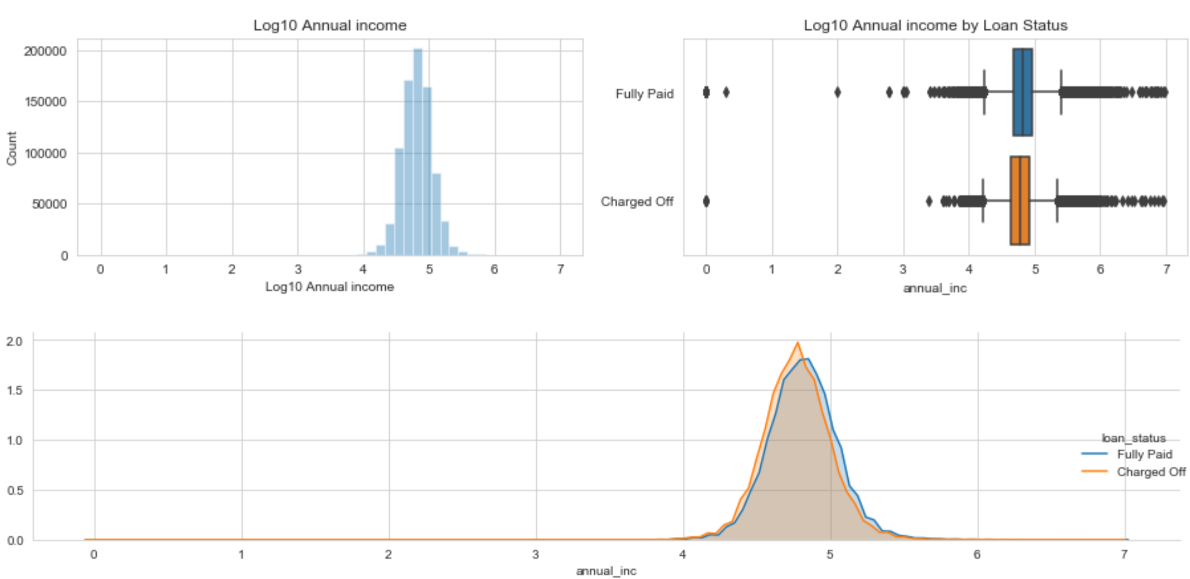
Out[68]:
```
count    8.149860e+05
mean     7.523039e+04
std      6.524373e+04
min      0.000000e+00
25%      4.500000e+04
50%      6.500000e+04
75%      9.000000e+04
max      9.550000e+06
Name: annual_inc, dtype: float64
```

In [69]:
```
df['annual_inc'] = df['annual_inc'].apply(lambda x:np.log10(x+1))
```

In [70]:
```
df['annual_inc'].describe()
```

Out[70]:
```
count    814986.000000
mean          4.810836
std           0.231893
min           0.000000
25%           4.653222
50%           4.812920
75%           4.954247
max           6.980003
Name: annual_inc, dtype: float64
```

In [71]:
```
plot_var('annual_inc', 'Log10 Annual income', continuous=True)
```



In [72]:
```
df.groupby('loan_status')['annual_inc'].describe()
```

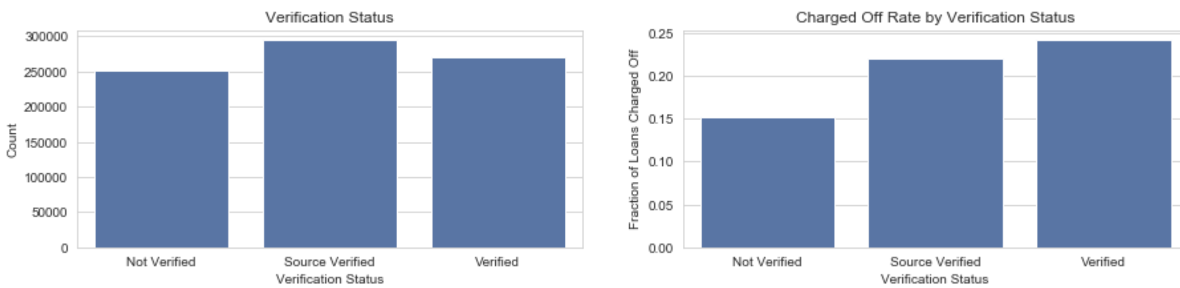
Out[72]:

loan_status	count	mean	std	min	25%	50%	75%	max
Charged Off	168084.0	4.777072	0.227015	0.0	4.632467	4.778158	4.915096	6.949393
Fully Paid	646902.0	4.819608	0.232342	0.0	4.672107	4.812920	4.963793	6.980003

In [73]:
```
df['verification_status'].value_counts()
```

Out[73]:
```
Source Verified    293897
Verified           269895
Not Verified       251194
Name: verification_status, dtype: int64
```

In [74]:
```
plot_var('verification_status', 'Verification Status', continuous=False)
```



In [75]:
```
df['purpose'].value_counts()
```

Out[75]:
```
debt_consolidation    481652
credit_card           175123
home_improvement       50793
other                  43900
major_purchase         17463
small_business         10214
car                     8936
medical                 8772
moving                  5725
vacation                5116
house                   4095
wedding                 2272
renewable_energy         599
educational              326
Name: purpose, dtype: int64
```

In [76]:
```
df.groupby('purpose')['loan_status'].value_counts(normalize=True)[:,'Charged O
ff'].sort_values(ascending=False)
```

Out[76]:
```
purpose
small_business        0.302428
renewable_energy      0.247078
moving                0.242969
medical               0.229366
debt_consolidation    0.217398
other                 0.216970
house                 0.214652
vacation              0.198788
major_purchase        0.183245
home_improvement      0.181383
credit_card           0.178412
educational           0.171779
car                   0.148053
wedding               0.121919
Name: loan_status, dtype: float64
```

In [77]:
```
df['title'].describe()
```

Out[77]:
```
count                 807068
unique                 60298
top       Debt consolidation
freq                  371874
Name: title, dtype: object
```

In [78]:
```
df['title'].value_counts().head(10)
```

Out[78]:
```
Debt consolidation         371874
Credit card refinancing    133334
Home improvement            39171
Other                       33265
Debt Consolidation          15059
Major purchase              12311
Medical expenses             6908
Business                     6666
Car financing                5667
Consolidation                5090
Name: title, dtype: int64
```

In [79]:
```
drop_cols('title')
```

In [80]:
```
df['zip_code'].describe()
```

Out[80]:
```
count     814986
unique       925
top        945xx
freq        9517
Name: zip_code, dtype: object
```

In [81]:
```
df['addr_state'].describe()
```

Out[81]:
```
count     814986
unique        51
top           CA
freq      124204
Name: addr_state, dtype: object
```

In [82]:
```
drop_cols('zip_code')
```

In [83]:
```
df.groupby('addr_state')['loan_status'].value_counts(normalize=True)[:,'Charge
d Off'].sort_values(ascending=False)
```

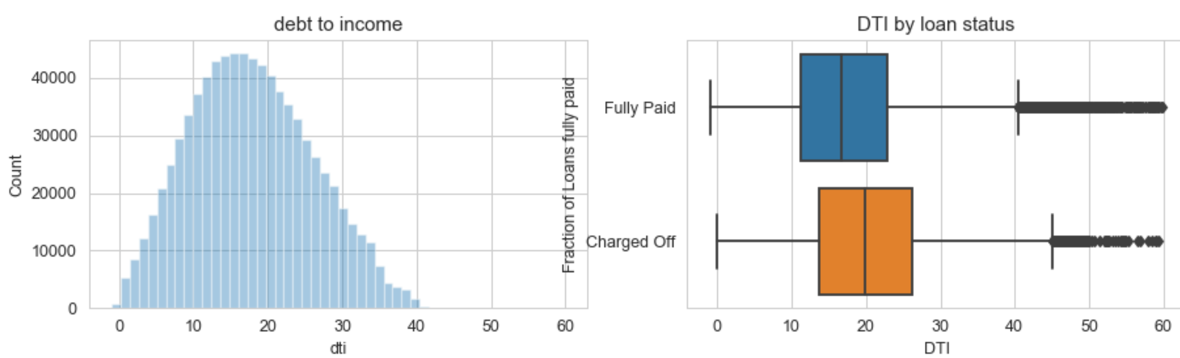
Out[83]:
```
addr_state
MS    0.275619
NE    0.267946
OK    0.248252
AL    0.247650
AR    0.243154
LA    0.237900
ND    0.237232
NV    0.234202
TN    0.230479
IN    0.228179
NY    0.227045
SD    0.225787
NM    0.225694
OH    0.225400
FL    0.222007
MO    0.219400
KY    0.216353
NJ    0.216208
NC    0.215282
MD    0.214845
PA    0.214776
MN    0.210363
MI    0.208880
VA    0.207942
DE    0.206575
HI    0.204535
AK    0.204141
TX    0.202286
AZ    0.199321
CA    0.198303
RI    0.194009
ID    0.193487
IL    0.193302
MA    0.192974
GA    0.191224
CT    0.183810
WV    0.182457
UT    0.179049
WY    0.178142
MT    0.177759
WI    0.175315
SC    0.172705
KS    0.171004
WA    0.166538
CO    0.158083
OR    0.152827
VT    0.149225
IA    0.142857
NH    0.142554
ME    0.136564
DC    0.130378
Name: loan_status, dtype: float64
```

In [84]:
```
df['dti'].describe()
```

Out[84]:
```
count    814950.000000
mean         17.867719
std           8.856477
min          -1.000000
25%          11.640000
50%          17.360000
75%          23.630000
max         999.000000
Name: dti, dtype: float64
```

In [85]:
```
f, (ax1, ax2) = plt.subplots(nrows=1, ncols=2, figsize=(12,3), dpi=90)
sns.distplot(df.loc[df['dti'].notnull() & (df['dti'] < 60), 'dti'], kde=False,
ax=ax1)
ax1.set_xlabel('dti')
ax1.set_ylabel('Count')
ax1.set_title('debt to income')
sns.boxplot(x=df.loc[df['dti'].notnull() & (df['dti'] < 60), 'dti'], y='loan_s
tatus', data=df, ax=ax2)
ax2.set_xlabel('DTI')
ax2.set_ylabel('Fraction of Loans fully paid')
ax2.set_title('Fully paid rate by debt to income')
ax2.set_title('DTI by loan status')
```

Out[85]:
```
Text(0.5, 1.0, 'DTI by loan status')
```



In [86]:
```
(df['dti'] > 40).sum() / (df['dti']).sum()
```

Out[86]:
```
0.0001017766442811112
```

In [87]:
```
(df['dti'] > 40).sum()
```

Out[87]:
```
1482
```

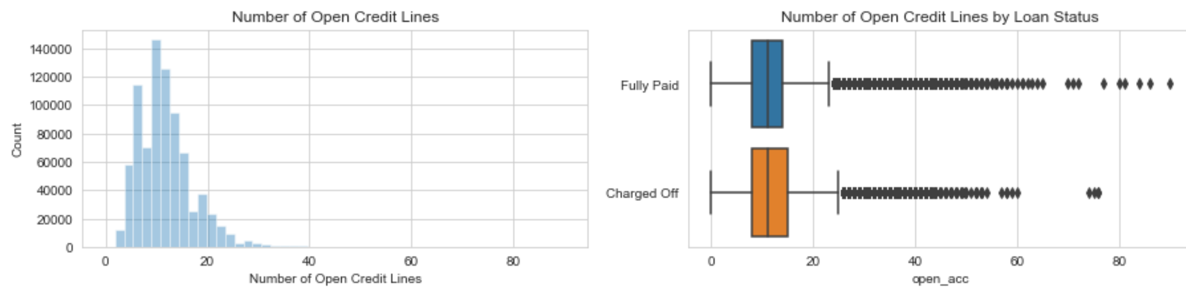
In [88]:
```
df.groupby('loan_status')['dti'].median()
```

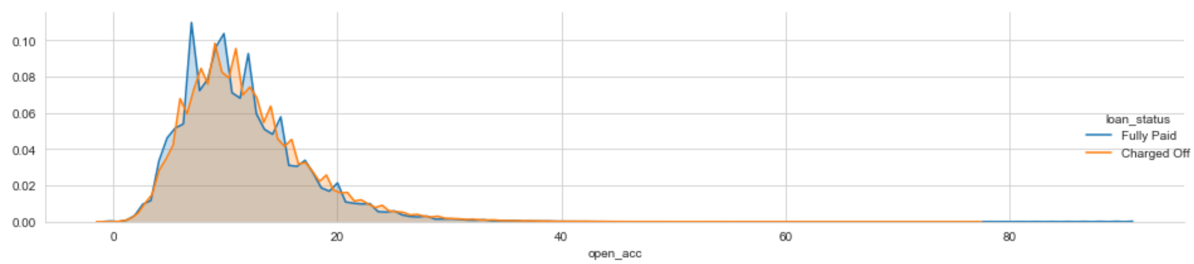
Out[88]:
```
loan_status
Charged Off    19.77
Fully Paid     16.77
Name: dti, dtype: float64
```

In [89]:
```
df['open_acc'].describe()
```

Out[89]:
```
count    814986.000000
mean         11.521099
std           5.325064
min           0.000000
25%           8.000000
50%          11.000000
75%          14.000000
max          90.000000
Name: open_acc, dtype: float64
```

In [90]:
```
plot_var('open_acc', 'Number of Open Credit Lines', continuous=True)
```





In [91]:
```
df.groupby('loan_status')['open_acc'].describe()
```

Out[91]:

loan_status	count	mean	std	min	25%	50%	75%	max
Charged Off	168084.0	11.883094	5.515590	0.0	8.0	11.0	15.0	76.0
Fully Paid	646902.0	11.427041	5.270369	0.0	8.0	11.0	14.0	90.0

In [92]:
```
df['earliest_cr_line'].sample(5)
```

Out[92]:
```
1631800    Feb-1995
391631     Nov-1999
3425       Apr-1999
605304     Nov-2001
1288196    Sep-2008
Name: earliest_cr_line, dtype: object
```

In [93]:
```
df['earliest_cr_line'].describe()
```

Out[93]:
```
count       814986
unique         712
top       Aug-2001
freq          6024
Name: earliest_cr_line, dtype: object
```

In [94]:
```
df['earliest_cr_line'].isnull().any()
```

Out[94]:
```
False
```

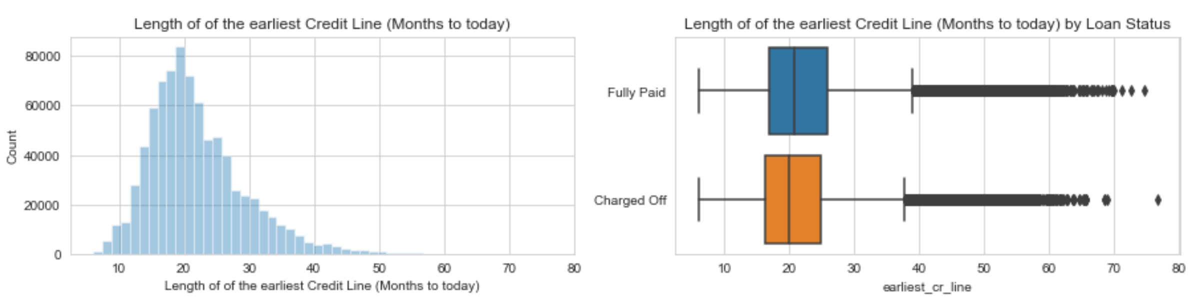
In [95]:
```
from datetime import datetime

df.earliest_cr_line = pd.to_datetime(df.earliest_cr_line)

dttoday = datetime.now().strftime('%Y-%m-%d')
df.earliest_cr_line = df.earliest_cr_line.apply(lambda x:(np.timedelta64((x - pd.Timestamp(dttoday)),'D').astype(int))/-365)

df.earliest_cr_line.shape
```

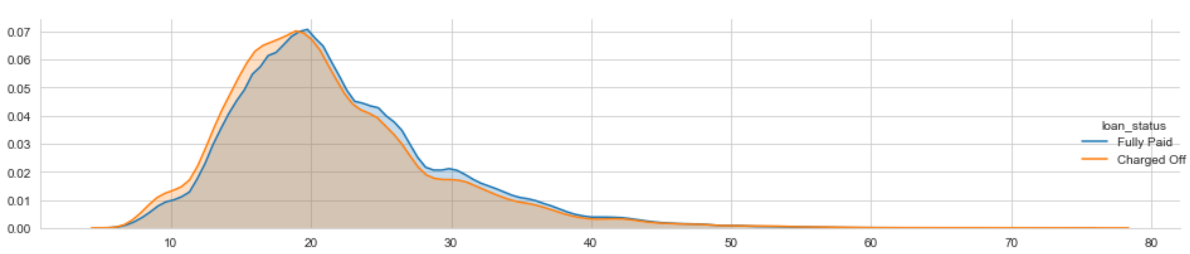
Out[95]:
```
(814986,)
```

In [96]:
```
df.earliest_cr_line.sample(5)
```

Out[96]:
```
821634     24.761644
868914     24.093151
1393786    33.019178
309103     22.093151
88834      16.087671
Name: earliest_cr_line, dtype: float64
```

In [97]:
```
plot_var('earliest_cr_line', 'Length of of the earliest Credit Line (Months to today)', continuous=True)
```





In [98]:
```
df.groupby('loan_status')['earliest_cr_line'].describe()
```

Out[98]:

loan_status	count	mean	std	min	25%	50%	75%	max
Charged Off	168084.0	21.244484	7.399904	6.167123	16.172603	19.838356	24.843836	76.545205
Fully Paid	646902.0	22.017798	7.382157	6.000000	16.923288	20.673973	25.761644	74.542466

In [99]:
```
df[['fico_range_low','fico_range_high']].describe()
```

Out[99]:

	fico_range_low	fico_range_high
count	814986.000000	814986.000000
mean	695.603151	699.603264
std	31.352251	31.352791
min	625.000000	629.000000
25%	670.000000	674.000000
50%	690.000000	694.000000
75%	710.000000	714.000000
max	845.000000	850.000000

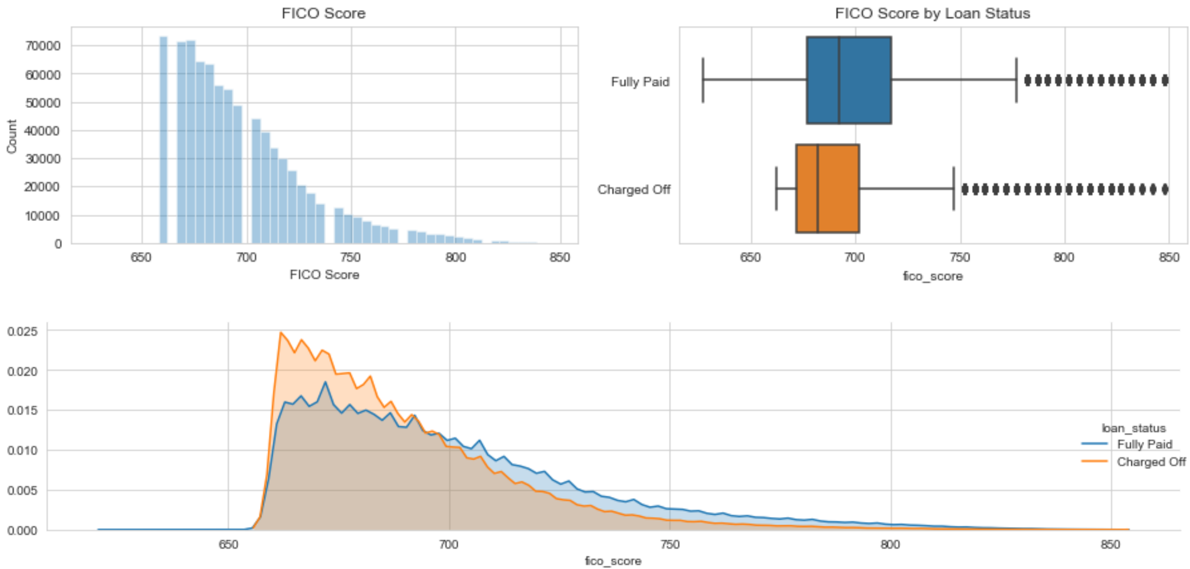
In [100]:
```
df[['fico_range_low','fico_range_high']].corr()
```

Out[100]:

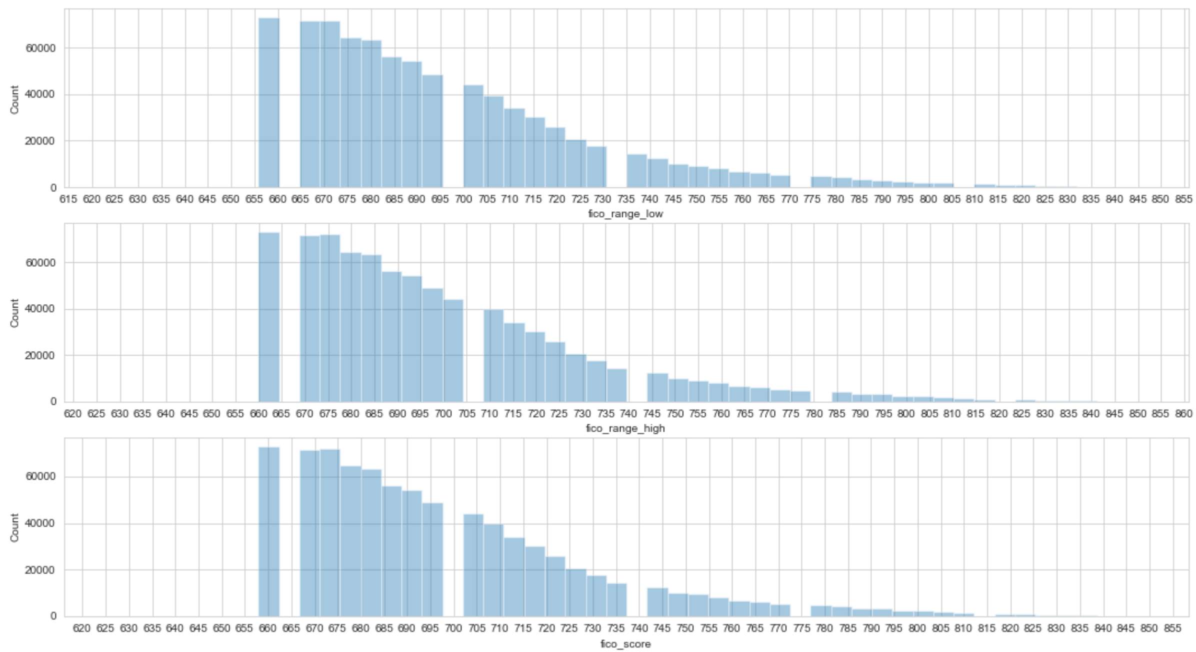
	fico_range_low	fico_range_high
fico_range_low	1.0	1.0
fico_range_high	1.0	1.0

In [101]:
```
df['fico_score'] = (df['fico_range_low'] + df['fico_range_high'])/2.
```

In [102]:
```
plot_var('fico_score', 'FICO Score', continuous=True)
```



In [103]:
```
import matplotlib.ticker as ticker

fig, (ax1, ax2, ax3) = plt.subplots(3, 1, sharex=False, figsize=(18,10))
sns.distplot(df.loc[df['fico_range_low'].notnull(), 'fico_range_low'], kde=Fal
se, ax=ax1)
ax1.xaxis.set_major_locator(ticker.MultipleLocator(5))
ax1.set_ylabel('Count')

sns.distplot(df.loc[df['fico_range_high'].notnull(), 'fico_range_high'], kde=F
alse, ax=ax2)
ax2.xaxis.set_major_locator(ticker.MultipleLocator(5))
ax2.set_ylabel('Count')

sns.distplot(df.loc[df['fico_score'].notnull(), 'fico_score'], kde=False, ax=a
x3)
ax3.set_ylabel('Count')
ax3.xaxis.set_major_locator(ticker.MultipleLocator(5))
```



In [104]:
```
df['fico_range_low'].value_counts().sort_index().head(5)
```

Out[104]:
```
625.0        1
630.0        1
660.0    73195
665.0    71431
670.0    71886
Name: fico_range_low, dtype: int64
```

In [105]:
```
df['fico_range_high'].value_counts().sort_index().head(5)
```

Out[105]:
```
629.0        1
634.0        1
664.0    73195
669.0    71431
674.0    71886
Name: fico_range_high, dtype: int64
```

In [106]:
```
df['fico_score'].value_counts().sort_index().head(5)
```

Out[106]:
```
627.0        1
632.0        1
662.0    73195
667.0    71431
672.0    71886
Name: fico_score, dtype: int64
```

In [107]:
```
df[['fico_score','open_acc','earliest_cr_line','dti']].corr()
```

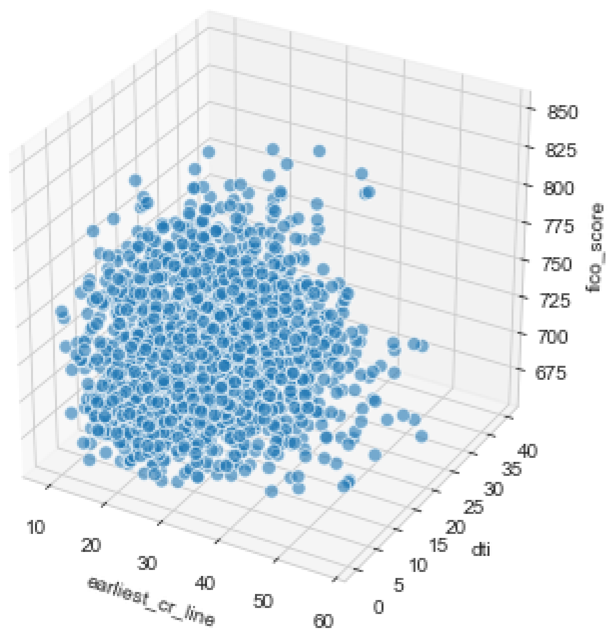
Out[107]:

	fico_score	open_acc	earliest_cr_line	dti
fico_score	1.000000	0.009944	0.114372	-0.093522
open_acc	0.009944	1.000000	0.121138	0.279120
earliest_cr_line	0.114372	0.121138	1.000000	0.016526
dti	-0.093522	0.279120	0.016526	1.000000

In [108]:
```
plot_df = df.query('fico_score > 650')[:3000]
```

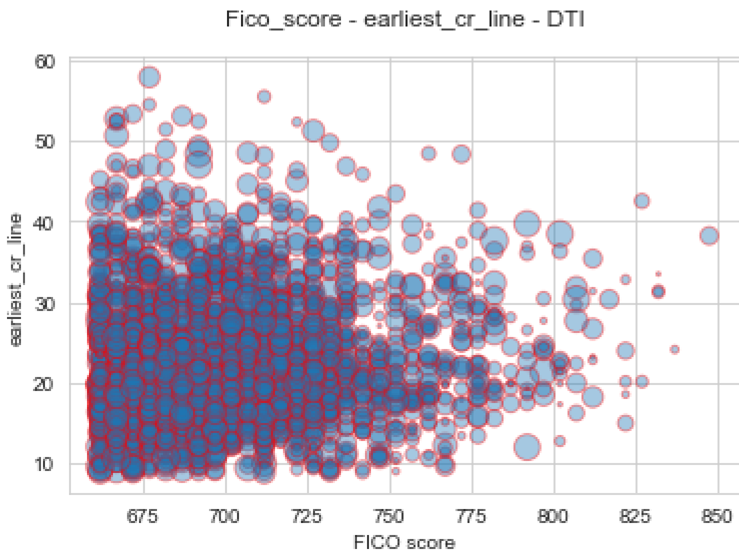
In [109]:
```
%matplotlib inline
# Visualizing 3-D numeric data with Scatter Plots
import matplotlib.pyplot as plt
from mpl_toolkits.mplot3d import Axes3D

fig = plt.figure(figsize=(13, 6))
#fig, (ax1) = plt.subplots(nrows=1, ncols=1, figsize=(8, 6))
ax1 = fig.add_subplot(121, projection='3d')

xs = plot_df['earliest_cr_line']
ys = plot_df['dti']
zs = plot_df['fico_score']
ax1.scatter(xs, ys, zs, s=50, alpha=0.6, edgecolors='w', cmap='greens')

ax1.set_xlabel('earliest_cr_line')
ax1.set_ylabel('dti')
ax1.set_zlabel('fico_score')
```

Out[109]:
```
Text(0.5, 0, 'fico_score')
```



In [110]:
```
%matplotlib inline
import matplotlib.pyplot as plt
# Visualizing 3-D numeric data with a bubble chart
plt.scatter(zs, xs, s=ys*5,
            alpha=0.4, edgecolors='red')

plt.xlabel('FICO score')
plt.ylabel('earliest_cr_line')
plt.title('Fico_score - earliest_cr_line - DTI',y=1.05)
```

Out[110]:
```
Text(0.5, 1.05, 'Fico_score - earliest_cr_line - DTI')
```



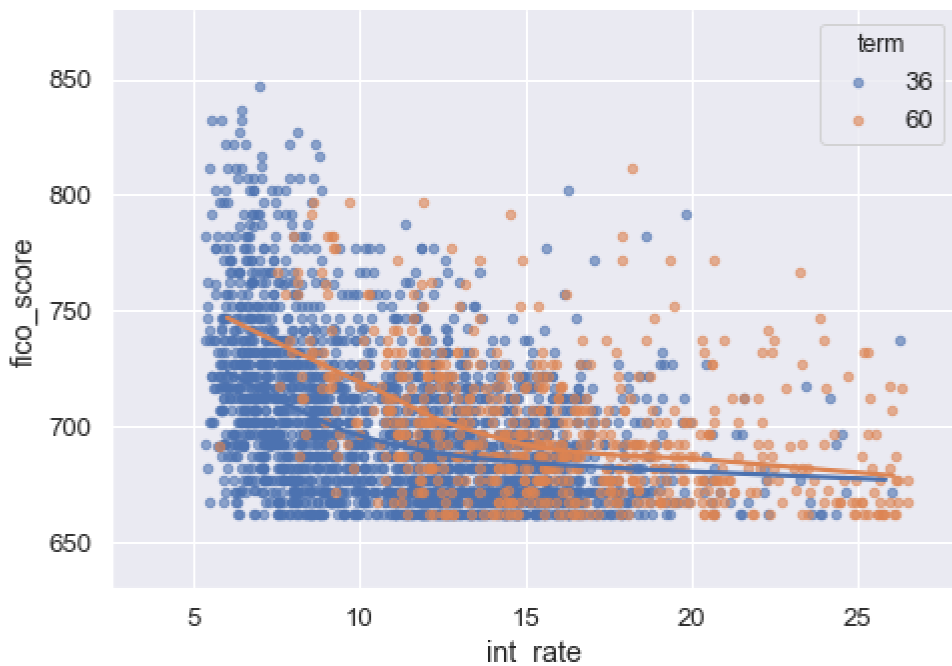
In [111]:
```
df[['fico_score','int_rate','term']].corr()
```

Out[111]:

	fico_score	int_rate	term
fico_score	1.000000	-0.425425	-0.005257
int_rate	-0.425425	1.000000	0.426839
term	-0.005257	0.426839	1.000000

In [112]:
```
%matplotlib inline
plot_df = df.query('fico_score > 650 & int_rate <28')[:3000]

sns.set(font_scale=1.2, rc={"lines.linewidth": 1.5})

g = sns.lmplot("int_rate", "fico_score", x_jitter= .7,  y_jitter= .1, data=plo
t_df, hue='term',lowess=True, size=5,aspect=1.4, legend_out=False, scatter_kws
={ 's':20, 'alpha':.6})

g.set(xlim=(2.5, 28),ylim=(630, 880),alpha = .5)

#g.savefig('1.png',transparent=True)
```

Out[112]: <seaborn.axisgrid.FacetGrid at 0x27d54550688>



In [113]:
```
drop_cols(['fico_range_high','fico_range_low'])
```

In [114]:
```
df['pub_rec'].describe()
```

Out[114]:
```
count    814986.000000
mean          0.205734
std           0.584933
min           0.000000
25%           0.000000
50%           0.000000
75%           0.000000
max          86.000000
Name: pub_rec, dtype: float64
```

In [115]:
```python
df['pub_rec'].value_counts().sort_values(ascending=False)
```

Out[115]:
```
0.0     681509
1.0     112483
2.0      14115
3.0       4107
4.0       1400
5.0        651
6.0        338
7.0        146
8.0         90
9.0         42
10.0        28
11.0        24
12.0        15
13.0        11
15.0         5
18.0         3
16.0         2
19.0         2
14.0         2
49.0         2
28.0         2
86.0         1
34.0         1
24.0         1
46.0         1
54.0         1
63.0         1
17.0         1
21.0         1
40.0         1
Name: pub_rec, dtype: int64
```

In [116]:
```python
%matplotlib inline
plot_var('pub_rec','Derogatory public records', continuous=False)
```

In [117]:
```
df.groupby('loan_status')['pub_rec'].describe()
```

Out[117]:

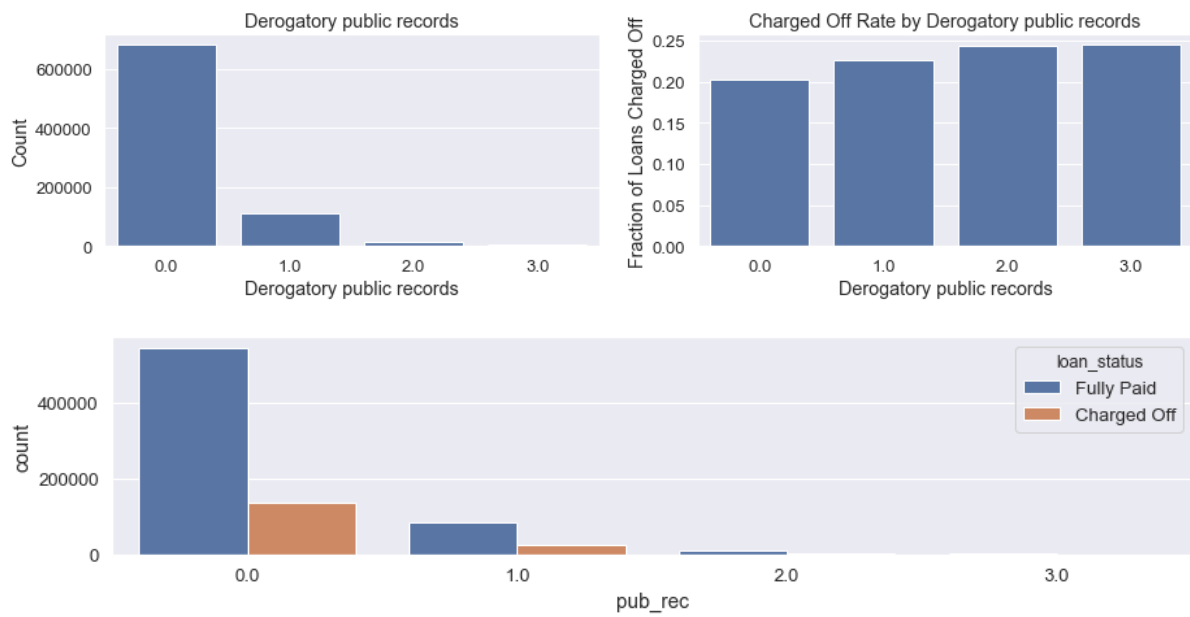
loan_status	count	mean	std	min	25%	50%	75%	max
Charged Off	168084.0	0.232247	0.640855	0.0	0.0	0.0	0.0	86.0
Fully Paid	646902.0	0.198845	0.569304	0.0	0.0	0.0	0.0	63.0

In [118]:
```
df.pub_rec = df.pub_rec.map(lambda x: 3 if x >2.0 else x)
```

In [119]:
```
df['pub_rec'].value_counts().sort_values(ascending=False)
```

Out[119]:
```
0.0    681509
1.0    112483
2.0     14115
3.0      6879
Name: pub_rec, dtype: int64
```

In [120]:
```
%matplotlib inline
plot_var('pub_rec','Derogatory public records', continuous=False)
```



In [121]:
```
df.groupby('loan_status')['pub_rec'].describe()
```

Out[121]:

loan_status	count	mean	std	min	25%	50%	75%	max
Charged Off	168084.0	0.222591	0.523628	0.0	0.0	0.0	0.0	3.0
Fully Paid	646902.0	0.191584	0.485842	0.0	0.0	0.0	0.0	3.0

In [122]:
```
%matplotlib inline
plot_var('pub_rec_bankruptcies', 'Number of public record bankruptcies', conti
nuous=False)
```

In [123]:
```
df[['pub_rec','pub_rec_bankruptcies']].corr()
```

Out[123]:

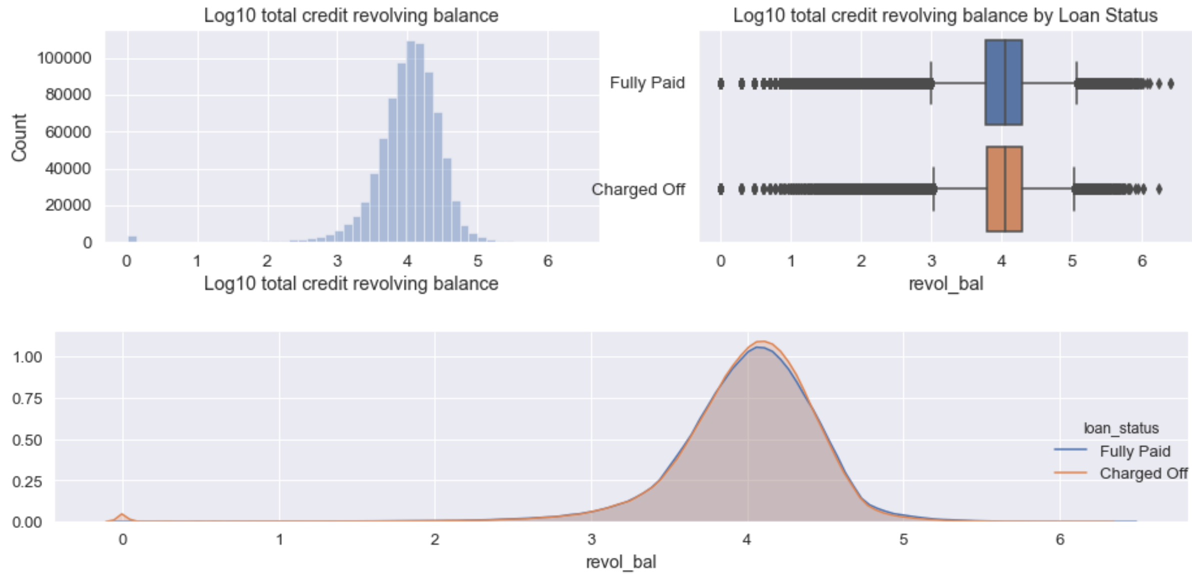
	pub_rec	pub_rec_bankruptcies
pub_rec	1.000000	0.750146
pub_rec_bankruptcies	0.750146	1.000000

In [124]:
```
df['revol_bal'].describe()
```

Out[124]:
```
count    8.149860e+05
mean     1.606864e+04
std      2.160500e+04
min      0.000000e+00
25%      6.014000e+03
50%      1.118500e+04
75%      1.972300e+04
max      2.568995e+06
Name: revol_bal, dtype: float64
```

In [125]:
```
df['revol_bal'] = df['revol_bal'].apply(lambda x:np.log10(x+1))
```

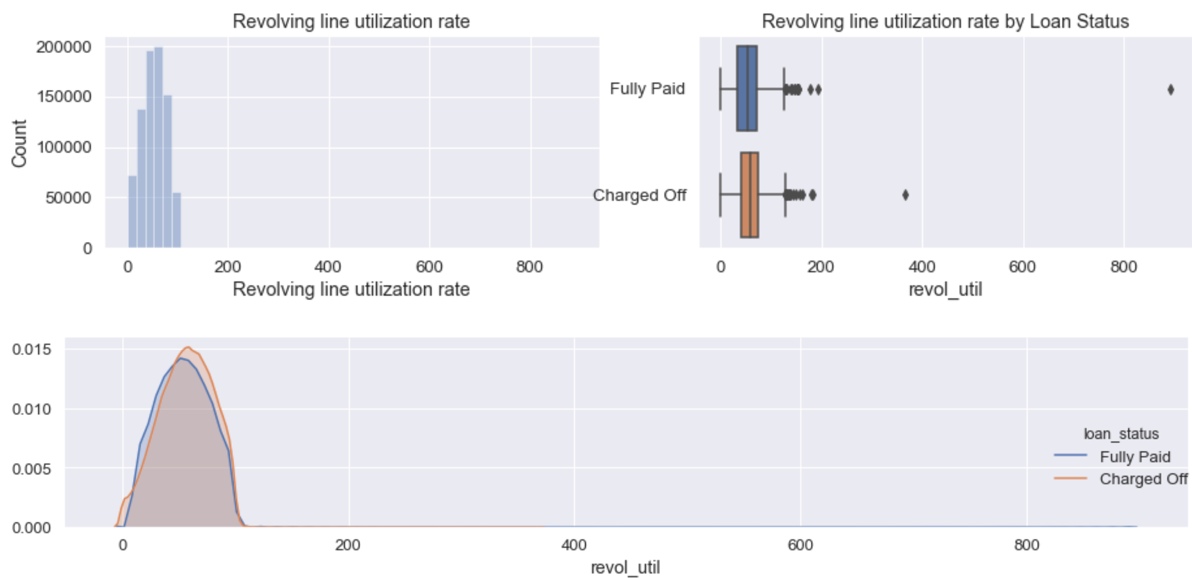
In [126]:
```
plot_var('revol_bal', 'Log10 total credit revolving balance', continuous=True)
```



In [127]:
```
df['revol_util'].describe()
```

Out[127]:
```
count    814496.000000
mean         53.031137
std          24.320981
min           0.000000
25%          35.000000
50%          53.700000
75%          71.900000
max         892.300000
Name: revol_util, dtype: float64
```

In [128]:
```
plot_var('revol_util', 'Revolving line utilization rate', continuous=True)
```



In [129]:
```
df.groupby('loan_status')['revol_util'].describe()
```

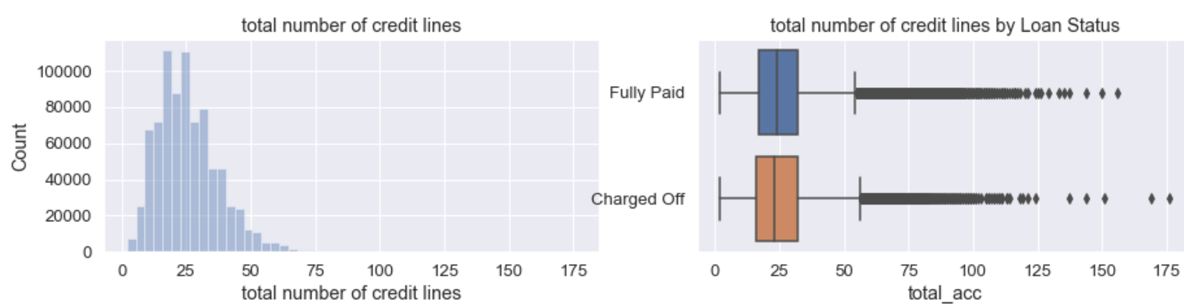
Out[129]:

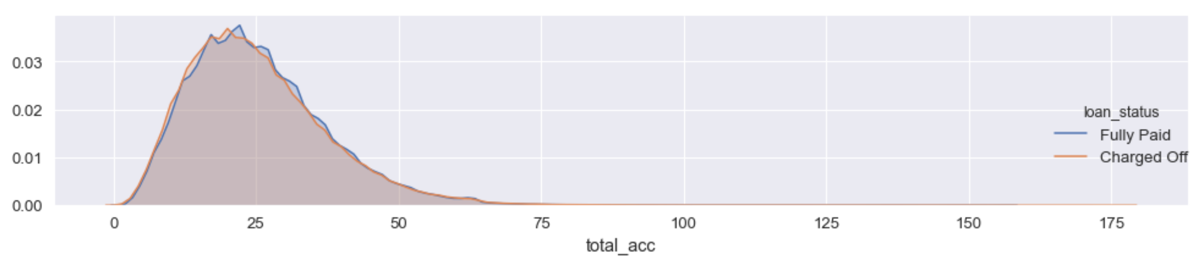
loan_status	count	mean	std	min	25%	50%	75%	max
Charged Off	167974.0	56.475417	23.566253	0.0	39.5	57.5	74.7	366.6
Fully Paid	646522.0	52.136273	24.433954	0.0	33.9	52.7	71.0	892.3

In [130]:
```
df['total_acc'].describe()
```

Out[130]:
```
count    814986.000000
mean         25.421359
std          11.970502
min           2.000000
25%          17.000000
50%          24.000000
75%          32.000000
max         176.000000
Name: total_acc, dtype: float64
```

In [131]:
```
plot_var('total_acc', 'total number of credit lines', continuous=True)
```

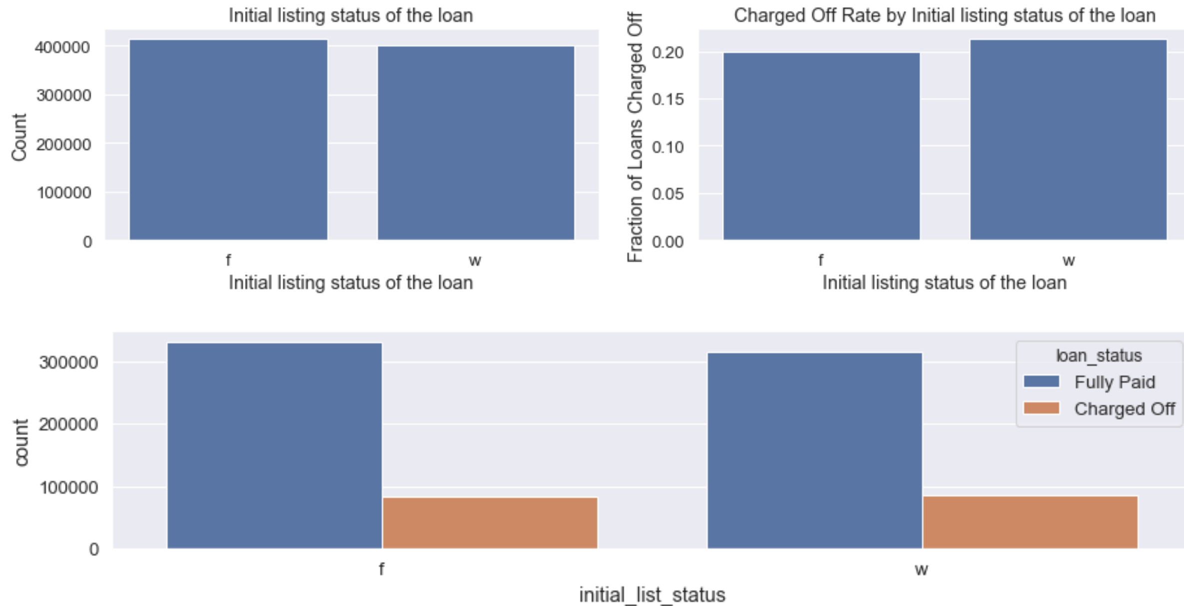




In [132]:
```
df['initial_list_status'].value_counts()
```

Out[132]:
```
f    413678
w    401308
Name: initial_list_status, dtype: int64
```

In [133]:
```python
plot_var('initial_list_status','Initial listing status of the loan', continuou
s=False)
```



In [134]:
```python
df['policy_code'].value_counts()
```

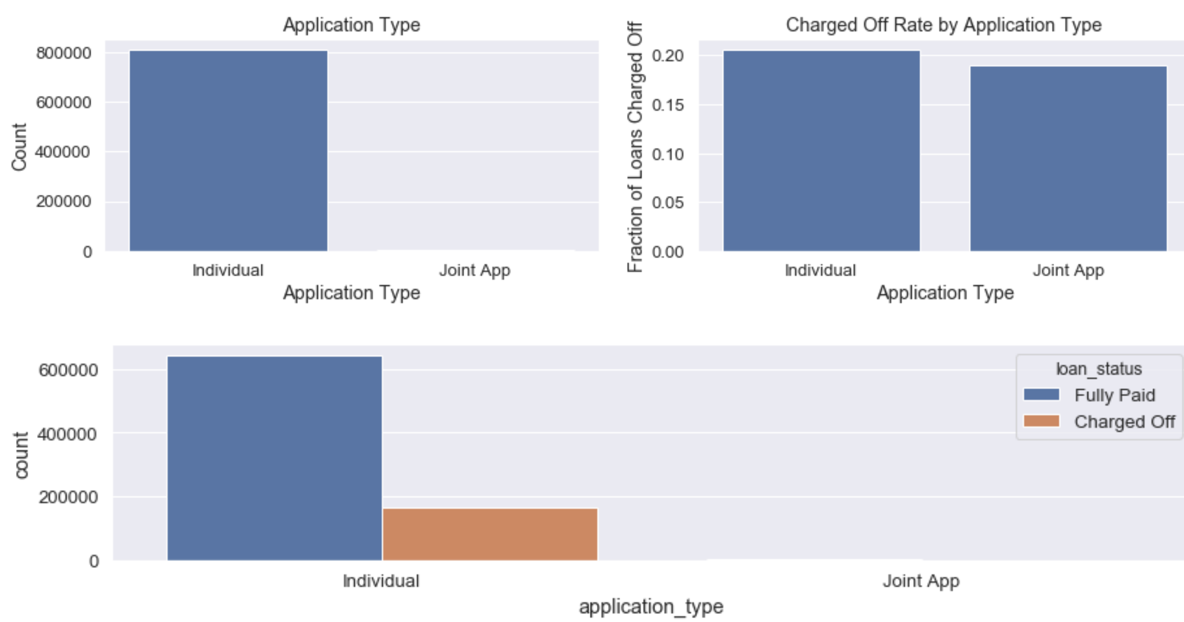
Out[134]:
```
1.0    814986
Name: policy_code, dtype: int64
```

In [135]:
```python
drop_cols('policy_code')
```

In [136]:
```python
df['application_type'].value_counts()
```

Out[136]:
```
Individual    811207
Joint App       3779
Name: application_type, dtype: int64
```

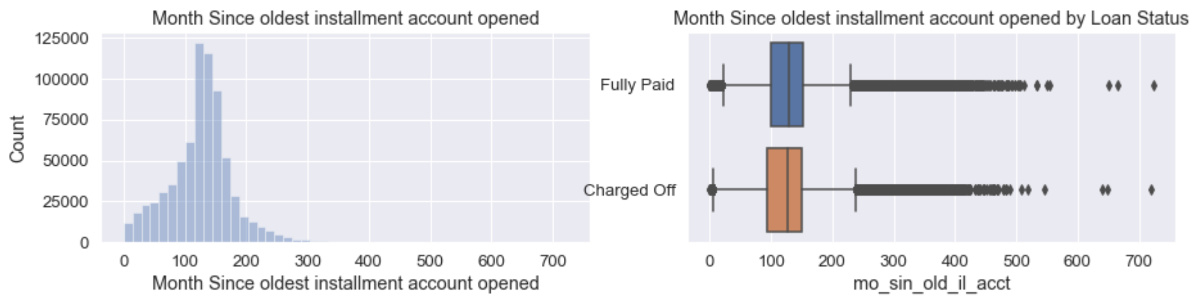
In [137]:
```python
plot_var('application_type', 'Application Type', continuous=False)
```

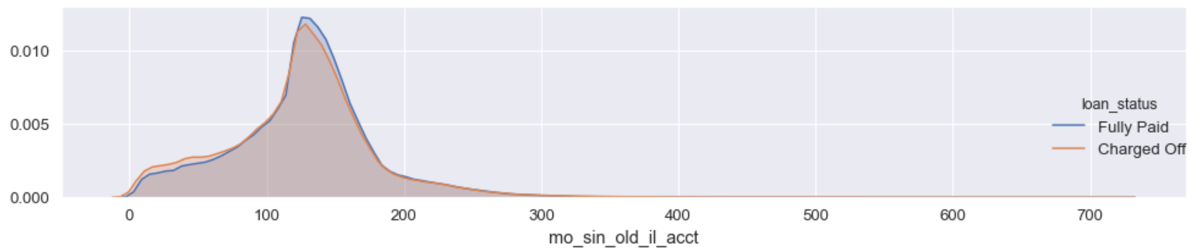


In [138]:
```
df['mo_sin_old_il_acct'].describe()
```

Out[138]:
```
count    725427.000000
mean        125.926232
std          51.554620
min           0.000000
25%          98.000000
50%         129.000000
75%         152.000000
max         724.000000
Name: mo_sin_old_il_acct, dtype: float64
```

In [139]:
```
plot_var('mo_sin_old_il_acct', 'Month Since oldest installment account opened'
, continuous=True)
```

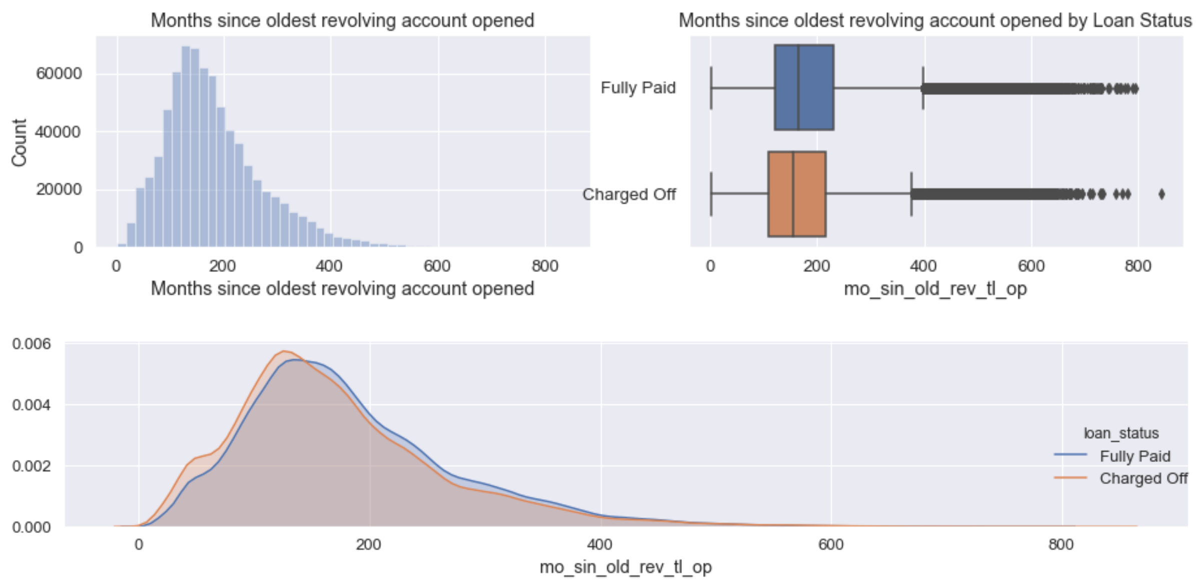




In [140]:
```
df['mo_sin_old_rev_tl_op'].describe()
```

Out[140]:
```
count    747458.000000
mean        180.843182
std          92.192939
min           2.000000
25%         117.000000
50%         164.000000
75%         228.000000
max         842.000000
Name: mo_sin_old_rev_tl_op, dtype: float64
```

In [141]:
```
plot_var('mo_sin_old_rev_tl_op', 'Months since oldest revolving account opene
d', continuous=True)
```



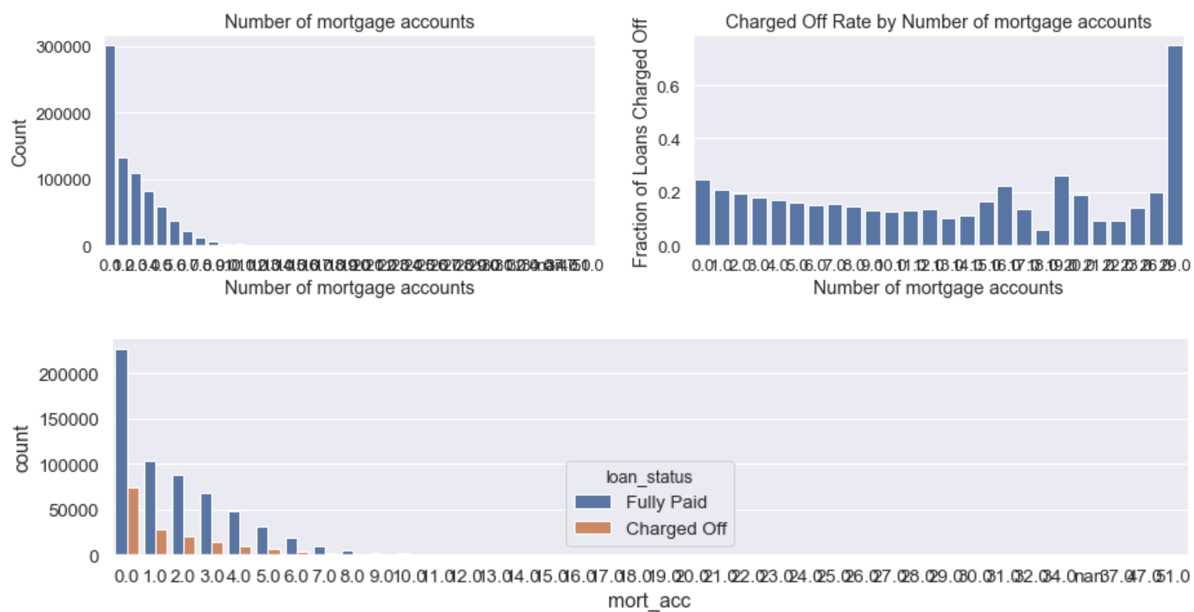
In [142]:
```
df['mort_acc'].describe()
```

Out[142]:

count	767705.000000
mean	1.758707
std	2.081730
min	0.000000
25%	0.000000
50%	1.000000
75%	3.000000
max	51.000000

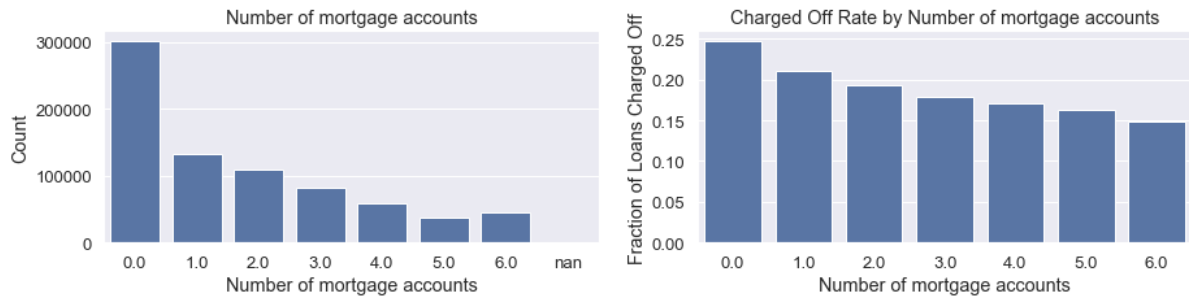
Name: mort_acc, dtype: float64

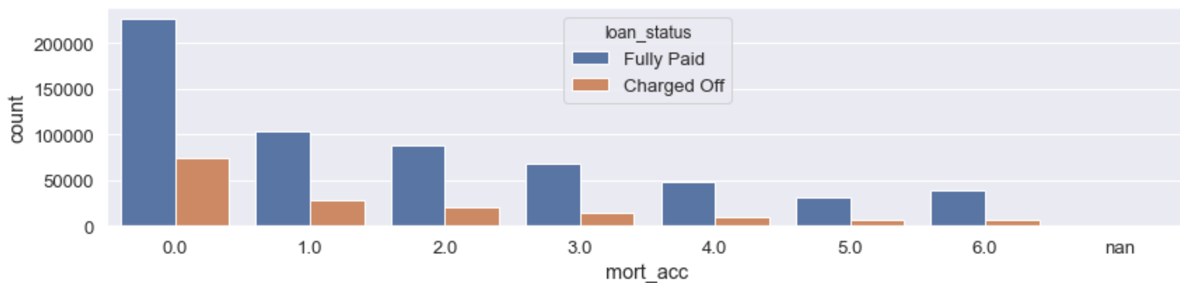
In [143]:
```
plot_var('mort_acc', 'Number of mortgage accounts', continuous=False)
```



In [144]:
```
df.mort_acc = df.mort_acc.map(lambda x: 6.0 if x > 6.0 else x)
```

In [145]:
```
plot_var('mort_acc', 'Number of mortgage accounts', continuous=False)
```





In [146]:
```
df.groupby('loan_status')['mort_acc'].describe()
```

Out[146]:

loan_status	count	mean	std	min	25%	50%	75%	max
Charged Off	161198.0	1.401177	1.737651	0.0	0.0	1.0	2.0	6.0
Fully Paid	606507.0	1.765027	1.881911	0.0	0.0	1.0	3.0	6.0

In [147]:
```
# Next, I will convert the "loan_status" column to a 0/1 "charged off" column.
Fully Paid:0 Charged Off: 1
df['Charged_Off'] = df['loan_status'].apply(lambda s: np.float(s == 'Charged O
ff'))
drop_cols('loan_status')
```

In [148]:
```
list_float = df.select_dtypes(exclude=['object']).columns
```

In [149]:
```
def run_KS_test(feature):
    dist1 = df.loc[df.Charged_Off == 0,feature]
    dist2 = df.loc[df.Charged_Off == 1,feature]
    print(feature+':')
    print(ks_2samp(dist1,dist2),'\n')
```

In [150]:
```
from statsmodels.stats.proportion import proportions_ztest
def run_proportion_Z_test(feature):
    dist1 = df.loc[df.Charged_Off == 0, feature]
    dist2 = df.loc[df.Charged_Off == 1, feature]
    n1 = len(dist1)
    p1 = dist1.sum()
    n2 = len(dist2)
    p2 = dist2.sum()
    z_score, p_value = proportions_ztest([p1, p2], [n1, n2])
    print(feature+':')
    print('z-score = {}; p-value = {}'.format(z_score, p_value),'\n')
```

In [151]:
```
from scipy.stats import chi2_contingency
def run_chi2_test(df, feature):

    dist1 = df.loc[df.loan_status == 'Fully Paid',feature].value_counts().sort
_index().tolist()
    dist2 = df.loc[df.loan_status == 'Charged Off',feature].value_counts().sor
t_index().tolist()
    chi2, p, dof, expctd = chi2_contingency([dist1,dist2])
    print(feature+':')
    print("chi-square test statistic:", chi2)
    print("p-value", p, '\n')
```

In [152]:
```
for i in list_float:
    run_KS_test(i)
```

```
loan_amnt:
Ks_2sampResult(statistic=0.07929615091065739, pvalue=0.0)

term:
Ks_2sampResult(statistic=0.1878843211069673, pvalue=0.0)

int_rate:
Ks_2sampResult(statistic=0.25494110149394783, pvalue=0.0)

installment:
Ks_2sampResult(statistic=0.06536048843842956, pvalue=0.0)

emp_length:
Ks_2sampResult(statistic=0.023675009354882204, pvalue=2.2208273629187616e-65)

annual_inc:
Ks_2sampResult(statistic=0.0820131215319414, pvalue=0.0)

dti:
Ks_2sampResult(statistic=0.13172341350693528, pvalue=0.0)

earliest_cr_line:
Ks_2sampResult(statistic=0.05313445396103783, pvalue=0.0)

open_acc:
Ks_2sampResult(statistic=0.03457677956795924, pvalue=5.6717399652287154e-139)

pub_rec:
Ks_2sampResult(statistic=0.0230215607998836, pvalue=7.631710963272179e-62)

revol_bal:
Ks_2sampResult(statistic=0.011420765232811325, pvalue=1.5333357736260159e-15)

revol_util:
Ks_2sampResult(statistic=0.07482343533269276, pvalue=0.0)

total_acc:
Ks_2sampResult(statistic=0.018250693539464735, pvalue=5.0232920926753094e-39)

mo_sin_old_il_acct:
Ks_2sampResult(statistic=0.04084630903322478, pvalue=9.021206427785575e-194)

mo_sin_old_rev_tl_op:
Ks_2sampResult(statistic=0.06805234769510238, pvalue=0.0)

mort_acc:
Ks_2sampResult(statistic=0.09730608428393561, pvalue=0.0)

pub_rec_bankruptcies:
Ks_2sampResult(statistic=0.01317583643442255, pvalue=1.5240583733016372e-20)

fico_score:
Ks_2sampResult(statistic=0.14589298735057676, pvalue=0.0)

Charged_Off:
Ks_2sampResult(statistic=1.0, pvalue=0.0)
```

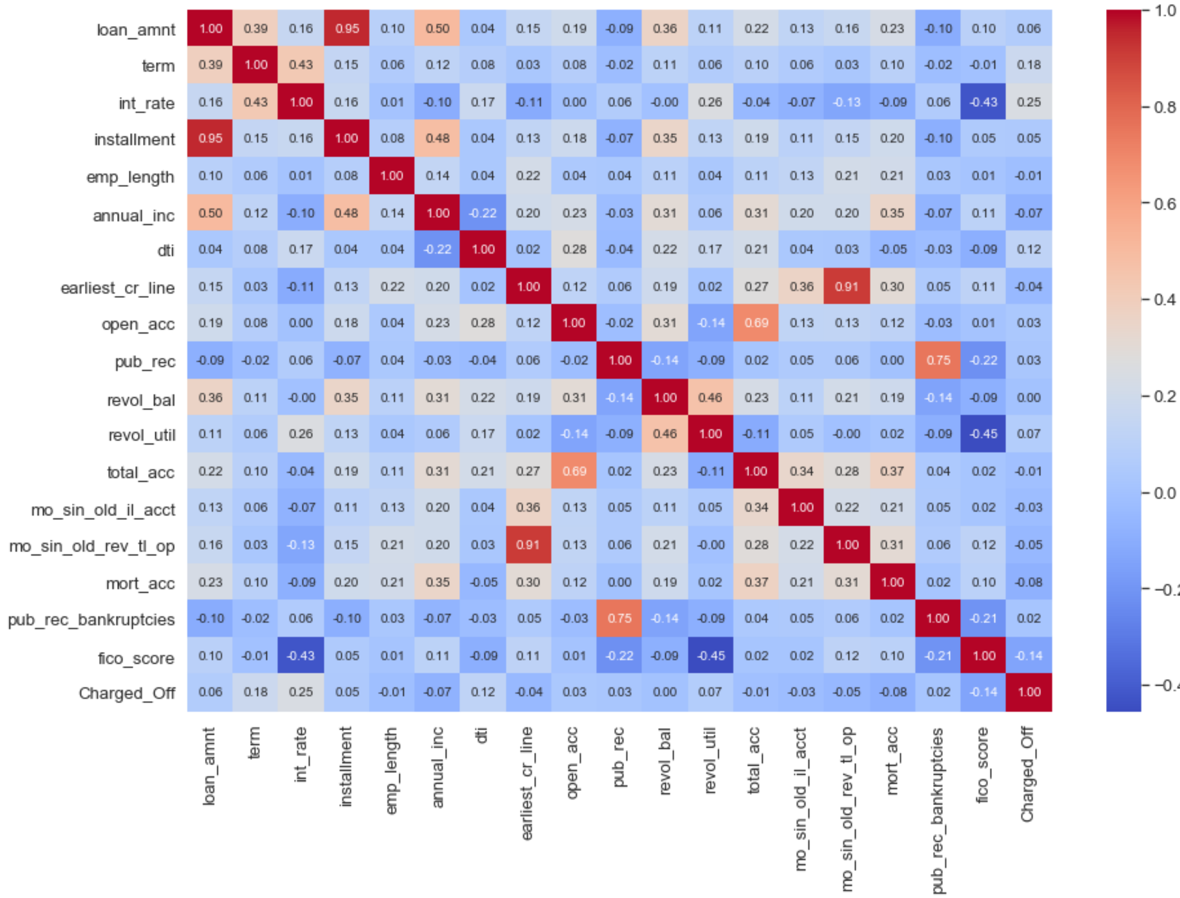
In [153]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 814986 entries, 0 to 1646792
Data columns (total 27 columns):
loan_amnt               814986 non-null float64
term                    814986 non-null int64
int_rate                814986 non-null float64
installment             814986 non-null float64
sub_grade               814986 non-null object
emp_length              772733 non-null float64
home_ownership          814986 non-null object
annual_inc              814986 non-null float64
verification_status     814986 non-null object
issue_d                 814986 non-null object
purpose                 814986 non-null object
addr_state              814986 non-null object
dti                     814950 non-null float64
earliest_cr_line        814986 non-null float64
open_acc                814986 non-null float64
pub_rec                 814986 non-null float64
revol_bal               814986 non-null float64
revol_util              814496 non-null float64
total_acc               814986 non-null float64
initial_list_status     814986 non-null object
application_type        814986 non-null object
mo_sin_old_il_acct      725427 non-null float64
mo_sin_old_rev_tl_op    747458 non-null float64
mort_acc                767705 non-null float64
pub_rec_bankruptcies    814289 non-null float64
fico_score              814986 non-null float64
Charged_Off             814986 non-null float64
dtypes: float64(18), int64(1), object(8)
memory usage: 214.1+ MB
```

In [154]:
```
list_float = df.select_dtypes(exclude=['object']).columns
list_float
```

Out[154]:
```
Index(['loan_amnt', 'term', 'int_rate', 'installment', 'emp_length',
       'annual_inc', 'dti', 'earliest_cr_line', 'open_acc', 'pub_rec',
       'revol_bal', 'revol_util', 'total_acc', 'mo_sin_old_il_acct',
       'mo_sin_old_rev_tl_op', 'mort_acc', 'pub_rec_bankruptcies',
       'fico_score', 'Charged_Off'],
      dtype='object')
```

In [155]:
```
fig, ax = plt.subplots(figsize=(15,10))         # Sample figsize in inches
cm_df = sns.heatmap(df[list_float].corr(),annot=True, fmt = ".2f", cmap = "coolwarm", ax=ax)
```



In [156]:
```
cor = df[list_float].corr()
cor.loc[:,:] = np.tril(cor, k=-1) # below main lower triangle of an array
cor = cor.stack()
cor[(cor > 0.1) | (cor < -0.1)]
```

Out[156]:
```
term                 loan_amnt              0.386449
int_rate             loan_amnt              0.158214
                     term                   0.426839
installment          loan_amnt              0.953588
                     term                   0.145842
                     int_rate               0.160821
annual_inc           loan_amnt              0.504394
                     term                   0.122812
                     int_rate              -0.102222
                     installment            0.483259
                     emp_length             0.136435
dti                  int_rate               0.170415
                     annual_inc            -0.215161
earliest_cr_line     loan_amnt              0.148525
                     int_rate              -0.112131
                     installment            0.131444
                     emp_length             0.216412
                     annual_inc             0.202806
open_acc             loan_amnt              0.193697
                     installment            0.183500
                     annual_inc             0.226926
                     dti                    0.279120
                     earliest_cr_line       0.121138
revol_bal            loan_amnt              0.363518
                     term                   0.110520
                     installment            0.349779
                     emp_length             0.107722
                     annual_inc             0.306059
                     dti                    0.219748
                     earliest_cr_line       0.189986
                     open_acc               0.305423
                     pub_rec               -0.140176
revol_util           loan_amnt              0.108488
                     int_rate               0.256850
                     installment            0.126761
                     dti                    0.173029
                     open_acc              -0.141107
                     revol_bal              0.462365
total_acc            loan_amnt              0.216434
                     installment            0.194081
                     emp_length             0.108882
                     annual_inc             0.306976
                     dti                    0.211689
                     earliest_cr_line       0.272654
                     open_acc               0.689616
                     revol_bal              0.228850
                     revol_util            -0.108681
mo_sin_old_il_acct   loan_amnt              0.125841
                     installment            0.105532
                     emp_length             0.132067
                     annual_inc             0.201579
                     earliest_cr_line       0.360532
                     open_acc               0.128233
                     revol_bal              0.111792
                     total_acc              0.337302
mo_sin_old_rev_tl_op loan_amnt              0.164298
                     int_rate              -0.131125
```

```
                      installment              0.145231
                      emp_length               0.211206
                      annual_inc               0.202146
                      earliest_cr_line         0.911349
                      open_acc                 0.132229
                      revol_bal                0.212607
                      total_acc                0.284477
                      mo_sin_old_il_acct       0.219667
mort_acc              loan_amnt                0.230501
                      term                     0.100799
                      installment              0.197997
                      emp_length               0.208462
                      annual_inc               0.350509
                      earliest_cr_line         0.302861
                      open_acc                 0.115478
                      revol_bal                0.187637
                      total_acc                0.373703
                      mo_sin_old_il_acct       0.206741
                      mo_sin_old_rev_tl_op     0.307306
pub_rec_bankruptcies  loan_amnt               -0.104761
                      pub_rec                  0.750146
                      revol_bal               -0.143372
fico_score            loan_amnt                0.100319
                      int_rate                -0.425425
                      annual_inc               0.108242
                      earliest_cr_line         0.114372
                      pub_rec                 -0.220529
                      revol_util              -0.454739
                      mo_sin_old_rev_tl_op     0.118714
                      mort_acc                 0.103025
                      pub_rec_bankruptcies    -0.206954
Charged_Off           term                     0.177708
                      int_rate                 0.247815
                      dti                      0.123031
                      fico_score              -0.139429
dtype: float64
```

In [157]:
```
df[["installment","loan_amnt","mo_sin_old_rev_tl_op","earliest_cr_line","total_acc","open_acc", "pub_rec_bankruptcies", "pub_rec"]].isnull().any()
```

Out[157]:
```
installment             False
loan_amnt               False
mo_sin_old_rev_tl_op     True
earliest_cr_line        False
total_acc               False
open_acc                False
pub_rec_bankruptcies     True
pub_rec                 False
dtype: bool
```

In [158]:
```
list_linear = ['installment', 'mo_sin_old_rev_tl_op','total_acc','pub_rec_bankruptcies']
```

In [159]:
```
linear_corr = pd.DataFrame()
```

In [160]:
```
# Pearson coefficients
for col in df[list_float].columns:
    linear_corr.loc[col, 'pearson_corr'] = df[col].corr(df['Charged_Off'])
linear_corr['abs_pearson_corr'] = abs(linear_corr['pearson_corr'])
```

In [161]:
```
linear_corr.sort_values('abs_pearson_corr', ascending=False, inplace=True)
linear_corr.drop('abs_pearson_corr', axis=1, inplace=True)
linear_corr.drop('Charged_Off', axis=0, inplace=True)
```

In [162]:
```
linear_corr.reset_index(inplace=True)
#linear_corr.rename(columns={'index':'variable'}, inplace=True)
linear_corr
```

Out[162]:

	index	pearson_corr
0	int_rate	0.247815
1	term	0.177708
2	fico_score	-0.139429
3	dti	0.123031
4	mort_acc	-0.079739
5	annual_inc	-0.074216
6	revol_util	0.072185
7	loan_amnt	0.064139
8	mo_sin_old_rev_tl_op	-0.048529
9	installment	0.046291
10	earliest_cr_line	-0.042325
11	open_acc	0.034652
12	mo_sin_old_il_acct	-0.026019
13	pub_rec	0.025395
14	pub_rec_bankruptcies	0.017314
15	emp_length	-0.012463
16	total_acc	-0.011187
17	revol_bal	0.002233

In [163]:
```
# Drop the linear correlated features
drop_cols(list_linear)
```

In [164]:
```
df.shape
```

Out[164]:
```
(814986, 23)
```

In [165]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 814986 entries, 0 to 1646792
Data columns (total 23 columns):
loan_amnt              814986 non-null float64
term                   814986 non-null int64
int_rate               814986 non-null float64
sub_grade              814986 non-null object
emp_length             772733 non-null float64
home_ownership         814986 non-null object
annual_inc             814986 non-null float64
verification_status    814986 non-null object
issue_d                814986 non-null object
purpose                814986 non-null object
addr_state             814986 non-null object
dti                    814950 non-null float64
earliest_cr_line       814986 non-null float64
open_acc               814986 non-null float64
pub_rec                814986 non-null float64
revol_bal              814986 non-null float64
revol_util             814496 non-null float64
initial_list_status    814986 non-null object
application_type       814986 non-null object
mo_sin_old_il_acct     725427 non-null float64
mort_acc               767705 non-null float64
fico_score             814986 non-null float64
Charged_Off            814986 non-null float64
dtypes: float64(14), int64(1), object(8)
memory usage: 189.2+ MB
```

In [166]:
```
df.sample(5)
```

Out[166]:

	loan_amnt	term	int_rate	sub_grade	emp_length	home_ownership	annual_inc	verifi
1283611	19000.0	36	11.99	B5	10.0	MORTGAGE	4.865782	
193794	35000.0	60	16.59	D1	0.0	MORTGAGE	5.152291	
870729	4000.0	36	11.55	B3	7.0	MORTGAGE	4.929424	S
1440663	18250.0	36	7.49	A4	0.0	RENT	5.041397	
1467913	30000.0	60	13.99	C3	10.0	MORTGAGE	4.838855	S

In [167]:
```
missing_values_table(df)
```

```
Your selected dataframe has 23 columns.
There are 5 columns that have missing values.
```

Out[167]:

	Missing Values	% of Total Values	type
mo_sin_old_il_acct	89559	11.0	float64
mort_acc	47281	5.8	float64
emp_length	42253	5.2	float64
revol_util	490	0.1	float64
dti	36	0.0	float64

In [168]:
```
dummy_list =['sub_grade','home_ownership','verification_status','purpose','add
r_state','initial_list_status','application_type']
```

In [169]:
```
df[dummy_list].isnull().any()
```

Out[169]:
```
sub_grade              False
home_ownership         False
verification_status    False
purpose                False
addr_state             False
initial_list_status    False
application_type       False
dtype: bool
```

In [170]:
```
df = pd.get_dummies(df, columns=dummy_list, drop_first=True)
```

In [171]:
```
df.shape
```

Out[171]:
```
(814986, 120)
```

In [172]:
```
df.head(1)
```

Out[172]:

	loan_amnt	term	int_rate	emp_length	annual_inc	issue_d	dti	earliest_cr_line	open_acc
0	15000.0	60	12.39	10.0	4.8921	Dec-2014	12.03	25.928767	6.0

In [173]:
```
df['issue_d'].sample()
```

Out[173]:
```
622071    Mar-2015
Name: issue_d, dtype: object
```

In [174]:
```
df['issue_d'] = pd.to_datetime(df['issue_d'])
```

In [175]:
```
df['issue_d'].sample()
```

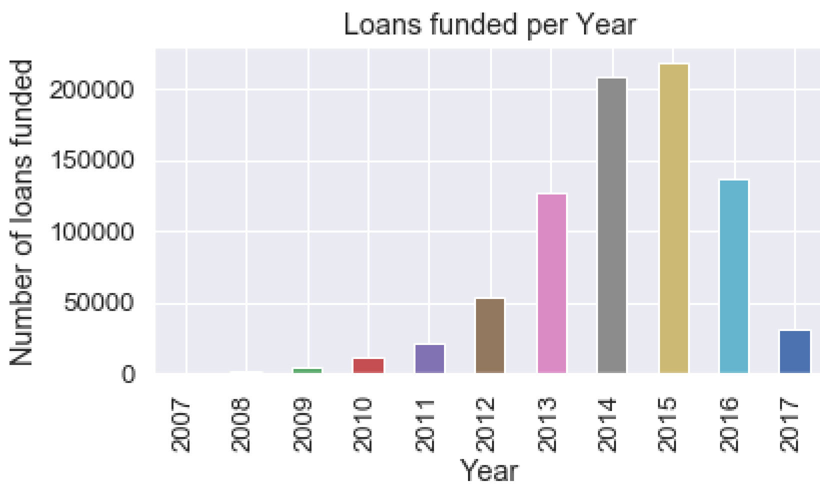
Out[175]:
```
856323   2013-09-01
Name: issue_d, dtype: datetime64[ns]
```

In [176]:
```
df['issue_d'].describe()
```

Out[176]:
```
count                 814986
unique                   124
top      2014-10-01 00:00:00
freq                   33699
first    2007-06-01 00:00:00
last     2017-09-01 00:00:00
Name: issue_d, dtype: object
```

In [177]:
```
plt.figure(figsize=(6,3))
df['issue_d'].dt.year.value_counts().sort_index().plot.bar()
plt.xlabel('Year')
plt.ylabel('Number of loans funded')
plt.title('Loans funded per Year')
```

Out[177]:
```
Text(0.5, 1.0, 'Loans funded per Year')
```



In [178]:
```
df_train = df.loc[df['issue_d']  < df['issue_d'].quantile(0.8)]
df_test =  df.loc[df['issue_d'] >= df['issue_d'].quantile(0.8)]
```

In [179]:
```
print('Number of loans in the partition:   ', df_train.shape[0] + df_test.shap
e[0])
print('Number of loans in the full dataset:', df.shape[0])
```

```
Number of loans in the partition:    814986
Number of loans in the full dataset: 814986
```

In [180]:
```
df_train['issue_d'].describe()
```

Out[180]:
```
count                  647071
unique                    103
top       2014-10-01 00:00:00
freq                    33699
first     2007-06-01 00:00:00
last      2015-12-01 00:00:00
Name: issue_d, dtype: object
```

In [181]:
```
df_test['issue_d'].describe()
```

Out[181]:
```
count                  167915
unique                     21
top       2016-03-01 00:00:00
freq                    22914
first     2016-01-01 00:00:00
last      2017-09-01 00:00:00
Name: issue_d, dtype: object
```

In [182]:
```
df_train.drop('issue_d', axis=1, inplace=True)
df_test.drop('issue_d', axis=1, inplace=True)
```

In [183]:
```
X_train = df_train.drop(['Charged_Off'], axis=1)
y_train = df_train.loc[:, 'Charged_Off']

X_test = df_test.drop(['Charged_Off'], axis=1)
y_test = df_test['Charged_Off']
```

In [184]:
```
X_all = df.drop(['Charged_Off'], axis=1)
Y_all = df.loc[:, 'Charged_Off']
```

In [185]:
```
# Create an imputer object with a median filling strategy
from sklearn.impute import SimpleImputer
imputer = SimpleImputer(missing_values=np.nan, strategy='median')

# Train on the training features
imputer.fit(X_train)

# Transform both training and testing data
X_train = pd.DataFrame(imputer.transform(X_train), columns=X_train.columns)
X_test = pd.DataFrame(imputer.transform(X_test), columns=X_test.columns)
```

In [186]:
```
missing_values_table(X_train)
```

```
Your selected dataframe has 118 columns.
There are 0 columns that have missing values.
```

Out[186]:

Missing Values	% of Total Values	type

In [187]:
```
missing_values_table(X_test)
```

```
Your selected dataframe has 118 columns.
There are 0 columns that have missing values.
```

Out[187]:

Missing Values	% of Total Values	type

In [188]:
```
from sklearn.preprocessing import StandardScaler
```

In [189]:
```
# Create an imputer object with a median filling strategy
scaler = StandardScaler()

# Train on the training features
scaler.fit(X_train)

# Transform both training and testing data
X_train = pd.DataFrame(scaler.transform(X_train), columns=X_train.columns)
X_test = pd.DataFrame(scaler.transform(X_test), columns=X_test.columns)
```

In [190]:
```
from sklearn.decomposition import PCA
pca = PCA(n_components=2)
principalComponents = pca.fit_transform(X_train.values)
principalDf = pd.DataFrame(data = principalComponents, columns = ['principal c
omponent 1', 'principal component 2'])
```

In [191]:
```
principalDf.head(5)
```

Out[191]:

	principal component 1	principal component 2
0	0.394576	-0.611590
1	-1.595676	-2.654997
2	0.643042	1.156310
3	-0.554531	1.883248
4	0.168311	0.516427

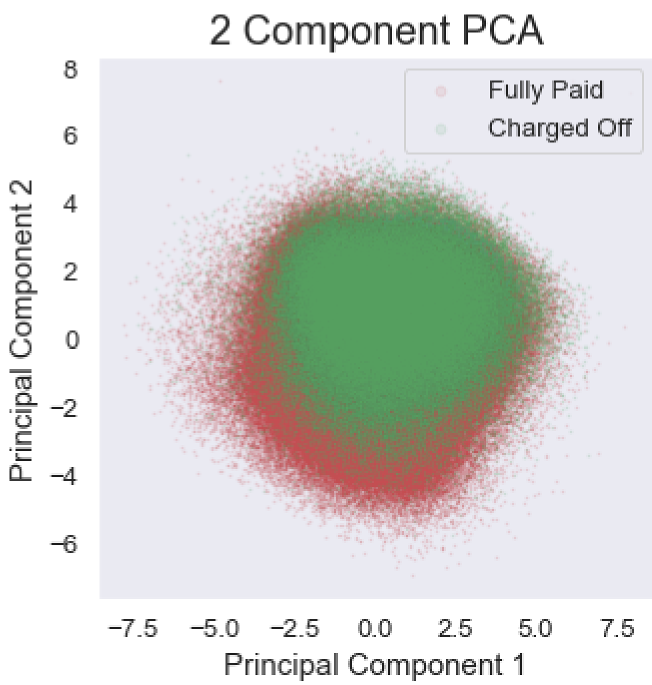
In [192]:
```
y_train_df = pd.DataFrame(data=y_train.values, columns=['Charged_Off'])
```

In [193]:
```
finalDf = pd.concat([principalDf, y_train_df], axis = 1)
finalDf.head(5)
```

Out[193]:

	principal component 1	principal component 2	Charged_Off
0	0.394576	-0.611590	0.0
1	-1.595676	-2.654997	1.0
2	0.643042	1.156310	0.0
3	-0.554531	1.883248	1.0
4	0.168311	0.516427	0.0

In [194]:
```
# visualize the PCA
fig = plt.figure(figsize = (5,5))
ax = fig.add_subplot(1,1,1)
ax.set_xlabel('Principal Component 1', fontsize = 15)
ax.set_ylabel('Principal Component 2', fontsize = 15)
ax.set_title('2 Component PCA', fontsize = 20)

targets = [0, 1]
colors = ['r', 'g']
for target, color in zip(targets,colors):
    indicesToKeep = finalDf['Charged_Off'] == target
    ax.scatter(finalDf.loc[indicesToKeep, 'principal component 1']
               , finalDf.loc[indicesToKeep, 'principal component 2']
               , c = color
               , s = 1, alpha=0.1)
ax.legend(['Fully Paid', 'Charged Off'], markerscale=5.)
ax.grid()
```



In [195]:
```
pca.explained_variance_ratio_
```

Out[195]:
```
array([0.02560507, 0.02453589])
```

In [196]:
```
linear_corr = pd.DataFrame()
```

In [197]:
```
# Pearson coefficients
for col in X_train.columns:
    linear_corr.loc[col, 'pearson_corr'] = X_train[col].corr(y_train)
linear_corr['abs_pearson_corr'] = abs(linear_corr['pearson_corr'])
```

In [198]:
```
linear_corr.sort_values('abs_pearson_corr', ascending=False, inplace=True)
linear_corr.drop('abs_pearson_corr', axis=1, inplace=True)
```

In [199]:
```
linear_corr.reset_index(inplace=True)
#linear_corr.rename(columns={'index':'variable'}, inplace=True)
```

In [200]:
```
linear_corr.head(10)
```

Out[200]:

	index	pearson_corr
0	verification_status_Verified	0.010210
1	revol_bal	0.009671
2	revol_util	0.008250
3	purpose_debt_consolidation	0.007217
4	initial_list_status_w	-0.006592
5	dti	0.006510
6	loan_amnt	0.006261
7	int_rate	0.006168
8	addr_state_NV	0.004709
9	fico_score	-0.004639

In [201]:
```
linear_corr.tail(10)
```

Out[201]:

	index	pearson_corr
108	addr_state_DE	-0.000282
109	addr_state_SC	0.000264
110	addr_state_RI	-0.000147
111	addr_state_MO	0.000137
112	addr_state_CA	0.000117
113	sub_grade_G1	0.000106
114	addr_state_OH	0.000071
115	sub_grade_D5	0.000049
116	addr_state_LA	-0.000012
117	addr_state_SD	-0.000009

In [202]:
```
# CV model with Kfold stratified cross val
kfold = 3
random_state = 42
```

In [203]:
```
from sklearn.linear_model import SGDClassifier
from sklearn.pipeline import Pipeline
```

In [204]:
```
pipeline_sgdlr = Pipeline([
    ('model', SGDClassifier(loss='log', max_iter=1000, tol=1e-3, random_state=
random_state, warm_start=False))
])
```

In [205]:
```
param_grid_sgdlr  = {
    'model__alpha': [10**-5, 10**-1, 10**2],
    'model__penalty': ['l1', 'l2']
}
```

In [206]:
```
grid_sgdlr = GridSearchCV(estimator=pipeline_sgdlr, param_grid=param_grid_sgdl
r, scoring='roc_auc', n_jobs=-1, pre_dispatch='2*n_jobs', cv=kfold, verbose=1,
return_train_score=False)
```

In [207]:
```
grid_sgdlr.fit(X_train, y_train)
```

```
Fitting 3 folds for each of 6 candidates, totalling 18 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 8 concurrent workers.
[Parallel(n_jobs=-1)]: Done  18 out of  18 | elapsed:  1.1min finished
```

Out[207]:
```
GridSearchCV(cv=3, error_score=nan,
             estimator=Pipeline(memory=None,
                                steps=[('model',
                                        SGDClassifier(alpha=0.0001,
                                                      average=False,
                                                      class_weight=None,
                                                      early_stopping=False,
                                                      epsilon=0.1, eta0=0.0,
                                                      fit_intercept=True,
                                                      l1_ratio=0.15,
                                                      learning_rate='optima
l',
                                                      loss='log', max_iter=10
00,
                                                      n_iter_no_change=5,
                                                      n_jobs=None, penalty='l
2',
                                                      power_t=0.5,
                                                      random_state=42,
                                                      shuffle=True, tol=0.00
1,
                                                      validation_fraction=0.
1,
                                                      verbose=0,
                                                      warm_start=False))],
                                verbose=False),
             iid='deprecated', n_jobs=-1,
             param_grid={'model__alpha': [1e-05, 0.1, 100],
                         'model__penalty': ['l1', 'l2']},
             pre_dispatch='2*n_jobs', refit=True, return_train_score=False,
             scoring='roc_auc', verbose=1)
```

In [208]:
```
sgdlr_estimator = grid_sgdlr.best_estimator_
print('Best score: ', grid_sgdlr.best_score_)
print('Best parameters set: \n', grid_sgdlr.best_params_)
```

```
Best score:  0.703608567929287
Best parameters set: 
 {'model__alpha': 0.1, 'model__penalty': 'l2'}
```

In [209]:
```
y_pred_sgdlr = sgdlr_estimator.predict(X_test)
y_prob_sgdlr = sgdlr_estimator.predict_proba(X_test)[:,1]
```

In [210]:
```
y_train_pred_sgdlr = sgdlr_estimator.predict(X_train)
y_train_prob_sgdlr = sgdlr_estimator.predict_proba(X_train)[:,1]
```

In [211]:
```
LRmodel_l2 = SGDClassifier(loss='log', max_iter=1000, tol=1e-3, random_state=r
andom_state, warm_start=False, alpha=0.1, penalty='l2')
```

In [212]:
```
LRmodel_l2.fit(X_train, y_train)
```

Out[212]:
```
SGDClassifier(alpha=0.1, average=False, class_weight=None, early_stopping=Fal
se,
              epsilon=0.1, eta0=0.0, fit_intercept=True, l1_ratio=0.15,
              learning_rate='optimal', loss='log', max_iter=1000,
              n_iter_no_change=5, n_jobs=None, penalty='l2', power_t=0.5,
              random_state=42, shuffle=True, tol=0.001, validation_fraction=
0.1,
              verbose=0, warm_start=False)
```

In [213]:
```
temp = sorted(zip(np.round(LRmodel_l2.coef_.reshape(-1),3), X_train.columns.va
lues), key=lambda x: -abs(x[0]))
weight = [x for x, _ in temp]
feature = [x for _, x in temp]
```

In [214]:
```
print("Logistic Regression (L2) Coefficients: Top 10")
pd.DataFrame({'weight': weight}, index = feature).head(10)
```

```
Logistic Regression (L2) Coefficients: Top 10
```

Out[214]:

	weight
term	0.181
int_rate	0.156
dti	0.125
fico_score	-0.114
annual_inc	-0.092
mort_acc	-0.066
home_ownership_RENT	0.063
loan_amnt	0.061
sub_grade_A4	-0.054
sub_grade_A2	-0.052

In [215]:
```
from sklearn.feature_selection import RFE
rfe_l2 = RFE(LRmodel_l2, n_features_to_select=1) # If None, half of the featur
es are selected.
rfe_l2.fit(X_train, y_train)
```

Out[215]:
```
RFE(estimator=SGDClassifier(alpha=0.1, average=False, class_weight=None,
                            early_stopping=False, epsilon=0.1, eta0=0.0,
                            fit_intercept=True, l1_ratio=0.15,
                            learning_rate='optimal', loss='log', max_iter=100
0,
                            n_iter_no_change=5, n_jobs=None, penalty='l2',
                            power_t=0.5, random_state=42, shuffle=True,
                            tol=0.001, validation_fraction=0.1, verbose=0,
                            warm_start=False),
    n_features_to_select=1, step=1, verbose=0)
```

In [216]:
```
temp = sorted(zip(map(lambda x: round(x, 4), rfe_l2.ranking_), X_train.columns
))
rank = [x for x, _ in temp]
feature = [x for _, x in temp]
print("Logistic Regression (L2) RFE Result: Top 10")
pd.DataFrame({'rank': rank}, index = feature).head(10)
```

```
Logistic Regression (L2) RFE Result: Top 10
```

Out[216]:

	rank
int_rate	1
term	2
dti	3
fico_score	4
mort_acc	5
annual_inc	6
loan_amnt	7
home_ownership_RENT	8
sub_grade_A4	9
sub_grade_A3	10

In [217]:
```
from sklearn.ensemble import RandomForestClassifier
```

In [218]:
```
rf = RandomForestClassifier(n_jobs=-1, n_estimators=100, random_state=random_s
tate,max_features='sqrt')
param_grid_rf = {
    #'n_estimators': [50, 100],
    'class_weight': [{0:1, 1:1}], #'model__class_weight': [{0:1, 1:1}, {0:1,1:
2}, {0:1, 1:3}, {0:1, 1:4}]
    #'model__min_samples_split':[2,3]
    #'model__max_features':[2,3,4,5],
    #"model__max_depth":range(8,13)
}
```

In [219]:
```
grid_rf = GridSearchCV(estimator=rf, param_grid=param_grid_rf, scoring='roc_au
c',n_jobs=-1,pre_dispatch='2*n_jobs', cv=kfold, verbose=1, return_train_score=
False)
```

In [220]:
```
grid_rf.fit(X_train, y_train)
```

```
Fitting 3 folds for each of 1 candidates, totalling 3 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 8 concurrent workers.
[Parallel(n_jobs=-1)]: Done   3 out of   3 | elapsed:  3.3min finished
```

Out[220]:
```
GridSearchCV(cv=3, error_score=nan,
             estimator=RandomForestClassifier(bootstrap=True, ccp_alpha=0.0,
                                              class_weight=None,
                                              criterion='gini', max_depth=Non
e,
                                              max_features='sqrt',
                                              max_leaf_nodes=None,
                                              max_samples=None,
                                              min_impurity_decrease=0.0,
                                              min_impurity_split=None,
                                              min_samples_leaf=1,
                                              min_samples_split=2,
                                              min_weight_fraction_leaf=0.0,
                                              n_estimators=100, n_jobs=-1,
                                              oob_score=False, random_state=4
2,
                                              verbose=0, warm_start=False),
             iid='deprecated', n_jobs=-1,
             param_grid={'class_weight': [{0: 1, 1: 1}]},
             pre_dispatch='2*n_jobs', refit=True, return_train_score=False,
             scoring='roc_auc', verbose=1)
```

In [221]:
```
rf_estimator = grid_rf.best_estimator_
print('Best score: ', grid_rf.best_score_)
print('Best parameters set: \n', grid_rf.best_params_)
```

```
Best score:  0.6587682992701517
Best parameters set:
 {'class_weight': {0: 1, 1: 1}}
```

In [222]:
```
y_pred_rf = rf_estimator.predict(X_test)
y_prob_rf = rf_estimator.predict_proba(X_test)[:,1]
```

In [223]:
```
y_train_pred_rf = rf_estimator.predict(X_train)
y_train_prob_rf = rf_estimator.predict_proba(X_train)[:,1]
```

In [224]:
```
names = list(X_train)
```

In [225]:
```
feature_importances = pd.DataFrame(grid_rf.best_estimator_.feature_importances
_,
                                   index = X_train.columns,
                                    columns=['importance']).sort_values('impor
tance',                                                                  ascen
ding=False)
```

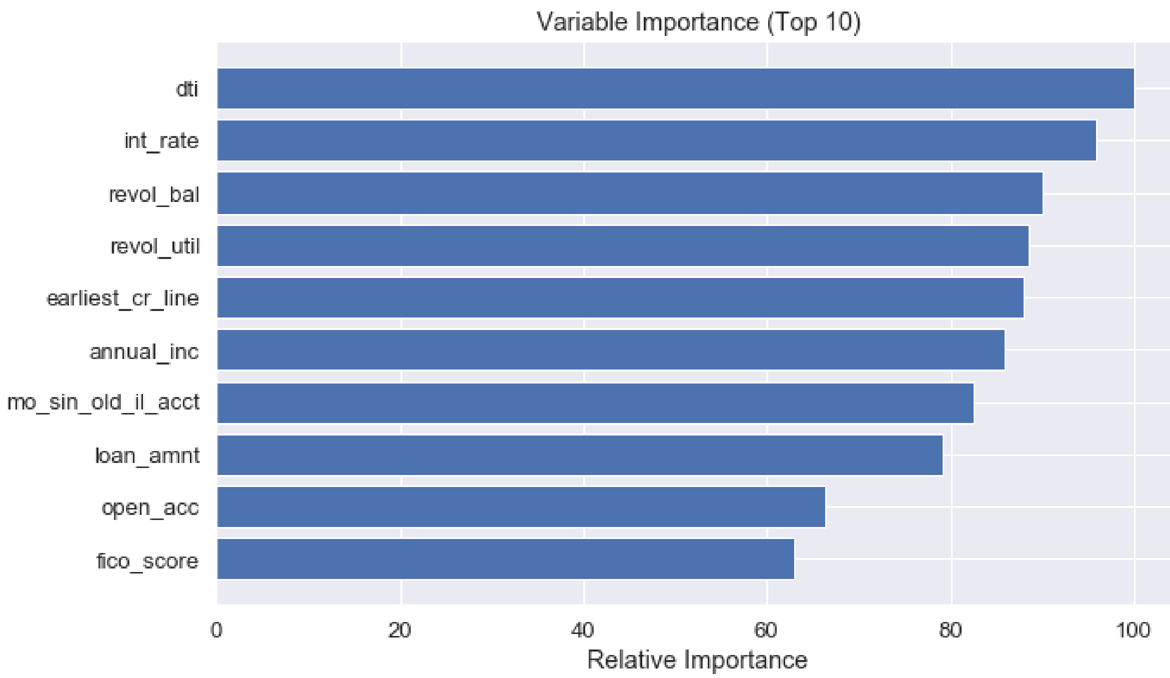
In [226]:
```
print("Features sorted by their score: Top 10")
feature_importances.head(10)
```

```
Features sorted by their score: Top 10
```

Out[226]:

	importance
dti	0.075722
int_rate	0.072573
revol_bal	0.068150
revol_util	0.067069
earliest_cr_line	0.066640
annual_inc	0.065099
mo_sin_old_il_acct	0.062485
loan_amnt	0.059981
open_acc	0.050188
fico_score	0.047617

In [227]:
```
# Normalize The Features and visulize the top 10 features
%matplotlib inline
feature_importance = 100.0 * (grid_rf.best_estimator_.feature_importances_ / g
rid_rf.best_estimator_.feature_importances_.max())
sorted_idx = sorted(range(len(feature_importance)), key=lambda i: feature_impo
rtance[i])[-10:]
pos = np.arange(len(sorted_idx)) + .5
plt.figure(figsize=(10, 6))

plt.barh(pos, feature_importance[sorted_idx], align='center')
plt.yticks(pos, np.asanyarray(X_train.columns.tolist())[sorted_idx])
plt.xlabel('Relative Importance')
plt.title('Variable Importance (Top 10)')
plt.show()
```



In [228]:
```
print("Features sorted by their score: Bottom 10")
feature_importances.tail(10)
```

```
Features sorted by their score: Bottom 10
```

Out[228]:

	importance
purpose_renewable_energy	0.000231
sub_grade_G4	0.000199
sub_grade_G5	0.000169
addr_state_ND	0.000131
purpose_educational	0.000123
application_type_Joint App	0.000111
home_ownership_OTHER	0.000105
addr_state_ME	0.000084
addr_state_ID	0.000004
addr_state_IA	0.000003

In [229]:
```
grid_rf.best_estimator_[1]
```

Out[229]:
```
DecisionTreeClassifier(ccp_alpha=0.0, class_weight=None, criterion='gini',
                       max_depth=None, max_features='sqrt', max_leaf_nodes=No
ne,
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=1, min_samples_split=2,
                       min_weight_fraction_leaf=0.0, presort='deprecated',
                       random_state=1273642419, splitter='best')
```

In [230]:
```
!pip install pydot
```

```
Requirement already satisfied: pydot in c:\users\puj83\anaconda3\lib\site-pac
kages (1.4.1)
Requirement already satisfied: pyparsing>=2.1.4 in c:\users\puj83\anaconda3\l
ib\site-packages (from pydot) (2.4.6)
```

In [231]:
```
# Import tools needed for visualization
from sklearn.tree import export_graphviz
import pydot
rf_big = RandomForestClassifier(n_jobs=-1, random_state=random_state, n_estima
tors=10, max_depth=6)
rf_big.fit(X_train, y_train)
```

Out[231]:
```
RandomForestClassifier(bootstrap=True, ccp_alpha=0.0, class_weight=None,
                       criterion='gini', max_depth=6, max_features='auto',
                       max_leaf_nodes=None, max_samples=None,
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=1, min_samples_split=2,
                       min_weight_fraction_leaf=0.0, n_estimators=10, n_jobs=
-1,
                       oob_score=False, random_state=42, verbose=0,
                       warm_start=False)
```

In [232]:
```
# Limit depth of tree to 3 levels
rf_small = RandomForestClassifier(n_jobs=-1, random_state=random_state, n_esti
mators=10, max_depth = 3)
rf_small.fit(X_train, y_train)
```

Out[232]:
```
RandomForestClassifier(bootstrap=True, ccp_alpha=0.0, class_weight=None,
                       criterion='gini', max_depth=3, max_features='auto',
                       max_leaf_nodes=None, max_samples=None,
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=1, min_samples_split=2,
                       min_weight_fraction_leaf=0.0, n_estimators=10, n_jobs=
-1,
                       oob_score=False, random_state=42, verbose=0,
                       warm_start=False)
```

In [233]:
```
from sklearn.neighbors import KNeighborsClassifier
from sklearn.feature_selection import RFECV
from sklearn import decomposition
```

In [234]:
```
#chaining a PCA and a knn
pipeline_knn = Pipeline([
    ('pca', decomposition.PCA()),
    ('model', KNeighborsClassifier(n_jobs=-1))
])

pipeline_knn2 = Pipeline([
    ('lda', LinearDiscriminantAnalysis()),
    ('model', KNeighborsClassifier(n_jobs=-1))
])
```

In [235]:
```
param_grid_knn = {
    'pca__n_components': range(3,6),
    'model__n_neighbors': [5, 25, 125]
}
param_grid_knn2 = {
    'lda__n_components': range(3,6),
    'model__n_neighbors': [5, 25, 125]
}
```

In [236]:
```
grid_knn = GridSearchCV(estimator=pipeline_knn, param_grid=param_grid_knn, scoring='roc_auc', n_jobs=-1, pre_dispatch='2*n_jobs', cv=kfold, verbose=1, return_train_score=False)
grid_knn2 = GridSearchCV(estimator=pipeline_knn2, param_grid=param_grid_knn2, scoring='roc_auc', n_jobs=-1, pre_dispatch='2*n_jobs', cv=kfold, verbose=1, return_train_score=False)
```

In [237]:
```
%%time
#grid_knn.fit(X_train, y_train) # very slow
```

```
Wall time: 0 ns
```

In [238]:
```
%%time
grid_knn2.fit(X_train, y_train)
```

```
Fitting 3 folds for each of 9 candidates, totalling 27 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 8 concurrent workers.
[Parallel(n_jobs=-1)]: Done  27 out of  27 | elapsed:  4.2min finished

Wall time: 4min 32s
```

Out[238]:
```
GridSearchCV(cv=3, error_score=nan,
             estimator=Pipeline(memory=None,
                                steps=[('lda',
                                        LinearDiscriminantAnalysis(n_componen
ts=None,
                                                                   priors=Non
e,
                                                                   shrinkage=
None,
                                                                   solver='sv
d',
                                                                   store_cova
riance=False,
                                                                   tol=0.000
1)),
                                       ('model',
                                        KNeighborsClassifier(algorithm='aut
o',
                                                             leaf_size=30,
                                                             metric='minkowsk
i',
                                                             metric_params=No
ne,
                                                             n_jobs=-1,
                                                             n_neighbors=5, p
=2,
                                                             weights='unifor
m'))],
                                verbose=False),
             iid='deprecated', n_jobs=-1,
             param_grid={'lda__n_components': range(3, 6),
                         'model__n_neighbors': [5, 25, 125]},
             pre_dispatch='2*n_jobs', refit=True, return_train_score=False,
             scoring='roc_auc', verbose=1)
```

In [239]:
```
knn_estimator2 = grid_knn2.best_estimator_
print('Best score: ', grid_knn2.best_score_)
print('Best parameters set: \n', grid_knn2.best_params_)
```

```
Best score:  0.6955012632654656
Best parameters set:
 {'lda__n_components': 3, 'model__n_neighbors': 125}
```

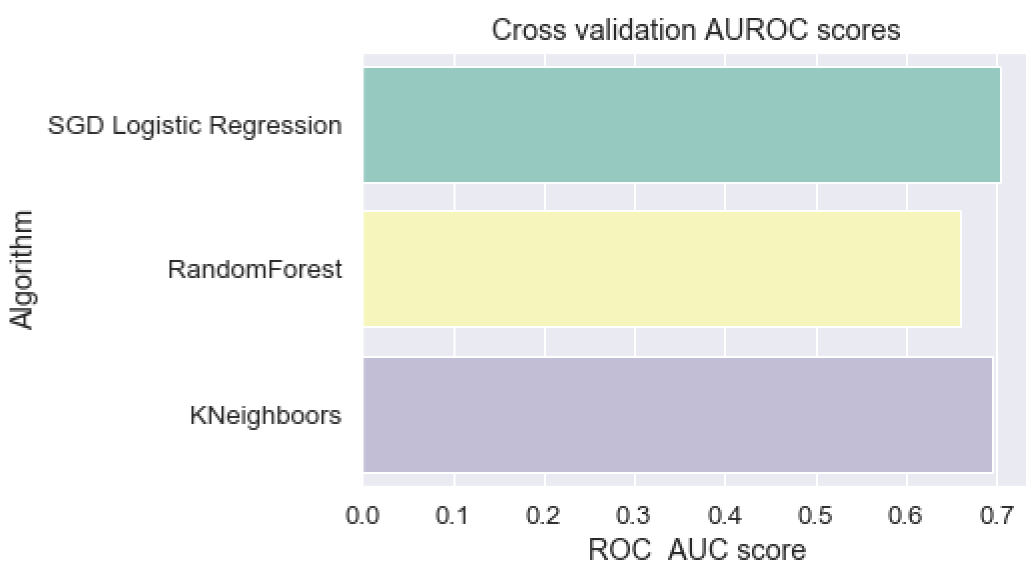
In [240]:
```
y_pred_knn = knn_estimator2.predict(X_test)
y_prob_knn = knn_estimator2.predict_proba(X_test)[:,1]
```

In [241]:
```
y_train_pred_knn = knn_estimator2.predict(X_train)
y_train_prob_knn = knn_estimator2.predict_proba(X_train)[:,1]
```

In [242]:
```
# plot the AUROC scores on the training dataset.
auroc_means = [grid_sgdlr.best_score_, grid_rf.best_score_,grid_knn2.best_scor
e_]
auroc_res = pd.DataFrame({"AUROC":auroc_means,"Algorithm":["SGD Logistic Regre
ssion",
"RandomForest","KNeighboors"]})

g = sns.barplot("AUROC","Algorithm", data = auroc_res, palette="Set3",orient =
"h")
g.set_xlabel("ROC_AUC score")
g = g.set_title("Cross validation AUROC scores")
auroc_res
```

Out[242]:

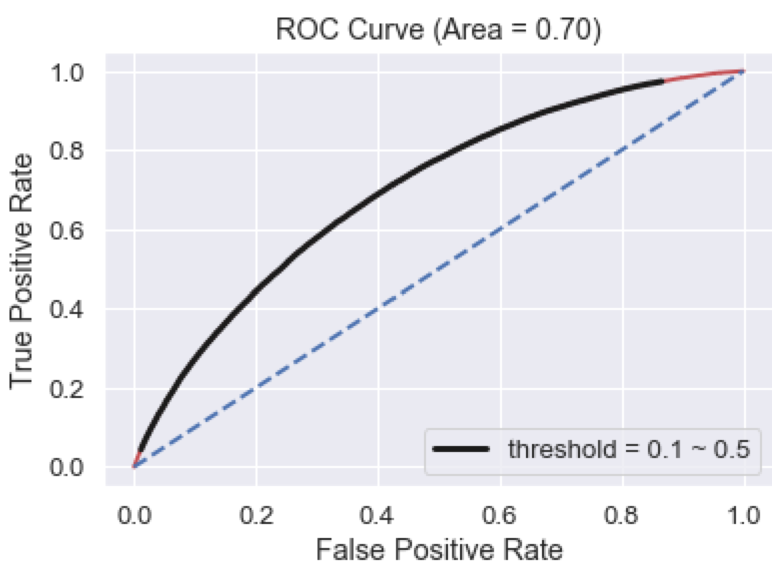
	AUROC	Algorithm
0	0.703609	SGD Logistic Regression
1	0.658768	RandomForest
2	0.695501	KNeighboors



In [243]:
```
def evaluation(X_train, X_test, Y_train, Y_test, Y_train_pred, Y_train_prob, Y
_pred, Y_prob):
    print("--- ROC AUC ---")
    print("Training Set:", roc_auc_score(Y_train, Y_train_prob))
    print("Test Set:", roc_auc_score(Y_test, Y_prob))

    print("\n--- Accuracy ---")
    print("Training Set:", accuracy_score(Y_train, Y_train_pred))
    print("Test Set:", accuracy_score(Y_test, Y_pred))

    tn, fp, fn, tp = confusion_matrix(Y_test, Y_pred).ravel()
    print("\n--- Confusion Matrix ---")
    print("True Positive:", tp)
    print("False Negative:", fn)
    print("True Negative:", tn)
    print("False Positive:", fp)

    print("\n--- Precision ---")
    print("Training Set:", precision_score(Y_train, Y_train_pred))
    print("Test Set:", precision_score(Y_test, Y_pred))

    print("\n--- Recall ---")
    print("Training Set:", recall_score(Y_train, Y_train_pred))
    print("Test Set:", recall_score(Y_test, Y_pred))

    print("\n--- F1 Score ---")
    print("Training Set:", f1_score(Y_train, Y_train_pred))
    print("Test Set:", f1_score(Y_test, Y_pred))

def plot_ROC(X_test, Y_test, Y_prob):

    #Y_prob = model.predict_proba(X_test)[:,1]
    fpr, tpr, thresh = roc_curve(Y_test, Y_prob, pos_label=1)
    roc_auc = roc_auc_score(Y_test, Y_prob)
    # These are the points at threshold = 0.1~0.5
    x1 = fpr[(thresh <= 0.5) & (thresh >= 0.1)]
    x2 = tpr[(thresh <= 0.5) & (thresh >= 0.1)]

    fig = plt.figure()
    plt.plot(fpr, tpr, color='r', lw=2)
    plt.plot([0, 1], [0, 1], color='b', lw=2, linestyle='--')
    plt.plot(x1, x2, color='k', lw=3, label='threshold = 0.1 ~ 0.5')
    plt.xlim([-0.05, 1.05])
    plt.ylim([-0.05, 1.05])
    plt.xlabel('False Positive Rate')
    plt.ylabel('True Positive Rate')
    plt.title('ROC Curve (Area = {:.2f})'.format(roc_auc))
    plt.legend(loc="lower right")
    plt.show()
```

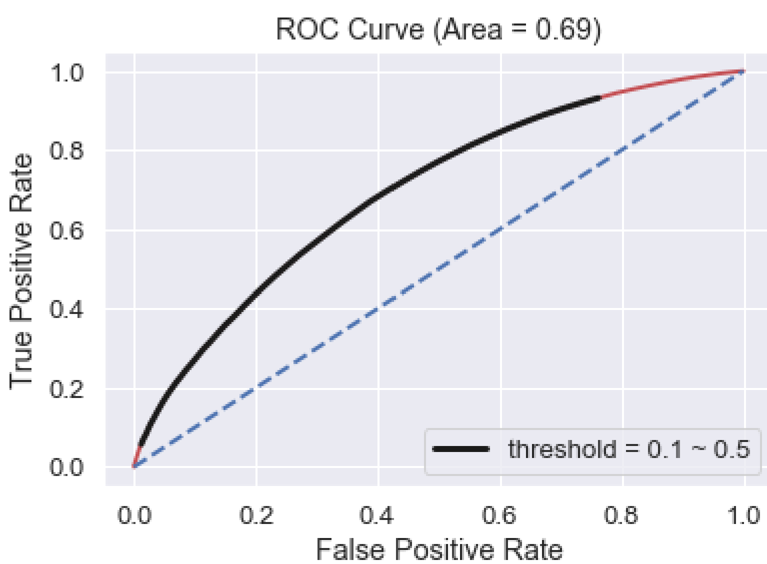
In [244]:
```
print('===== Logistic Regression =====')
evaluation(X_train, X_test, y_train, y_test, y_train_pred_sgdlr, y_train_prob_
sgdlr, y_pred_sgdlr, y_prob_sgdlr)
plot_ROC(X_test, y_test, y_prob_sgdlr)
```

```
===== Logistic Regression =====
--- ROC AUC ---
Training Set: 0.7137630660464039
Test Set: 0.6986531748959774

--- Accuracy ---
Training Set: 0.7993156856048255
Test Set: 0.7793705148438198

--- Confusion Matrix ---
True Positive: 1627
False Negative: 35570
True Negative: 129241
False Positive: 1477

--- Precision ---
Training Set: 0.6361713379164463
Test Set: 0.5241623711340206

--- Recall ---
Training Set: 0.01838226867450549
Test Set: 0.043740086566120925

--- F1 Score ---
Training Set: 0.03573205414757665
Test Set: 0.08074241333961937
```



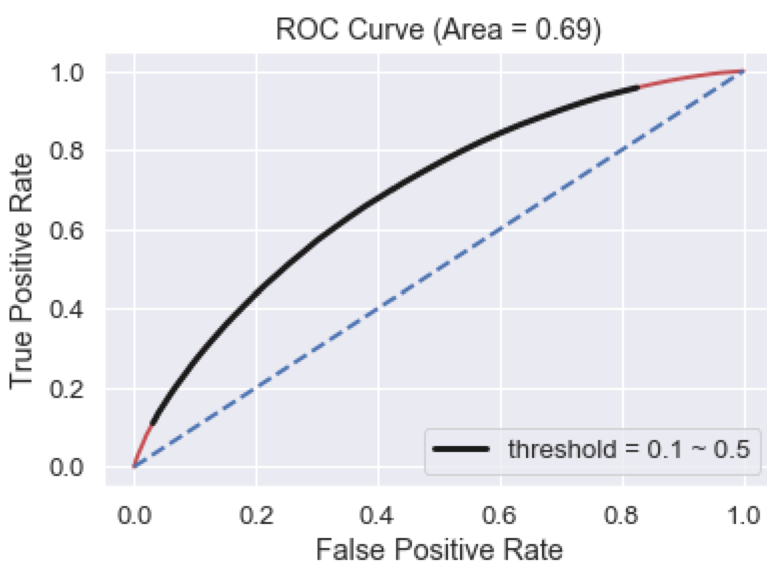
In [245]:
```
print('===== KNN =====')
evaluation(X_train, X_test, y_train, y_test, y_train_pred_knn, y_train_prob_kn
n, y_pred_knn, y_prob_knn)
plot_ROC(X_test, y_test, y_prob_knn)
```

```
===== KNN =====
--- ROC AUC ---
Training Set: 0.7259935585320744
Test Set: 0.6943610459406439

--- Accuracy ---
Training Set: 0.8014669178498186
Test Set: 0.7820504421880118

--- Confusion Matrix ---
True Positive: 1942
False Negative: 35255
True Negative: 129376
False Positive: 1342

--- Precision ---
Training Set: 0.5544808349829045
Test Set: 0.5913520097442144

--- Recall ---
Training Set: 0.09416519593236915
Test Set: 0.05220851143909455

--- F1 Score ---
Training Set: 0.160990105476276
Test Set: 0.09594624638719398
```



In [246]:
```
print('===== Random Forest =====')
evaluation(X_train, X_test, y_train, y_test, y_train_pred_rf, y_train_prob_rf,
y_pred_rf, y_prob_rf)
plot_ROC(X_test, y_test, y_prob_rf)
```

```
===== Random Forest =====
--- ROC AUC ---
Training Set: 1.0
Test Set: 0.6927022770326954

--- Accuracy ---
Training Set: 0.9999845457453664
Test Set: 0.7795134443021767

--- Confusion Matrix ---
True Positive: 3723
False Negative: 33474
True Negative: 127169
False Positive: 3549

--- Precision ---
Training Set: 1.0
Test Set: 0.511963696369637

--- Recall ---
Training Set: 0.9999235982183104
Test Set: 0.10008871683200259

--- F1 Score ---
Training Set: 0.9999617976497914
Test Set: 0.167442488025366
```



In [247]:
```
# bank
score_bank = sum(y_test == 0) - sum(y_test == 1)

# my Logistic regression model
tn, fp, fn, tp = confusion_matrix(y_test, grid_sgdlr.predict(X_test)).ravel()
score_lr = tn - fn

print("The bank scores {} points".format(score_bank))
print("The Logistic regression model scores {} points".format(score_lr))
```

```
The bank scores 93521 points
The Logistic regression model scores 93671 points
```