ZP_LC_pt3

October 12, 2018

1 Kaggle Lending Club Loan Data

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1.1 Part 1

1.1.1 Import Python packages

```
In [1]: from __future__ import print_function
        import datetime
        import itertools
        import re
        import numpy as np
        import pandas as pd
        import sqlite3
        import scipy
        import sklearn
        from sklearn import preprocessing as pp
        from sklearn.model_selection import train_test_split, cross_val_score
        from sklearn.linear_model import LogisticRegression
        from sklearn.metrics import accuracy_score, roc_auc_score, confusion_matrix
        from sklearn.feature_selection import RFE
        import matplotlib.pyplot as plt
        import seaborn as sns
        from plotly.offline import download_plotlyjs, init_notebook_mode, plot, iplot
        import plotly.graph_objs as go

        # Ignore pandas warnings when writing slice back to orig df
        pd.options.mode.chained_assignment = None  # default='warn'
        # Display all columns when viewing pandas df
        pd.set_option('display.max_columns', None)
        # Set plotly offline notebook mode
        init_notebook_mode(connected=True)
```

A few user-defined functions to help later with model assessment

```
In [2]: 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]
                print("Normalized confusion matrix")
            else:
                print('Confusion matrix, without normalization')

            print(cm)

            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')

        def confusion_metrics(cm):
            """
            Metrics on confusion matrix for binary classification where
            cm is 2D np.array of form [[TP, FN], [FP, TN]]
            """
            cm = cm.astype(float)
            print('Accuracy = ' + str((cm[0][0] + cm[1][1]) / cm.sum()))
            print('Misclassification Rate = ' + str((cm[0][1] + cm[1][0]) / cm.sum()))
            print('TP Rate = ' + str(cm[1][1] / cm.sum(axis=1)[1]))
            print('FP Rate = ' + str(cm[1][0] / cm.sum(axis=1)[1]))
            print('TN Rate = ' + str(cm[0][0] / cm.sum(axis=1)[0]))
            print('FN Rate = ' + str(cm[0][1] / cm.sum(axis=1)[0]))
```

```
print('Specifity = ' + str(cm[1][1] / cm.sum(axis=1)[1]))
print('Precision = ' + str(cm[0][0] / cm.sum(axis=0)[0]))
print('Prevalence = ' + str(cm.sum(axis=1)[0] / cm.sum()))
```

1.1.2 Pull data into environment

In [3]:
```
df = pd.read_csv('lc_loan_data/loan.csv', low_memory=False)
```

In [4]:
```
df.head(2)
```

Out[4]:
```
        id  member_id  loan_amnt  funded_amnt  funded_amnt_inv        term  \
0  1077501    1296599     5000.0       5000.0           4975.0   36 months
1  1077430    1314167     2500.0       2500.0           2500.0   60 months

   int_rate  installment grade sub_grade emp_title emp_length home_ownership  \
0     10.65       162.87     B        B2       NaN  10+ years           RENT
1     15.27        59.83     C        C4     Ryder   < 1 year           RENT

   annual_inc verification_status   issue_d  loan_status pymnt_plan  \
0     24000.0            Verified  Dec-2011   Fully Paid          n
1     30000.0     Source Verified  Dec-2011  Charged Off          n

                                                 url  \
0  https://www.lendingclub.com/browse/loanDetail...
1  https://www.lendingclub.com/browse/loanDetail...

                                                desc      purpose     title  \
0    Borrower added on 12/22/11 > I need to upgra...  credit_card  Computer
1    Borrower added on 12/22/11 > I plan to use t...          car      bike

  zip_code addr_state    dti  delinq_2yrs earliest_cr_line  inq_last_6mths  \
0    860xx         AZ  27.65          0.0         Jan-1985             1.0
1    309xx         GA   1.00          0.0         Apr-1999             5.0

   mths_since_last_delinq  mths_since_last_record  open_acc  pub_rec  \
0                     NaN                     NaN       3.0      0.0
1                     NaN                     NaN       3.0      0.0

   revol_bal  revol_util  total_acc initial_list_status  out_prncp  \
0    13648.0        83.7        9.0                   f        0.0
1     1687.0         9.4        4.0                   f        0.0

   out_prncp_inv  total_pymnt  total_pymnt_inv  total_rec_prncp  \
0            0.0  5861.071414          5831.78          5000.00
1            0.0  1008.710000          1008.71           456.46

   total_rec_int  total_rec_late_fee  recoveries  collection_recovery_fee  \
0         861.07                 0.0        0.00                     0.00
```

```
1        435.17                 0.0      117.08                      1.11

  last_pymnt_d  last_pymnt_amnt next_pymnt_d last_credit_pull_d  \
0     Jan-2015           171.62          NaN           Jan-2016
1     Apr-2013           119.66          NaN           Sep-2013

   collections_12_mths_ex_med  mths_since_last_major_derog  policy_code  \
0                         0.0                          NaN          1.0
1                         0.0                          NaN          1.0

  application_type  annual_inc_joint  dti_joint verification_status_joint  \
0       INDIVIDUAL               NaN        NaN                       NaN
1       INDIVIDUAL               NaN        NaN                       NaN

   acc_now_delinq  tot_coll_amt  tot_cur_bal  open_acc_6m  open_il_6m  \
0             0.0           NaN          NaN          NaN         NaN
1             0.0           NaN          NaN          NaN         NaN

   open_il_12m  open_il_24m  mths_since_rcnt_il  total_bal_il  il_util  \
0          NaN          NaN                 NaN           NaN      NaN
1          NaN          NaN                 NaN           NaN      NaN

   open_rv_12m  open_rv_24m  max_bal_bc  all_util  total_rev_hi_lim  inq_fi  \
0          NaN          NaN         NaN       NaN               NaN     NaN
1          NaN          NaN         NaN       NaN               NaN     NaN

   total_cu_tl  inq_last_12m
0          NaN           NaN
1          NaN           NaN
```

Let's check the dataframe dimensions.

```
In [5]: def df_shape(data):
            print('Number of columns: ' + str(data.shape[1]))
            print('Number of rows: ' + str(data.shape[0]))

In [6]: df_shape(df)

Number of columns: 74
Number of rows: 887379


In [7]: df.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 887379 entries, 0 to 887378
Data columns (total 74 columns):
id                             887379 non-null int64
member_id                      887379 non-null int64
```

```
loan_amnt                      887379 non-null float64
funded_amnt                    887379 non-null float64
funded_amnt_inv                887379 non-null float64
term                           887379 non-null object
int_rate                       887379 non-null float64
installment                    887379 non-null float64
grade                          887379 non-null object
sub_grade                      887379 non-null object
emp_title                      835922 non-null object
emp_length                     887379 non-null object
home_ownership                 887379 non-null object
annual_inc                     887375 non-null float64
verification_status            887379 non-null object
issue_d                        887379 non-null object
loan_status                    887379 non-null object
pymnt_plan                     887379 non-null object
url                            887379 non-null object
desc                           126029 non-null object
purpose                        887379 non-null object
title                          887228 non-null object
zip_code                       887379 non-null object
addr_state                     887379 non-null object
dti                            887379 non-null float64
delinq_2yrs                    887350 non-null float64
earliest_cr_line               887350 non-null object
inq_last_6mths                 887350 non-null float64
mths_since_last_delinq         433067 non-null float64
mths_since_last_record         137053 non-null float64
open_acc                       887350 non-null float64
pub_rec                        887350 non-null float64
revol_bal                      887379 non-null float64
revol_util                     886877 non-null float64
total_acc                      887350 non-null float64
initial_list_status            887379 non-null object
out_prncp                      887379 non-null float64
out_prncp_inv                  887379 non-null float64
total_pymnt                    887379 non-null float64
total_pymnt_inv                887379 non-null float64
total_rec_prncp                887379 non-null float64
total_rec_int                  887379 non-null float64
total_rec_late_fee             887379 non-null float64
recoveries                     887379 non-null float64
collection_recovery_fee        887379 non-null float64
last_pymnt_d                   869720 non-null object
last_pymnt_amnt                887379 non-null float64
next_pymnt_d                   634408 non-null object
last_credit_pull_d             887326 non-null object
collections_12_mths_ex_med     887234 non-null float64
```

```
mths_since_last_major_derog    221703 non-null float64
policy_code                    887379 non-null float64
application_type               887379 non-null object
annual_inc_joint               511 non-null float64
dti_joint                      509 non-null float64
verification_status_joint      511 non-null object
acc_now_delinq                 887350 non-null float64
tot_coll_amt                   817103 non-null float64
tot_cur_bal                    817103 non-null float64
open_acc_6m                    21372 non-null float64
open_il_6m                     21372 non-null float64
open_il_12m                    21372 non-null float64
open_il_24m                    21372 non-null float64
mths_since_rcnt_il             20810 non-null float64
total_bal_il                   21372 non-null float64
il_util                        18617 non-null float64
open_rv_12m                    21372 non-null float64
open_rv_24m                    21372 non-null float64
max_bal_bc                     21372 non-null float64
all_util                       21372 non-null float64
total_rev_hi_lim               817103 non-null float64
inq_fi                         21372 non-null float64
total_cu_tl                    21372 non-null float64
inq_last_12m                   21372 non-null float64
dtypes: float64(49), int64(2), object(23)
memory usage: 501.0+ MB
```

Looking at the initial information on the data shows that there are a lot of missing values. The rightmost part of the dataframe looks to be pretty sparse with a lot of fields having only 21,372 non-null values.

1.1.3 Subset columns for EDA

In [8]:
```
fields = ['loan_amnt', 'funded_amnt', 'term', 'int_rate', 'grade', 'annual_inc',
          'issue_d', 'dti', 'revol_bal', 'total_pymnt', 'loan_status']
df_eda = df[fields]
```

In [9]:
```
df_eda.head()
```

Out[9]:
```
   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

     dti  revol_bal  total_pymnt  loan_status
0  27.65    13648.0  5861.071414   Fully Paid
```

```
1   1.00     1687.0   1008.710000  Charged Off
2   8.72     2956.0   3003.653644   Fully Paid
3  20.00     5598.0  12226.302212   Fully Paid
4  17.94    27783.0   3242.170000      Current
```

```
In [10]: df_shape(df_eda)
```

```
Number of columns: 11
Number of rows: 887379
```

1.1.4 Grab summary statistics for the new dataset

```
In [11]: df_eda.describe()
```

```
Out[11]:             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
```

For all numerical variables, the mean is greater than the median indicating a positive skew.

1.1.5 Missing data

```
In [12]: print('Which columns have null values?\n')
         print(df_eda.isnull().any())

         print('\n')

         print('How many null values does each column have?\n')
         print(df_eda.isnull().sum().sort_values(ascending=False))
```

```
Which columns have null values?
```

```
loan_amnt       False
funded_amnt     False
term            False
int_rate        False
grade           False
annual_inc       True
issue_d         False
dti             False
revol_bal       False
total_pymnt     False
loan_status     False
dtype: bool


How many null values does each column have?

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

There are only 4 missing values in the dataset. Let's take a look at them.

```
In [13]: df_eda[df_eda['annual_inc'].isnull()]
```

```
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  dti  revol_bal  total_pymnt  \
         42449  Aug-2007  1.0        0.0      5593.46
         42450  Aug-2007  1.0        0.0      7867.53
         42480  Jul-2007  1.0        0.0      7530.42
         42533  Jun-2007  4.0        0.0      7373.83

                                                  loan_status
         42449  Does not meet the credit policy. Status:Fully ...
```

```
42450  Does not meet the credit policy. Status:Fully ...
42480  Does not meet the credit policy. Status:Fully ...
42533  Does not meet the credit policy. Status:Fully ...
```

All 4 rows with a missing value for **annual_inc** is a loan that does not meet the credit policy with notes that it was fully paid. Looking at the **total_pymnt** field, I would assume that these are old loans which have been paid, however, they no longer meet the current credit policy. As you need to provide your annual income to get a loan, I do not think that these are records where the borrower did not provide information. I think it is safe to remove these records from the dataset rather than perform imputation.

```
In [14]: init_len = df_eda.shape[0]
         df_eda = df_eda.dropna()
         new_len = df_eda.shape[0]
         print('{} rows were dropped from the dataset. This is a {:.2f}% reduction of rows.'.for
```

```
4 rows were dropped from the dataset. This is a 0.00% reduction of rows.
```

```
In [15]: df_shape(df_eda)
```

```
Number of columns: 11
Number of rows: 887375
```

1.1.6 Distribution of categorical variables

We will take a look at the value counts for **grade**, **term**, and **loan_status**. While **issue_d** is currently strictly categorical due to the formatting. It makes sense to look at the distribution at the moment but I assume it will be dispersed across all months from 2007-2015. It is worth noting that it makes sense to transform **term** into a numerical variable by removing the 'months' suffix resulting in values of 36 or 60. It will clearly still only have 2 levels.

Grade (grade)

```
In [16]: print('Grade Counts')
         pd.value_counts(df_eda['grade']).to_frame().reset_index()
```

```
Grade Counts
```

Out[16]:

	index	grade
0	B	254535
1	C	245860
2	A	148198
3	D	139542
4	E	70705
5	F	23046
6	G	5489

```
In [17]: print('Grade Bucket Counts and Percentages\n\n')
         print('Number of mid-grade loans (B/C/D): ' + str(df_eda[df_eda['grade'].isin(['B', 'C'
         print('Percentage of total loans: {:.2f}%'.format(100*df_eda[df_eda['grade'].isin(['B',
         print('\n')

         print('Number of high-grade loans (A): ' + str(df_eda[df_eda['grade'] == 'A']['grade'].
         print('Percentage of total loans: {:.2f}%'.format(100*df_eda[df_eda['grade'] == 'A']['g
         print('\n')

         print('Number of low-grade loans (E/F/G): ' + str(df_eda[df_eda['grade'].isin(['E', 'F'
         print('Percentage of total loans: {:.2f}%'.format(100*df_eda[df_eda['grade'].isin(['E',
```

```
Grade Bucket Counts and Percentages


Number of mid-grade loans (B/C/D): 639937
Percentage of total loans: 72.12%


Number of high-grade loans (A): 148198
Percentage of total loans: 16.70%


Number of low-grade loans (E/F/G): 99240
Percentage of total loans: 11.18%
```

A majority of loans are mid-grade (B/C/D), followed by high-grade (A) loans with risky, low-grade (E/F/G) loans making up the tail. This distribution makes sense as I would not expect a majority of loans to be high-grade and at the same time Lending Club does not want a lot of risky loans.

Term (term)

```
In [18]: print('Term Counts')
         pd.value_counts(df_eda['term']).to_frame().reset_index()
```

```
Term Counts
```

Out[18]:

	index	term
0	36 months	621121
1	60 months	266254

```
In [19]: print('Term Percentages')
         pd.value_counts(df_eda['term'], normalize=True).to_frame().reset_index()
```

```
Term Percentages
```

```
Out[19]:         index      term
        0   36 months  0.699953
        1   60 months  0.300047
```

The loans in the dataset only have 36-month and 60-month terms as noted in the data dictionary. 70% of the loans have 36-month terms while the remaining 30% have 60-month terms. This is a clear indication that a majority of the loans through Lending Club are shorter-term loans.

Loan status (loan_status)

```
In [20]: print('Loan Status Counts')
         pd.value_counts(df_eda['loan_status']).to_frame().reset_index()
```

```
Loan Status Counts
```

```
Out[20]:                                                index  loan_status
        0                                             Current       601779
        1                                          Fully Paid       207723
        2                                         Charged Off        45248
        3                                  Late (31-120 days)        11591
        4                                              Issued         8460
        5                                     In Grace Period         6253
        6                                   Late (16-30 days)         2357
        7  Does not meet the credit policy. Status:Fully ...         1984
        8                                             Default         1219
        9   Does not meet the credit policy. Status:Charge...          761
```

```
In [21]: print('Loan Status Percentages')
         pd.value_counts(df_eda['loan_status'], normalize=True).to_frame().reset_index()
```

```
Loan Status Percentages
```

```
Out[21]:                                                index  loan_status
        0                                             Current     0.678156
        1                                          Fully Paid     0.234087
        2                                         Charged Off     0.050991
        3                                  Late (31-120 days)     0.013062
        4                                              Issued     0.009534
        5                                     In Grace Period     0.007047
        6                                   Late (16-30 days)     0.002656
        7  Does not meet the credit policy. Status:Fully ...     0.002236
        8                                             Default     0.001374
        9   Does not meet the credit policy. Status:Charge...     0.000858
```

A majority of the loans are current (67.8%) with the second largest group being those that have been fully paid (23.4%). There are a fair amount of loans which have been charged off (5%) and an even smaller percentage which are late (~1.5%). Loans that have defaulted constitute a very small portion of the dataset (0.1%) which is a good sign for Lending Club. There are still loans in the dataset with a loan status indicating that they do not meet the credit policy (2,745 or 0.3%). From a consistency standpoint, it would make sense to remove these loans as we did earlier with the loans that were missing data for **annual_inc**. ##### Let's remove the loans that do not meet the credit policy

```
In [22]: init_len = df_eda.shape[0]
         df_eda = df_eda[~df_eda['loan_status'].str.contains('Does not meet', na=False)]
         new_len = df_eda.shape[0]
         print('{} rows were dropped from the dataset. This is a {:.2f}% reduction of rows.'.for
```

```
2745 rows were dropped from the dataset. This is a 0.31% reduction of rows.
```

Issue Date (issue_d)

```
In [23]: print('Issue Date counts')
         pd.value_counts(df_eda['issue_d']).to_frame().reset_index()
```

```
Issue Date counts
```

Out[23]:

	index	issue_d
0	Oct-2015	48631
1	Jul-2015	45962
2	Dec-2015	44342
3	Oct-2014	38782
4	Nov-2015	37530
5	Aug-2015	35886
6	Apr-2015	35427
7	Jan-2015	35107
8	May-2015	31913
9	Jul-2014	29306
10	Sep-2015	28641
11	Jun-2015	28485
12	Mar-2015	25400
13	Nov-2014	25054
14	Feb-2015	23770
15	May-2014	19099
16	Apr-2014	19071
17	Aug-2014	18814
18	Jun-2014	17179
19	Mar-2014	16513
20	Jan-2014	15628
21	Feb-2014	15269
22	Dec-2013	15020
23	Nov-2013	14676
24	Oct-2013	14114
25	Sep-2013	12987

```
26   Aug-2013    12674
27   Jul-2013    11910
28   Jun-2013    10899
29   Sep-2014    10606
..        ...      ...
73   Jan-2010      589
74   Oct-2009      545
75   Sep-2009      449
76   Aug-2009      408
77   Jul-2009      374
78   Jun-2009      356
79   May-2009      319
80   Apr-2009      290
81   Mar-2009      276
82   Feb-2009      260
83   Jan-2009      239
84   Mar-2008      236
85   Dec-2008      223
86   Nov-2008      184
87   Feb-2008      174
88   Jan-2008      171
89   Apr-2008      155
90   Oct-2008       96
91   Dec-2007       85
92   Jul-2008       83
93   May-2008       71
94   Aug-2008       71
95   Jun-2008       66
96   Oct-2007       47
97   Nov-2007       37
98   Aug-2007       33
99   Sep-2008       32
100  Jul-2007       30
101  Sep-2007       18
102  Jun-2007        1

[103 rows x 2 columns]
```

In [24]:
```
print('Issue Date percentages')
pd.value_counts(df_eda['issue_d'], normalize=True).to_frame().reset_index()
```

```
Issue Date percentages
```

Out[24]:
```
        index   issue_d
0    Oct-2015  0.054973
1    Jul-2015  0.051956
2    Dec-2015  0.050125
```

3	Oct-2014	0.043840
4	Nov-2015	0.042425
5	Aug-2015	0.040566
6	Apr-2015	0.040047
7	Jan-2015	0.039686
8	May-2015	0.036075
9	Jul-2014	0.033128
10	Sep-2015	0.032376
11	Jun-2015	0.032200
12	Mar-2015	0.028713
13	Nov-2014	0.028321
14	Feb-2015	0.026870
15	May-2014	0.021590
16	Apr-2014	0.021558
17	Aug-2014	0.021268
18	Jun-2014	0.019419
19	Mar-2014	0.018667
20	Jan-2014	0.017666
21	Feb-2014	0.017260
22	Dec-2013	0.016979
23	Nov-2013	0.016590
24	Oct-2013	0.015955
25	Sep-2013	0.014681
26	Aug-2013	0.014327
27	Jul-2013	0.013463
28	Jun-2013	0.012320
29	Sep-2014	0.011989
..	...	...
73	Jan-2010	0.000666
74	Oct-2009	0.000616
75	Sep-2009	0.000508
76	Aug-2009	0.000461
77	Jul-2009	0.000423
78	Jun-2009	0.000402
79	May-2009	0.000361
80	Apr-2009	0.000328
81	Mar-2009	0.000312
82	Feb-2009	0.000294
83	Jan-2009	0.000270
84	Mar-2008	0.000267
85	Dec-2008	0.000252
86	Nov-2008	0.000208
87	Feb-2008	0.000197
88	Jan-2008	0.000193
89	Apr-2008	0.000175
90	Oct-2008	0.000109
91	Dec-2007	0.000096
92	Jul-2008	0.000094

```
93   May-2008  0.000080
94   Aug-2008  0.000080
95   Jun-2008  0.000075
96   Oct-2007  0.000053
97   Nov-2007  0.000042
98   Aug-2007  0.000037
99   Sep-2008  0.000036
100  Jul-2007  0.000034
101  Sep-2007  0.000020
102  Jun-2007  0.000001

[103 rows x 2 columns]
```

As suspected, the loans are distributed across all months from mid-2007 through the end of 2015. Interestingly, the latter years tend to contain a majority of the loans. I assume this is due to the financial crisis of 2007-08.

1.1.7 Transformations

Let's transform the non-numerical fields from **df_eda** into numerical fields so that we may run some more in-depth analysis.

Remove the 'months' string from **term** (e.g. '36 months' to 36)
Encode **grade** to numerical (e.g. 'A' = 0, 'B' = 1, etc.)
Transform **issue_d** into date
Encode **loan_status** as numerical (e.g. 'Fully Paid' = 0, 'Charged Off' = 1, etc.)

In [25]:
```
df_eda.head()
```

Out[25]:
```
   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

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

In [26]:
```
df_num = df_eda.copy()
df_num.head()
```

Out[26]:
```
   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

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

In [27]:
```python
# term
df_num['term'] = df_num['term'].apply(lambda x: re.findall(r'\d+', x))
df_num['term'] = df_num['term'].apply(lambda x: int(x[0]))

# grade
le = pp.LabelEncoder()
le.fit(df_num['grade'])
df_num['grade'] = le.transform(df_num['grade'])

# issue_d
df_num['issue_d'] = pd.to_datetime(df_num['issue_d'])

# loan_status
le = pp.LabelEncoder()
le.fit(df_num['loan_status'])
df_num['loan_status'] = le.transform(df_num['loan_status'])
```

In [28]:
```python
df_num.head()
```

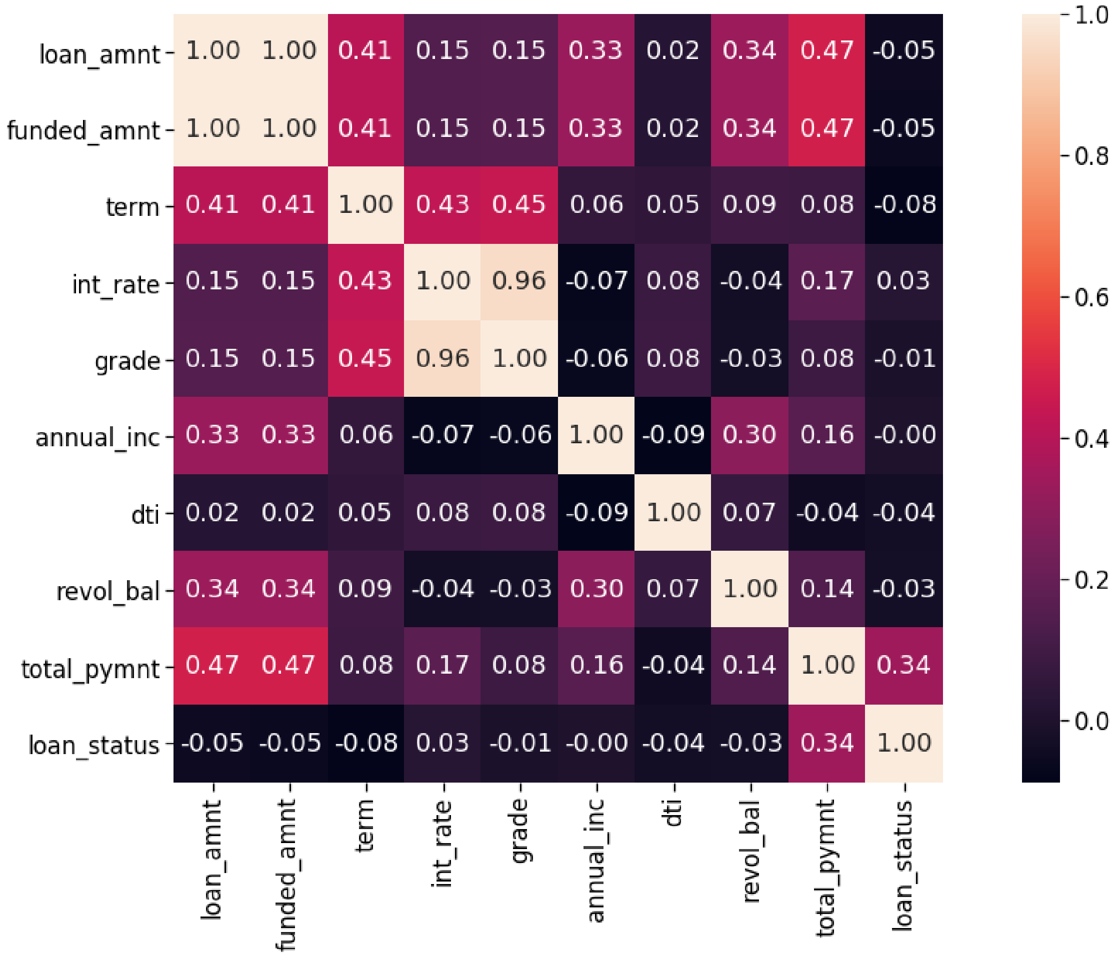
Out[28]:
```
   loan_amnt  funded_amnt  term  int_rate  grade  annual_inc    issue_d  \
0     5000.0       5000.0    36     10.65      1     24000.0 2011-12-01
1     2500.0       2500.0    60     15.27      2     30000.0 2011-12-01
2     2400.0       2400.0    36     15.96      2     12252.0 2011-12-01
3    10000.0      10000.0    36     13.49      2     49200.0 2011-12-01
4     3000.0       3000.0    60     12.69      1     80000.0 2011-12-01

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

1.1.8 Correlation matrix (heatmap)

In [29]:
```python
%matplotlib inline
plt.figure(figsize=(20,10))
sns.set_context("notebook", font_scale=1.5)
sns.heatmap(df_num.corr(), vmax=1, square=True, annot=True, fmt='.2f')
```

```
Out[29]: <matplotlib.axes._subplots.AxesSubplot at 0x13f549550>
```



Summary: **loan_amnt** and **funded_amnt** have a perfect correlation of 1

The second highest correlation is between **grade** and **int_rate** (0.96); this more than likely implies that one is used to determine the other

grade is also decently correlated with **term** (0.45); regarding the last bullet, **int_rate** is also rather correlated with **term** though not identical to **grade**/**term** correlation (0.43)

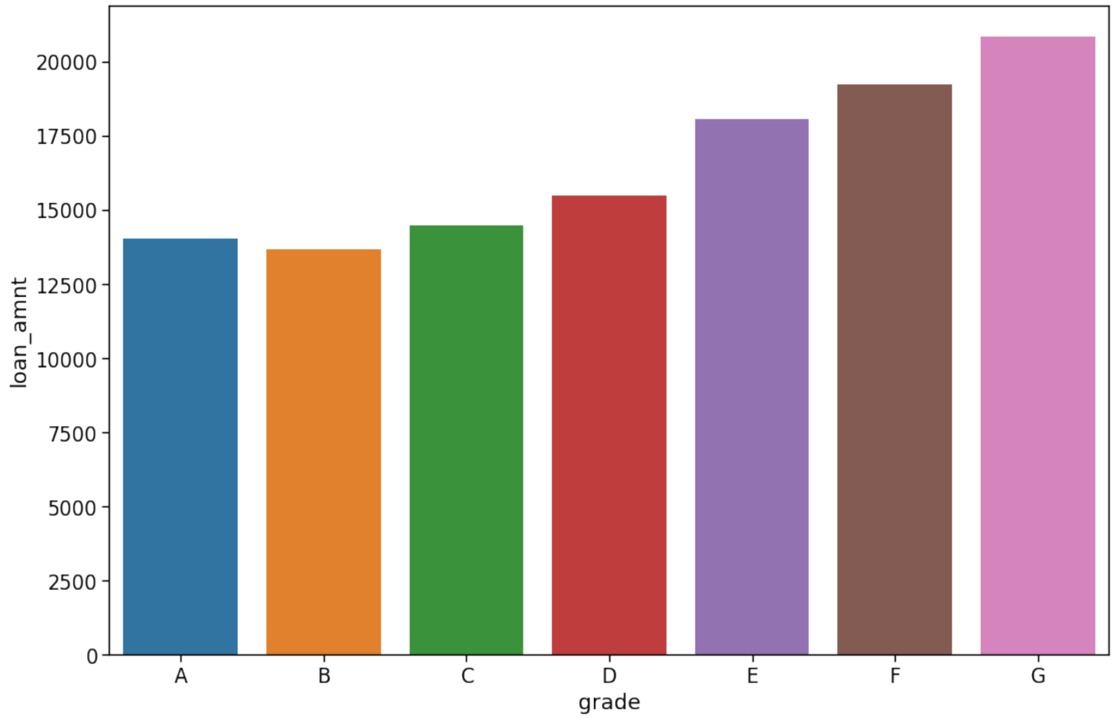
There is pretty strong correlation between **total_pymnt** and **loan_amnt**/**funded_amnt** (0.47)

There aren't many variables that are inversely correlated with the largest being **dti** and **annual_inc** (-0.09)

1.1.9 Average Loan Amount by Grade

```
In [30]: by_grade = df_eda.groupby('grade').mean()
         avg_loan_amnt = by_grade['loan_amnt'].reset_index()
         plt.subplots(figsize=(15,10))
         sns.barplot(x='grade', y='loan_amnt', data=avg_loan_amnt)
```

```
Out[30]: <matplotlib.axes._subplots.AxesSubplot at 0x13f6d4c90>
```




```
In [31]: avg_loan_amnt.sort_values('loan_amnt', ascending=False)
```

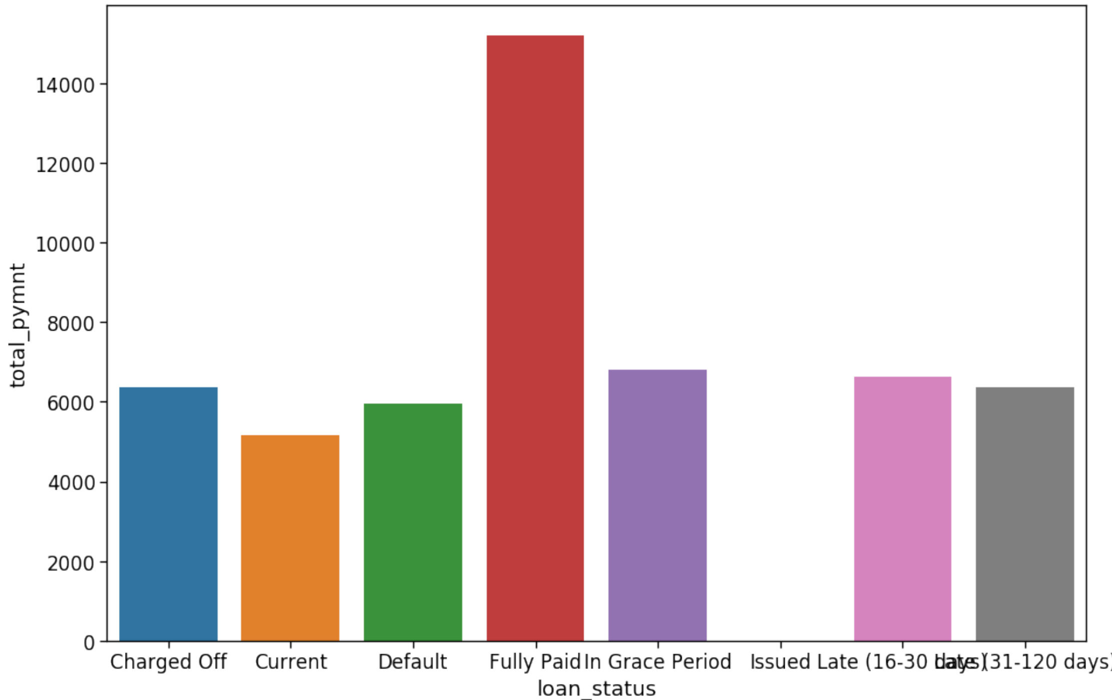
```
Out[31]:   grade     loan_amnt
         6     G  20855.868744
         5     F  19217.782578
         4     E  18071.066995
         3     D  15494.357081
         2     C  14480.310503
         0     A  14044.276151
         1     B  13650.167695
```

Summary When looking at loan amounts (**loan_amnt**) by **grade**, we can see that riskier loans have higher average loan amounts. This seems like a recipe for disaster but at the same time, I am led to believe that **loan_amnt** is used to calculate the **grade** and higher loan amounts will result in a lower **grade**. The only outlier to this trend is that the average loan amount for grade A loans is larger than grade B loans.

1.1.10 Average Total Payment by Loan Status

```
In [32]: by_status = df_eda.groupby('loan_status').mean()
         avg_total_pymnt = by_status['total_pymnt'].reset_index()
         plt.subplots(figsize=(15,10))
         sns.barplot(x='loan_status', y='total_pymnt', data=avg_total_pymnt)
```

```
Out[32]: <matplotlib.axes._subplots.AxesSubplot at 0x115dc7d10>
```




```
In [33]: avg_total_pymnt.sort_values('total_pymnt', ascending=False)
```

Out[33]:

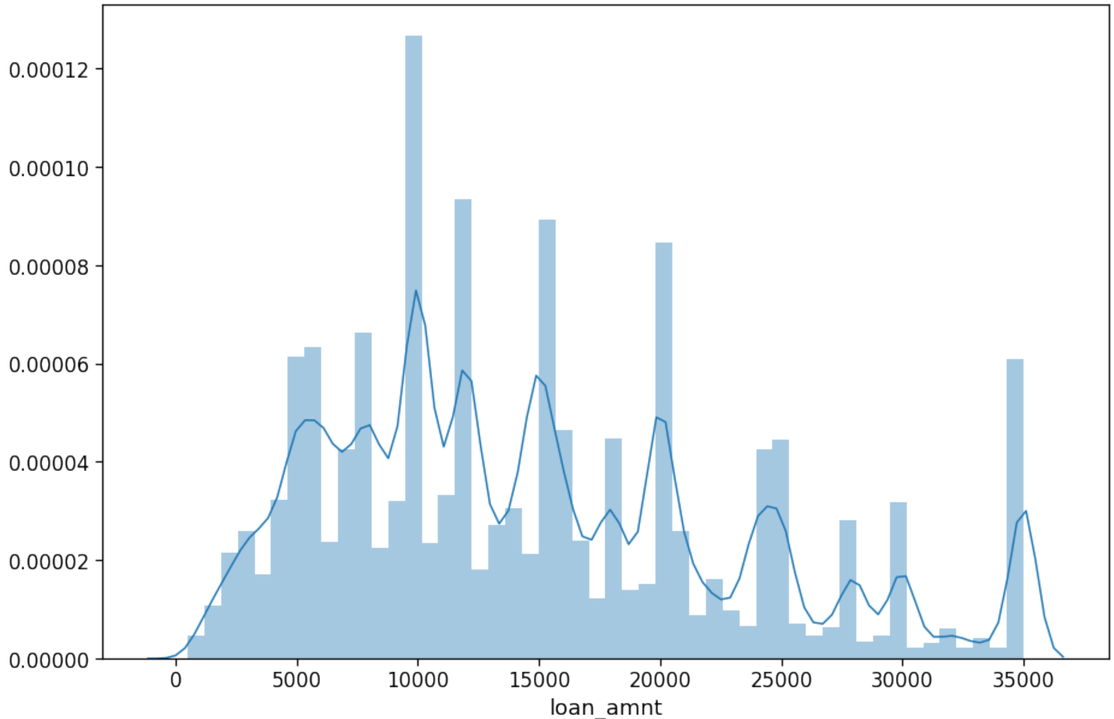
	loan_status	total_pymnt
3	Fully Paid	15186.680773
4	In Grace Period	6792.092241
6	Late (16-30 days)	6617.883309
0	Charged Off	6369.612648
7	Late (31-120 days)	6367.870714
2	Default	5947.982329
1	Current	5152.886189
5	Issued	9.307895

Summary We dug into the total payment amount (**total_pymnt**) by **loan_status** because **total_pymnt** had the highest correlation with **loan_status** out of all variables. One can see that the Fully Paid loans have the largest average total payment. This makes perfect sense as the loans were paid off. The loans with a status indicating they are late have a higher average total payment amount than those with a status of 'Current' which is probably due to interest.

1.1.11 Distribution of Loan Amount

```
In [34]: plt.subplots(figsize=(15,10))
         sns.distplot(df['loan_amnt'])
```

Out[34]: <matplotlib.axes._subplots.AxesSubplot at 0x115e32850>




```
In [35]: from scipy.stats import skew, kurtosis
         print('The skewness of ''loan_amnt'' is: {:.3f}'.format(skew(df_eda['loan_amnt'])))
         print('The excess kurtosis of ''loan_amnt'' is: {:.3f}'.format(kurtosis(df_eda['loan_am
```

```
The skewness of loan_amnt is: 0.681
The excess kurtosis of loan_amnt is: -0.259
```

Summary As seen in the **loan_amnt** distribution plot, there is tail to the right; the positive skew value of 0.681 confirms this

The kurtosis value of -0.259 indicates that the peakedness is pretty close to normal

1.2 Part 2

Create a dataset containing strictly 36 month loans.

```
In [36]: df_36 = df_eda.copy()
         df_36 = df_36[df_36['term'].str.contains('36')]
         df_36_num = df_num.copy()
         df_36_num = df_36_num[df_36_num['term'] == 36]
```

```
In [37]: print(df_36.shape)
         df_36.head()
```

```
(618687, 11)
```

```
Out[37]:    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
        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
        5      5000.0       5000.0   36 months      7.90     A     36000.0  Dec-2011
        7      3000.0       3000.0   36 months     18.64     E     48000.0  Dec-2011

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

```
In [38]: print('Term Counts')
         pd.value_counts(df_36['term']).to_frame().reset_index()
```

```
Term Counts
```

```
Out[38]:          index    term
        0   36 months  618687
```

```
In [39]: print(df_36_num.shape)
         df_36_num.head()
```

```
(618687, 11)
```

```
Out[39]:    loan_amnt  funded_amnt  term  int_rate  grade  annual_inc    issue_d  \
        0      5000.0       5000.0    36     10.65      1     24000.0 2011-12-01
        2      2400.0       2400.0    36     15.96      2     12252.0 2011-12-01
        3     10000.0      10000.0    36     13.49      2     49200.0 2011-12-01
        5      5000.0       5000.0    36      7.90      0     36000.0 2011-12-01
        7      3000.0       3000.0    36     18.64      4     48000.0 2011-12-01

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

```
In [40]: print('Term Counts')
         pd.value_counts(df_36_num['term']).to_frame().reset_index()
```

```
Term Counts
```

```
Out[40]:    index    term
         0     36  618687
```

After performing sanity check, data looks good to proceed.

1.2.1 #1

Percentage of loans fully paid.

```
In [41]: print('Number of Fully Paid 36-month loans: ' + str(df_36[df_36['loan_status'] == 'Full
         print('Percentage of total loans: {:.2f}%'.format(100*df_36[df_36['loan_status'] == 'Fu
```

```
Number of Fully Paid 36-month loans: 167575
Percentage of total loans: 27.09%
```

27.09% of the 36-month loans have been fully paid.

1.2.2 #2

Bucket by origination year and grade. Which bucket has highest rate of default? Assume that any loan not fully paid has defaulted.

```
In [42]: # Convert to date then year
         df_36['orig_year'] = pd.to_datetime(df_36['issue_d'])
         df_36['orig_year'] = df_36['orig_year'].apply(lambda x: x.year)

         # Group year and grade
         df_36['year_grade'] = df_36['orig_year'].map(str) + ' ' + df_36['grade'].map(str)

         # Create default variable; if 'Fully Paid' then 'No' else 'Yes'
         df_36['default'] = np.where(df_36['loan_status'] == 'Fully Paid', 'No', 'Yes')

In [43]: df_36_default = df_36[df_36['default'] == 'Yes']
         pd.value_counts(df_36_default['default']).to_frame().reset_index()
```

```
Out[43]:   index  default
         0   Yes   451112
```

```
In [44]: pd.value_counts(df_36_default['year_grade'], normalize=True).to_frame().reset_index().h
```

```
Out[44]:     index  year_grade
         0  2015 B    0.193065
         1  2015 C    0.160016
         2  2015 A    0.148515
         3  2014 B    0.086963
```

```
4   2014 C     0.072113
5   2015 D     0.066977
6   2014 A     0.059129
7   2013 B     0.047252
8   2014 D     0.033814
9   2013 C     0.029966
```

Loans that originated in 2015 with a B grade constitute the largest portion of loans that have defaulted.

1.2.3 #3

Bucket by origination year and grade. What annualized rate of return have the loans generated on average? Assume that `Annualized Rate of Return = (total_pymnt / funded_amnt -1) ^ (1/3)`.

```
In [45]: from __future__ import division
         df_36['ann_rate'] = (df_36['total_pymnt'] / df_36['funded_amnt'] - 1) ** (1/3)
```

```
In [46]: print('Overall average rate of return: ' + str(df_36['ann_rate'].mean()))

         by_year_grade = df_36.groupby('year_grade').mean()
         avg_ann_rate = by_year_grade['ann_rate'].reset_index()
         avg_ann_rate.sort_values('ann_rate', ascending=False).head(10)
```

```
Overall average rate of return: 0.475485541756
```

```
Out[46]:    year_grade  ann_rate
         33     2011 G  0.683785
         40     2012 G  0.674487
         26     2010 G  0.671978
         39     2012 F  0.661811
         38     2012 E  0.648165
         32     2011 F  0.628126
         31     2011 E  0.627589
         11     2008 F  0.618044
         37     2012 D  0.617703
         12     2008 G  0.612983
```

Looking at all of the loans, the average annual rate of return was 0.475.

Looking at buckets, loans that originated in 2011 (0.684), 2012 (0.674), and 2010 (0.672) with a G grade had the highest average annual rates of return.

1.3 Part 3

Building off of Part 2, build a logistic regression model that predicts loan defaults as defined above (if loan_status == 'Fully Paid' then 0 else 1).

Assume that (i) you are given the ability to invest in each loan independently; (ii) you invest immediately following loan origination and hold to maturity (36 months); and (iii) all loan fields that would be known upon origination are made available to you.

```
In [47]: df_3 = df_36.copy()
         df_3.head()
```

```
Out[47]:    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
         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
         5     5000.0       5000.0   36 months      7.90     A     36000.0  Dec-2011
         7     3000.0       3000.0   36 months     18.64     E     48000.0  Dec-2011

              dti  revol_bal   total_pymnt loan_status  orig_year year_grade default  \
         0  27.65    13648.0   5861.071414  Fully Paid       2011     2011 B      No
         2   8.72     2956.0   3003.653644  Fully Paid       2011     2011 C      No
         3  20.00     5598.0  12226.302212  Fully Paid       2011     2011 C      No
         5  11.20     7963.0   5631.377753  Fully Paid       2011     2011 A      No
         7   5.35     8221.0   3938.144334  Fully Paid       2011     2011 E      No

            ann_rate
         0  0.556361
         2  0.631237
         3  0.606077
         5  0.501695
         7  0.678760
```

Update the df_3 dataframe to be numerical (run same transformations that were used to create df_36_num) Remove the **year_grade** feature that was created for bucketing purposes

Remove the **loan_status** feature because we will be using the **default** field as our target variable.

Drop the **term** feature because it has no predictive power due to lack of variance (every value = '36 months').

Encode **grade** to numerical (e.g. 'A' = 0, 'B' = 1, etc.)

Transform **issue_d** into date

Transform **default** to binary 1/0 rather than Yes/No

```
In [48]: # Drop year_grade
         df_3 = df_3.drop('year_grade', axis=1)

         # Drop loan_status
         df_3 = df_3.drop('loan_status', axis=1)
```

```
# Drop term
df_3 = df_3.drop('term', axis=1)

# Convert to date then year
df_3['orig_year'] = pd.to_datetime(df_3['issue_d'])
df_3['orig_year'] = df_3['orig_year'].apply(lambda x: x.year)

# grade
le = pp.LabelEncoder()
le.fit(df_3['grade'])
df_3['grade'] = le.transform(df_3['grade'])

# issue_d
df_3['issue_d'] = pd.to_datetime(df_3['issue_d'])

# default
df_3['default'] = np.where(df_3['default'] == 'Yes', 1, 0)
```

ann_rate will be null for any value where the total_pymnt is less than funded_amnt These null values cannot be fed into our model. While I would love to just remove them and use the annual rate as an input, this would skew the model. We cannot only look at loans where the **total_pymnt** is greater than the **funded_amnt** when we are trying to predict loan defaults. We should remove the **ann_rate** feature from our dataset.

```
In [49]: df_3 = df_3.drop('ann_rate', axis=1)

In [50]: df_3.head()
```

```
Out[50]:    loan_amnt  funded_amnt  int_rate  grade  annual_inc    issue_d    dti  \
         0     5000.0       5000.0     10.65      1     24000.0 2011-12-01  27.65
         2     2400.0       2400.0     15.96      2     12252.0 2011-12-01   8.72
         3    10000.0      10000.0     13.49      2     49200.0 2011-12-01  20.00
         5     5000.0       5000.0      7.90      0     36000.0 2011-12-01  11.20
         7     3000.0       3000.0     18.64      4     48000.0 2011-12-01   5.35

            revol_bal   total_pymnt  orig_year  default
         0    13648.0   5861.071414       2011        0
         2     2956.0   3003.653644       2011        0
         3     5598.0  12226.302212       2011        0
         5     7963.0   5631.377753       2011        0
         7     8221.0   3938.144334       2011        0
```

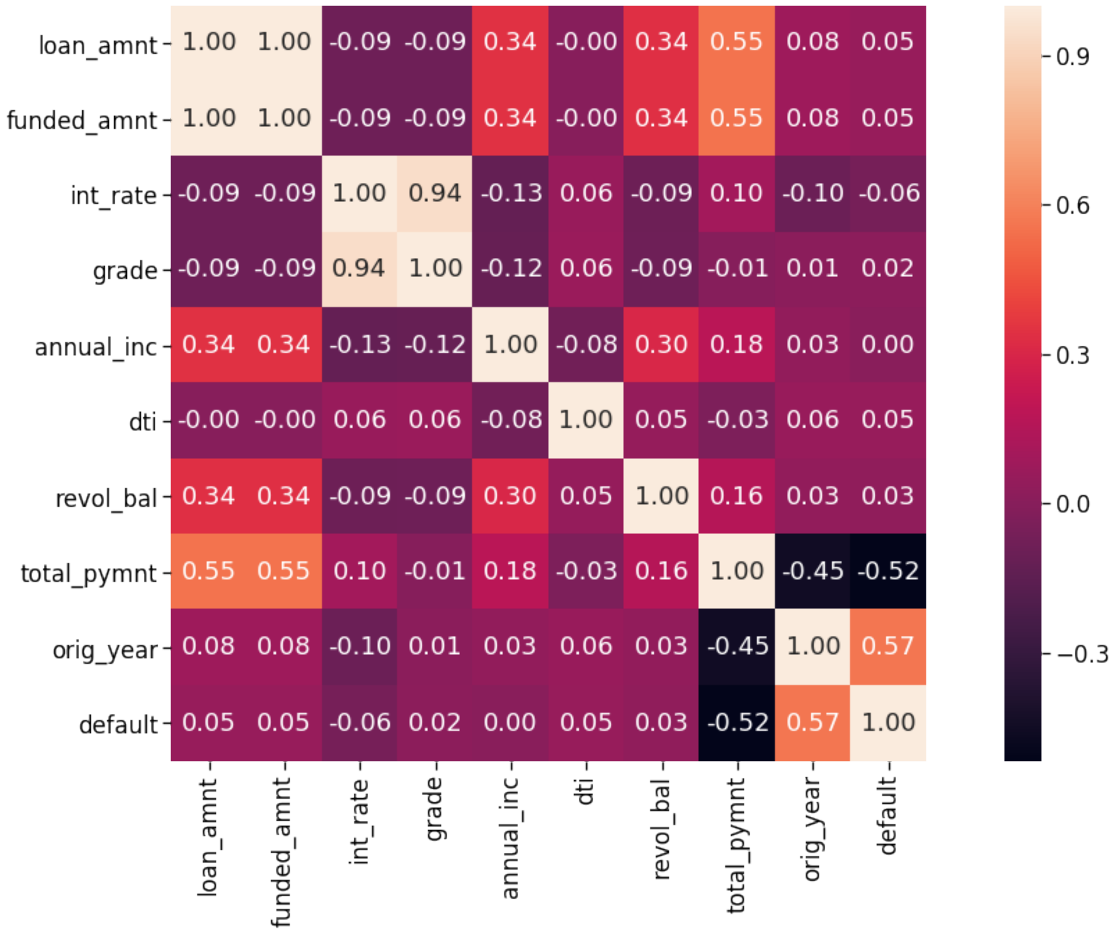
Feature Selection

Test for multicollinearity via correlation matrix (heatmap)

```
In [51]: %matplotlib inline
         plt.figure(figsize=(20,10))
```

```
sns.set_context("notebook", font_scale=1.5)
sns.heatmap(df_3.corr(), vmax=1, square=True, annot=True, fmt='.2f')
```

Out[51]: <matplotlib.axes._subplots.AxesSubplot at 0x1162ebe10>



Summary **loan_amnt** and **funded_amnt** have a correlation of 1 so we can remove one of these features; they both have the same correlation to the target variable, **default**, so it won't matter which we keep in our model

grade and **int_rate** have a strong correlation fo 0.94 so let's remove one of these features as well; **int_rate** has a stronger absolute correlation with **default** so let's remove **grade**

Let's go with **orig_year** rather than **issue_d** for the date feature; when looking at the correlation matrix and analysis from part 2, it seems it will be a good feature; I don't think it's necessary to look at the date on a monthly level

Let's take a quick peak at how many loans have **loan_amnt** not equal to **funded_amnt**

In [52]:
```
print('Number of loans where ''loan_amnt'' is not equal to ''funded_amnt'': ' + str(df_
print('Percentage of loans in dataset: {:.2f}%'.format(100 * df_3[df_3['loan_amnt'] !=
```

```
Number of loans where loan_amnt is not equal to funded_amnt: 769
Percentage of loans in dataset: 0.12%
```

It is such a small percentage of loans which is why the correlation of the 2 features with every other feature is the same (to 2 decimal places). I think it makes more sense to go with the **loan_amnt** beacause the data dictionary says that if at some point the credit department reduces the loan amount, it is reflected in this value.

```
In [53]: X, y = df_3.drop(['default', 'funded_amnt', 'grade', 'issue_d'], axis=1), df_3['default
```

```
In [54]: X.head()
```

Out[54]:

	loan_amnt	int_rate	annual_inc	dti	revol_bal	total_pymnt	orig_year
0	5000.0	10.65	24000.0	27.65	13648.0	5861.071414	2011
2	2400.0	15.96	12252.0	8.72	2956.0	3003.653644	2011
3	10000.0	13.49	49200.0	20.00	5598.0	12226.302212	2011
5	5000.0	7.90	36000.0	11.20	7963.0	5631.377753	2011
7	3000.0	18.64	48000.0	5.35	8221.0	3938.144334	2011

Split into train and test sets Split the dataset into train and test sets for the logistic regression model. The train/test split should be 70%/30%. We will set a random seed to initialize the sampling.

```
In [55]: X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=2
```

Build model We will use the default parameters for the sake of simplicity. 1. Create model with sklearn LogisticRegression() 2. Fit the model 3. Predict 4. Assess accuracy

```
In [56]: clf = LogisticRegression()

In [57]: clf.fit(X_train, y_train)

Out[57]: LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=True,
                   intercept_scaling=1, max_iter=100, multi_class='ovr', n_jobs=1,
                   penalty='l2', random_state=None, solver='liblinear', tol=0.0001,
                   verbose=0, warm_start=False)

In [58]: preds = clf.predict(X_test)

In [59]: print('Accuracy Score: ' + str(accuracy_score(y_test, preds)))
         print('AUC of ROC: ' + str(roc_auc_score(y_test, preds)))
         print('Cross-validation Score: ' + str(cross_val_score(clf, X_train, y_train).mean()))

Accuracy Score: 0.960885095928
AUC of ROC: 0.967970510179
Cross-validation Score: 0.960794772328
```

Summary The model performed strongly with an accuracy classification score of 0.961 (meaning it correctly predicted loan default 96.1% of the time).

The area under the ROC was used as a second form of validating model accuracy. The score of 0.967 is very close to 1 implying that the model does a good job of differentiating between loans that do/do not default.

The cross-validation score of 0.961 is also strong. This method applies k-fold cross validation which can be used to evaluate and compare models. A higher value indicates a stronger model.

Appy Recursive Feature Elimination Let's apply RFE to see if we can generate a stronger logistic regression model.

```
In [60]: rfe = RFE(clf)
         rfe.fit(X_train, y_train)
```

```
Out[60]: RFE(estimator=LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=Tr
                   intercept_scaling=1, max_iter=100, multi_class='ovr', n_jobs=1,
                   penalty='l2', random_state=None, solver='liblinear', tol=0.0001,
                   verbose=0, warm_start=False),
           n_features_to_select=None, step=1, verbose=0)
```

```
In [61]: print("Num Features: %d"% rfe.n_features_)
         print("Selected Features: %s"% rfe.support_)
         print("Feature Ranking: %s"% rfe.ranking_)
```

```
Num Features: 3
Selected Features: [ True  True False False False  True False]
Feature Ranking: [1 1 5 2 4 1 3]
```

```
In [62]: X_train.head()
```

```
Out[62]:         loan_amnt  int_rate  annual_inc    dti  revol_bal  total_pymnt  \
         619590     2800.0     12.69     28000.0  25.63     8989.0       373.75
         493417     3200.0     13.18     24000.0   3.60      422.0       105.76
         533316    12000.0     10.99     30000.0   4.35     3384.0       770.97
         773334     4800.0     14.65     26000.0  26.50     5287.0      1320.73
         631820     6000.0      6.89     44400.0  34.38     2444.0       735.29

                 orig_year
         619590       2015
         493417       2015
         533316       2015
         773334       2015
         631820       2015
```

Summary RFE has identified that **loan_amnt**, **int_rate**, and **total_pymnt** are the strongest features in our logistic regression model. Let's limit the feature space to these 3 variables and create a new model.

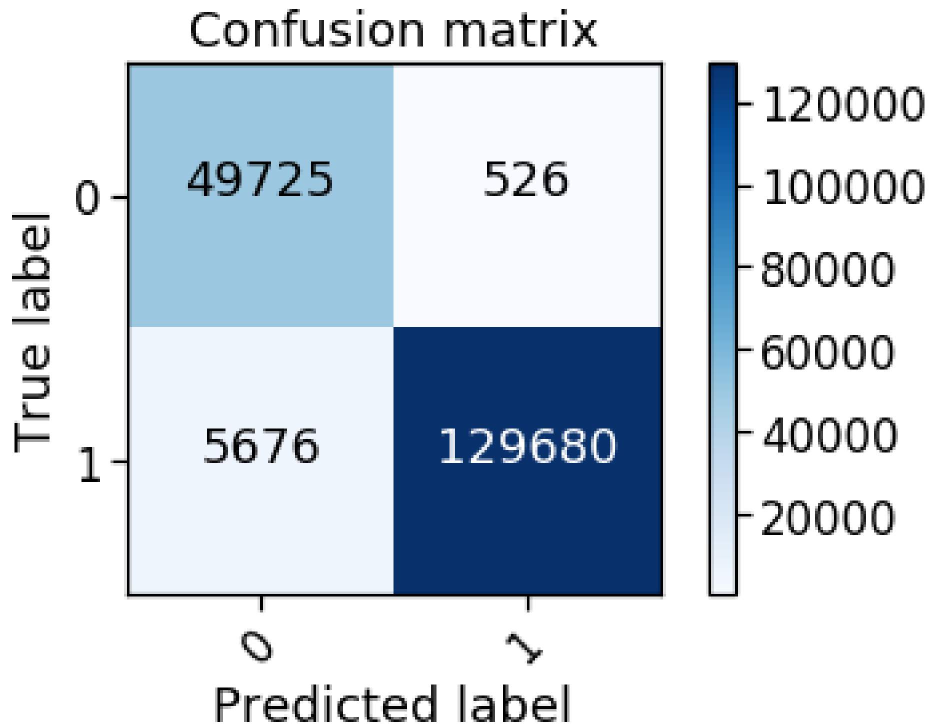
Build new model

```
In [63]: X_train_2 = X_train[['loan_amnt', 'int_rate', 'total_pymnt']]
         X_test_2 = X_test[['loan_amnt', 'int_rate', 'total_pymnt']]
         clf = LogisticRegression()
         clf.fit(X_train_2, y_train)
         preds = clf.predict(X_test_2)
         print('Accuracy Score: ' + str(accuracy_score(y_test, preds)))
         print('AUC of ROC: ' + str(roc_auc_score(y_test, preds)))
         print('Cross-validation Score: ' + str(cross_val_score(clf, X_train, y_train).mean()))
```

```
Accuracy Score: 0.966585311976
AUC of ROC: 0.973799341661
Cross-validation Score: 0.960794772328
```

```
In [64]: # Confusion matrix
         cm = confusion_matrix(y_test, preds)
         classes = set(y_test)
         plot_confusion_matrix(cm, classes)
         confusion_metrics(cm)
```

```
Confusion matrix, without normalization
[[ 49725    526]
 [  5676 129680]]
Accuracy = 0.966585311976
Misclassification Rate = 0.0334146880236
TP Rate = 0.958066136706
FP Rate = 0.0419338632938
TN Rate = 0.989532546616
FN Rate = 0.010467453384
Specifity = 0.958066136706
Precision = 0.897546975686
Prevalence = 0.270738711363
```



Summary The model performed strongly with an accuracy classification score of 0.967 (meaning it correctly predicted loan default 96.7% of the time). This is only a 0.006 point improvement over the classification score for the previous model.

The area under the ROC is 0.973 which is even closer to 1 than our previous model. This implies that the model does a better job of differentiating between loans that do/do not default.

The cross-validation score of 0.961 is also strong. This is almost equivalent to the previous model's cross-validation score.

Looking at the confusion matrix for the model, we can see that the model predicts defaults when the loan has actually defaulted roughy 96% of the time and predicts no default when the loan has not defaulted roughly 99% of the time. Let's look at this from an investment perspective at the loan-level and decide we want to invest in loans that the model predicts will not default. The result will be that 90% of the loans we have invested in will not default (labeled above as precision).

Conclusion

Model Selection Our initial model used the following features:

loan_amnt, **int_rate**, **annual_inc**, **dti**, **revol_bal**, **total_pymnt**, **orig_year** The second model used the following features:

loan_amnt, **int_rate**, **total_pymnt** The second model performed slightly better than the initial model. Reducing the feature space led to an improved classification accuracy score and larger area under the ROC (implying the model is better at differentiating between loans that default and loans that do not). While the performance of the second model is not that much better than the initial model, it makes more sense to go with this model. A smaller feature space can reduce any chance of overfitting and at the same time improves model interpretability. It is safe to say that the loan amount (**loan_amnt**), interest rate (**int_rate**), and total payment amount (**total_pymnt**) are strong features for predicting loan default.

Final Model: Logistic Regression with target variable = 'default' and feature variables ['loan_amnt', 'int_rate', 'total_pymnt']