Part_I_exploration_template

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1 Part I - Loans Data from Prosper Exploration

1.1 by Milcah Maina

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 several 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
```

Load in your dataset and describe its properties through the questions below. Try and motivate your exploration goals through this section.

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

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

  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]
```

In [3]: df.info()

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 113937 entries, 0 to 113936
Data columns (total 81 columns):
ListingKey                             113937 non-null object
ListingNumber                          113937 non-null int64
ListingCreationDate                    113937 non-null object
CreditGrade                            28953 non-null object
Term                                   113937 non-null int64
LoanStatus                             113937 non-null object
ClosedDate                             55089 non-null object
BorrowerAPR                            113912 non-null float64
BorrowerRate                           113937 non-null float64
LenderYield                            113937 non-null float64
EstimatedEffectiveYield                84853 non-null float64
```

```
EstimatedLoss                        84853 non-null float64
EstimatedReturn                      84853 non-null float64
ProsperRating (numeric)              84853 non-null float64
ProsperRating (Alpha)                84853 non-null object
ProsperScore                         84853 non-null float64
ListingCategory (numeric)            113937 non-null int64
BorrowerState                        108422 non-null object
Occupation                           110349 non-null object
EmploymentStatus                     111682 non-null object
EmploymentStatusDuration             106312 non-null float64
IsBorrowerHomeowner                  113937 non-null bool
CurrentlyInGroup                     113937 non-null bool
GroupKey                             13341 non-null object
DateCreditPulled                     113937 non-null object
CreditScoreRangeLower                113346 non-null float64
CreditScoreRangeUpper                113346 non-null float64
FirstRecordedCreditLine              113240 non-null object
CurrentCreditLines                   106333 non-null float64
OpenCreditLines                      106333 non-null float64
TotalCreditLinespast7years           113240 non-null float64
OpenRevolvingAccounts                113937 non-null int64
OpenRevolvingMonthlyPayment          113937 non-null float64
InquiriesLast6Months                 113240 non-null float64
TotalInquiries                       112778 non-null float64
CurrentDelinquencies                 113240 non-null float64
AmountDelinquent                     106315 non-null float64
DelinquenciesLast7Years              112947 non-null float64
PublicRecordsLast10Years             113240 non-null float64
PublicRecordsLast12Months            106333 non-null float64
RevolvingCreditBalance               106333 non-null float64
BankcardUtilization                  106333 non-null float64
AvailableBankcardCredit              106393 non-null float64
TotalTrades                          106393 non-null float64
TradesNeverDelinquent (percentage)   106393 non-null float64
TradesOpenedLast6Months              106393 non-null float64
DebtToIncomeRatio                    105383 non-null float64
IncomeRange                          113937 non-null object
IncomeVerifiable                     113937 non-null bool
StatedMonthlyIncome                  113937 non-null float64
LoanKey                              113937 non-null object
TotalProsperLoans                    22085 non-null float64
TotalProsperPaymentsBilled           22085 non-null float64
OnTimeProsperPayments                22085 non-null float64
ProsperPaymentsLessThanOneMonthLate  22085 non-null float64
ProsperPaymentsOneMonthPlusLate      22085 non-null float64
ProsperPrincipalBorrowed             22085 non-null float64
ProsperPrincipalOutstanding          22085 non-null float64
ScorexChangeAtTimeOfListing          18928 non-null float64
```

```
LoanCurrentDaysDelinquent              113937 non-null int64
LoanFirstDefaultedCycleNumber          16952 non-null float64
LoanMonthsSinceOrigination             113937 non-null int64
LoanNumber                             113937 non-null int64
LoanOriginalAmount                     113937 non-null int64
LoanOriginationDate                    113937 non-null object
LoanOriginationQuarter                 113937 non-null object
MemberKey                              113937 non-null object
MonthlyLoanPayment                     113937 non-null float64
LP_CustomerPayments                    113937 non-null float64
LP_CustomerPrincipalPayments           113937 non-null float64
LP_InterestandFees                     113937 non-null float64
LP_ServiceFees                         113937 non-null float64
LP_CollectionFees                      113937 non-null float64
LP_GrossPrincipalLoss                  113937 non-null float64
LP_NetPrincipalLoss                    113937 non-null float64
LP_NonPrincipalRecoverypayments        113937 non-null float64
PercentFunded                          113937 non-null float64
Recommendations                        113937 non-null int64
InvestmentFromFriendsCount             113937 non-null int64
InvestmentFromFriendsAmount            113937 non-null float64
Investors                              113937 non-null int64
dtypes: bool(3), float64(50), int64(11), object(17)
memory usage: 68.1+ MB
```

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

Out[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]

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

Out[5]:
```
(113937, 81)
```

1.3.1 What is the structure of your dataset?

This dataset contains 113,937 rows and 81 columns. It therefore has multiple features that can be observed (81). Most of the data is numeric, although there is also some descriptive data. For example, the Loan Status provides information on whether or not a loan has been paid back in full.

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

This data evidently contains numerous features, most of which will not be explored. To start off, the main interests I have in this dataset is the interest rate, as well as the APR and the effect this may have on the Loan Amount borrowed by customers.

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

Features in the dataset that may have influence on the APR include: Prosper Score, Employment Status. I'd also like to see the yield/return for each loan, in relation to the APR.

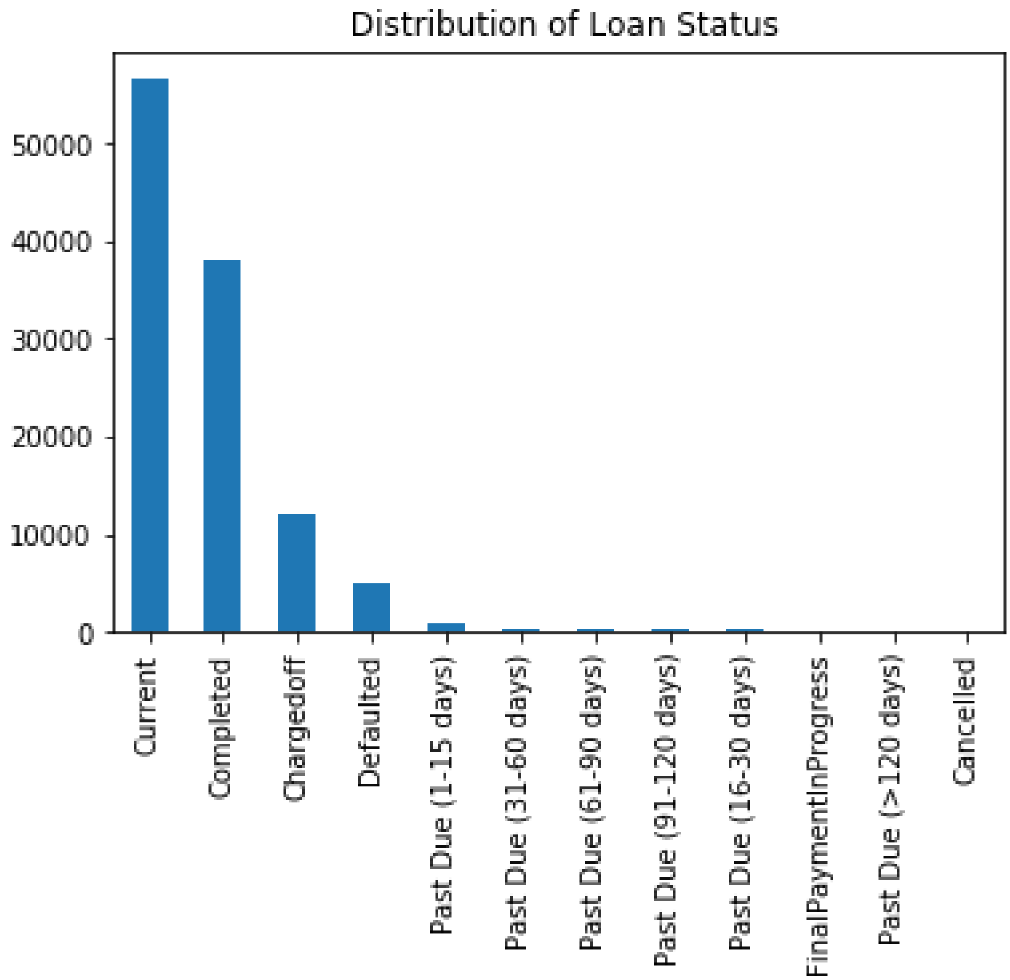
1.4 Univariate Exploration

In this section, investigate distributions of individual variables. If you see unusual points or outliers, take a deeper look to clean things up and prepare yourself to look at relationships between variables.

First, let's observe the distribution of the loan status.

```
In [6]: df['LoanStatus'].value_counts(sort = True).plot(kind='bar', color = sb.color_palette()[0
                                                         title=' Distribution of Loan Status',)
```

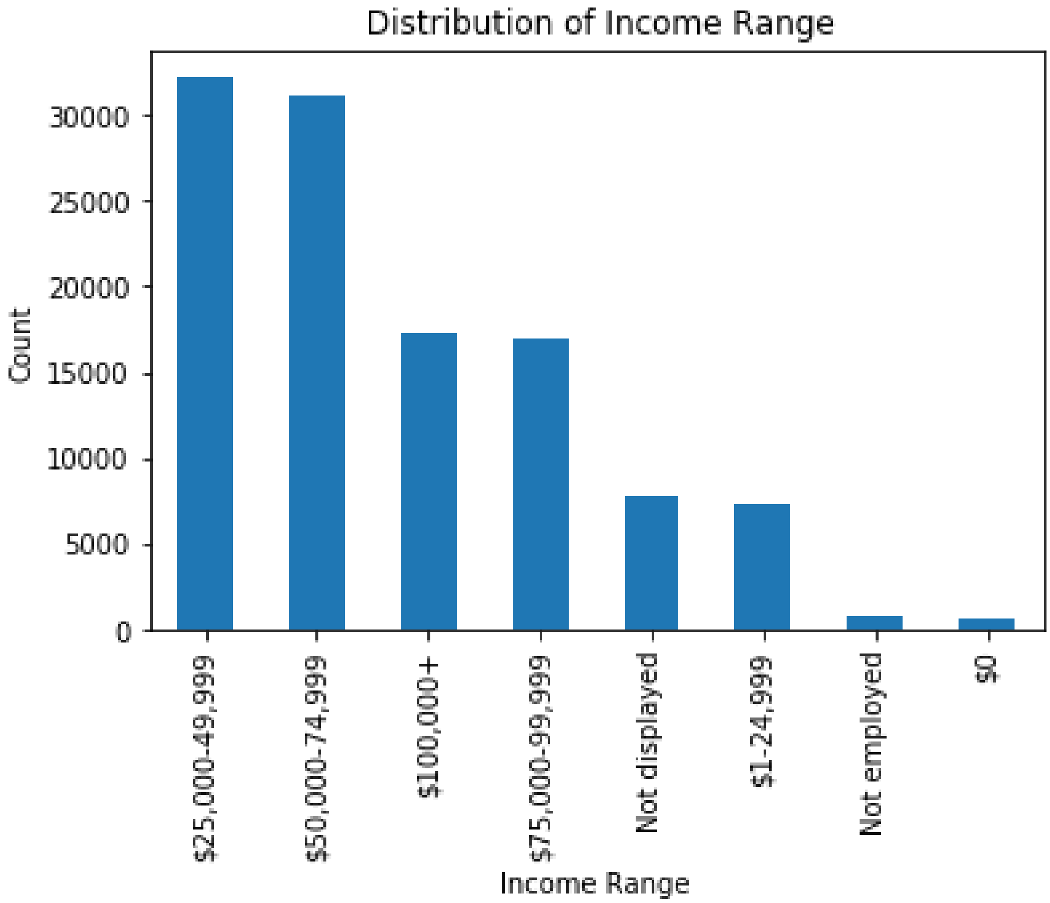
```
Out[6]: <matplotlib.axes._subplots.AxesSubplot at 0x7f32523a6a90>
```



Most loans are current or completed. Some of the variables that could have an effect on this include Employment Status and Income Range. We'll examine if these variables have an effect on the loan status later.

Next, let's look at the income range for the customers.

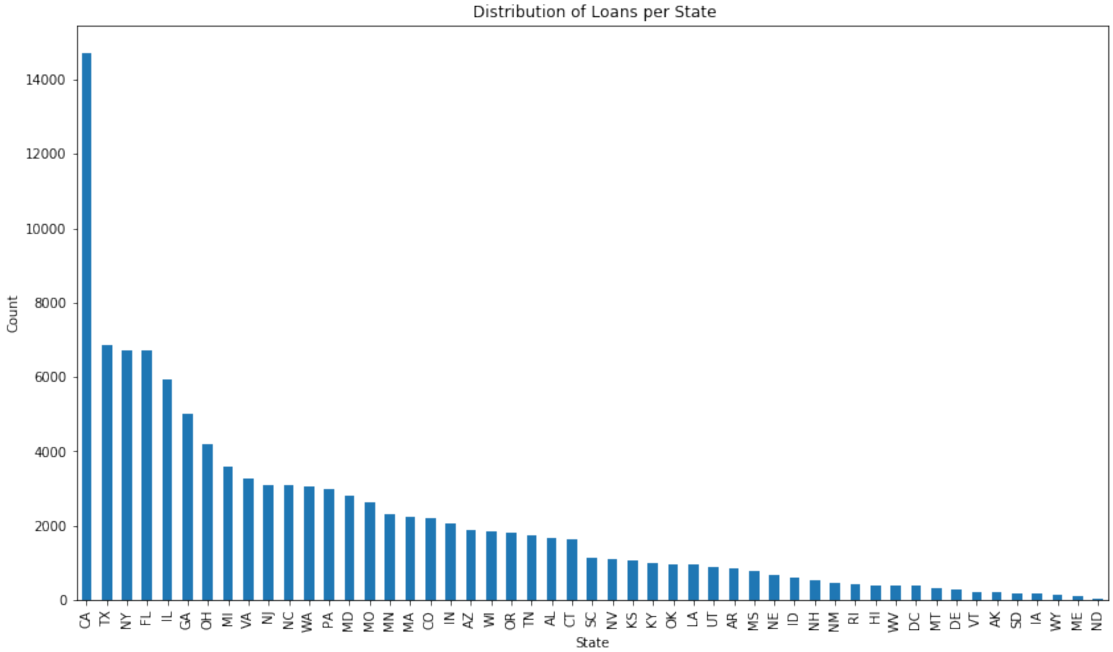
```
In [7]: df['IncomeRange'].value_counts(sort = True).plot(kind='bar', color = sb.color_palette()[
                                                        title=' Distribution of Income Range',)
        plt.xlabel('Income Range');
        plt.ylabel('Count');
```



This is a relatively typical distribution. Most people earn between USD 25,000 - USD 50,000. Again, we'll look into any correlation between this and features such as Loan Amounts taken, Loan Term, etc.

Let's observe the number of loans taken per state.

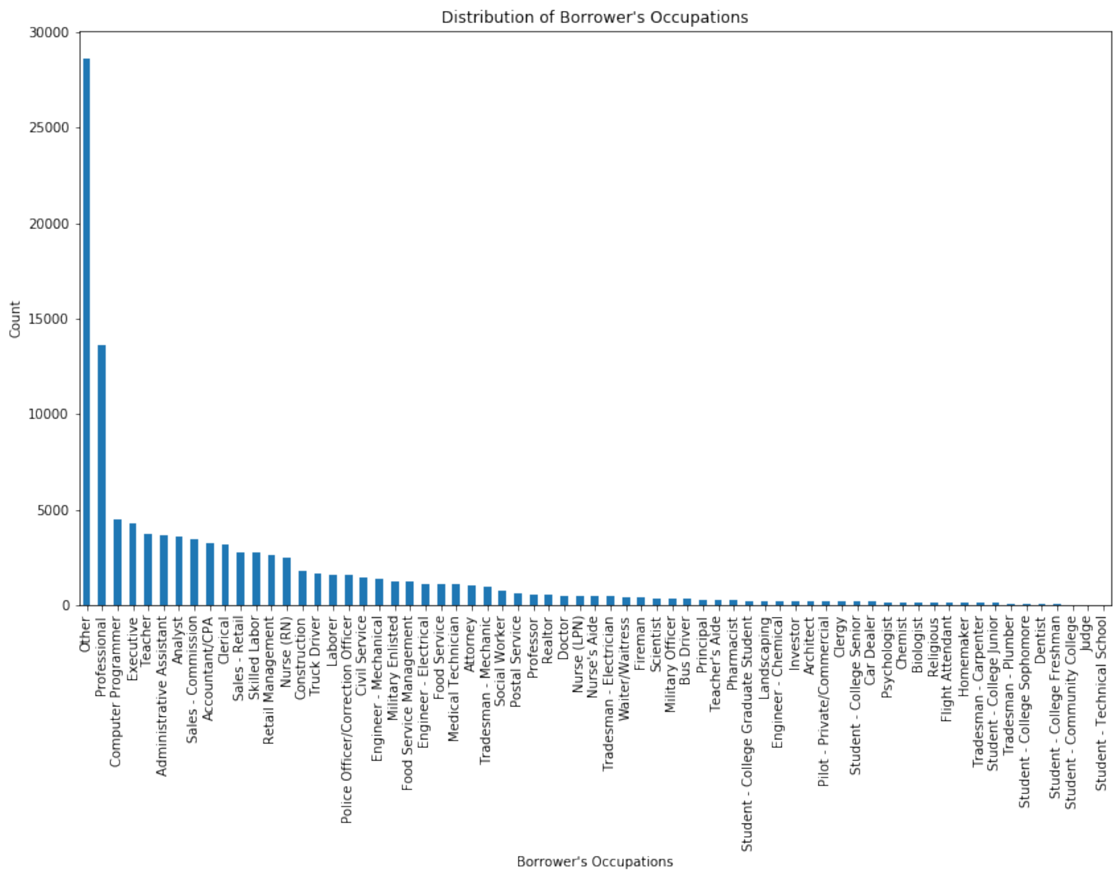
```
In [8]: df['BorrowerState'].value_counts(sort = True).plot(kind='bar', color = sb.color_palette(
                                                              title=' Distribution of Loans per State'
        plt.xlabel('State');
        plt.ylabel('Count');
```



It seems most borrowers come from California, Texas and New York. In the bivariate analysis section, I will examine the employment status and/or income range per state as this would be hepful in understanding if this could be reaso for the high amounts of borrowing in California, Texas, New York, etc.

It would be interesting to discover the distribution of occupations across the entire set of customers.

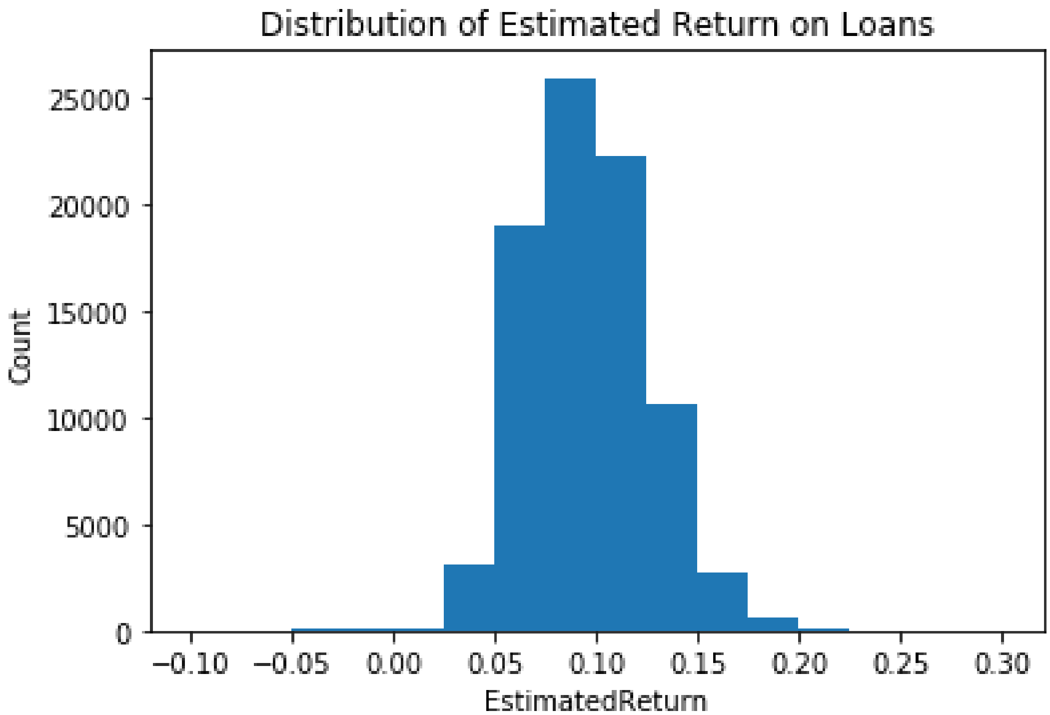
```
In [9]: df['Occupation'].value_counts(sort = True).plot(kind='bar', color = sb.color_palette()[0
                                                       title= "Distribution of Borrower's Occup
        plt.xlabel("Borrower's Occupations");
        plt.ylabel('Count');
```



Wow. As the number of occupations is quite high, it may be difficult to obtain definitive correlations between this and other data.While it may be possible to further classify these occupations, we already have quite a large set of features which may provide more useful information. Let's proceed with our other variables for now.

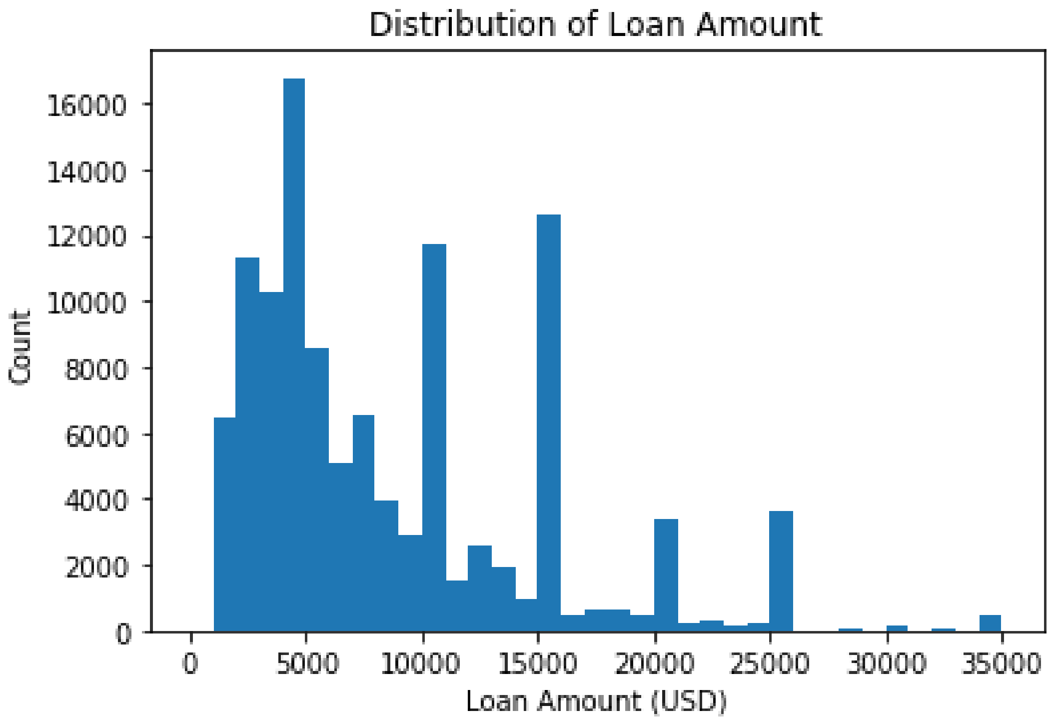
Let's examine the estimated return for the loans borrowed.

```
In [10]: x= df['EstimatedReturn'].dropna().values
         bins = np.arange(-0.1, df['EstimatedReturn'].max()+0.025, 0.025)
         def hist(x, xlabel, ylabel, title):

             ax = plt.subplot(1,1,1)
             ax.hist(x, bins = bins)
             ax.set_xlabel(xlabel)
             ax.set_ylabel(ylabel)
             ax.set_title(title)
             plt.show()
         hist(x, 'EstimatedReturn', 'Count', 'Distribution of Estimated Return on Loans')
```



It seems most loans are expected to provide returns of about 8-10%. This seems pretty standard as customers would likely shy away from high interest rates. Again, we'll later examine any correlation between this and features such as Loan Amounts taken, Loan Term, etc.

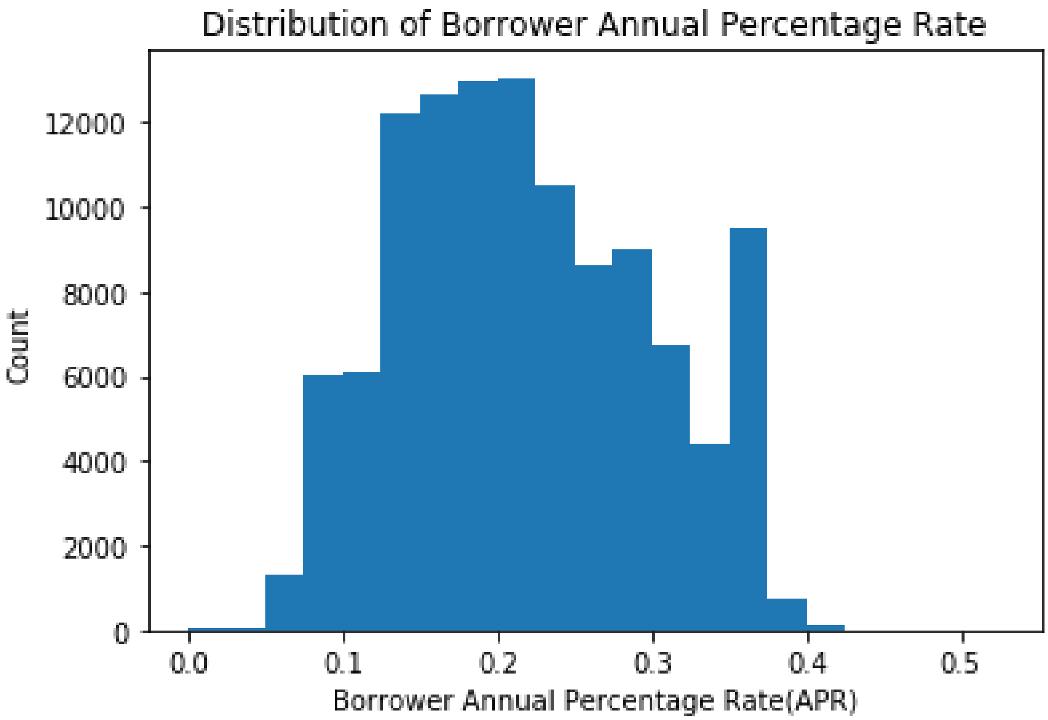
```
In [11]: x= df['LoanOriginalAmount'].dropna().values
         bins = np.arange(0, df['LoanOriginalAmount'].max()+1000, 1000)
         hist(x, 'Loan Amount (USD)', 'Count', 'Distribution of Loan Amount')
```



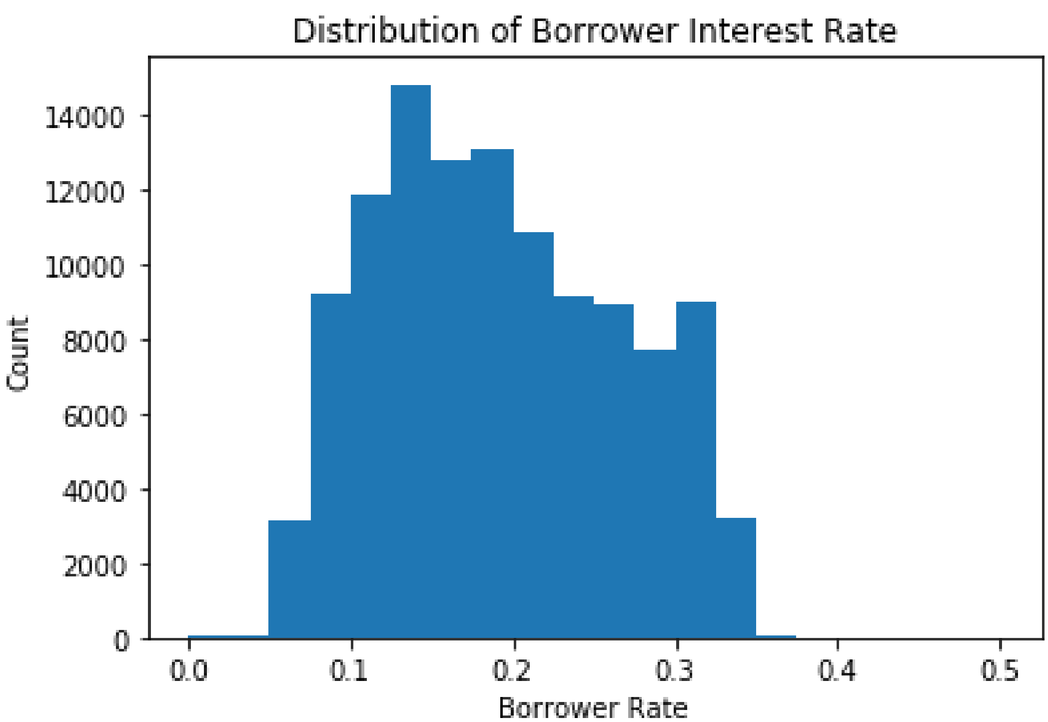
The most common amount customers tended to borrow is USD 5,000. Also interesting to note is tendency to borrow sums to the nearest 5,000. (10,000, 15,000, 20,000 etc)

Let's observe the distribution of the Annual Percentage Rate for borrowers

```
In [12]: x= df['BorrowerAPR'].dropna().values
         bins = np.arange(0, df['BorrowerAPR'].max()+0.025, 0.025)
         hist(x, 'Borrower Annual Percentage Rate(APR)', 'Count', 'Distribution of Borrower Annu
```



In [13]:
```
x= df['BorrowerRate'].dropna().values
bins = np.arange(0, df['BorrowerRate'].max()+0.025, 0.025)
hist(x, 'Borrower Rate', 'Count', 'Distribution of Borrower Interest Rate')
```

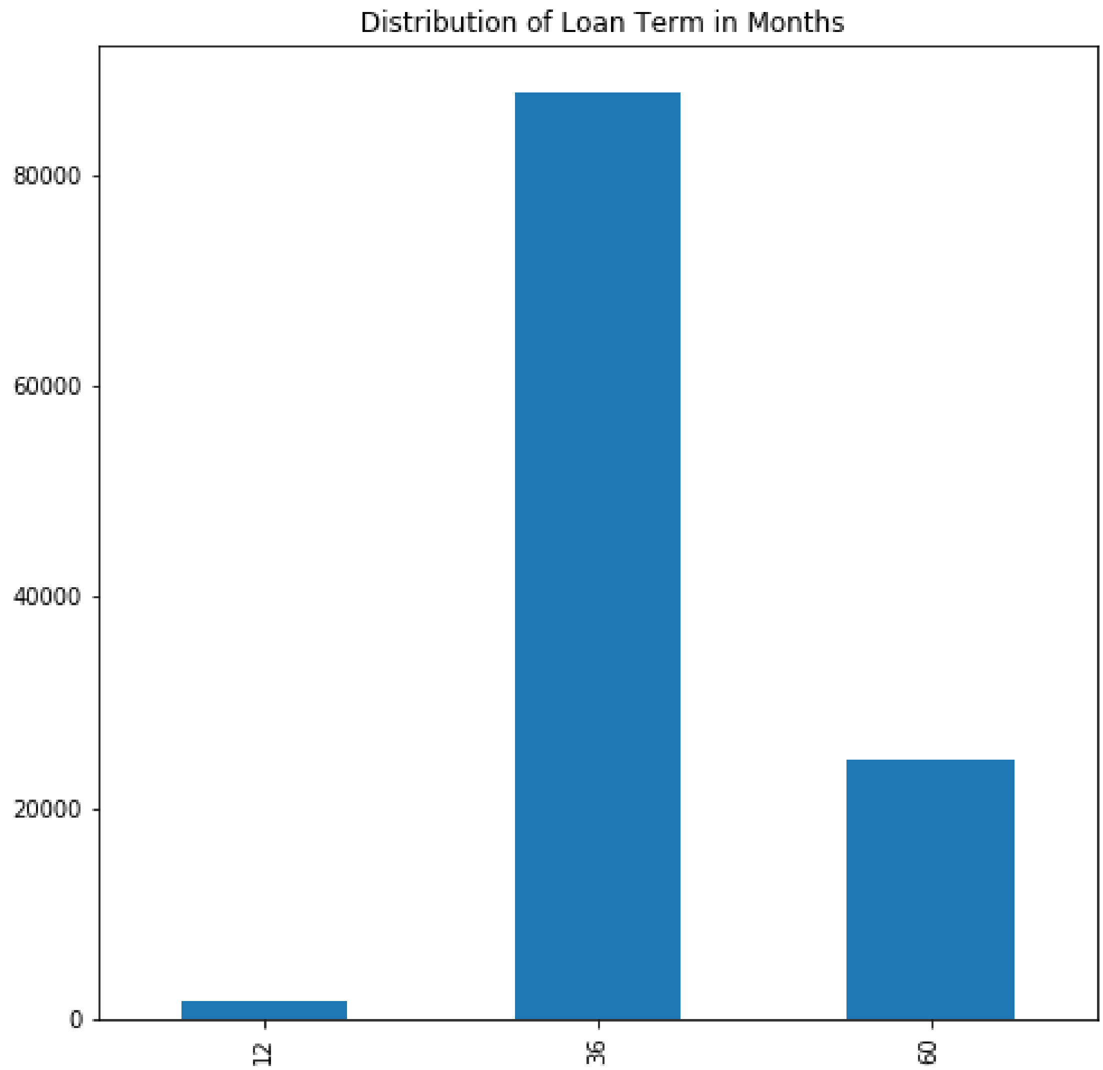


The distribution of the interest rate and the APR seems quite similar. To simplify the rest of the explorations, let's use the APR.

Let's examine how many months it takes to pay back a loan.

```
In [14]: df['Term'].value_counts(sort = False).plot(kind='bar', color = sb.color_palette()[0], f
                                                         title=' Distribution of Loan Term in Mo
```

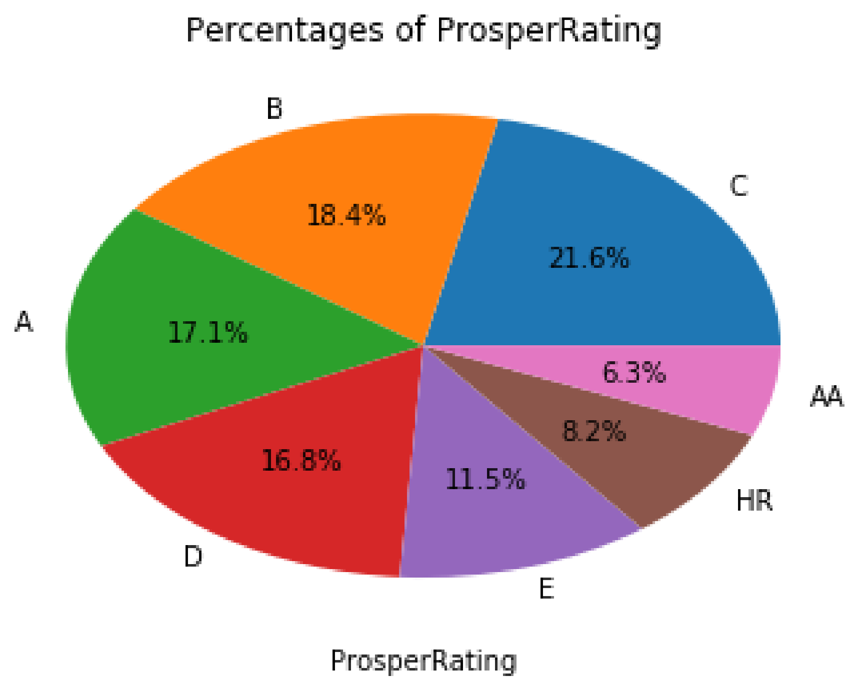
```
Out[14]: <matplotlib.axes._subplots.AxesSubplot at 0x7f3251e35f60>
```



More than half the customers prefer to pay the loan back in 36 months. Later, we'll examine the relationship between this variable and the amount of the loan borrowed to see if there's any correlation.

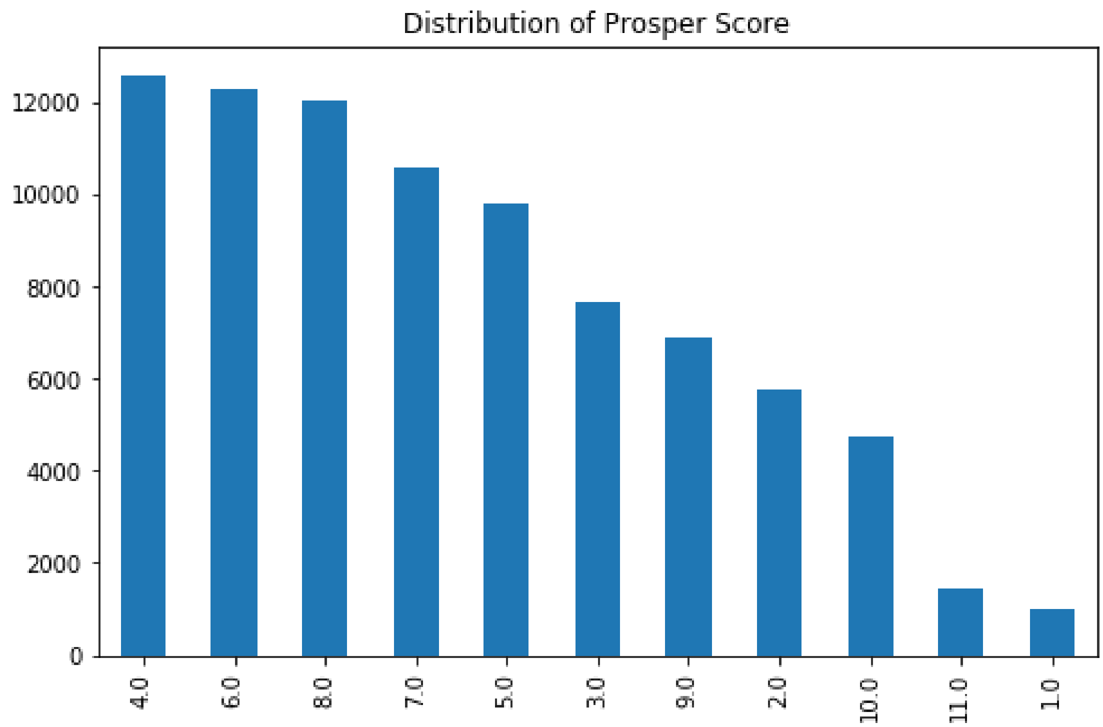
Let's visualise the distribution of the rating using a pie chart

```
In [15]: #Creating a pie chart to visualise the Prosper Rating as percentages
         x = df['ProsperRating (Alpha)'].value_counts()
         labels = ['C', 'B', 'A', 'D', 'E', 'HR', 'AA']

         def pie_plot(x,  xlabel, title):

              ax = plt.subplot(1,1,1)
              ax.pie(x, autopct='%1.1f%%', labels = labels)
              ax.set_xlabel(xlabel)
              ax.set_title(title)
              plt.show()

         pie_plot(x, 'ProsperRating', 'Percentages of ProsperRating')
```



However, the prosper rating doesn't provide much information as it is not ordered. Let's try and get the distribution from the Prosper Score instead.

```
In [16]: df['ProsperScore'].value_counts(sort = True).plot(kind='bar', color = sb.color_palette(
                                                         title= "Distribution of Prosper Score",

Out[16]: <matplotlib.axes._subplots.AxesSubplot at 0x7f324f984da0>
```



From the distribution above, it is evident that most customers are associated with an average risk in terms of paying back the loan. It is also interesting to note that the smallest group is 1.0, hence very few customers are associated with extreme risk.

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?

Initially, I was interested in the APR and the interest rate. However, their distributions are quite similar and therefore to simplify this exploration, I'll examine the relationship between other variables and just the APR. As of this stage, for the variables I chose to examine, no transformations were necessary.

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?

I was suprised that the loan amount distribution was skewed to the left, meaning that most borrowers take loans of less than 10,000 USD, and am keen to explore whether factors such as income range or employment status contribute to the loan amount. As of this stage, for the variables I chose to examine, no transformations were necessary.

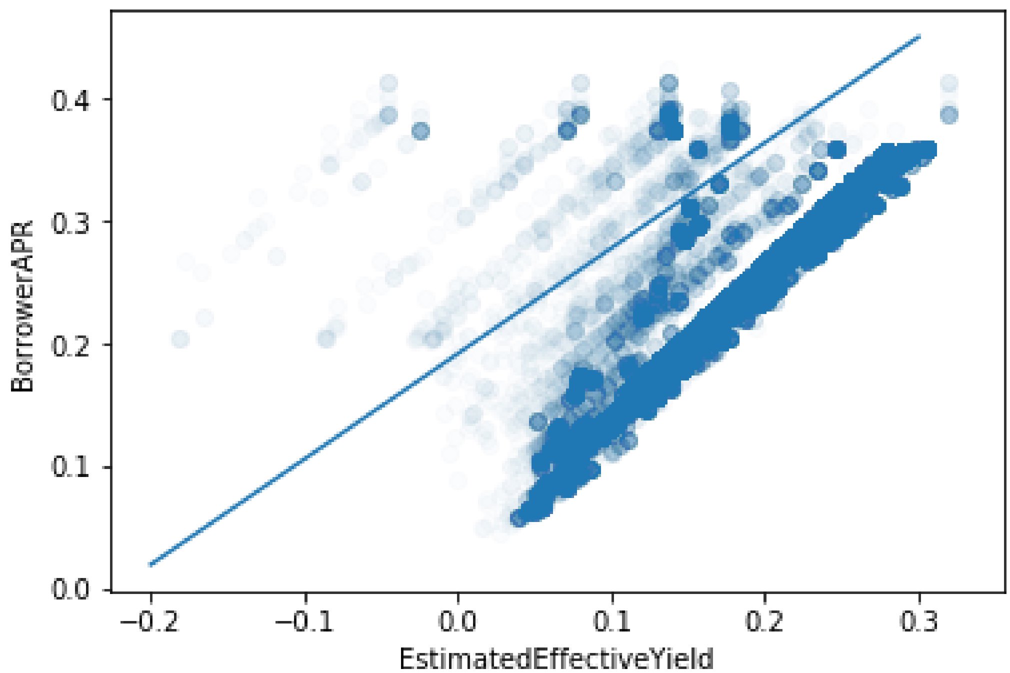
1.5 Bivariate Exploration

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).

We'll begin by examining the effect between the Estimated Effective Yield and the Borrower APR

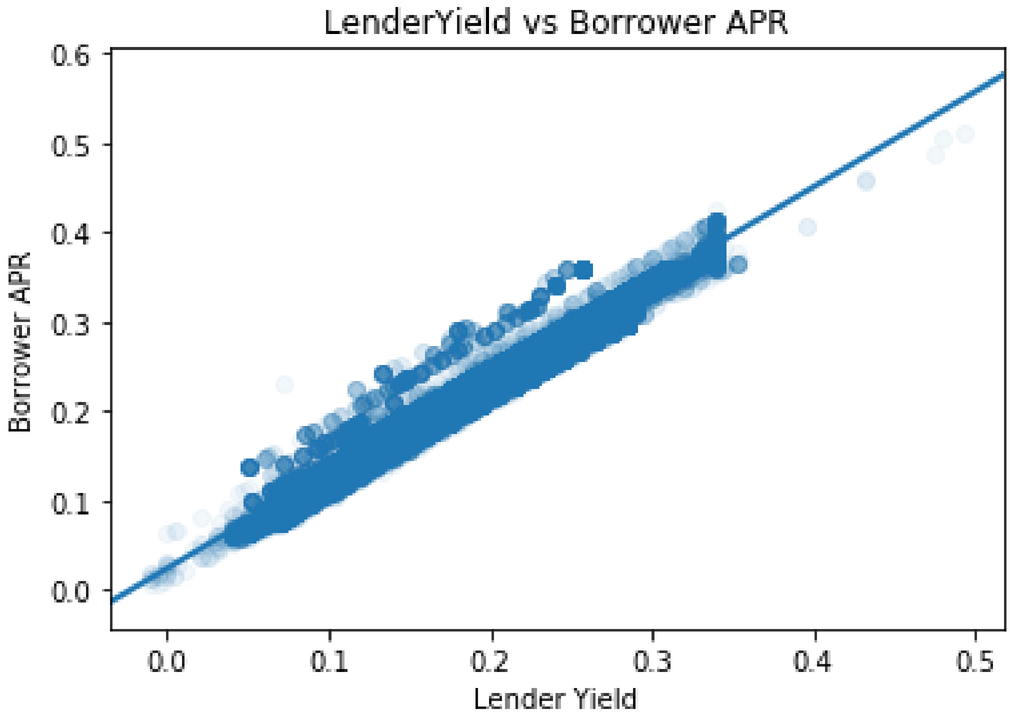
```
In [17]: plt.scatter(data = df, x = 'EstimatedEffectiveYield', y = 'BorrowerAPR', alpha = 0.02);
         plt.xlabel('EstimatedEffectiveYield')
         plt.ylabel('BorrowerAPR')
         plt.plot([-0.2, 0.3], [0.02 ,0.45])
```

```
Out[17]: [<matplotlib.lines.Line2D at 0x7f324f9ba588>]
```



It seems that there's a strong, positive correlation btween the Estimated Effective Yield and the BorrowerAPR.

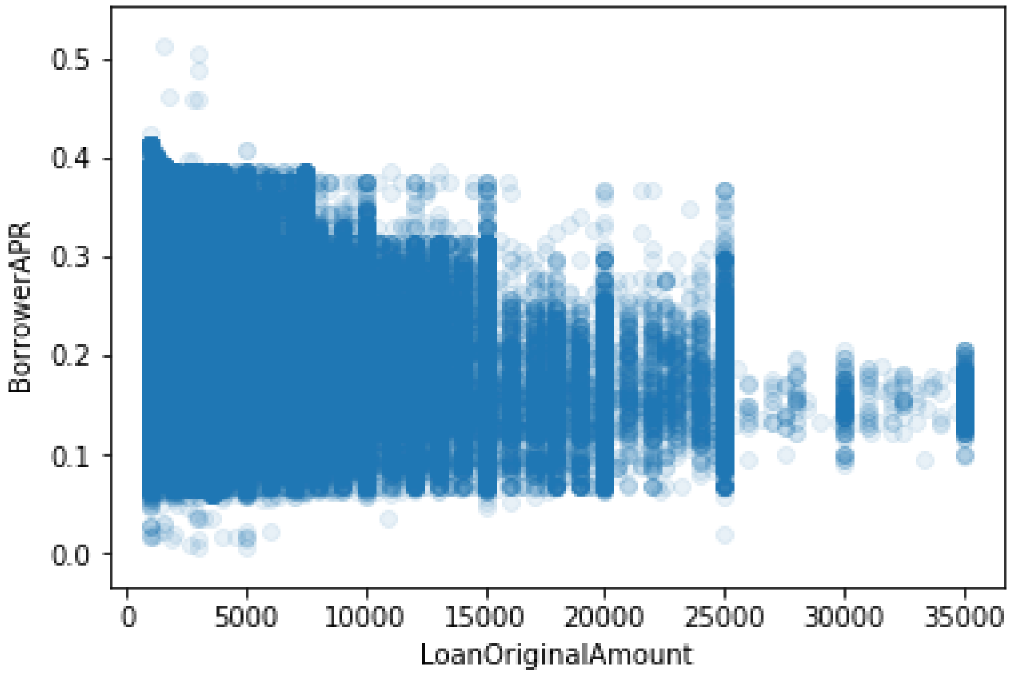
```
In [18]: sb.regplot(data = df, x = 'LenderYield', y = 'BorrowerAPR', truncate=False, x_jitter=0.
         plt.title('LenderYield vs Borrower APR' );
         plt.xlabel('Lender Yield');
         plt.ylabel('Borrower APR');
```



Once again, it is evident that the Lender Yield and the Borrowers' Annual Percentage Rate is positively correlated, i.e the higher a borrower's annual percentage rate, the greater the yield(return) on the loan.

Next, let's examine if there's any correlation between the annual percentage rate for borrowers and the loan amount.

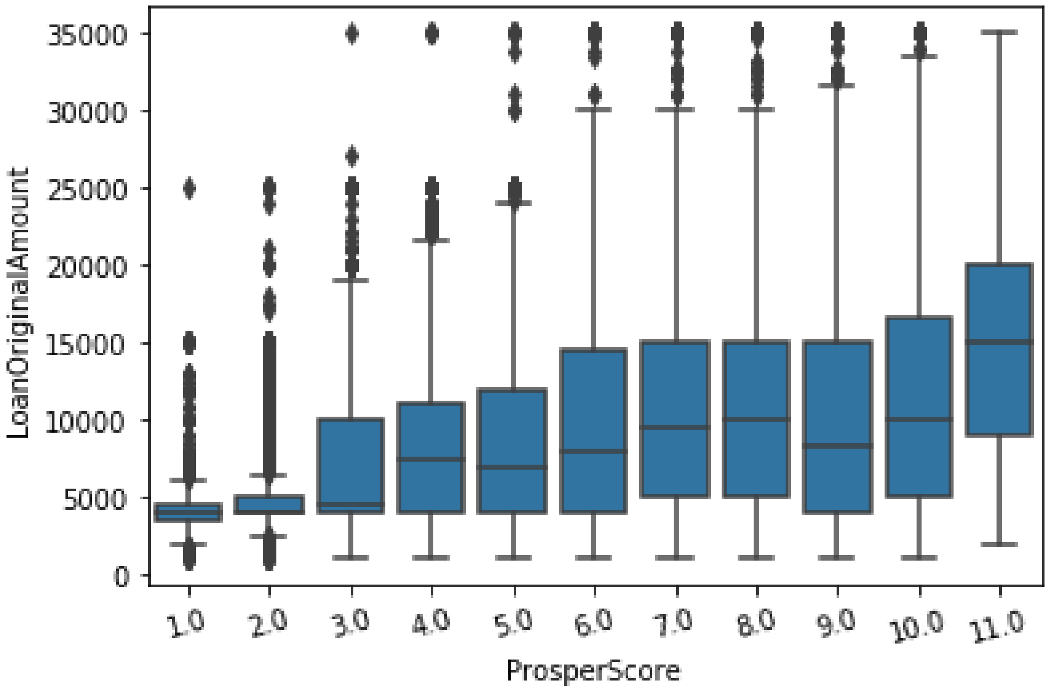
```
In [19]: plt.scatter(data = df, x = 'LoanOriginalAmount', y = 'BorrowerAPR', alpha = 0.1);
         plt.xlabel('LoanOriginalAmount')
         plt.ylabel('BorrowerAPR  ')

Out[19]: Text(0,0.5,'BorrowerAPR  ')
```



This plot indicates a slight negative correlation betweenthe two variables which means that customers who take out larger loans have lower interest rates. This may be a strategy from the bank to get customers to borrower larger amounts of loans.

Let's examine if there's any correlation between the Prosper Score for borrowers and the loan amount.

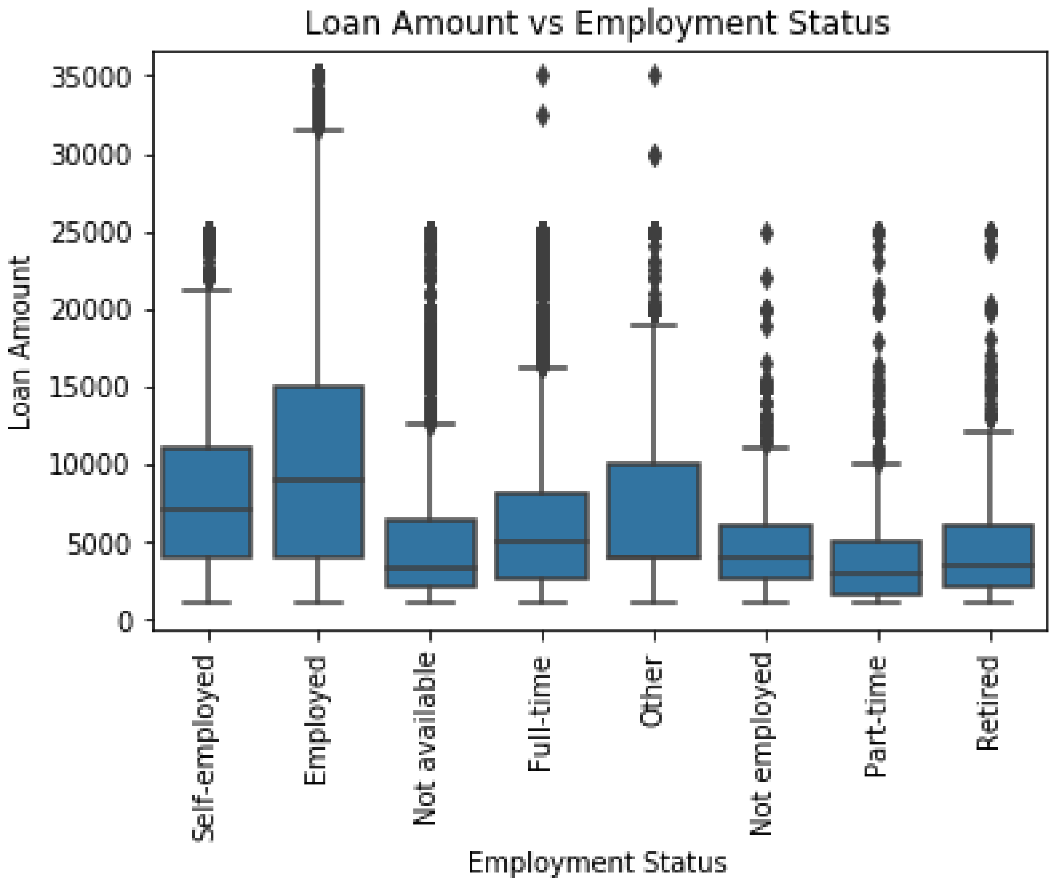
```
In [20]: sb.boxplot(data=df, x='ProsperScore', y='LoanOriginalAmount', color = sb.color_palette(
         plt.xticks(rotation=15);
```



As seen from the box plot above, and as expected, the Prosper score (which is a a custom risk score built using historical Prosper data which ranges from 1-10, with 10 being the best, or lowest risk score)is directly proportional to the loan amount. This plot makes sense because one would expect that a customer with the lowest risk score would obtain the highest loan amount. It's also interesting to note the outliers on lower Prosper Scores. For example, the outlier(s) with a score of 2.0 meaning there is significant risk but still able to obtain a loan of $ 35000 +.

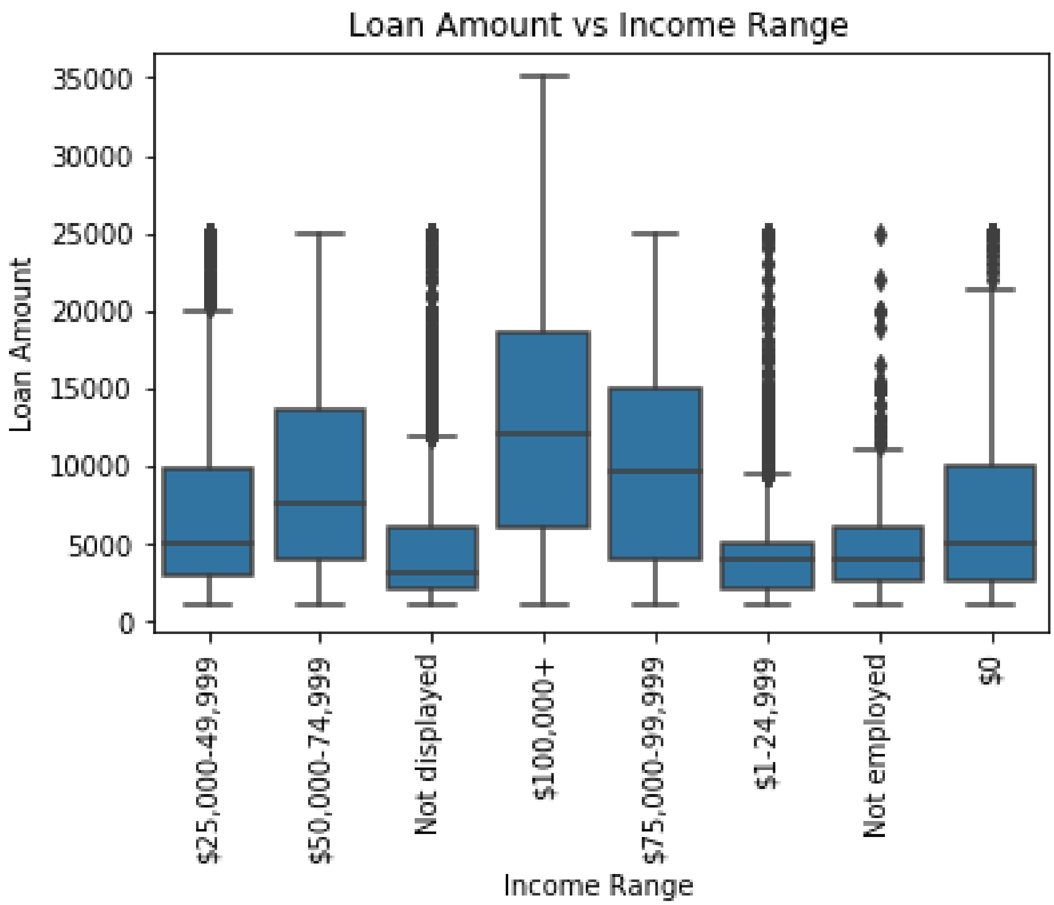
Let's see if one's employment status has an effect on the Loan Amount.

```
In [21]: sb.boxplot(data=df, x='EmploymentStatus', y='LoanOriginalAmount', color = sb.color_pale

         plt.xticks(rotation=90);
         plt.title('Loan Amount vs Employment Status' );
         plt.xlabel('Employment Status');
         plt.ylabel('Loan Amount');
```



Evidently, employed people take out/ are eligible for the highest amount of loans.
Let's examine if one's income range has an effect on the Loan Amount.

```
In [22]: sb.boxplot(data=df, x='IncomeRange', y='LoanOriginalAmount', color = sb.color_palette()
         plt.xticks(rotation=90);
         plt.title('Loan Amount vs Income Range' );
         plt.xlabel('Income Range');
         plt.ylabel('Loan Amount');
```

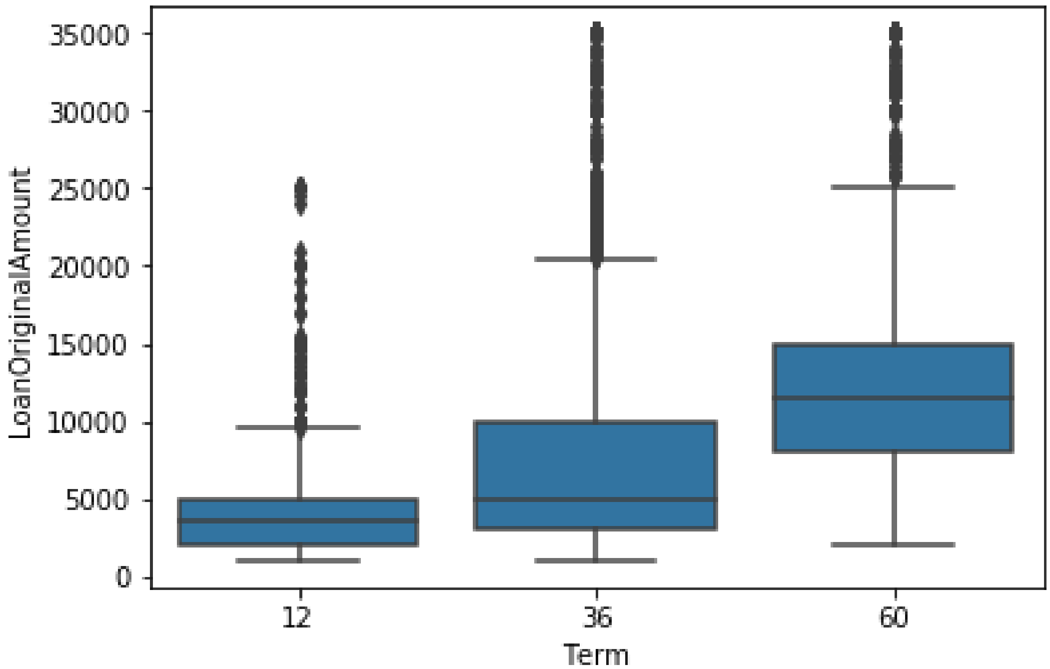


To a certain extent, income range is directly proportional to the loan amount. We can see that the highest loan amounts are taken by customers who earn USD 100, 000+, followed by those who earn between 75,000 - 99,999 and so on. However it is also interesting to note that customers who earn no income are alos eligible for a significant amount in loans (up to USD 10,000)

Let's observe the relationship between the loan amount and the term take to repay the loan.

```
In [23]: sb.boxplot(data=df, x='Term', y='LoanOriginalAmount', color = sb.color_palette()[0])
```

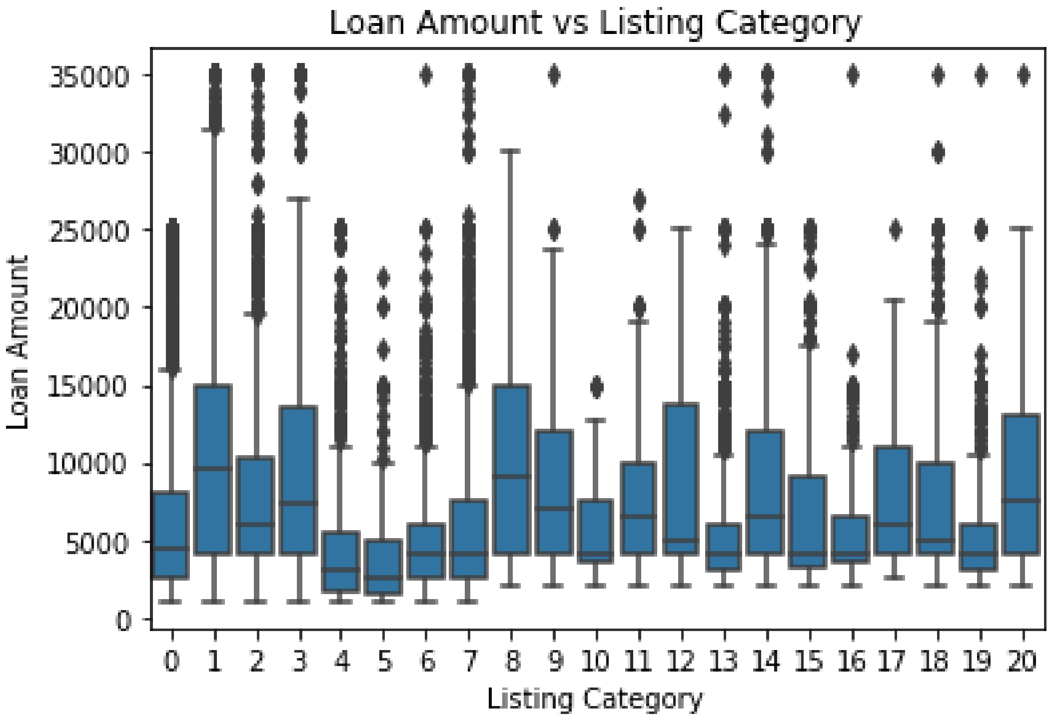
```
Out[23]: <matplotlib.axes._subplots.AxesSubplot at 0x7f324f8b0f98>
```



As expected, term is directly proportional to the Loan Amount. This is intuitive because the larger the amount, the more likely that one would need a longer period of time to pay it off.

Is there a correlation between the Listing Category (the reason the loan was taken) and the amount borrowed?

```
In [24]: sb.boxplot(data=df, x='ListingCategory (numeric)', y='LoanOriginalAmount', color = sb.c
         plt.title('Loan Amount vs Listing Category');
         plt.xlabel('Listing Category');
         plt.ylabel('Loan Amount');
```



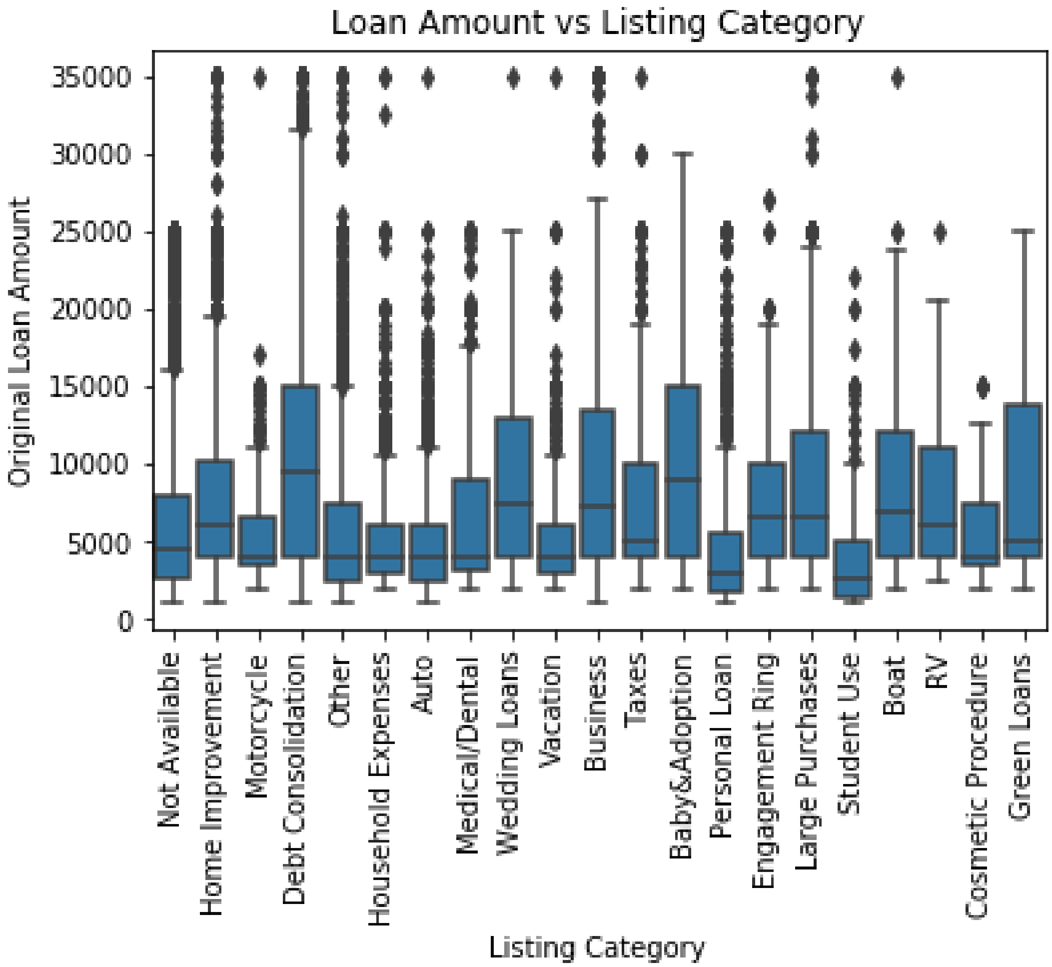
The listing categories as they are do not provide us with much information. Let's replace the numeric values with the categories that they represent.

```
In [25]: df2 = df.copy()
```

```
In [26]: df2['ListingCategory (numeric)']=df2['ListingCategory (numeric)'].replace([0, 1, 2, 3,
                                          15, 16, 17, 18, 19, 20],
                                          ['Not Available', 'Debt Consolidation', 'Home Improveme
                                          'Student Use', 'Auto', 'Other', 'Baby&Adoption', 'Boat'
                                          'Engagement Ring', 'Green Loans', 'Household Expenses',
                                          'Motorcycle', 'RV', 'Taxes', 'Vacation', 'Wedding Loans
```

```
In [27]: df2.rename(columns = {'ListingCategory (numeric)':'ListingCategory'}, inplace = True)
         #df2.info()
```

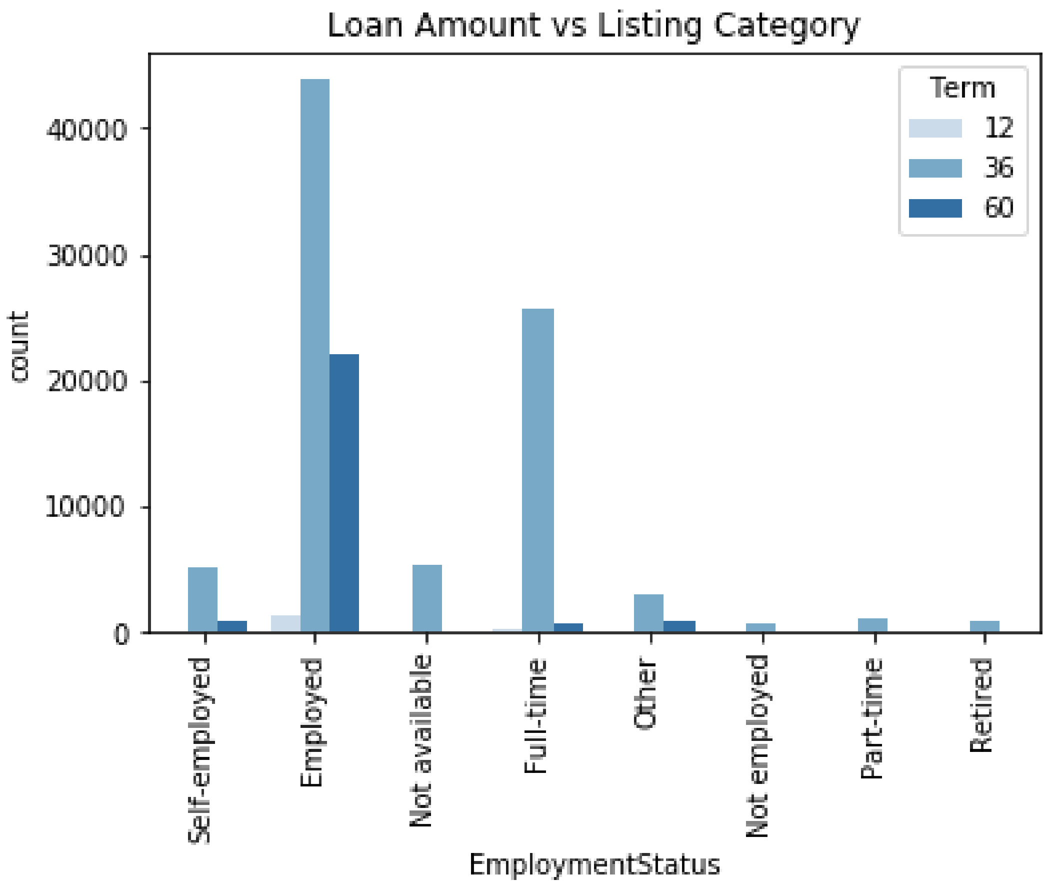
```
In [28]: # plt.figure(figsize=[8, 5]);
         sb.boxplot(data=df2, x='ListingCategory', y='LoanOriginalAmount', color = sb.color_pale
         plt.xticks(rotation=90);
         plt.title('Loan Amount vs Listing Category');
         plt.xlabel ('Listing Category');
         plt.ylabel ('Original Loan Amount');
```



From this plot, it is clear that the top categories that largest loan amounts are for the following reasons: 1. Debt Consolidation 2. Wedding Loans 3. Baby & Adoption

This either means that these categories are expensive, e.g.Weddings in the United States are known to be quite costly, or it could also mean that a large number of the population is taking up loans for these reasons.

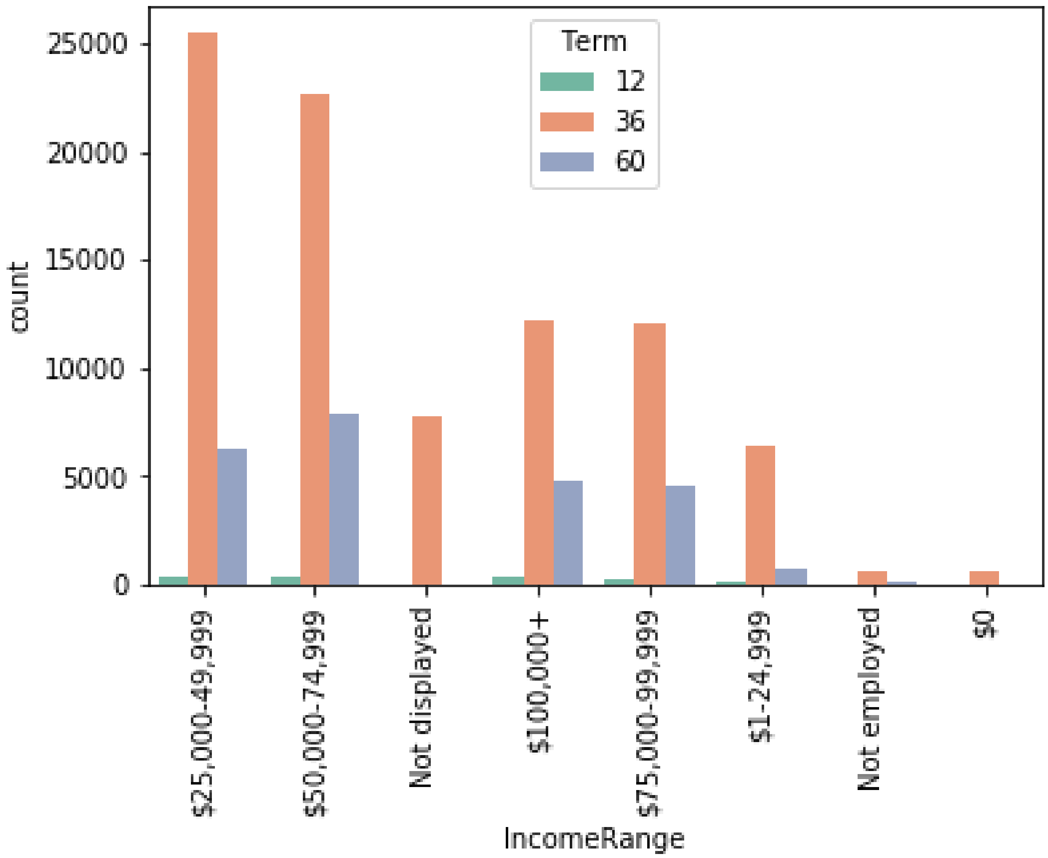
```
In [29]: sb.countplot(data = df, x = 'EmploymentStatus', hue = 'Term', palette = 'Blues')
         plt.xticks(rotation = 90);
         plt.title('Loan Amount vs Listing Category');
```



Regardless of employement status, it is evident that most people do not opt for a 12 month term. 36 months was the most popular term followed by 60 months. It's also interesting to note that 60 months is remarkably common among employed customers. This is likely due to the fact that they have a consistent income stream and would be able to sustain payments over a longer period of time.

Let's explore whether there's any correlation between the term and the income range for the borrower.

```
In [30]: sb.countplot(data = df, x = 'IncomeRange', hue = 'Term', palette = 'Set2');
         plt.xticks(rotation = 90);
```



Similarly, at each income level, there is a clear order of preference with respect to the preferred term for loan repayment. That is, most people prefer a 36 month term, some people opt for a 60 month term, and very few people opt for a 12 month term.

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?

As as expected, the Prosper score is directly proportional to the loan amount. This means because that a customer with the lowest risk score would obtain the highest loan amount. It was evident also that the Lender Yield and Estimated Effective Yield are both positively correlated with the APR i.e the higher a borrower's annual percentage rate, the greater the yield(return) on the loan. Another notable factor was that the loan term was not directly proportional to either income range or employment status. Regardless of the employment status and / or income range, most customers opted for a 36 month term.

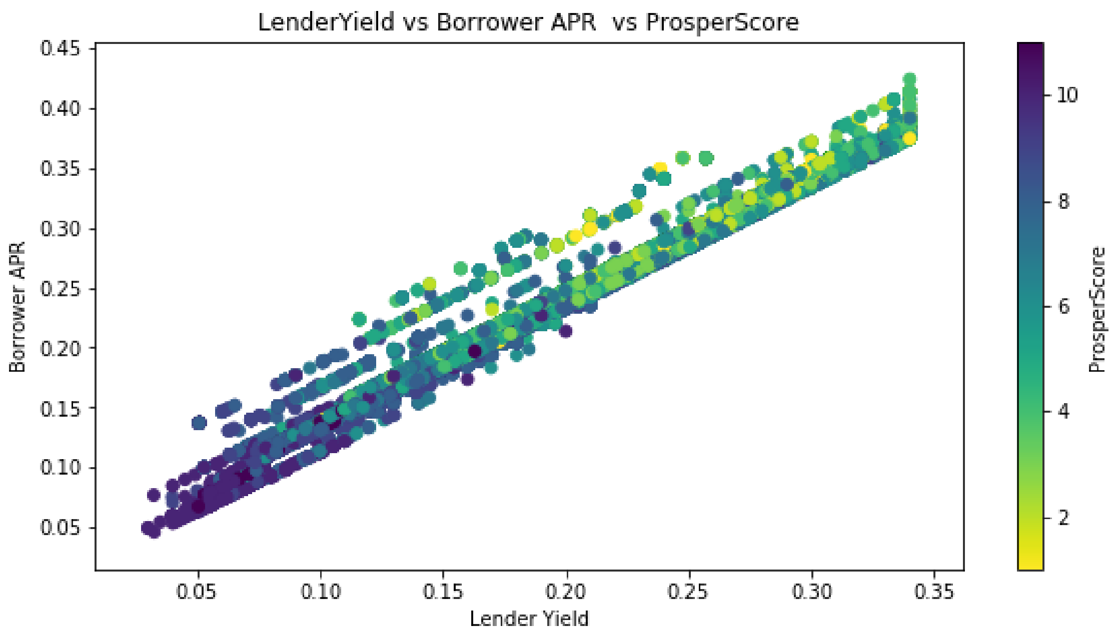
1.5.2 Did you observe any interesting relationships between the other features (not the main feature(s) of interest)?

Employed people take out/ are eligible for the highest amount of loans. To a certain extent, income range is directly proportional to the loan amount. We observed that the highest loan amounts are taken by customers who earn USD 100, 000+, followed by those who earn between 75,000 - 99,999 and so on. However it was also interesting to note that customers who earn no income are also eligible for a significant amount in loans (up to USD 10,000)

1.6 Multivariate Exploration

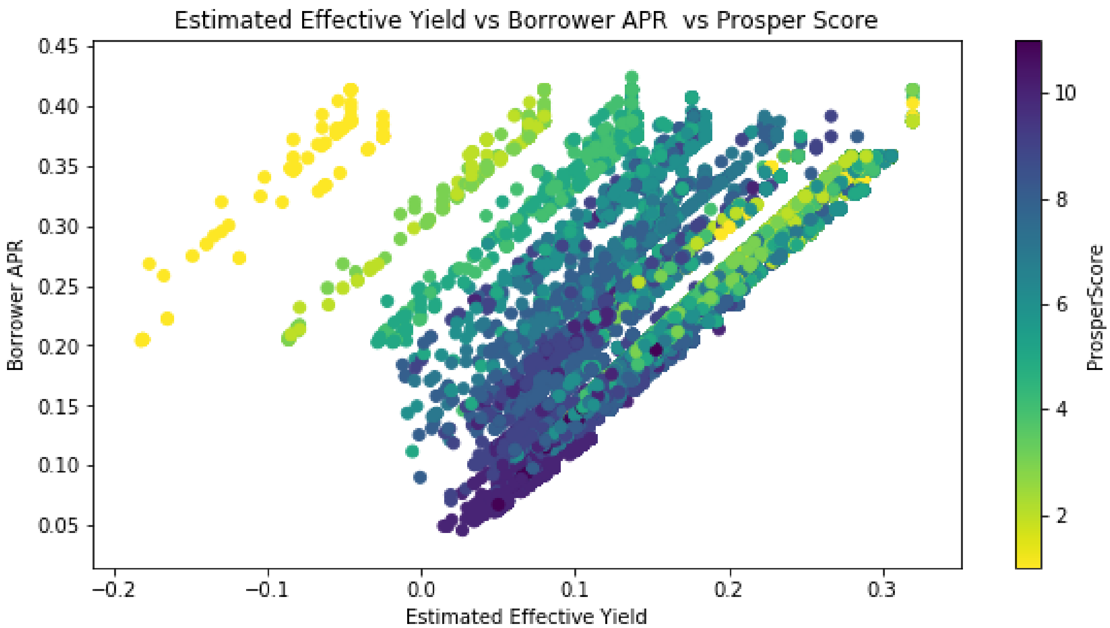
Create plots of three or more variables to investigate your data even further. Make sure that your investigations are justified, and follow from your work in the previous sections.

```
In [31]: plt.figure(figsize = [10, 5])
         plt.scatter(data=df,x='LenderYield',y = 'BorrowerAPR',c='ProsperScore',cmap = 'viridis_
         plt.colorbar(label = 'ProsperScore');
         plt.title('LenderYield vs Borrower APR  vs ProsperScore');
         plt.xlabel('Lender Yield');
         plt.ylabel('Borrower APR');
```



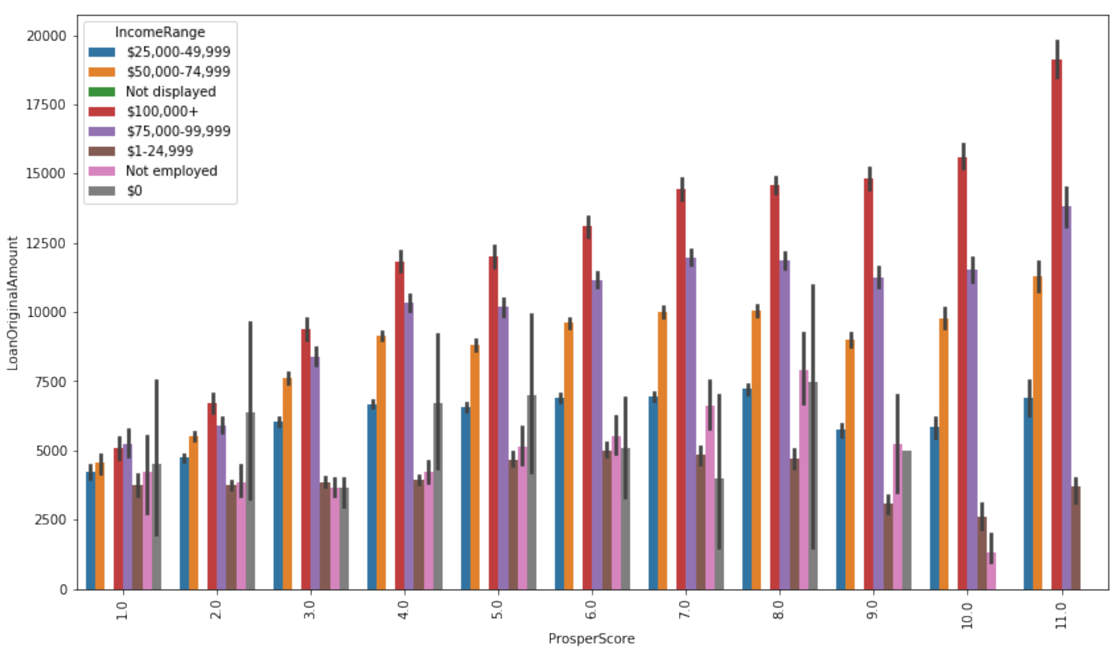
We observe that prosper score is negatively correlated with the APR. This is likely due to the fact that customers with lower risk classifications are offered lower annual percentage rates.

```
In [32]: plt.figure(figsize = [10, 5])
         plt.scatter(data=df,x='EstimatedEffectiveYield',y = 'BorrowerAPR',c='ProsperScore',cmap
         plt.colorbar(label = 'ProsperScore');
         plt.title('Estimated Effective Yield vs Borrower APR  vs Prosper Score');
         plt.xlabel('Estimated Effective Yield');
         plt.ylabel('Borrower APR');
```



As with the previous plot, we observe that prosper score is largely, negatively correlated with the APR. This is likely due to the fact that customers with lower risk classifications are offered lower annual percentage rates.

```
In [33]: plt.figure(figsize=[14, 8])
         ax = sb.barplot(data = df, x = 'ProsperScore', y = 'LoanOriginalAmount', hue = 'IncomeR
         plt.xticks(rotation=90);
```



From the above plot, we can observe that at each Prosper Rating, customers who make USD 100,000 + are able to obtain/ take out larger loan amounts. Additionally, this plot confirms the direct proportionality between the loan amount obtained and the prosper score rating(i.e the highest loan amounts are obtained by those with the lowest risk classification.)

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?

Using multivariate plots the relationship between the original amount, the Propser Score and the income range was analysed. The correlation between the amount and the income range was as observed in the previous section with customers earning USD 100, 000 + obtaining the highest amount of loans. We observed that prosper score is negatively correlated with the APR. This is likely due to the fact that customers with lower risk classifications are offered lower annual percentage rates.

1.6.2 Were there any interesting or surprising interactions between features?

Yes it was interesting to observe that even users who's income was 0 USD were able to get loans, and sometimes larger amounts than users with a higher income range.