Part I - Prosper Loan Data Exploration

by Isaac Godwin

Introduction

```
This notebook document explores a dataset which contain 113,937 loan records in 81
colomns. The dataset which is a prosper loan data that was provided by Udacity for
the porpose of this project.
```

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
import warnings
warnings.simplefilter("ignore")
```

> Loading the dataset in order to describe its properties.

In [2]:

```
loan_df = pd.read_csv('prosperloandata.csv')
loan_df.shape
```

Out[2]:

```
(113937, 81)
```

In [3]:

```
loan_df.head()
```

Out[3]:

	ListingKey	ListingNumber	ListingCreationDate	CreditGrade	Term	LoanStatus	ClosedDate	Borrc
0	1021339766868145413AB3B	193129	2007-08-26 19:09:29.263000000	C	36	Completed	2009-08-14 00:00:00	
1	10273602499503308B223C1	1209647	2014-02-27 08:28:07.900000000	NaN	36	Current	NaN	
2	0EE9337825851032864889A	81716	2007-01-05 15:00:47.090000000	HR	36	Completed	2009-12-17 00:00:00	
3	0EF5356002482715299901A	658116	2012-10-22 11:02:35.010000000	NaN	36	Current	NaN	
4	0F023589499656230C5E3E2	909464	2013-09-14 18:38:39.097000000	NaN	36	Current	NaN	

5 rows × 81 columns

In [4]:
```
loan_df.tail()
```

Out[4]:

	ListingKey	ListingNumber	ListingCreationDate	CreditGrade	Term	LoanStatus	C
113932	E6D9357655724827169606C	753087	2013-04-14 05:55:02.663000000	NaN	36	Current	
113933	E6DB353036033497292EE43	537216	2011-11-03 20:42:55.333000000	NaN	36	FinalPaymentInProgress	
113934	E6E13596170052029692BB1	1069178	2013-12-13 05:49:12.703000000	NaN	60	Current	
113935	E6EB3531504622671970D9E	539056	2011-11-14 13:18:26.597000000	NaN	60	Completed	2
113936	E6ED3600409833199F711B7	1140093	2014-01-15 09:27:37.657000000	NaN	36	Current	

5 rows × 81 columns

In [5]:
```
loan_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
```

In [6]:

```
loan_df.describe()
```

Out[6]:

	ListingNumber	Term	BorrowerAPR	BorrowerRate	LenderYield	EstimatedEffectiveYield	Estimate
count	1.139370e+05	113937.000000	113912.000000	113937.000000	113937.000000	84853.000000	84853.0
mean	6.278857e+05	40.830248	0.218828	0.192764	0.182701	0.168661	0.0
std	3.280762e+05	10.436212	0.080364	0.074818	0.074516	0.068467	0.0
min	4.000000e+00	12.000000	0.006530	0.000000	-0.010000	-0.182700	0.0
25%	4.009190e+05	36.000000	0.156290	0.134000	0.124200	0.115670	0.0
50%	6.005540e+05	36.000000	0.209760	0.184000	0.173000	0.161500	0.0
75%	8.926340e+05	36.000000	0.283810	0.250000	0.240000	0.224300	0.1

	ListingNumber	Term	BorrowerAPR	BorrowerRate	LenderYield	EstimatedEffectiveYield	Estimate
max	1.255725e+06	60.000000	0.512290	0.497500	0.492500	0.319900	0.3

8 rows × 61 columns

What is the structure of the dataset?

```
The dataset contains 113937 observations with 81 variables on each loan records
```

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

```
The main variables of interest in this dataset are the ones with discriptive
information related to the profile of the borrowers and the loan borrowed.
```

What features in the dataset will help support the investigation into the feature(s) of interest?

```
Some of the variables to explore in order to investigate the relationship between
the variable of interest which are the borrowers informations and the loan they
borrowed. they are; EmploymentStatus, Occupation, StatedMonthlyIncome, BorrowerAPR,
BorrowerRate, BorrowerState, DebtToIncomeRatio, LoanStatus, LoanOriginalAmount,
LoanOriginationDate, TotalProsperLoans, IncomeVerifiable,
```

Univariate Exploration

Each variable will be exploired in this section

In [7]:

```
# subseting the data frame by selecting variable of interest
col = ['EmploymentStatus', 'Occupation', 'StatedMonthlyIncome','BorrowerState',  'Borrower
        'IncomeVerifiable', 'DebtToIncomeRatio', 'IsBorrowerHomeowner', 'LoanOriginalAmour
       'ProsperRating (Alpha)', 'Term','TotalProsperLoans']
loan_subset = loan_df[col]
loan_subset.head()
```

Out[7]:

	EmploymentStatus	Occupation	StatedMonthlyIncome	BorrowerState	BorrowerAPR	BorrowerRate	LoanStatus	I
0	Self-employed	Other	3083.333333	CO	0.16516	0.1580	Completed	
1	Employed	Professional	6125.000000	CO	0.12016	0.0920	Current	
2	Not available	Other	2083.333333	GA	0.28269	0.2750	Completed	
3	Employed	Skilled Labor	2875.000000	GA	0.12528	0.0974	Current	
4	Employed	Executive	9583.333333	MN	0.24614	0.2085	Current	

In [8]:

```
# shape of the dataframe
loan_subset.shape
```

Out[8]: (113937, 16)

In [9]:

```
# checking loan statistics
loan_subset.describe()
```

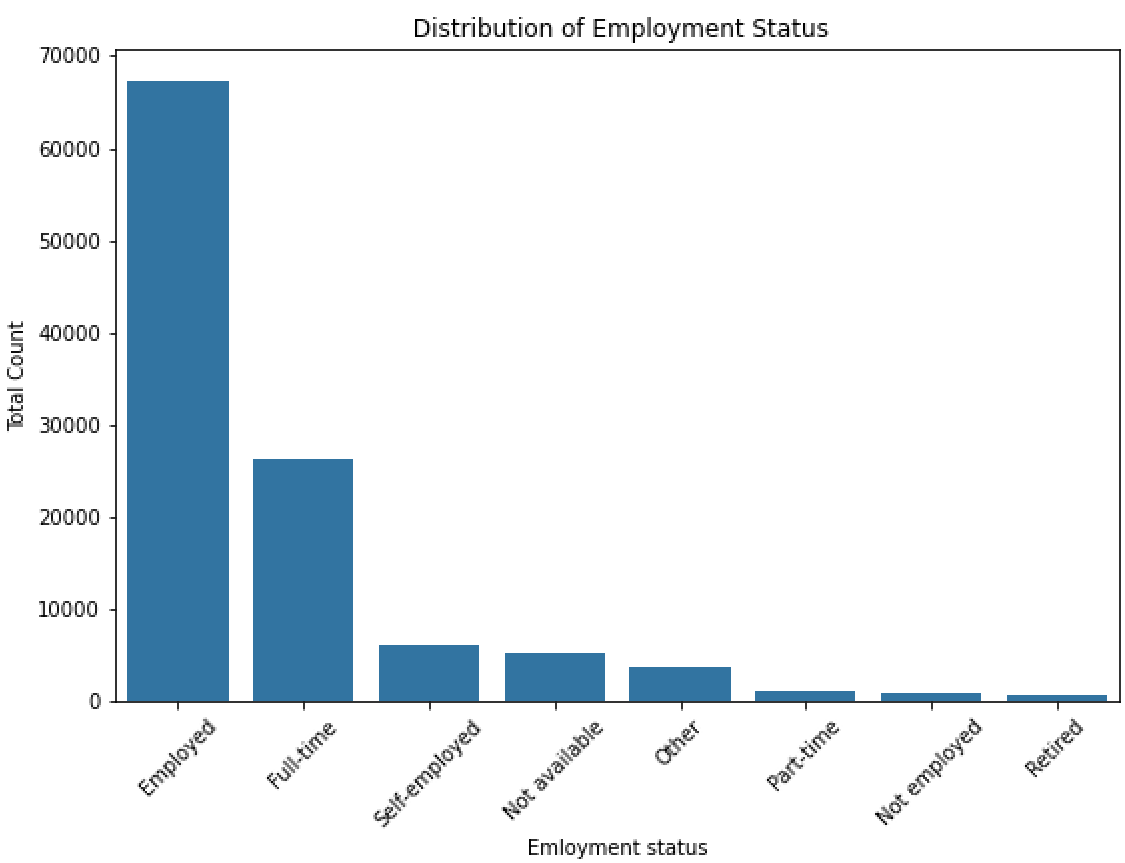
Out[9]:

	StatedMonthlyIncome	BorrowerAPR	BorrowerRate	DebtToIncomeRatio	LoanOriginalAmount	Term
count	1.139370e+05	113912.000000	113937.000000	105383.000000	113937.00000	113937.00000(
mean	5.608026e+03	0.218828	0.192764	0.275947	8337.01385	40.83024(
std	7.478497e+03	0.080364	0.074818	0.551759	6245.80058	10.43621(
min	0.000000e+00	0.006530	0.000000	0.000000	1000.00000	12.00000(
25%	3.200333e+03	0.156290	0.134000	0.140000	4000.00000	36.00000(
50%	4.666667e+03	0.209760	0.184000	0.220000	6500.00000	36.00000(
75%	6.825000e+03	0.283810	0.250000	0.320000	12000.00000	36.00000(
max	1.750003e+06	0.512290	0.497500	10.010000	35000.00000	60.00000(

what are the EmploymentStatus of the borrowers

In [10]:

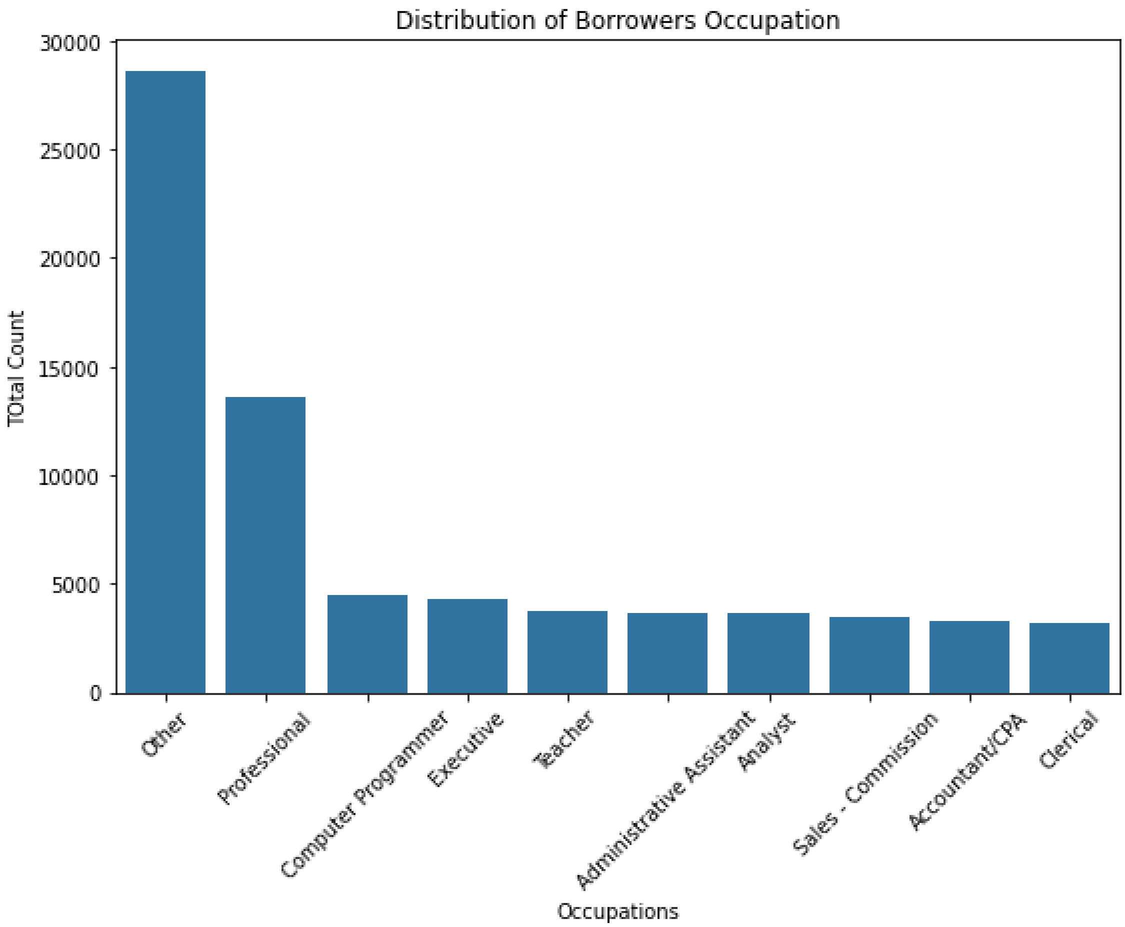
```
#checking the Borrower's employment status
plt.figure(figsize = [9, 6])
color_pal = sb.color_palette()[0]
employ = loan_subset['EmploymentStatus'].value_counts().index
sb.countplot(data= loan_subset, x= 'EmploymentStatus', color = color_pal, order = employ)
plt.title(" Distribution of Employment Status")
plt.xlabel('Emloyment status')
plt.ylabel('Total Count')
plt.xticks(rotation = 45);
```



From data it shows that most of the borrowers were either Employed, full-time, self employed, the employment status is not available or other

what are the occupations of most of the borrowers

In [11]:
```
#checking the borrowers occupations
plt.figure(figsize = [9, 6])
color_pal = sb.color_palette()[0]
order = loan_subset['Occupation'].value_counts().iloc[:10].index
sb.countplot(data= loan_subset, x= 'Occupation', color = color_pal, order = order)
plt.title("Distribution of Borrowers Occupation")
plt.xlabel('Occupations')
plt.ylabel('TOtal Count')
plt.xticks(rotation = 45);
```

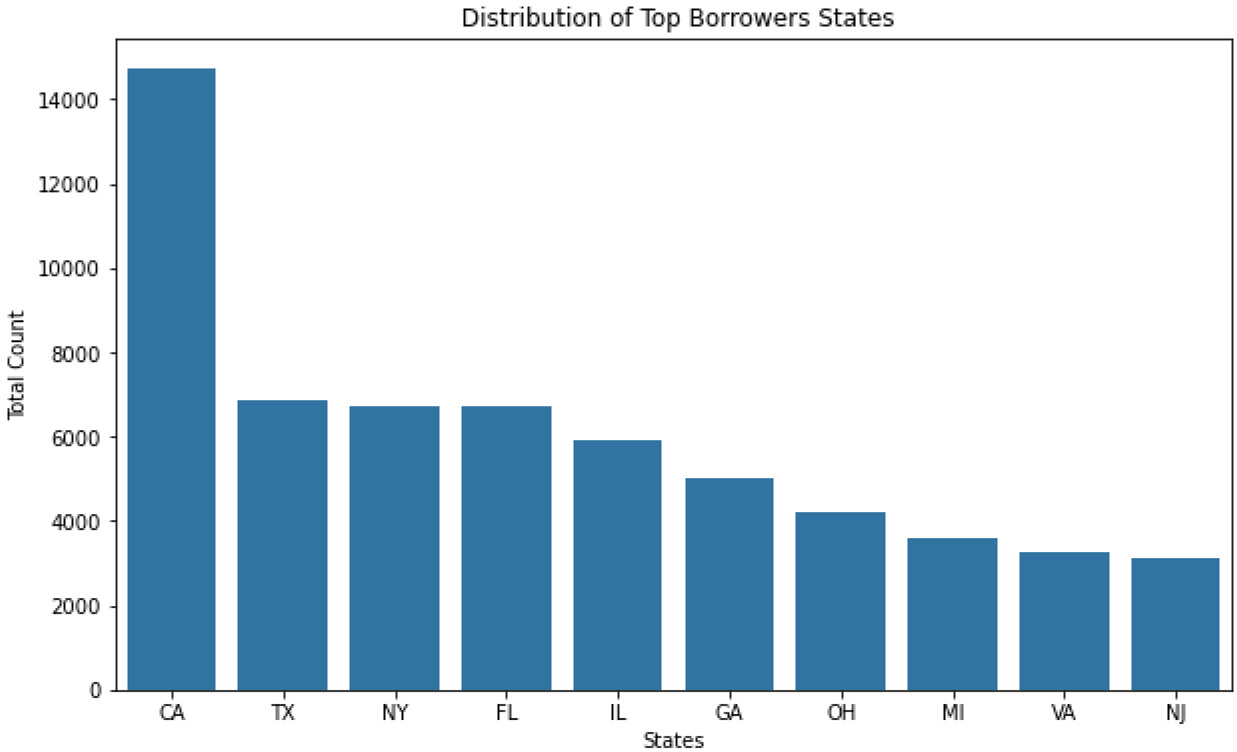


The chart shows that most of the occupation of the borrowers are others which is an indication that most of their occupation are outside the options provided

How is the loan distributed by BorrowerState

In [12]:
```
plt.figure(figsize = [10, 6])
color_pal = sb.color_palette()[0]

b_state = loan_subset['BorrowerState'].value_counts().iloc[:10].index
sb.countplot(data= loan_subset, x= 'BorrowerState', color = color_pal, order = b_state)
plt.title(" Distribution of Top Borrowers States")
plt.xlabel('States')
plt.ylabel('Total Count');
```

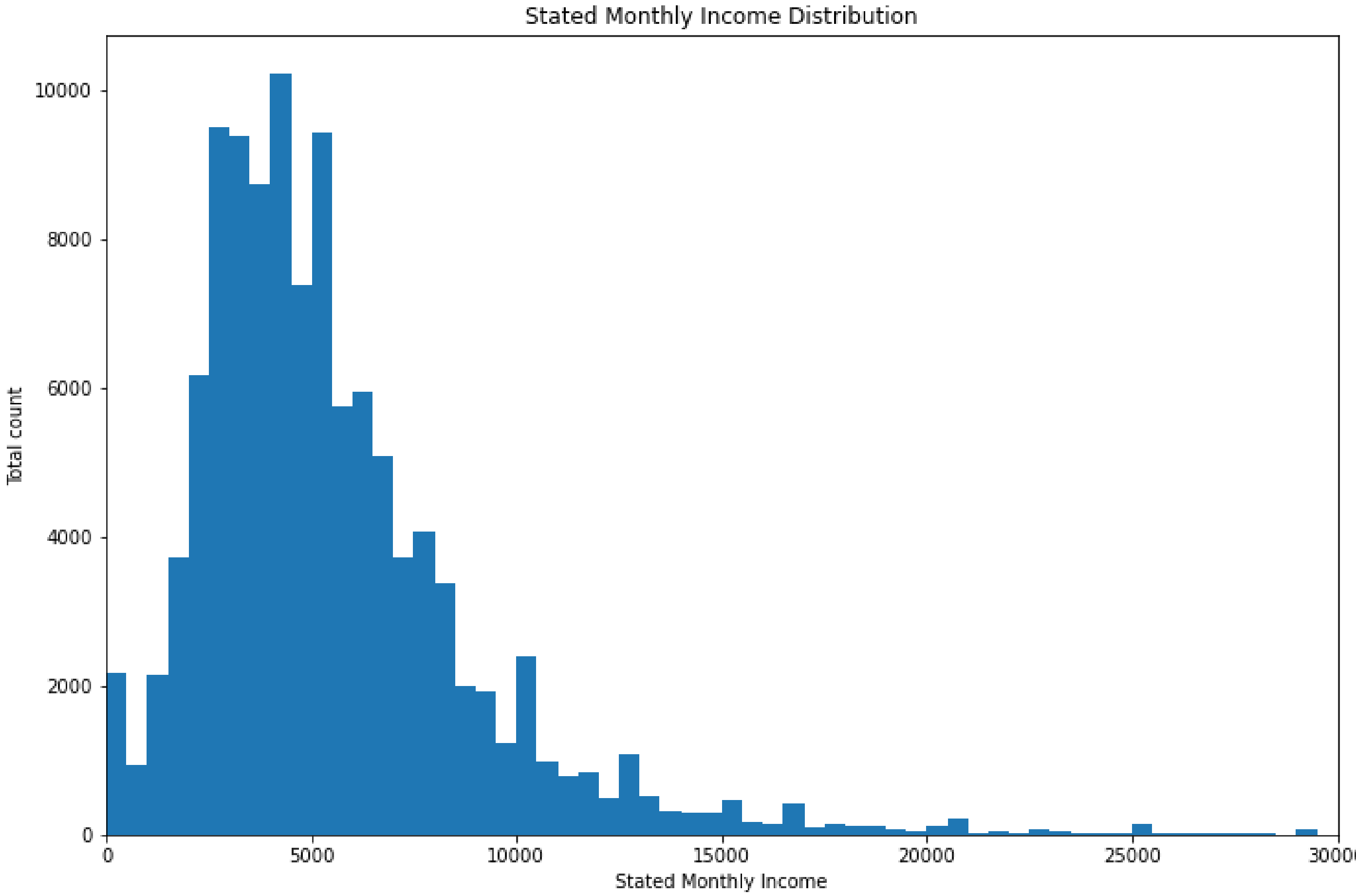


from the data it show that the highest distribution of borrowers states is CA, follows by TX, NY, FL and IL.

the Stated Monthly Income of the borrowers

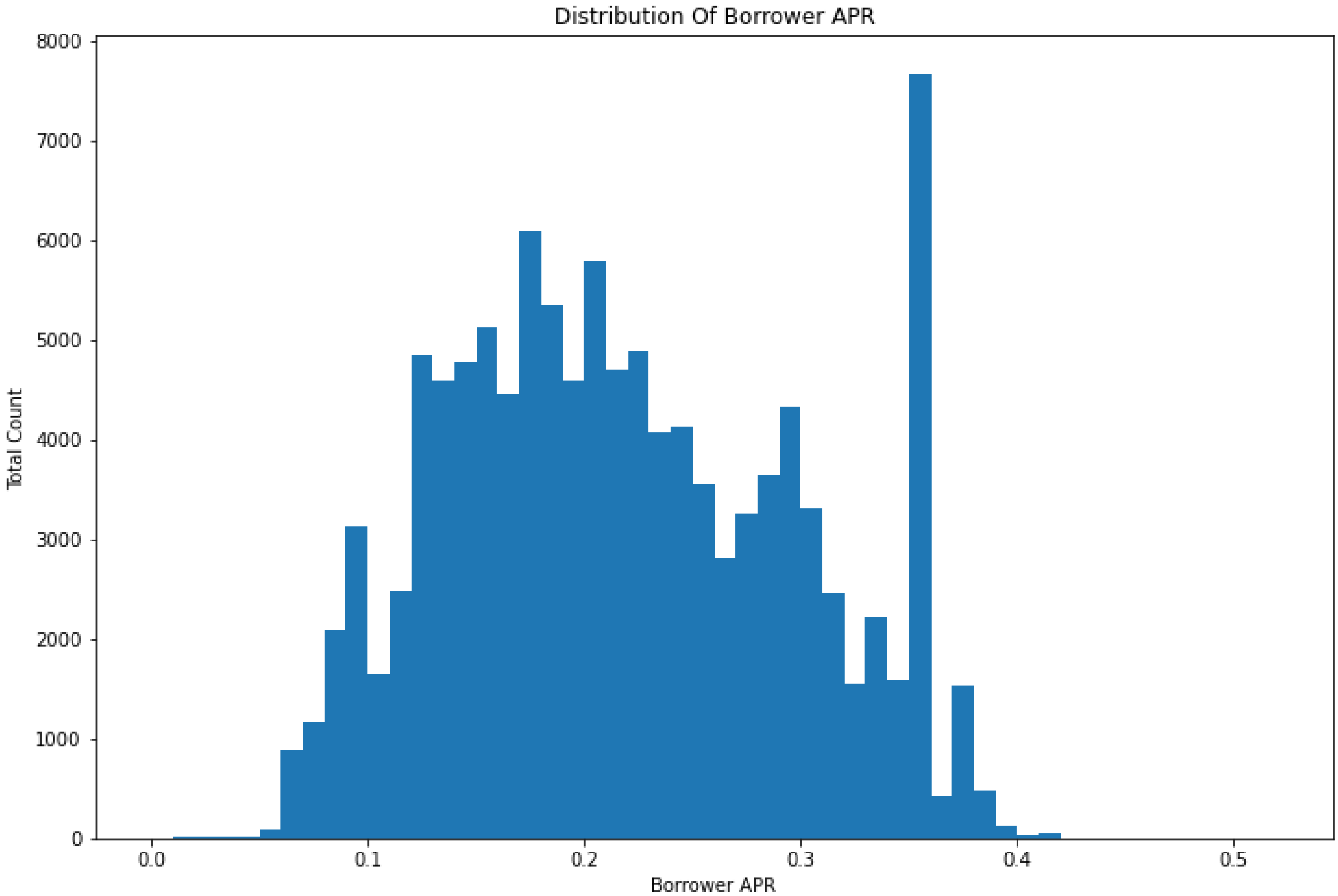
In [13]:

```
# creating a Histogram to show the Stated Monthly Income the Borrower
plt.figure(figsize = [12, 8])
bin_edges= np.arange(0, loan_subset['StatedMonthlyIncome'].max()+500, 500)
plt.hist(data= loan_subset, x = 'StatedMonthlyIncome', bins= bin_edges)
plt.xlim(0, 30000)
plt.xlabel('Stated Monthly Income')
plt.ylabel('Total count')
plt.title('Stated Monthly Income Distribution');
```



From the data displayed, it shows that the distribution of stated monthly income is right-skewed. in which most stated monthly income are less than 30k.

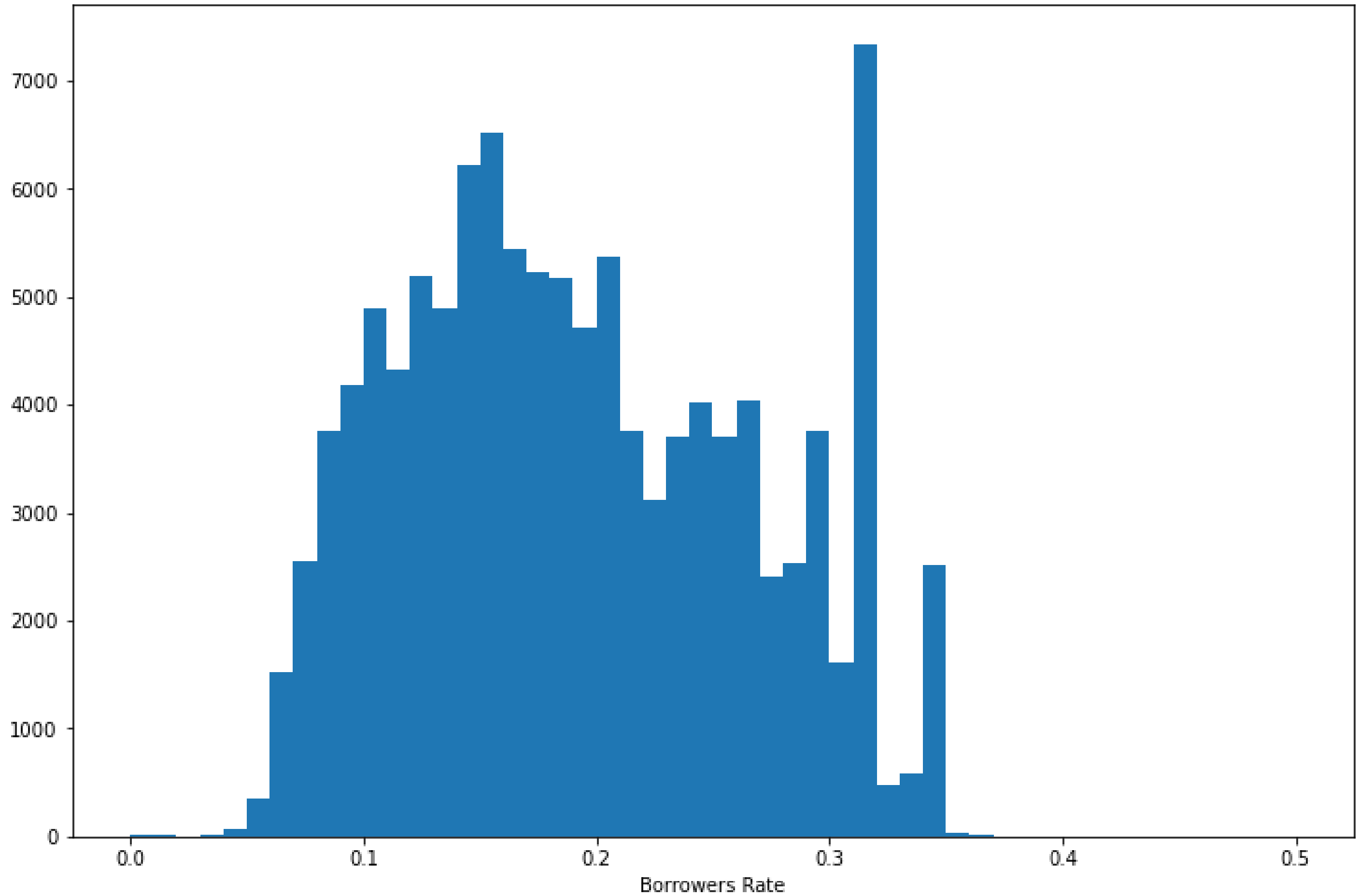
In [14]:
```
# creating a histogram to show the distribution of the borrowers APR
plt.figure(figsize = [12, 8])
bin_edge = np.arange(0, loan_subset.BorrowerAPR.max() + 0.01, 0.01)
plt.hist(data = loan_subset, x = 'BorrowerAPR', bins = bin_edge)
plt.xlabel('Borrower APR')
plt.ylabel('Total Count')
plt.title('Distribution Of Borrower APR');
```



From the distribution it shows that the peak was at 0.2. afterward, it goes on a downward trend with a peak at 0.3 and a sudden rise at 0.35.

In [15]:

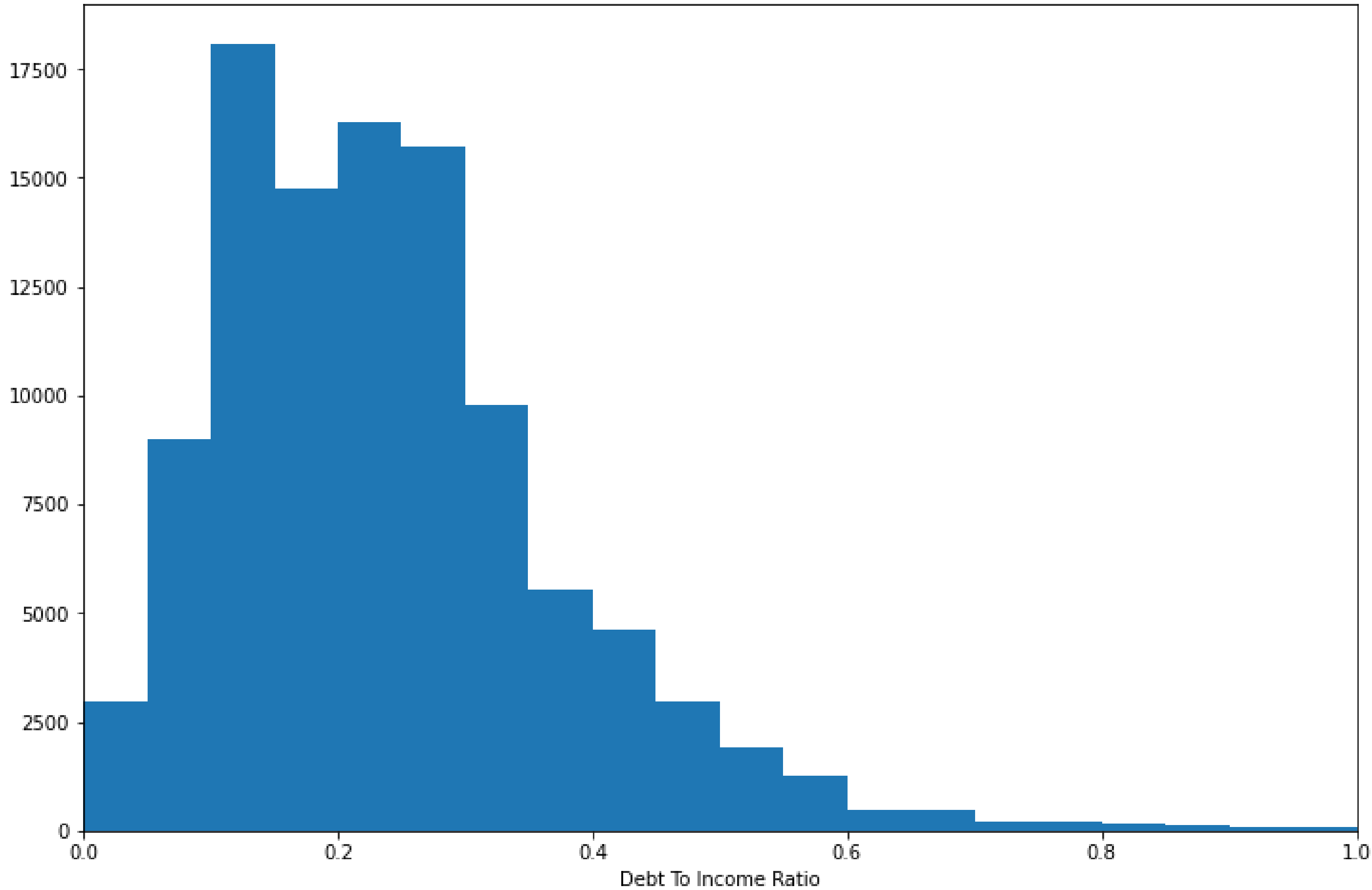
```
# creating an Histogram to show the distribution of the Borrower's Rate
plt.figure(figsize = [12, 8])
bin_edge= np.arange(0, loan_subset['BorrowerRate'].max()+0.01, 0.01)
plt.hist(data= loan_subset, x = 'BorrowerRate', bins= bin_edge)
plt.xlabel('Borrowers Rate');
```



The distribution shows almost identical to that of BorrowerAPR. with The peak around 0.15 and there is another peak a little over 0.3, which happens to be the highest peak.

In [16]:

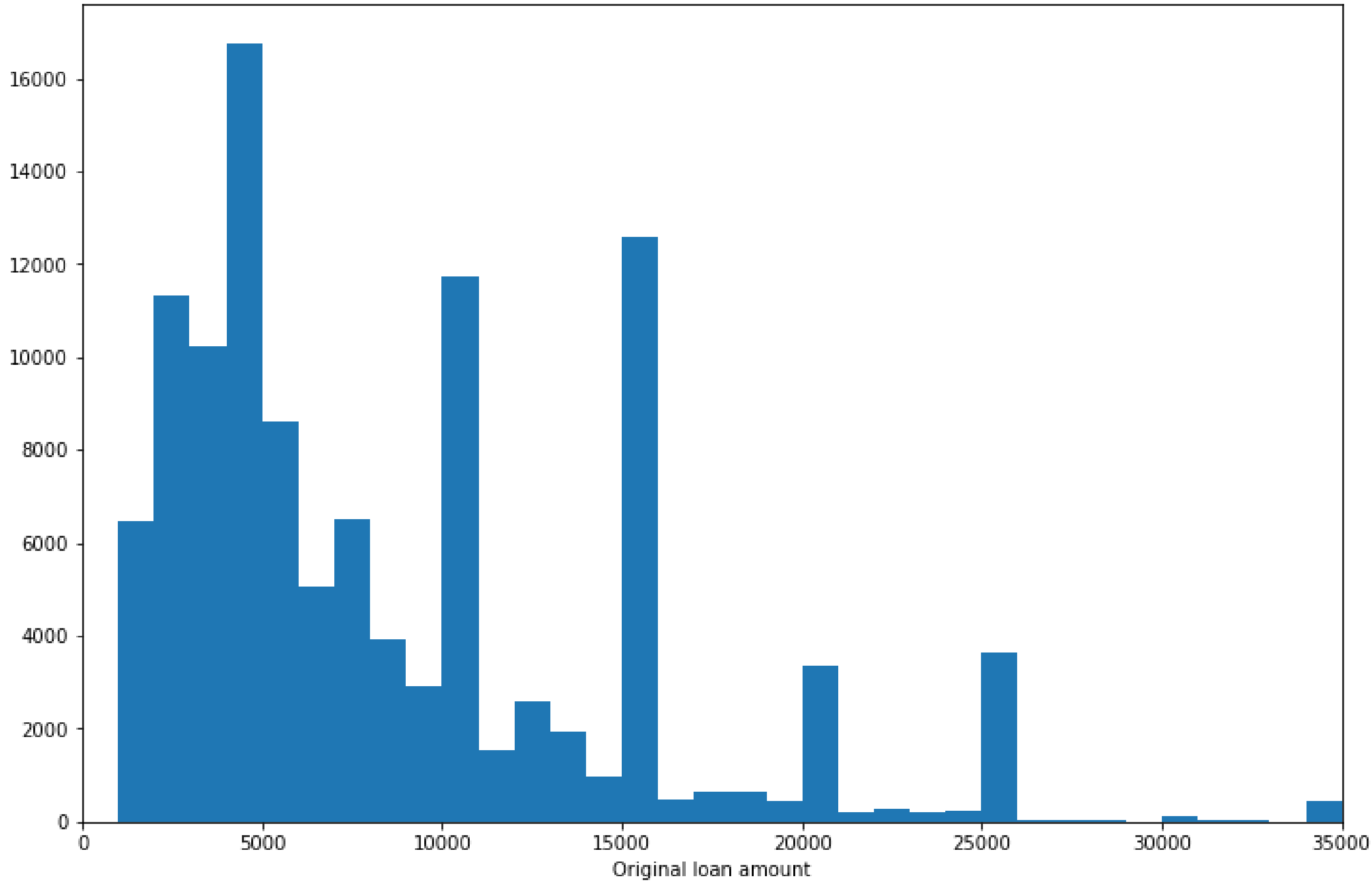
```
# creating an Histogram to show the distribution of the Borrower's DebtToIncomeRatio
plt.figure(figsize = [12, 8])
bin_edge= np.arange(0, loan_subset['DebtToIncomeRatio'].max()+0.05, 0.05)
plt.hist(data= loan_subset, x = 'DebtToIncomeRatio', bins= bin_edge)
plt.xlim(0, 1)
plt.xlabel('Debt To Income Ratio');
```



The plot shows that debt to income ratio is skewed to the right

In [17]:

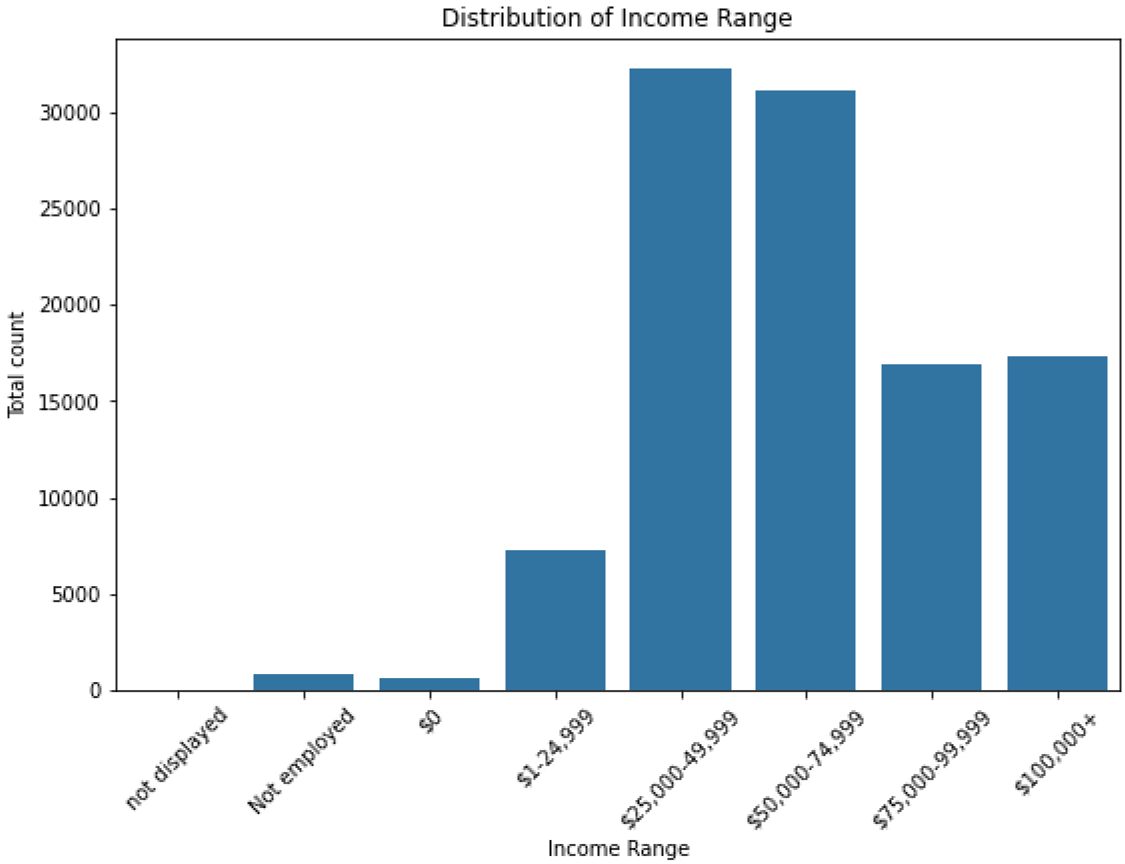
```
# creating an Histogram to show the distribution of the original loan amount
plt.figure(figsize = [12, 8])
bin_edge= np.arange(0, loan_subset['LoanOriginalAmount'].max()+1000, 1000)
plt.hist(data= loan_subset, x = 'LoanOriginalAmount', bins= bin_edge)
plt.xlim(0, 35000)
plt.xlabel('Original loan amount');
```



The original loan amount distribution shows a very large spikes at 5k, 10k, 15k, 20k, 25k respectively.

In [18]:

```
# Creating a barchart to show the distribution of IncomeRange
plt.figure(figsize = [9, 6])
color_pal = sb.color_palette()[0]
order_type = ['not displayed', 'Not employed', '$0', '$1-24,999', '$25,000-49,999',
              '$50,000-74,999','$75,000-99,999', '$100,000+']
sb.countplot(data= loan_subset, x = 'IncomeRange', color = color_pal, order = order_type)
plt.title("Distribution of Income Range")
plt.xlabel("Income Range")
plt.ylabel("Total count")
plt.xticks(rotation = 45);
```



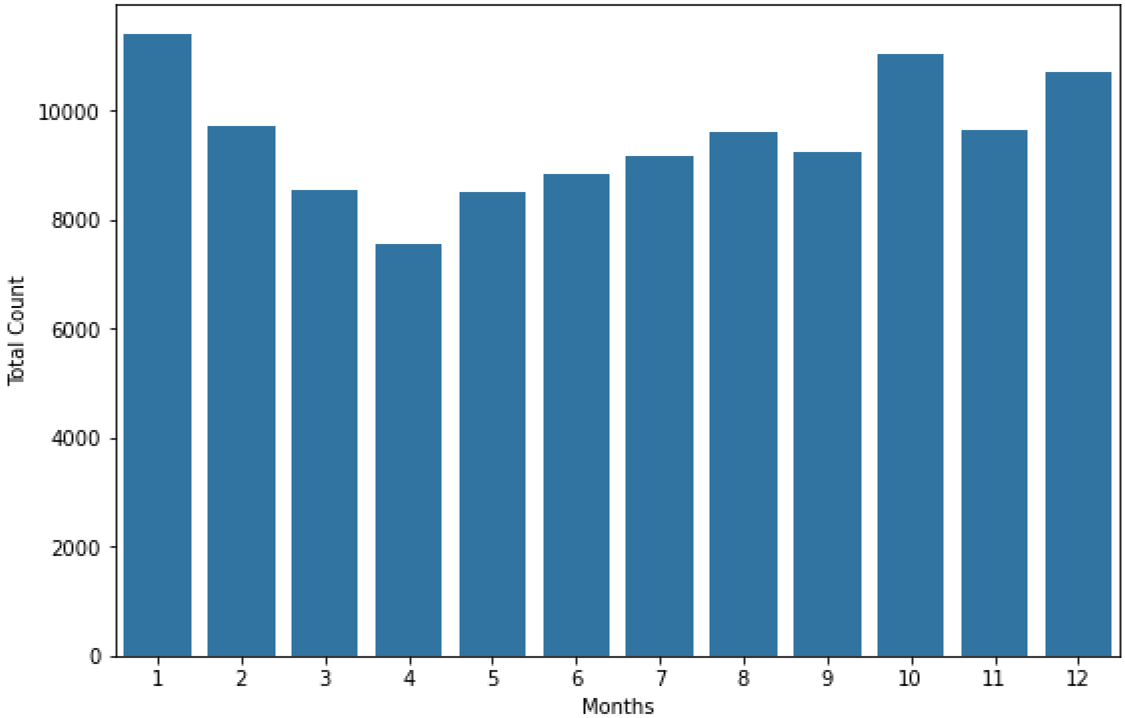
The distribution indicated that Most of the borrowers have income between the range of ($)25,000-74,999

In [19]:

```
# creating month and year columns from LoanOriginationDate
loan_subset['Month']= pd.DatetimeIndex(loan_subset['LoanOriginationDate']).month
loan_subset['Year']= pd.DatetimeIndex(loan_subset['LoanOriginationDate']).year
```

In [20]:

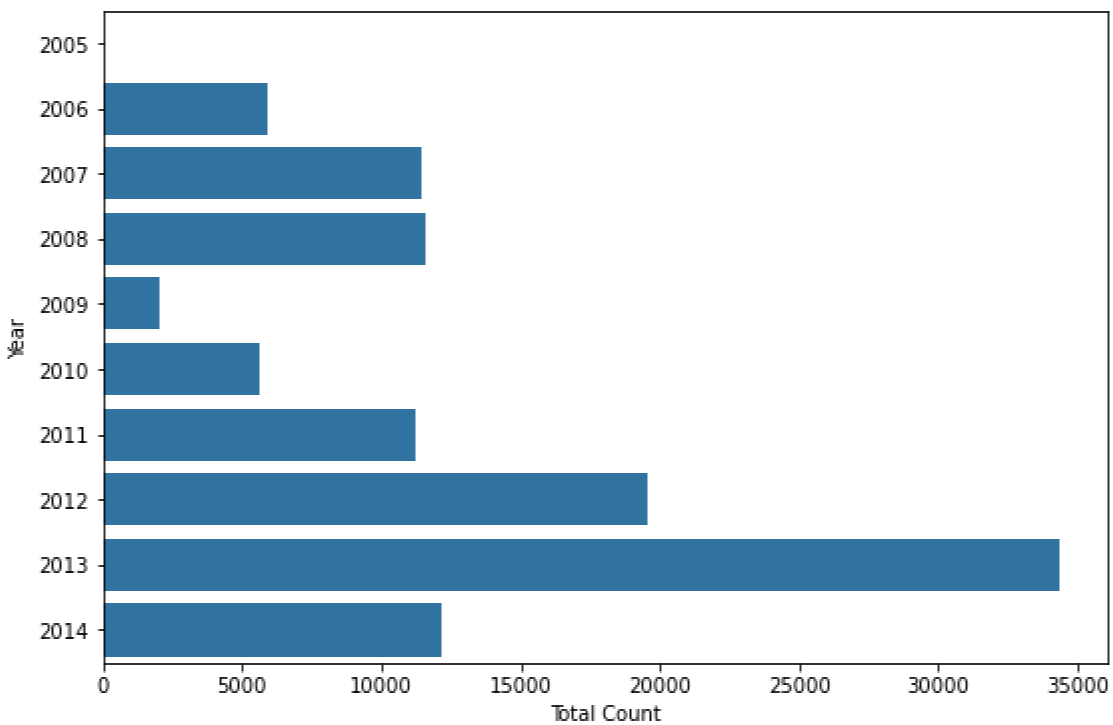
```
#creating bar chart to show the distribution of loans across months
plt.figure(figsize = [9, 6])
color_pal = sb.color_palette()[0]
sb.countplot(data= loan_subset, x = 'Month', color = color_pal)
plt.xlabel("Months")
plt.ylabel("Total Count");
```



from the distribution there are no clear indication that a particular month are the most time of loan. but it can be said that january, october,december and february has the highest

In [21]:

```
#creating bar chart to show the years distribution
plt.figure(figsize = [9, 6])
color_pal = sb.color_palette()[0]
sb.countplot(data= loan_subset, y= 'Year', color = color_pal)
plt.xlabel("Total Count")
plt.ylabel('Year');
```

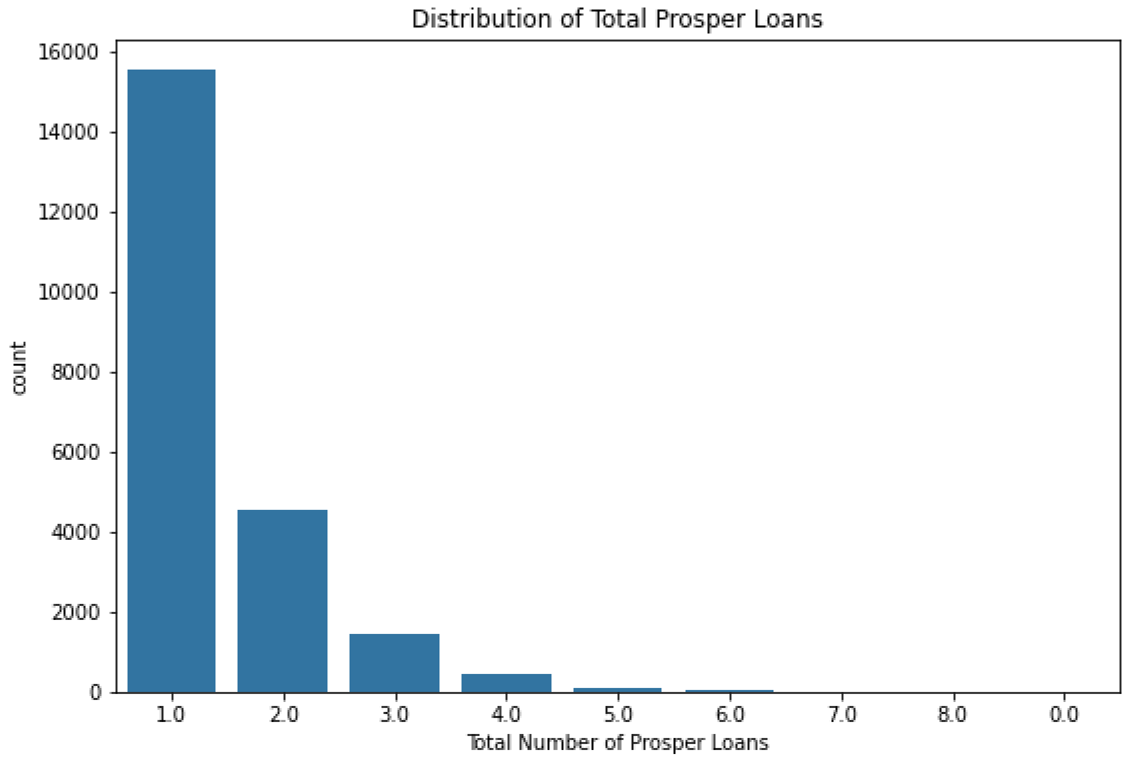


The data shows that Vast majority of the loans were taken in 2013

In [22]:

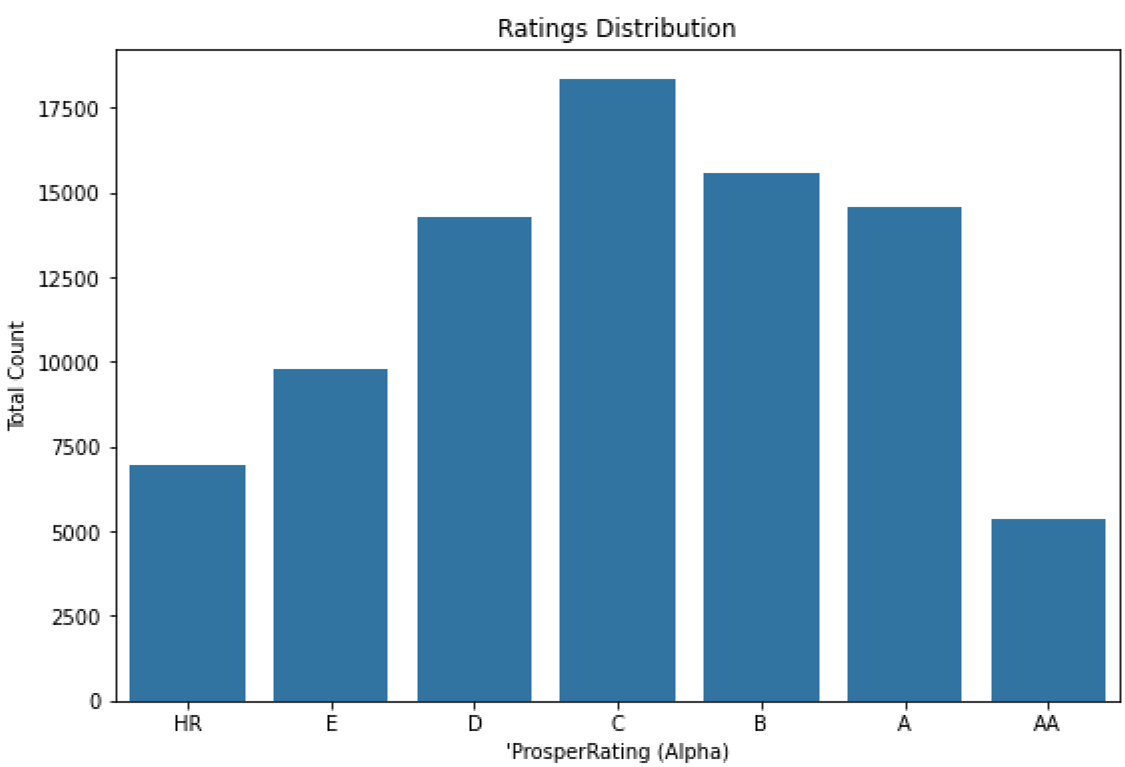
```
#creating bar chart to show the distribution of total number of loans collected by borrowe
plt.figure(figsize = [9, 6])
color_pal = sb.color_palette()[0]
```

```
num_of_loan = loan_subset['TotalProsperLoans'].value_counts().index
sb.countplot(data= loan_subset, x = 'TotalProsperLoans', color = color_pal, order = num_of
plt.xlabel('Total Number of Prosper Loans');
plt.title("Distribution of Total Prosper Loans");
```



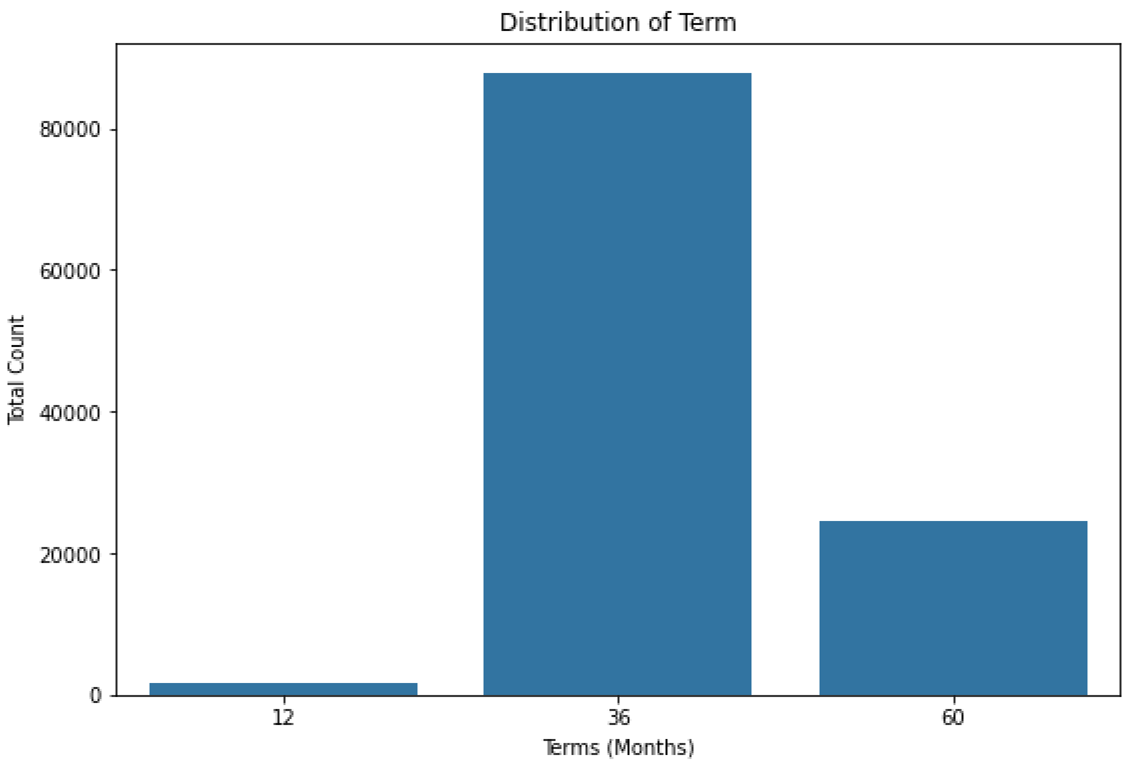
The distribution shows that most borrowers who apply for a loan have only a single prosper loan

In [23]:
```
plt.figure(figsize = [9, 6])
color_pal = sb.color_palette()[0]
rating_order = ['HR', 'E', 'D', 'C', 'B', 'A', 'AA']
sb.countplot(data= loan_subset, x= 'ProsperRating (Alpha)', color = color_pal, order = rat
plt.title('Ratings Distribution')
plt.xlabel("'ProsperRating (Alpha)")
plt.ylabel("Total Count");
```



It seems that most borrowers has the ratings, A-D. with C having the highest number of ratings

In [24]:
```
#creating bar chart to show the loan terms distribution
plt.figure(figsize = [9, 6])
color_pal = sb.color_palette()[0]
order_type = [12, 36, 60]
sb.countplot(data= loan_subset, x= 'Term', color = color_pal, order = order_type)
plt.title("Distribution of Term")
plt.xlabel("Terms (Months)")
plt.ylabel("Total Count");
```



The distribution shows that the duration (Terms) of most of the loans are 36 months

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

looking at the variables of interest,It was observed that most of the borrowers were employed and fultime, looking further to their occupations and it was observed that vast majority of the borrowers occupations were OTHERS which was an indication that thier occupation were not amongs the ones listed, i looked at Borrower's state and discovered CA has the highest borrowers and Their monthly income distribution is skewed to the right and they are usually less than 30k. Their income ratio is right skewed. The distribution also shows that the borrowers APR peak at 0.2 afterward it went on a downward trend and then peak at 0.3 and a suden spike at 0.35.i look at the borrower Rate, it has a similar distribution as the borrower APR with peak at around 0.15 and a little over 0.3 as well as their income range which mostly ranges from 25,000-74,999. Their monthly income distribution is skewed to the right and they are usually less than 30k. Their income ratio is right skewed. Most of the loans have a loan term of 36 months, instead of 12 or 60 months.

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?

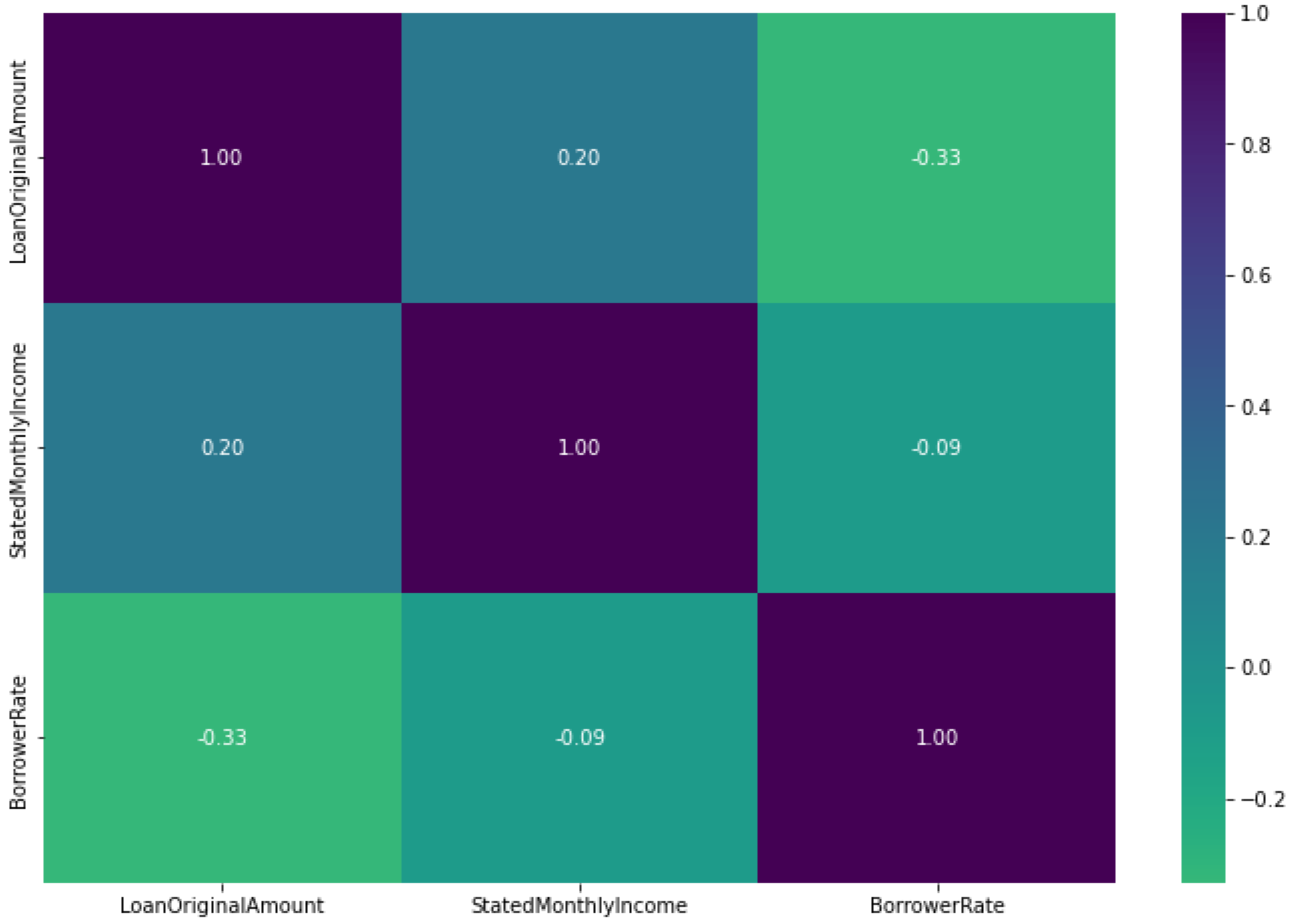
I reorder the ProsperRating (Alpha) ratings and I extracted the months and years of the loans from the loan original date and I discovered alot of loans were taken in 2013.

Bivariate Exploration

Numeric Variables and categorical Variables

In [25]:
```
numeric_vars = [ 'LoanOriginalAmount','StatedMonthlyIncome', 'BorrowerRate']
categoric_vars = ['IncomeRange', 'EmploymentStatus', 'Term', 'Year', 'IsBorrowerHomeowner'
```

In [26]:
```
# showing correlation using a heatmap plot
plt.figure(figsize = [12, 8])
sb.heatmap(loan_subset[numeric_vars].corr(), annot = True, fmt = '.2f',
           cmap = 'viridis_r', center = 0);
```



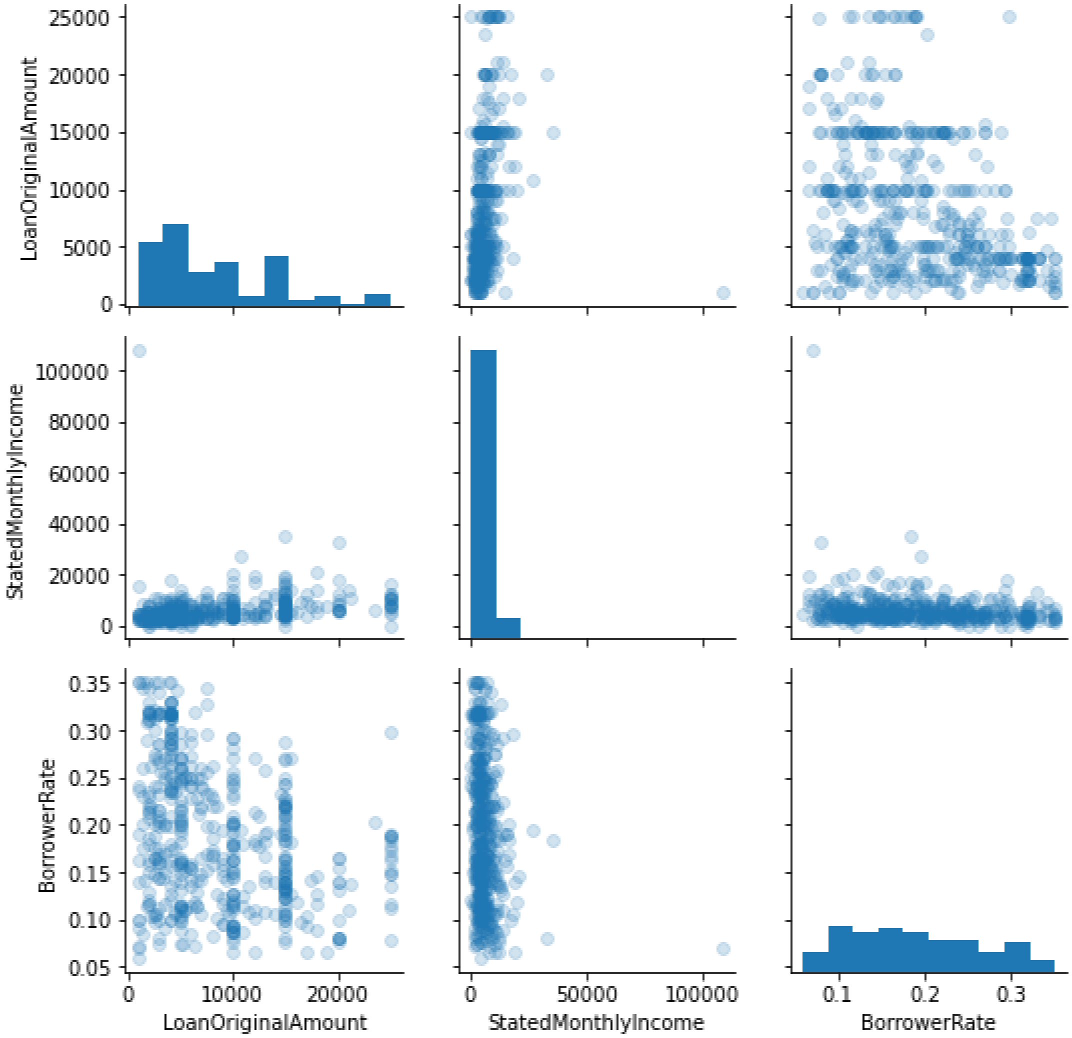
- From the heatmap it shows that Loan original amount and borrowers rate are nagatively correleted with a value of - 0.33 this indicated that the higer the borrower original amount the lowre the borrower rate on the loan.
- It also reveal that stated monthly income and loan original amount were positively correlated with a value point of 0.20 this indicated that the the higer the monthly income stated by the borrower the higher the loan gotten.
- However there is a low and nagative The correlation between stated monthly income and borrower rate with a value of -0.09.

In [27]:
```
# plot matrix: sample 500 observation so that plots are clearer and they render faster
print("loan_subset.shape=",loan_subset.shape)
loan_subset_samp = loan_subset.sample(n=500, replace = False)
print("loan_subset_samp.shape=",loan_subset_samp.shape)

g = sb.PairGrid(data = loan_subset_samp, vars = numeric_vars)
```

```
g = g.map_diag(plt.hist, bins = 10);
g.map_offdiag(plt.scatter , alpha = 1/5);
```

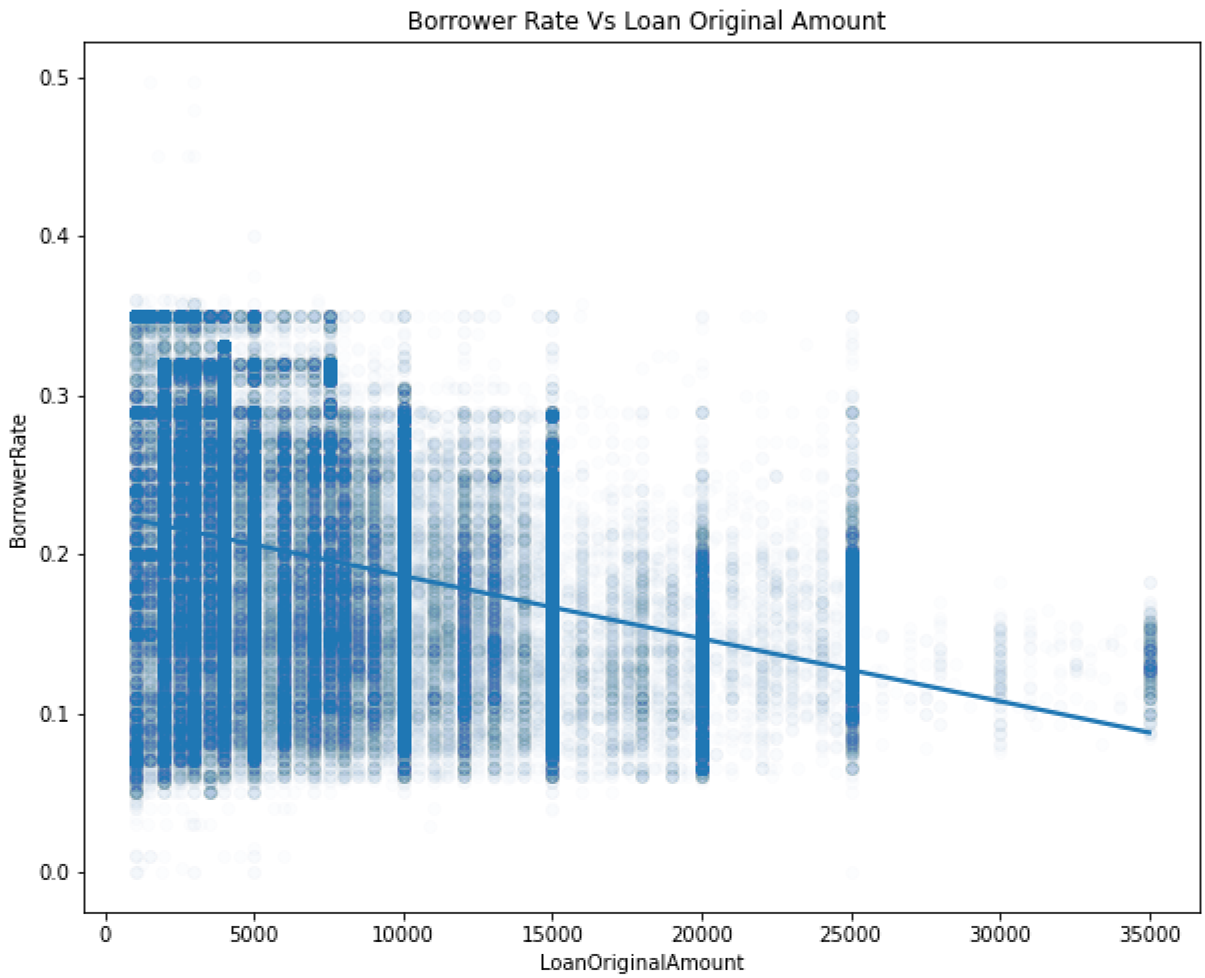
```
loan_subset.shape= (113937, 18)
loan_subset_samp.shape= (500, 18)
```



- The loan original amount is positively correlated with the stated monthly income.
- The borrowerRate is negatively correlated with loan amount.

In [28]:

```
# looking at how borrowerRate and loan original amount are related to one another for all
plt.figure(figsize = [10, 8])
sb.regplot(data = loan_subset, x = 'LoanOriginalAmount', y = 'BorrowerRate', scatter_kws=
plt.title(' Borrower Rate Vs Loan Original Amount');
```

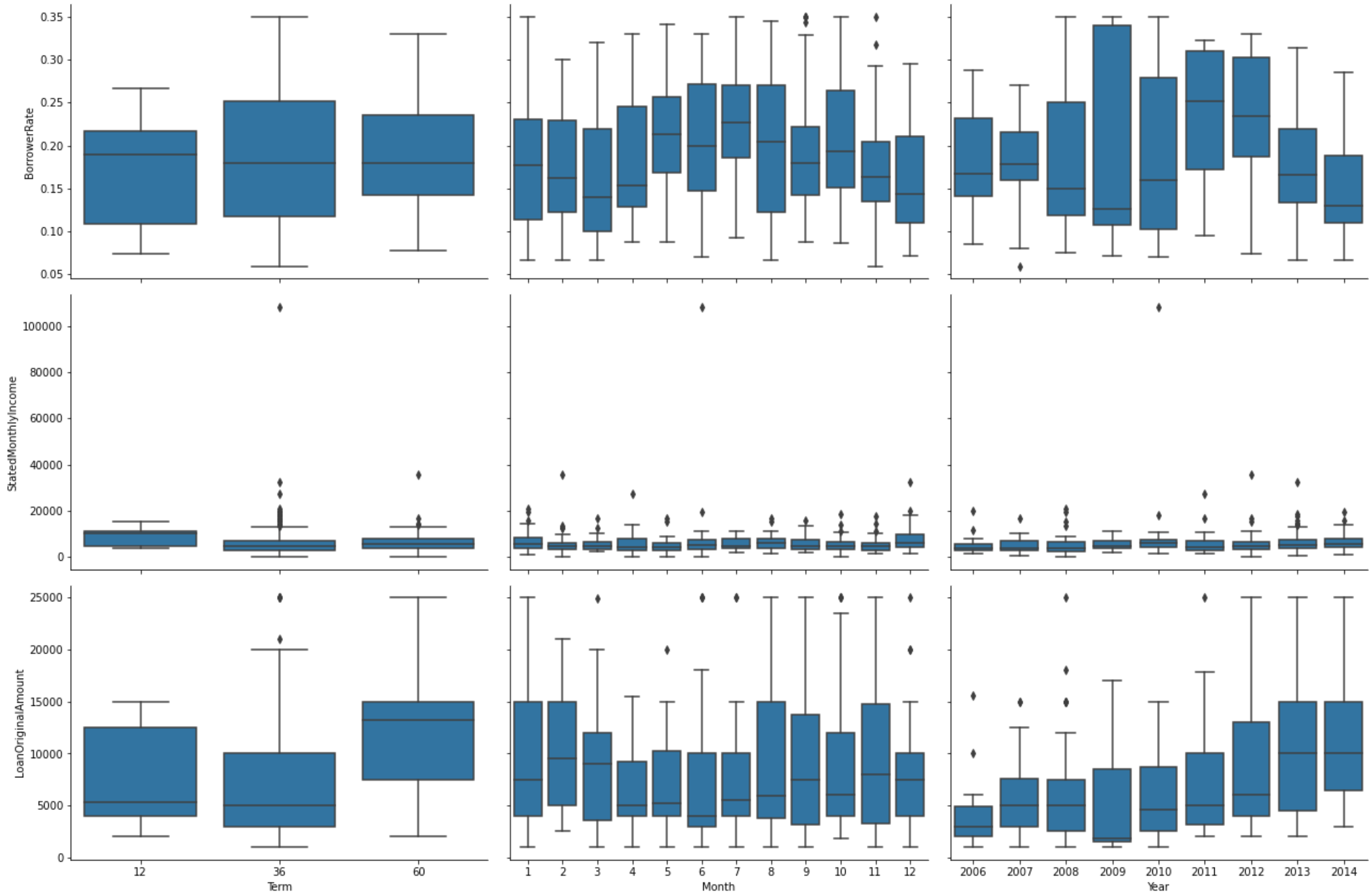


the plots indicated that at different size of the loan amount, the BorrowerRate has a large range, but the range of BorrowerRate decrease with the increase of loan amount.

In [29]:
```
#Looking at how borrower Rate, stated monthly income and loan original amount correlate wi
#plotting matrix of numeric features against categorical features.
categorical_vars = ['Term', 'Month','Year']
#def boxgrid function
def boxgrid(x, y, **kwargs):
    """ Quick hack for creating box plots with seaborn's PairGrid. """
    default_color = sb.color_palette()[0]
    sb.boxplot(x, y, color = default_color)

plt.figure(figsize = [12, 8])
g = sb.PairGrid(data = loan_subset_samp, y_vars = ['BorrowerRate', 'StatedMonthlyIncome',
                x_vars = categorical_vars, height = 4, aspect = 1.5)
g.map(boxgrid);
```

```
<Figure size 864x576 with 0 Axes>
```



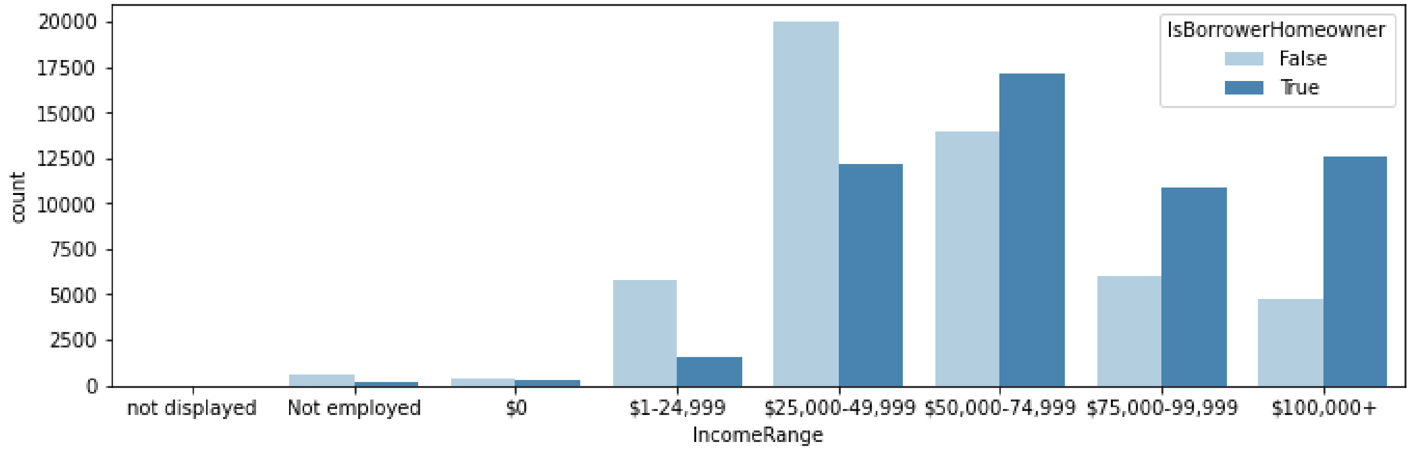
from the visuals is can be observed that thereare a strong positive relationship between term and loan amount that is the longer the loan term, the larger the loan I observed that in 2009 there was a large dip in loan origination then went back up in 2013.

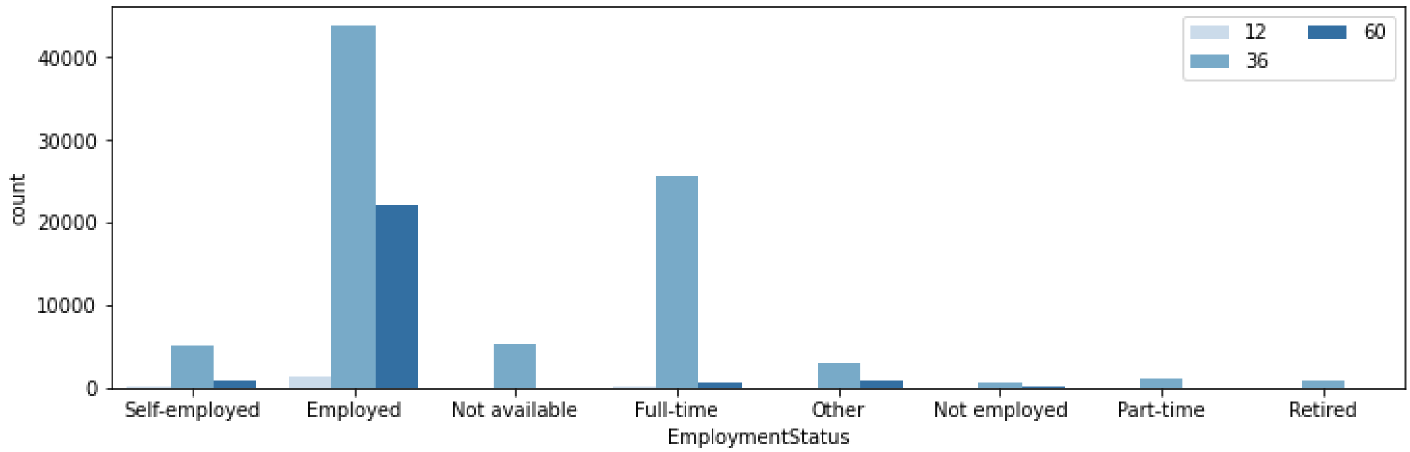
In [30]:

```
#further investigation into relationship between variables
plt.figure(figsize = [12, 8])
order = ['not displayed', 'Not employed', '$0', '$1-24,999', '$25,000-49,999', '$50,000-74
# subplot 1: Income Range vs Is BorrowerHomeowner
plt.subplot(2, 1, 1)
sb.countplot(data = loan_subset, x = 'IncomeRange', hue = 'IsBorrowerHomeowner', order=orc

# subplot 2: employment status vs. term
ax = plt.subplot(2, 1, 2)
sb.countplot(data = loan_subset, x = 'EmploymentStatus', hue = 'Term', palette = 'Blues')

ax.legend(loc = 1, ncol = 2);
```





- Borrowers with income range from ($)50,000-100,000+ are mostly homeowners
- Borrowers with full time employment status tend to take loans with term duration of 12months while
- Borrowers that Employed tend to take loans of term duration as 36 months

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?

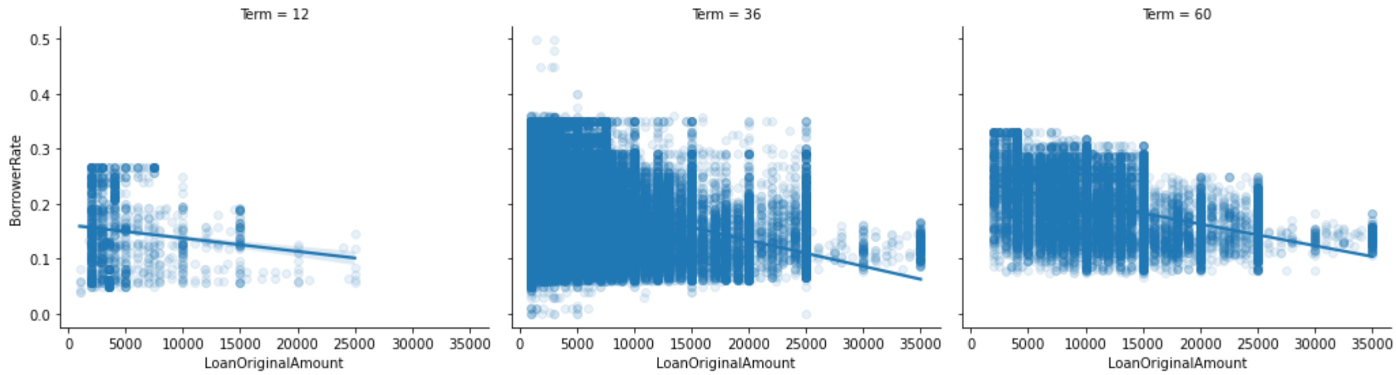
The borrower interest Rate is negatively correlated with the loan original amount, which mean the more the loan amount, the lower the Borrower Rate. It also shows that at different size of the loan amount, the Rate has a large range, but the range of interest Rate decrease with the increase of loan amount. The loan original amount is positively correlated with the stated monthly income. That is, the higher their stated monthly income, the higher the loan amount borrowed. Borrowers with verified income tend to have a higher average loan amount than borrowers without verified income. Borrowers who are employed and fulltime on average take out larger loans than other groups.

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

I observed that Borrowers with income ranging from ($)50,000-100,000+ aremostly homeowners and also Borrowers with full time employment status tend to take loans with term duration of 12 months Employed borrowers tend to take loans of term duration as 36months. i also observed that from the visuals is can be observed that thereare a strong positive relationship between term and loan amount that is the longer the loan term, the larger the loan I observed that in 2009 there was a large dip in loan origination then went back up in 2013.

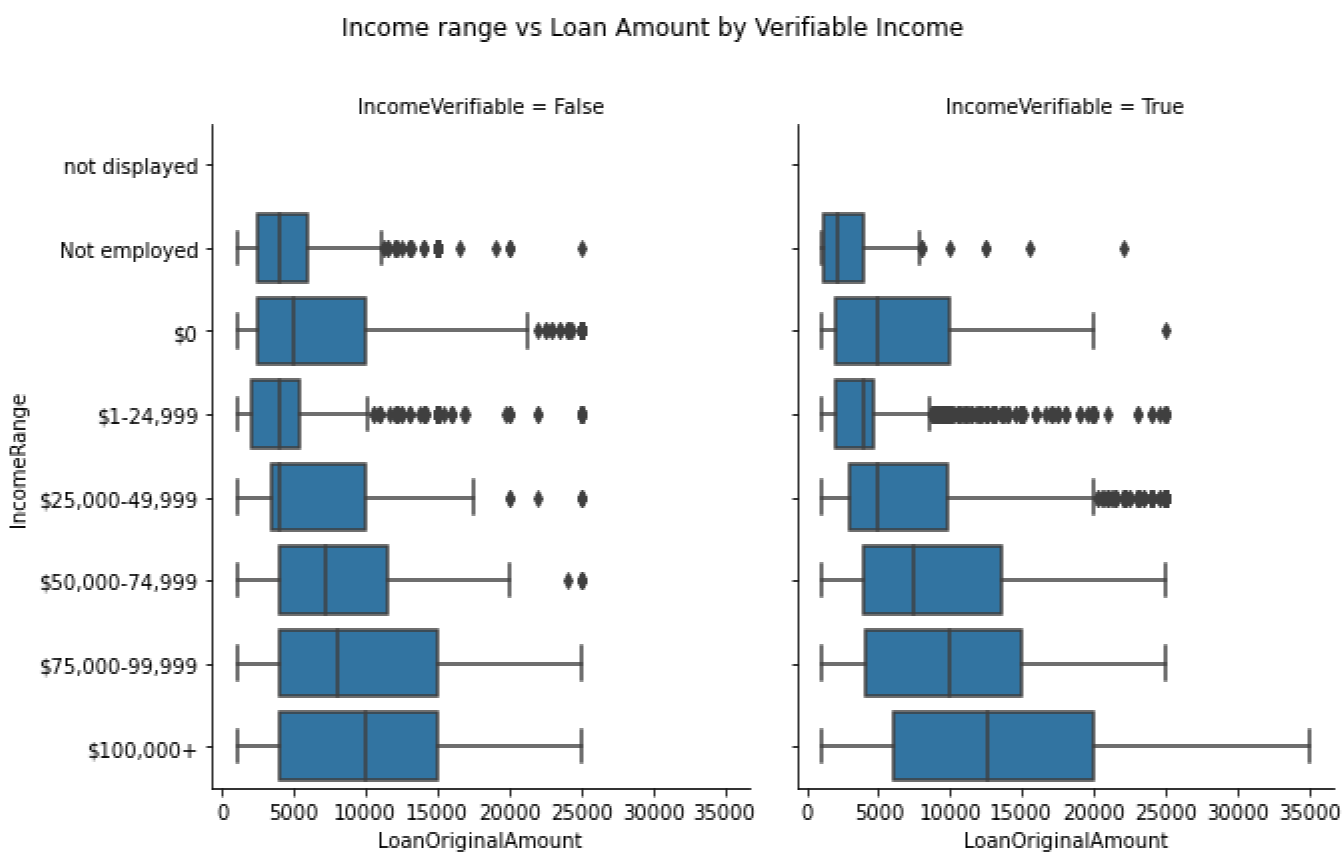
Multivariate Exploration

In [31]:
```
# investigating further the Term effect on relationship of BorrowerRate and loan amount
g=sb.FacetGrid(data=loan_subset, aspect=1.2, height=4, col='Term', col_wrap=3)
g.map(sb.regplot, 'LoanOriginalAmount', 'BorrowerRate', x_jitter=0.04, scatter_kws={'alpha
g.add_legend();
```



Its shows that Term doesnt really seem to have effect on the relationship between borrower rate and loan original amount

In [32]:
```
# investigating the effect a verified income has on the relationship between loan origina
order = ['not displayed', 'Not employed', '$0', '$1-24,999', '$25,000-49,999', '$50,000-74
box= sb.FacetGrid(data= loan_subset, col = 'IncomeVerifiable', height = 4)
box.map(sb.boxplot, 'LoanOriginalAmount', 'IncomeRange', order = order)
plt.suptitle('Income range vs Loan Amount by Verifiable Income', y = 1.04)
box.fig.set_size_inches(10,6);
```



The data shows that those who earn 100,000+ and have verified their income tend to get larger loan original amount than those whose income are not verifiable. The borrowers with verified incomes tend to get higher loan amounts.

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 does'nt really seem to have effect on the relationship between borrower rate
and loan original amount
```

Were there any interesting or surprising interactions between features?

```
The data shows that those who earn 100,000+ and have verified their income tend to
get larger loan original amount than those whose income are not verifiable. The
borrowers with verified incomes tend to get higher loan amounts.
```

Conclusions

For this exploratory analysis, my main interest was to analyze the information related to the profile of the borrowers and the loan borrowed. Exploring the distribution of uni variables of interest, one of the insightful information discovered was that most of the borrowers were employed and fultime, looking also further to their occupations and it was observed that vast majority of the borrowers occupations were OTHERS which was an indication that thier occupation were not amongs the ones listed, i looked at Borrower's state and discovered CA (califonia) has the highest borrowers and Their monthly income distribution is skewed to the right and they are usually less than 30k. the borrowers income mostly ranges from 25,000-74,999. Their monthly income distribution is skewed to the right and they are usually less than 30k. Their income ratio is right skewed. Most of the loans have a loan term of 36 months, instead of 12 or 60 months.when i extracted the months and years of the loans from the loan original date and I discovered alot of loans were taken in 2013. Investigating further to observe the relationships between 2 variables each of the data, then i discovered that the borrower interest Rate is negatively correlated with the loan original amount, which mean the more the loan amount, the lower the Borrower Rate. It also shows that at different size of the loan amount, the Rate has a large range, but the range of interest Rate decrease with the increase of loan amount. The loan original amount is positively correlated with the stated monthly income. That is, the higher their stated monthly income, the higher the loan amount borrowed. Borrowers with verified income tend to have a higher average loan amount than borrowers without verified income. Borrowers who are employed and fulltime on average take out larger loans than other groups. I observed that Borrowers with income ranging from 50,000-100,000+ aremostly homeowners and also Borrowers with full time employment status tend to take loans with term duration of 12 months Employed borrowers tend to take loans of term duration as 36months. i also observed that from the visuals is can be observed that thereare a strong positive relationship between term and loan amount that is the longer the loan term, the larger the loan I observed that in 2009 there was a large dip in loan origination then went back up in 2013. Further investigation using multiple variables,i found out that loan term doesn't really seems to have an effect on the relationship between borrower rate and loan original amount and i also observed that those who earn 100,000+ and have verified their income tend to get larger loan original amount than those whose income are not verifiable. The borrowers with verified incomes tend to get higher loan.

The major challenge faced in this project was deciding on which variables of interest to really focus on as the loan dataset has 81 variables.

I referenced Stackoverflow and Udacity platform and other online platforms in the course of working on this projects.

In [ ]: