Part_I_exploration_template

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1 Part I - (Prosper Loan Data Exploration)

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1.2 Introduction

This data set contains 113,937 loans with 81 variables on each loan, including loan amount, borrower rate (or interest rate), current loan status, borrower income, and many others.

1.3 Preliminary Wrangling

In [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

%matplotlib inline
```

In [2]:
```
# load in dataset
prosper_loan= pd.read_csv('prosperLoanData.csv')
prosper_loan.head(10)
```

Out[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
5  0F05359734824199381F61D        1074836  2013-12-14 08:26:37.093000000
6  0F0A3576754255009D63151         750899  2013-04-12 09:52:56.147000000
7  0F1035772717087366F9EA7         768193  2013-05-05 06:49:27.493000000
8  0F043596202561788EA13D5        1023355  2013-12-02 10:43:39.117000000
9  0F043596202561788EA13D5        1023355  2013-12-02 10:43:39.117000000

  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
5         NaN    60    Current                  NaN      0.15425
6         NaN    36    Current                  NaN      0.31032
7         NaN    36    Current                  NaN      0.23939
8         NaN    36    Current                  NaN      0.07620
9         NaN    36    Current                  NaN      0.07620

   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
5        0.1314       0.1214    ...             -25.33                0.0
6        0.2712       0.2612    ...             -22.95                0.0
7        0.2019       0.1919    ...             -69.21                0.0
8        0.0629       0.0529    ...             -16.77                0.0
9        0.0629       0.0529    ...             -16.77                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
5                    0.0                  0.0                             0.0
6                    0.0                  0.0                             0.0
7                    0.0                  0.0                             0.0
8                    0.0                  0.0                             0.0
9                    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
5            1.0                0                          0
6            1.0                0                          0
7            1.0                0                          0
8            1.0                0                          0
9            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                          0.0       1
6                          0.0       1
7                          0.0       1
8                          0.0       1
9                          0.0       1

[10 rows x 81 columns]
```

```
In [3]: print(prosper_loan.shape)
        print(prosper_loan.dtypes)
```

```
(113937, 81)
ListingKey                               object
ListingNumber                             int64
ListingCreationDate                      object
CreditGrade                              object
Term                                      int64
LoanStatus                               object
ClosedDate                               object
BorrowerAPR                             float64
BorrowerRate                            float64
LenderYield                             float64
EstimatedEffectiveYield                 float64
EstimatedLoss                           float64
EstimatedReturn                         float64
ProsperRating (numeric)                 float64
ProsperRating (Alpha)                    object
ProsperScore                            float64
ListingCategory (numeric)                 int64
BorrowerState                            object
Occupation                               object
EmploymentStatus                         object
EmploymentStatusDuration                float64
IsBorrowerHomeowner                        bool
CurrentlyInGroup                           bool
GroupKey                                 object
DateCreditPulled                         object
CreditScoreRangeLower                   float64
CreditScoreRangeUpper                   float64
FirstRecordedCreditLine                  object
CurrentCreditLines                      float64
OpenCreditLines                         float64
                                         ...
TotalProsperLoans                       float64
```

```
TotalProsperPaymentsBilled             float64
OnTimeProsperPayments                  float64
ProsperPaymentsLessThanOneMonthLate    float64
ProsperPaymentsOneMonthPlusLate        float64
ProsperPrincipalBorrowed               float64
ProsperPrincipalOutstanding            float64
ScorexChangeAtTimeOfListing            float64
LoanCurrentDaysDelinquent                int64
LoanFirstDefaultedCycleNumber          float64
LoanMonthsSinceOrigination               int64
LoanNumber                               int64
LoanOriginalAmount                       int64
LoanOriginationDate                     object
LoanOriginationQuarter                  object
MemberKey                               object
MonthlyLoanPayment                     float64
LP_CustomerPayments                    float64
LP_CustomerPrincipalPayments           float64
LP_InterestandFees                     float64
LP_ServiceFees                         float64
LP_CollectionFees                      float64
LP_GrossPrincipalLoss                  float64
LP_NetPrincipalLoss                    float64
LP_NonPrincipalRecoverypayments        float64
PercentFunded                          float64
Recommendations                          int64
InvestmentFromFriendsCount               int64
InvestmentFromFriendsAmount            float64
Investors                                int64
Length: 81, dtype: object
```

1.3.1 What is the structure of your dataset?

There are 113,937 loans with 81 variables on each loan including loan original amount, borrower rate (or interest rate), Employment status, Stated Monthly income, and many others. Most variables are numeric in nature, others are either stored as object (i.e. text) or as bool. But the variables ProsperRating, ProsperScore are ordered variables with the following levels.

(WORST TO BEST) - ProsperRating (Alpha): HR,E,D,C,B,A,AA - ProsperScore: 1,2,3,4,5,6,7,8,9,10

We could also consider Employment Status as an ordered variable with the following levels - EmploymentStatus : Employed, Self-employed, Full-time, Part-time, Retired, Other, Not employed, Not available.

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

I'm highly interested in features that are likely to predict a borrower's interest rate for a loan(BorrowerRate).

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

I personally expect that the higher the LoanOriginalAmount, the higher the interest rate should be. Other features like StatedMonthlyIncome, EmploymentStatus, Term, ProsperRating (Alpha) are likely to have effect on a borrower's interest rate.

In [4]:
```
# Subset dataframe by selecting features of interest
cols= ['LoanOriginalAmount', 'StatedMonthlyIncome','EmploymentStatus','Term',
       'ProsperRating (Alpha)', 'BorrowerRate']
loan= prosper_loan[cols]
```

In [5]:
```
loan.head()
```

Out[5]:
```
   LoanOriginalAmount  StatedMonthlyIncome EmploymentStatus  Term  \
0                9425          3083.333333    Self-employed    36
1               10000          6125.000000         Employed    36
2                3001          2083.333333    Not available    36
3               10000          2875.000000         Employed    36
4               15000          9583.333333         Employed    36

  ProsperRating (Alpha)  BorrowerRate
0                   NaN        0.1580
1                     A        0.0920
2                   NaN        0.2750
3                     A        0.0974
4                     D        0.2085
```

In [6]:
```
# loan records with missing values
loan.isna().sum()
```

Out[6]:
```
LoanOriginalAmount           0
StatedMonthlyIncome          0
EmploymentStatus          2255
Term                         0
ProsperRating (Alpha)    29084
BorrowerRate                 0
dtype: int64
```

In [7]:
```
# remove loan with missing values
loan.dropna(inplace= True)
```

```
/opt/conda/lib/python3.6/site-packages/ipykernel_launcher.py:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/indexing.html#
```

In [8]:
```
# to check if missing records have been dropped
loan.isna().sum()
```

```
Out[8]: LoanOriginalAmount       0
        StatedMonthlyIncome      0
        EmploymentStatus         0
        Term                     0
        ProsperRating (Alpha)    0
        BorrowerRate             0
        dtype: int64
```

```
In [9]: # descriptive statistics for numeric variables
        loan.describe()
```

Out[9]:

	LoanOriginalAmount	StatedMonthlyIncome	Term	BorrowerRate
count	84853.000000	8.485300e+04	84853.000000	84853.000000
mean	9083.440515	5.931175e+03	42.486135	0.196022
std	6287.860058	8.239944e+03	11.640346	0.074631
min	1000.000000	0.000000e+00	12.000000	0.040000
25%	4000.000000	3.434000e+03	36.000000	0.135900
50%	7500.000000	5.000000e+03	36.000000	0.187500
75%	13500.000000	7.083333e+03	60.000000	0.257400
max	35000.000000	1.750003e+06	60.000000	0.360000

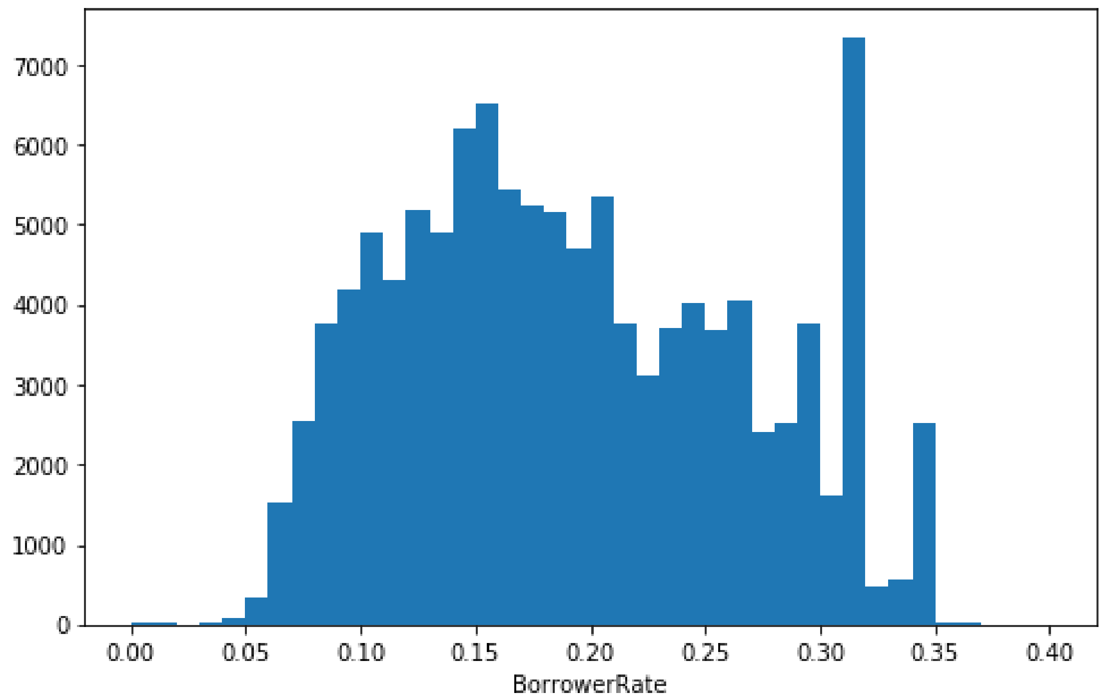
After removing missing loan records (which a wrangling procedure), we have a total of 84,853 loans to work with for this exploration project.

1.4 Univariate Exploration

I'll start with the main variable of interest: BorrowerRate.

Since BorrowerRate is a quantitative variable, I will be making use of a histogram.

```
In [10]: bins = np.arange(0, loan.BorrowerRate.max()+0.05, 0.01)
         plt.figure(figsize=[8, 5])
         plt.hist(data = prosper_loan, x = 'BorrowerRate', bins = bins);
         plt.xlabel('BorrowerRate');
```



This distribution looks roughly multimodal with a small peak at 0.1 and a large peak a little after 0.15. We also have another small peak at 0.20 then another at almost 0.30. Additionally, we have a very sharp peak at approximately 0.32 and then another slight jump right before 0.35.

We have a few loans with an interest rate greater than 0.32. Let's check that out.

```
In [11]: # check for loans with interest rate greater than 0.32
         loan[loan.BorrowerRate> 0.32]
```

```
Out[11]:        LoanOriginalAmount  StatedMonthlyIncome EmploymentStatus  Term  \
         91                   3500          2250.000000         Employed    36
         242                  7500          4504.166667         Employed    36
         269                  2500          3958.333333        Full-time    36
         305                  1500          2916.666667         Employed    36
         354                  2500          4166.666667    Self-employed    36
         406                  8000          8083.333333        Full-time    36
         407                  4000          7083.333333         Employed    60
         415                  7500          4333.333333         Employed    36
         425                  2500          2750.000000        Full-time    36
         527                  1500          5916.666667         Employed    36
         543                  3000          4166.666667        Full-time    36
         607                  4000          5500.000000         Employed    60
         664                  4000          5126.666667         Employed    60
         704                  4000          2250.000000        Full-time    60
         717                  4000          6250.000000        Full-time    36
         728                  1000          7083.333333    Self-employed    36
```

768	1500	4916.666667	Full-time	36
988	1000	0.000000	Not employed	36
1071	4000	4291.666667	Employed	60
1179	1500	3833.333333	Retired	36
1289	5700	4295.750000	Full-time	36
1321	2000	5000.000000	Self-employed	36
1349	1800	3577.000000	Full-time	36
1360	1500	5083.333333	Full-time	36
1423	2000	2916.666667	Employed	36
1424	2500	8750.000000	Full-time	36
1452	4000	7250.000000	Full-time	36
1487	3500	1500.000000	Employed	60
1504	3000	9000.000000	Employed	36
1547	5000	5583.333333	Full-time	36
...	...	...	...	...
112091	2500	2750.000000	Full-time	36
112175	3000	6250.000000	Employed	36
112218	2500	4666.666667	Full-time	36
112268	5000	2725.000000	Full-time	36
112312	3000	4888.000000	Employed	36
112344	3150	1666.666667	Other	36
112482	5000	5261.916667	Full-time	36
112494	5000	3666.666667	Full-time	36
112539	7500	2550.000000	Employed	36
112558	2000	5800.000000	Full-time	36
112708	3500	3041.666667	Full-time	36
112759	2000	2200.000000	Employed	36
112826	4000	4500.000000	Full-time	36
112831	7500	5583.333333	Full-time	36
112938	3500	9166.666667	Employed	36
112970	4000	4833.333333	Full-time	36
112986	4100	4300.000000	Full-time	36
113253	4000	5833.333333	Full-time	36
113351	4000	4833.333333	Employed	60
113355	2000	3200.000000	Employed	36
113371	4000	7750.000000	Employed	60
113387	1500	4000.000000	Employed	36
113405	4000	3750.000000	Employed	60
113503	3200	2000.000000	Full-time	36
113610	4000	1833.333333	Employed	36
113617	6000	4333.333333	Self-employed	36
113674	1000	933.333333	Part-time	36
113783	4000	7166.666667	Employed	60
113787	3000	7083.333333	Full-time	36
113908	7500	2833.333333	Employed	36

	ProsperRating (Alpha)	BorrowerRate
91	E	0.3220

242	E	0.3220
269	HR	0.3495
305	E	0.3435
354	HR	0.3400
406	D	0.3250
407	E	0.3304
415	E	0.3435
425	C	0.3400
527	HR	0.3269
543	HR	0.3500
607	E	0.3232
664	E	0.3304
704	E	0.3304
717	HR	0.3500
728	E	0.3500
768	HR	0.3500
988	E	0.3220
1071	E	0.3232
1179	E	0.3395
1289	D	0.3395
1321	HR	0.3390
1349	HR	0.3500
1360	E	0.3299
1423	HR	0.3500
1424	HR	0.3500
1452	HR	0.3500
1487	E	0.3304
1504	HR	0.3300
1547	E	0.3500
...	...	...
112091	E	0.3500
112175	E	0.3220
112218	HR	0.3495
112268	E	0.3300
112312	E	0.3435
112344	E	0.3220
112482	E	0.3423
112494	HR	0.3400
112539	HR	0.3500
112558	HR	0.3500
112708	HR	0.3500
112759	HR	0.3500
112826	HR	0.3500
112831	E	0.3400
112938	E	0.3220
112970	HR	0.3500
112986	HR	0.3500
113253	HR	0.3500

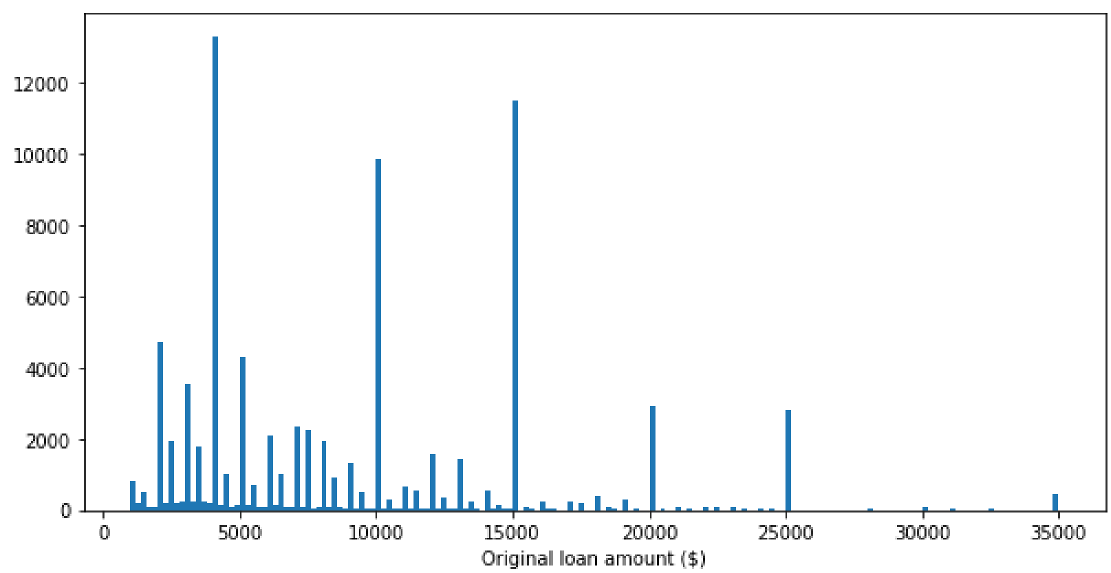
```
113351                          E         0.3304
113355                          E         0.3220
113371                          E         0.3304
113387                         HR         0.3500
113405                          E         0.3304
113503                          D         0.3400
113610                         HR         0.3500
113617                         HR         0.3500
113674                          E         0.3500
113783                          E         0.3232
113787                          E         0.3300
113908                          E         0.3220

[1904 rows x 6 columns]
```

From the above, most borrowers with interest rate higher than 0.32 are employed and they also have low Prosper Ratings. Also, the terms of their loans are either 36months or higher.

Next, let's take a look at our main predictor variables:LoanOriginalAmount

This is also a quantitative variable so a histogram it is.

```
In [12]: bins = np.arange(1000, loan.LoanOriginalAmount.max()+200, 200)
         plt.figure(figsize=[10, 5])
         plt.hist(data = loan, x = 'LoanOriginalAmount', bins = bins);
         plt.xlabel('Original loan amount ($)');
```

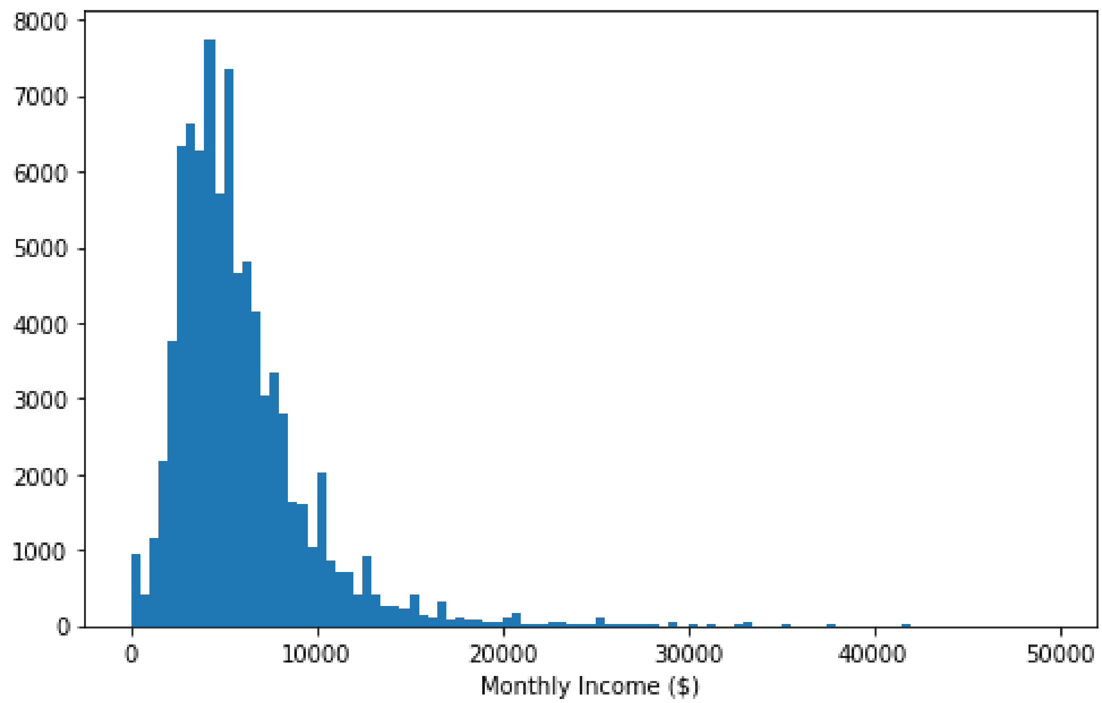


There are very large spikes which occur at almost 5,000, 10,000 and 15,000. We also have some spikes on 20,000, 25,000. Then a smaller spike at 35,000. This shows that most loans are in multiples of a thousand (1k).

Now, let's take a look at another predictor variable: StatedMonthlyIncome

This is also a quantitative variable, so we plot a histogram.

```
In [13]: plt.figure(figsize=[8,5])
         bins= np.arange(0, 50000, 500 )
         plt.hist(data= loan, x= 'StatedMonthlyIncome', bins= bins)
         plt.xlabel('Monthly Income ($)');
```



This distribution of Stated Monthly Income is highly skewed to the right. It also shows that most of the stated monthly income is less than 30,000.

Let's check out the stated monthly income that are greater than 30k.

```
In [14]: # checking monthly income greater than 30k
         (loan.StatedMonthlyIncome>30000).sum()

Out[14]: 249
```

```
In [15]: # get percentage of monthly income greater than 30k
         (loan.StatedMonthlyIncome>30000).sum()/float(loan.shape[0])

Out[15]: 0.0029344867005291504
```

Less than 0.3% borrowers have stated monthly income greater than 30k. It is a minor amount compared to the rest of the dataset so these could be regarded as outliers for this analysis and it is better if it is removed.

```
In [16]: # remove records of stated monthly income greater than 30k which we regard as outliers
         loan= loan[loan.StatedMonthlyIncome<=30000]
```

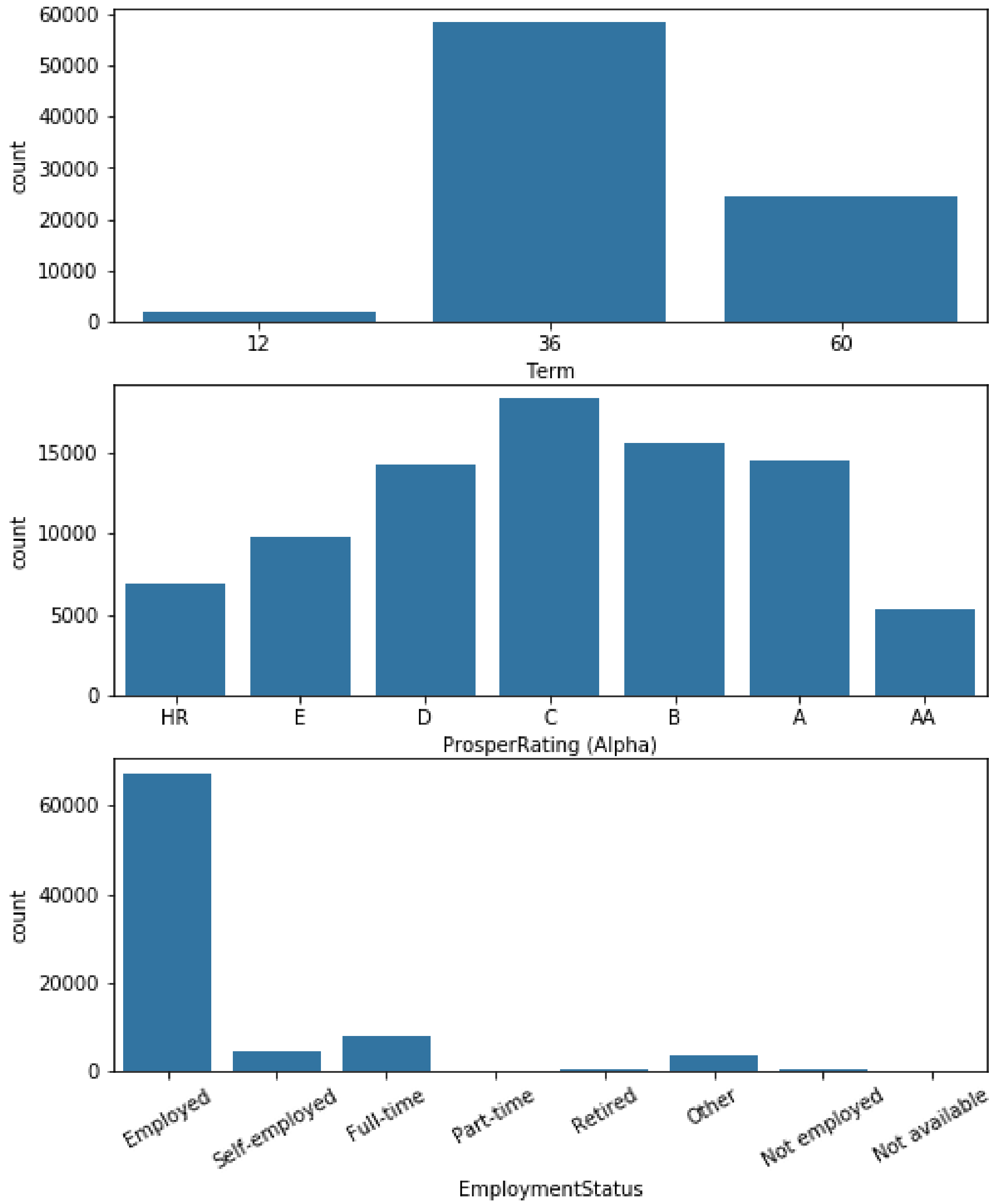
```
In [17]: # to check if these records have been successfully removed
         (loan.StatedMonthlyIncome>30000).sum()
```

```
Out[17]: 0
```

Let us take a look at other features of interest: Term, EmploymentStatus, ProsperRating
Before we make any plots, let's first convert them to ordered categorical variables.

```
In [18]: # convert ProsperRating to ordered categorical variables
         rating_order= ['HR','E','D','C','B','A','AA']
         ordered_var= pd.api.types.CategoricalDtype(ordered= True, categories= rating_order)
         loan['ProsperRating (Alpha)']= loan['ProsperRating (Alpha)'].astype(ordered_var)

         # convert EmploymentStatus to ordered categorical variables
         employ_order= ['Employed','Self-employed','Full-time','Part-time','Retired','Other','No
         ordered_var= pd.api.types.CategoricalDtype(ordered= True, categories= employ_order)
         loan['EmploymentStatus']= loan['EmploymentStatus'].astype(ordered_var)
```

```
In [19]: # distribution plot
         fig, ax = plt.subplots(nrows=3, figsize = [8,10])
         plot_color = sb.color_palette()[0]
         sb.countplot(data = loan, x = 'Term', color = plot_color, ax = ax[0])
         sb.countplot(data = loan, x = 'ProsperRating (Alpha)', color = plot_color, ax = ax[1])
         sb.countplot(data = loan, x = 'EmploymentStatus', color = plot_color, ax = ax[2]);
         plt.xticks(rotation=30);
```



The distribution plot above shows us 3 diifferent things. They include: - The length of most of the loans is 36 months. - Most of the borrower's Prosper ratings is between D and A. - Majority of the borrowers are employed.

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

The distribution of the BorrowerRate looks multimodal. Most of the values fell in between 0.05 and 0.35. There are no unusual points so I did not need to perform any transformations.

1.4.2 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?

The distribution of the Stated Monthly Income is highly skewed to the right. Also, most of the stated monthly income are less than 30,000(30k). There are very few borrowers with monthly income greater than 30k with a percentage of 0.3 which we regarded as outliers and therefore removed them.

There is no need to perform any transformations.

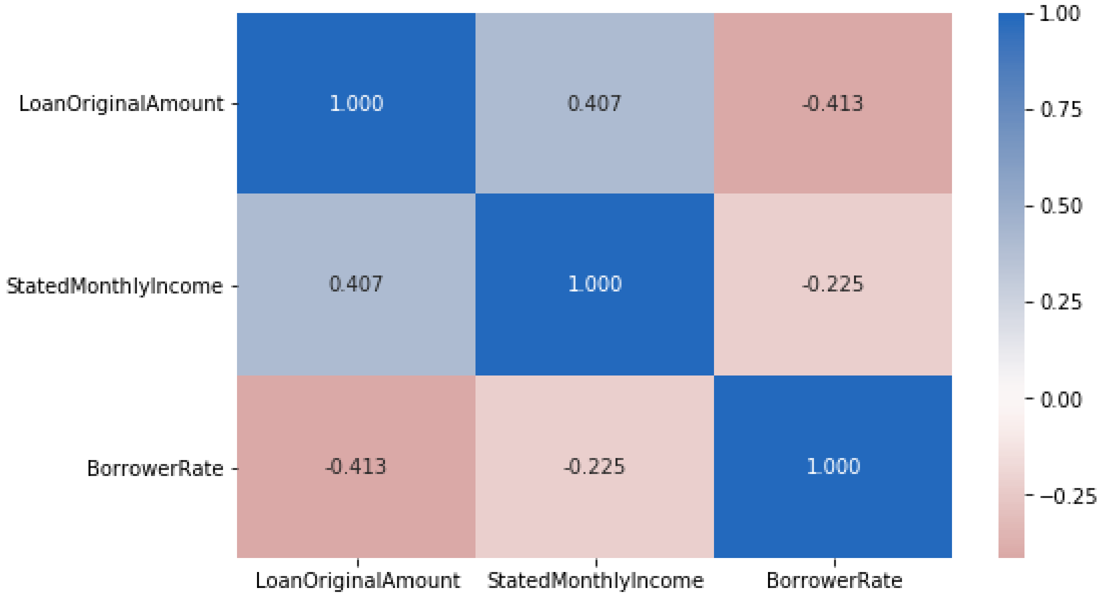
1.5 Bivariate Exploration

In this section, investigate relationships between pairs of variables in your data. Make sure the variables that you cover here have been introduced in some fashion in the previous section (univariate exploration).

To start off with, I want to take a look at the pairwise correlations between the features of interest in this dataset.

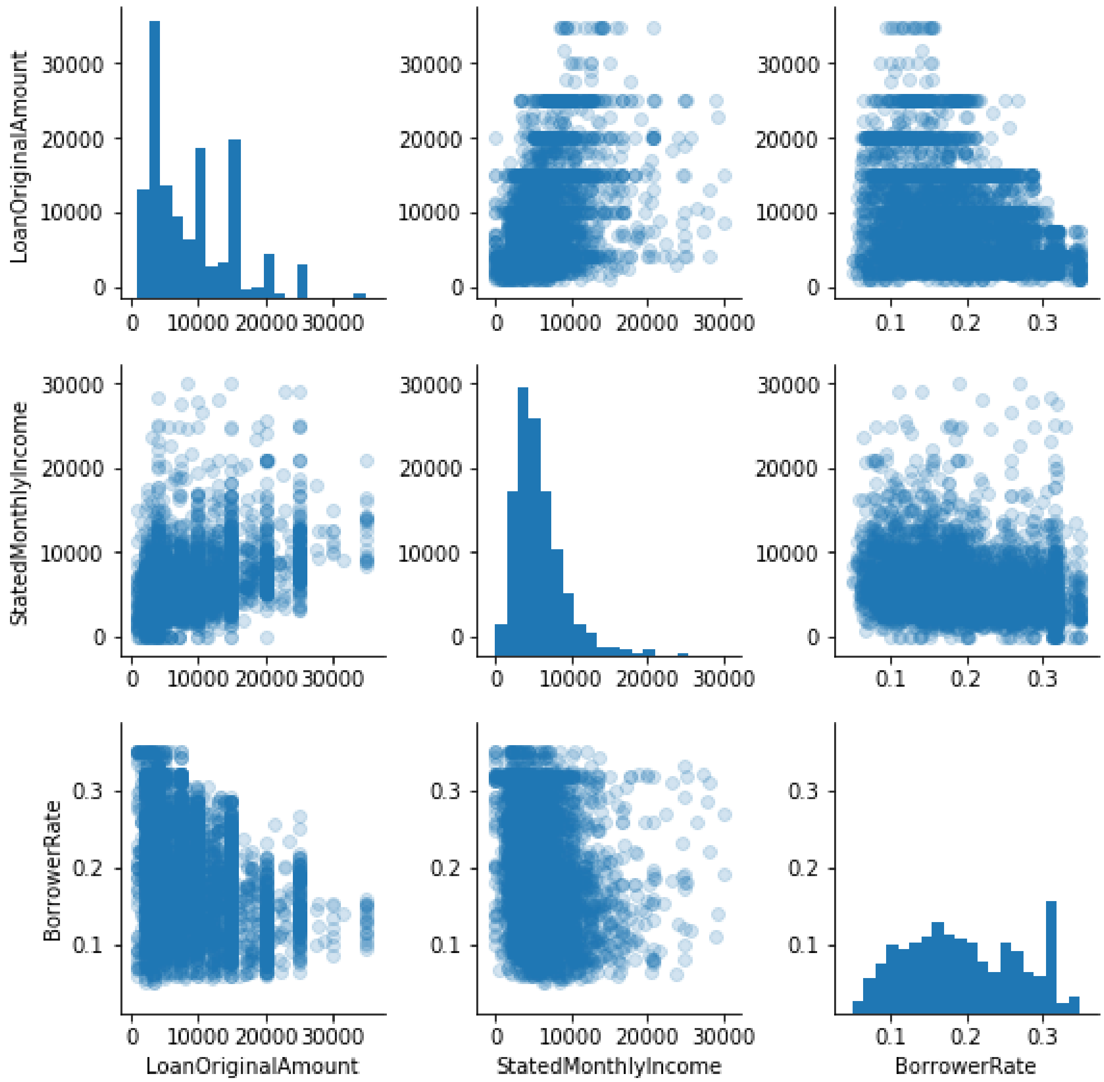
```
In [20]: numeric_vars= ['LoanOriginalAmount','StatedMonthlyIncome','BorrowerRate']
         categorical_vars= ['Term','ProsperRating (Alpha)','EmploymentStatus']
```

```
In [21]: # correlation plot
         plt.figure(figsize = [8, 5])
         sb.heatmap(loan[numeric_vars].corr(), annot = True, fmt = '.3f',
                    cmap = 'vlag_r', center = 0)
         plt.show()
```




```
In [22]: # plot matrix: sample 5000 loans so that plots are clearer and render faster
         print("loan.shape=",loan.shape)
         loan_samp = loan.sample(5000)
         print("loan_samp.shape=",loan_samp.shape)
         g = sb.PairGrid(data = loan_samp.dropna(), vars = numeric_vars)
         g = g.map_diag(plt.hist, bins=20)
         g.map_offdiag(plt.scatter, alpha= 0.2);
```

```
loan.shape= (84604, 6)
loan_samp.shape= (5000, 6)
```



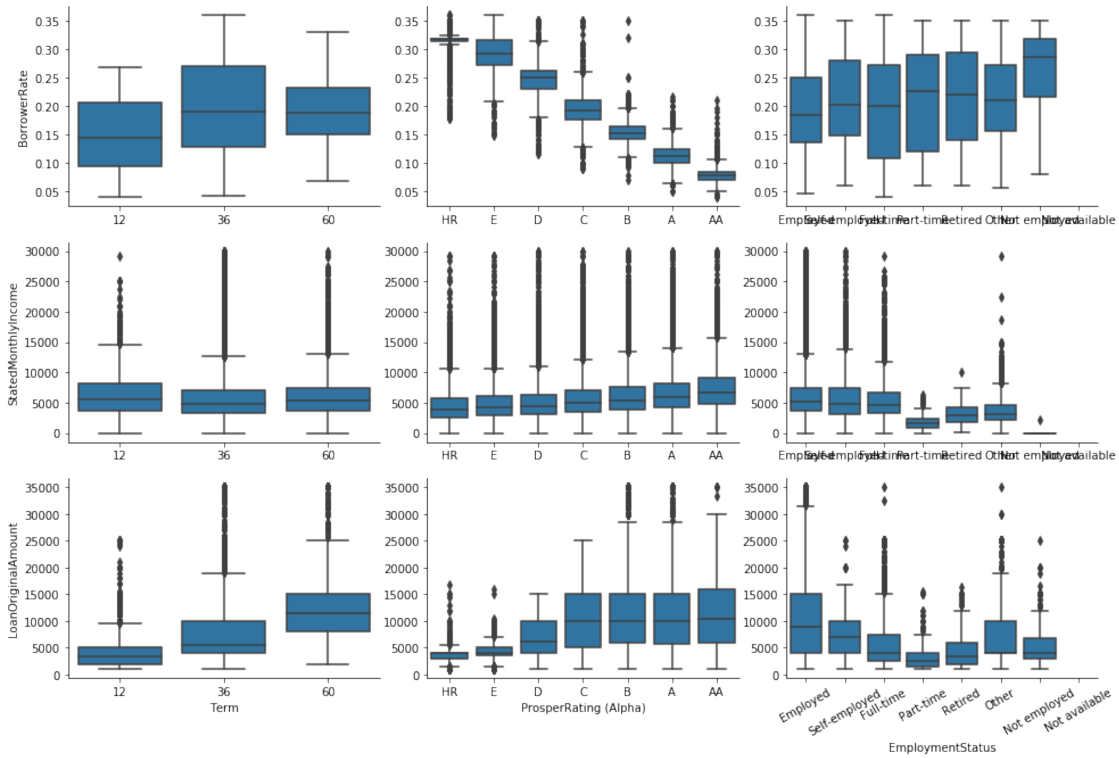
The correlation coefficient of BorrowerRate and and LoanOriginalAmount is -0.413. The scatter plot also shows that there is a negative correlation between BorrowerRate and LoanOriginalAmount which disagrees with my hypothesis: the higher the loan amount, the higher the interest rate. Instead, the plot shows that the higher the loan amount, the lower the interest rate. The plot also shows that there is a positive correlation between StatedMonthlyIncome and LoanOriginalAmount which makes sense because borrower's with higher income get to loan high amount of money.

Let's check out the correlation between the numeric variables and the categorical variables.

```
In [23]: # plot matrix
         def boxgrid(x, y, **kwargs):
             # Quick hack for creating box plots with seaborn's PairGrid.
             plot_color = sb.color_palette()[0]
             sb.boxplot(x, y, color = plot_color)
```

```
plt.figure(figsize = [10, 10])
g = sb.PairGrid(data = loan, y_vars = ['BorrowerRate', 'StatedMonthlyIncome', 'LoanOrig
                x_vars = categorical_vars, size = 3, aspect = 1.5)
g.map(boxgrid);
plt.xticks(rotation=30);
```

```
<matplotlib.figure.Figure at 0x7fdcaf6e8940>
```

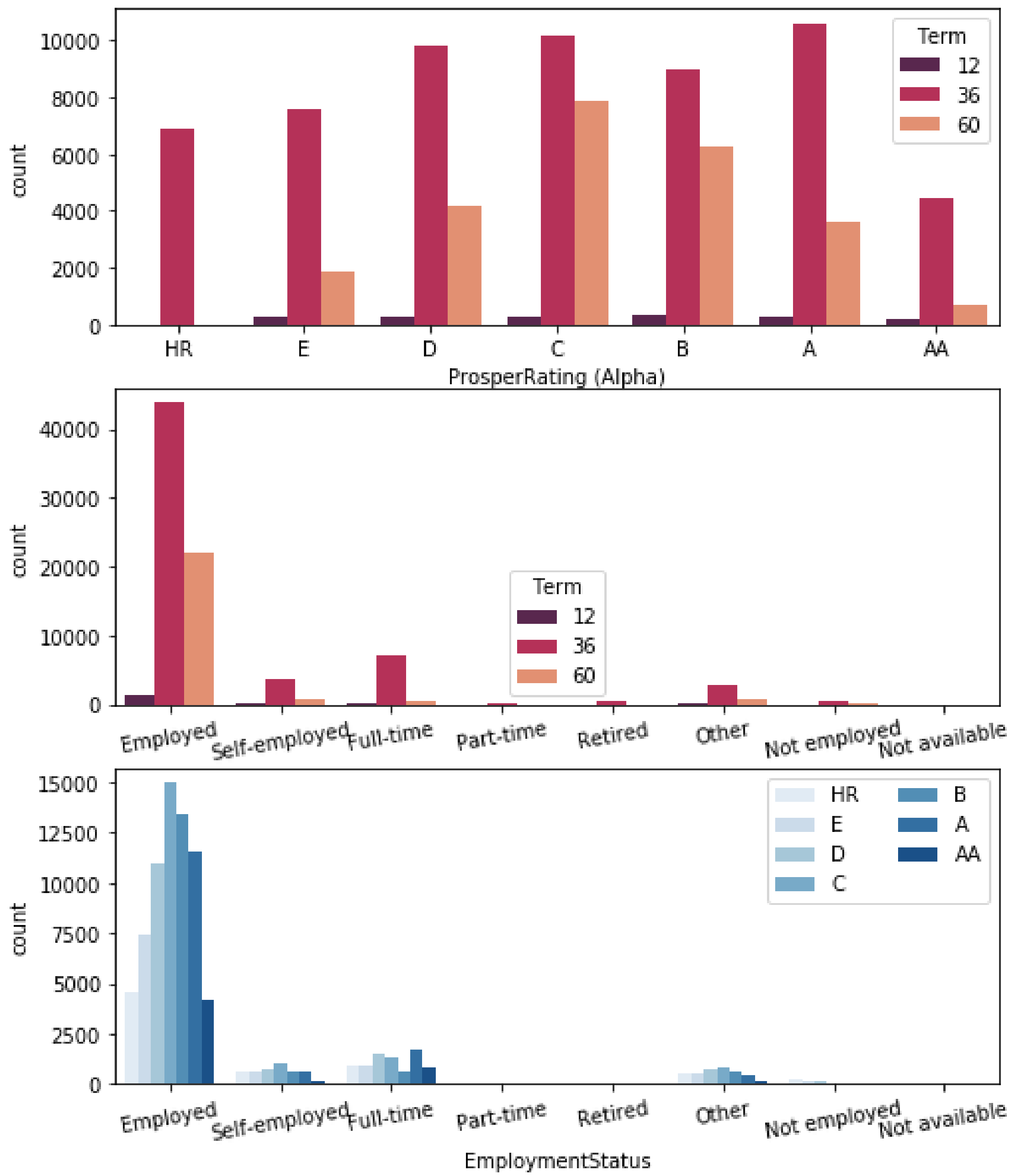


The figure above shows us variety of observations. They include the following: - The loan amount increases as the loan term increases. - The BorrowerRate decreases with better ratings. Borrowers with the best ratings have the lowest interest rate. This shows that Prosper Ratings has a strong effect on a borrower's interest rate. - The Loan Amount increases with better ratings. - Borrowers with high stated monthly income also have good prosper ratings. - Employed, self-employed and full time borrowers have more monthly income and loan amount than part-time, retired and not employed borrowers.

Finally, let's take a look at relationship between the three categorical variables.

```
In [24]: plt.figure(figsize = [8, 10])

         # subplot 1: Prosper Rating vs Term
         plt.subplot(3, 1, 1)
         sb.countplot(data = loan, x = 'ProsperRating (Alpha)', hue = 'Term', palette = 'rocket'
```

```python
# subplot 2: Employment status vs Term
ax = plt.subplot(3, 1, 2)
sb.countplot(data = loan, x = 'EmploymentStatus', hue = 'Term', palette = 'rocket')
plt.xticks(rotation=10)

# subplot 3: Prosper rating vs. employment status, use different color palette
ax = plt.subplot(3, 1, 3)
sb.countplot(data = loan, x = 'EmploymentStatus', hue = 'ProsperRating (Alpha)', palett
ax.legend(loc = 1, ncol = 2); # re-arrange legend to remove overlapping
plt.xticks(rotation=10);
```

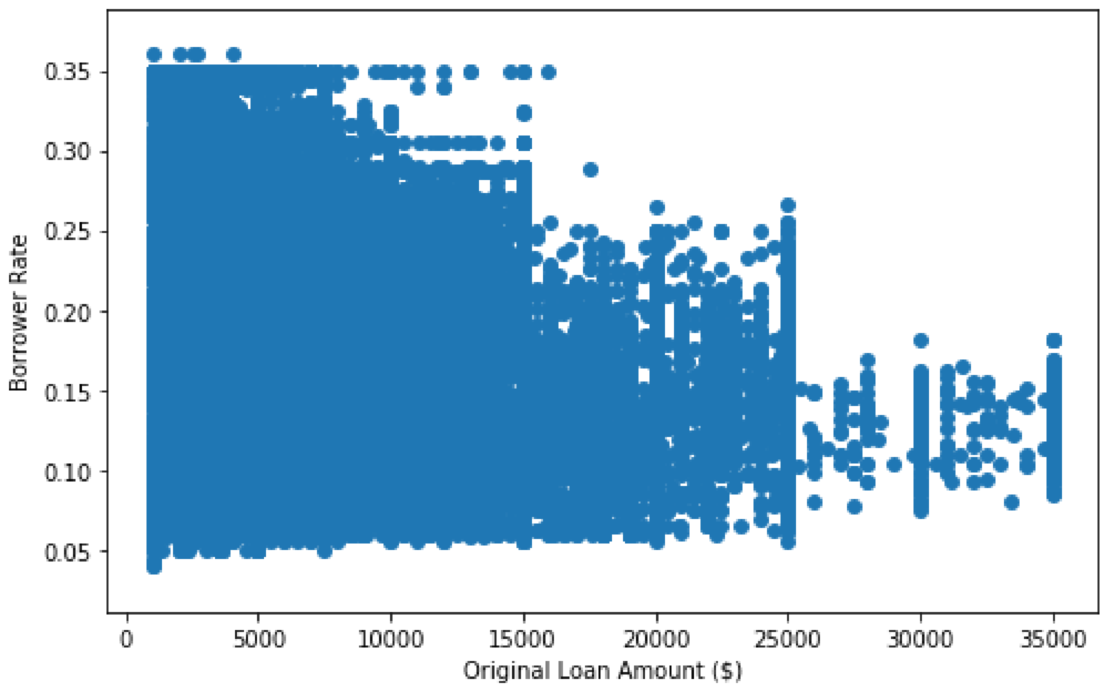


From the plot above, it visible that all levels have ratings have loan terms of 36months. Ratings of D,C,B,A have loan terms of 60months. There are not much data available to show the interaction of Part-time, Retired and Not employed with the loan terms. Same applies to the plot of Ratings against EmploymentStatus. Majority of the borrowers that are employed are on loan terms of 36months, lesser borrowers on terms of 60months.

Let's take a look at the relationship between our main predictor variable (LoanOriginalAmount) and our main variable of interest (BorrowerRate)

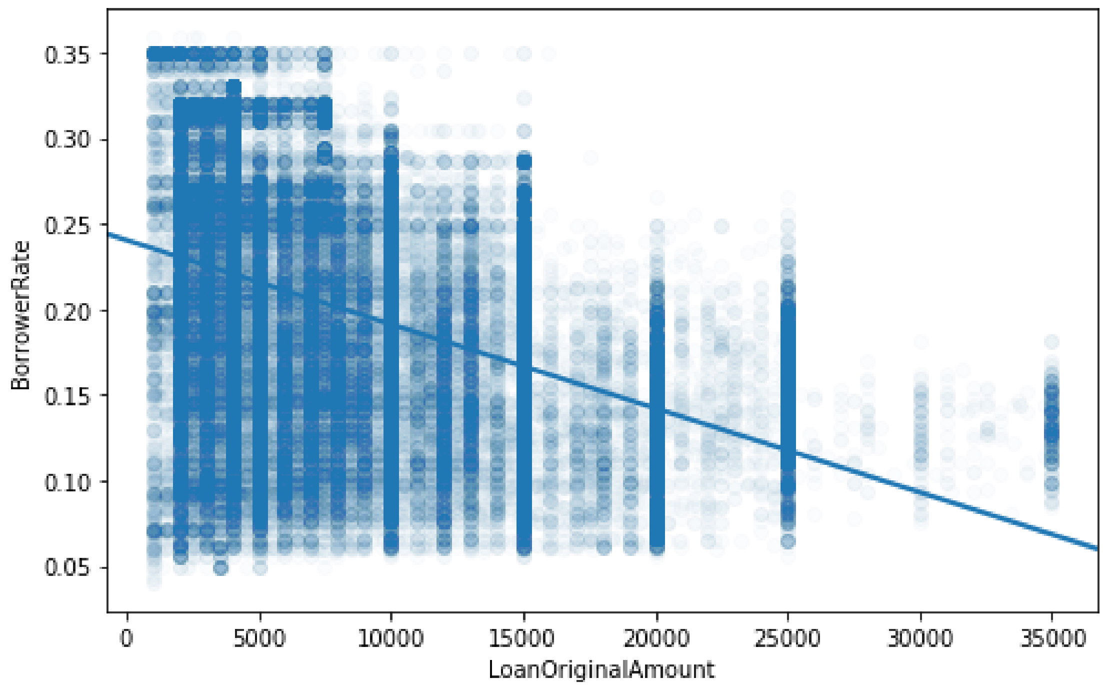
Both of the variables above are quantitative variable, therefore a scatterplot would be the best suitable plot to show their relationship.

In [25]:
```
plt.figure(figsize=[8,5])
plt.scatter(data= loan, x= 'LoanOriginalAmount', y= 'BorrowerRate')
plt.xlabel('Original Loan Amount ($)')
plt.ylabel('Borrower Rate');
```



The strength of the relationship is fairly unclear due to overplotting, so I will make use of transparency with the use of the *alpha* parameter using the *regplot() function.*

In [26]:
```
plt.figure(figsize=[8,5])
sb.regplot(data= loan, x= 'LoanOriginalAmount', y= 'BorrowerRate', scatter_kws= {'alpha
```



The plot shows a negative correlation between BorrowerRate and LoanOriginalAmount with a fitted regression line. It is visible that the more loan amounts, the lesser the interest rates. There are a lot of plotted data points between amounts of 5000 and 15,000.

1.5.1 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?

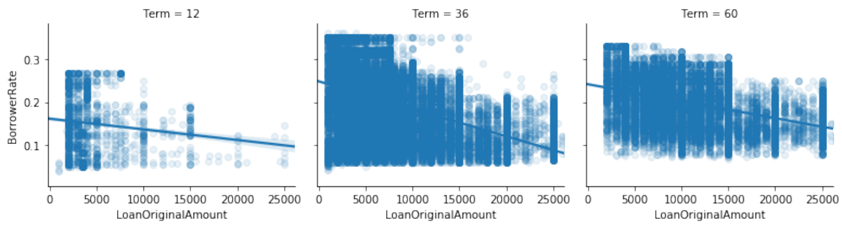
There is a negative correlation between the Borrower Rate and the Loan Amount, which means the more loan amounts, the less the rates. Prosper Ratings has a strong effect on a borrower's interest rate. The BorrowerRate decreases with better ratings. Borrowers with the best ratings have the lowest interest rate. ### Did you observe any interesting relationships between the other features (not the main feature(s) of interest)?

There is a positive correlation between Stated Monthly Income and Loan Amount as well as ProsperRatings. Borrowers with higher stated monthly income have better ratings and more loans than borrowers with lesser monthly income. Also, most borrowers that are employed, full-time or self employed tend to have more income than retired, part time, not available and not employed borrowers.

1.6 Multivariate Exploration

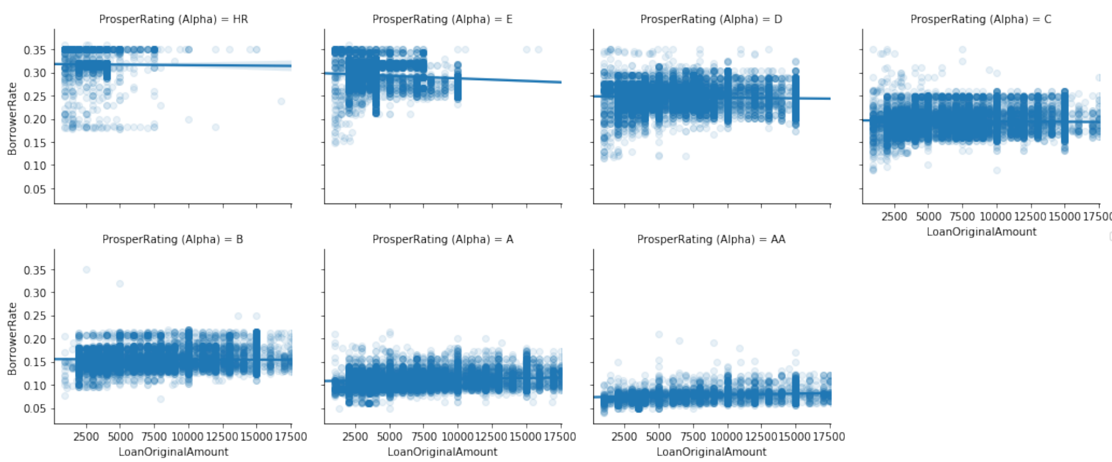
Here, the main thing I want to explore is the effect of two of the categorical variables (Term, Prosper Ratings) on BorrowerRate and LoanOriginalAmount.

```
In [27]: # Effect of Term on Loan Amount and Borrower Rate
         g=sb.FacetGrid(data=loan, aspect=1.2, col='Term', col_wrap=4)
         g.map(sb.regplot, 'LoanOriginalAmount', 'BorrowerRate', x_jitter=0.04, scatter_kws={'al
         g.add_legend();
```



From the above, it shows that loan terms doesn't affect either Loan Amount or Borrower Rate. It is negatively correlated.

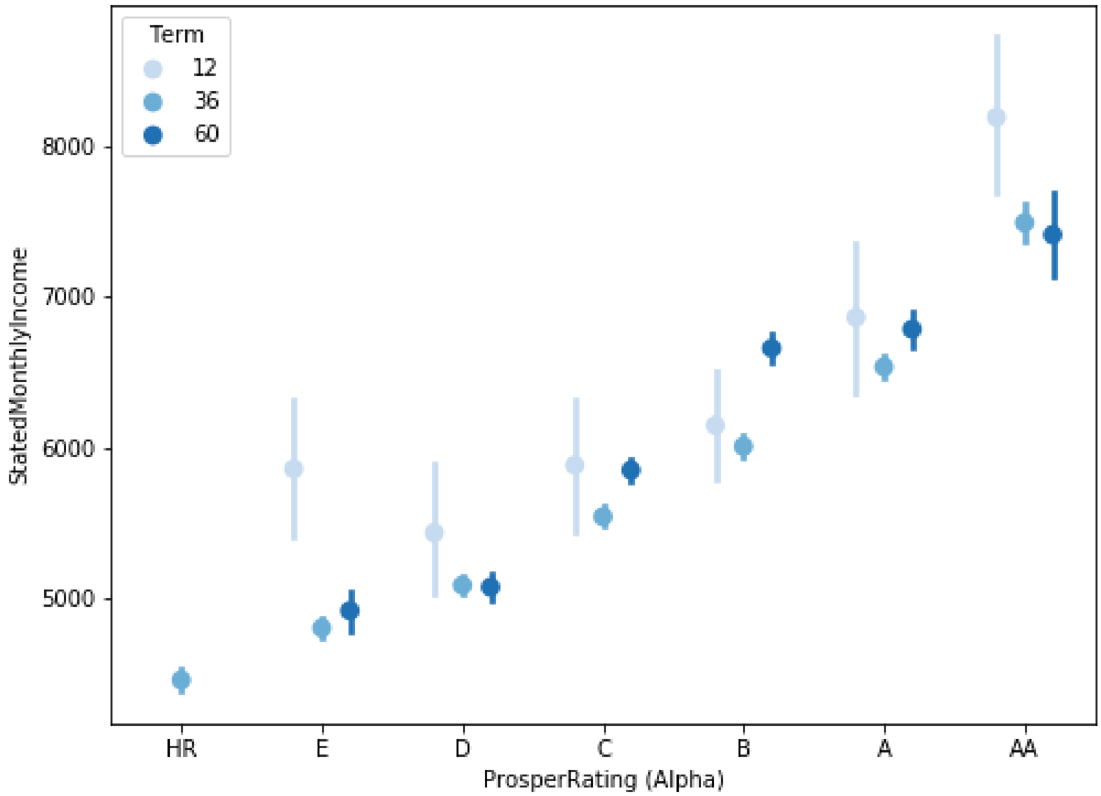
```
In [28]: # Effect of Prosper Ratings on Loan Amount and Borrower Rate
         g=sb.FacetGrid(data=loan, aspect=1.2, col='ProsperRating (Alpha)', col_wrap=4)
         g.map(sb.regplot, 'LoanOriginalAmount', 'BorrowerRate', x_jitter=0.04, scatter_kws={'al
         g.add_legend();
```



From the plot above, it appears that as the ratings range from worst to best, there's a slight shift from negative correlation to a bit of a positive correlation. With this we can say that, borrowers realised that they get better ratings as they loan more money so borrowers that loan less before tend to increase their loan amounts so they can get better Prosper Ratings. This is pretty interesting.

Also, let's explore the effect of term and ratings on Stated Monthly Income.

```
In [29]: plt.figure(figsize=[8,6])
         sb.pointplot(data = loan, x = 'ProsperRating (Alpha)', y = 'StatedMonthlyIncome', hue =
                      palette = 'Blues', linestyles = '', dodge = 0.4);
```



It shows above that there's really no effect of term and ratings on StatedMonthlyIncome.

1.6.1 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?

Term and Rating didn't really have any effect on Stated Monthly income. Also, Terms did not have any effect on Loan Amount and BorrowerRate. But when it comes to Ratings against Loan Amount and Borrower rate, it appears that as the ratings range from worst to best, there's a slight shift from negative correlation to a bit of a positive correlation.

1.6.2 Were there any interesting or surprising interactions between features?

A surprising and interesting interaction is that the BorrowerRate and Original-LoanAmount is negatively correlated when the Prosper ratings are from HR to B, but the correlation is shifted over to be positive when the ratings are A and AA.

1.7 Conclusions

During the course of exploration for this project, I performed a Preliminary Wrangling by choosing and focusing on my features of interest and then performed a bit of cleaning by dropping missing loan records of the variables of interest. Also, I removed some outliers which were not needed for this analysis.

The main purpose of this exploration was to identify features that are likely to have effect on BorrowerRate. After series of visualizations ranging from univariate-bivariate-multivariate visualizations, I realized that Stated Monthly Income, Employment Status and Prosper Ratings have major effect on a Borrower's interest rate on a loan.

```
In [ ]:
```