Yao Yao Patientfi Data Challenge

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1 Yao Yao

Patientfi Data Challenge

1.0.1 You will find a file labeled data.csv in the link that contains loan data including the credit attributes and loan status, etc. Your goal is to predict the likelihood of a loan to "charge off" (column "loan_status").

1.0.2 The credit default prediction is central to managing risk in a consumer lending business, as it allows lenders to optimize lending decisions. You'll apply your machine learning skills to predict credit default by the dataset we provided to you. You're free to explore any techniques to create the most powerful model, from creating features to using the data in a more organic way within a model.

1.0.3 Please build your model with a detailed description/explanation, as it will help us understand and evaluate how you approach the problem.

[1]:
```
import sys
try:
    sys.getwindowsversion()
except AttributeError:
    isWindows = False
else:
    isWindows = True
if isWindows:
    import win32api,win32process,win32con
    pid = win32api.GetCurrentProcessId()
    handle = win32api.OpenProcess(win32con.PROCESS_ALL_ACCESS, True, pid)
    win32process.SetPriorityClass(handle, win32process.HIGH_PRIORITY_CLASS)
import warnings
warnings.filterwarnings('ignore')

import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split, GridSearchCV,␣
 ↪RandomizedSearchCV
from sklearn.ensemble import RandomForestClassifier,RandomForestRegressor
```

```python
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, classification_report,␣
 ↪confusion_matrix, roc_auc_score, roc_curve
from sklearn.tree import DecisionTreeClassifier
from sklearn.preprocessing import MinMaxScaler
from sklearn import metrics
from datetime import datetime
import time
from sklearn.model_selection import KFold, StratifiedKFold
import itertools
import os
from PIL import Image
os.environ["PATH"] += os.pathsep + 'C:/Program Files (x86)/Graphviz2.38/bin/'

%matplotlib inline
```

2 Import data and create data summary

[2]:
```python
df=pd.read_csv("data.csv", engine = 'c')
```

[3]:
```python
df.describe().T
```

[3]:
```
                               count          mean           std  \
id                          199999.0  6.229635e+07  3.941126e+06
member_id                        0.0           NaN           NaN
loan_amnt                   199999.0  1.527812e+04  8.651139e+03
funded_amnt                 199999.0  1.527812e+04  8.651139e+03
funded_amnt_inv             199999.0  1.526947e+04  8.646325e+03
…                                …           …           …
hardship_payoff_balance_amount    1409.0  1.001451e+04  6.313702e+03
hardship_last_payment_amount      1409.0  1.860614e+02  1.812045e+02
settlement_amount             5840.0  5.015406e+03  3.557532e+03
settlement_percentage         5840.0  4.710027e+01  5.753855e+00
settlement_term               5840.0  1.348545e+01  7.537550e+00

                               min          25%          50%  \
id                          56705.00  59411733.00  62217538.00
member_id                        NaN          NaN          NaN
loan_amnt                    1000.00      8500.00     14000.00
funded_amnt                  1000.00      8500.00     14000.00
funded_amnt_inv               900.00      8475.00     14000.00
…                                …           …           …
hardship_payoff_balance_amount  55.73      4708.77      8879.16
hardship_last_payment_amount     0.02        44.95       134.56
settlement_amount              130.00      2192.49      4344.99
settlement_percentage           20.00        45.00        45.00
```

```
settlement_term                        0.00         8.00        13.50

                                        75%          max
id                              65644568.00  68617057.00
member_id                               NaN          NaN
loan_amnt                          20000.00     35000.00
funded_amnt                        20000.00     35000.00
funded_amnt_inv                    20000.00     35000.00
…                                       …          …
hardship_payoff_balance_amount     14383.87     29401.04
hardship_last_payment_amount         275.29       927.79
settlement_amount                   7000.00     26242.50
settlement_percentage                 50.00        97.66
settlement_term                       18.00        65.00

[115 rows x 8 columns]
```

[4]:
```python
df.isnull().T.any().T.sum()
```

[4]:
```
199999
```

3 Given that there are a lot of values missing, remove columns that have over 80% missing for the sake of the exercise and time. 'Default' for loan status is removed because it only has one result

[5]:
```python
df = df[df.columns[df.isnull().mean() < 0.8]]
df = df[df.columns[df.isna().mean() < 0.8]]
df = df[df['loan_status']!='Default'].reset_index(drop=True)
df
```

[5]:
```
              id  loan_amnt  funded_amnt  funded_amnt_inv        term  \
0       68407277       3600         3600           3600.0   36 months
1       68355089      24700        24700          24700.0   36 months
2       68341763      20000        20000          20000.0   60 months
3       66310712      35000        35000          35000.0   60 months
4       68476807      10400        10400          10400.0   60 months
…            …          …            …                …          …
199993  56059770       4000         4000           4000.0   36 months
199994  56080425      12000        12000          12000.0   36 months
199995  55909672      21000        21000          21000.0   36 months
199996  54414556      27500        27500          27500.0   60 months
199997  56109383       7000         7000           7000.0   36 months

        int_rate  installment grade sub_grade                    emp_title  \
0          13.99       123.03     C        C4                      leadman
```

```
1          11.99      820.28    C        C1                          Engineer
2          10.78      432.66    B        B4                      truck driver
3          14.85      829.90    C        C5  Information Systems Officer
4          22.45      289.91    F        F1           Contract Specialist
…          …           …   …    …                                   …
199993     12.29      133.42    C        C1                           Teacher
199994     12.69      402.54    C        C2                      Truck driver
199995     12.29      700.42    C        C1                          Attorney
199996     14.65      649.19    C        C5                         hvac tech
199997     10.99      229.14    B        B4           Nursing Office Manager

        … percent_bc_gt_75 pub_rec_bankruptcies  tax_liens tot_hi_cred_lim  \
0       …              0.0                    0          0          178050
1       …              7.7                    0          0          314017
2       …             50.0                    0          0          218418
3       …              0.0                    0          0          381215
4       …             60.0                    0          0          439570
…     …               …                    …          …             …
199993  …             83.3                    0          0          194282
199994  …             50.0                    0          0           32176
199995  …            100.0                    0          0          181446
199996  …              0.0                    0          0           53653
199997  …            100.0                    0          0          134023

       total_bal_ex_mort total_bc_limit total_il_high_credit_limit  \
0                   7746           2400                      13734
1                  39475          79300                      24667
2                  18696           6200                      14877
3                  52226          62500                      18000
4                  95768          20300                      88097
…                  …             …                          …
199993             29295          24400                       7000
199994             27413          13800                       5784
199995            173683          15000                     157346
199996             30750          18500                      35153
199997             38802           4200                      22492

       hardship_flag disbursement_method  debt_settlement_flag
0                  N                Cash                     N
1                  N                Cash                     N
2                  N                Cash                     N
3                  N                Cash                     N
4                  N                Cash                     N
…             …                 …                    …
199993             N                Cash                     N
199994             N                Cash                     N
199995             N                Cash                     N
```

```
199996                 N                 Cash                          N
199997                 N                 Cash                          N

[199998 rows x 94 columns]
```

[6]:
```
df.isnull().T.any().T.sum()
```

[6]:
```
176141
```

[7]:
```
#df.to_csv('df.csv',index=False)
```

4 Convert certain strings into continuous variables

[8]:
```
df.describe().T
```

[8]:
```
                            count          mean           std       min  \
id                       199998.0  6.229633e+07  3.941125e+06  56705.00
loan_amnt                199998.0  1.527802e+04  8.651048e+03   1000.00
funded_amnt              199998.0  1.527802e+04  8.651048e+03   1000.00
funded_amnt_inv          199998.0  1.526937e+04  8.646234e+03    900.00
int_rate                 199998.0  1.236171e+01  4.242075e+00      5.32
…                             …             …             …        …
tax_liens                199998.0  6.433564e-02  4.656492e-01      0.00
tot_hi_cred_lim          199998.0  1.770256e+05  1.779942e+05   2500.00
total_bal_ex_mort        199998.0  5.281753e+04  4.949148e+04      0.00
total_bc_limit           199998.0  2.258573e+04  2.234689e+04      0.00
total_il_high_credit_limit 199998.0  4.413560e+04  4.447859e+04    0.00

                                 25%          50%          75%          max
id                       59411731.00  62217530.00  65644565.25  68617057.00
loan_amnt                    8500.00     14000.00     20000.00     35000.00
funded_amnt                  8500.00     14000.00     20000.00     35000.00
funded_amnt_inv              8475.00     14000.00     20000.00     35000.00
int_rate                        9.17        12.29        14.65        28.99
…                                  …            …            …            …
tax_liens                       0.00         0.00         0.00        85.00
tot_hi_cred_lim             52205.00    115187.50    255110.50   9999999.00
total_bal_ex_mort           22736.00     40069.00     66654.50   2652799.00
total_bc_limit               8000.00     15700.00     29500.00    834300.00
total_il_high_credit_limit  15850.25     33575.50     59213.00   2101913.00

[74 rows x 8 columns]
```

5 Convert term into continuous variable

[9]:
```
df['term'] = df['term'].str[:3].astype('int')
df['term']
```

[9]:
```
0         36
1         36
2         60
3         60
4         60
          ..
199993    36
199994    36
199995    36
199996    60
199997    36
Name: term, Length: 199998, dtype: int32
```

6 Make Grade numeric multiplied by 10, and Sub Grade numeric multiplied by 2 minus 2 to keep it at scale

[10]:
```
df['grade'] = df['grade'].to_numpy().astype('<U1').view(np.uint32)-64
df['grade']
```

[10]:
```
0         3
1         3
2         2
3         3
4         6
         ..
199993    3
199994    3
199995    3
199996    3
199997    2
Name: grade, Length: 199998, dtype: uint32
```

[11]:
```
df['sub_grade'] = df['sub_grade'].str[1:].astype('int')*2-2
df['sub_grade']
```

[11]:
```
0         6
1         0
2         6
3         8
4         0
         ..
```

```
199993    0
199994    2
199995    0
199996    8
199997    6
Name: sub_grade, Length: 199998, dtype: int32
```

[12]:
```
df['grade'] = df['grade']*10+df['sub_grade']
df['grade']
```

[12]:
```
0         36
1         30
2         26
3         38
4         60
          ..
199993    30
199994    32
199995    30
199996    38
199997    26
Name: grade, Length: 199998, dtype: int64
```

7 Make the titles lowercase, trim whitespace, and then make dummy variables for the words separated by space later

[13]:
```
df['emp_title'] = df['emp_title'].str.lower().str.strip()
df['emp_title']
```

[13]:
```
0                              leadman
1                             engineer
2                         truck driver
3          information systems officer
4                  contract specialist
                          …
199993                         teacher
199994                    truck driver
199995                        attorney
199996                       hvac tech
199997         nursing office manager
Name: emp_title, Length: 199998, dtype: object
```

make the length of the career numeric, simplified

8 Change length of title to numerical

[14]:
```
df['emp_length'] = df['emp_length'].str.split(' ', 1, expand=True)[0].str.
    ↪extract('(\d+)', expand=False).replace('None', np.nan).astype('float')
df['emp_length']
```

[14]:
```
0         10.0
1         10.0
2         10.0
3         10.0
4          3.0
          …
199993    10.0
199994     1.0
199995     8.0
199996    10.0
199997     7.0
Name: emp_length, Length: 199998, dtype: float64
```

9 Zip code can be converted into numeric given there that is a pattern in geo labeling

[15]:
```
df['zip_code'] = df['zip_code'].str[:3].replace('None', np.nan).astype('int')
df['zip_code']
```

[15]:
```
0         190
1         577
2         605
3          76
4         174
         …
199993    850
199994    983
199995    113
199996    983
199997    846
Name: zip_code, Length: 199998, dtype: int32
```

10 Convert the dates into datetime format

[16]:
```
df['earliest_cr_line'] = pd.to_datetime(df['earliest_cr_line'], format='%b-%y')
df['earliest_cr_line']
```

[16]:
```
0        2003-08-01
1        1999-12-01
2        2000-08-01
```

```
3         2008-09-01
4         1998-06-01
             …
199993    1997-06-01
199994    2003-09-01
199995    2001-10-01
199996    2002-06-01
199997    1990-11-01
Name: earliest_cr_line, Length: 199998, dtype: datetime64[ns]
```

[17]:
```
df['earliest_cr_line'].min()
```

[17]:
```
Timestamp('1969-01-01 00:00:00')
```

[18]:
```
df['last_credit_pull_d'] = pd.to_datetime(df['last_credit_pull_d'],␣
 ↪format='%b-%y')
df['last_credit_pull_d']
```

[18]:
```
0         2019-03-01
1         2019-03-01
2         2019-03-01
3         2019-03-01
4         2018-03-01
             …
199993    2019-02-01
199994    2016-02-01
199995    2018-09-01
199996    2016-02-01
199997    2019-03-01
Name: last_credit_pull_d, Length: 199998, dtype: datetime64[ns]
```

[19]:
```
df['last_pymnt_d'] = pd.to_datetime(df['last_pymnt_d'], format='%b-%y')
df['last_pymnt_d']
```

[19]:
```
0         2019-01-01
1         2016-06-01
2         2017-06-01
3         2019-02-01
4         2016-07-01
             …
199993    2018-06-01
199994    2016-01-01
199995    2018-08-01
199996    2016-03-01
199997    2018-08-01
Name: last_pymnt_d, Length: 199998, dtype: datetime64[ns]
```

11 Earliest credit line, credit pull, and last payment dates are less arbitritray when relative to each other, so I made new columns showing the difference in days among those dates

[20]:
```
df['diff credit pull credit line'] = (df['last_credit_pull_d'] -␣
 ↪df['earliest_cr_line']).dt.days
df['diff credit pull credit line']
```

[20]:
```
0          5691.0
1          7030.0
2          6786.0
3          3833.0
4          7213.0
           …
199993     7915.0
199994     4536.0
199995     6179.0
199996     4993.0
199997    10347.0
Name: diff credit pull credit line, Length: 199998, dtype: float64
```

[21]:
```
df['diff payment credit line'] = (df['last_pymnt_d'] - df['earliest_cr_line']).
 ↪dt.days
df['diff payment credit line']
```

[21]:
```
0          5632.0
1          6027.0
2          6148.0
3          3805.0
4          6605.0
           …
199993     7670.0
199994     4505.0
199995     6148.0
199996     5022.0
199997    10135.0
Name: diff payment credit line, Length: 199998, dtype: float64
```

[22]:
```
df['diff credit pull payment'] = (df['last_credit_pull_d'] -␣
 ↪df['last_pymnt_d']).dt.days
df['diff credit pull payment']
```

[22]:
```
0           59.0
1         1003.0
2          638.0
3           28.0
4          608.0
```

```
                …
199993     245.0
199994      31.0
199995      31.0
199996     -29.0
199997     212.0
Name: diff credit pull payment, Length: 199998, dtype: float64
```

12 converted datetime to year month on the same scale

[23]:
```
df['earliest_cr_line'] = pd.DatetimeIndex(df['earliest_cr_line']).year * 100 +␣
↪(pd.DatetimeIndex(df['earliest_cr_line']).month - 1)* 100/12
df['earliest_cr_line']
```

[23]:
```
0         200358.333333
1         199991.666667
2         200058.333333
3         200866.666667
4         199841.666667
              …
199993    199741.666667
199994    200366.666667
199995    200175.000000
199996    200241.666667
199997    199083.333333
Name: earliest_cr_line, Length: 199998, dtype: float64
```

13 Converted month and year into one continuous variable

[24]:
```
df['last_credit_pull_d'] = pd.DatetimeIndex(df['last_credit_pull_d']).year *␣
↪100 + (pd.DatetimeIndex(df['last_credit_pull_d']).month - 1)* 100/12
df['last_credit_pull_d']
```

[24]:
```
0         201916.666667
1         201916.666667
2         201916.666667
3         201916.666667
4         201816.666667
              …
199993    201908.333333
199994    201608.333333
199995    201866.666667
199996    201608.333333
199997    201916.666667
Name: last_credit_pull_d, Length: 199998, dtype: float64
```

[25]:
```
df['last_pymnt_d'] = pd.DatetimeIndex(df['last_pymnt_d']).year * 100 + (pd.
↪DatetimeIndex(df['last_pymnt_d']).month - 1)* 100/12
df['last_pymnt_d']
```

[25]:
```
0         201900.000000
1         201641.666667
2         201741.666667
3         201908.333333
4         201650.000000
               …
199993    201841.666667
199994    201600.000000
199995    201858.333333
199996    201616.666667
199997    201858.333333
Name: last_pymnt_d, Length: 199998, dtype: float64
```

14 Sub grade was combined into grade. funded amount is redundant to loan amount. issue date, and distribution method have no variance, so they are dropped

[26]:
```
df = df.drop(columns =␣
↪['issue_d','sub_grade','disbursement_method','funded_amnt']).fillna(-1)
df
```

[26]:
```
              id  loan_amnt  funded_amnt_inv  term  int_rate  installment  \
0       68407277       3600           3600.0    36     13.99       123.03
1       68355089      24700          24700.0    36     11.99       820.28
2       68341763      20000          20000.0    60     10.78       432.66
3       66310712      35000          35000.0    60     14.85       829.90
4       68476807      10400          10400.0    60     22.45       289.91
…            …          …                …     …         …
199993  56059770       4000           4000.0    36     12.29       133.42
199994  56080425      12000          12000.0    36     12.69       402.54
199995  55909672      21000          21000.0    36     12.29       700.42
199996  54414556      27500          27500.0    60     14.65       649.19
199997  56109383       7000           7000.0    36     10.99       229.14

        grade                     emp_title  emp_length home_ownership  …  \
0          36                       leadman        10.0       MORTGAGE  …
1          30                      engineer        10.0       MORTGAGE  …
2          26                  truck driver        10.0       MORTGAGE  …
3          38  information systems officer        10.0       MORTGAGE  …
4          60           contract specialist         3.0       MORTGAGE  …
…         …                             …          …              …  …
199993     30                       teacher        10.0       MORTGAGE  …
```

```
199994     32                truck driver         1.0            RENT  …
199995     30                    attorney         8.0            RENT  …
199996     38                   hvac tech        10.0            RENT  …
199997     26       nursing office manager         7.0        MORTGAGE  …

        tax_liens tot_hi_cred_lim total_bal_ex_mort total_bc_limit  \
0               0          178050              7746           2400
1               0          314017             39475          79300
2               0          218418             18696           6200
3               0          381215             52226          62500
4               0          439570             95768          20300
…               …               …                 …              …
199993          0          194282             29295          24400
199994          0           32176             27413          13800
199995          0          181446            173683          15000
199996          0           53653             30750          18500
199997          0          134023             38802           4200

        total_il_high_credit_limit hardship_flag  debt_settlement_flag  \
0                            13734             N                     N
1                            24667             N                     N
2                            14877             N                     N
3                            18000             N                     N
4                            88097             N                     N
…                                …             …                     …
199993                        7000             N                     N
199994                        5784             N                     N
199995                      157346             N                     N
199996                       35153             N                     N
199997                       22492             N                     N

        diff credit pull credit line  diff payment credit line  \
0                             5691.0                    5632.0
1                             7030.0                    6027.0
2                             6786.0                    6148.0
3                             3833.0                    3805.0
4                             7213.0                    6605.0
…                                  …                         …
199993                        7915.0                    7670.0
199994                        4536.0                    4505.0
199995                        6179.0                    6148.0
199996                        4993.0                    5022.0
199997                       10347.0                   10135.0

        diff credit pull payment
0                           59.0
1                         1003.0
```

```
2                       638.0
3                        28.0
4                       608.0
…                         …
199993                  245.0
199994                   31.0
199995                   31.0
199996                  -29.0
199997                  212.0

[199998 rows x 93 columns]
```

[27]:
```
df.isna().any().sum()
```

[27]:
```
0
```

15 Summary of variables after clean up

[28]:
```
df.describe()
```

[28]:
```
                 id      loan_amnt  funded_amnt_inv           term  \
count  1.999980e+05  199998.000000    199998.000000  199998.000000
mean   6.229633e+07   15278.018530     15269.374289      43.842678
std    3.941125e+06    8651.048016      8646.233566      11.256878
min    5.670500e+04    1000.000000       900.000000      36.000000
25%    5.941173e+07    8500.000000      8475.000000      36.000000
50%    6.221753e+07   14000.000000     14000.000000      36.000000
75%    6.564457e+07   20000.000000     20000.000000      60.000000
max    6.861706e+07   35000.000000     35000.000000      60.000000

            int_rate    installment          grade     emp_length  \
count  199998.000000  199998.000000  199998.000000  199998.000000
mean       12.361711     441.381145      31.132161       5.509750
std         4.242075     247.050693      12.686827       4.106834
min         5.320000      14.770000      10.000000      -1.000000
25%         9.170000     261.880000      22.000000       2.000000
50%        12.290000     383.810000      30.000000       6.000000
75%        14.650000     580.730000      38.000000      10.000000
max        28.990000    1445.460000      78.000000      10.000000

         annual_inc       zip_code  …  percent_bc_gt_75  \
count  1.999980e+05  199998.000000  …     199998.000000
mean   7.815054e+04     507.370864  …         46.015581
std    8.051398e+04     309.216121  …         36.389153
min    0.000000e+00       7.000000  …         -1.000000
25%    4.756650e+04     231.000000  …         11.100000
```

```
50%     6.500000e+04      468.000000  …          50.000000
75%     9.340000e+04      797.000000  …          75.000000
max     9.000000e+06      999.000000  …         100.000000

       pub_rec_bankruptcies      tax_liens  tot_hi_cred_lim  \
count         199998.000000  199998.000000     1.999980e+05
mean               0.132301       0.064336     1.770256e+05
std                0.384264       0.465649     1.779942e+05
min                0.000000       0.000000     2.500000e+03
25%                0.000000       0.000000     5.220500e+04
50%                0.000000       0.000000     1.151875e+05
75%                0.000000       0.000000     2.551105e+05
max                9.000000      85.000000     9.999999e+06

       total_bal_ex_mort  total_bc_limit  total_il_high_credit_limit  \
count       1.999980e+05   199998.000000                1.999980e+05
mean        5.281753e+04    22585.728182                4.413560e+04
std         4.949148e+04    22346.885365                4.447859e+04
min         0.000000e+00        0.000000                0.000000e+00
25%         2.273600e+04     8000.000000                1.585025e+04
50%         4.006900e+04    15700.000000                3.357550e+04
75%         6.665450e+04    29500.000000                5.921300e+04
max         2.652799e+06   834300.000000                2.101913e+06

       diff credit pull credit line  diff payment credit line  \
count                 199998.000000             199998.000000
mean                    7116.756833               6838.951250
std                     3029.208281               3054.193244
min                   -19390.000000             -19390.000000
25%                     5264.000000               4960.000000
50%                     6664.000000               6390.000000
75%                     8644.000000               8401.000000
max                    18321.000000              18262.000000

       diff credit pull payment
count             199998.000000
mean                 273.524955
std                  313.447481
min                -1308.000000
25%                    0.000000
50%                  181.000000
75%                  457.000000
max                 1311.000000

[8 rows x 83 columns]
```

[29]:
```
df[df.columns[df.dtypes == "O"]].describe().T
```

[29]:

	count	unique	top	freq
emp_title	199998	53276	-1	12130
home_ownership	199998	4	MORTGAGE	99617
verification_status	199998	3	Source Verified	84755
loan_status	199998	6	Fully Paid	140991
pymnt_plan	199998	2	n	199976
addr_state	199998	49	CA	27304
initial_list_status	199998	2	w	142654
application_type	199998	2	Individual	199487
hardship_flag	199998	2	N	199967
debt_settlement_flag	199998	2	N	194158

16 For the sake of the exercise, if the title appears 200 times, which is 1/1000 of the dataset, create a dummy variable for that title

[30]:
```
len(df)/1000
```

[30]: 199.998

[31]:
```
counts = pd.value_counts(df['emp_title'])
mask = df['emp_title'].isin(counts[counts > 200].index)
dummies = pd.get_dummies(df['emp_title'][mask], prefix='emp_title')
df = pd.concat([df, dummies], axis=1).fillna(0)
dummies
```

[31]:

	emp_title_-1	emp_title_account executive	emp_title_account manager \
1	0	0	0
2	0	0	0
8	0	0	0
10	0	0	0
14	0	0	0
…	…	…	…
199986	0	0	0
199990	0	0	0
199993	0	0	0
199994	0	0	0
199995	0	0	0

	emp_title_accountant	emp_title_accounting manager \
1	0	0
2	0	0
8	0	0
10	0	0
14	0	0
…	…	…

```
199986                          0                            0
199990                          0                            0
199993                          0                            0
199994                          0                            0
199995                          0                            0

        emp_title_administrative assistant  emp_title_administrator  \
1                                        0                        0
2                                        0                        0
8                                        0                        0
10                                       0                        0
14                                       0                        0
…                                      …                      …
199986                                   0                        0
199990                                   0                        0
199993                                   0                        0
199994                                   0                        0
199995                                   0                        0

        emp_title_analyst  emp_title_assistant manager  emp_title_associate  \
1                       0                            0                    0
2                       0                            0                    0
8                       0                            0                    0
10                      0                            0                    0
14                      0                            0                    0
…                     …                          …                  …
199986                  0                            0                    0
199990                  0                            0                    0
199993                  0                            0                    0
199994                  0                            0                    0
199995                  0                            0                    0

        …  emp_title_supervisor  emp_title_teacher  emp_title_team leader  \
1       …                     0                  0                      0
2       …                     0                  0                      0
8       …                     0                  0                      0
10      …                     0                  0                      0
14      …                     0                  0                      0
…     …                   …                …                    …
199986  …                     1                  0                      0
199990  …                     0                  0                      0
199993  …                     0                  1                      0
199994  …                     0                  0                      0
199995  …                     0                  0                      0

        emp_title_tech  emp_title_technician  emp_title_truck driver  \
1                    0                     0                       0
```

```
2                         0                         0                           1
8                         0                         0                           0
10                        0                         0                           0
14                        0                         0                           0
…                     …                       …                          …
199986                    0                         0                           0
199990                    0                         0                           0
199993                    0                         0                           0
199994                    0                         0                           1
199995                    0                         0                           0

        emp_title_underwriter  emp_title_vice president  emp_title_vp  \
1                           0                          0             0
2                           0                          0             0
8                           0                          0             0
10                          0                          0             0
14                          0                          0             0
…                         …                        …            …
199986                      0                          0             0
199990                      0                          0             0
199993                      0                          0             0
199994                      0                          0             0
199995                      0                          0             0

        emp_title_welder
1                      0
2                      0
8                      0
10                     0
14                     0
…                    …
199986                 0
199990                 0
199993                 0
199994                 0
199995                 0

[72084 rows x 97 columns]
```

[32]:

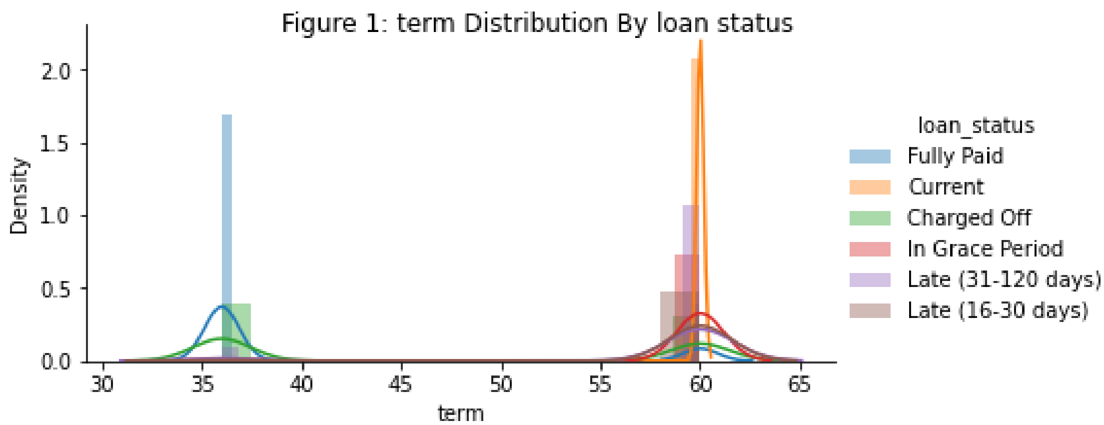
```
# list(df.select_dtypes(exclude='O').columns.values)
colnames = ['term',
 'int_rate',
 'grade',
 'emp_length',
 'dti',
 'delinq_2yrs',
 'inq_last_6mths',
```

```
 'mths_since_last_delinq',
 'open_acc',
 'pub_rec',
 'total_rec_late_fee',
 'last_pymnt_d',
 'last_credit_pull_d',
 'collections_12_mths_ex_med',
 'mths_since_last_major_derog',
 'policy_code',
 'acc_now_delinq',
 'acc_open_past_24mths',
 'bc_open_to_buy',
 'bc_util',
 'chargeoff_within_12_mths',
 'mo_sin_rcnt_rev_tl_op',
 'mo_sin_rcnt_tl',
 'mort_acc',
 'mths_since_recent_bc',
 'mths_since_recent_bc_dlq',
 'mths_since_recent_inq',
 'mths_since_recent_revol_delinq',
 'num_accts_ever_120_pd',
 'num_actv_bc_tl',
 'num_actv_rev_tl',
 'num_bc_sats',
 'num_bc_tl',
 'num_il_tl',
 'num_op_rev_tl',
 'num_rev_accts',
 'num_rev_tl_bal_gt_0',
 'num_sats',
 'num_tl_120dpd_2m',
 'num_tl_30dpd',
 'num_tl_90g_dpd_24m',
 'num_tl_op_past_12m',
 'pct_tl_nvr_dlq',
 'percent_bc_gt_75',
 'pub_rec_bankruptcies',
 'tax_liens']
len(colnames)
```

[32]: 46

17 For the continuous variables, plot the distribution by loan status

[33]:
```
plt.rcParams['figure.max_open_warning']=40
# colnames=list(df.select_dtypes(exclude='O').columns.values)
for i in colnames[0:]:
    facet = sns.FacetGrid(df,hue='loan_status',aspect=2)
    facet.map(sns.distplot,i)
    facet.add_legend()
    facet.fig.suptitle(''.join(map(str, list(["Figure ",colnames.index(i)+1,":␣
↪",i," Distribution By loan status"]))))
    plt.show()
```



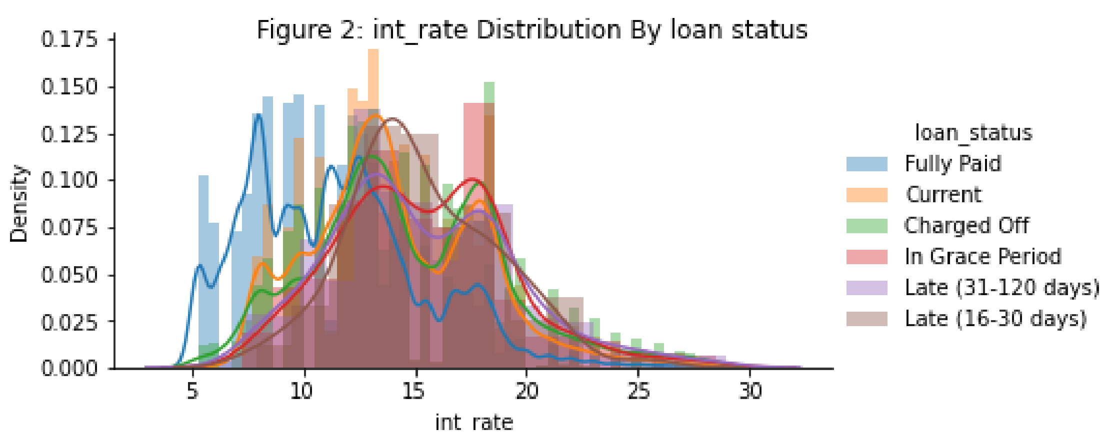


Figure 3: grade Distribution By loan status

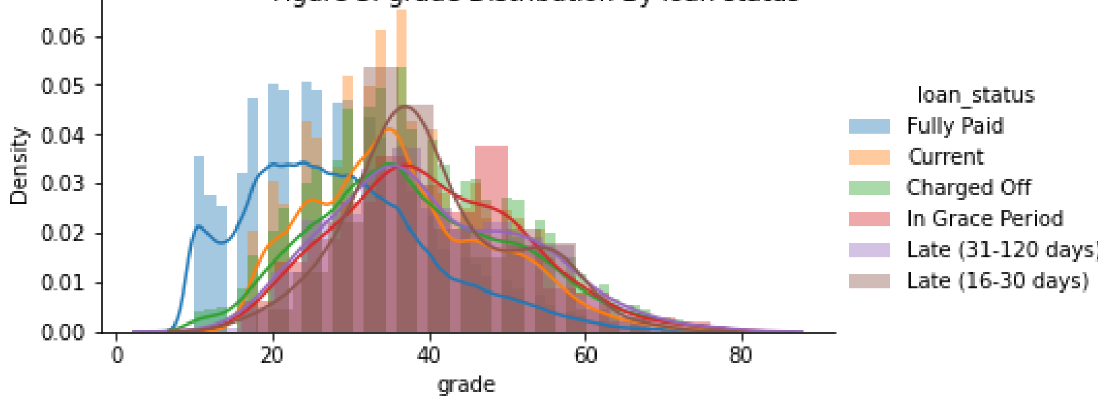


Figure 4: emp_length Distribution By loan status

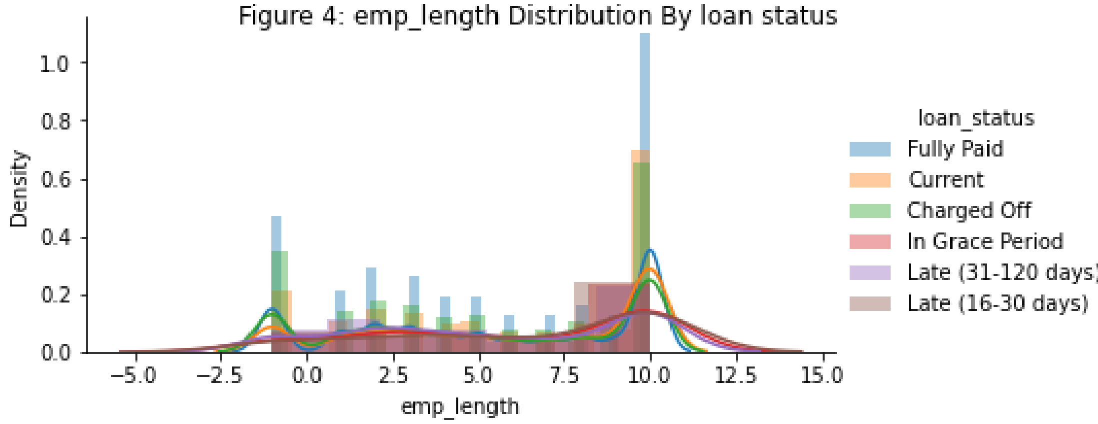
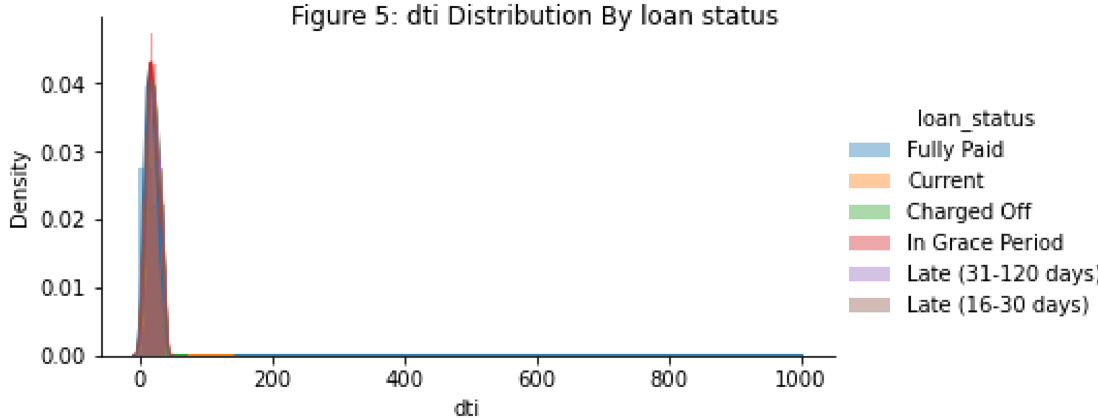


Figure 5: dti Distribution By loan status



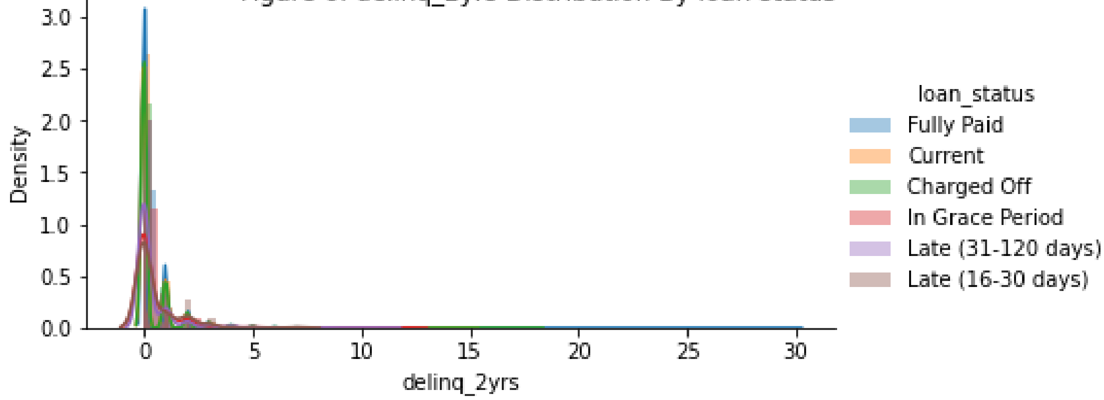


Figure 6: delinq_2yrs Distribution By loan status

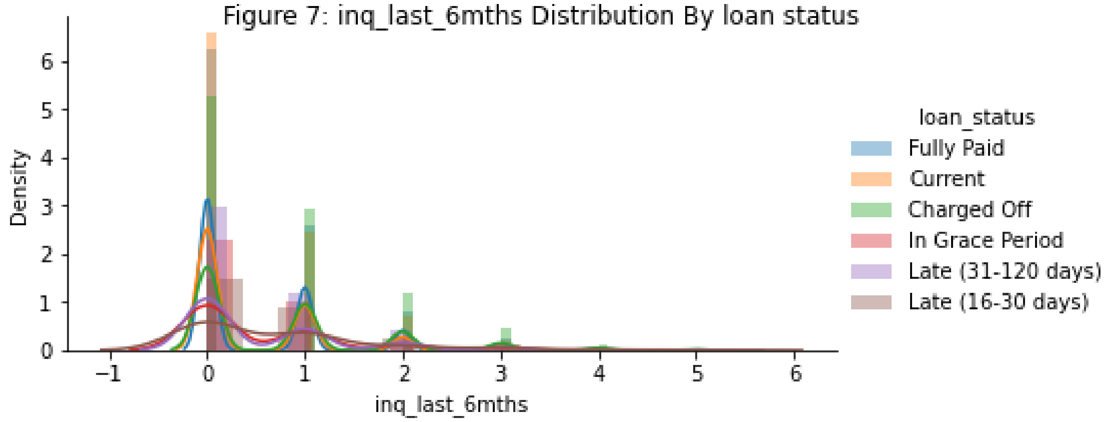


Figure 7: inq_last_6mths Distribution By loan status

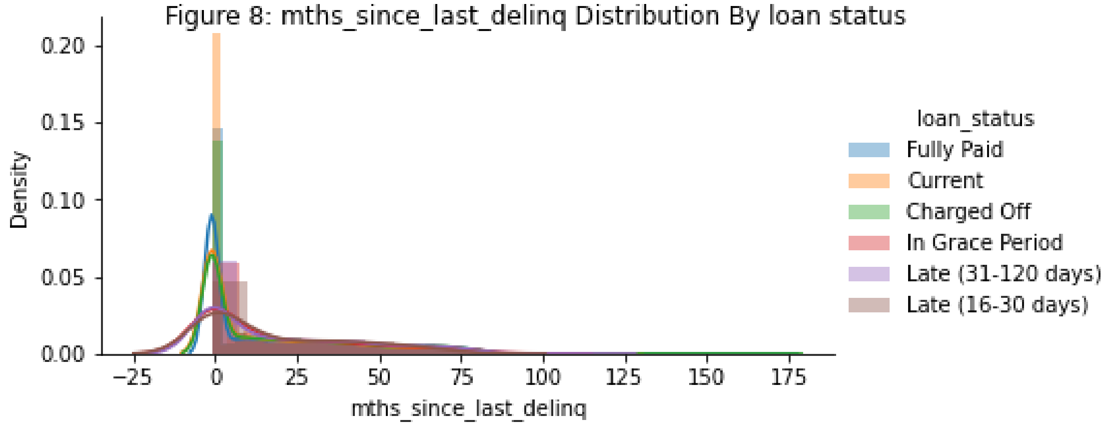


Figure 8: mths_since_last_delinq Distribution By loan status

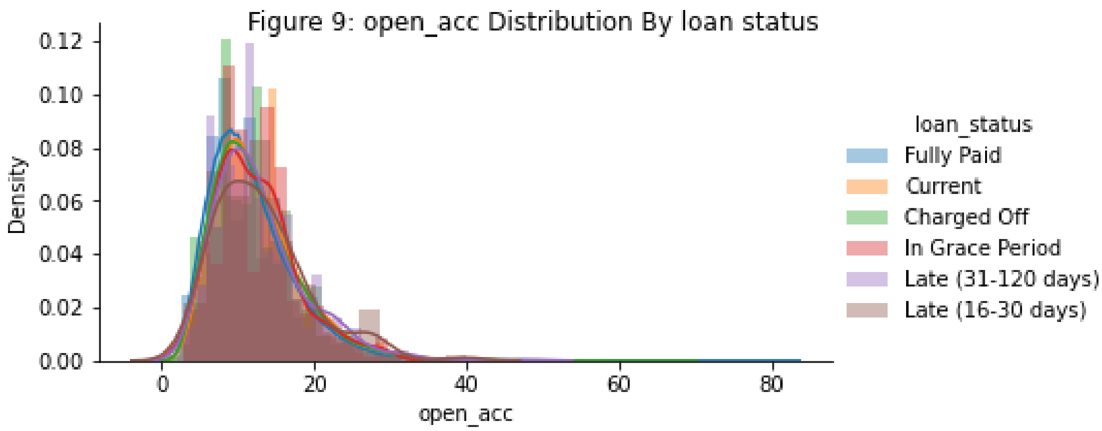


Figure 9: open_acc Distribution By loan status
Density
open_acc
loan_status
Fully Paid
Current
Charged Off
In Grace Period
Late (31-120 days)
Late (16-30 days)

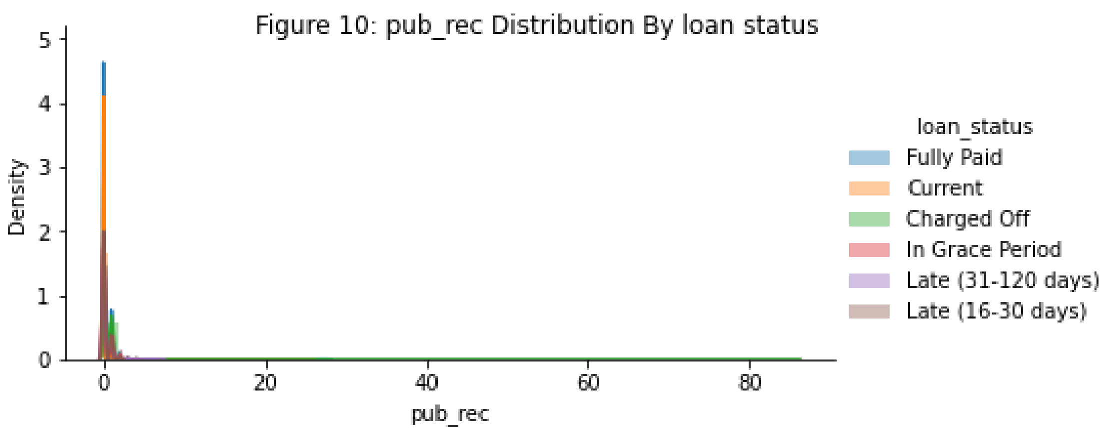


Figure 10: pub_rec Distribution By loan status
Density
pub_rec
loan_status
Fully Paid
Current
Charged Off
In Grace Period
Late (31-120 days)
Late (16-30 days)

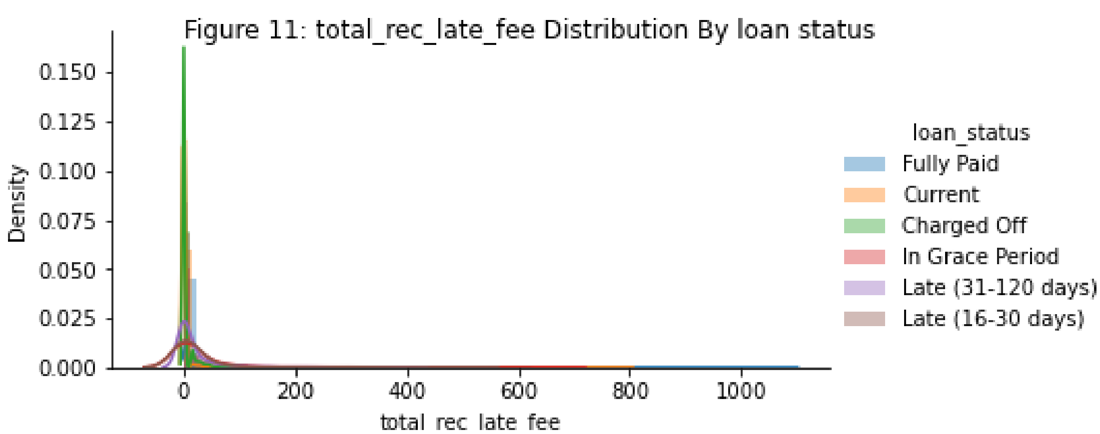


Figure 11: total_rec_late_fee Distribution By loan status
Density
total_rec_late_fee
loan_status
Fully Paid
Current
Charged Off
In Grace Period
Late (31-120 days)
Late (16-30 days)

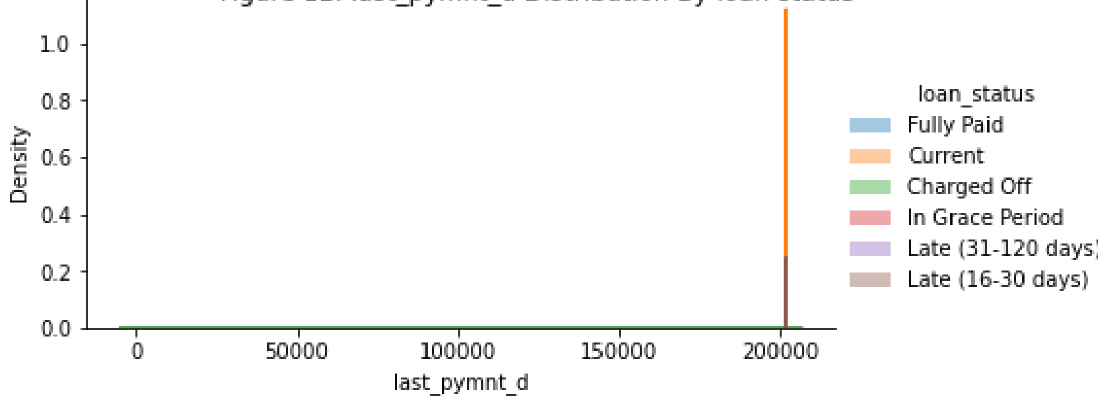


Figure 12: last_pymnt_d Distribution By loan status

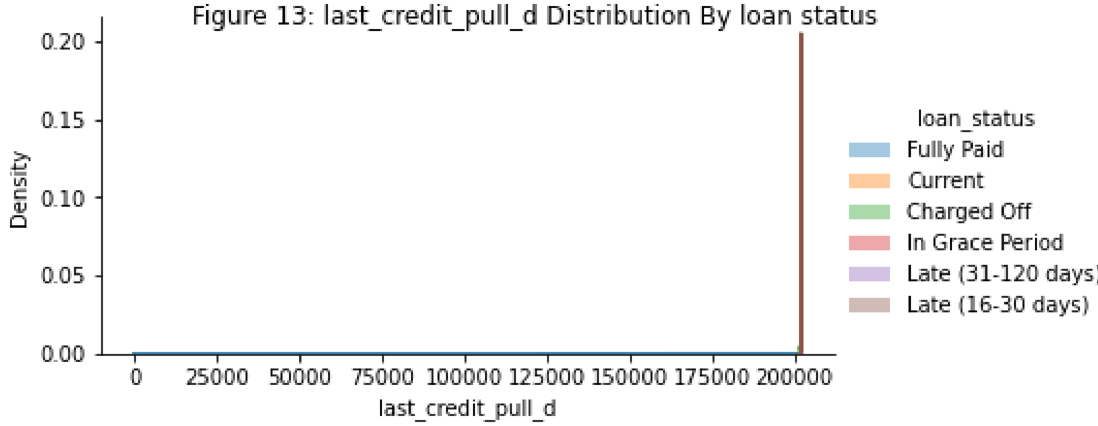


Figure 13: last_credit_pull_d Distribution By loan status

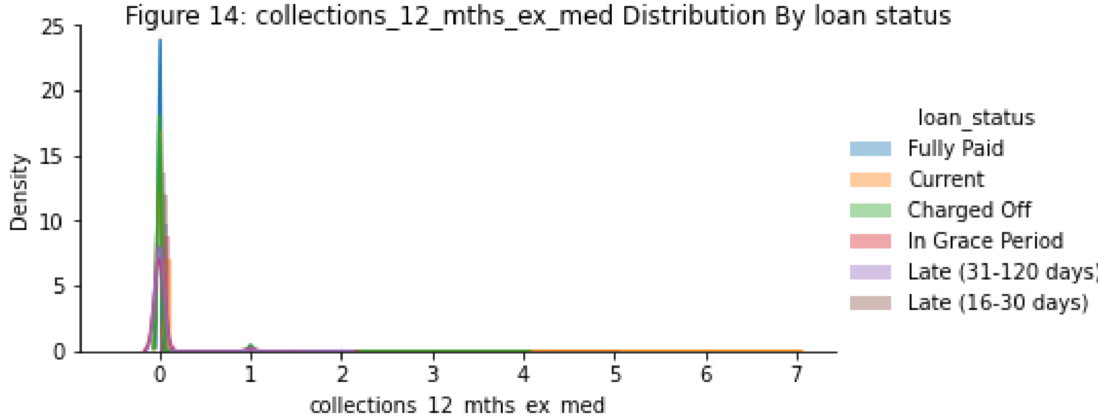


Figure 14: collections_12_mths_ex_med Distribution By loan status

Figure 15: mths_since_last_major_derog Distribution By loan status

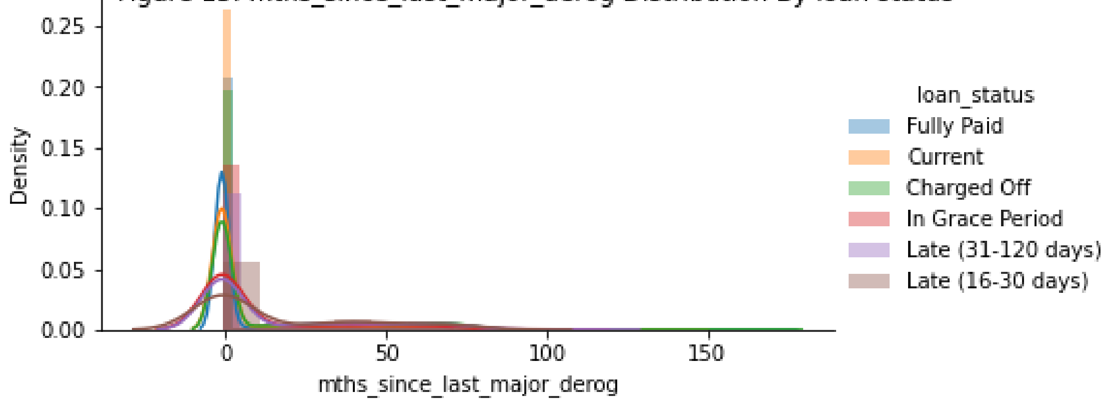


Figure 16: policy_code Distribution By loan status

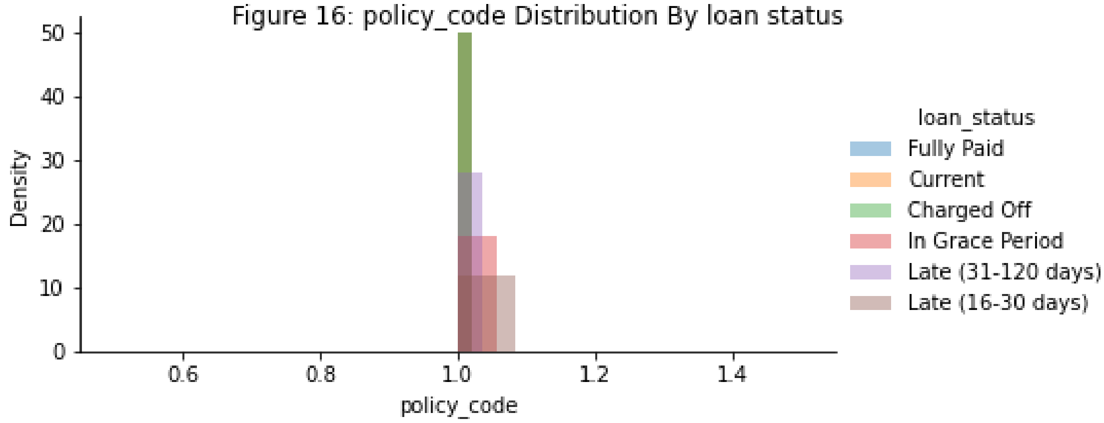
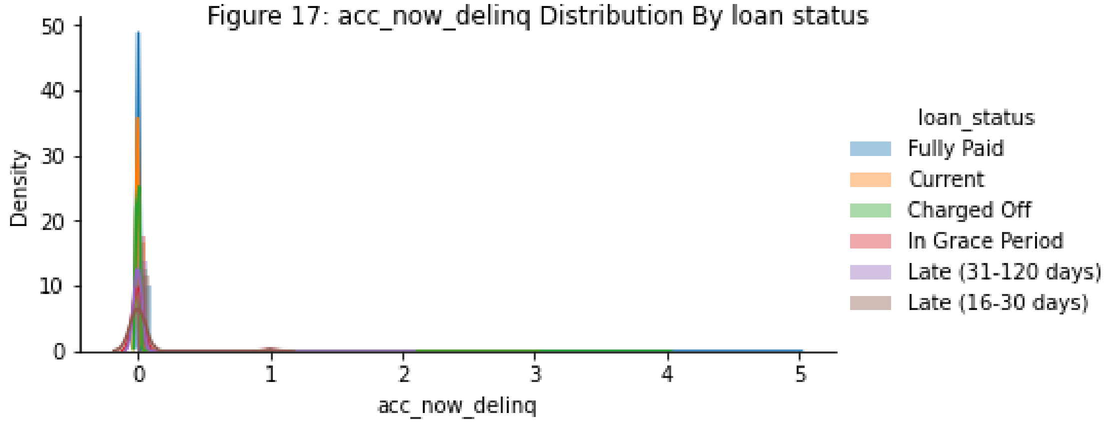


Figure 17: acc_now_delinq Distribution By loan status



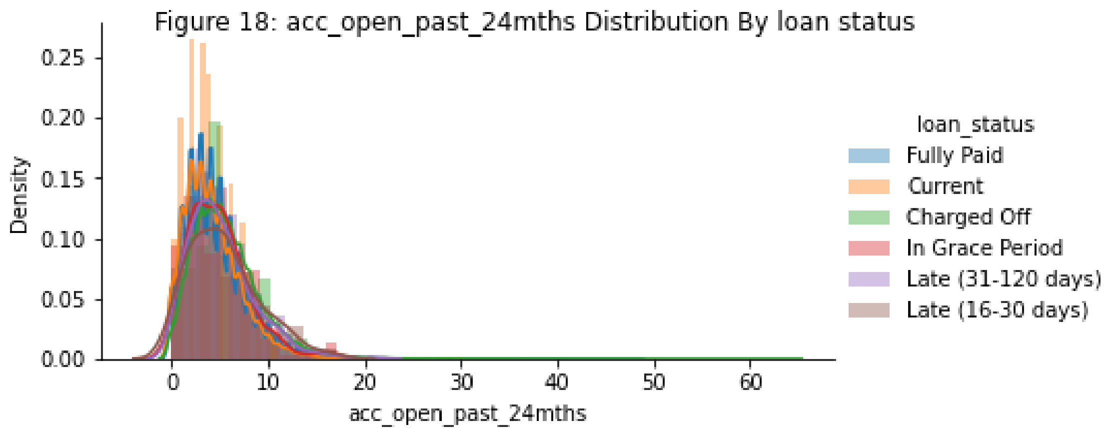


Figure 18: acc_open_past_24mths Distribution By loan status
Density
0.25
0.20
0.15
0.10
0.05
0.00
0
10
20
30
40
50
60
acc_open_past_24mths
loan_status
Fully Paid
Current
Charged Off
In Grace Period
Late (31-120 days)
Late (16-30 days)

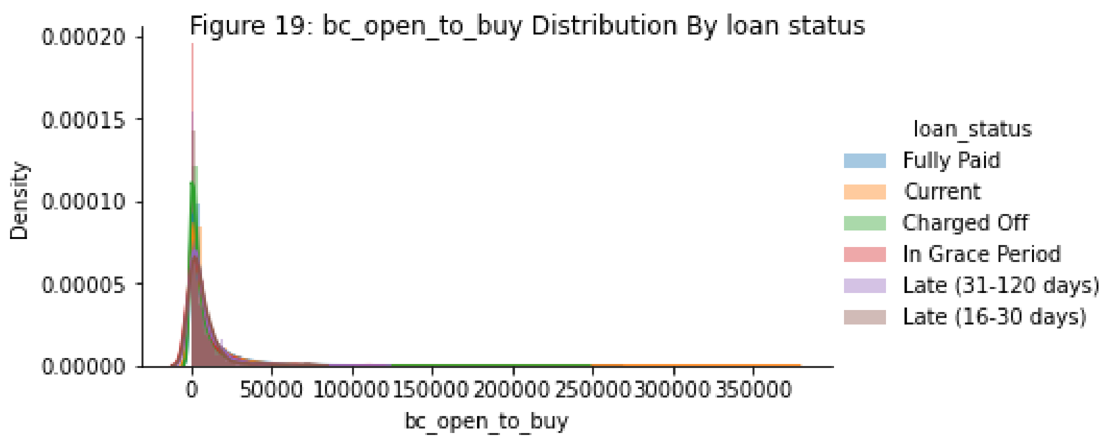


Figure 19: bc_open_to_buy Distribution By loan status
Density
0.00020
0.00015
0.00010
0.00005
0.00000
0
50000
100000
150000
200000
250000
300000
350000
bc_open_to_buy
loan_status
Fully Paid
Current
Charged Off
In Grace Period
Late (31-120 days)
Late (16-30 days)

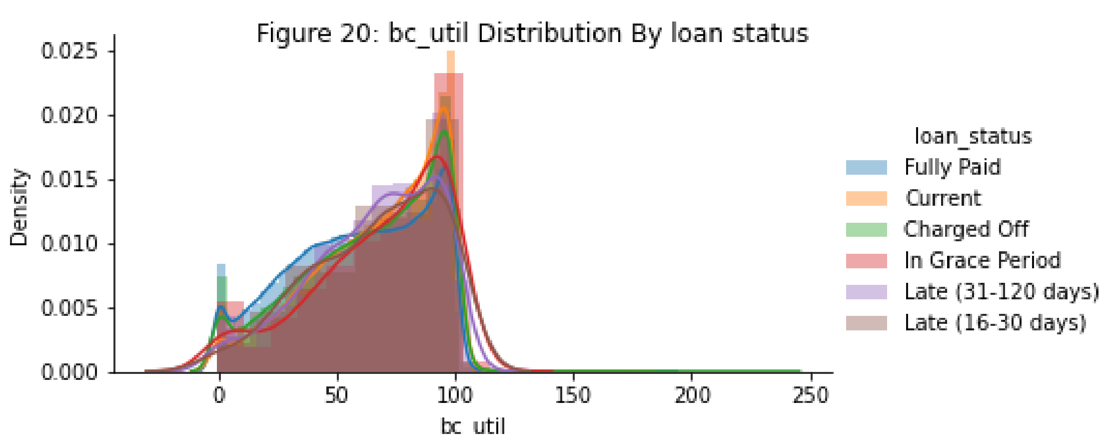


Figure 20: bc_util Distribution By loan status
Density
0.025
0.020
0.015
0.010
0.005
0.000
0
50
100
150
200
250
bc_util
loan_status
Fully Paid
Current
Charged Off
In Grace Period
Late (31-120 days)
Late (16-30 days)

Figure 21: chargeoff_within_12_mths Distribution By loan status

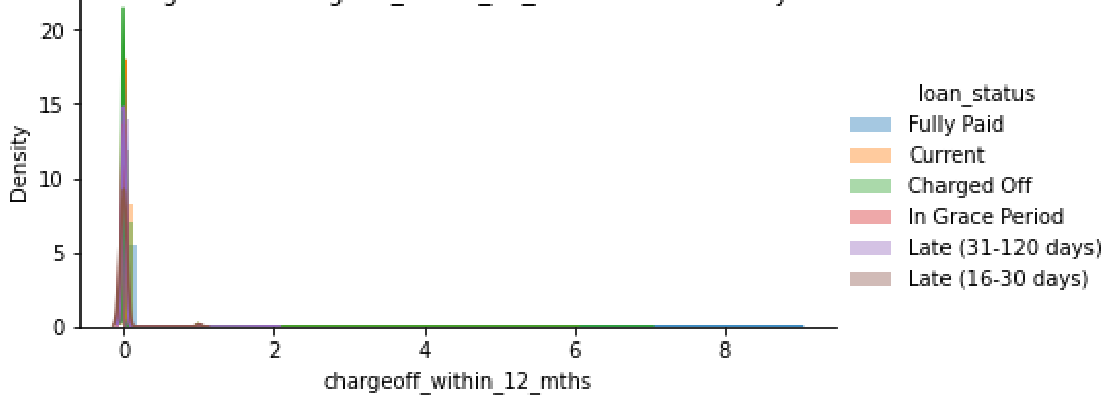


Figure 22: mo_sin_rcnt_rev_tl_op Distribution By loan status

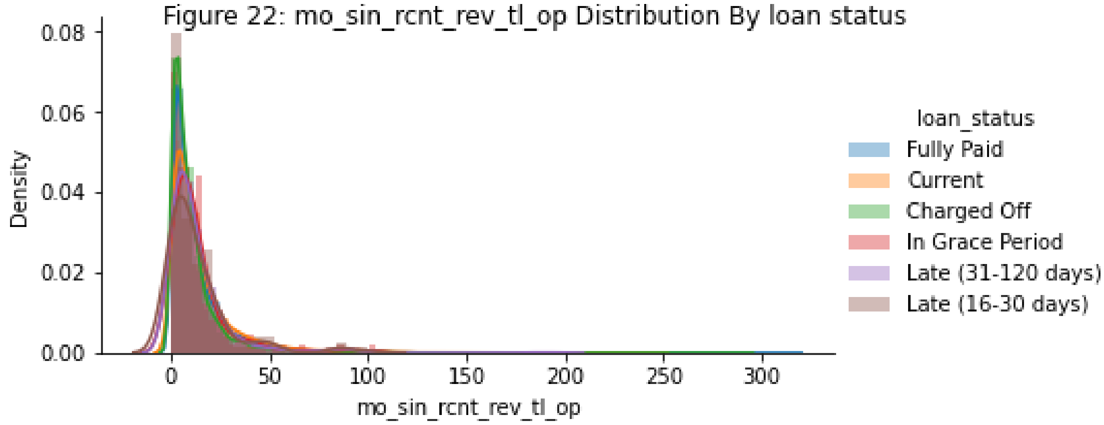


Figure 23: mo_sin_rcnt_tl Distribution By loan status

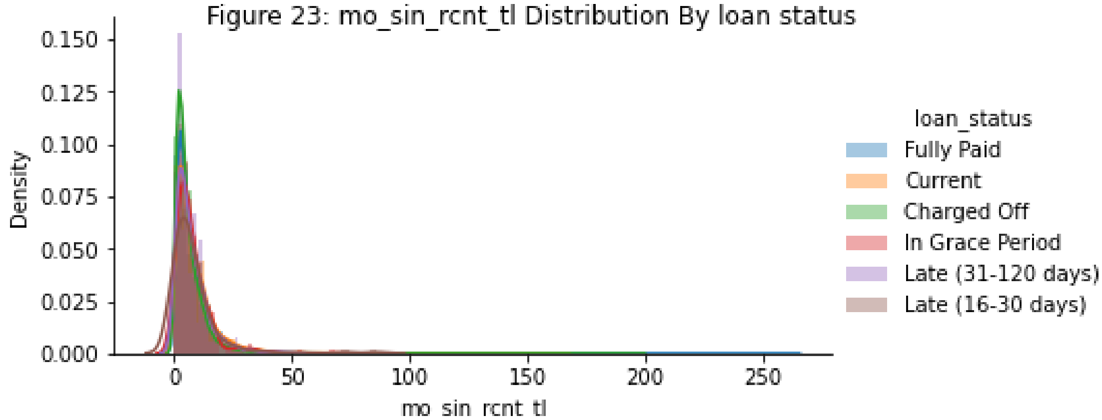


Figure 24: mort_acc Distribution By loan status

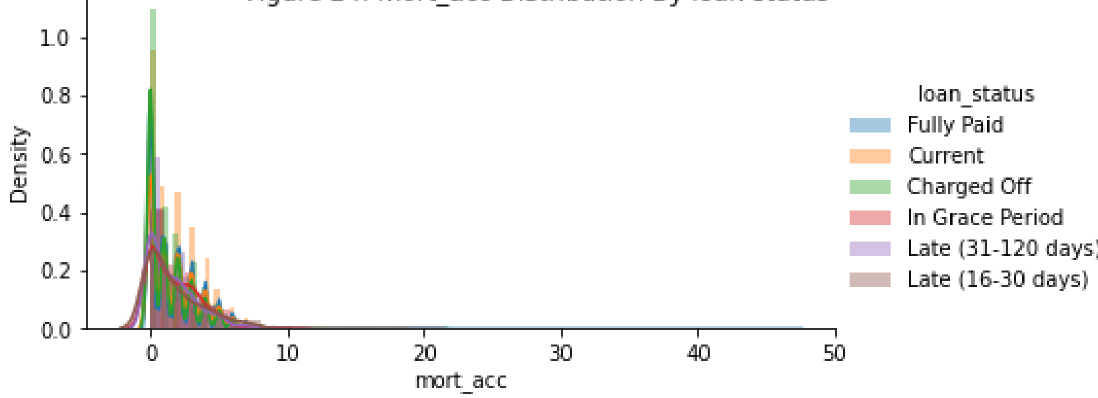


Figure 25: mths_since_recent_bc Distribution By loan status

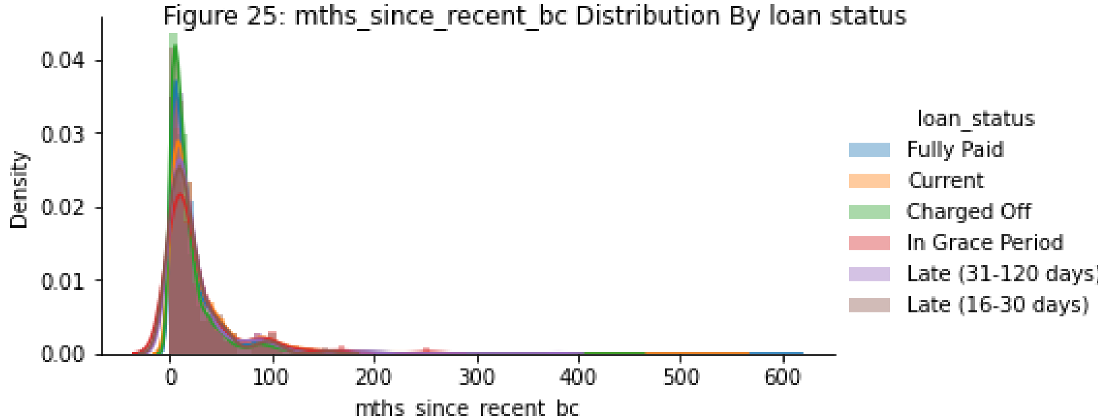
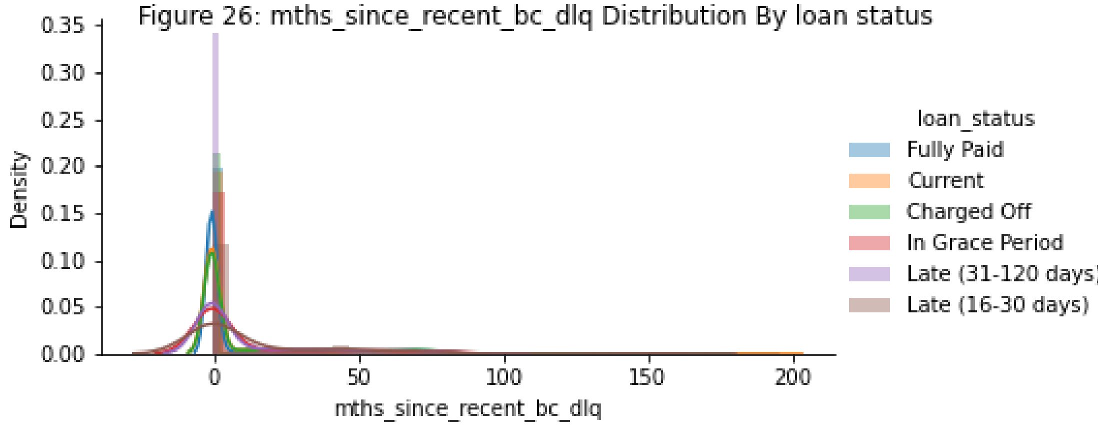


Figure 26: mths_since_recent_bc_dlq Distribution By loan status



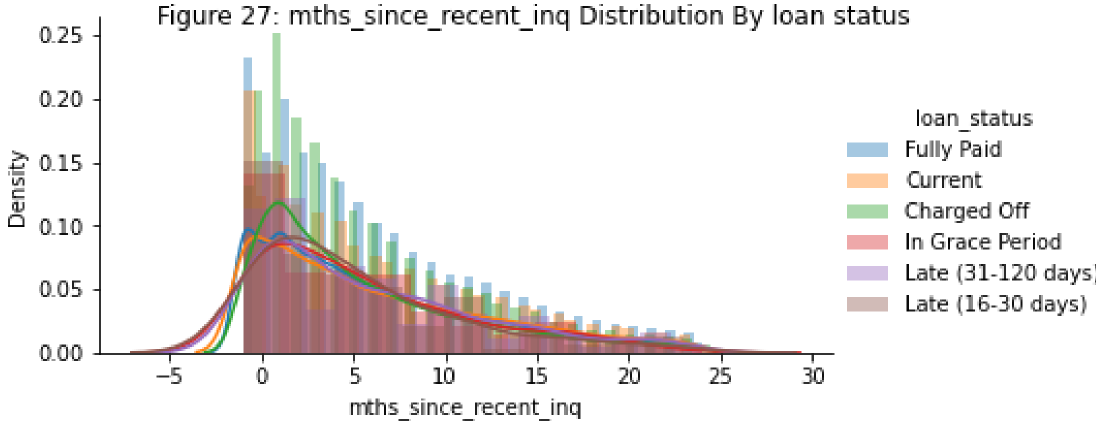


Figure 27: mths_since_recent_inq Distribution By loan status

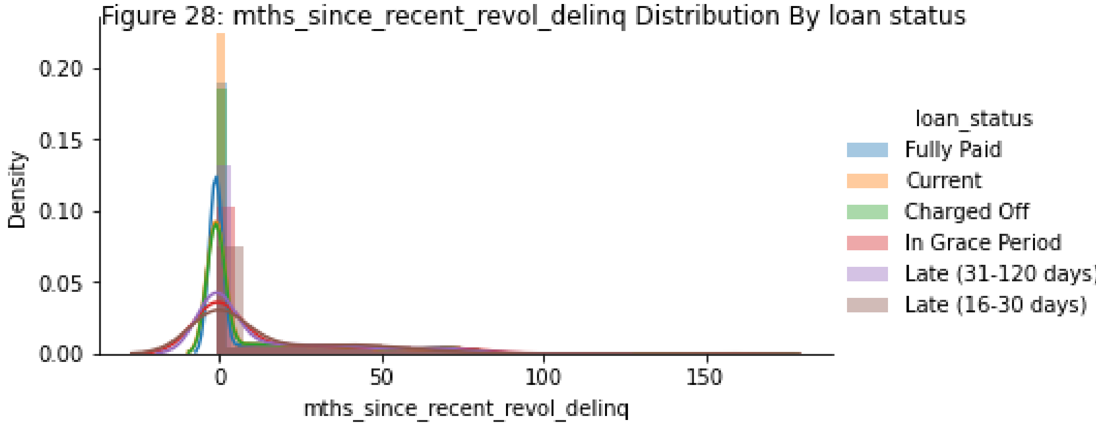


Figure 28: mths_since_recent_revol_delinq Distribution By loan status

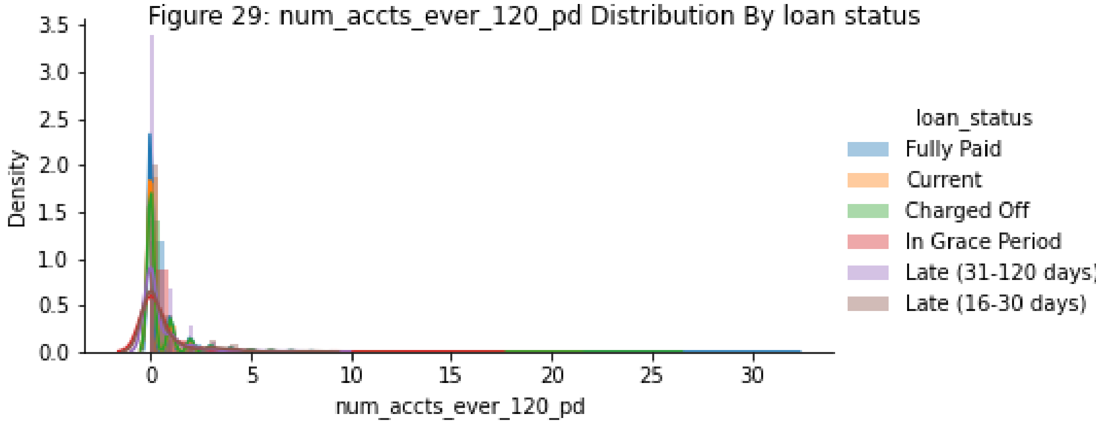


Figure 29: num_accts_ever_120_pd Distribution By loan status

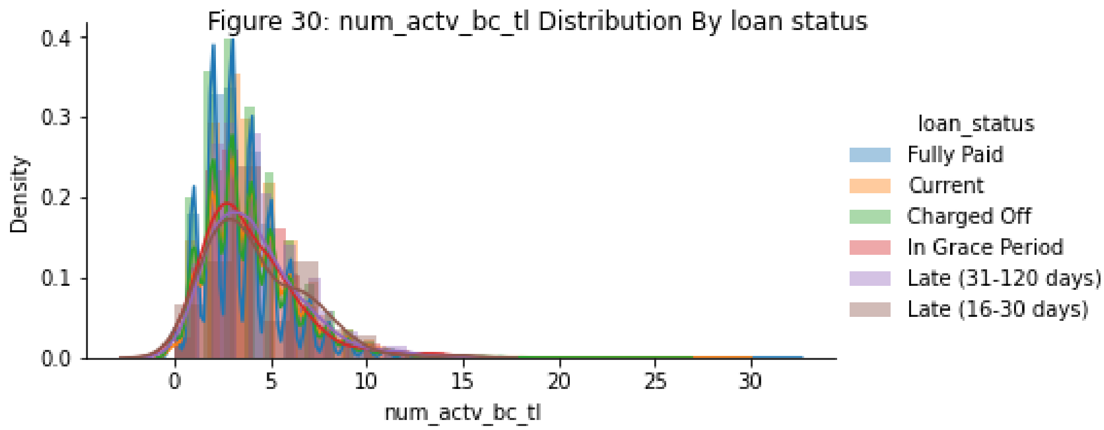


Figure 30: num_actv_bc_tl Distribution By loan status
Density
num_actv_bc_tl
loan_status
Fully Paid
Current
Charged Off
In Grace Period
Late (31-120 days)
Late (16-30 days)

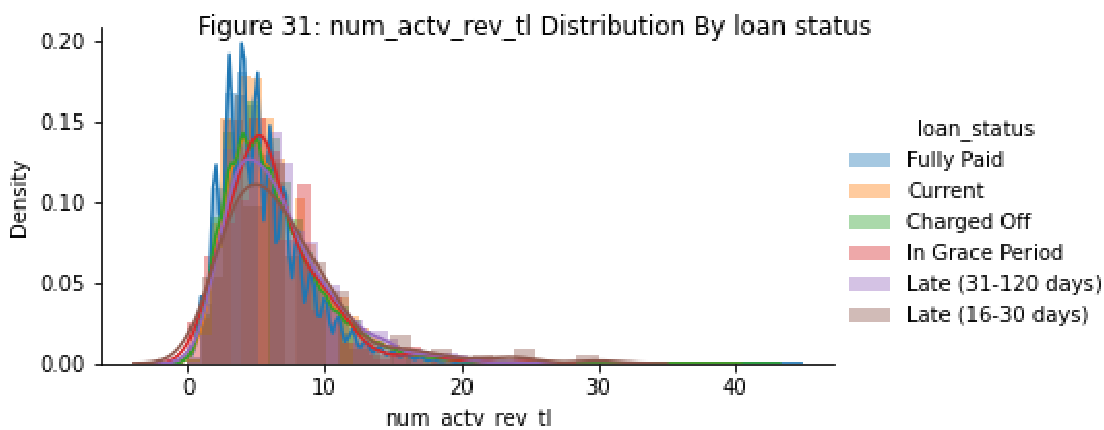


Figure 31: num_actv_rev_tl Distribution By loan status
Density
num_actv_rev_tl
loan_status
Fully Paid
Current
Charged Off
In Grace Period
Late (31-120 days)
Late (16-30 days)

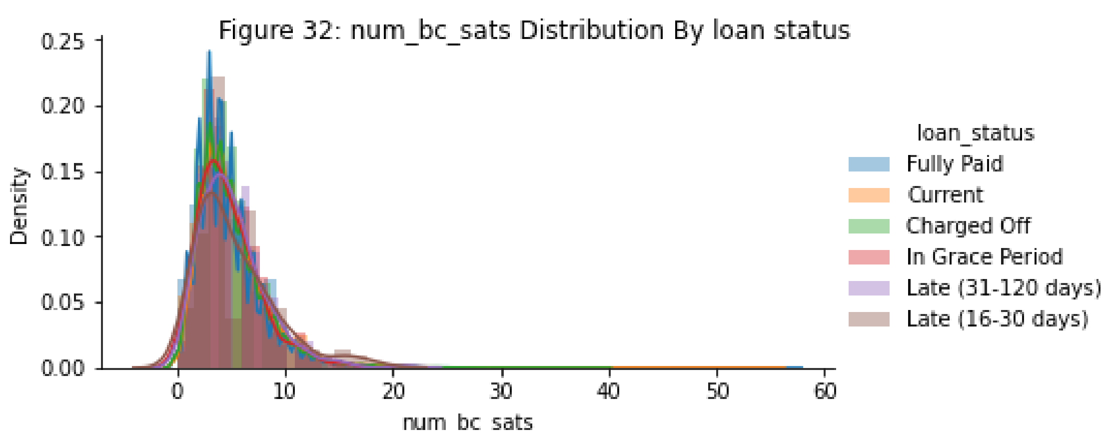


Figure 32: num_bc_sats Distribution By loan status
Density
num_bc_sats
loan_status
Fully Paid
Current
Charged Off
In Grace Period
Late (31-120 days)
Late (16-30 days)

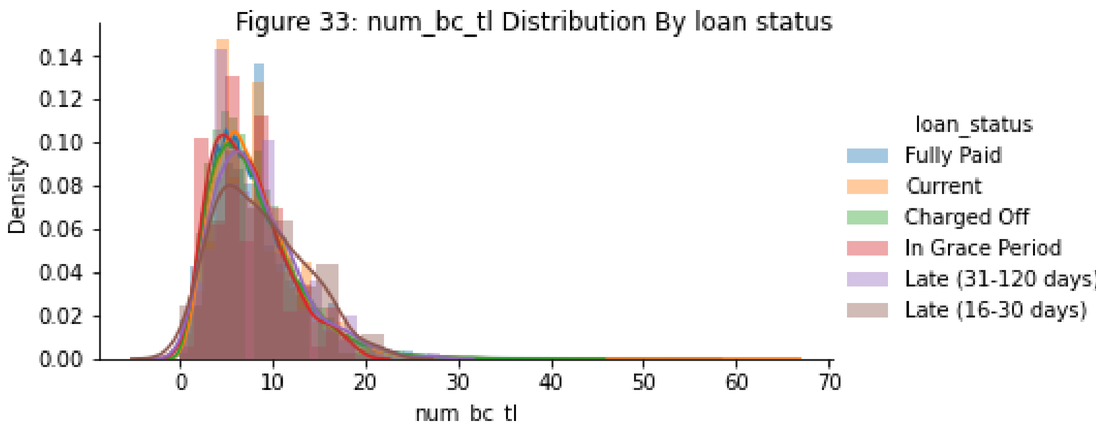


Figure 33: num_bc_tl Distribution By loan status
Density
num_bc_tl
loan_status
Fully Paid
Current
Charged Off
In Grace Period
Late (31-120 days)
Late (16-30 days)

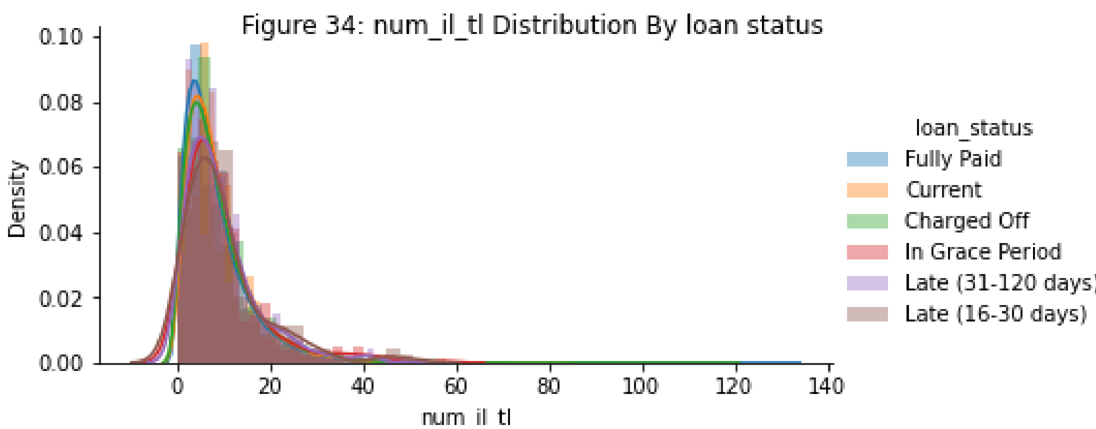


Figure 34: num_il_tl Distribution By loan status
Density
num_il_tl
loan_status
Fully Paid
Current
Charged Off
In Grace Period
Late (31-120 days)
Late (16-30 days)

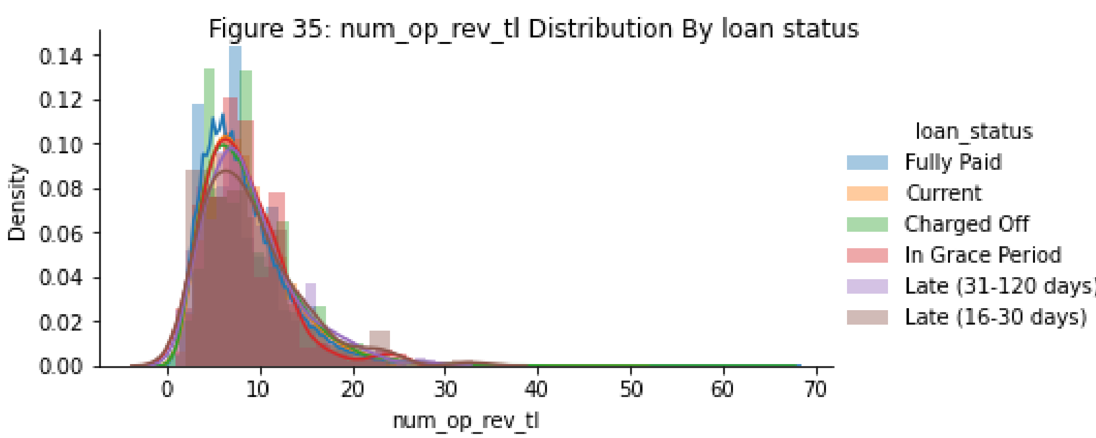


Figure 35: num_op_rev_tl Distribution By loan status
Density
num_op_rev_tl
loan_status
Fully Paid
Current
Charged Off
In Grace Period
Late (31-120 days)
Late (16-30 days)

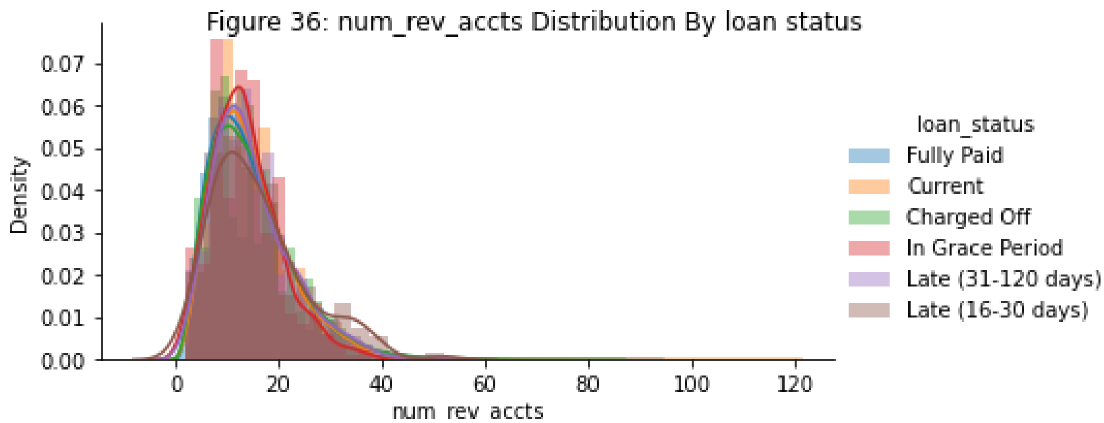


Figure 36: num_rev_accts Distribution By loan status
Density
0.00
0.01
0.02
0.03
0.04
0.05
0.06
0.07
0
20
40
60
80
100
120
num_rev_accts
loan_status
Fully Paid
Current
Charged Off
In Grace Period
Late (31-120 days)
Late (16-30 days)

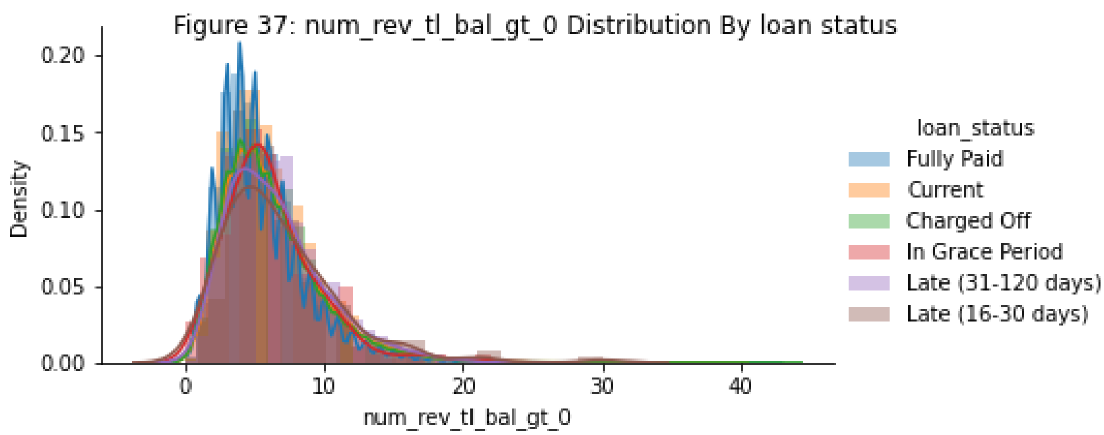


Figure 37: num_rev_tl_bal_gt_0 Distribution By loan status
Density
0.00
0.05
0.10
0.15
0.20
0
10
20
30
40
num_rev_tl_bal_gt_0
loan_status
Fully Paid
Current
Charged Off
In Grace Period
Late (31-120 days)
Late (16-30 days)

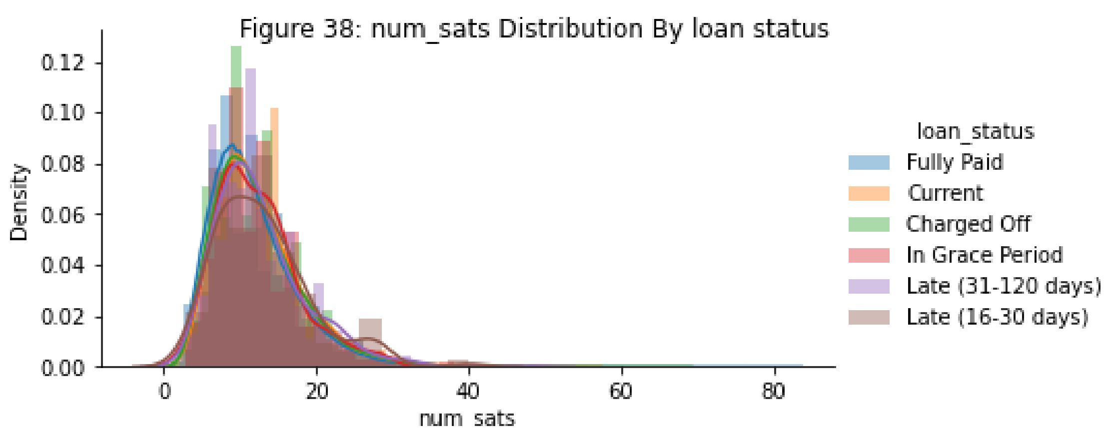


Figure 38: num_sats Distribution By loan status
Density
0.00
0.02
0.04
0.06
0.08
0.10
0.12
0
20
40
60
80
num_sats
loan_status
Fully Paid
Current
Charged Off
In Grace Period
Late (31-120 days)
Late (16-30 days)

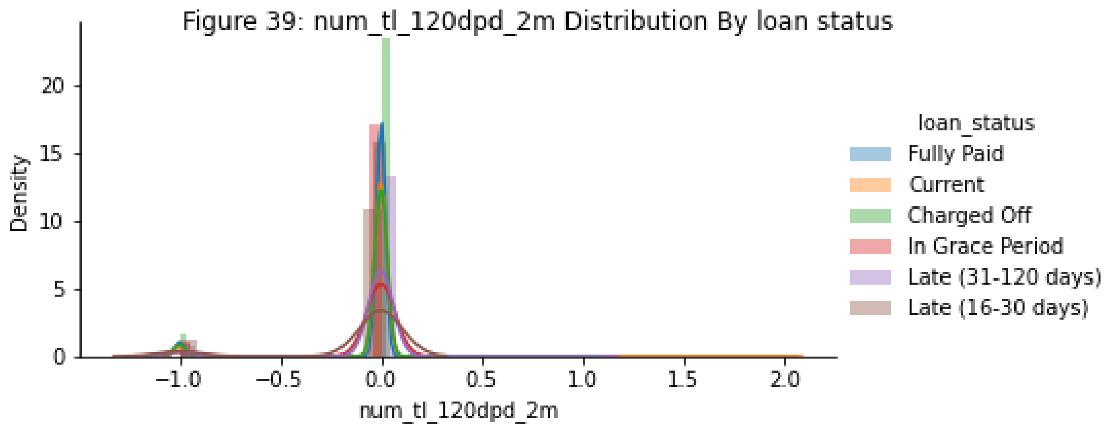


Figure 39: num_tl_120dpd_2m Distribution By loan status
Density
num_tl_120dpd_2m
loan_status
Fully Paid
Current
Charged Off
In Grace Period
Late (31-120 days)
Late (16-30 days)

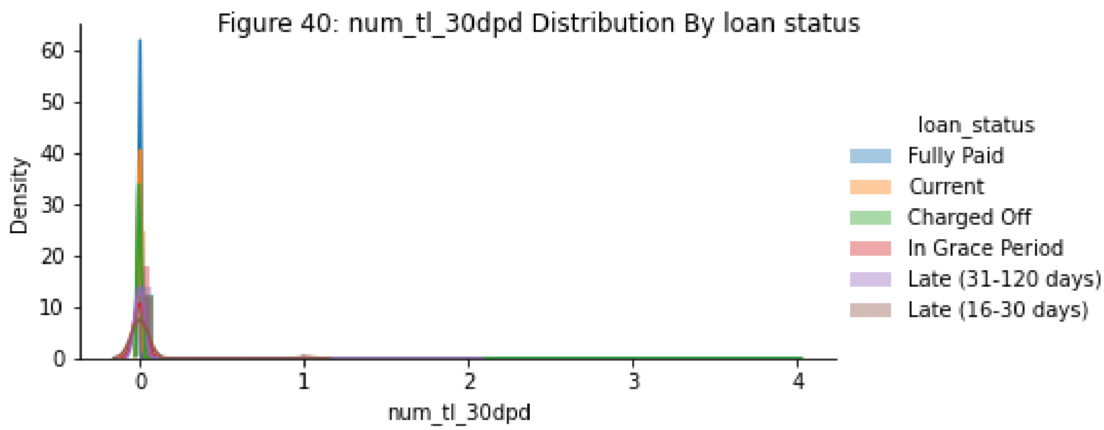


Figure 40: num_tl_30dpd Distribution By loan status
Density
num_tl_30dpd
loan_status
Fully Paid
Current
Charged Off
In Grace Period
Late (31-120 days)
Late (16-30 days)

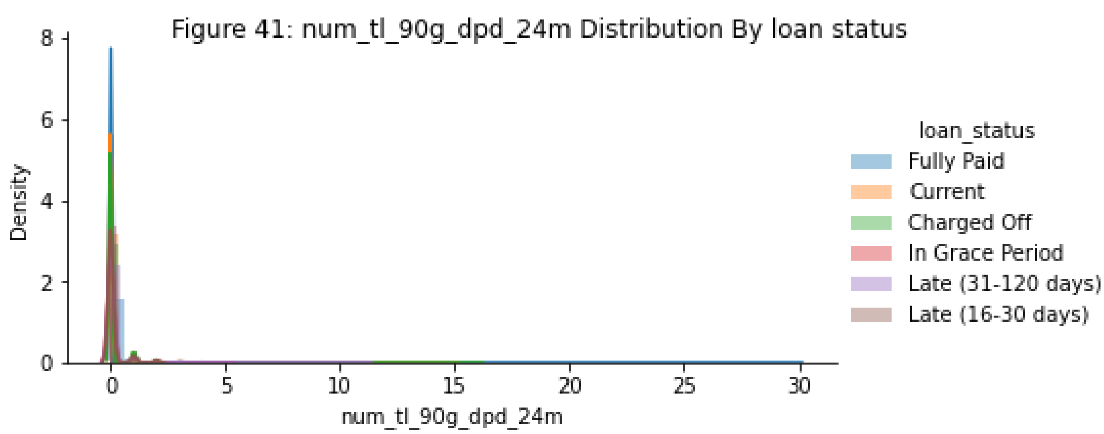


Figure 41: num_tl_90g_dpd_24m Distribution By loan status
Density
num_tl_90g_dpd_24m
loan_status
Fully Paid
Current
Charged Off
In Grace Period
Late (31-120 days)
Late (16-30 days)

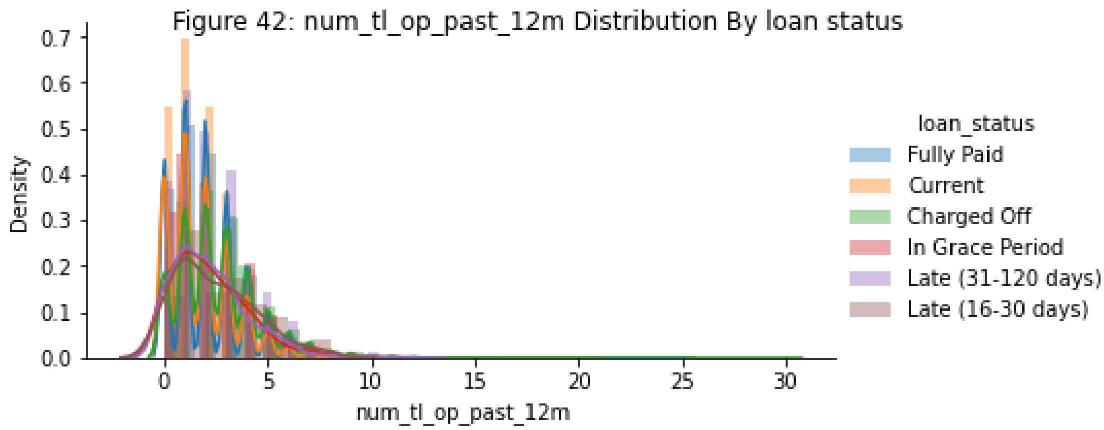


Figure 42: num_tl_op_past_12m Distribution By loan status

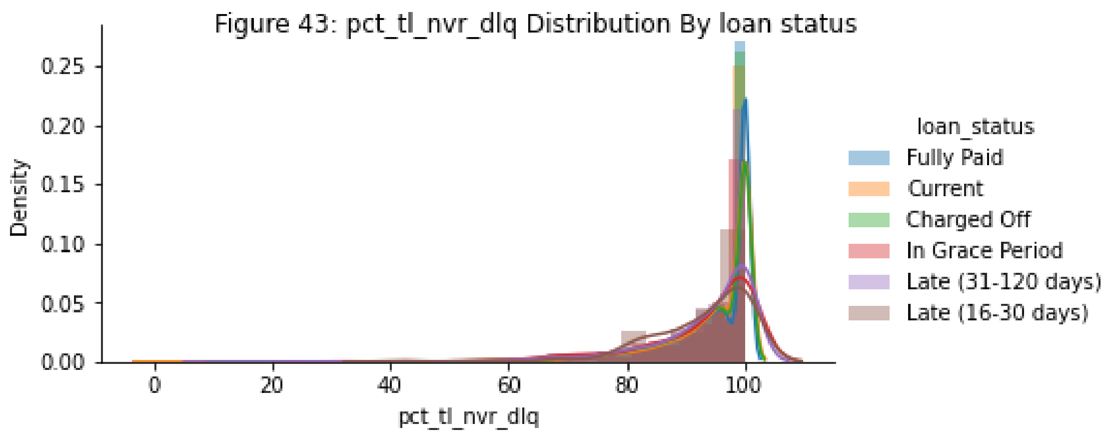


Figure 43: pct_tl_nvr_dlq Distribution By loan status

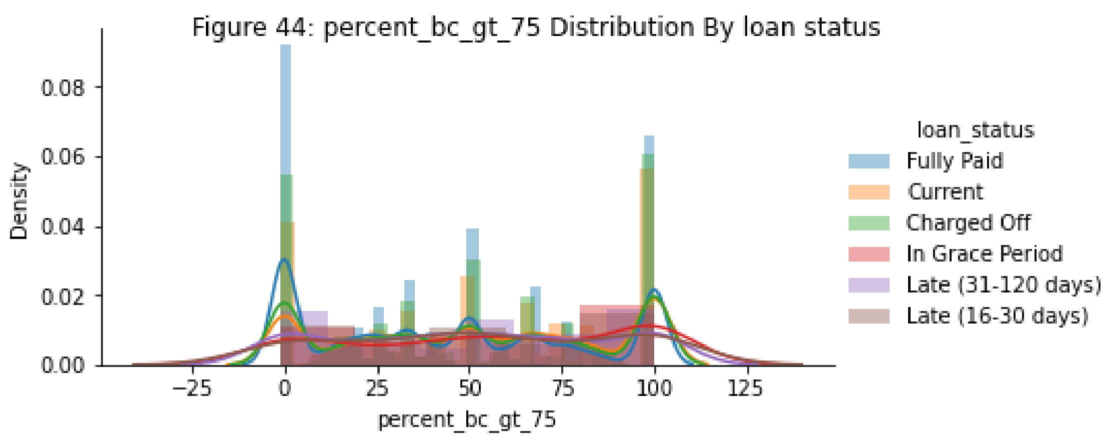
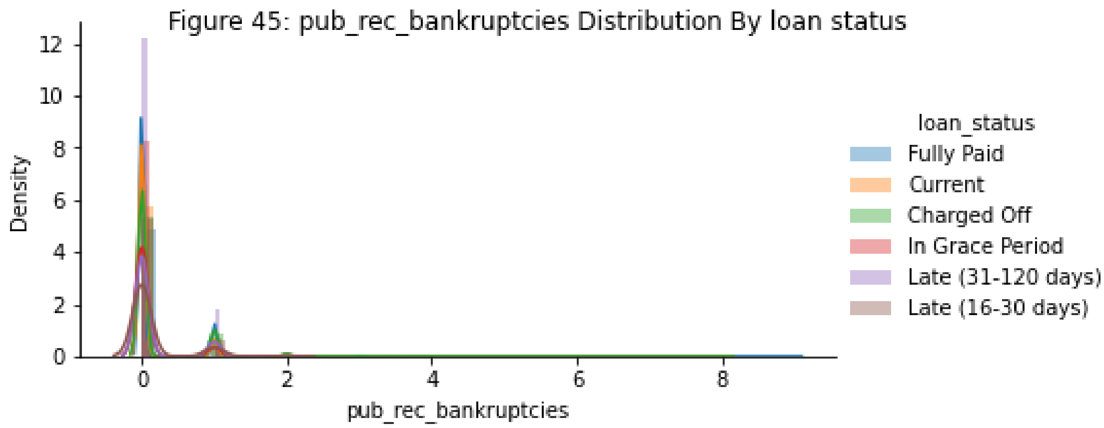
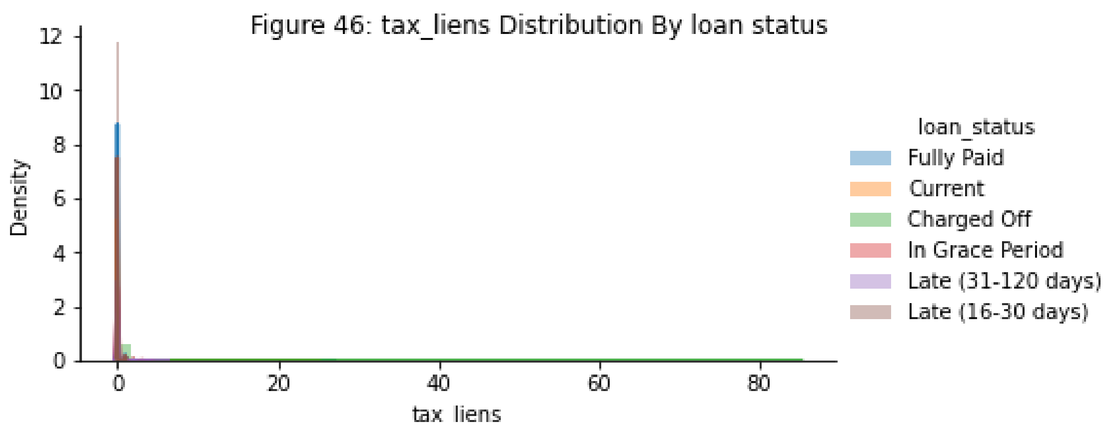


Figure 44: percent_bc_gt_75 Distribution By loan status





[34]:

```
# colnames=list(df.select_dtypes(include='O').columns.values)
colnames=['home_ownership',
 'verification_status',
 'loan_status',
 'pymnt_plan',
 'addr_state',
 'initial_list_status',
 'application_type',
 'hardship_flag',
 'debt_settlement_flag']
```

18 Visualization of categorical variables

[35]:
```
plt.rcParams['figure.max_open_warning']=40
# colnames=list(df.select_dtypes(include='O').columns.values)
for i in colnames[0:]:
    ax = plt.axes()
    sns.countplot(x=i, data=df, ax = ax)
    ax.set_title(''.join(map(str, list(["Figure ",colnames.index(i)+47,": ",i,"␣
↪Distribution"]))))
    plt.show()
```

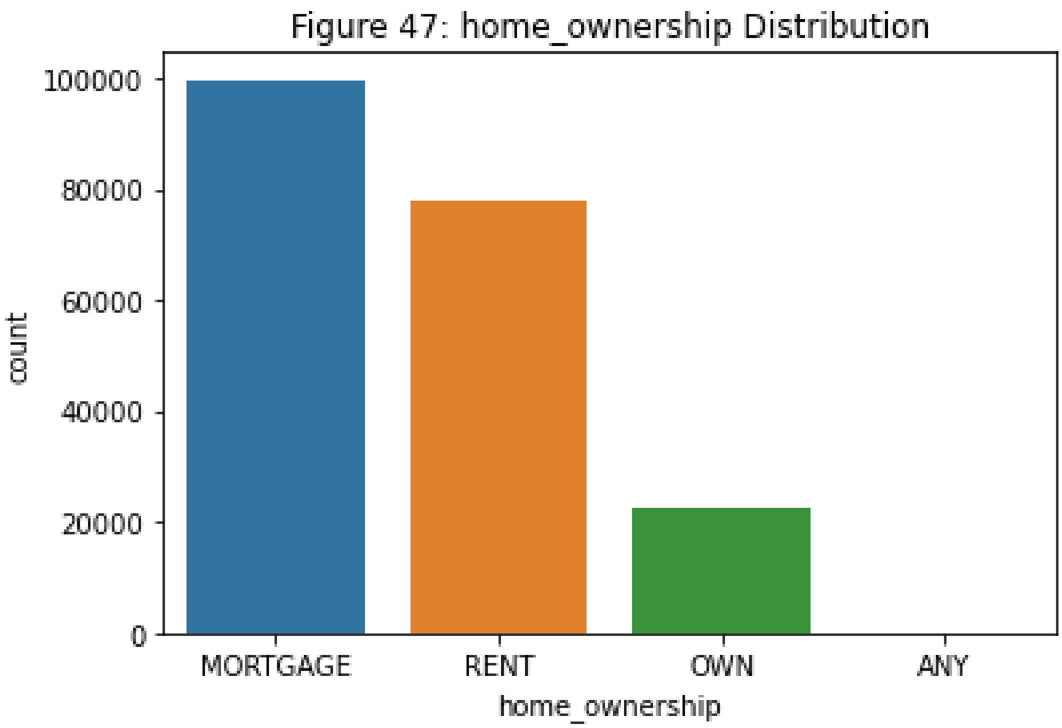


Figure 48: verification_status Distribution

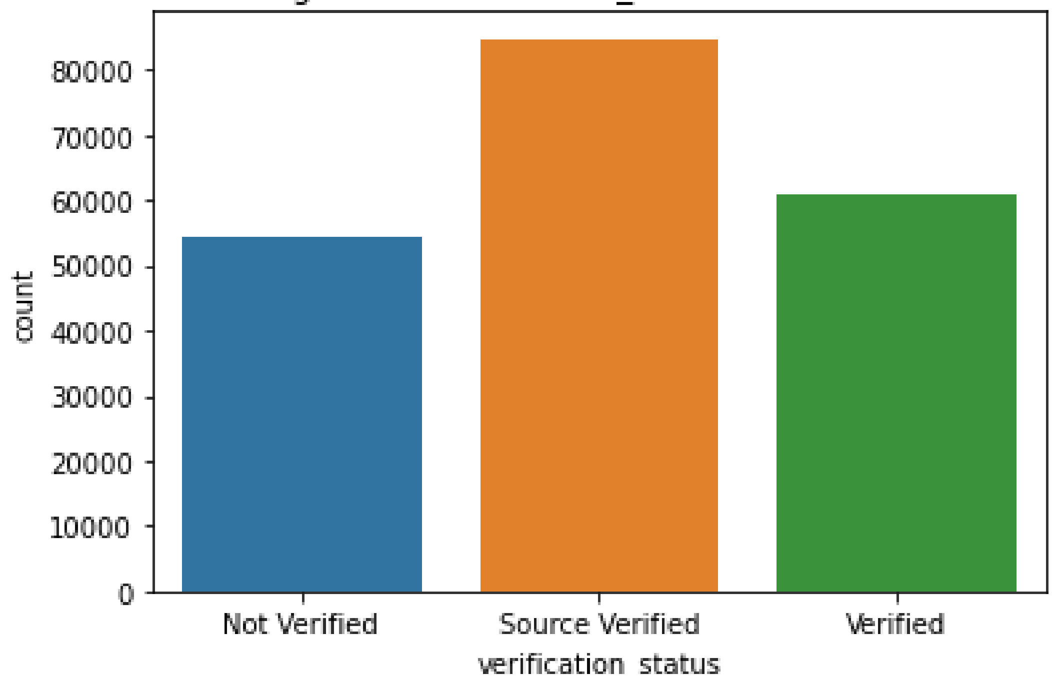


Figure 49: loan_status Distribution

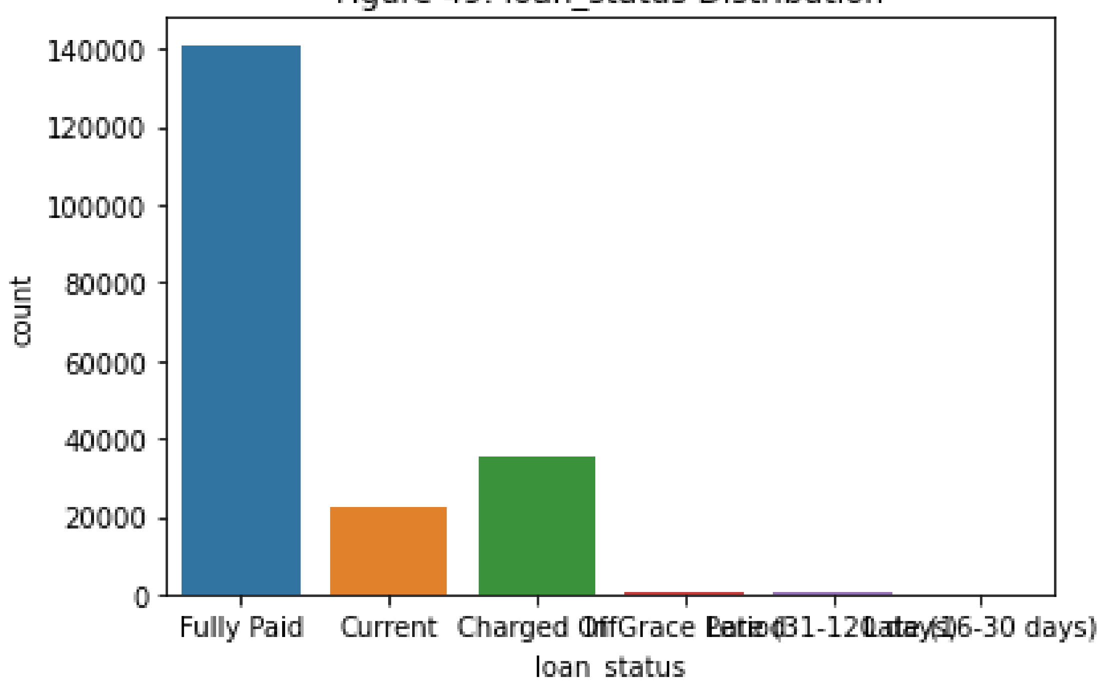


Figure 50: pymnt_plan Distribution

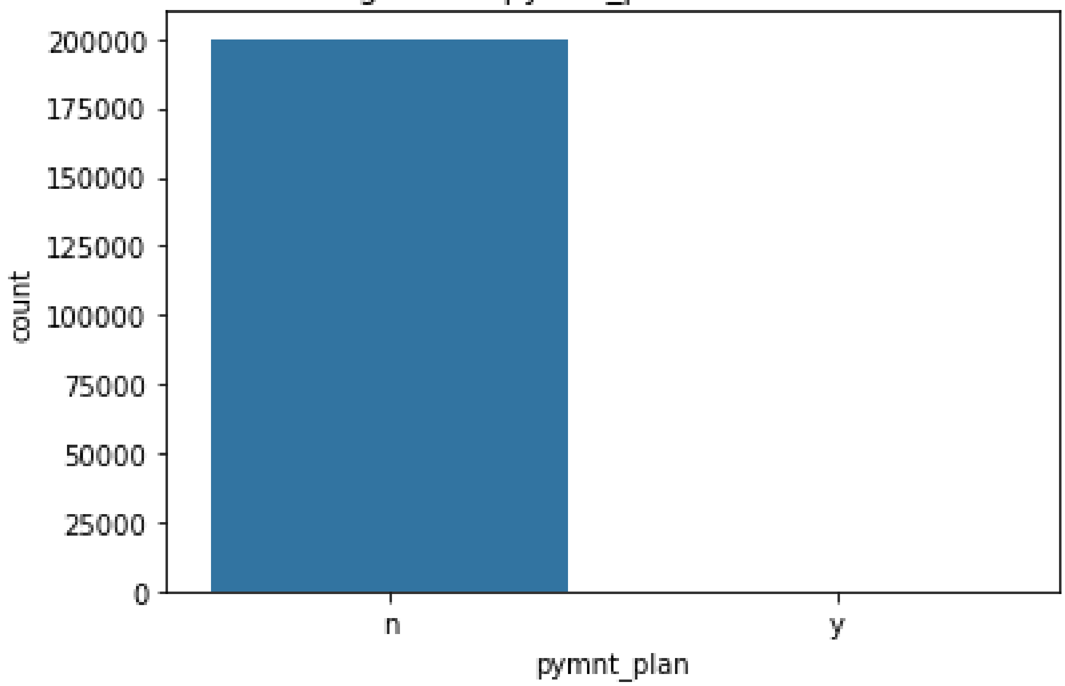


Figure 51: addr_state Distribution

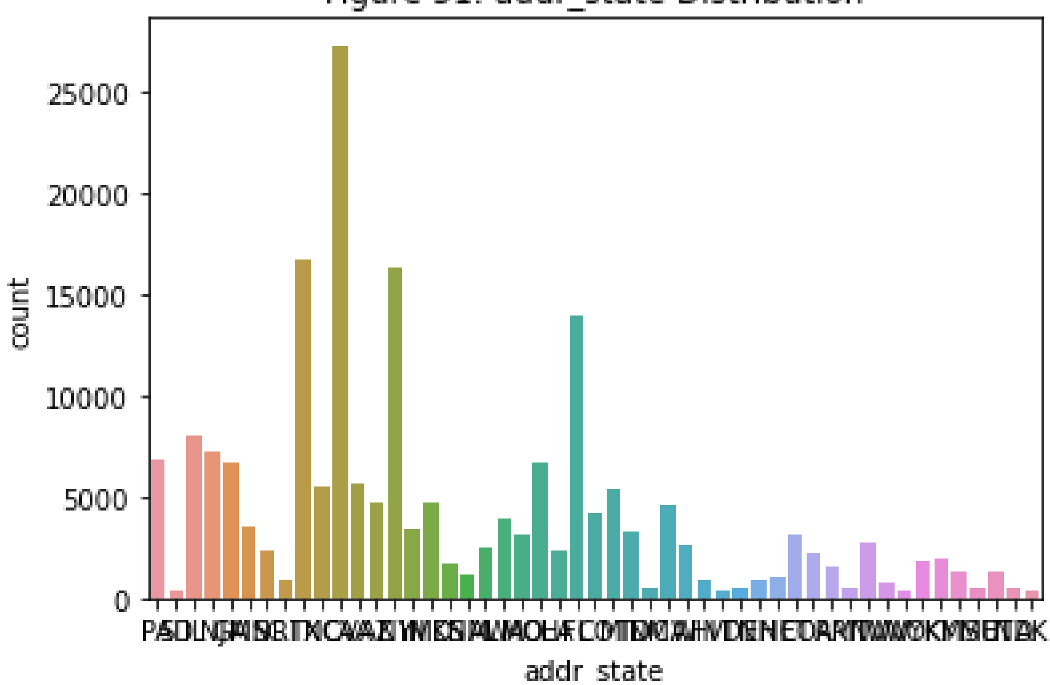


Figure 52: initial_list_status Distribution

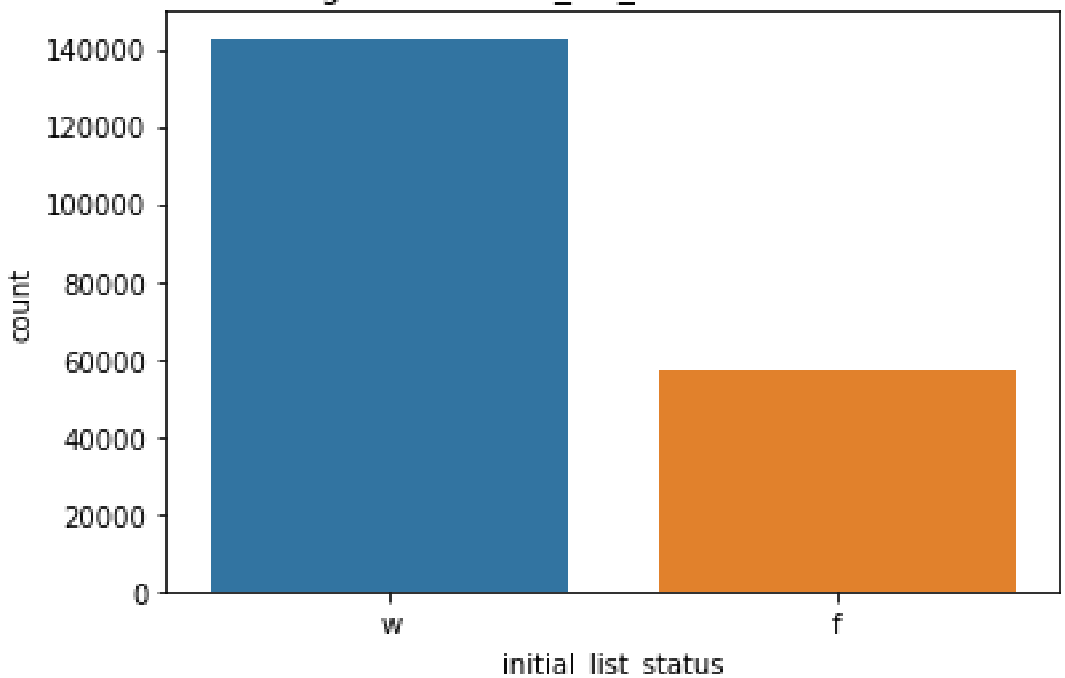
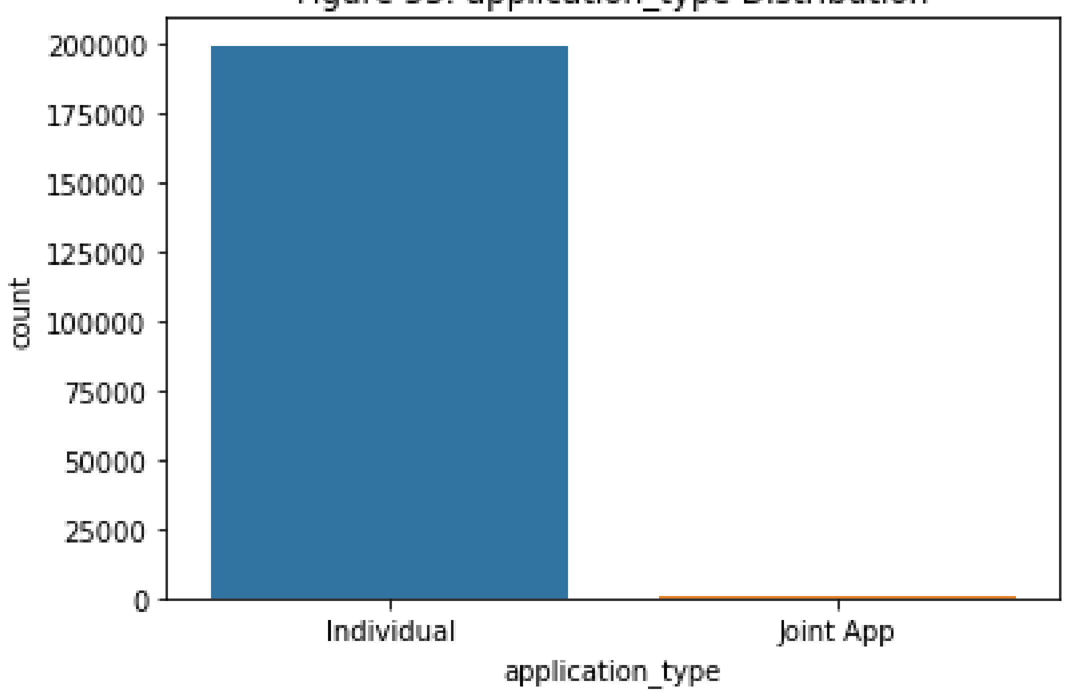


Figure 53: application_type Distribution



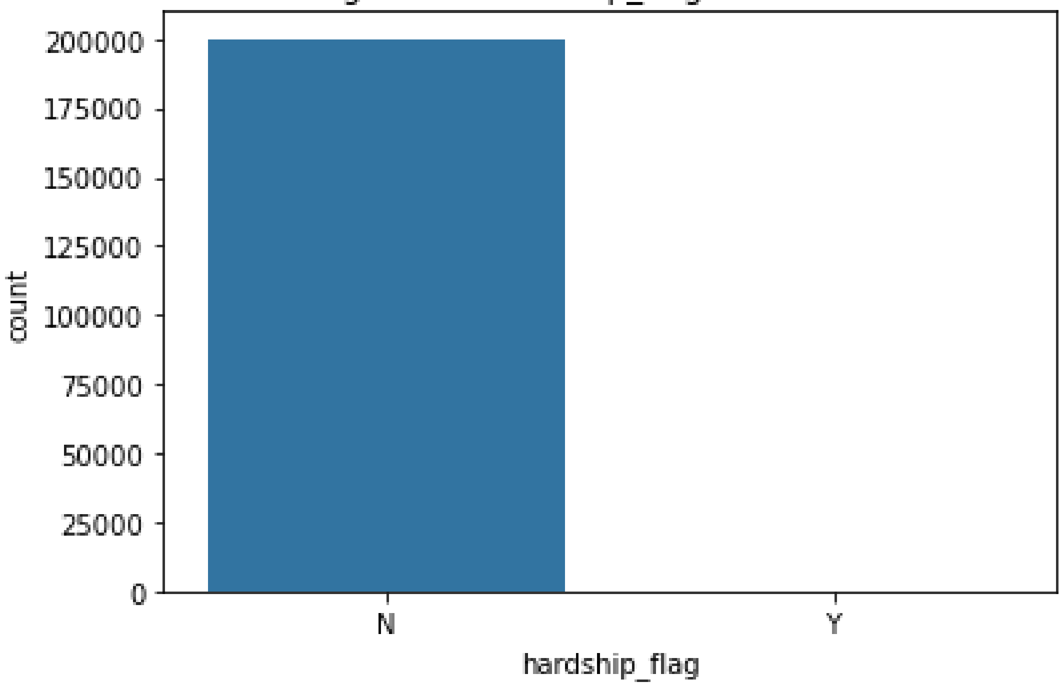


Figure 54: hardship_flag Distribution

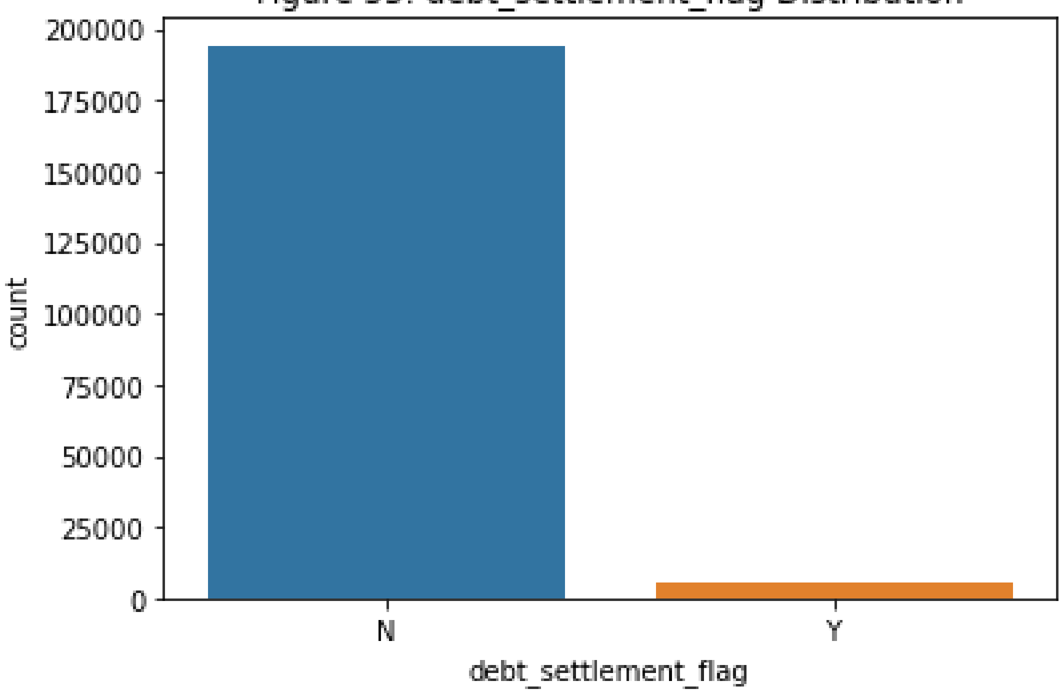
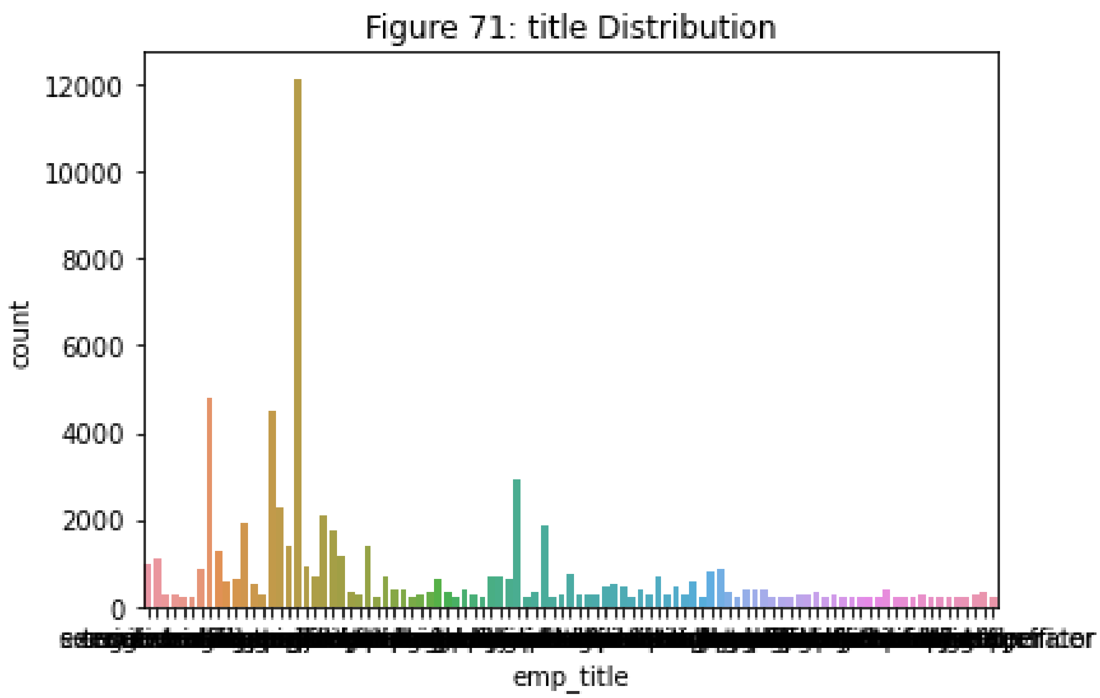


Figure 55: debt_settlement_flag Distribution

[36]:
```
ax = plt.axes()
sns.countplot(x=df['emp_title'][mask], data=df, ax = ax)
ax.set_title(''.join(map(str, list(["Figure ",colnames.index(i)+63,":
↪",'title'," Distribution"]))))
plt.show()
```



19 Separate the Target Variable from the rest of the dataset

[37]:
```
y = df.pop('loan_status')
```

[38]:
```
colnames.remove('loan_status')
```

20 Make dummy variables for select categorical variables

[39]:
```
for i in colnames[0:]:
    # Fill missing data with the word "Missing"
    df[i].fillna("Missing", inplace=True)
    # Create array of dummies
    dummies = pd.get_dummies(df[i], prefix=i)
    # Update X to include dummies and drop the main variable
    df = pd.concat([df, dummies], axis=1)
    df.drop([i], axis=1, inplace=True)
```

```
df.drop('emp_title', axis=1, inplace=True)
```

21 Use minmaxscalar to scale all the dataset on a 0 to 1 scale for coefficient comparisons later for important features. Use stratified K fold with a set random state to shuffle the sampling set yet keep the results reproducible with the set random state

[40]:
```
columns = df.columns
sc = MinMaxScaler(feature_range=(0, 1))
df = sc.fit_transform(df)
df = pd.DataFrame(df, columns=columns)

#x_train, x_test, y_train, y_test = train_test_split(df, y_int, test_size=0.33,␣
 ↪random_state=2, stratify=y_int)
skf = StratifiedKFold(n_splits = 3, shuffle = True, random_state = 2)
```

22 Using a decision tree classifed with default parameters, the metrics are already very good for the metrics of precision, recall, and f1-score. Recall is type 1 errors, which is when a person is predicted not to pay and pays. Precision is type 2 errors, which is when a person is predicted to pay and does not pay. F1 score is the balance between recall and precision, while accuracy is the overall reliability of the prediction

[41]:
```
model2 = DecisionTreeClassifier()

for train_idx, test_idx in skf.split(df, y):
    y_score = model2.fit(df.loc[train_idx],y.loc[train_idx])
    print(classification_report(y.loc[test_idx],model2.predict(df.
 ↪loc[test_idx])))
```

```
                    precision    recall  f1-score   support

       Charged Off       0.98      0.98      0.98     11697
           Current       0.97      0.97      0.97      7546
        Fully Paid       1.00      1.00      1.00     46997
   In Grace Period       0.06      0.08      0.07       115
 Late (16-30 days)       0.06      0.06      0.06        49
Late (31-120 days)       0.76      0.81      0.78       262

          accuracy                           0.99     66666
         macro avg       0.64      0.65      0.64     66666
      weighted avg       0.99      0.99      0.99     66666
```

```
                    precision    recall  f1-score   support

       Charged Off       0.98      0.98      0.98     11696
           Current       0.97      0.97      0.97      7546
        Fully Paid       0.99      0.99      0.99     46997
   In Grace Period       0.10      0.10      0.10       116
 Late (16-30 days)       0.02      0.02      0.02        49
Late (31-120 days)       0.75      0.76      0.75       262

          accuracy                           0.99     66666
         macro avg       0.63      0.64      0.64     66666
      weighted avg       0.99      0.99      0.99     66666

                    precision    recall  f1-score   support

       Charged Off       0.98      0.98      0.98     11697
           Current       0.97      0.97      0.97      7545
        Fully Paid       0.99      0.99      0.99     46997
   In Grace Period       0.08      0.08      0.08       116
 Late (16-30 days)       0.13      0.12      0.12        50
Late (31-120 days)       0.76      0.81      0.78       261

          accuracy                           0.99     66666
         macro avg       0.65      0.66      0.66     66666
      weighted avg       0.99      0.99      0.99     66666
```

23 The metrics for random forest classifier is also already very good

[42]:
```
model3 = RandomForestClassifier(random_state=2, n_jobs=-1)

for train_idx, test_idx in skf.split(df, y):
    model3.fit(df.loc[train_idx],y.loc[train_idx])
    print(classification_report(y.loc[test_idx],model3.predict(df.
 ↪loc[test_idx])))
```

```
                    precision    recall  f1-score   support

       Charged Off       1.00      0.97      0.99     11697
           Current       0.97      1.00      0.98      7546
        Fully Paid       0.99      1.00      1.00     46997
   In Grace Period       0.00      0.00      0.00       115
 Late (16-30 days)       0.00      0.00      0.00        49
Late (31-120 days)       0.99      0.79      0.88       262
```

```
       accuracy                           0.99     66666
      macro avg       0.66      0.63      0.64     66666
   weighted avg       0.99      0.99      0.99     66666

                 precision    recall  f1-score   support

    Charged Off       1.00      0.97      0.98     11696
        Current       0.97      0.99      0.98      7546
     Fully Paid       0.99      1.00      1.00     46997
In Grace Period       0.00      0.00      0.00       116
Late (16-30 days)     0.00      0.00      0.00        49
Late (31-120 days)    0.99      0.71      0.83       262

       accuracy                           0.99     66666
      macro avg       0.66      0.61      0.63     66666
   weighted avg       0.99      0.99      0.99     66666

                 precision    recall  f1-score   support

    Charged Off       1.00      0.97      0.98     11697
        Current       0.97      0.99      0.98      7545
     Fully Paid       0.99      1.00      1.00     46997
In Grace Period       0.00      0.00      0.00       116
Late (16-30 days)     0.00      0.00      0.00        50
Late (31-120 days)    0.99      0.77      0.86       261

       accuracy                           0.99     66666
      macro avg       0.66      0.62      0.64     66666
   weighted avg       0.99      0.99      0.99     66666
```

24 Logistic regression is used to see if I could extrapolate if certain features could be removed from the model if they would cause overfitting because of too much noise from the dataset

[43]:
```
model4 = LogisticRegression(penalty='l1', C=0.5, max_iter=100,␣
 ↪solver='liblinear', multi_class='auto', random_state=2, n_jobs=-1)

for train_idx, test_idx in skf.split(df, y):
    model4.fit(df.loc[train_idx],y.loc[train_idx])
    print(classification_report(y.loc[test_idx],model4.predict(df.
 ↪loc[test_idx])))
```

```
                 precision    recall  f1-score   support

    Charged Off       1.00      0.99      0.99     11697
        Current       0.96      0.99      0.97      7546
```

```
         Fully Paid       1.00      1.00      1.00     46997
    In Grace Period       0.00      0.00      0.00       115
  Late (16-30 days)       0.00      0.00      0.00        49
 Late (31-120 days)       0.82      0.18      0.29       262

           accuracy                           0.99     66666
          macro avg       0.63      0.53      0.54     66666
       weighted avg       0.99      0.99      0.99     66666

                    precision    recall  f1-score   support

        Charged Off       1.00      0.99      0.99     11696
            Current       0.95      0.99      0.97      7546
         Fully Paid       0.99      1.00      1.00     46997
    In Grace Period       1.00      0.01      0.02       116
  Late (16-30 days)       0.00      0.00      0.00        49
 Late (31-120 days)       0.87      0.15      0.25       262

           accuracy                           0.99     66666
          macro avg       0.80      0.52      0.54     66666
       weighted avg       0.99      0.99      0.99     66666

                    precision    recall  f1-score   support

        Charged Off       1.00      0.99      0.99     11697
            Current       0.95      0.99      0.97      7545
         Fully Paid       0.99      1.00      1.00     46997
    In Grace Period       0.00      0.00      0.00       116
  Late (16-30 days)       1.00      0.02      0.04        50
 Late (31-120 days)       0.76      0.11      0.19       261

           accuracy                           0.99     66666
          macro avg       0.79      0.52      0.53     66666
       weighted avg       0.99      0.99      0.99     66666
```

25 here are the features that are certain, likely, possible, and unlikely towards contributing towards the prediction of the model

[44]:
```
for b,c in enumerate(['certain','likely','possible','unlikely']):
    feature_importances = pd.Series(model4.coef_[b], index=df.columns)
    feature_importances.sort_values()[-30:].plot(kind="barh", figsize=(10,10),
                                       title = "Figure 64: Order of "+c+"␣
↪Features for Logistic Regression Classifier");
    plt.show()
```

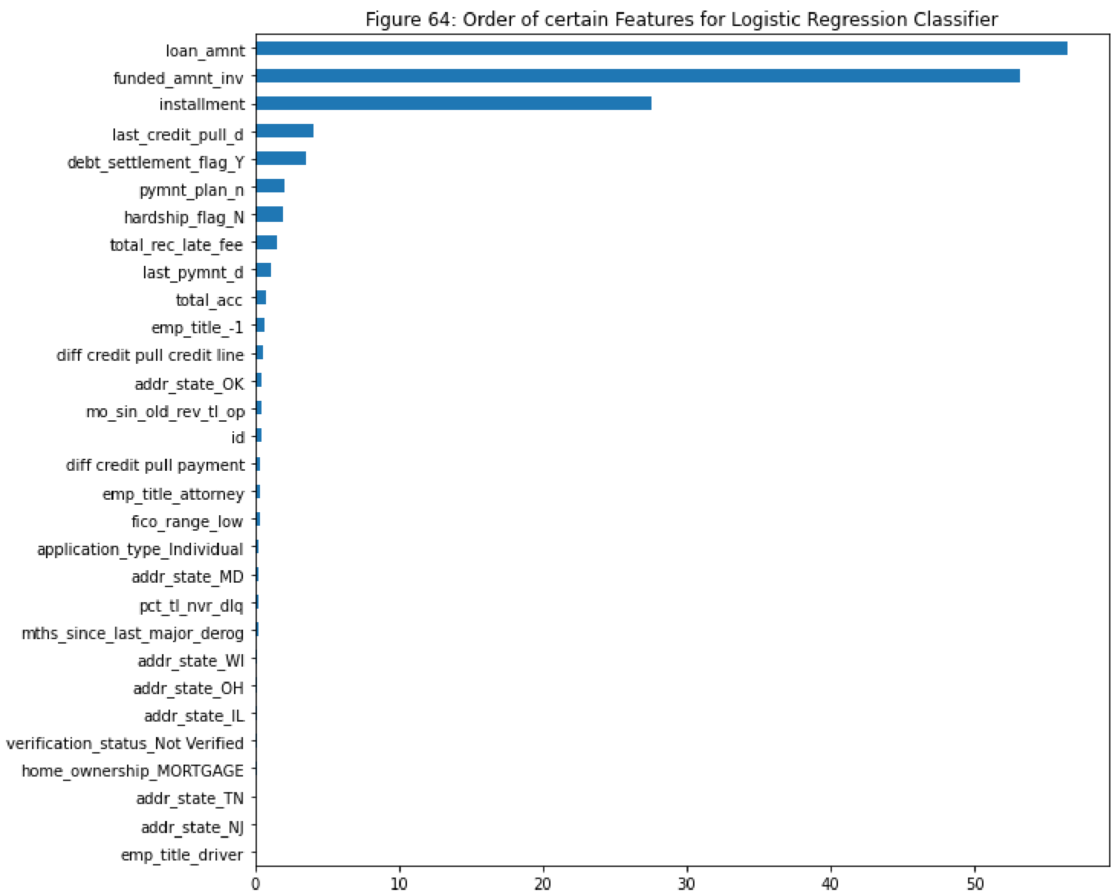


Figure 64: Order of certain Features for Logistic Regression Classifier
loan_amnt
funded_amnt_inv
installment
last_credit_pull_d
debt_settlement_flag_Y
pymnt_plan_n
hardship_flag_N
total_rec_late_fee
last_pymnt_d
total_acc
emp_title_-1
diff credit pull credit line
addr_state_OK
mo_sin_old_rev_tl_op
id
diff credit pull payment
emp_title_attorney
fico_range_low
application_type_Individual
addr_state_MD
pct_tl_nvr_dlq
mths_since_last_major_derog
addr_state_WI
addr_state_OH
addr_state_IL
verification_status_Not Verified
home_ownership_MORTGAGE
addr_state_TN
addr_state_NJ
emp_title_driver
0
10
20
30
40
50

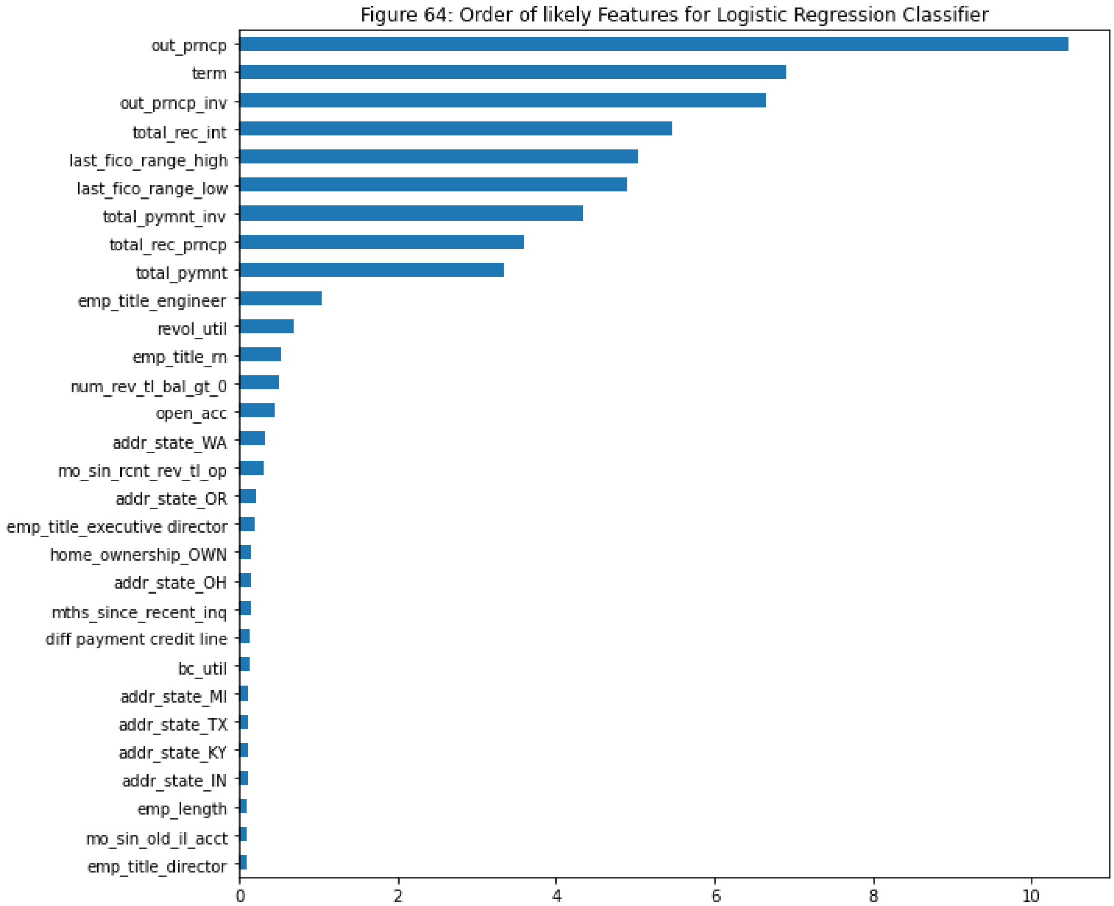


Figure 64: Order of likely Features for Logistic Regression Classifier
out_prncp
term
out_prncp_inv
total_rec_int
last_fico_range_high
last_fico_range_low
total_pymnt_inv
total_rec_prncp
total_pymnt
emp_title_engineer
revol_util
emp_title_rn
num_rev_tl_bal_gt_0
open_acc
addr_state_WA
mo_sin_rcnt_rev_tl_op
addr_state_OR
emp_title_executive director
home_ownership_OWN
addr_state_OH
mths_since_recent_inq
diff payment credit line
bc_util
addr_state_MI
addr_state_TX
addr_state_KY
addr_state_IN
emp_length
mo_sin_old_il_acct
emp_title_director
0
2
4
6
8
10

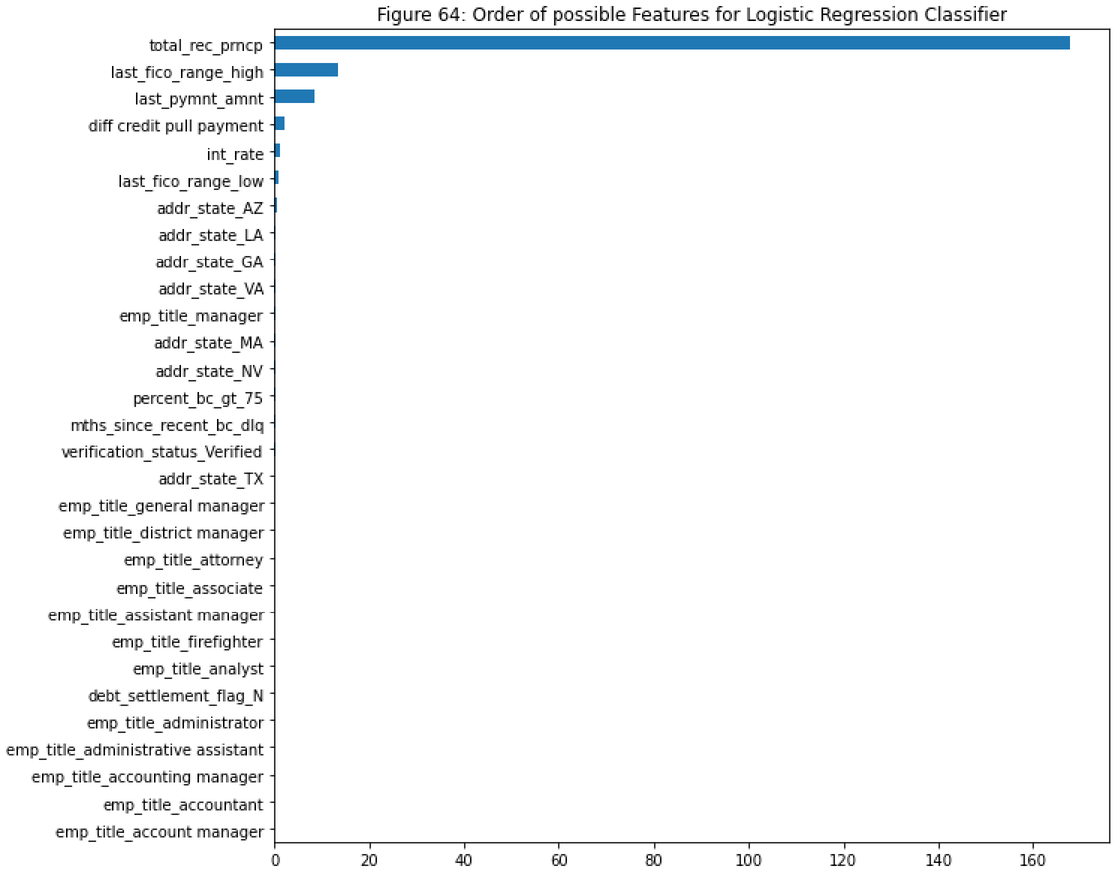
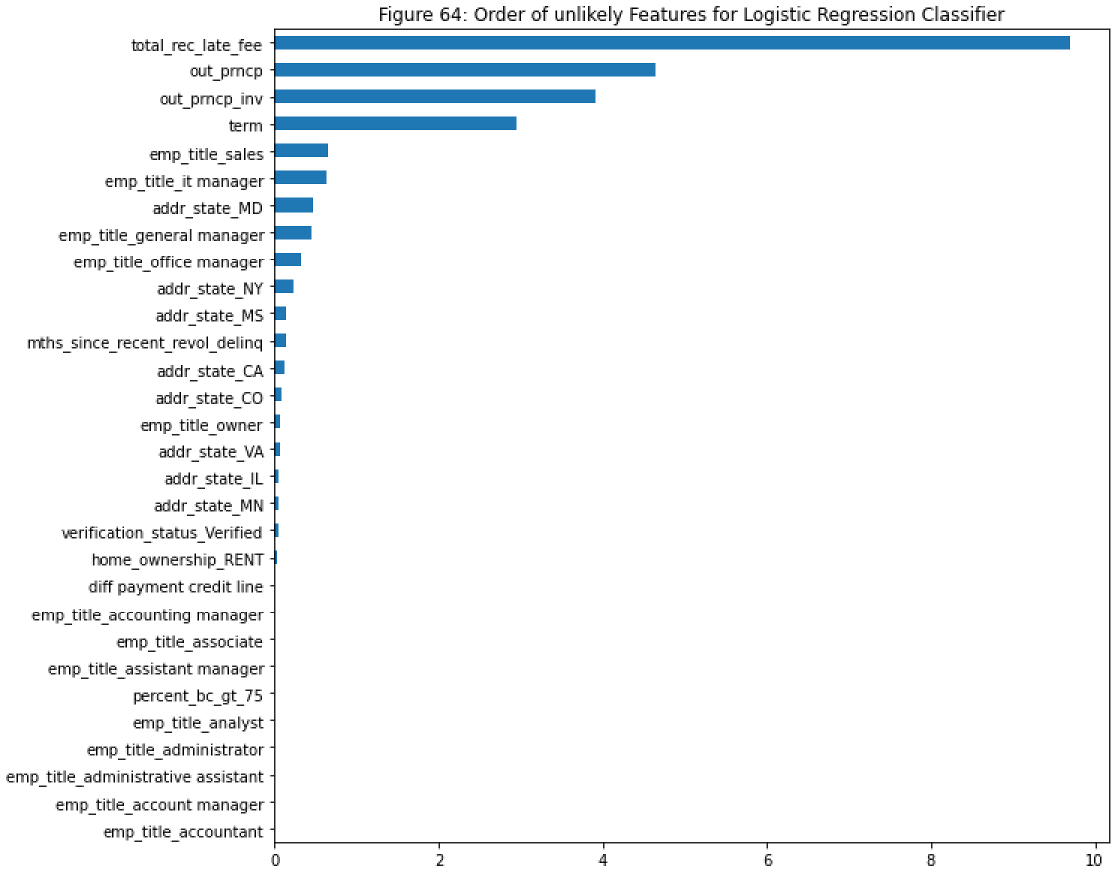
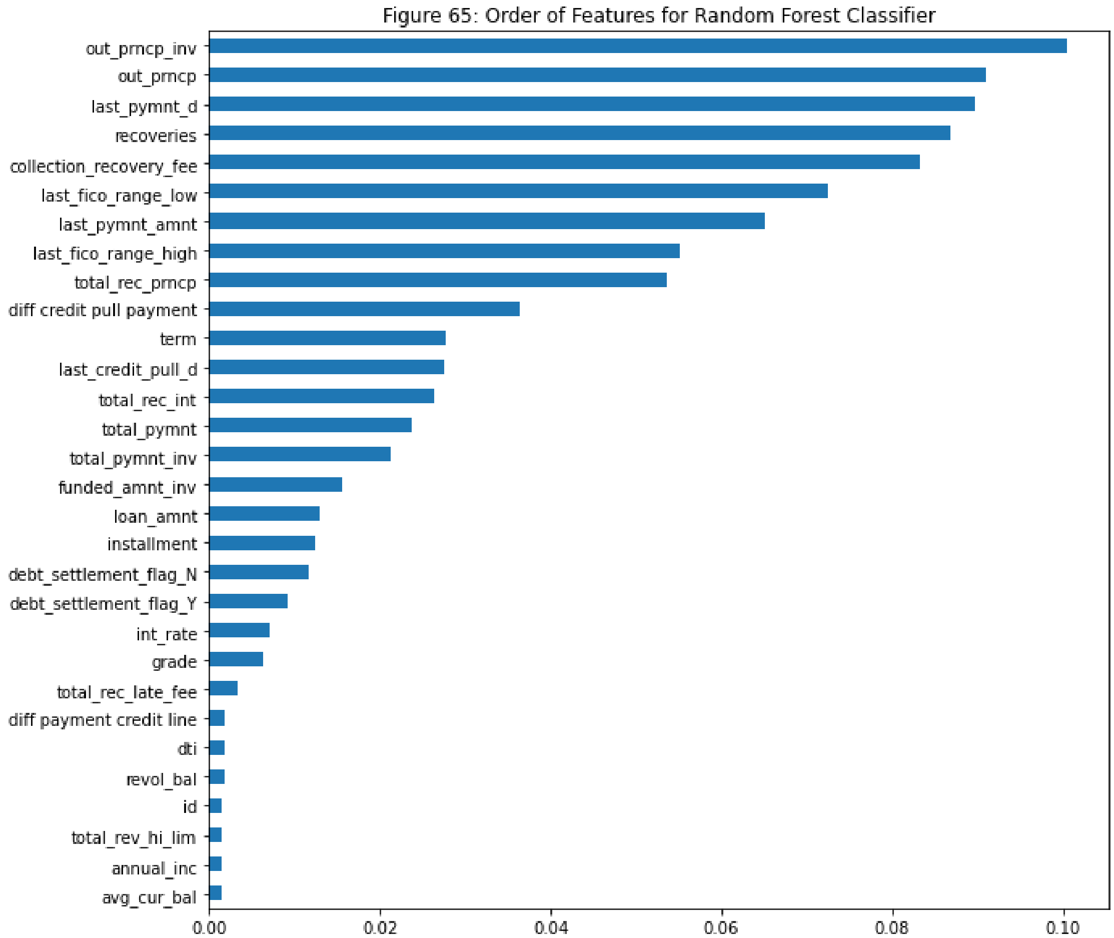


Figure 64: Order of possible Features for Logistic Regression Classifier
total_rec_prncp
last_fico_range_high
last_pymnt_amnt
diff credit pull payment
int_rate
last_fico_range_low
addr_state_AZ
addr_state_LA
addr_state_GA
addr_state_VA
emp_title_manager
addr_state_MA
addr_state_NV
percent_bc_gt_75
mths_since_recent_bc_dlq
verification_status_Verified
addr_state_TX
emp_title_general manager
emp_title_district manager
emp_title_attorney
emp_title_associate
emp_title_assistant manager
emp_title_firefighter
emp_title_analyst
debt_settlement_flag_N
emp_title_administrator
emp_title_administrative assistant
emp_title_accounting manager
emp_title_accountant
emp_title_account manager
0
20
40
60
80
100
120
140
160



26 For the important features that contribute to the model, only the ones above 0.0015 is included in the subset of the dataset

[45]:
```
feature_importances = pd.Series(model3.feature_importances_, index=df.columns)
feature_importances.sort_values()[-30:].plot(kind="barh", figsize=(10,10),
                                             title = "Figure 65: Order of Features␣
↪for Random Forest Classifier");
```



[46]:
```
feature_importances.sort_values()[-29:]
```

[46]:
```
annual_inc                 0.001511
total_rev_hi_lim           0.001511
id                         0.001520
revol_bal                  0.001851
dti                        0.001858
diff payment credit line   0.001879
total_rec_late_fee         0.003359
grade                      0.006336
int_rate                   0.007127
debt_settlement_flag_Y     0.009116
debt_settlement_flag_N     0.011632
installment                0.012405
loan_amnt                  0.012987
funded_amnt_inv            0.015543
total_pymnt_inv            0.021356
```

```
total_pymnt                  0.023656
total_rec_int                0.026341
last_credit_pull_d           0.027415
term                         0.027676
diff credit pull payment     0.036426
total_rec_prncp              0.053586
last_fico_range_high         0.055023
last_pymnt_amnt              0.065148
last_fico_range_low          0.072411
collection_recovery_fee      0.083234
recoveries                   0.086810
last_pymnt_d                 0.089739
out_prncp                    0.091004
out_prncp_inv                0.100441
dtype: float64
```

27 Once the data is subsetted with just the important variables, the model is ran again to see if the accuracy would increase towards the important features

[47]:
```
df = df[feature_importances.sort_values()[-29:].index]
df
```

[47]:
```
        annual_inc  total_rev_hi_lim        id  revol_bal      dti  \
0         0.006111          0.005666  0.996940   0.001695  0.00691
1         0.007222          0.068117  0.996179   0.013165  0.01706
2         0.007000          0.008530  0.995985   0.004825  0.01178
3         0.012222          0.041004  0.966360   0.004784  0.01806
4         0.011604          0.020715  0.997954   0.013447  0.02637
…              …                 …         …          …        …
199993    0.008778          0.015293  0.816843   0.014690  0.01674
199994    0.009444          0.016024  0.817145   0.013206  0.01082
199995    0.008889          0.014683  0.814654   0.012660  0.01462
199996    0.006111          0.011272  0.792847   0.003521  0.01723
199997    0.004444          0.021751  0.817567   0.018202  0.02629

        diff payment credit line  total_rec_late_fee     grade  int_rate  \
0                       0.664560        8.649259e-12  0.382353  0.366286
1                       0.675050        8.649259e-12  0.294118  0.281791
2                       0.678264        8.649259e-12  0.235294  0.230672
3                       0.616036        8.649259e-12  0.411765  0.402619
4                       0.690402        8.649259e-12  0.735294  0.723701
…                              …                   …         …         …
199993                  0.718687        8.649259e-12  0.294118  0.294466
199994                  0.634628        8.649259e-12  0.323529  0.311365
199995                  0.678264        3.188390e-02  0.294118  0.294466
```

```
199996                  0.648359        8.649259e-12  0.411765  0.394170
199997                  0.784155        8.649259e-12  0.235294  0.239544

        debt_settlement_flag_Y  …  diff credit pull payment  \
0                          0.0  …                  0.521955
1                          0.0  …                  0.882398
2                          0.0  …                  0.743032
3                          0.0  …                  0.510118
4                          0.0  …                  0.731577
…                         …  …                        …
199993                     0.0  …                  0.592974
199994                     0.0  …                  0.511264
199995                     0.0  …                  0.511264
199996                     0.0  …                  0.488354
199997                     0.0  …                  0.580374

        total_rec_prncp  last_fico_range_high  last_pymnt_amnt  \
0              0.102857              0.663529         0.003379
1              0.705714              0.822353         0.025514
2              0.571429              0.828235         0.435544
3              0.545781              0.798824         0.022858
4              0.297143              0.828235         0.278981
…                   …                    …                …
199993         0.114286              0.804706         0.010941
199994         0.342857              0.845882         0.210610
199995         0.600000              0.734118         0.018569
199996         0.785714              0.822353         0.434945
199997         0.200000              0.822353         0.006309

        last_fico_range_low  collection_recovery_fee  recoveries  \
0                  0.662722                      0.0         0.0
1                  0.822485                      0.0         0.0
2                  0.828402                      0.0         0.0
3                  0.798817                      0.0         0.0
4                  0.828402                      0.0         0.0
…                       …                      …          …
199993             0.804734                      0.0         0.0
199994             0.846154                      0.0         0.0
199995             0.733728                      0.0         0.0
199996             0.822485                      0.0         0.0
199997             0.822485                      0.0         0.0

        last_pymnt_d  out_prncp  out_prncp_inv
0           0.999917   0.000000       0.000000
1           0.998638   0.000000       0.000000
2           0.999133   0.000000       0.000000
3           0.999959   0.700577       0.700577
```

```
4          0.998679  0.000000         0.000000
…                 …         …                …
199993     0.999629  0.000000         0.000000
199994     0.998432  0.000000         0.000000
199995     0.999711  0.000000         0.000000
199996     0.998514  0.000000         0.000000
199997     0.999711  0.000000         0.000000

[199998 rows x 29 columns]
```

28 The metrics of the prediction is very good if not better with just the important features for less overfitting

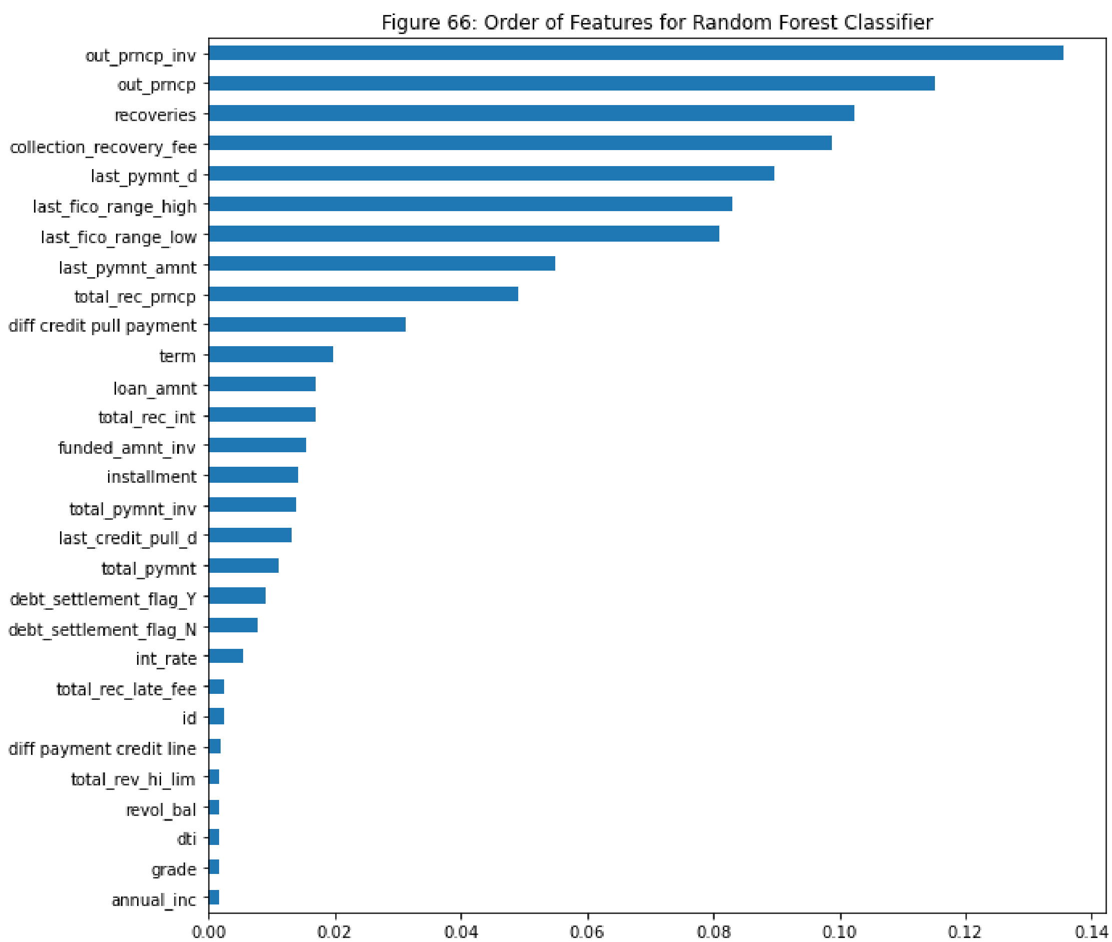
[48]:
```python
model5 = RandomForestClassifier(random_state=2, n_jobs=-1)

for train_idx, test_idx in skf.split(df, y):
    model5.fit(df.loc[train_idx],y.loc[train_idx])
    print(classification_report(y.loc[test_idx],model5.predict(df.
 ↪loc[test_idx])))
```

```
                    precision    recall  f1-score   support

       Charged Off       1.00      0.99      0.99     11697
           Current       0.97      0.99      0.98      7546
        Fully Paid       1.00      1.00      1.00     46997
   In Grace Period       0.00      0.00      0.00       115
 Late (16-30 days)       0.00      0.00      0.00        49
Late (31-120 days)       0.96      0.81      0.88       262

          accuracy                           0.99     66666
         macro avg       0.66      0.63      0.64     66666
      weighted avg       0.99      0.99      0.99     66666

                    precision    recall  f1-score   support

       Charged Off       1.00      0.99      0.99     11696
           Current       0.97      0.99      0.98      7546
        Fully Paid       1.00      1.00      1.00     46997
   In Grace Period       0.00      0.00      0.00       116
 Late (16-30 days)       0.00      0.00      0.00        49
Late (31-120 days)       0.95      0.74      0.83       262

          accuracy                           0.99     66666
         macro avg       0.65      0.62      0.63     66666
      weighted avg       0.99      0.99      0.99     66666

                    precision    recall  f1-score   support
```

Charged Off	1.00	0.99	0.99	11697
Current	0.97	0.99	0.98	7545
Fully Paid	1.00	1.00	1.00	46997
In Grace Period	1.00	0.01	0.02	116
Late (16-30 days)	0.50	0.04	0.07	50
Late (31-120 days)	0.96	0.78	0.86	261
accuracy			0.99	66666
macro avg	0.90	0.64	0.65	66666
weighted avg	0.99	0.99	0.99	66666

29 These are the important features ordered by importance

[49]:
```
feature_importances = pd.Series(model5.feature_importances_, index=df.columns)
feature_importances.sort_values().plot(kind="barh", figsize=(10,10),
                                        title = "Figure 66: Order of Features␣
↪for Random Forest Classifier");
```



30 The overall problem with random forest coefficients is that they are all positive so both debt settlement yes and no contribute towards the accurate prediction without realizing which feature is negatively or positively contributing towards the prediction, but these metrics is what the company should pull in regards to if a person will pay a loan and the model would determine what category of loan status the person would be in

[50]:
```
feature_importances.sort_values()
```

[50]:
```
annual_inc                  0.001619
grade                       0.001634
dti                         0.001741
revol_bal                   0.001794
total_rev_hi_lim            0.001795
diff payment credit line    0.001846
id                          0.002417
total_rec_late_fee          0.002418
int_rate                    0.005609
debt_settlement_flag_N      0.007780
debt_settlement_flag_Y      0.009154
total_pymnt                 0.011034
last_credit_pull_d          0.013124
total_pymnt_inv             0.013795
installment                 0.014062
funded_amnt_inv             0.015527
total_rec_int               0.016861
loan_amnt                   0.017084
term                        0.019709
diff credit pull payment    0.031190
total_rec_prncp             0.049074
last_pymnt_amnt             0.054992
last_fico_range_low         0.081046
last_fico_range_high        0.082950
last_pymnt_d                0.089769
collection_recovery_fee     0.098753
recoveries                  0.102494
out_prncp                   0.115178
out_prncp_inv               0.135549
dtype: float64
```

31 Fit the truncated dataset with hyperparameter optimization using gridsearch on the random forest model. The accuracy and other metrics are already very good.

[51]:
```
hyperparameters = {'max_features': ['auto', 'sqrt', 'log2'],
                   'min_samples_split': [2,3,4]
                  }
rfc = RandomForestClassifier(criterion='entropy', n_jobs=-1, random_state=2,␣
 ↪n_estimators=100)

search = GridSearchCV(rfc, hyperparameters, cv=3, scoring='accuracy',
                               verbose=3)

search.fit(df.loc[train_idx],y.loc[train_idx])

print(search.best_estimator_)
```

```
Fitting 3 folds for each of 9 candidates, totalling 27 fits
[CV 1/3] END max_features=auto, min_samples_split=2;, score=0.991 total time=
16.7s
[CV 2/3] END max_features=auto, min_samples_split=2;, score=0.993 total time=
11.1s
[CV 3/3] END max_features=auto, min_samples_split=2;, score=0.993 total time=
10.9s
[CV 1/3] END max_features=auto, min_samples_split=3;, score=0.992 total time=
10.8s
[CV 2/3] END max_features=auto, min_samples_split=3;, score=0.993 total time=
11.0s
[CV 3/3] END max_features=auto, min_samples_split=3;, score=0.992 total time=
10.9s
[CV 1/3] END max_features=auto, min_samples_split=4;, score=0.991 total time=
10.6s
[CV 2/3] END max_features=auto, min_samples_split=4;, score=0.993 total time=
10.8s
[CV 3/3] END max_features=auto, min_samples_split=4;, score=0.993 total time=
10.8s
[CV 1/3] END max_features=sqrt, min_samples_split=2;, score=0.991 total time=
10.5s
[CV 2/3] END max_features=sqrt, min_samples_split=2;, score=0.993 total time=
10.9s
[CV 3/3] END max_features=sqrt, min_samples_split=2;, score=0.993 total time=
10.7s
[CV 1/3] END max_features=sqrt, min_samples_split=3;, score=0.992 total time=
10.8s
[CV 2/3] END max_features=sqrt, min_samples_split=3;, score=0.993 total time=
10.7s
[CV 3/3] END max_features=sqrt, min_samples_split=3;, score=0.992 total time=
```

```
10.7s
[CV 1/3] END max_features=sqrt, min_samples_split=4;, score=0.991 total time=
10.1s
[CV 2/3] END max_features=sqrt, min_samples_split=4;, score=0.993 total time=
11.3s
[CV 3/3] END max_features=sqrt, min_samples_split=4;, score=0.993 total time=
11.3s
[CV 1/3] END max_features=log2, min_samples_split=2;, score=0.992 total time=
9.6s
[CV 2/3] END max_features=log2, min_samples_split=2;, score=0.993 total time=
9.4s
[CV 3/3] END max_features=log2, min_samples_split=2;, score=0.993 total time=
9.2s
[CV 1/3] END max_features=log2, min_samples_split=3;, score=0.992 total time=
9.5s
[CV 2/3] END max_features=log2, min_samples_split=3;, score=0.993 total time=
9.2s
[CV 3/3] END max_features=log2, min_samples_split=3;, score=0.992 total time=
9.5s
[CV 1/3] END max_features=log2, min_samples_split=4;, score=0.992 total time=
8.9s
[CV 2/3] END max_features=log2, min_samples_split=4;, score=0.993 total time=
9.2s
[CV 3/3] END max_features=log2, min_samples_split=4;, score=0.992 total time=
9.4s
RandomForestClassifier(criterion='entropy', min_samples_split=3, n_jobs=-1,
                       random_state=2)
```

32 The best parameter for random forest classifier is entropy, 3 sample split, and auto, which is then plugged in to retrieve the metrics with the subset important features of the dataset

[52]:
```python
rfc = search.best_estimator_

for train_idx, test_idx in skf.split(df, y):
    rfc.fit(df.loc[train_idx],y.loc[train_idx])
    print(classification_report(y.loc[test_idx],rfc.predict(df.loc[test_idx])))
```

```
                    precision    recall  f1-score   support

       Charged Off       1.00      0.99      0.99     11697
           Current       0.97      0.99      0.98      7546
        Fully Paid       1.00      1.00      1.00     46997
   In Grace Period       0.00      0.00      0.00       115
 Late (16-30 days)       0.00      0.00      0.00        49
Late (31-120 days)       0.97      0.79      0.87       262
```

```
          accuracy                           0.99     66666
         macro avg       0.66      0.63      0.64     66666
      weighted avg       0.99      0.99      0.99     66666

                    precision    recall  f1-score   support

       Charged Off       1.00      0.99      0.99     11696
           Current       0.97      0.99      0.98      7546
        Fully Paid       1.00      1.00      1.00     46997
   In Grace Period       0.00      0.00      0.00       116
 Late (16-30 days)       0.00      0.00      0.00        49
Late (31-120 days)       0.95      0.73      0.83       262

          accuracy                           0.99     66666
         macro avg       0.65      0.62      0.63     66666
      weighted avg       0.99      0.99      0.99     66666

                    precision    recall  f1-score   support

       Charged Off       1.00      0.99      0.99     11697
           Current       0.97      0.99      0.98      7545
        Fully Paid       1.00      1.00      1.00     46997
   In Grace Period       0.00      0.00      0.00       116
 Late (16-30 days)       0.50      0.02      0.04        50
Late (31-120 days)       0.96      0.76      0.85       261

          accuracy                           0.99     66666
         macro avg       0.74      0.63      0.64     66666
      weighted avg       0.99      0.99      0.99     66666
```

33 These are the most important features for the best model towards prediction of loan status

[53]:
```
feature_importances = pd.Series(rfc.feature_importances_, index=df.columns)
feature_importances.sort_values().plot(kind="barh", figsize=(10,10),
                                       title = "Figure 67: Order of Features␣
 ↪for Random Forest Classifier");
```

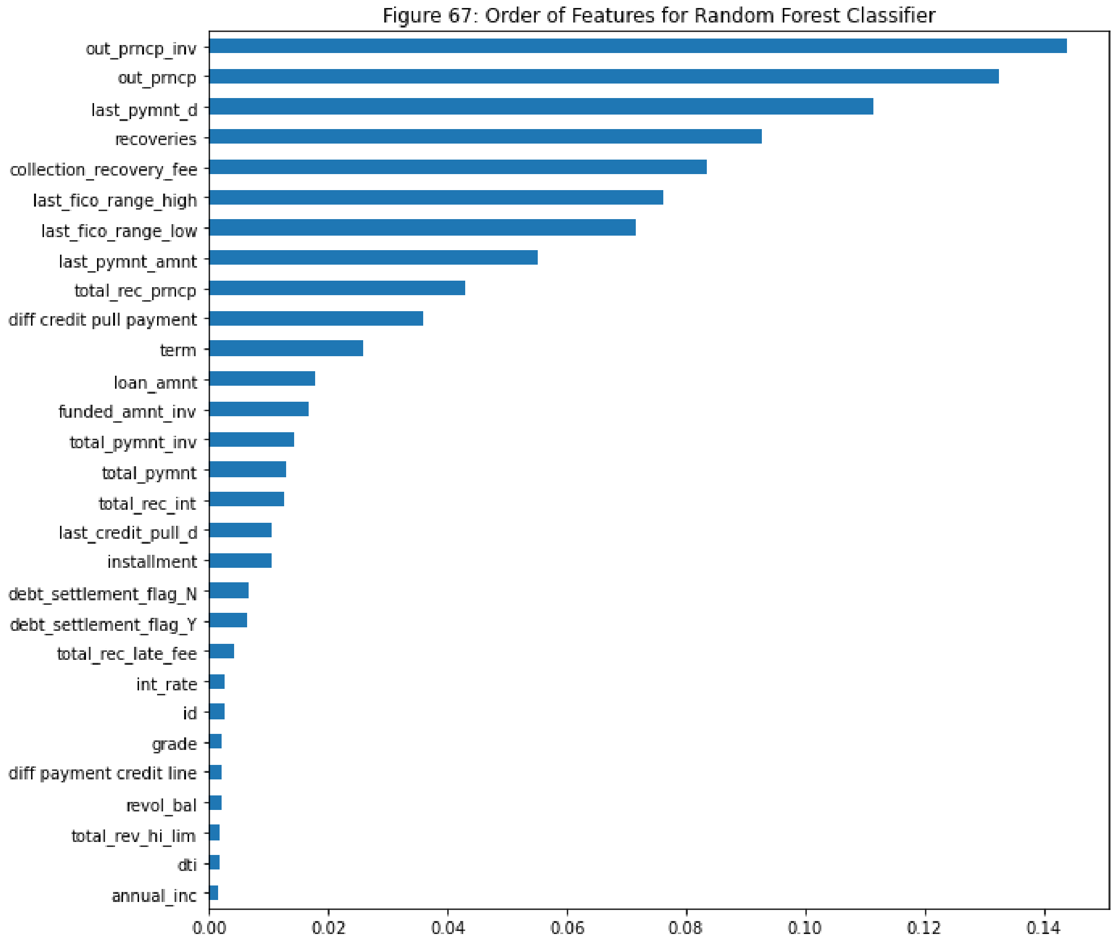
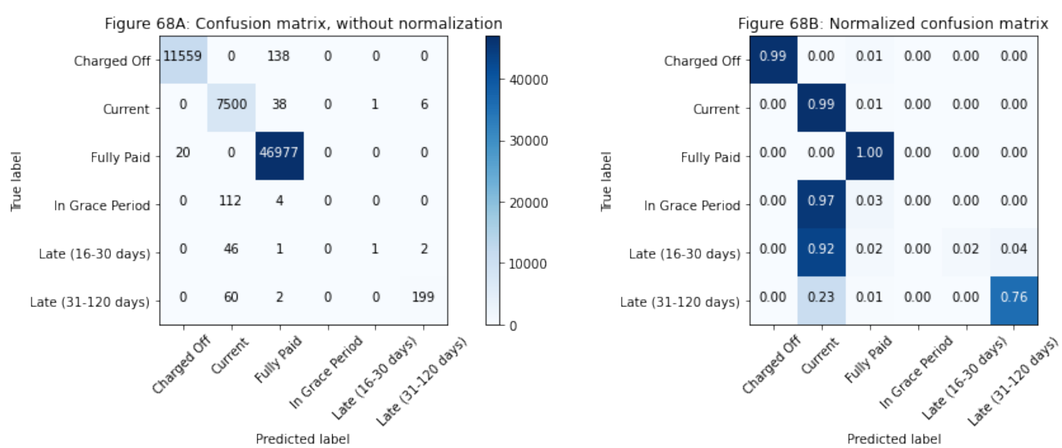


Figure 67: Order of Features for Random Forest Classifier
out_prncp_inv
out_prncp
last_pymnt_d
recoveries
collection_recovery_fee
last_fico_range_high
last_fico_range_low
last_pymnt_amnt
total_rec_prncp
diff credit pull payment
term
loan_amnt
funded_amnt_inv
total_pymnt_inv
total_pymnt
total_rec_int
last_credit_pull_d
installment
debt_settlement_flag_N
debt_settlement_flag_Y
total_rec_late_fee
int_rate
id
grade
diff payment credit line
revol_bal
total_rev_hi_lim
dti
annual_inc
0.00
0.02
0.04
0.06
0.08
0.10
0.12
0.14

34 Using a confusion matrix, here is the normalized and non-normalized labeling of the random forest classifier prediction label compared to the actual label. Type 1 error is a false positive depicted in the upper right of the diagonal while type 2 error is a false negative depicted in the bottom left of the diagonal. Given that loan companies make money off interest if people don't pay on time, they are more concerned if a person is labeled to not pay but pays on time, which would affect the bottom line and is a type 2 error. If a person if labeled as a someone who would pay but does not, that would be benefitial for the loan company to earn interest on the loan, which is a type 1 error.

[54]:
```python
def plot_confusion_matrix(cm, classes,
                          normalize=False,
                          title='Confusion matrix',
                          cmap=plt.cm.Blues):
    """
    This function prints and plots the confusion matrix.
    Normalization can be applied by setting `normalize=True`.
    """
    if normalize:
        cm = cm.astype('float') / cm.sum(axis=1)[:, np.newaxis]

    plt.imshow(cm, interpolation='nearest', cmap=cmap)
    plt.title(title)
    plt.colorbar()
    tick_marks = np.arange(len(classes))
    plt.xticks(tick_marks, classes, rotation=45)
    plt.yticks(tick_marks, classes)

    fmt = '.2f' if normalize else 'd'
    thresh = cm.max() / 2.
    for i, j in itertools.product(range(cm.shape[0]), range(cm.shape[1])):
        plt.text(j, i, format(cm[i, j], fmt),
                 horizontalalignment="center",
                 color="white" if cm[i, j] > thresh else "black")

    plt.tight_layout()
    plt.ylabel('True label')
    plt.xlabel('Predicted label')

# Compute confusion matrix
cnf_matrix = confusion_matrix(y.loc[test_idx],rfc.predict(df.loc[test_idx]))
```

```python
np.set_printoptions(precision=2)

class_names = ['Charged Off', 'Current', 'Fully Paid', 'In Grace Period', 'Late (16-30 days)', 'Late (31-120 days)']

# Plot non-normalized confusion matrix
plt.figure(figsize = (15,5))
plt.subplot(1, 2, 1)
plot_confusion_matrix(cnf_matrix, classes=class_names, title='Figure 68A: Confusion matrix, without normalization')

# Plot normalized confusion matrix
plt.subplot(1, 2, 2)
plot_confusion_matrix(cnf_matrix, classes=class_names, normalize=True, title='Figure 68B: Normalized confusion matrix')

plt.tight_layout()
plt.show()
```



35 Even though the grace period and late are mislabeled by the confusion matrix, the target variable of Charged off is 0.99, along with fully paid and current at 0.99 and 1.00 in prediction accuracy, respectively

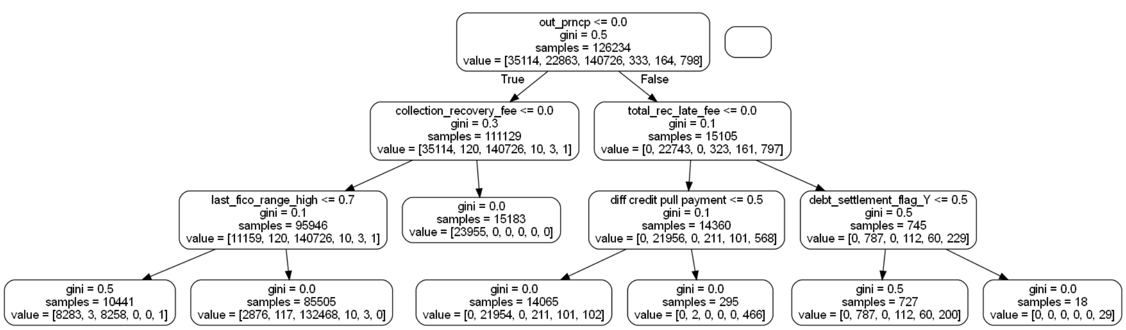
[55]:
```python
feature_list = list(df.columns)

# Import tools needed for visualization
from sklearn.tree import export_graphviz
import pydot
```

```
# Pull out one tree from the forest
tree = rfc.estimators_[5]
# Export the image to a dot file
export_graphviz(tree, out_file = 'tree.dot', feature_names = feature_list,␣
↪rounded = True, precision = 1)
# Use dot file to create a graph
(graph, ) = pydot.graph_from_dot_file('tree.dot')
```

36 here is a graphic of random forest showing the decision trees in which a label is chosen from the dataset

[56]:
```
# Limit depth of tree to 3 levels
rf_small = RandomForestClassifier(n_estimators=10, max_depth = 3)
rf_small.fit(df,y)
# Extract the small tree
tree_small = rf_small.estimators_[5]
# Save the tree as a png image
export_graphviz(tree_small, out_file = 'small_tree.dot', feature_names =␣
↪feature_list, rounded = True, precision = 1)
(graph, ) = pydot.graph_from_dot_file('small_tree.dot')
graph.write_png('small_tree.png');
```

[57]:
```
display(Image.open('small_tree.png'))
```



37 if a new people with the same data columns were to be added to the dataset with no label of their loan status, I could use the model to predict their label given that the accuracy of the model is already very high

[ ]:
```

```

[ ]:
```

```

```
[ ]:
```