ZP_LC_pt1

October 11, 2018

1 Kaggle Lending Club Loan Data

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1.1 Part 1

1.1.1 Import Python packages

```
In [112]: 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
          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)
```

1.1.2 Pull data into environment

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

```
In [8]: df.head(2)
```

Out[8]:
```
        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 [26]: def df_shape(data):
             print('Number of columns: ' + str(data.shape[1]))
             print('Number of rows: ' + str(data.shape[0]))
```

```
In [27]: df_shape(df)
```

```
Number of columns: 74
Number of rows: 887379
```

```
In [13]: 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 [176]: 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 [177]: df_eda.head()
```

```
Out[177]:    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 [178]: df_shape(df_eda)
```

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

1.1.4 Grab summary statistics for the new dataset

In [179]:
```
df_eda.describe()
```

Out[179]:
```
          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 [180]:
```
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 [181]: df_eda[df_eda['annual_inc'].isnull()]
```

```
Out[181]:        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 [182]: 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.'.fo
```

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

In [183]:
```
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 [184]:
```
print('Grade Counts')
pd.value_counts(df_eda['grade']).to_frame().reset_index()
```

```
Grade Counts
```

Out[184]:

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

In [185]:
```
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']['
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 [186]: print('Term Counts')
          pd.value_counts(df_eda['term']).to_frame().reset_index()
```

```
Term Counts
```

Out[186]:

	index	term
0	36 months	621121
1	60 months	266254

```
In [187]: print('Term Percentages')
          pd.value_counts(df_eda['term'], normalize=True).to_frame().reset_index()
```

```
Term Percentages
```

Out[187]:

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

```
Loan Status Counts
```

Out[188]:

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

```
Loan Status Percentages
```

Out[189]:

	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 [190]: 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.'.fo
```

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

Issue Date (issue_d)

```
In [191]: print('Issue Date counts')
          pd.value_counts(df_eda['issue_d']).to_frame().reset_index()
```

```
Issue Date counts
```

```
Out[191]:        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 [192]: print('Issue Date percentages')
          pd.value_counts(df_eda['issue_d'], normalize=True).to_frame().reset_index()
```

```
Issue Date percentages
```

```
Out[192]:       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 [197]: df_eda.head()
```

```
Out[197]:    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 [198]: df_num = df_eda.copy()
          df_num.head()
```

```
Out[198]:    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 [199]:
```
# 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 [200]:
```
df_num.head()
```

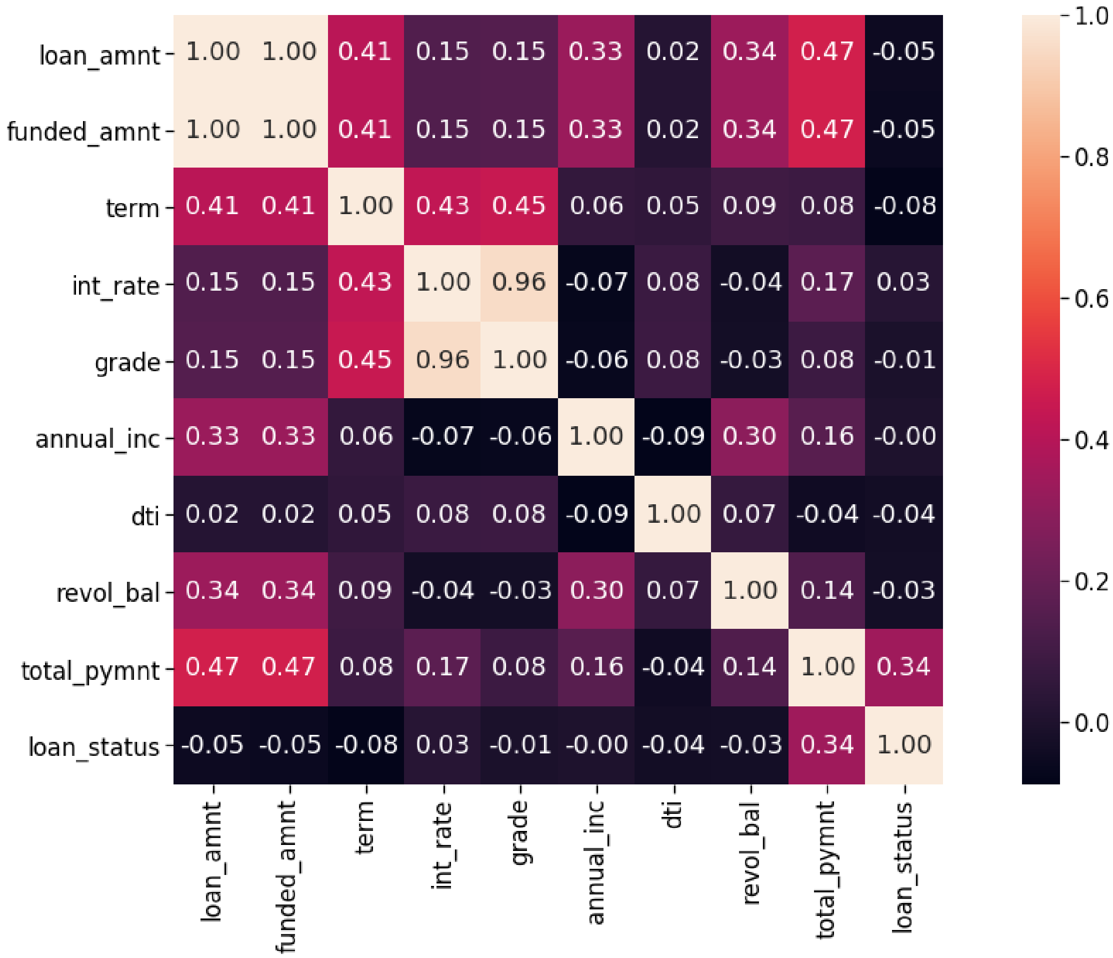
Out[200]:
```
   loan_amnt  funded_amnt  term  int_rate  grade  annual_inc    issue_d  \
0     5000.0       5000.0    36     10.65      1     24000.0 2011-12-01
1     2500.0       2500.0    60     15.27      2     30000.0 2011-12-01
2     2400.0       2400.0    36     15.96      2     12252.0 2011-12-01
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 [201]:
```
%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[201]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x15b2fce90>
```



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)

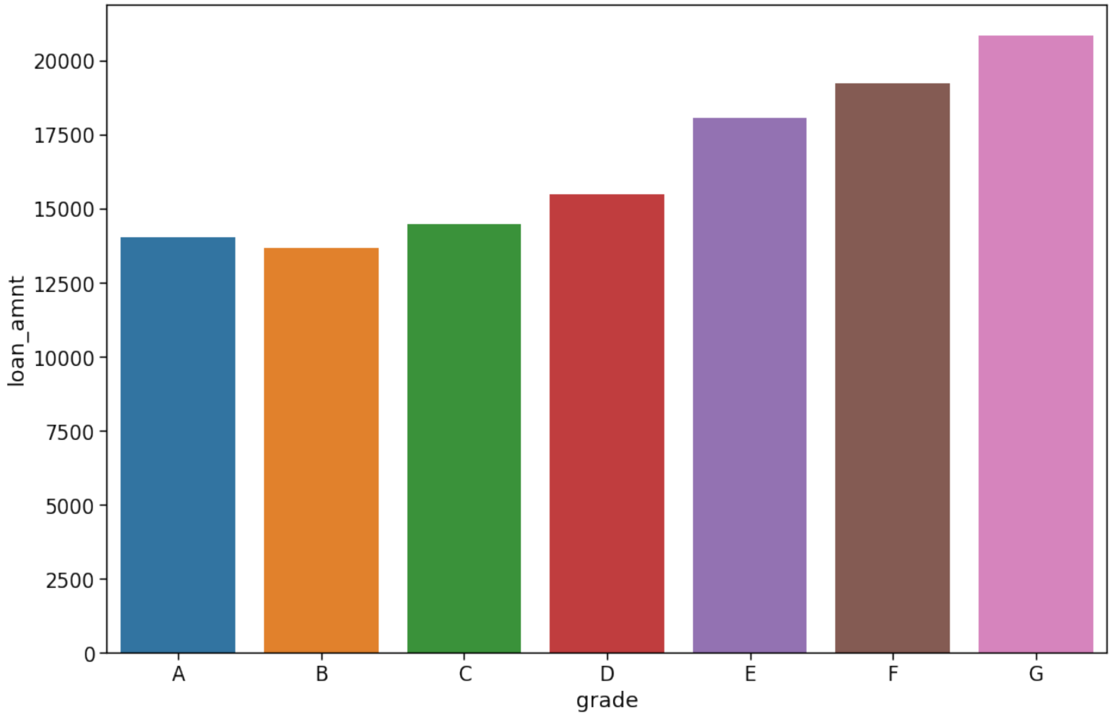
There is pretty strong correlation between **total_pymnt** and **loan_amnt**/**funded_amnt** (0.47)

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 [213]: 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[213]: <matplotlib.axes._subplots.AxesSubplot at 0x190ed2590>
```




```
In [214]: avg_loan_amnt.sort_values('loan_amnt', ascending=False)
```

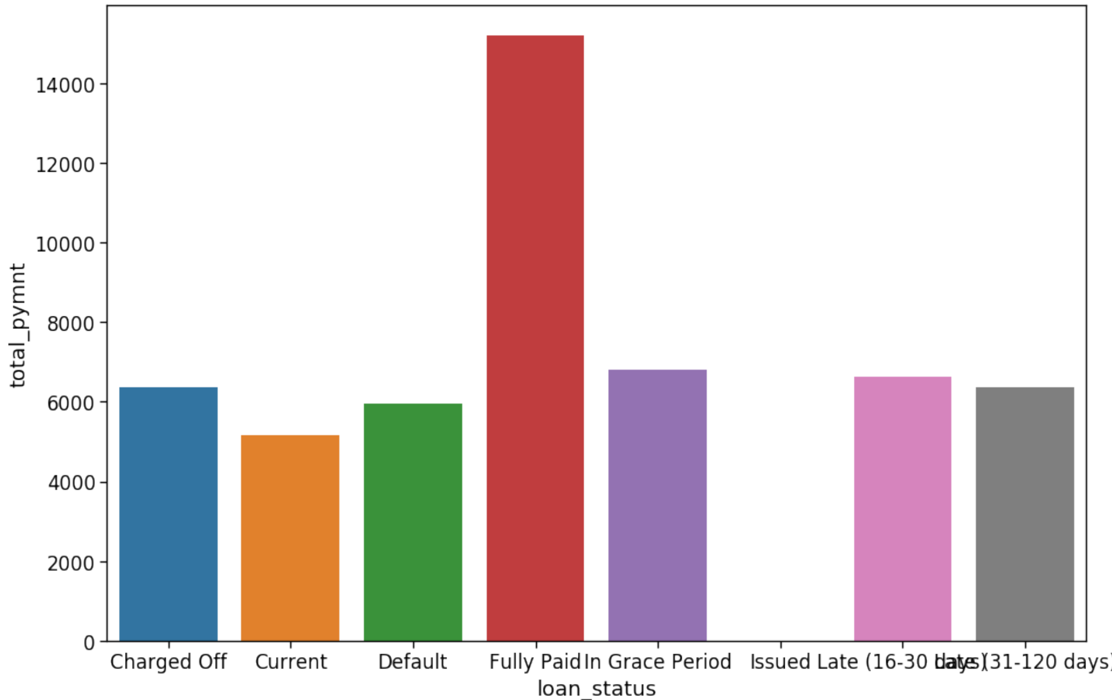
```
Out[214]:   grade     loan_amnt
          6     G  20855.868744
          5     F  19217.782578
          4     E  18071.066995
          3     D  15494.357081
          2     C  14480.310503
          0     A  14044.276151
          1     B  13650.167695
```

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 [218]: 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[218]: <matplotlib.axes._subplots.AxesSubplot at 0x191538d50>
```




```
In [220]: avg_total_pymnt.sort_values('total_pymnt', ascending=False)
```

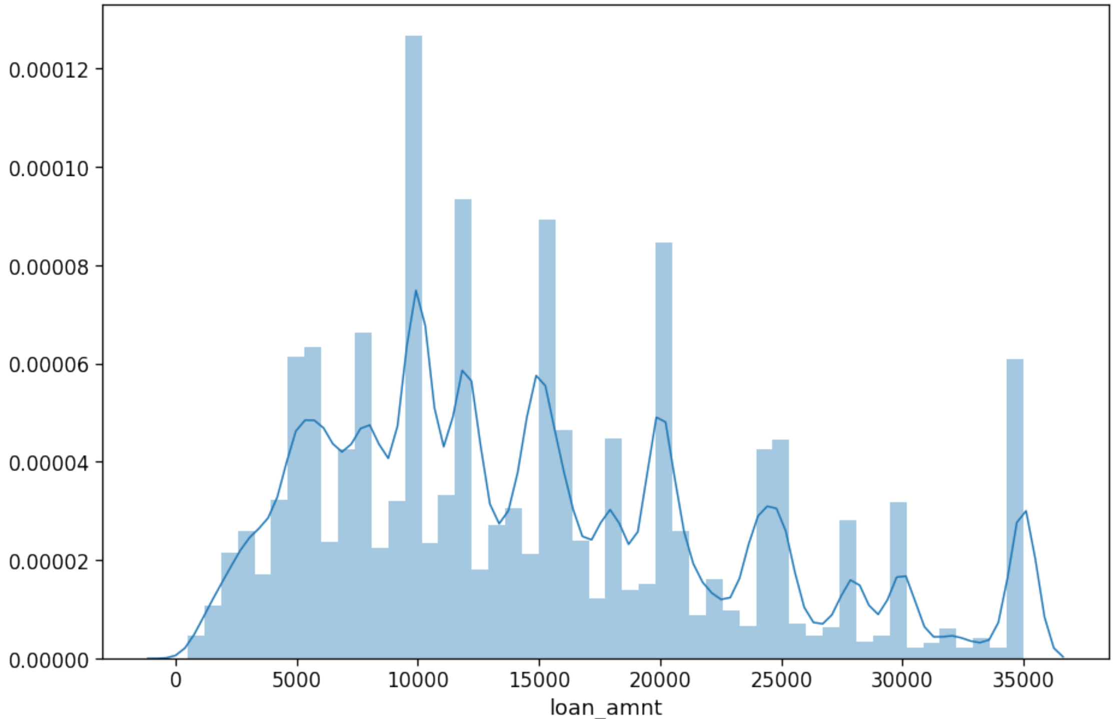
```
Out[220]:           loan_status   total_pymnt
          3          Fully Paid  15186.680773
          4     In Grace Period   6792.092241
          6   Late (16-30 days)   6617.883309
          0         Charged Off   6369.612648
          7  Late (31-120 days)   6367.870714
          2             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 [221]: plt.subplots(figsize=(15,10))
          sns.distplot(df['loan_amnt'])
```

```
Out[221]: <matplotlib.axes._subplots.AxesSubplot at 0x1918433d0>
```




```
In [227]: 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_a
```

```
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 [230]: 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 [235]: print(df_36.shape)
          df_36.head()
```

```
(618687, 11)
```

```
Out[235]:    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 [236]: print('Term Counts')
          pd.value_counts(df_36['term']).to_frame().reset_index()
```

```
Out[236]:        index    term
          0   36 months  618687
```

```
In [234]: print(df_36_num.shape)
          df_36_num.head()
```

```
(618687, 11)
```

```
Out[234]:    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 [237]: print('Term Counts')
          pd.value_counts(df_36_num['term']).to_frame().reset_index()
```

```
Term Counts
```

```
Out[237]:    index    term
          0     36  618687
```

After performing sanity check, data looks good to proceed.

1.2.1 #1

Percentage of loans fully paid.

```
In [240]: print('Number of Fully Paid 36-month loans: ' + str(df_36[df_36['loan_status'] == 'Ful
          print('Percentage of total loans: {:.2f}%'.format(100*df_36[df_36['loan_status'] == 'F
```

```
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 [248]: # Convert to date then year
          df_36['orig_year'] = pd.to_datetime(df_num['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 [269]: df_36_default = df_36[df_36['default'] == 'Yes']
          pd.value_counts(df_36_default['default']).to_frame().reset_index()
```

```
Out[269]:   index  default
          0   Yes   451112
```

```
In [271]: pd.value_counts(df_36_default['year_grade'], normalize=True).to_frame().reset_index().
```

```
Out[271]:     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 [283]:
```
from __future__ import division
df_36['ann_rate'] = (df_36['total_pymnt'] / df_36['funded_amnt'] - 1) ** (1/3)
```

In [292]:
```
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[292]:

	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.

In [ ]: