Part_I_exploration_template

January 14, 2023

1 Part I - Prosper Loan Data Exploration

1.1 by James Franchino

1.2 Introduction

This data set contains information on P2P (peer-to-peer) loans facilitated through Prosper Funding LLC.

1.3 Preliminary Wrangling

[1]:
```
# import all packages and set plots to be embedded inline
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sb
import re
import requests

%matplotlib inline
```

[2]:
```
url = 'https://s3.amazonaws.com/udacity-hosted-downloads/ud651/prosperLoanData.
  ↪csv'
data = requests.get(url)
with open (url.split('/')[-1], mode='wb') as file:
    file.write(data.content)
```

[2]:
```
df = pd.read_csv('prosperLoanData.csv')
df.head()
```

[2]:
```
                ListingKey  ListingNumber            ListingCreationDate  \
0  1021339766868145413AB3B         193129  2007-08-26 19:09:29.263000000
1  10273602499503308B223C1        1209647  2014-02-27 08:28:07.900000000
2  0EE9337825851032864889A          81716  2007-01-05 15:00:47.090000000
3  0EF5356002482715299901A         658116  2012-10-22 11:02:35.010000000
4  0F023589499656230C5E3E2         909464  2013-09-14 18:38:39.097000000

  CreditGrade  Term LoanStatus           ClosedDate  BorrowerAPR  \
```

```
0           C    36  Completed  2009-08-14 00:00:00      0.16516
1         NaN    36    Current                  NaN      0.12016
2          HR    36  Completed  2009-12-17 00:00:00      0.28269
3         NaN    36    Current                  NaN      0.12528
4         NaN    36    Current                  NaN      0.24614

   BorrowerRate  LenderYield  …  LP_ServiceFees  LP_CollectionFees  \
0        0.1580       0.1380  …         -133.18                0.0
1        0.0920       0.0820  …            0.00                0.0
2        0.2750       0.2400  …          -24.20                0.0
3        0.0974       0.0874  …         -108.01                0.0
4        0.2085       0.1985  …          -60.27                0.0

   LP_GrossPrincipalLoss  LP_NetPrincipalLoss LP_NonPrincipalRecoverypayments  \
0                    0.0                  0.0                             0.0
1                    0.0                  0.0                             0.0
2                    0.0                  0.0                             0.0
3                    0.0                  0.0                             0.0
4                    0.0                  0.0                             0.0

   PercentFunded  Recommendations InvestmentFromFriendsCount  \
0            1.0                0                          0
1            1.0                0                          0
2            1.0                0                          0
3            1.0                0                          0
4            1.0                0                          0

  InvestmentFromFriendsAmount Investors
0                         0.0       258
1                         0.0         1
2                         0.0        41
3                         0.0       158
4                         0.0        20

[5 rows x 81 columns]
```

[3]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 113937 entries, 0 to 113936
Data columns (total 81 columns):
 #   Column                               Non-Null Count   Dtype
---  ------                               --------------   -----
 0   ListingKey                           113937 non-null  object
 1   ListingNumber                        113937 non-null  int64
 2   ListingCreationDate                  113937 non-null  object
 3   CreditGrade                          28953 non-null   object
```

```
4   Term                                 113937 non-null  int64
5   LoanStatus                           113937 non-null  object
6   ClosedDate                           55089 non-null   object
7   BorrowerAPR                          113912 non-null  float64
8   BorrowerRate                         113937 non-null  float64
9   LenderYield                          113937 non-null  float64
10  EstimatedEffectiveYield              84853 non-null   float64
11  EstimatedLoss                        84853 non-null   float64
12  EstimatedReturn                      84853 non-null   float64
13  ProsperRating (numeric)              84853 non-null   float64
14  ProsperRating (Alpha)                84853 non-null   object
15  ProsperScore                         84853 non-null   float64
16  ListingCategory (numeric)            113937 non-null  int64
17  BorrowerState                        108422 non-null  object
18  Occupation                           110349 non-null  object
19  EmploymentStatus                     111682 non-null  object
20  EmploymentStatusDuration             106312 non-null  float64
21  IsBorrowerHomeowner                  113937 non-null  bool
22  CurrentlyInGroup                     113937 non-null  bool
23  GroupKey                             13341 non-null   object
24  DateCreditPulled                     113937 non-null  object
25  CreditScoreRangeLower                113346 non-null  float64
26  CreditScoreRangeUpper                113346 non-null  float64
27  FirstRecordedCreditLine              113240 non-null  object
28  CurrentCreditLines                   106333 non-null  float64
29  OpenCreditLines                      106333 non-null  float64
30  TotalCreditLinespast7years           113240 non-null  float64
31  OpenRevolvingAccounts                113937 non-null  int64
32  OpenRevolvingMonthlyPayment          113937 non-null  float64
33  InquiriesLast6Months                 113240 non-null  float64
34  TotalInquiries                       112778 non-null  float64
35  CurrentDelinquencies                 113240 non-null  float64
36  AmountDelinquent                     106315 non-null  float64
37  DelinquenciesLast7Years              112947 non-null  float64
38  PublicRecordsLast10Years             113240 non-null  float64
39  PublicRecordsLast12Months            106333 non-null  float64
40  RevolvingCreditBalance               106333 non-null  float64
41  BankcardUtilization                  106333 non-null  float64
42  AvailableBankcardCredit              106393 non-null  float64
43  TotalTrades                          106393 non-null  float64
44  TradesNeverDelinquent (percentage)   106393 non-null  float64
45  TradesOpenedLast6Months              106393 non-null  float64
46  DebtToIncomeRatio                    105383 non-null  float64
47  IncomeRange                          113937 non-null  object
48  IncomeVerifiable                     113937 non-null  bool
49  StatedMonthlyIncome                  113937 non-null  float64
50  LoanKey                              113937 non-null  object
51  TotalProsperLoans                    22085 non-null   float64
```

```
 52  TotalProsperPaymentsBilled          22085 non-null   float64
 53  OnTimeProsperPayments               22085 non-null   float64
 54  ProsperPaymentsLessThanOneMonthLate 22085 non-null   float64
 55  ProsperPaymentsOneMonthPlusLate     22085 non-null   float64
 56  ProsperPrincipalBorrowed            22085 non-null   float64
 57  ProsperPrincipalOutstanding         22085 non-null   float64
 58  ScorexChangeAtTimeOfListing         18928 non-null   float64
 59  LoanCurrentDaysDelinquent           113937 non-null  int64
 60  LoanFirstDefaultedCycleNumber       16952 non-null   float64
 61  LoanMonthsSinceOrigination          113937 non-null  int64
 62  LoanNumber                          113937 non-null  int64
 63  LoanOriginalAmount                  113937 non-null  int64
 64  LoanOriginationDate                 113937 non-null  object
 65  LoanOriginationQuarter              113937 non-null  object
 66  MemberKey                           113937 non-null  object
 67  MonthlyLoanPayment                  113937 non-null  float64
 68  LP_CustomerPayments                 113937 non-null  float64
 69  LP_CustomerPrincipalPayments        113937 non-null  float64
 70  LP_InterestandFees                  113937 non-null  float64
 71  LP_ServiceFees                      113937 non-null  float64
 72  LP_CollectionFees                   113937 non-null  float64
 73  LP_GrossPrincipalLoss               113937 non-null  float64
 74  LP_NetPrincipalLoss                 113937 non-null  float64
 75  LP_NonPrincipalRecoverypayments     113937 non-null  float64
 76  PercentFunded                       113937 non-null  float64
 77  Recommendations                     113937 non-null  int64
 78  InvestmentFromFriendsCount          113937 non-null  int64
 79  InvestmentFromFriendsAmount         113937 non-null  float64
 80  Investors                           113937 non-null  int64
dtypes: bool(3), float64(50), int64(11), object(17)
memory usage: 68.1+ MB
```

[4]:
```
df.describe()
```

[4]:
```
       ListingNumber           Term    BorrowerAPR   BorrowerRate  \
count   1.139370e+05  113937.000000  113912.000000  113937.000000
mean    6.278857e+05      40.830248       0.218828       0.192764
std     3.280762e+05      10.436212       0.080364       0.074818
min     4.000000e+00      12.000000       0.006530       0.000000
25%     4.009190e+05      36.000000       0.156290       0.134000
50%     6.005540e+05      36.000000       0.209760       0.184000
75%     8.926340e+05      36.000000       0.283810       0.250000
max     1.255725e+06      60.000000       0.512290       0.497500

         LenderYield  EstimatedEffectiveYield  EstimatedLoss  EstimatedReturn  \
count  113937.000000             84853.000000   84853.000000     84853.000000
mean        0.182701                 0.168661       0.080306         0.096068
```

std	0.074516	0.068467	0.046764	0.030403
min	-0.010000	-0.182700	0.004900	-0.182700
25%	0.124200	0.115670	0.042400	0.074080
50%	0.173000	0.161500	0.072400	0.091700
75%	0.240000	0.224300	0.112000	0.116600
max	0.492500	0.319900	0.366000	0.283700

	ProsperRating (numeric)	ProsperScore	…	LP_ServiceFees \
count	84853.000000	84853.000000	…	113937.000000
mean	4.072243	5.950067	…	-54.725641
std	1.673227	2.376501	…	60.675425
min	1.000000	1.000000	…	-664.870000
25%	3.000000	4.000000	…	-73.180000
50%	4.000000	6.000000	…	-34.440000
75%	5.000000	8.000000	…	-13.920000
max	7.000000	11.000000	…	32.060000

	LP_CollectionFees	LP_GrossPrincipalLoss	LP_NetPrincipalLoss \
count	113937.000000	113937.000000	113937.000000
mean	-14.242698	700.446342	681.420499
std	109.232758	2388.513831	2357.167068
min	-9274.750000	-94.200000	-954.550000
25%	0.000000	0.000000	0.000000
50%	0.000000	0.000000	0.000000
75%	0.000000	0.000000	0.000000
max	0.000000	25000.000000	25000.000000

	LP_NonPrincipalRecoverypayments	PercentFunded	Recommendations \
count	113937.000000	113937.000000	113937.000000
mean	25.142686	0.998584	0.048027
std	275.657937	0.017919	0.332353
min	0.000000	0.700000	0.000000
25%	0.000000	1.000000	0.000000
50%	0.000000	1.000000	0.000000
75%	0.000000	1.000000	0.000000
max	21117.900000	1.012500	39.000000

	InvestmentFromFriendsCount	InvestmentFromFriendsAmount	Investors
count	113937.000000	113937.000000	113937.000000
mean	0.023460	16.550751	80.475228
std	0.232412	294.545422	103.239020
min	0.000000	0.000000	1.000000
25%	0.000000	0.000000	2.000000
50%	0.000000	0.000000	44.000000
75%	0.000000	0.000000	115.000000
max	33.000000	25000.000000	1189.000000

```
[8 rows x 61 columns]
```

[5]:
```
df.sample(10)
```

[5]:
```
                      ListingKey  ListingNumber            ListingCreationDate  \
43177  7F4E36005962233195F35AC        1170068  2014-01-28 04:00:46.123000000
4702   697D3600654440857E58B22        1150191  2014-01-20 08:16:23.007000000
65371  E51135808779908018AF605         816338  2013-06-20 16:01:30.417000000
81095  4EB2359393538369623 57A3         999938  2013-11-07 08:39:37.167000000
18168  D0FE3603752974193828195        1169266  2014-02-19 19:18:07.203000000
73424  0ADB3556601727893139318         636417  2012-09-09 13:35:58.427000000
23189  6029354716668757966 3747         585508  2012-05-03 11:45:24.253000000
40572  919E3418931173018CFB3C5         324254  2008-05-02 11:44:48.570000000
96266  C3AD3414518761151447B17         286322  2008-02-29 16:02:50.780000000
34588  B952359543527059893 8C85        1032928  2013-12-07 09:51:21.713000000

      CreditGrade  Term LoanStatus           ClosedDate  BorrowerAPR  \
43177         NaN    36    Current                  NaN      0.09030
4702          NaN    60    Current                  NaN      0.17685
65371         NaN    36    Current                  NaN      0.26528
81095         NaN    36    Current                  NaN      0.20268
18168         NaN    36    Current                  NaN      0.12117
73424         NaN    36    Current                  NaN      0.27060
23189         NaN    12  Completed  2012-07-11 00:00:00      0.17969
40572           A    36  Completed  2011-05-09 00:00:00      0.08511
96266           A    36  Completed  2011-02-28 00:00:00      0.08874
34588         NaN    36    Current                  NaN      0.17151

       BorrowerRate  LenderYield  …  LP_ServiceFees  LP_CollectionFees  \
43177        0.0769       0.0669  …           -3.18                0.0
4702         0.1535       0.1435  …          -12.74                0.0
65371        0.2272       0.2172  …          -39.27                0.0
81095        0.1660       0.1560  …           -5.37                0.0
18168        0.0930       0.0830  …            0.00                0.0
73424        0.2324       0.2224  …          -45.80                0.0
23189        0.1224       0.1124  …           -3.83                0.0
40572        0.0714       0.0614  …         -158.43                0.0
96266        0.0750       0.0650  …          -20.33                0.0
34588        0.1355       0.1255  …          -58.79                0.0

       LP_GrossPrincipalLoss  LP_NetPrincipalLoss  \
43177                    0.0                  0.0
4702                     0.0                  0.0
65371                    0.0                  0.0
81095                    0.0                  0.0
18168                    0.0                  0.0
73424                    0.0                  0.0
```

```
23189                   0.0                  0.0
40572                   0.0                  0.0
96266                   0.0                  0.0
34588                   0.0                  0.0

      LP_NonPrincipalRecoverypayments  PercentFunded  Recommendations  \
43177                             0.0            1.0                0
4702                              0.0            1.0                0
65371                             0.0            1.0                0
81095                             0.0            1.0                0
18168                             0.0            1.0                0
73424                             0.0            1.0                0
23189                             0.0            1.0                0
40572                             0.0            1.0                1
96266                             0.0            1.0                0
34588                             0.0            1.0                0

      InvestmentFromFriendsCount InvestmentFromFriendsAmount Investors
43177                          0                        0.00        85
4702                           0                        0.00         1
65371                          0                        0.00         1
81095                          0                        0.00         2
18168                          0                        0.00         1
73424                          0                        0.00        32
23189                          0                        0.00        55
40572                          4                      650.78       231
96266                          0                        0.00        36
34588                          0                        0.00       560

[10 rows x 81 columns]
```

[6]:
```
df.shape
```

[6]:
```
(113937, 81)
```

This Dataset includes 81 columns. For the purpose of this analysis I am going to focus on a handful of the most useful columns. I will determine which columns to use by looking at the Variable Definitions found here https://docs.google.com/spreadsheets/d/1gDyi_L4UvIrLTEC6Wri5nbaMmkGmLQBk-Yx3z0XDEtI/edit#gid=0

[7]:
```
columns_keep =  [
    'Term', 'LoanStatus', 'BorrowerRate', 'ProsperRating (Alpha)',␣
 ↪'ListingCategory (numeric)', 'EmploymentStatus',
    'DelinquenciesLast7Years', 'StatedMonthlyIncome', 'TotalProsperLoans',␣
 ↪'LoanOriginalAmount',
    'LoanOriginationDate', 'Recommendations', 'Investors'
```

```
]
```

[8]:
```
new_df = df[columns_keep]
```

[9]:
```
new_df.shape
```

[9]:
```
(113937, 13)
```

[10]:
```
new_df.head()
```

[10]:
```
   Term LoanStatus  BorrowerRate ProsperRating (Alpha)  \
0    36  Completed        0.1580                   NaN
1    36    Current        0.0920                     A
2    36  Completed        0.2750                   NaN
3    36    Current        0.0974                     A
4    36    Current        0.2085                     D

   ListingCategory (numeric) EmploymentStatus  DelinquenciesLast7Years  \
0                          0    Self-employed                      4.0
1                          2         Employed                      0.0
2                          0    Not available                      0.0
3                         16         Employed                     14.0
4                          2         Employed                      0.0

   StatedMonthlyIncome  TotalProsperLoans  LoanOriginalAmount  \
0          3083.333333                NaN                9425
1          6125.000000                NaN               10000
2          2083.333333                NaN                3001
3          2875.000000                NaN               10000
4          9583.333333                1.0               15000

   LoanOriginationDate  Recommendations  Investors
0  2007-09-12 00:00:00                0        258
1  2014-03-03 00:00:00                0          1
2  2007-01-17 00:00:00                0         41
3  2012-11-01 00:00:00                0        158
4  2013-09-20 00:00:00                0         20
```

[11]:
```
new_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 113937 entries, 0 to 113936
Data columns (total 13 columns):
 #   Column                      Non-Null Count   Dtype
---  ------                      --------------   -----
 0   Term                        113937 non-null  int64
 1   LoanStatus                  113937 non-null  object
```

```
 2   BorrowerRate               113937 non-null  float64
 3   ProsperRating (Alpha)      84853 non-null   object
 4   ListingCategory (numeric)  113937 non-null  int64
 5   EmploymentStatus           111682 non-null  object
 6   DelinquenciesLast7Years    112947 non-null  float64
 7   StatedMonthlyIncome        113937 non-null  float64
 8   TotalProsperLoans          22085 non-null   float64
 9   LoanOriginalAmount         113937 non-null  int64
 10  LoanOriginationDate        113937 non-null  object
 11  Recommendations            113937 non-null  int64
 12  Investors                  113937 non-null  int64
dtypes: float64(4), int64(5), object(4)
memory usage: 11.3+ MB
```

[12]:
```
new_df.describe()
```

[12]:
```
                Term   BorrowerRate  ListingCategory (numeric)  \
count  113937.000000  113937.000000              113937.000000
mean       40.830248       0.192764                   2.774209
std        10.436212       0.074818                   3.996797
min        12.000000       0.000000                   0.000000
25%        36.000000       0.134000                   1.000000
50%        36.000000       0.184000                   1.000000
75%        36.000000       0.250000                   3.000000
max        60.000000       0.497500                  20.000000

       DelinquenciesLast7Years  StatedMonthlyIncome  TotalProsperLoans  \
count            112947.000000         1.139370e+05       22085.000000
mean                  4.154984         5.608026e+03           1.421100
std                  10.160216         7.478497e+03           0.764042
min                   0.000000         0.000000e+00           0.000000
25%                   0.000000         3.200333e+03           1.000000
50%                   0.000000         4.666667e+03           1.000000
75%                   3.000000         6.825000e+03           2.000000
max                  99.000000         1.750003e+06           8.000000

       LoanOriginalAmount  Recommendations      Investors
count        113937.00000    113937.000000  113937.000000
mean           8337.01385         0.048027      80.475228
std            6245.80058         0.332353     103.239020
min            1000.00000         0.000000       1.000000
25%            4000.00000         0.000000       2.000000
50%            6500.00000         0.000000      44.000000
75%           12000.00000         0.000000     115.000000
max           35000.00000        39.000000    1189.000000
```

ProsperRating (Alpha) uses Prosper's own proprietary rating system which was initiated in July 2009. With so many null values these null values should be dropped

[13]:
```
new_df = new_df.dropna(subset=['ProsperRating (Alpha)']).reset_index()
```

I will convert 'LoanOriginationDate' to a datetime format

[14]:
```
new_df['LoanOriginationDate'] = pd.to_datetime(new_df['LoanOriginationDate'])
```

[15]:
```
new_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 84853 entries, 0 to 84852
Data columns (total 14 columns):
 #   Column                     Non-Null Count  Dtype
---  ------                     --------------  -----
 0   index                      84853 non-null  int64
 1   Term                       84853 non-null  int64
 2   LoanStatus                 84853 non-null  object
 3   BorrowerRate               84853 non-null  float64
 4   ProsperRating (Alpha)      84853 non-null  object
 5   ListingCategory (numeric)  84853 non-null  int64
 6   EmploymentStatus           84853 non-null  object
 7   DelinquenciesLast7Years    84853 non-null  float64
 8   StatedMonthlyIncome        84853 non-null  float64
 9   TotalProsperLoans          19797 non-null  float64
 10  LoanOriginalAmount         84853 non-null  int64
 11  LoanOriginationDate        84853 non-null  datetime64[ns]
 12  Recommendations            84853 non-null  int64
 13  Investors                  84853 non-null  int64
dtypes: datetime64[ns](1), float64(4), int64(6), object(3)
memory usage: 9.1+ MB
```

'TotalProsperLoans' has many null values, I will replace them with '0' to fill out our data

[16]:
```
new_df['TotalProsperLoans'] = new_df['TotalProsperLoans'].fillna(0)
```

[17]:
```
new_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 84853 entries, 0 to 84852
Data columns (total 14 columns):
 #   Column                     Non-Null Count  Dtype
---  ------                     --------------  -----
 0   index                      84853 non-null  int64
 1   Term                       84853 non-null  int64
 2   LoanStatus                 84853 non-null  object
 3   BorrowerRate               84853 non-null  float64
 4   ProsperRating (Alpha)      84853 non-null  object
 5   ListingCategory (numeric)  84853 non-null  int64
 6   EmploymentStatus           84853 non-null  object
```

```
 7   DelinquenciesLast7Years    84853 non-null  float64
 8   StatedMonthlyIncome        84853 non-null  float64
 9   TotalProsperLoans          84853 non-null  float64
 10  LoanOriginalAmount         84853 non-null  int64
 11  LoanOriginationDate        84853 non-null  datetime64[ns]
 12  Recommendations            84853 non-null  int64
 13  Investors                  84853 non-null  int64
dtypes: datetime64[ns](1), float64(4), int64(6), object(3)
memory usage: 9.1+ MB
```

1.3.1 What is the structure of your dataset?

We have 13 columns with 84,853 rows of data about peer-to-peer loans made through Prosper.

1.3.2 What is/are the main feature(s) of interest in your dataset?

What metrics can be used to predict credit defaults? What metrics go into Prosper's proprietary rating system? Does the loan term have an effect on default?

1.3.3 What features in the dataset do you think will help support your investigation into your feature(s) of interest?

Prosper rating, loan amount, loan term.

1.4 Univariate Exploration

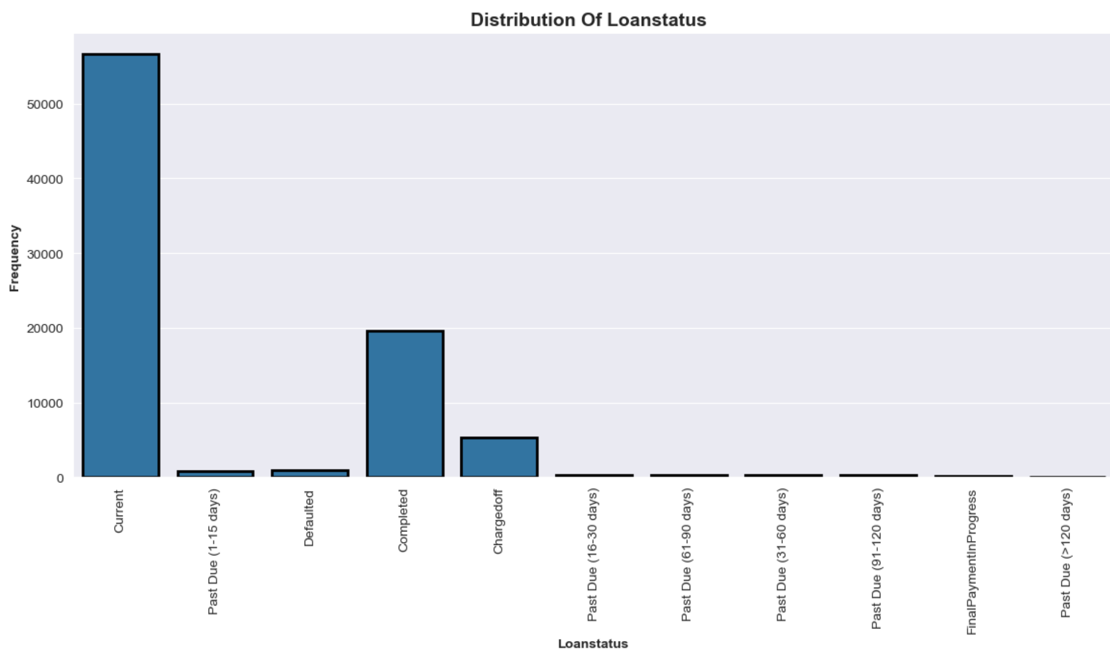
1.4.1 Loan Status

[18]:
```
# setting color and style
base_color = sb.color_palette()[0];
sb.set_style('darkgrid');
```

[19]:
```
def MyCountPlot(df, xVar, hue=None, color=0, palette=None, order=None,␣
↪hue_order=None):
    '''
    Inputs: data, variable. hue, color, palette, order and hue_order are␣
↪optional

    Output: A countplot
    '''

    # set plot dimensions
    plt.figure(figsize=[14, 6])

    # plot
    sb.countplot(data=new_df, x=xVar, hue=hue, color=sb.color_palette()[color],␣
↪palette=palette, order=order, edgecolor='black', linewidth=2,␣
↪hue_order=hue_order)
```

```
    # clean up variable names
    xVar=xVar.replace("_", " ") # replaces _ with a space
    if hue:
        hue=hue.replace("_", " ")

    # add title and format it
    plt.title(f'''Distribution of {xVar} {'by' if hue else ''} {hue if hue else␣
↪''}'''.title(), fontsize=14, weight="bold")

    # add xlabel and format it
    plt.xlabel(xVar.title(), fontsize=10, weight="bold")

    # add ylabel and format it
    plt.ylabel('Frequency'.title(), fontsize=10, weight="bold")
```

[20]:
```
# 1st plot

MyCountPlot(new_df, 'LoanStatus')
plt.xticks(rotation = 90);
```



Observation 1:

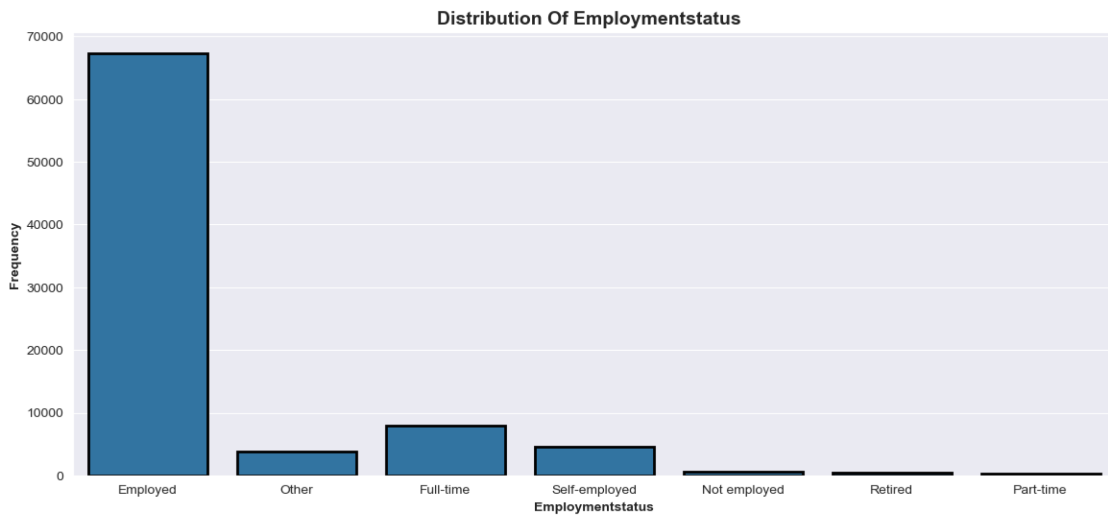
Most of the loans are current, not late or in default.

Completed loans are our second biggest category.

Past due loans are split into several categories based on the amount of days past due.

1.4.2 Employment status

[21]:
```
# 2nd plot

MyCountPlot(new_df, 'EmploymentStatus')
```



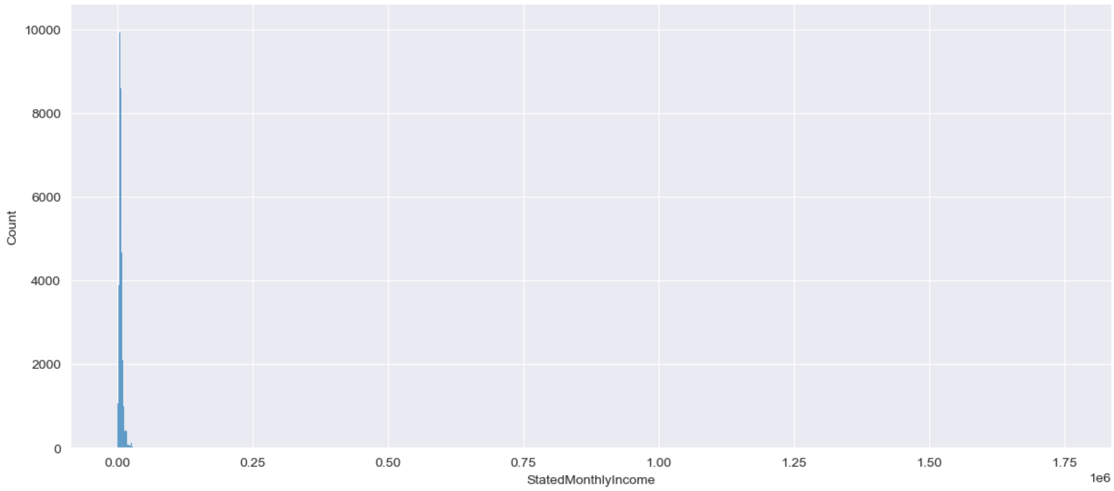
Observation 2:

Of the 84853 records, the vast majority (~ 68,000 or 97%) are listed as employed.

Full-Time makes up the second largest group. There is no information available on the difference between Employed and Full-Time

1.4.3 Monthly Income

[22]:
```
# 3rd plot

plt.figure(figsize=[14, 6])
sb.histplot(data = new_df, x='StatedMonthlyIncome', bins=2500);
```

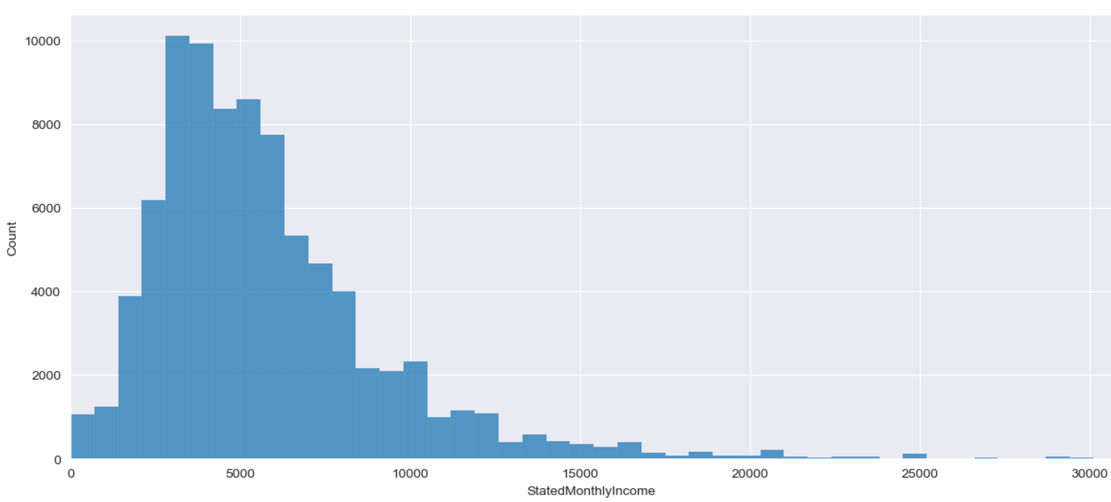


This histogram is heavily right skewed with many outliers, and I will need to drill down to get more information.

[23]:
```
income_standard = new_df['StatedMonthlyIncome'].std()
income_mean = new_df['StatedMonthlyIncome'].mean()
boundary = income_mean + income_standard * 3
len(new_df[new_df['StatedMonthlyIncome'] >= boundary])
```

[23]: 245

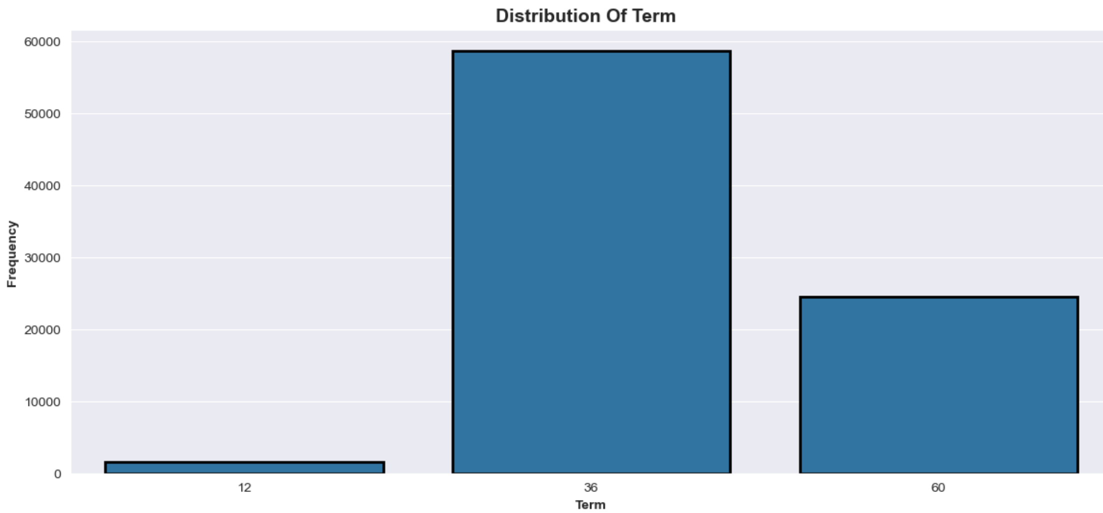
[24]:
```
# 4th plot

plt.figure(figsize=[14, 6])
sb.histplot(data=new_df, x='StatedMonthlyIncome', bins = 2500);
plt.xlim(0, boundary);
```



Observation 3:

We still have a right skewed graph even after drilling down but we can see that the majority of lendees land around $5000 in monthly income.

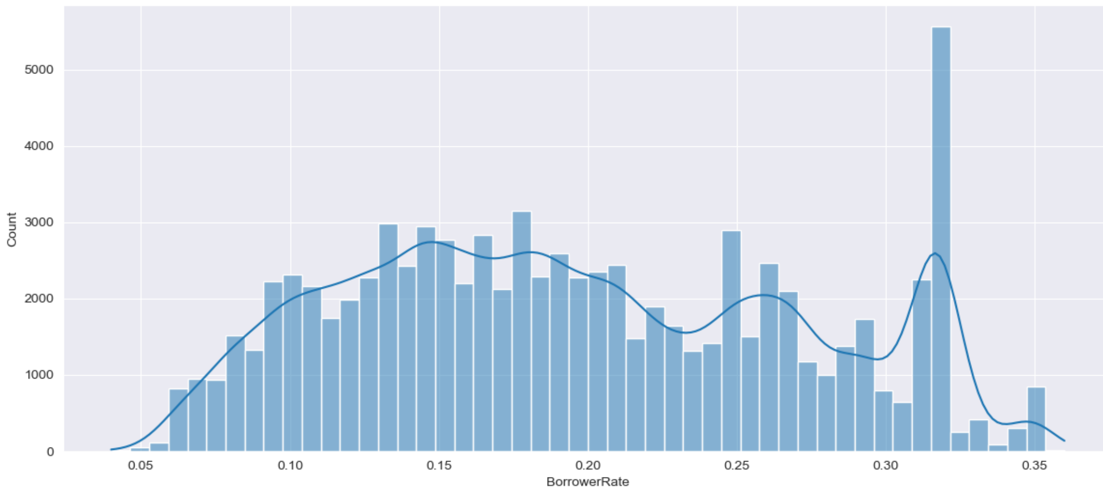
[25]:
```
# 5th plot

MyCountPlot(new_df, 'Term')
```



Observation 4:

The majority of loans made are 3 year (36 month) terms.

[26]:
```
# 6th plot

plt.figure(figsize=[14, 6])
sb.histplot(data=new_df, x='BorrowerRate', bins = 50, kde=True);
```



[27]:
```
new_df['BorrowerRate'].value_counts()
```

[27]:
```
0.3177    3672
0.3199    1645
0.2699    1314
0.1099     932
0.3500     802
          …
0.3094       1
0.1525       1
0.2125       1
0.2784       1
0.2665       1
Name: BorrowerRate, Length: 1229, dtype: int64
```

Observation 5:

Here we have a left skewed plot. We see a more uniform distribution of rates until we get to 0.3177. We should plot this against terms to see if there is a correlation

1.4.4 Discuss the distribution(s) of your variable(s) of interest. Were there any unusual points? Did you need to perform any transformations?

Both monthly income and borrower rate are heavily skewed with outliers.

1.4.5 Of the features you investigated, were there any unusual distributions? Did you perform any operations on the data to tidy, adjust, or change the form of the data? If so, why did you do this?

Both monthly income and borrower rate are heavily skewed with outliers.

1.5 Bivariate Exploration

[28]:
```
# Transforming the 'LoanStatus' Column
# Selecting the categories

new_df = new_df.query('LoanStatus in ["Completed", "Chargedoff", "Defaulted"]').
↪copy()

# np.where(condition[, x, y]) When True, yield x, otherwise yield y

new_df['LoanStatus'] = np.where(new_df['LoanStatus'] == 'Chargedoff',␣
↪'Defaulted', new_df['LoanStatus'])

# Check

new_df['LoanStatus'].value_counts()
```

[28]:
```
Completed    19664
Defaulted     6341
Name: LoanStatus, dtype: int64
```

19664 completed loans and 6341 defaulted loans

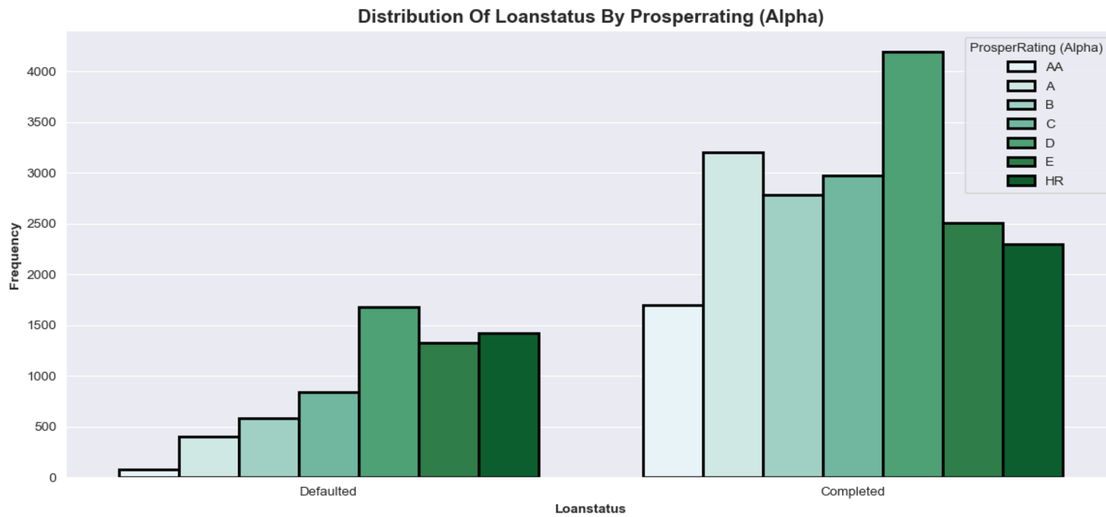
[29]:
```
# Reducing the number of categories

categories = {1: 'Debt Consolidation', 2: 'Home Improvement', 3: 'Business', 6:␣
↪'Auto', 7: 'Other'}

# Use .map() to map categories and fill NaN with 'Other'

new_df['ListingCategory (numeric)'] = new_df['ListingCategory (numeric)'].
↪map(categories).fillna('Other')

# Check
new_df['ListingCategory (numeric)'].value_counts()
```

[29]:
```
Debt Consolidation    12740
Other                  7083
Home Improvement       2612
Business               2366
Auto                   1204
Name: ListingCategory (numeric), dtype: int64
```

1.5.1 Status and Prosper Rating:

[34]:
```
credit_rating = ['AA', 'A', 'B', 'C', 'D', 'E', 'HR']
```

[35]:
```
# 7th plot

MyCountPlot(new_df, 'LoanStatus', hue = 'ProsperRating (Alpha)', hue_order =␣
↪credit_rating, palette = 'BuGn')
```



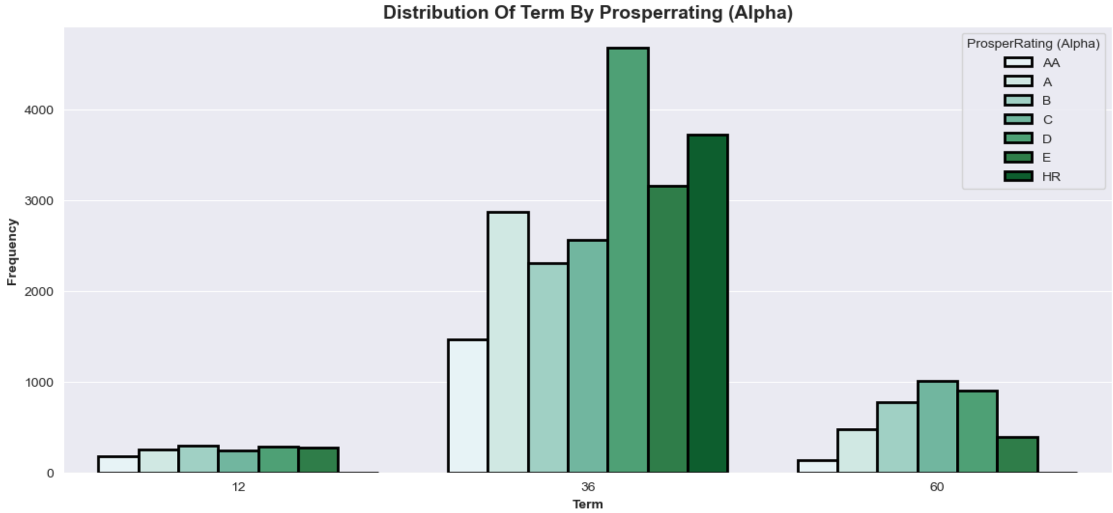
Observation 6:

The most frequent rating among defaulted loans is rating D.

The most frequent rating among completed loans is also D and second highest is A. This may explain why so many with a D rating were able to get loans.

1.5.2 Prosper rating vs loan length

[36]:
```
# 8th plot

MyCountPlot(new_df, 'Term', hue = 'ProsperRating (Alpha)', hue_order =␣
↪credit_rating, palette = 'BuGn')
```

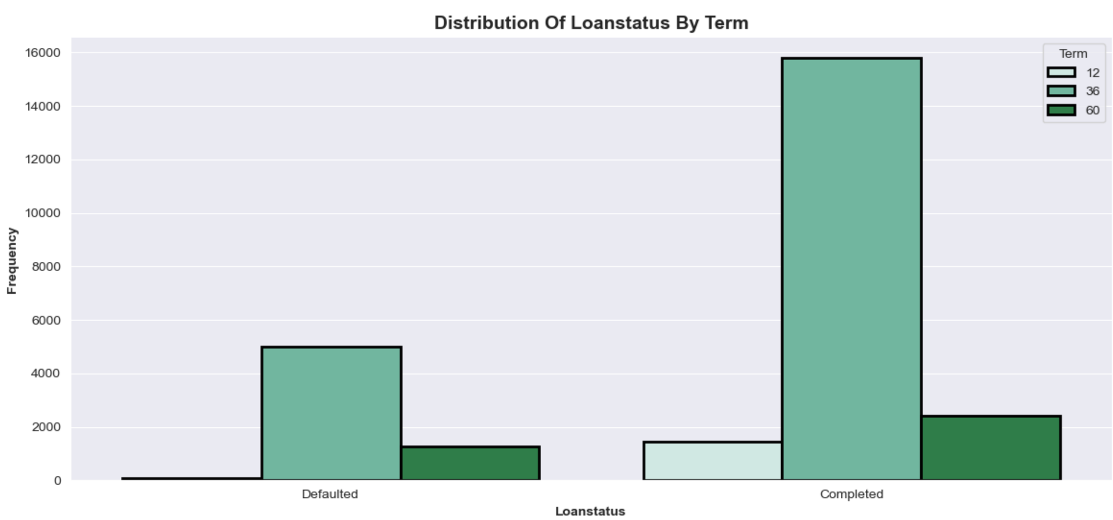


Observation 7:

> The amount of 12 month term loans is nearly uniform with the exception of the HR category
>
> 36 month term loans have the highest amount of loans in the HR category

1.5.3 Loan status vs loan term

[37]:
```python
# 9th plot

MyCountPlot(new_df, 'LoanStatus', hue = 'Term', palette = 'BuGn')
```



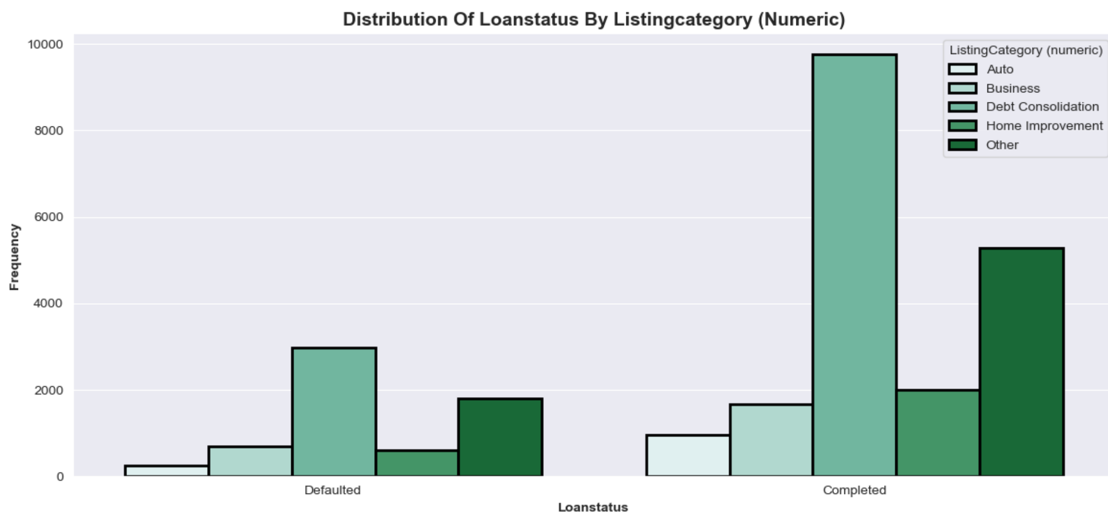
Observation 8:

In both Completed and Charged Off loans, the most common term is 36 months.

1.5.4 Loan status vs Loan reason (category)

[39]:
```
listing = ['Auto', 'Business', 'Debt Consolidation', 'Home Improvement',␣
↪'Other']
```

[40]:
```
# 10th plot

MyCountPlot(new_df, 'LoanStatus', hue = 'ListingCategory (numeric)', hue_order␣
↪= listing, palette = 'BuGn')

# sb.countplot(data = new_df, x = 'LoanStatus', hue = 'ListingCategory␣
↪(numeric)', palette = 'BuGn', edgecolor='black', linewidth=2);
```

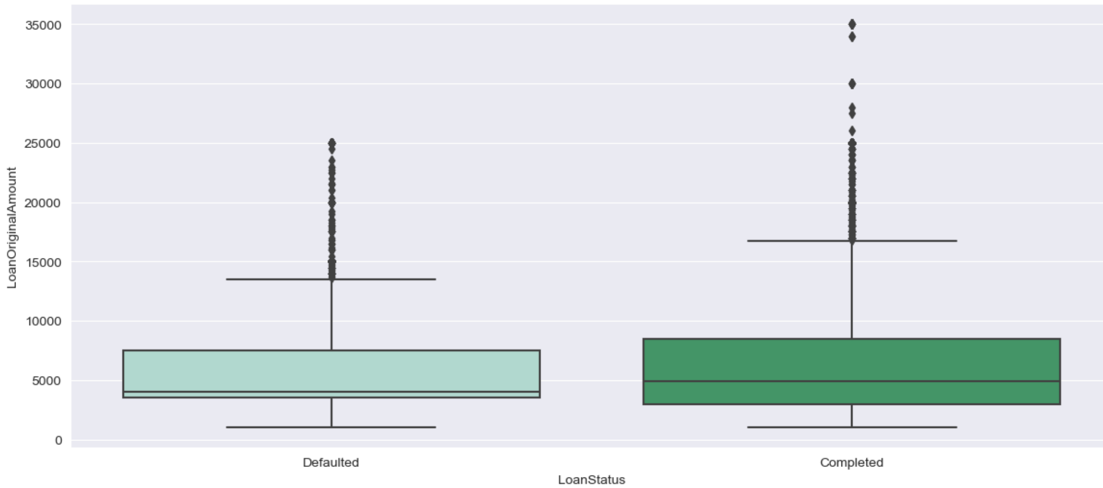


observation 9:

In both completed and charged off loans, 'other' was the most frequent category

1.5.5 Loan status vs loan amount

[41]:
```
# 11th plot

plt.figure(figsize=[14, 6])
sb.boxplot(data = new_df, x = 'LoanStatus', y = 'LoanOriginalAmount', palette =␣
↪'BuGn');
```

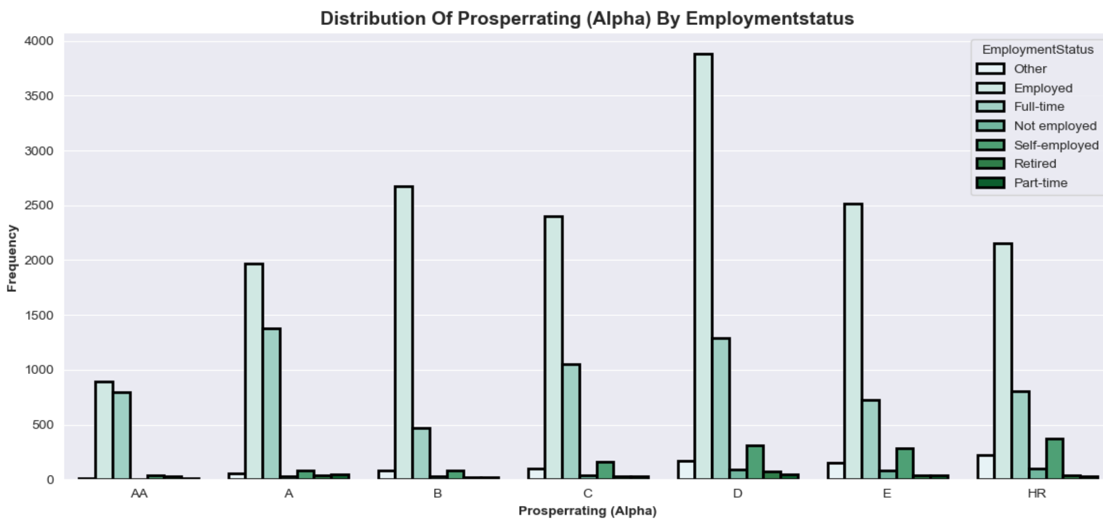


observation 9:

Charged off loans tend to be smaller than completed loans

1.5.6 Employment status by credit rating

[44]:
```
# 12th plot

MyCountPlot(new_df, 'ProsperRating (Alpha)', hue = 'EmploymentStatus', order =␣
↪credit_rating, palette = 'BuGn')
```



observation 10:

Not Employed, Self-employed, Retired and Part-Time are more common among the lower prosper ratings

1.5.7 Talk about some of the relationships you observed in this part of the investigation. How did the feature(s) of interest vary with other features in the dataset?

In Loan status vs Loan amount defaulted loans tend to be smaller than completed loans. Employment status of individuals with lower ratings tends to be 'Not employed', 'Self-employed', 'Retired' or 'Part-time'. The higher the rating the more likely the borrower is to be employed.

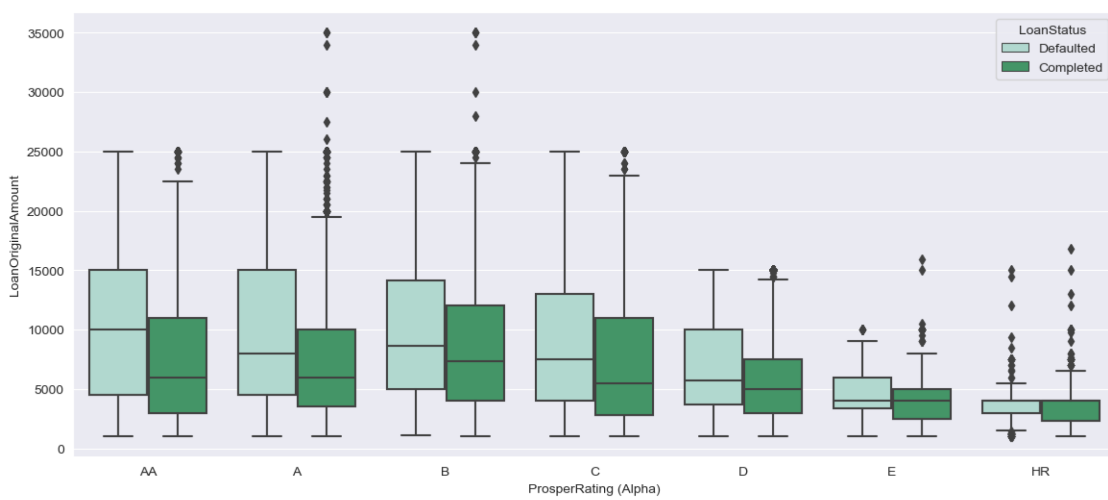
1.5.8 Did you observe any interesting relationships between the other features (not the main feature(s) of interest)?

Interestingly, the Prosper rating 'D' is the most frequent rating among both defaulted and completed loans.

1.6 Multivariate Exploration

1.6.1 Rating, loan amount, loan status

[46]:
```
# 13th plot

plt.figure(figsize = [14, 6])
sb.boxplot(data = new_df, x = 'ProsperRating (Alpha)', y =␣
↪'LoanOriginalAmount', hue = 'LoanStatus', order = credit_rating, palette =␣
↪'BuGn');
```



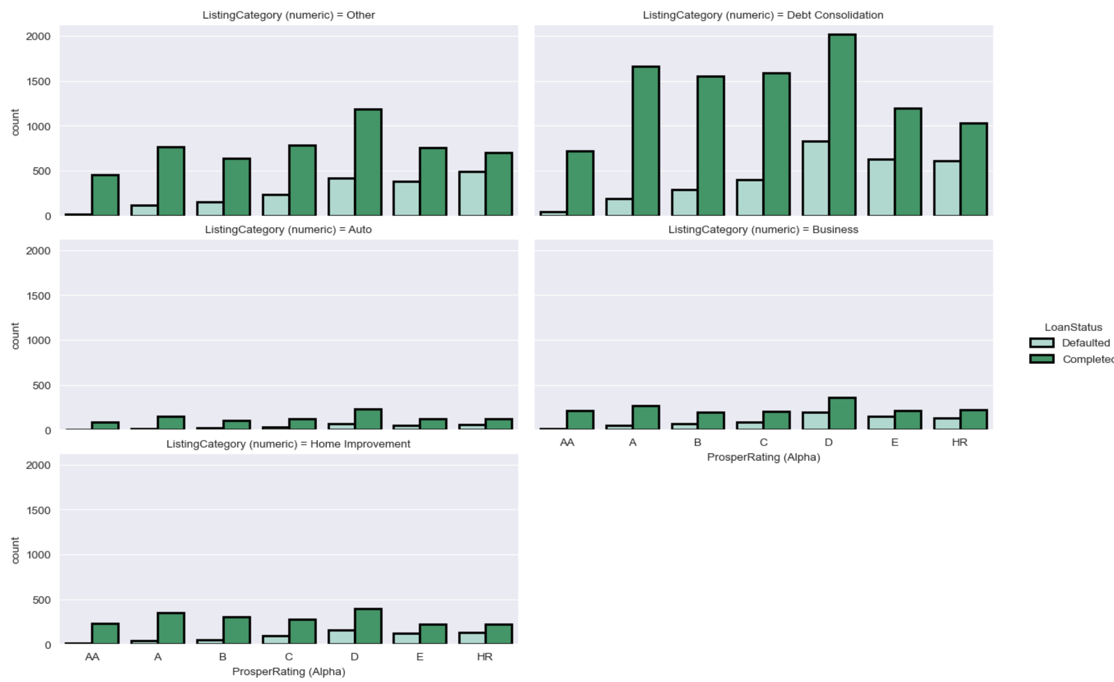
Observation 11:

Except for the HR rating, defaulted loans are larger than completed loans.

Most of the defaulted loans come from individuals with a low Prosper rating.

1.6.2 Loan category, credit rating, and loan outcomes.

[48]:
```
# 14th plot

g = sb.catplot(x = 'ProsperRating (Alpha)', hue = 'LoanStatus', col = 'ListingCategory (numeric)', order = credit_rating,
               data = new_df, kind = 'count', palette = 'BuGn', col_wrap = 2, edgecolor='black', linewidth=2);

# set plot dimensions

g.fig.set_size_inches(14, 8);
```



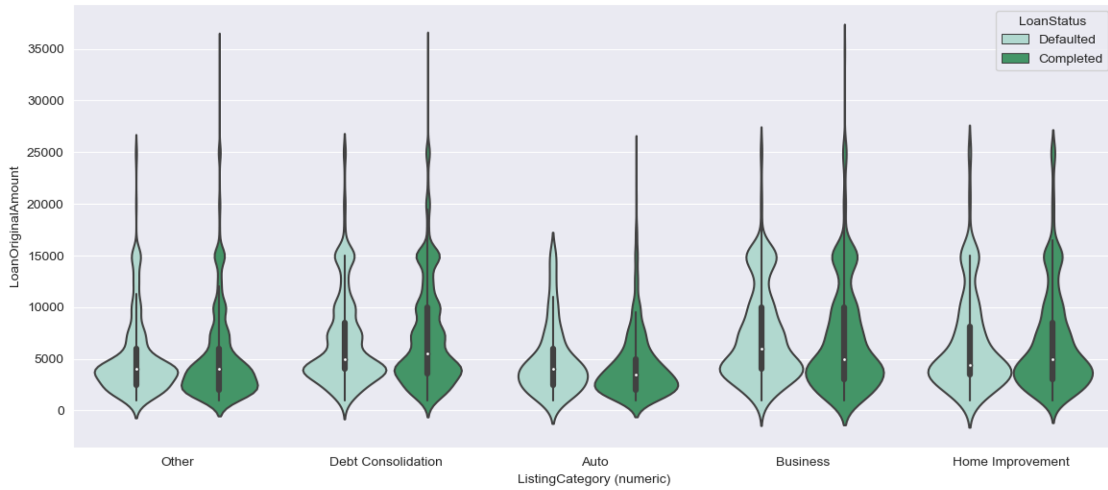
Observation 12:

Debt consolidation loans make up the largest category of loans, and have the largest disparity between Completed and Charged Off loans.

1.6.3 Loan amount, loan category, and loan status

[49]:
```
# 15th plot

plt.figure(figsize = [14, 6])
```

```
sb.violinplot(data = new_df, x = 'ListingCategory (numeric)', y =
 'LoanOriginalAmount', hue = 'LoanStatus', palette = 'BuGn');
```



Observation 13:

With the exception of the Home Improvement category, the loan amount of charged off loans is smaller than the completed loans.

The top dollar amount of loans in both the Debt Consolidation and business categories are very close

1.6.4 Talk about some of the relationships you observed in this part of the investigation. Were there features that strengthened each other in terms of looking at your feature(s) of interest?

Our initial assumptions were strengthened. Most of the defaulted credits comes from individuals with low Prosper rating and Business category tend to have larger amount.

1.6.5 Were there any interesting or surprising interactions between features?

I found it interesting that in the 36 month loan term category lenders seemed the most willing to loan to those with a poor Prosper credit rating

1.7 Conclusions

This data set was fairly clean with only a little cleaning and transformation needed. Prosper's 2 biggest loan categories are Business and debt consolidation. Their most popular loan term is 36 months and lenders seem to be far more willing to make loans to people with lower credit ratings.

[ ]: