LoanPerformance_CaseStudy

January 6, 2019

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1 Loan Performance Case Study

1.0.1 Imports

```
In [111]: import numpy as np
          import copy
          import pandas as pd
          import seaborn as sns
          import matplotlib.pyplot as plt
          import statsmodels.api as sm
          import datetime as dt
          import math
          from dateutil.relativedelta import relativedelta
          from scipy import stats
          from sklearn.linear_model import LogisticRegression
          from sklearn.linear_model import LogisticRegressionCV
          from sklearn.preprocessing import OneHotEncoder
          from sklearn.preprocessing import StandardScaler
          from sklearn.model_selection import train_test_split
          from sklearn.utils.fixes import signature
          from sklearn import metrics
          from collections import defaultdict
```

1.0.2 Read In Data

```
In [2]: df = pd.read_csv("loan.csv", usecols=["loan_amnt", "funded_amnt", "term", "int_rate", "g
                                               "issue_d", "dti", "revol_bal", "total_pymnt", "l
```

1.0.3 Data / Data Types

First we can take a quick look at our data.

```
In [3]: df.head()
```

```
Out[3]:    loan_amnt  funded_amnt        term  int_rate grade  annual_inc   issue_d  \
        0     5000.0       5000.0   36 months     10.65     B     24000.0  Dec-2011
```

```
1     2500.0       2500.0   60 months     15.27     C     30000.0  Dec-2011
2     2400.0       2400.0   36 months     15.96     C     12252.0  Dec-2011
3    10000.0      10000.0   36 months     13.49     C     49200.0  Dec-2011
4     3000.0       3000.0   60 months     12.69     B     80000.0  Dec-2011

   loan_status    dti  revol_bal   total_pymnt
0   Fully Paid  27.65    13648.0   5861.071414
1  Charged Off   1.00     1687.0   1008.710000
2   Fully Paid   8.72     2956.0   3003.653644
3   Fully Paid  20.00     5598.0  12226.302212
4      Current  17.94    27783.0   3242.170000
```

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

```
Out[4]: (887379, 11)
```

And the associated inferred datatypes from Pandas.

```
In [5]: df.dtypes
```

```
Out[5]: loan_amnt      float64
        funded_amnt    float64
        term            object
        int_rate       float64
        grade           object
        annual_inc     float64
        issue_d         object
        loan_status     object
        dti            float64
        revol_bal      float64
        total_pymnt    float64
        dtype: object
```

Based on the data these inferred types seem reasonable, as we have float types inferred for apparent numeric columns and object (String) types inferred for the apparent string columns displayed above. One small change we will make, for ease of analysis, is to convert the 'issue_d' column to datetime.

```
In [6]: df["issue_d"] = pd.to_datetime(df["issue_d"])
```

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

```
Out[7]: loan_amnt             float64
        funded_amnt           float64
        term                   object
        int_rate              float64
        grade                  object
        annual_inc            float64
        issue_d        datetime64[ns]
```

```
loan_status            object
dti                   float64
revol_bal             float64
total_pymnt           float64
dtype: object
```

1.1 1. Exploratory Data Analysis

1.1.1 Step 1 - Checking NULL / Empty Strings / Missing Values

First we will check numeric columns for NULL values.

```
In [8]: df.isna().sum()
```

```
Out[8]: loan_amnt      0
        funded_amnt    0
        term           0
        int_rate       0
        grade          0
        annual_inc     4
        issue_d        0
        loan_status    0
        dti            0
        revol_bal      0
        total_pymnt    0
        dtype: int64
```

Next we will check all values of object (String/str) columns for blank or odd values.

```
In [9]: df["term"].unique()
```

```
Out[9]: array([' 36 months', ' 60 months'], dtype=object)
```

```
In [10]: df["grade"].unique()
```

```
Out[10]: array(['B', 'C', 'A', 'E', 'F', 'D', 'G'], dtype=object)
```

```
In [11]: df["issue_d"].unique()
```

```
Out[11]: array(['2011-12-01T00:00:00.000000000', '2011-11-01T00:00:00.000000000',
                '2011-10-01T00:00:00.000000000', '2011-09-01T00:00:00.000000000',
                '2011-08-01T00:00:00.000000000', '2011-07-01T00:00:00.000000000',
                '2011-06-01T00:00:00.000000000', '2011-05-01T00:00:00.000000000',
                '2011-04-01T00:00:00.000000000', '2011-03-01T00:00:00.000000000',
                '2011-02-01T00:00:00.000000000', '2011-01-01T00:00:00.000000000',
                '2010-12-01T00:00:00.000000000', '2010-11-01T00:00:00.000000000',
                '2010-10-01T00:00:00.000000000', '2010-09-01T00:00:00.000000000',
                '2010-08-01T00:00:00.000000000', '2010-07-01T00:00:00.000000000',
                '2010-06-01T00:00:00.000000000', '2010-05-01T00:00:00.000000000',
                '2010-04-01T00:00:00.000000000', '2010-03-01T00:00:00.000000000',
```

```
               '2010-02-01T00:00:00.000000000', '2010-01-01T00:00:00.000000000',
               '2009-12-01T00:00:00.000000000', '2009-11-01T00:00:00.000000000',
               '2009-10-01T00:00:00.000000000', '2009-09-01T00:00:00.000000000',
               '2009-08-01T00:00:00.000000000', '2009-07-01T00:00:00.000000000',
               '2009-06-01T00:00:00.000000000', '2009-05-01T00:00:00.000000000',
               '2009-04-01T00:00:00.000000000', '2009-03-01T00:00:00.000000000',
               '2009-02-01T00:00:00.000000000', '2009-01-01T00:00:00.000000000',
               '2008-12-01T00:00:00.000000000', '2008-11-01T00:00:00.000000000',
               '2008-10-01T00:00:00.000000000', '2008-09-01T00:00:00.000000000',
               '2008-08-01T00:00:00.000000000', '2008-07-01T00:00:00.000000000',
               '2008-06-01T00:00:00.000000000', '2008-05-01T00:00:00.000000000',
               '2008-04-01T00:00:00.000000000', '2008-03-01T00:00:00.000000000',
               '2008-02-01T00:00:00.000000000', '2008-01-01T00:00:00.000000000',
               '2007-12-01T00:00:00.000000000', '2007-11-01T00:00:00.000000000',
               '2007-10-01T00:00:00.000000000', '2007-09-01T00:00:00.000000000',
               '2007-08-01T00:00:00.000000000', '2007-07-01T00:00:00.000000000',
               '2007-06-01T00:00:00.000000000', '2013-12-01T00:00:00.000000000',
               '2013-11-01T00:00:00.000000000', '2013-10-01T00:00:00.000000000',
               '2013-09-01T00:00:00.000000000', '2013-08-01T00:00:00.000000000',
               '2013-07-01T00:00:00.000000000', '2013-06-01T00:00:00.000000000',
               '2013-05-01T00:00:00.000000000', '2013-04-01T00:00:00.000000000',
               '2013-03-01T00:00:00.000000000', '2013-02-01T00:00:00.000000000',
               '2013-01-01T00:00:00.000000000', '2012-12-01T00:00:00.000000000',
               '2012-11-01T00:00:00.000000000', '2012-10-01T00:00:00.000000000',
               '2012-09-01T00:00:00.000000000', '2012-08-01T00:00:00.000000000',
               '2012-07-01T00:00:00.000000000', '2012-06-01T00:00:00.000000000',
               '2012-05-01T00:00:00.000000000', '2012-04-01T00:00:00.000000000',
               '2012-03-01T00:00:00.000000000', '2012-02-01T00:00:00.000000000',
               '2012-01-01T00:00:00.000000000', '2014-12-01T00:00:00.000000000',
               '2014-11-01T00:00:00.000000000', '2014-10-01T00:00:00.000000000',
               '2014-09-01T00:00:00.000000000', '2014-08-01T00:00:00.000000000',
               '2014-07-01T00:00:00.000000000', '2014-06-01T00:00:00.000000000',
               '2014-05-01T00:00:00.000000000', '2014-04-01T00:00:00.000000000',
               '2014-03-01T00:00:00.000000000', '2014-02-01T00:00:00.000000000',
               '2014-01-01T00:00:00.000000000', '2015-12-01T00:00:00.000000000',
               '2015-11-01T00:00:00.000000000', '2015-10-01T00:00:00.000000000',
               '2015-09-01T00:00:00.000000000', '2015-08-01T00:00:00.000000000',
               '2015-07-01T00:00:00.000000000', '2015-06-01T00:00:00.000000000',
               '2015-05-01T00:00:00.000000000', '2015-04-01T00:00:00.000000000',
               '2015-03-01T00:00:00.000000000', '2015-02-01T00:00:00.000000000',
               '2015-01-01T00:00:00.000000000'], dtype='datetime64[ns]')
```

```
In [12]: df["loan_status"].unique()
```

```
Out[12]: array(['Fully Paid', 'Charged Off', 'Current', 'Default',
               'Late (31-120 days)', 'In Grace Period', 'Late (16-30 days)',
               'Does not meet the credit policy. Status:Fully Paid',
               'Does not meet the credit policy. Status:Charged Off', 'Issued'],
              dtype=object)
```

Based on the above analysis, it appears there are missing values in the 'annual_inc' column. All other columns appear to have no NULL, blank, or otherwise missing values. We can take a close look at the rows corresponding to NULL values in the 'annual_inc' column.

```
In [13]: df[df.isnull().any(axis=1)]
```

```
Out[13]:        loan_amnt  funded_amnt        term  int_rate grade  annual_inc  \
         42449     5000.0       5000.0   36 months      7.43     A         NaN
         42450     7000.0       7000.0   36 months      7.75     A         NaN
         42480     6700.0       6700.0   36 months      7.75     A         NaN
         42533     6500.0       6500.0   36 months      8.38     A         NaN

                  issue_d                                       loan_status  dti  \
         42449 2007-08-01  Does not meet the credit policy. Status:Fully ...  1.0
         42450 2007-08-01  Does not meet the credit policy. Status:Fully ...  1.0
         42480 2007-07-01  Does not meet the credit policy. Status:Fully ...  1.0
         42533 2007-06-01  Does not meet the credit policy. Status:Fully ...  4.0

                revol_bal  total_pymnt
         42449        0.0      5593.46
         42450        0.0      7867.53
         42480        0.0      7530.42
         42533        0.0      7373.83
```

These NULL/NaN values are clustered in the mid-2007 period. This could also be due to internal issues with the LendingClub database or lack of requirements for reporting annual income within the database / front end. We will avoid dropping these records for now. If there is a business case to fill in these values then additional techniques such as imputation (using mean, MICE, or other methods) could be explored at a later time.

```
In [14]: df.shape
```

```
Out[14]: (887379, 11)
```

1.1.2 Step 2 - Initial EDA

```
In [15]: df_desc = df.describe()
         display(df_desc)
```

```
           loan_amnt    funded_amnt       int_rate   annual_inc  \
count  887379.000000  887379.000000  887379.000000  8.873750e+05
mean    14755.264605   14741.877625      13.246740  7.502759e+04
std      8435.455601    8429.897657       4.381867  6.469830e+04
min       500.000000     500.000000       5.320000  0.000000e+00
25%      8000.000000    8000.000000       9.990000  4.500000e+04
50%     13000.000000   13000.000000      12.990000  6.500000e+04
75%     20000.000000   20000.000000      16.200000  9.000000e+04
max     35000.000000   35000.000000      28.990000  9.500000e+06
```

```
             dti     revol_bal    total_pymnt
count  887379.000000  8.873790e+05  887379.000000
mean       18.157039  1.692079e+04    7558.826684
std        17.190626  2.242679e+04    7871.243336
min         0.000000  0.000000e+00       0.000000
25%        11.910000  6.443000e+03    1914.590000
50%        17.650000  1.187500e+04    4894.999117
75%        23.950000  2.082900e+04   10616.814231
max      9999.000000  2.904836e+06   57777.579870
```

Initial Observations:

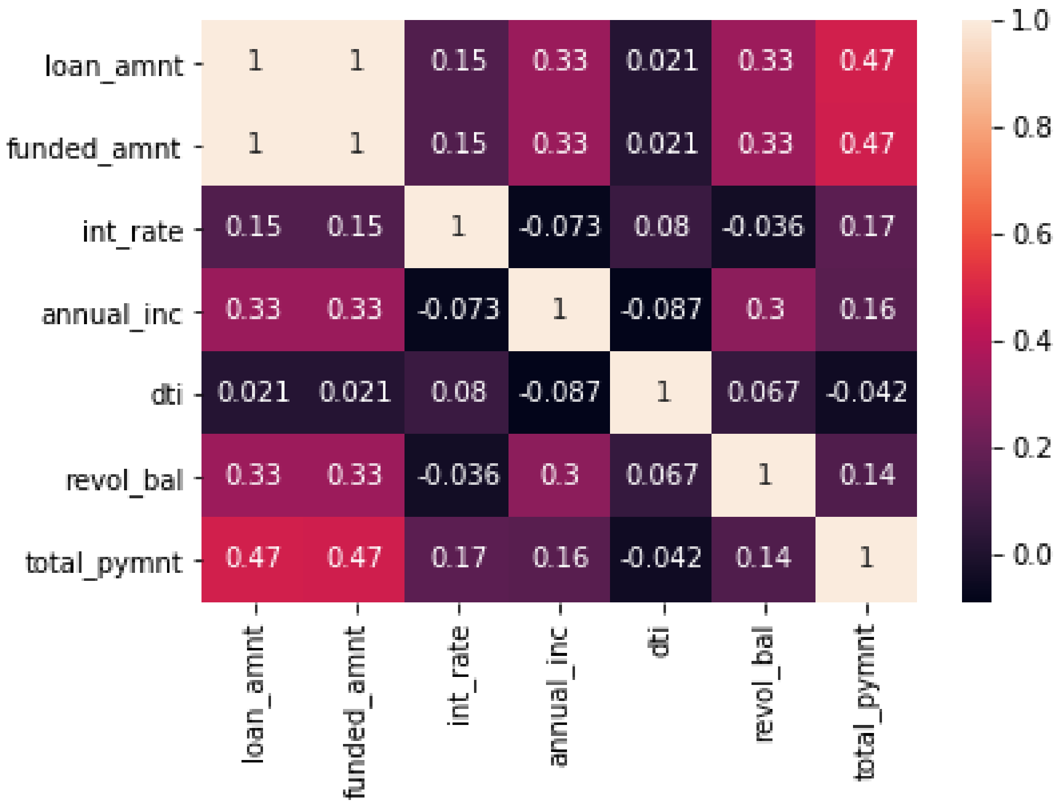
1. Loan application amount and funded amount appear to have very similar distributions, we will verify this later.
2. Interest rates seem have somewhat higher variance than expected.
3. Annual income seems to be right skewed as expected.
4. Debt-to-income seems to have relatively high variance.

```
In [16]: df.corr()
```

```
Out[16]:              loan_amnt  funded_amnt  int_rate  annual_inc       dti  \
         loan_amnt     1.000000     0.999263  0.145023    0.332698  0.020675
         funded_amnt   0.999263     1.000000  0.145160    0.332466  0.021075
         int_rate      0.145023     0.145160  1.000000   -0.072786  0.079903
         annual_inc    0.332698     0.332466 -0.072786    1.000000 -0.087410
         dti           0.020675     0.021075  0.079903   -0.087410  1.000000
         revol_bal     0.333580     0.333435 -0.035708    0.295784  0.067277
         total_pymnt   0.474626     0.473286  0.170506    0.160879 -0.041529

                      revol_bal  total_pymnt
         loan_amnt     0.333580     0.474626
         funded_amnt   0.333435     0.473286
         int_rate     -0.035708     0.170506
         annual_inc    0.295784     0.160879
         dti           0.067277    -0.041529
         revol_bal     1.000000     0.138328
         total_pymnt   0.138328     1.000000
```

```
In [17]: corr = df.corr()
         sns.heatmap(corr,
                 xticklabels=corr.columns,
                 yticklabels=corr.columns, annot=True)
```

```
Out[17]: <matplotlib.axes._subplots.AxesSubplot at 0x1a20751e10>
```



Correlation Observations:

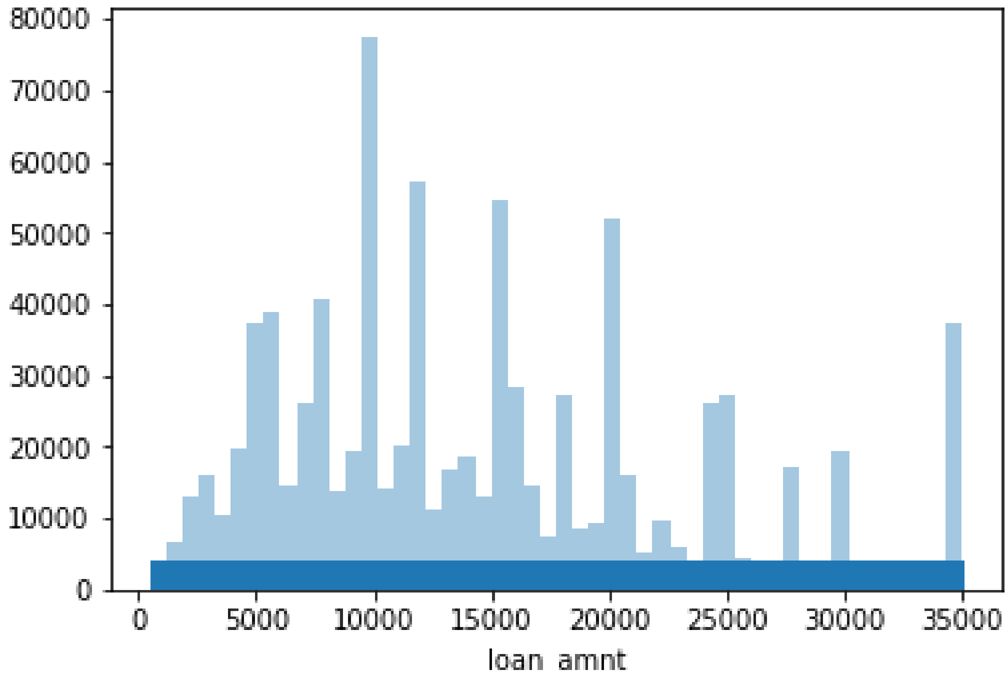
1. Loan application amount and funding amount appear to be highly correlated (approaching 1.0).
2. Loan application amount, funding amount, annual income, revolving balance, and total payment all appear to be moderate-highly positively correlated.

All of these correlations seem reasonable and conform to my expectations about the loan application process, credit requirements, and nature of these fields.

Next we will plot distributions for the numeric columns.

```
In [18]: sns.distplot(df["loan_amnt"], kde=False, rug=True);
```

```
/Users/Samuel/anaconda3/lib/python3.6/site-packages/scipy/stats/stats.py:1713: FutureWarning: Us
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```

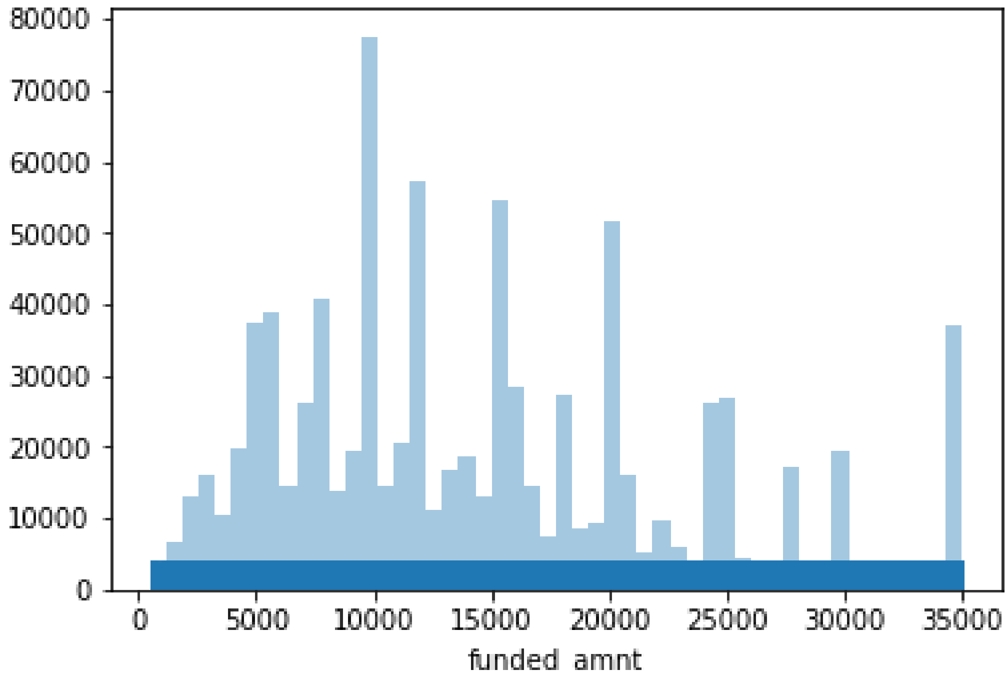



```
In [19]: df.groupby(["loan_amnt"]).size().reset_index(name='count').sort_values(['count'], ascen
```

```
Out[19]:       loan_amnt  count
         371     10000.0  61837
         451     12000.0  50183
         571     15000.0  47210
         771     20000.0  46932
         1371    35000.0  36368
         291      8000.0  27870
         171      5000.0  27167
         211      6000.0  26207
         971     25000.0  24125
         611     16000.0  23708
         931     24000.0  22323
         691     18000.0  22136
         1171    30000.0  17588
         1091    28000.0  14909
         251      7000.0  14135
         531     14000.0  13363
         811     21000.0  12060
         331      9000.0  11144
         131      4000.0  10524
         91       3000.0   9714
```

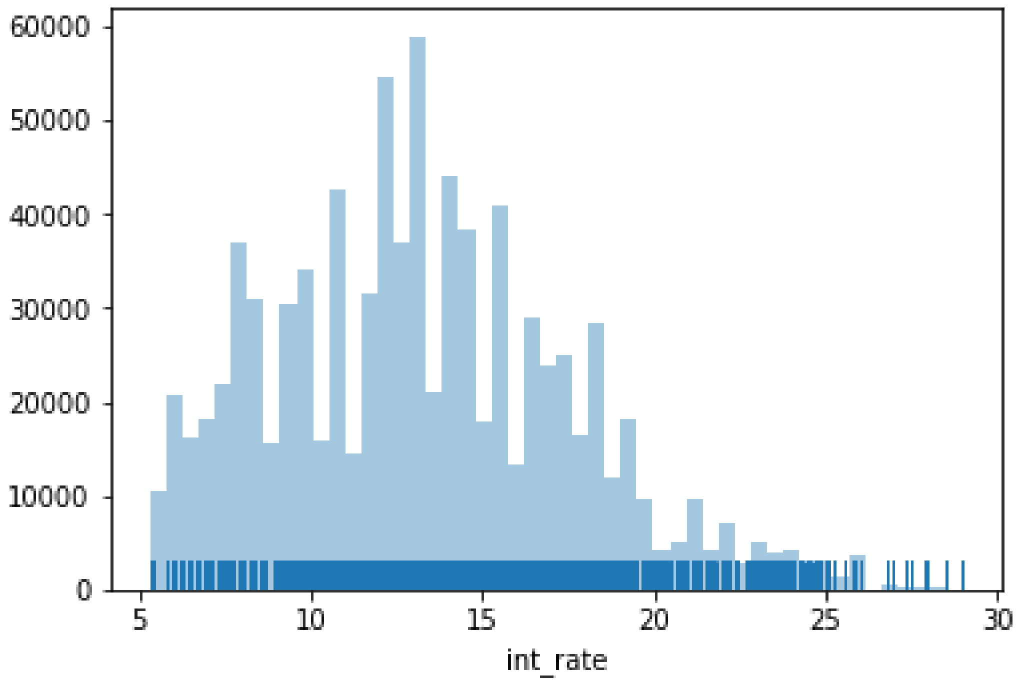
Loan application amount appears to be reasonably normally distribution in most cases. There are several values, including 10,000; 12,000; 15,000; 25,000; and 35,000 dollars, along with others that appear to be overly represented based on standard distributional assumptions. This is likely due to human preference for these numbers.

```
In [20]: sns.distplot(df["funded_amnt"], kde=False, rug=True)
         plt.show()
```



The distribution of funding amount closely mimics the distribution of loan application amount as expected.

```
In [21]: sns.distplot(df["int_rate"], kde=False, rug=True)
         plt.show()
```



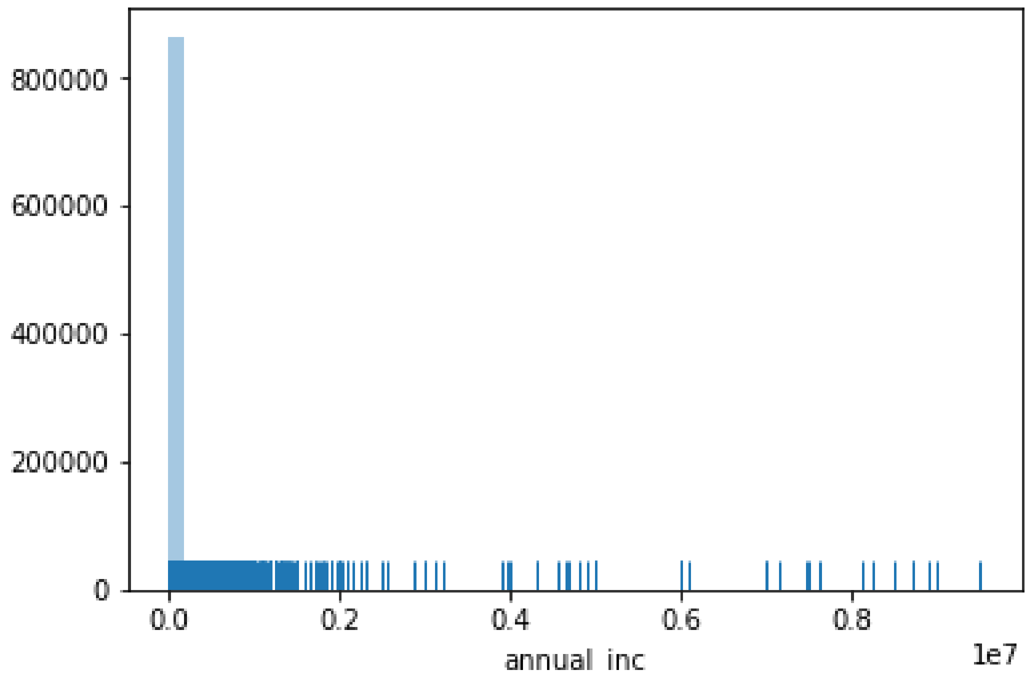

```
In [22]: df.groupby(["int_rate"]).size().reset_index(name='count').sort_values(['count'], ascend
```

Out[22]:

	int_rate	count
110	10.99	34624
59	9.17	25720
287	15.61	25201
80	9.99	21553
38	7.89	20311

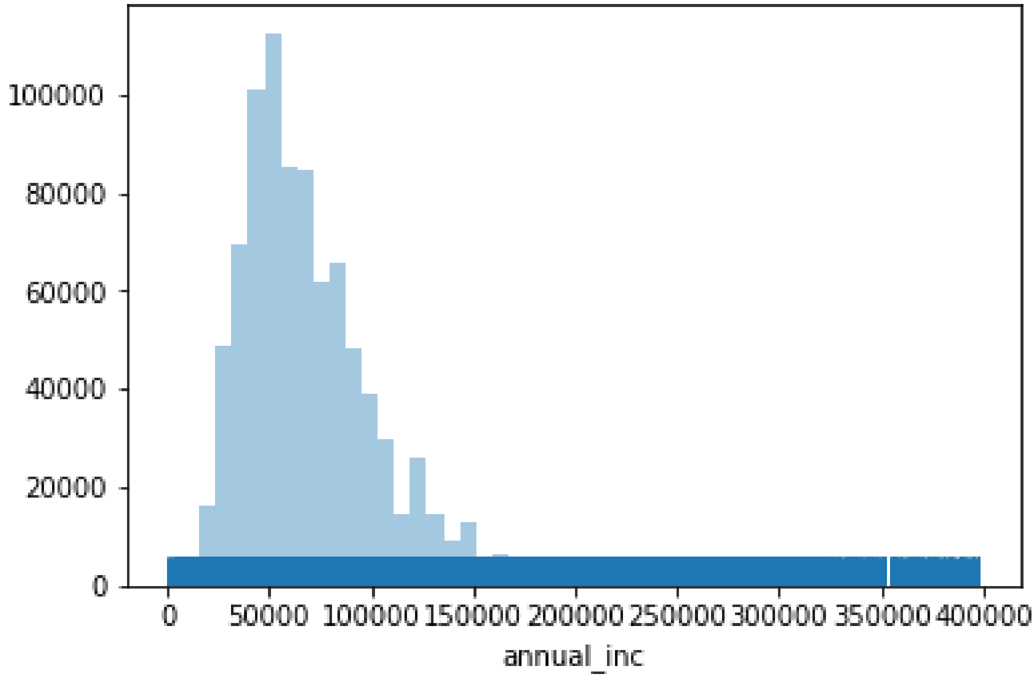
Interest rates appear to be reasonably distributed at first glance with no observable outliers. It is interesting to note the changes in density between different rate values in the plot.

```
In [23]: sns.distplot(df["annual_inc"].dropna(), kde=False, rug=True)
         plt.show()
```




```
In [24]: thresh = 5*df_desc["annual_inc"]["std"]
         print(thresh)
         sns.distplot(df[abs(df["annual_inc"]-df_desc["annual_inc"]["mean"]) < thresh]["annual_i
         plt.show()
```

```
323491.50071200065
```

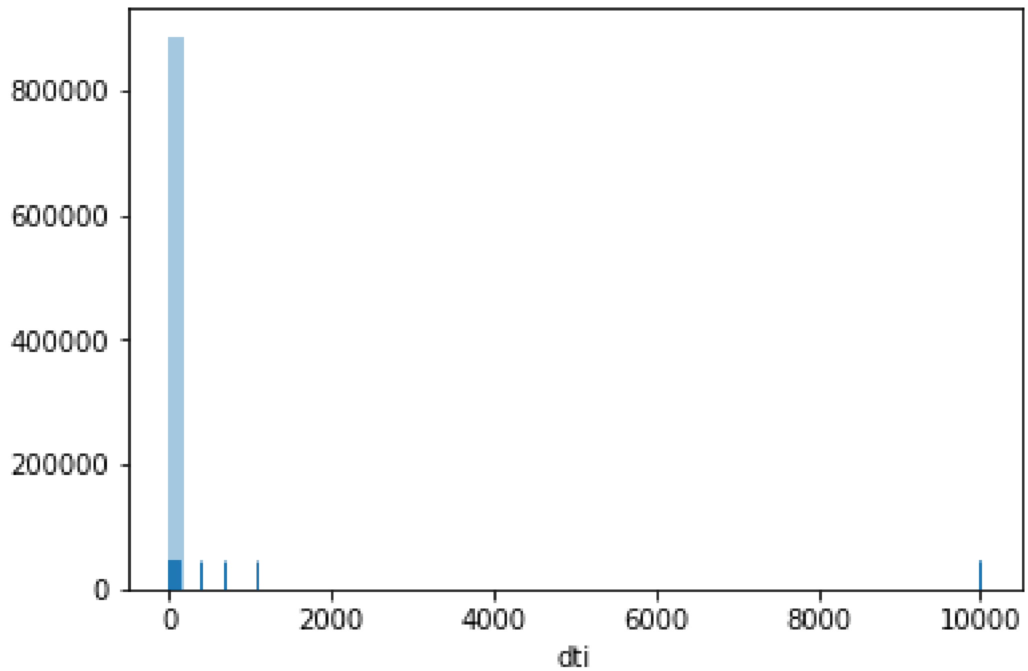



```
In [25]: df.groupby(["annual_inc"]).size().reset_index(name='count').sort_values(['count'], asce
```

```
Out[25]:        annual_inc  count
         24048     60000.0  34281
         17805     50000.0  30575
         26762     65000.0  25498
         29378     70000.0  24121
         11305     40000.0  23943
```

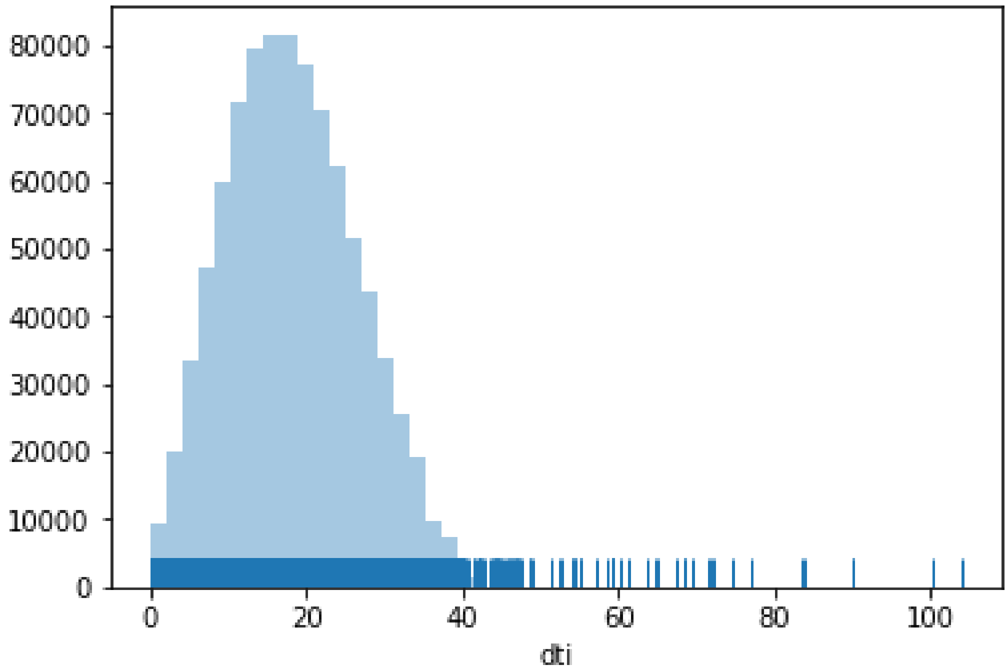
It appears there are some outliers for annual income and the distribution appears to be right skewed.

```
In [26]: sns.distplot(df["dti"], kde=False, rug=True)
         plt.show()
```




```
In [27]: thresh = 5*df_desc["dti"]["std"]
         print(thresh)
         sns.distplot(df[abs(df["dti"]-df_desc["dti"]["mean"]) < thresh]["dti"], kde=False, rug=
         plt.show()
```

```
85.95312843970368
```

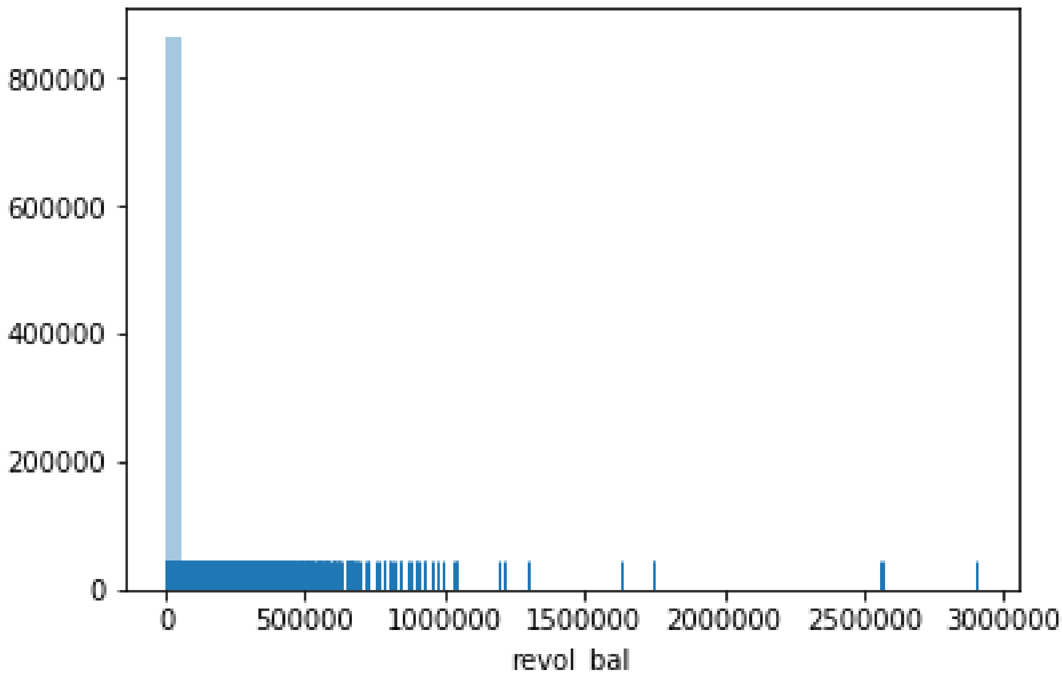



```
In [28]: df.groupby(["dti"]).size().reset_index(name='count').sort_values(['count'], ascending=F
```

```
Out[28]:        dti  count
         1920  19.2    684
         1440  14.4    674
         1800  18.0    661
         1320  13.2    638
         1680  16.8    632
```

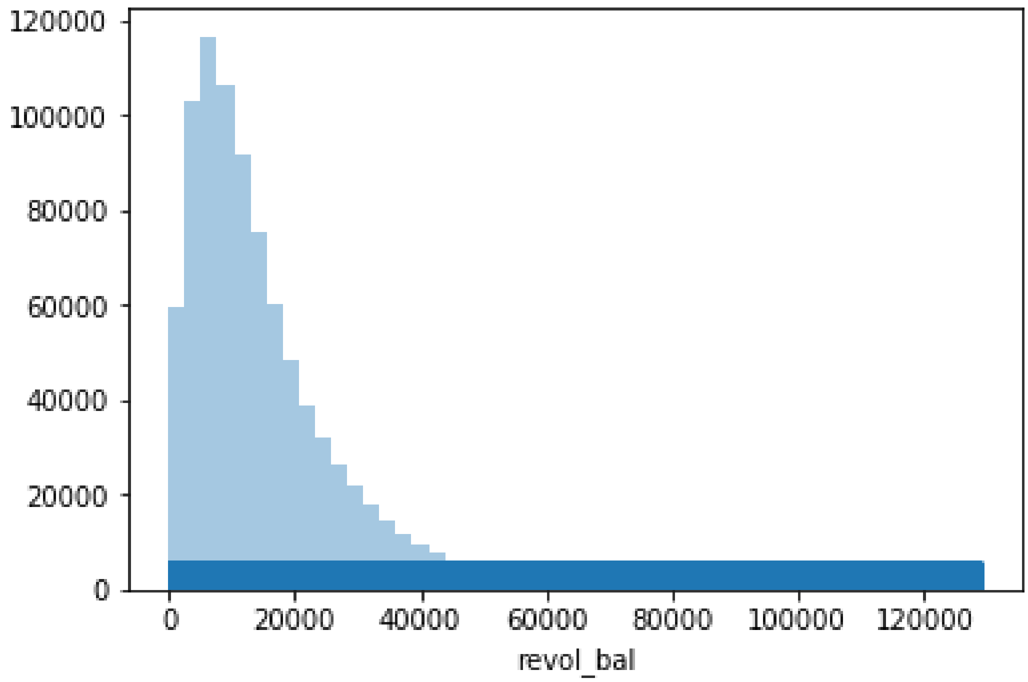
There appear to be some outliers for the 'debt-to-income' variable.

```
In [29]: sns.distplot(df["revol_bal"], kde=False, rug=True)
         plt.show()
```




```
In [30]: thresh = 5*df_desc["revol_bal"]["std"]
         print(thresh)
         sns.distplot(df[abs(df["revol_bal"]-df_desc["revol_bal"]["mean"]) < thresh]["revol_bal"
         plt.show()
```

```
112133.95947981573
```

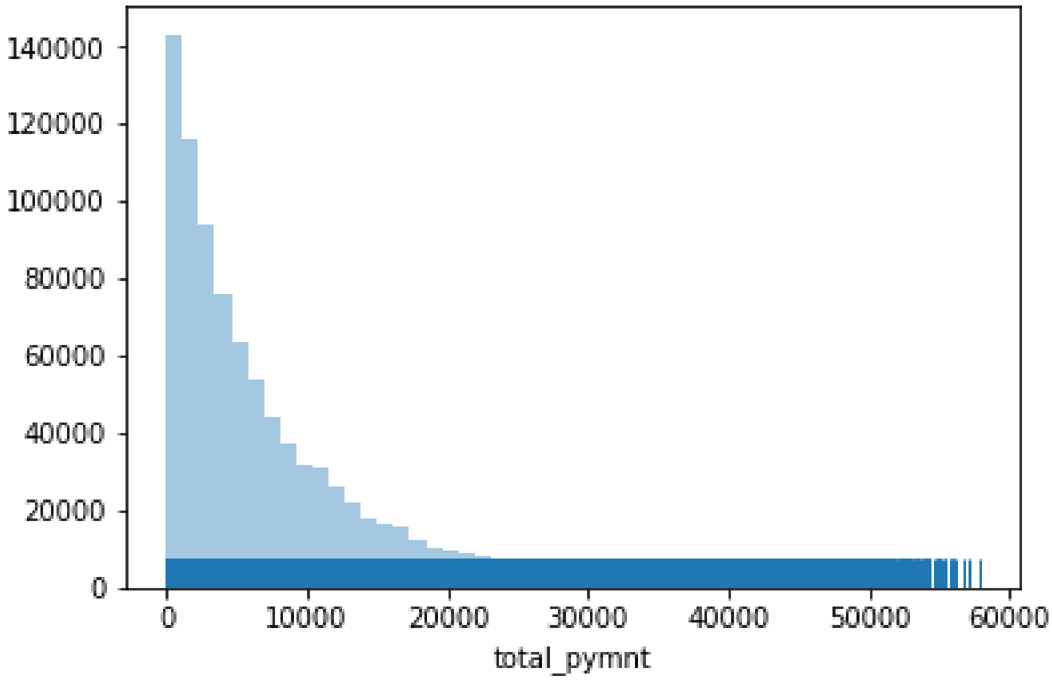



```
In [31]: df.groupby(["revol_bal"]).size().reset_index(name='count').sort_values(['count'], ascen
```

```
Out[31]:       revol_bal  count
         0          0.0   3402
         5235    5235.0     74
         5466    5466.0     72
         4479    4479.0     68
         6969    6969.0     67
```

The appears to be some right-skew and outliers for the revolving balance variable.

```
In [32]: sns.distplot(df["total_pymnt"], kde=False, rug=True)
         plt.show()
```




```
In [33]: df.groupby(["total_pymnt"]).size().reset_index(name='count').sort_values(['count'], asc
```

```
Out[33]:        total_pymnt  count
         0             0.00  17759
         23309       648.57    135
         35679       938.06    134
         22207       623.86    131
         61829      1566.46    117
```

There appears to be a large right skew for the total payment distribution.
Now we will explore our categorical variables.

```
In [34]: df["term"].value_counts()
```

```
Out[34]:  36 months    621125
          60 months    266254
         Name: term, dtype: int64
```

A 36 month loan term appears to be most common, representing 70.00% of the dataset.

```
In [35]: df["grade"].value_counts()
```

```
Out[35]: B    254535
         C    245860
         A    148202
```

```
D    139542
E     70705
F     23046
G      5489
Name: grade, dtype: int64
```

B grade loans are the most common, closely followed by C grade loans. The next most common grades, A and D grades, also have similar counts.

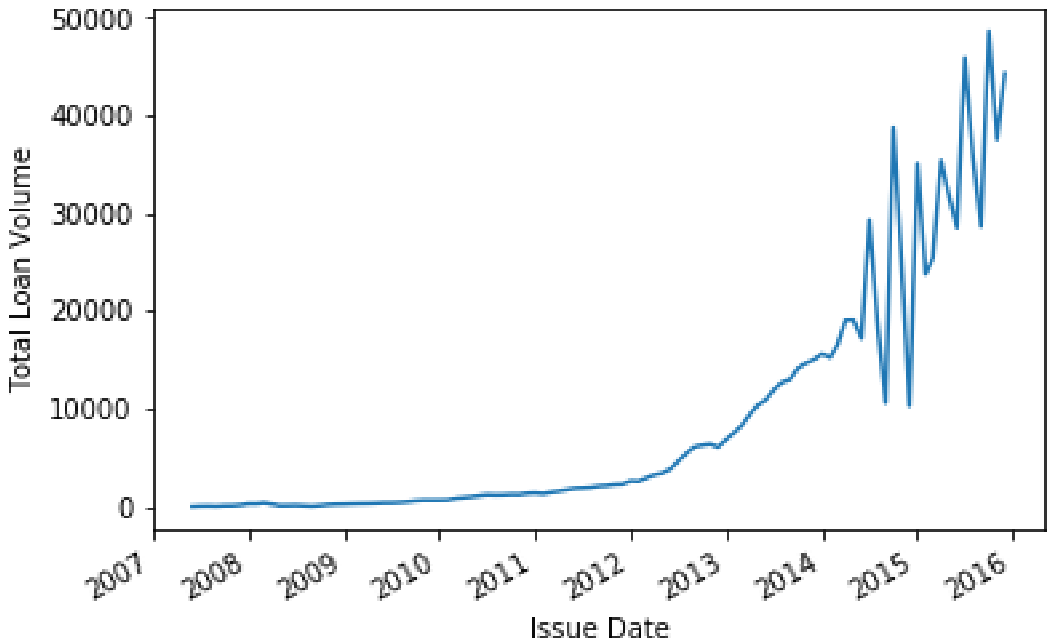
```
In [36]: df["issue_d"].value_counts()
```

```
Out[36]: 2015-10-01    48631
         2015-07-01    45962
         2015-12-01    44342
         2014-10-01    38782
         2015-11-01    37530
         2015-08-01    35886
         2015-04-01    35427
         2015-01-01    35107
         2015-05-01    31913
         2014-07-01    29306
         2015-09-01    28641
         2015-06-01    28485
         2015-03-01    25400
         2014-11-01    25054
         2015-02-01    23770
         2014-05-01    19099
         2014-04-01    19071
         2014-08-01    18814
         2014-06-01    17179
         2014-03-01    16513
         2014-01-01    15628
         2014-02-01    15269
         2013-12-01    15020
         2013-11-01    14676
         2013-10-01    14114
         2013-09-01    12987
         2013-08-01    12674
         2013-07-01    11910
         2013-06-01    10899
         2014-09-01    10606
                       ...
         2009-12-01      658
         2009-10-01      604
         2009-09-01      507
         2009-08-01      446
         2009-07-01      411
         2009-06-01      406
```

```
2008-03-01      402
2009-05-01      359
2009-04-01      333
2009-03-01      324
2008-02-01      306
2008-01-01      305
2009-02-01      302
2009-01-01      269
2008-04-01      259
2008-12-01      253
2008-11-01      209
2007-12-01      172
2008-07-01      141
2008-06-01      124
2008-10-01      122
2008-05-01      115
2007-11-01      112
2007-10-01      105
2008-08-01      100
2007-08-01       74
2007-07-01       63
2008-09-01       57
2007-09-01       53
2007-06-01       24
Name: issue_d, Length: 103, dtype: int64
```

It appears that loan volumes have increased over time. We can look at this relationship below.

```
In [37]: count_df = df.groupby(["issue_d"]).size().reset_index(name="count").sort_values(["count
         count_df[["issue_d","count"]].set_index("issue_d").plot(legend=False)
         plt.xlabel("Issue Date")
         plt.ylabel("Total Loan Volume")
         plt.show()
```



Loan volumes have indeed trended up over time. Interestingly, it appears that loan volumes have gotten much more variable during and after 2015.

```
In [38]: df["loan_status"].value_counts()
```

```
Out[38]: Current                                                601779
         Fully Paid                                             207723
         Charged Off                                             45248
         Late (31-120 days)                                      11591
         Issued                                                   8460
         In Grace Period                                          6253
         Late (16-30 days)                                        2357
         Does not meet the credit policy. Status:Fully Paid       1988
         Default                                                  1219
         Does not meet the credit policy. Status:Charged Off       761
         Name: loan_status, dtype: int64
```

The most common loan status is 'Current' followed by 'Fully Paid'. The other categories aside from 'Issued' represent loans which are at risk of default, are in default, or are charged off. 7.82% of all loans are in these categories.

```
In [39]: loan_status_agg = (df.groupby(["loan_status", "grade"]).size()/df.groupby(["grade"]).si
         (loan_status_agg["Current"]+loan_status_agg["Fully Paid"])*100
```

```
Out[39]: grade
         A    96.490601
         B    93.614238
```

```
C    91.048971
D    87.431741
E    84.844070
F    79.471492
G    73.947896
dtype: float64
```

There appears to be a correlation between grades and associated loan status- 96.491% of A grade loans are "Current" or "Fully Paid" while only 73.948% of G grade loans are "Current" or "Fully Paid".

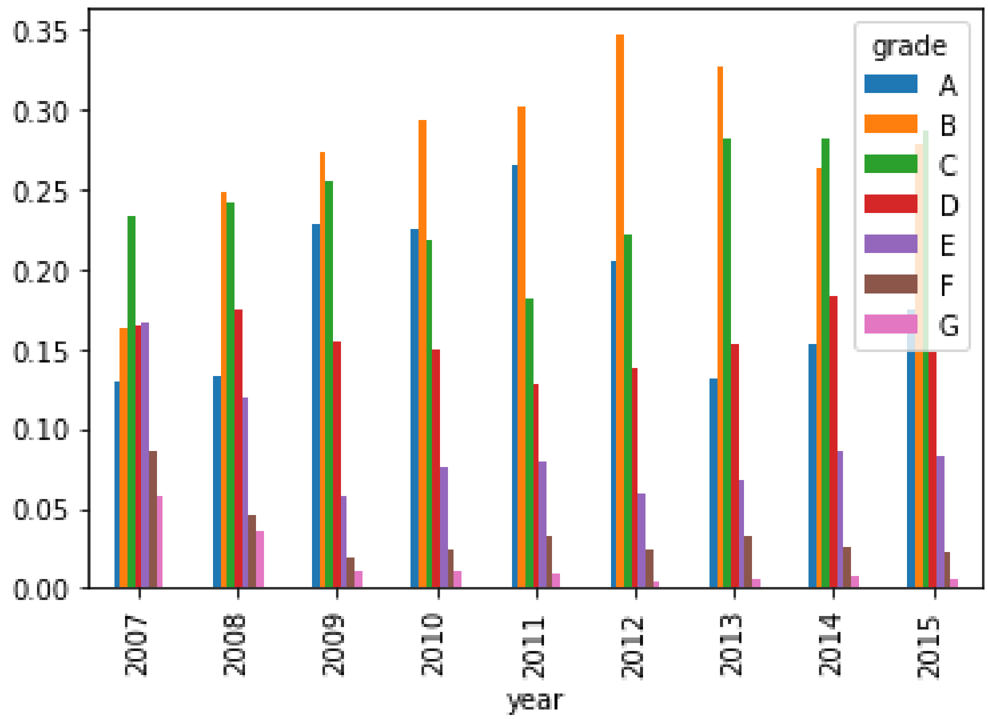
```
In [40]: df["year"] = df["issue_d"].apply(lambda x: x.year)
         df_grade_agg = df.groupby(["grade", "year"]).size()/df.groupby(["year"]).size()
         df_grade_agg.head()
```

```
Out[40]: grade  year
         A      2007    0.129353
                2008    0.132888
                2009    0.227798
                2010    0.225732
                2011    0.264905
         dtype: float64
```

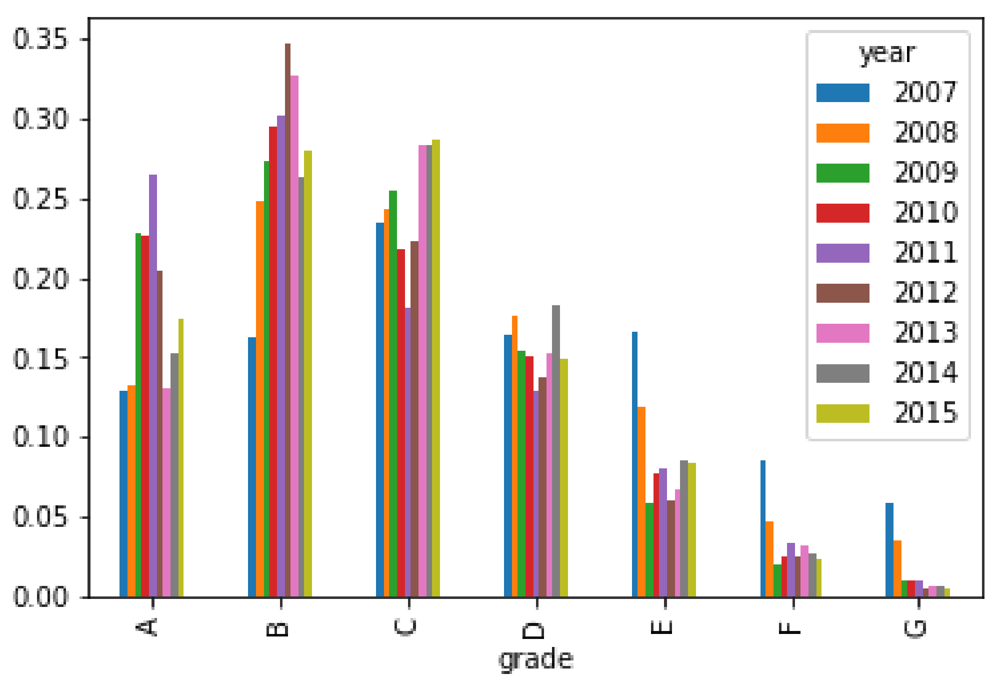
```
In [41]: df_year_agg = df.groupby(["year", "grade"]).size()/df.groupby(["year"]).size()
         df_year_agg.head()
```

```
Out[41]: year  grade
         2007  A        0.129353
               B        0.162521
               C        0.233831
               D        0.164179
               E        0.165837
         dtype: float64
```

```
In [42]: df_grade_agg.unstack(level=0).plot(kind='bar', subplots=False)
         plt.show()
```




```
In [43]: df_year_agg.unstack(level=0).plot(kind='bar', subplots=False)
         plt.show()
```



Some interesting trends appear in the data: 1. We see that grade A loans peaked in popularity around 2011 (this may be due to tighter standards / more limited risk appetites after the financial crisis.) 2. Grade B loans peaked in popularity around 2012. 3. Grade C loans are now the most popular. 4. Grade F and G loans were more popular in 2007 than any time after.

1.1.3 Step 3 - Discussion of Outliers

Based on the above EDA there are apparent outliers in the following columns:

1. Annual Income
2. Debt to Income
3. Revolving Balance

We can initially quantify outliers using a 4 standard deviation cutoff from the mean, and will check for the presence of outliers in other columns.

In [44]:
```
thresh1 = 4*df_desc["loan_amnt"]["std"]
len(df[abs(df["loan_amnt"]-df_desc["loan_amnt"]["mean"]) >= thresh1])
```

Out[44]: 0

In [45]:
```
thresh2 = 4*df_desc["funded_amnt"]["std"]
len(df[abs(df["funded_amnt"]-df_desc["funded_amnt"]["mean"]) >= thresh2])
```

Out[45]: 0

In [46]:
```
thresh3 = 4*df_desc["int_rate"]["std"]
len(df[abs(df["int_rate"]-df_desc["int_rate"]["mean"]) >= thresh3])
```

Out[46]: 0

In [47]:
```
thresh4 = 4*df_desc["annual_inc"]["std"]
len(df[abs(df["annual_inc"]-df_desc["annual_inc"]["mean"]) >= thresh4])
```

Out[47]: 3641

In [48]:
```
thresh5 = 4*df_desc["dti"]["std"]
len(df[abs(df["dti"]-df_desc["dti"]["mean"]) >= thresh5])
```

Out[48]: 13

In [49]:
```
thresh6 = 4*df_desc["revol_bal"]["std"]
len(df[abs(df["revol_bal"]-df_desc["revol_bal"]["mean"]) >= thresh6])
```

Out[49]: 6893

In [50]:
```
thresh7 = 4*df_desc["total_pymnt"]["std"]
len(df[abs(df["total_pymnt"]-df_desc["total_pymnt"]["mean"]) >= thresh7])
```

Out[50]: 5526

Based on this rule, total payments appears to have outlier values as well.

```
In [51]: len(df[(abs(df["annual_inc"]-df_desc["annual_inc"]["mean"] >= thresh4)) | (abs(df["dti"]
```

Out[51]: 15103

Given a somewhat crude rule of [abs(value-mean) > 4*sd] representing an outlier for a given numeric attribute, we can identify 15,103 records corresponding to this rule when when considering all numeric attributes. If there was time to further dive into working on outlier detection we could look at techniques such as one-class SVM or isolation forests. We will not exclude the idenfitied outliers for now and will deal with them later during the modeling phase.

1.1.4 Step 4 - Summary of Findings

Note: The two(+) data visualizations and summary statistics to support the findings below can be found above.

Based on our exploratory data analysis, there are several important findings:

1. Four records with NULL or otherwise blank values were found.
2. Loan amount and funding amount appear to be highly correlated.
3. Loan amount, funding amount, annual incoming, revolving balance, and total payments all appear to be moderately-highly correlated.
4. Approximately 15,103 outliers were found in our numeric data using a 4 standard deviation cutoff.
5. Total loan volumes have trended up over time.
6. Loans that are in good standing make up the bulk of the loan portfolio (92.18%).
7. Higher grade loans appear to have better payback characteristics.
8. There appear to be time trends in the distribution of loan grades, potentially due to lender demand or regulatory requirements.

2 2. Business Analysis

We will subset to include only loans with 36 month terms.

```
In [52]: ba_df = copy.deepcopy(df)
         ba_df = ba_df[ba_df.term == " 36 months"]

In [53]: ba_df.head()
```

```
Out[53]:    loan_amnt  funded_amnt        term  int_rate grade  annual_inc    issue_d  \
         0     5000.0       5000.0   36 months     10.65     B     24000.0 2011-12-01
         2     2400.0       2400.0   36 months     15.96     C     12252.0 2011-12-01
         3    10000.0      10000.0   36 months     13.49     C     49200.0 2011-12-01
         5     5000.0       5000.0   36 months      7.90     A     36000.0 2011-12-01
         7     3000.0       3000.0   36 months     18.64     E     48000.0 2011-12-01

           loan_status    dti  revol_bal   total_pymnt  year
```

```
0  Fully Paid  27.65    13648.0   5861.071414  2011
2  Fully Paid   8.72     2956.0   3003.653644  2011
3  Fully Paid  20.00     5598.0  12226.302212  2011
5  Fully Paid  11.20     7963.0   5631.377753  2011
7  Fully Paid   5.35     8221.0   3938.144334  2011
```

```
In [54]: ba_df.shape
```

```
Out[54]: (621125, 12)
```

Now we will exclude loans with less than 36 months of data. We can utilize a date difference from the maximum date (12/2015) to the loan issue date.

```
In [55]: end_date = max(ba_df["issue_d"])
         print(end_date)
```

```
2015-12-01 00:00:00
```

```
In [56]: ba_df["months_diff"] = ((end_date - ba_df["issue_d"])/np.timedelta64(1, 'M')).astype(in
```

```
In [57]: ba_df.head()
```

```
Out[57]:    loan_amnt  funded_amnt        term  int_rate grade  annual_inc    issue_d  \
         0     5000.0       5000.0   36 months     10.65     B     24000.0 2011-12-01
         2     2400.0       2400.0   36 months     15.96     C     12252.0 2011-12-01
         3    10000.0      10000.0   36 months     13.49     C     49200.0 2011-12-01
         5     5000.0       5000.0   36 months      7.90     A     36000.0 2011-12-01
         7     3000.0       3000.0   36 months     18.64     E     48000.0 2011-12-01

           loan_status    dti  revol_bal   total_pymnt  year  months_diff
         0  Fully Paid  27.65    13648.0   5861.071414  2011           48
         2  Fully Paid   8.72     2956.0   3003.653644  2011           48
         3  Fully Paid  20.00     5598.0  12226.302212  2011           48
         5  Fully Paid  11.20     7963.0   5631.377753  2011           48
         7  Fully Paid   5.35     8221.0   3938.144334  2011           48
```

```
In [58]: ba_df_valid = copy.deepcopy(ba_df[ba_df["months_diff"] >= 36])
```

```
In [59]: ba_df_valid.head()
```

```
Out[59]:    loan_amnt  funded_amnt        term  int_rate grade  annual_inc    issue_d  \
         0     5000.0       5000.0   36 months     10.65     B     24000.0 2011-12-01
         2     2400.0       2400.0   36 months     15.96     C     12252.0 2011-12-01
         3    10000.0      10000.0   36 months     13.49     C     49200.0 2011-12-01
         5     5000.0       5000.0   36 months      7.90     A     36000.0 2011-12-01
         7     3000.0       3000.0   36 months     18.64     E     48000.0 2011-12-01

           loan_status    dti  revol_bal   total_pymnt  year  months_diff
         0  Fully Paid  27.65    13648.0   5861.071414  2011           48
```

```
2  Fully Paid   8.72     2956.0   3003.653644  2011            48
3  Fully Paid  20.00     5598.0  12226.302212  2011            48
5  Fully Paid  11.20     7963.0   5631.377753  2011            48
7  Fully Paid   5.35     8221.0   3938.144334  2011            48
```

```
In [60]: ba_df_valid.shape
```

```
Out[60]: (70200, 13)
```

2.0.1 Question 1

```
In [61]: def default_check(row):
             if row["loan_status"] == "Fully Paid":
                 return 0
             else:
                 return 1

         ba_df_valid["default_flag"] = ba_df_valid.apply(default_check, axis=1)
```

```
In [62]: len(ba_df_valid[ba_df_valid["default_flag"] == 0]) / len(ba_df_valid)
```

```
Out[62]: 0.8432336182336182
```

84.323% of matured 36-month loans have been fully paid.

2.0.2 Question 2

```
In [63]: ba_df_valid["year"] = ba_df["issue_d"].apply(lambda x: x.year)
         ba_df_valid["month"] = ba_df["issue_d"].apply(lambda x: x.month)

         # Setting model_df here to avoid duplicating transformations.
         model_df = copy.deepcopy(ba_df_valid.drop(["months_diff", "loan_status", "term"], axis=
```

```
In [64]: grp_default_df = ba_df_valid[ba_df_valid["default_flag"] == 1].groupby(["year", "grade"
```

```
In [65]: grp_df = ba_df_valid.groupby(["year", "grade"]).size()
```

```
In [66]: grp_delta_df = grp_default_df / grp_df
         display(grp_delta_df)
```

```
year  grade
2007  A        0.282051
      B        0.459184
      C        0.567376
      D        0.777778
      E        0.910000
      F        0.903846
      G        1.000000
2008  A        0.125786
      B        0.271044
```

```
     C        0.379310
     D        0.599045
     E        0.778947
     F        0.900901
     G        0.976744
2009 A        0.086451
     B        0.163322
     C        0.245549
     D        0.334149
     E        0.399351
     F        0.495238
     G        0.727273
2010 A        0.053370
     B        0.134403
     C        0.224155
     D        0.294493
     E        0.348214
     F        0.505495
     G        0.647059
2011 A        0.063990
     B        0.105676
     C        0.155243
     D        0.180809
     E        0.205882
     F        0.240741
     G        0.400000
2012 A        0.074203
     B        0.129363
     C        0.178265
     D        0.215827
     E        0.213333
     F        0.197674
     G        0.181818
dtype: float64
```

```
In [67]: grp_delta_df.idxmax()
```

```
Out[67]: (2007, 'G')
```

Grade 'G' loans issued in 2007 have the highest rate of default.

2.0.3 Question 3

```
In [68]: ba_df_valid["rate_of_return"] = (((ba_df_valid["total_pymnt"]/ba_df_valid["funded_amnt"
```

```
In [69]: ror_df = ba_df_valid.groupby(["year", "grade"]).agg("mean")["rate_of_return"]
         display(ror_df)
```

```
year  grade
2007  A         0.027138
      B        -0.001888
      C        -0.008031
      D        -0.014353
      E        -0.015099
      F        -0.079863
      G        -0.044102
2008  A         0.023445
      B        -0.000428
      C        -0.004508
      D        -0.018365
      E        -0.003337
      F        -0.045138
      G        -0.007913
2009  A         0.021337
      B         0.014358
      C         0.011975
      D         0.013982
      E        -0.000270
      F         0.002615
      G         0.002985
2010  A         0.021611
      B         0.021892
      C         0.022227
      D         0.012545
      E         0.013981
      F        -0.007814
      G        -0.007685
2011  A         0.014910
      B         0.021848
      C         0.017563
      D         0.021422
      E         0.024065
      F         0.022267
      G        -0.020399
2012  A         0.014938
      B         0.022425
      C         0.021012
      D         0.022788
      E         0.033121
      F         0.031940
      G         0.038493
Name: rate_of_return, dtype: float64
```

```
In [70]: ror_df.idxmax()
```

```
Out[70]: (2012, 'G')
```

Interestingly, Grade 'G' loans issued in 2012 have the highest rate of return.

3 3. Logistic Regression Model

Note: For this question I will focus on 36-month loans using the criteria as defined above.

```
In [71]: # Using model_df as set above.
         model_df.head()

Out[71]:    loan_amnt  funded_amnt  int_rate grade  annual_inc    issue_d    dti  \
         0     5000.0       5000.0     10.65     B     24000.0 2011-12-01  27.65
         2     2400.0       2400.0     15.96     C     12252.0 2011-12-01   8.72
         3    10000.0      10000.0     13.49     C     49200.0 2011-12-01  20.00
         5     5000.0       5000.0      7.90     A     36000.0 2011-12-01  11.20
         7     3000.0       3000.0     18.64     E     48000.0 2011-12-01   5.35

            revol_bal   total_pymnt  year  default_flag  month
         0    13648.0   5861.071414  2011             0     12
         2     2956.0   3003.653644  2011             0     12
         3     5598.0  12226.302212  2011             0     12
         5     7963.0   5631.377753  2011             0     12
         7     8221.0   3938.144334  2011             0     12

In [72]: model_df.shape

Out[72]: (70200, 12)
```

3.0.1 Dealing with NULL/NaN Values and Outliers Identified Above

First we will drop the NULL / NaN values identified above in order to train our logistic regression model. This seems especially reasonable considering the limited number of observations (4). Additional imputation methods could be considered at a later time depending on business requirements. It is also a requirement for scikit's training and testing that no NULL/NaN values are present.

```
In [73]: model_df = model_df.dropna()

In [74]: model_df.head()

Out[74]:    loan_amnt  funded_amnt  int_rate grade  annual_inc    issue_d    dti  \
         0     5000.0       5000.0     10.65     B     24000.0 2011-12-01  27.65
         2     2400.0       2400.0     15.96     C     12252.0 2011-12-01   8.72
         3    10000.0      10000.0     13.49     C     49200.0 2011-12-01  20.00
         5     5000.0       5000.0      7.90     A     36000.0 2011-12-01  11.20
         7     3000.0       3000.0     18.64     E     48000.0 2011-12-01   5.35

            revol_bal   total_pymnt  year  default_flag  month
         0    13648.0   5861.071414  2011             0     12
         2     2956.0   3003.653644  2011             0     12
```

```
3      5598.0   12226.302212  2011              0      12
5      7963.0    5631.377753  2011              0      12
7      8221.0    3938.144334  2011              0      12
```

3.0.2 Relevant Column Selection

Loan application amount, funded amount, interest rate, grade, annual income, issue date, debt-to-income, and revolving balances are variables that should be present at loan issuance.

```
In [75]: model_df = model_df[["loan_amnt", "funded_amnt", "int_rate", "grade", "annual_inc", "is
```

```
In [76]: model_df.shape
```

```
Out[76]: (70196, 11)
```

3.0.3 Outlier Removal

We can also exclude records that were identified as outliers above. Additional analysis or methods such as imputation may be needed depending on business requirements / model output requirements regarding dataset completeness.

```
In [77]: model_df = model_df[((abs(model_df["annual_inc"]-df_desc["annual_inc"]["mean"] < thresh
```

```
In [78]: model_df.shape
```

```
Out[78]: (69636, 11)
```

3.0.4 Feature Selection

Since loan application amount is extremely highly correlated with funding amount and wouldn't seem to have a long term bearing on defaults we will exclude that column from consideration for our regression modeling.

```
In [79]: model_df = model_df[["funded_amnt", "int_rate", "grade", "annual_inc", "issue_d", "dti"
```

Because we are using L2 regularization we do not need to be as concerned about multicollinearity in this case. A deep dive into multicollinearity and some PCA / factor analysis would be a next step here and will help with regression coefficient interpretation.

Next we will need to one-hot encode our categorical variables in order to perform logistic regression.

```
In [80]: model_df_one_hot = pd.concat([model_df[["funded_amnt", "int_rate", "annual_inc", "revol
                                       pd.get_dummies(model_df["grade"], prefix="grade"),
                                       pd.get_dummies(model_df["year"], prefix="year")],axis=1)
```

```
In [81]: model_df_one_hot.corr()
```

Out[81]:

	funded_amnt	int_rate	annual_inc	revol_bal	dti
funded_amnt	1.000000	0.193897	0.411876	0.332515	0.051064
int_rate	0.193897	1.000000	0.025042	0.093209	0.155424
annual_inc	0.411876	0.025042	1.000000	0.394318	-0.171021
revol_bal	0.332515	0.093209	0.394318	1.000000	0.238943
dti	0.051064	0.155424	-0.171021	0.238943	1.000000
default_flag	-0.027009	0.175632	-0.075310	-0.007097	0.037826
grade_A	-0.093148	-0.771472	0.019019	-0.069182	-0.129491
grade_B	-0.018733	-0.054535	-0.034928	0.015718	0.057536
grade_C	-0.011272	0.359583	-0.025183	0.006638	0.052748
grade_D	0.100831	0.491458	0.021496	0.029918	0.023116
grade_E	0.105750	0.277830	0.048020	0.038999	-0.002711
grade_F	0.047839	0.154211	0.027796	0.034636	0.007779
grade_G	0.024373	0.119593	0.023640	0.031992	0.021610
year_2007	-0.038301	-0.003857	-0.017830	-0.022314	-0.052788
year_2008	-0.063426	0.004279	-0.018113	0.014716	-0.044663
year_2009	-0.032857	0.036938	0.002861	0.011979	-0.094106
year_2010	-0.056839	-0.071214	0.002612	-0.019971	-0.104124
year_2011	-0.085263	-0.194544	0.007921	-0.049317	-0.094660
year_2012	0.154434	0.184689	0.000150	0.045702	0.222112

	default_flag	grade_A	grade_B	grade_C	grade_D	grade_E
funded_amnt	-0.027009	-0.093148	-0.018733	-0.011272	0.100831	0.105750
int_rate	0.175632	-0.771472	-0.054535	0.359583	0.491458	0.277830
annual_inc	-0.075310	0.019019	-0.034928	-0.025183	0.021496	0.048020
revol_bal	-0.007097	-0.069182	0.015718	0.006638	0.029918	0.038999
dti	0.037826	-0.129491	0.057536	0.052748	0.023116	-0.002711
default_flag	1.000000	-0.145737	-0.048959	0.061076	0.103989	0.103938
grade_A	-0.145737	1.000000	-0.456108	-0.324911	-0.226943	-0.105188
grade_B	-0.048959	-0.456108	1.000000	-0.384847	-0.268807	-0.124592
grade_C	0.061076	-0.324911	-0.384847	1.000000	-0.191486	-0.088754
grade_D	0.103989	-0.226943	-0.268807	-0.191486	1.000000	-0.061993
grade_E	0.103938	-0.105188	-0.124592	-0.088754	-0.061993	1.000000
grade_F	0.089157	-0.051861	-0.061428	-0.043758	-0.030564	-0.014166
grade_G	0.096722	-0.035330	-0.041848	-0.029811	-0.020822	-0.009651
year_2007	0.125294	-0.031406	-0.035488	0.005550	0.013088	0.076616
year_2008	0.147329	-0.059744	-0.039969	0.012284	0.033379	0.104570
year_2009	0.042324	-0.031797	-0.045893	0.028630	0.032054	0.052127
year_2010	0.007854	0.003678	-0.035975	0.009628	0.021977	0.019603
year_2011	-0.066537	0.131843	-0.016968	-0.071865	-0.044172	-0.026590
year_2012	-0.050162	-0.064681	0.083132	0.030890	-0.010602	-0.071117

	grade_F	grade_G	year_2007	year_2008	year_2009	year_2010
funded_amnt	0.047839	0.024373	-0.038301	-0.063426	-0.032857	-0.056839
int_rate	0.154211	0.119593	-0.003857	0.004279	0.036938	-0.071214
annual_inc	0.027796	0.023640	-0.017830	-0.018113	0.002861	0.002612
revol_bal	0.034636	0.031992	-0.022314	0.014716	0.011979	-0.019971
dti	0.007779	0.021610	-0.052788	-0.044663	-0.094106	-0.104124

```
default_flag  0.089157  0.096722   0.125294   0.147329   0.042324   0.007854
grade_A      -0.051861 -0.035330  -0.031406  -0.059744  -0.031797   0.003678
grade_B      -0.061428 -0.041848  -0.035488  -0.039969  -0.045893  -0.035975
grade_C      -0.043758 -0.029811   0.005550   0.012284   0.028630   0.009628
grade_D      -0.030564 -0.020822   0.013088   0.033379   0.032054   0.021977
grade_E      -0.014166 -0.009651   0.076616   0.104570   0.052127   0.019603
grade_F       1.000000 -0.004758   0.085718   0.086391   0.043695   0.012521
grade_G      -0.004758  1.000000   0.083960   0.099110   0.032167   0.003615
year_2007     0.085718  0.083960   1.000000  -0.017044  -0.025917  -0.035360
year_2008     0.086391  0.099110  -0.017044   1.000000  -0.052686  -0.071883
year_2009     0.043695  0.032167  -0.025917  -0.052686   1.000000  -0.109303
year_2010     0.012521  0.003615  -0.035360  -0.071883  -0.109303   1.000000
year_2011    -0.018635 -0.022261  -0.045953  -0.093417  -0.142047  -0.193803
year_2012    -0.063385 -0.052646  -0.101859  -0.207065  -0.314859  -0.429578

              year_2011  year_2012
funded_amnt   -0.085263   0.154434
int_rate      -0.194544   0.184689
annual_inc     0.007921   0.000150
revol_bal     -0.049317   0.045702
dti           -0.094660   0.222112
default_flag  -0.066537  -0.050162
grade_A        0.131843  -0.064681
grade_B       -0.016968   0.083132
grade_C       -0.071865   0.030890
grade_D       -0.044172  -0.010602
grade_E       -0.026590  -0.071117
grade_F       -0.018635  -0.063385
grade_G       -0.022261  -0.052646
year_2007     -0.045953  -0.101859
year_2008     -0.093417  -0.207065
year_2009     -0.142047  -0.314859
year_2010     -0.193803  -0.429578
year_2011      1.000000  -0.558268
year_2012     -0.558268   1.000000
```

In [82]:
```
predictors = model_df_one_hot.drop("default_flag", axis=1)
target = model_df_one_hot["default_flag"]
```

In [83]:
```
predictors.head()
```

Out[83]:
```
   funded_amnt  int_rate  annual_inc  revol_bal    dti  grade_A  grade_B  \
0       5000.0     10.65     24000.0    13648.0  27.65        0        1
2       2400.0     15.96     12252.0     2956.0   8.72        0        0
3      10000.0     13.49     49200.0     5598.0  20.00        0        0
5       5000.0      7.90     36000.0     7963.0  11.20        1        0
7       3000.0     18.64     48000.0     8221.0   5.35        0        0
```

```
   grade_C  grade_D  grade_E  grade_F  grade_G  year_2007  year_2008  \
0        0        0        0        0        0          0          0
2        1        0        0        0        0          0          0
3        1        0        0        0        0          0          0
5        0        0        0        0        0          0          0
7        0        0        1        0        0          0          0

   year_2009  year_2010  year_2011  year_2012
0          0          0          1          0
2          0          0          1          0
3          0          0          1          0
5          0          0          1          0
7          0          0          1          0
```

In [84]:
```python
target.head()
```

Out[84]:
```
0    0
2    0
3    0
5    0
7    0
Name: default_flag, dtype: int64
```

3.0.5 Scaling

We now need to scale our numerical predictors to be mean 0 and unit variance. This is especially critical due to the regularization encorporated in the sklearn logistic regression method and is generally best practice for preprocessing.

In [85]:
```python
scalar = StandardScaler()
scaled_predictors = copy.deepcopy(predictors)
scaled_predictors[["funded_amnt", "int_rate", "annual_inc", "dti", "revol_bal"]] = scal
```

In [86]:
```python
scaled_predictors.describe()
```

Out[86]:
```
        funded_amnt      int_rate    annual_inc     revol_bal           dti  \
count  6.963600e+04  6.963600e+04  6.963600e+04  6.963600e+04  6.963600e+04
mean   5.685121e-15  6.983701e-15 -8.190677e-17 -6.309718e-16  1.865279e-17
std    1.000007e+00  1.000007e+00  1.000007e+00  1.000007e+00  1.000007e+00
min   -1.497521e+00 -1.805667e+00 -1.685277e+00 -1.020973e+00 -2.011219e+00
25%   -7.326330e-01 -8.446114e-01 -6.590923e-01 -6.381062e-01 -7.582490e-01
50%   -1.439690e-01  4.464156e-02 -2.416595e-01 -2.555928e-01 -1.969854e-02
75%    5.271830e-01  6.549674e-01  4.181537e-01  3.111469e-01  7.256029e-01
max    3.676723e+00  3.571275e+00  7.231735e+00  7.347348e+00  2.713073e+00

            grade_A       grade_B       grade_C       grade_D       grade_E  \
count  69636.000000  69636.000000  69636.000000  69636.000000  69636.000000
mean       0.278017      0.350752      0.215162      0.117971      0.027931
std        0.448025      0.477209      0.410937      0.322576      0.164776
```

```
min        0.000000      0.000000      0.000000      0.000000      0.000000
25%        0.000000      0.000000      0.000000      0.000000      0.000000
50%        0.000000      0.000000      0.000000      0.000000      0.000000
75%        1.000000      1.000000      0.000000      0.000000      0.000000
max        1.000000      1.000000      1.000000      1.000000      1.000000

              grade_F       grade_G     year_2007     year_2008     year_2009  \
count  69636.000000  69636.000000  69636.000000  69636.000000  69636.000000
mean       0.006936      0.003231      0.008315      0.033488      0.074171
std        0.082994      0.056751      0.090806      0.179909      0.262052
min        0.000000      0.000000      0.000000      0.000000      0.000000
25%        0.000000      0.000000      0.000000      0.000000      0.000000
50%        0.000000      0.000000      0.000000      0.000000      0.000000
75%        0.000000      0.000000      0.000000      0.000000      0.000000
max        1.000000      1.000000      1.000000      1.000000      1.000000

            year_2010     year_2011     year_2012
count  69636.000000  69636.000000  69636.000000
mean       0.129775      0.201189      0.553062
std        0.336058      0.400892      0.497180
min        0.000000      0.000000      0.000000
25%        0.000000      0.000000      0.000000
50%        0.000000      0.000000      1.000000
75%        0.000000      0.000000      1.000000
max        1.000000      1.000000      1.000000
```

3.0.6 Modeling Training and Testing

We will now split our dataset into a train and test set. This is critical to identify how our regresssion performs out of sample.

```
In [87]: predictors_train, predictors_test, target_train, target_test = train_test_split(scaled_
```

Next we can get our class probabilities of our outcome variables for our train and test sets.

```
In [88]: target_train.value_counts()/len(target_train)

Out[88]: 0    0.846236
         1    0.153764
         Name: default_flag, dtype: float64

In [89]: target_test.value_counts()/len(target_test)

Out[89]: 0    0.84356
         1    0.15644
         Name: default_flag, dtype: float64
```

Next we can build and fit our regression model. A few notes on the fitting:

1. We will use CV to help with hyperparameter selection for regularization.

2. I have found the regularization selection (L1/L2) does not change the resultant coefficients in this case. In general L2 regularization is preferred, especially in cases of potential multicollinearity, so that is my selection.
3. We will use the balanced class weight parameter which should help in this unbalanced case. Testing showed that removing this parameter increases precision for both classes but drastically reduces recall. If we considered recall as being more important than precision for this case, Ie. a false negative is more damaging than a false positive for the loan default scenario, then this is valuable.

```
In [90]: clf = LogisticRegressionCV(cv=5, random_state=0, solver='lbfgs', penalty='l2', class_we
```

```
In [91]: pd.set_option('display.float_format', lambda x: '%.3f' % x)
         coefficients = pd.concat([pd.DataFrame(predictors.columns),pd.DataFrame(np.transpose(np
         display(coefficients)
```

	0	0
0	funded_amnt	0.958
1	int_rate	1.144
2	annual_inc	0.775
3	revol_bal	1.014
4	dti	1.073
5	grade_A	0.303
6	grade_B	0.501
7	grade_C	0.724
8	grade_D	0.883
9	grade_E	1.230
10	grade_F	2.052
11	grade_G	4.826
12	year_2007	4.320
13	year_2008	2.090
14	year_2009	0.810
15	year_2010	0.630
16	year_2011	0.475
17	year_2012	0.541

```
In [92]: clf.score(predictors_train, target_train)

Out[92]: 0.6509130658436214
```

```
In [93]: probabilities_train = clf.predict_proba(predictors_train)[::,1]
         print(probabilities_train)

[0.44438477 0.43466474 0.28810599 ... 0.68830438 0.4625606  0.50112447]
```

```
In [94]: predicted_train = clf.predict(predictors_train)
         print(predicted_train)
```

```
[0 0 0 ... 1 0 1]
```

```
In [95]: predicted_train_df = pd.DataFrame({'Probabilities':probabilities_train, 'Predicted':pre
         predicted_train_df.head()
```

Out[95]:

	Probabilities	Predicted
0	0.444	0
1	0.435	0
2	0.288	0
3	0.376	0
4	0.480	0

```
In [96]: clf.score(predictors_test, target_test)

Out[96]: 0.6458659704090514

In [97]: probabilities_test = clf.predict_proba(predictors_test)[::,1]
         print(probabilities_test)

[0.3042541  0.35938146 0.43413551 ... 0.49756599 0.91573313 0.5690408 ]


In [98]: predicted_test = clf.predict(predictors_test)
         print(predicted_test)

[0 0 0 ... 0 1 1]


In [99]: np.bincount(predicted_test)

Out[99]: array([14043,  8937])

In [100]: predicted_test_df = pd.DataFrame({'Probabilities': probabilities_test, 'Predicted': pr
          predicted_test_df.head()
```

Out[100]:

	Probabilities	Predicted
0	0.304	0
1	0.359	0
2	0.434	0
3	0.644	1
4	0.292	0

```
In [101]: metrics.confusion_matrix(target_test, predicted_test)

Out[101]: array([[12645,  6740],
                 [ 1398,  2197]])

In [102]: tn, fp, fn, tp = metrics.confusion_matrix(target_test, predicted_test).ravel()

In [103]: print(tn, fp, fn, tp)
```

```
12645 6740 1398 2197
```

```
In [104]: print(metrics.classification_report(target_test, predicted_test))
```

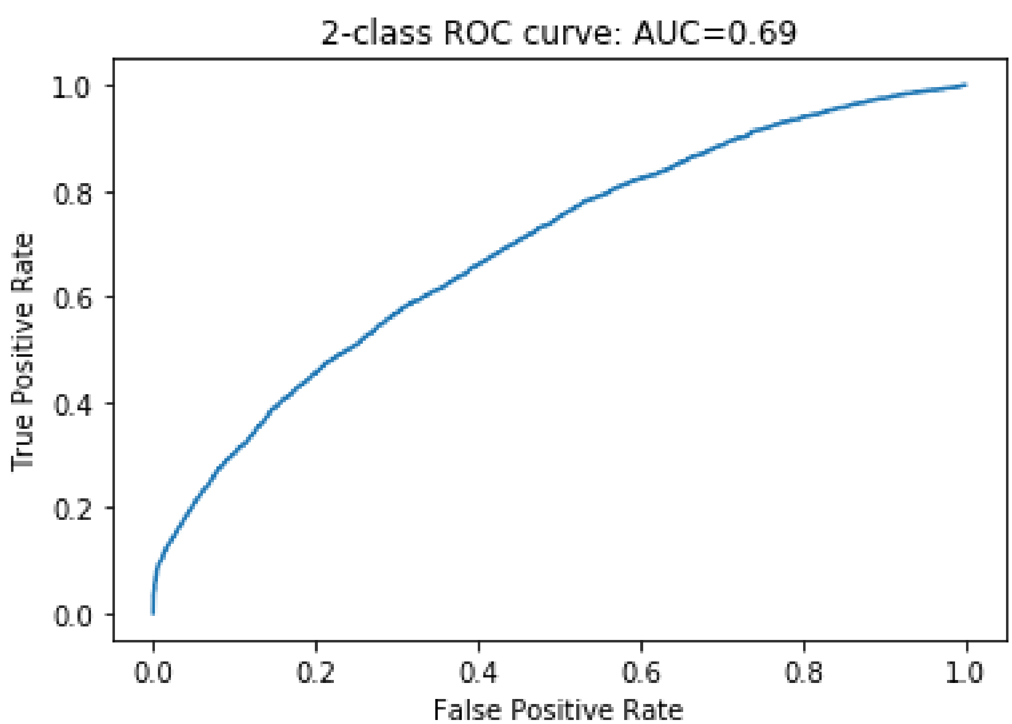
```
             precision    recall  f1-score   support

          0       0.90      0.65      0.76     19385
          1       0.25      0.61      0.35      3595

avg / total       0.80      0.65      0.69     22980
```

Thus our model yields a precision of our positive class of 2178/(2178+6662) or .246 and a recall rate of 2,178/(2,178+1,430) or .604 for the given decision threshold (.5).

```
In [105]: auc_score = metrics.roc_auc_score(target_test, probabilities_test)
          print(auc_score)
```

```
0.6918361593980118
```

```
In [106]: fpr, tpr, _ = metrics.roc_curve(target_test, probabilities_test)
          plt.plot(fpr,tpr)
          plt.xlabel('False Positive Rate')
          plt.ylabel('True Positive Rate')
          plt.title('2-class ROC curve: AUC={0:0.2f}'.format(
                    auc_score))
          plt.show()
```



Overall our ROC curve indicates our model performs better than a naive guess, with an AUC=0.69. However, AUC is not always the best metric for unbalanced class cases such as this due to the inherent inbalance between false positives and true negatives in such a scenario.

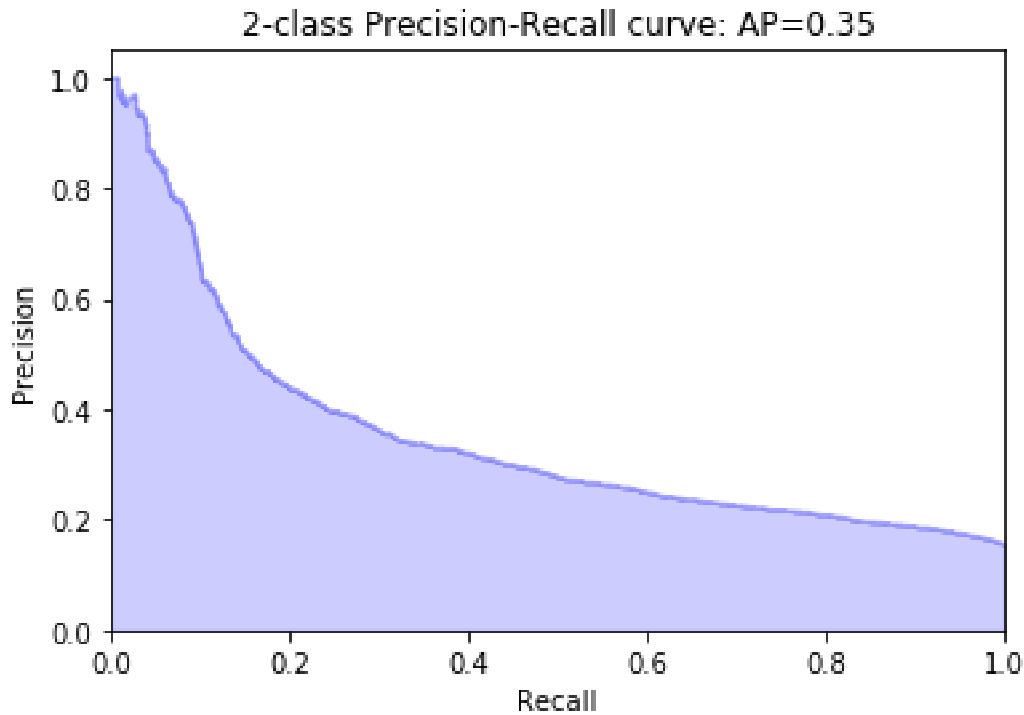
We will now turn to precision-recall curves. Precision-recall curves are valuable because, especially in the unbalanced class case, they give the practicioner a better sense of how well the model is representing the underpresented class.

```
In [107]: average_precision = metrics.average_precision_score(target_test, probabilities_test)
          print(average_precision)
```

```
0.3509579932267077
```

```
In [108]: precision, recall, _ = metrics.precision_recall_curve(target_test, probabilities_test)
```

```
In [109]: step_kwargs = ({'step': 'post'}
                         if 'step' in signature(plt.fill_between).parameters
                         else {})
          plt.step(recall, precision, color='b', alpha=0.2,
                   where='post')
          plt.fill_between(recall, precision, alpha=0.2, color='b', **step_kwargs)

          plt.xlabel('Recall')
          plt.ylabel('Precision')
          plt.ylim([0.0, 1.05])
          plt.xlim([0.0, 1.0])
          plt.title('2-class Precision-Recall curve: AP={0:0.2f}'.format(
                    average_precision))
          plt.show()
```



Here we find average precision over all possible decision thresholds to be .35. Overall this is lower than we would like, indicating a lot of false positives are being generated from our model. However, given the business case this may be more desirable than decreased recall and increased precision as was seen when tweaking our hyperparameters.

3.0.7 Final Model Comments

Overall our model did not seem to perform as well as hoped, even with hyper-parameter tuning and feature selection. There are several next steps that could be taken to improve the model, including:

1) Trying different classifiers aside from logistic regressions.

2) Bringing in new features or datasets to improve precision/recall.

3) Further exploring feature engineering in the given dataset.

4) Gathering more data.

All of these steps could be used to help improve accuracy, precision, and recall rates of our model.