Part_I_notebook

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1 Part I - Loan Data from Prosper Dataset Exploration

1.1 by Isaac Mwendwa

1.2 Introduction

- The Loan Data from Prosper Dataset is a dataset of loans taken between 2005 and 2013 from Prosper
- The dataset contains 113,937 rows (loans) with 81 columns (loan variables) on each row
- In this exploratory analysis, we will be seeking to find insights on the relationships between the various loan variables e.g. > Borrower's APR, Prosper Score, Income Range, Debt to Income Ratio, Employment Status, Stated Monthly Income, Loan Year, and Employment Duration

1.2.1 Preliminary Wrangling

Importing Packages

```
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]: # Checking path of working directory
        !pwd
```

```
/home/workspace
```

1.2.2 Loading Dataset

Defining Path of Working Directory

```
In [3]: # Working Directory Path
        working_dir = '/home/workspace/'
```

```
In [4]: # Reading dataset into Pandas Dataframe

        original_loans_df = pd.read_csv(working_dir + "prosperLoanData.csv")

In [5]: # Making copy of dataset
        loans_df = original_loans_df.copy()
```

Data Exploration

```
In [6]: # Checking shape of dataframe
        loans_df.shape

Out[6]: (59412, 81)

In [7]: # Displaying columns
        loans_df.columns

Out[7]: Index(['ListingKey', 'ListingNumber', 'ListingCreationDate', 'CreditGrade',
               'Term', 'LoanStatus', 'ClosedDate', 'BorrowerAPR', 'BorrowerRate',
               'LenderYield', 'EstimatedEffectiveYield', 'EstimatedLoss',
               'EstimatedReturn', 'ProsperRating (numeric)', 'ProsperRating (Alpha)',
               'ProsperScore', 'ListingCategory (numeric)', 'BorrowerState',
               'Occupation', 'EmploymentStatus', 'EmploymentStatusDuration',
               'IsBorrowerHomeowner', 'CurrentlyInGroup', 'GroupKey',
               'DateCreditPulled', 'CreditScoreRangeLower', 'CreditScoreRangeUpper',
               'FirstRecordedCreditLine', 'CurrentCreditLines', 'OpenCreditLines',
               'TotalCreditLinespast7years', 'OpenRevolvingAccounts',
               'OpenRevolvingMonthlyPayment', 'InquiriesLast6Months', 'TotalInquiries',
               'CurrentDelinquencies', 'AmountDelinquent', 'DelinquenciesLast7Years',
               'PublicRecordsLast10Years', 'PublicRecordsLast12Months',
               'RevolvingCreditBalance', 'BankcardUtilization',
               'AvailableBankcardCredit', 'TotalTrades',
               'TradesNeverDelinquent (percentage)', 'TradesOpenedLast6Months',
               'DebtToIncomeRatio', 'IncomeRange', 'IncomeVerifiable',
               'StatedMonthlyIncome', 'LoanKey', 'TotalProsperLoans',
               'TotalProsperPaymentsBilled', 'OnTimeProsperPayments',
               'ProsperPaymentsLessThanOneMonthLate',
               'ProsperPaymentsOneMonthPlusLate', 'ProsperPrincipalBorrowed',
               'ProsperPrincipalOutstanding', 'ScorexChangeAtTimeOfListing',
               'LoanCurrentDaysDelinquent', 'LoanFirstDefaultedCycleNumber',
               'LoanMonthsSinceOrigination', 'LoanNumber', 'LoanOriginalAmount',
               'LoanOriginationDate', 'LoanOriginationQuarter', 'MemberKey',
               'MonthlyLoanPayment', 'LP_CustomerPayments',
               'LP_CustomerPrincipalPayments', 'LP_InterestandFees', 'LP_ServiceFees',
               'LP_CollectionFees', 'LP_GrossPrincipalLoss', 'LP_NetPrincipalLoss',
               'LP_NonPrincipalRecoverypayments', 'PercentFunded', 'Recommendations',
               'InvestmentFromFriendsCount', 'InvestmentFromFriendsAmount',
               'Investors'],
              dtype='object')
```

```
In [8]: # Checking info
        loans_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 59412 entries, 0 to 59411
Data columns (total 81 columns):
ListingKey                          59412 non-null object
ListingNumber                       59412 non-null int64
ListingCreationDate                 59412 non-null object
CreditGrade                         15113 non-null object
Term                                59412 non-null int64
LoanStatus                          59412 non-null object
ClosedDate                          28811 non-null object
BorrowerAPR                         59405 non-null float64
BorrowerRate                        59412 non-null float64
LenderYield                         59412 non-null float64
EstimatedEffectiveYield             44233 non-null float64
EstimatedLoss                       44233 non-null float64
EstimatedReturn                     44233 non-null float64
ProsperRating (numeric)             44233 non-null float64
ProsperRating (Alpha)               44233 non-null object
ProsperScore                        44233 non-null float64
ListingCategory (numeric)           59412 non-null int64
BorrowerState                       56538 non-null object
Occupation                          57573 non-null object
EmploymentStatus                    58250 non-null object
EmploymentStatusDuration            55419 non-null float64
IsBorrowerHomeowner                 59412 non-null bool
CurrentlyInGroup                    59412 non-null bool
GroupKey                            6960 non-null object
DateCreditPulled                    59412 non-null object
CreditScoreRangeLower               59102 non-null float64
CreditScoreRangeUpper               59102 non-null float64
FirstRecordedCreditLine             59052 non-null object
CurrentCreditLines                  55433 non-null float64
OpenCreditLines                     55433 non-null float64
TotalCreditLinespast7years          59052 non-null float64
OpenRevolvingAccounts               59412 non-null int64
OpenRevolvingMonthlyPayment         59412 non-null float64
InquiriesLast6Months                59052 non-null float64
TotalInquiries                      58808 non-null float64
CurrentDelinquencies                59052 non-null float64
AmountDelinquent                    55423 non-null float64
DelinquenciesLast7Years             58893 non-null float64
PublicRecordsLast10Years            59052 non-null float64
PublicRecordsLast12Months           55433 non-null float64
RevolvingCreditBalance              55433 non-null float64
BankcardUtilization                 55433 non-null float64
```

```
AvailableBankcardCredit                55456 non-null float64
TotalTrades                            55456 non-null float64
TradesNeverDelinquent (percentage)     55456 non-null float64
TradesOpenedLast6Months                55456 non-null float64
DebtToIncomeRatio                      55017 non-null float64
IncomeRange                            59412 non-null object
IncomeVerifiable                       59412 non-null bool
StatedMonthlyIncome                    59412 non-null float64
LoanKey                                59412 non-null object
TotalProsperLoans                      11488 non-null float64
TotalProsperPaymentsBilled             11488 non-null float64
OnTimeProsperPayments                  11488 non-null float64
ProsperPaymentsLessThanOneMonthLate    11488 non-null float64
ProsperPaymentsOneMonthPlusLate        11488 non-null float64
ProsperPrincipalBorrowed               11488 non-null float64
ProsperPrincipalOutstanding            11488 non-null float64
ScorexChangeAtTimeOfListing            9807 non-null float64
LoanCurrentDaysDelinquent              59412 non-null int64
LoanFirstDefaultedCycleNumber          8802 non-null float64
LoanMonthsSinceOrigination             59412 non-null int64
LoanNumber                             59412 non-null int64
LoanOriginalAmount                     59412 non-null int64
LoanOriginationDate                    59412 non-null object
LoanOriginationQuarter                 59412 non-null object
MemberKey                              59412 non-null object
MonthlyLoanPayment                     59412 non-null float64
LP_CustomerPayments                    59412 non-null float64
LP_CustomerPrincipalPayments           59412 non-null float64
LP_InterestandFees                     59412 non-null float64
LP_ServiceFees                         59412 non-null float64
LP_CollectionFees                      59412 non-null float64
LP_GrossPrincipalLoss                  59412 non-null float64
LP_NetPrincipalLoss                    59412 non-null float64
LP_NonPrincipalRecoverypayments        59412 non-null float64
PercentFunded                          59412 non-null float64
Recommendations                        59412 non-null int64
InvestmentFromFriendsCount             59411 non-null float64
InvestmentFromFriendsAmount            59411 non-null float64
Investors                              59411 non-null float64
dtypes: bool(3), float64(52), int64(9), object(17)
memory usage: 35.5+ MB
```

```
In [9]: # Checking first 5 rows
        loans_df.head()
```

```
Out[9]:                 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                        0.0
1            1.0               0                        0.0
2            1.0               0                        0.0
3            1.0               0                        0.0
4            1.0               0                        0.0

  InvestmentFromFriendsAmount Investors
0                         0.0     258.0
1                         0.0       1.0
2                         0.0      41.0
3                         0.0     158.0
4                         0.0      20.0

[5 rows x 81 columns]
```

In [10]:
```
# Summary Statistics
loans_df.describe()
```

Out[10]:
```
        ListingNumber          Term   BorrowerAPR  BorrowerRate   LenderYield  \
count    5.941200e+04  59412.000000  59405.000000  59412.000000  59412.000000
mean     6.278298e+05     40.839022      0.218537      0.192533      0.182472
```

```
std     3.279907e+05     10.428700      0.080479      0.074928      0.074631
min     6.000000e+00     12.000000      0.008640      0.000000     -0.010000
25%     4.011632e+05     36.000000      0.156290      0.133400      0.123400
50%     5.998795e+05     36.000000      0.209310      0.183000      0.173000
75%     8.927868e+05     36.000000      0.283700      0.250000      0.240000
max     1.255725e+06     60.000000      0.512290      0.497500      0.492500

       EstimatedEffectiveYield  EstimatedLoss  EstimatedReturn  \
count             44233.000000   44233.000000     44233.000000
mean                  0.168491       0.080243         0.095954
std                   0.068681       0.046867         0.030486
min                  -0.182700       0.004900        -0.182700
25%                   0.115670       0.042400         0.074080
50%                   0.161500       0.069900         0.091670
75%                   0.224300       0.112000         0.116000
max                   0.319900       0.366000         0.266700

       ProsperRating (numeric)  ProsperScore      ...       LP_ServiceFees  \
count             44233.000000  44233.000000      ...         59412.000000
mean                  4.076278      5.963037      ...           -54.826156
std                   1.674205      2.380051      ...            60.945439
min                   1.000000      1.000000      ...          -664.870000
25%                   3.000000      4.000000      ...           -73.100000
50%                   4.000000      6.000000      ...           -34.345000
75%                   5.000000      8.000000      ...           -13.820000
max                   7.000000     11.000000      ...            32.060000

       LP_CollectionFees  LP_GrossPrincipalLoss  LP_NetPrincipalLoss  \
count       59412.000000           59412.000000         59412.000000
mean          -14.342215             700.978853           681.918460
std           113.685235            2390.357809          2361.600427
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                     59412.000000   59412.000000     59412.000000
mean                         25.072823       0.998644         0.046590
std                         273.595838       0.017434         0.334387
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       1.004500        39.000000

       InvestmentFromFriendsCount  InvestmentFromFriendsAmount     Investors
```

```
count                59411.000000                59411.000000  59411.000000
mean                     0.022689                   16.091847     80.434785
std                      0.251955                  292.990208    103.120866
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   1035.000000

[8 rows x 61 columns]
```

```
In [11]: # Remove loans with missing missing features of interest
         loans_df = loans_df[~loans_df['BorrowerAPR'].isna()]
         loans_df = loans_df[~loans_df['ProsperScore'].isna()]
         loans_df = loans_df[~loans_df['EmploymentStatusDuration'].isna()]
         loans_df = loans_df[~loans_df['DebtToIncomeRatio'].isna()]

         loans_df.shape
```

```
Out[11]: (40481, 81)
```

1.2.3 What is the structure of your dataset?

- The dataset contains 113,937 rows (loans) with 81 columns (loan variables)
- The loan variables consist of qualitative (ordinal and nominal) and quantitative features

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

The main features of interest (response variables) in the dataset include: * Borrower's APR * Prosper Score * Debt to Income Ratio

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

The predictor features include: * Income Range * Employment Status * Stated Monthly Income * Loan Year * Employment Duration

1.3 Univariate Exploration

- Here, we will look at the distributions of single variables
- The exploration will first start with the distribution of the response features, and then proceed to the distribution of the predictor variables
- We will define some univariate plotting functions, to prevent code repetition and increase code re-usability

1.3.1 Definition of Plotting Functions

Vertical Bar Chart Function Definition

```
In [12]: # function to draw vertical bar chart

         def vertical_bar_chart(df, column):

             base_color = sb.color_palette()[0]
             sb.countplot(data = df, x = column, color = base_color)
```

Horizontal Bar Chart Function Definition

```
In [13]: # Function to plot horizontal bar chart

         def draw_horizontal_bar(df_column, title):
           data_series = df_column.value_counts().sort_values()
           ax = data_series.plot(kind="barh", figsize=(10, 6), color='#6495ED', zorder=2, width=
           ax.set_title(title, weight='bold', size=12)
           # Draw vertical axis lines
           vals = ax.get_xticks()
           for tick in vals:
             ax.axvline(x=tick, linestyle='dashed', alpha=0.4, color='#eeeeee', zorder=1)
```

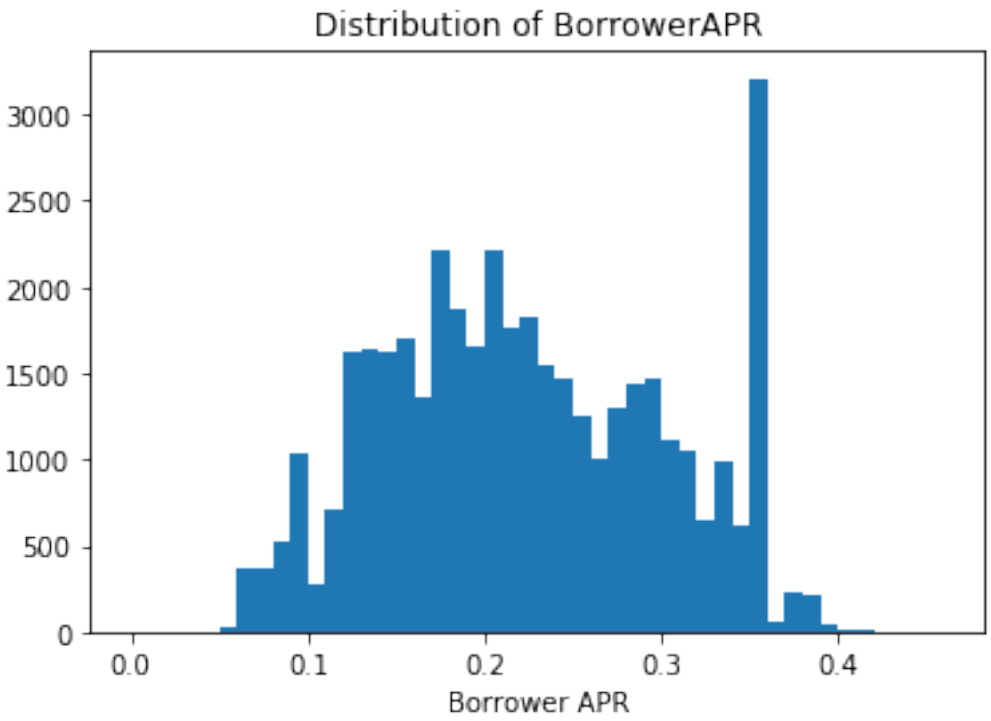
Histogram Function Definition

```
In [14]: # function to draw histogram

         def histogram(df, column):
           sb.displot(df[column])
```

1.3.2 Univariate Exploration Plots

Plot 1: What is the Distribution of Borrower APR? Definition: **BorrowerAPR** * The Borrower's Annual Percentage Rate (APR) for the loan

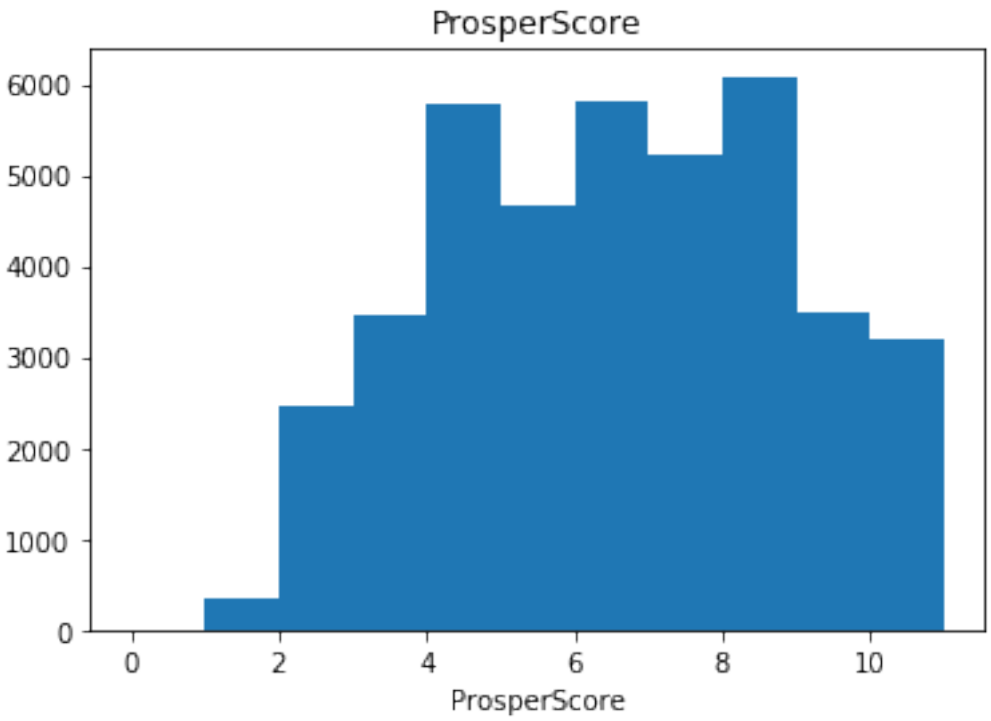
```
In [15]: bins = np.arange(0, loans_df['BorrowerAPR'].max() + 0.05, 0.01)
         plt.hist(data = loans_df, x = 'BorrowerAPR', bins = bins);
         plt.xlabel('Borrower APR');
         plt.title('Distribution of BorrowerAPR');
```



- The distribution of BorrowerAPR is largely multimodal, with small peaks around 0.1 and 0.3
- There is a large peak around 0.2; and a big steep peak around 0.35
- The steep peak around 0.35 is of interest; and will be explored further

Plot 2: What is the Distribution of ProsperScore? Definition: **ProsperScore** * A custom risk score built using historical Prosper data. * The score ranges from 1-10, with 10 being the best, or lowest risk score

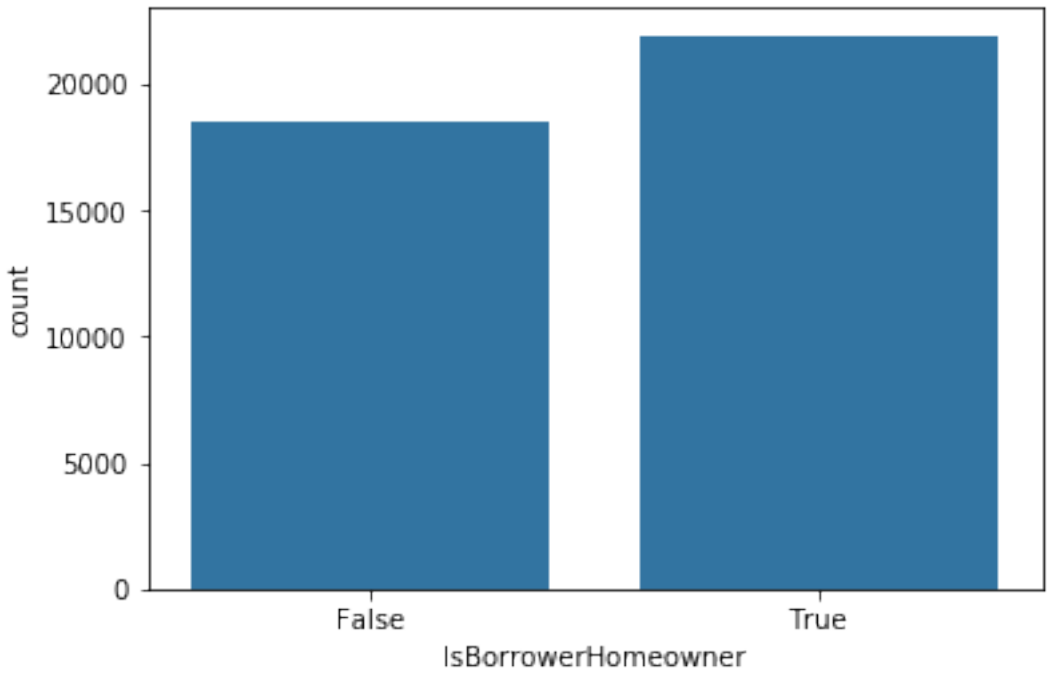
```
In [16]: bins = np.arange(0, loans_df['ProsperScore'].max() + 1, 1)
         plt.hist(data = loans_df, x = 'ProsperScore', bins = bins);
         plt.xlabel('ProsperScore');
         plt.title('ProsperScore');
```



- The distribution of ProsperScore is multimodal, and fairly symmetric
- There a 3 peaks (around 4.5, 6.5, and 8.5)

Plot 3: How many Borrowers are Home-owners? Definition: **IsBorrowerHomeowner** * A Borrower will be classified as a homowner if they have a mortgage on their credit profile or provide documentation confirming they are a homeowner

```
In [17]: # Calling Vertical Bar Chart Drawing Function
         vertical_bar_chart(loans_df, 'IsBorrowerHomeowner')
```



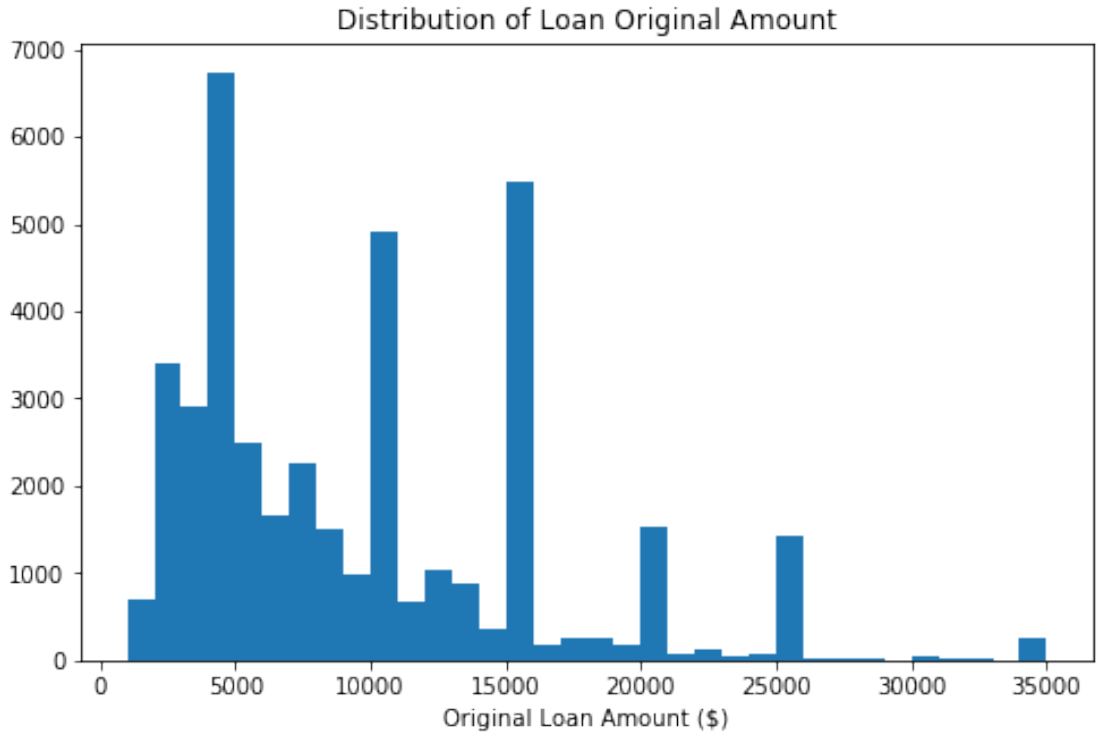
- There is a small difference between the number of borrowers who are home-owners and those who are not home-owners
- This implies that the variable does not have a major influence on borrowing

Plot 4: What is the Distribution of Loan Original Amount? Definition: **LoanOriginalAmount** * The origination amount of the loan

```
In [18]: # Defining min and max of LoanOriginalAmount Column
         min = loans_df['LoanOriginalAmount'].min()
         max = loans_df['LoanOriginalAmount'].max()

         print("Min:", min)
         print("Max:", max)
```

```
Min: 1000
Max: 35000
```

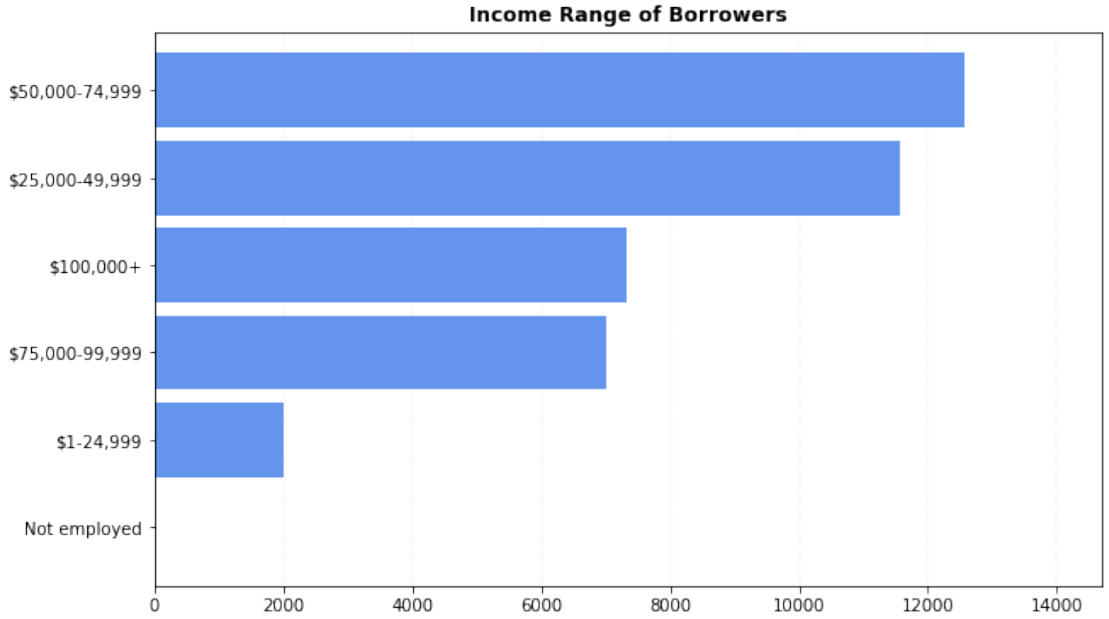
```
In [19]: # Plotting histogram

         bins = np.arange(min, max + 1000, 1000)
         plt.figure(figsize=[8, 5])
         plt.hist(data = loans_df, x = 'LoanOriginalAmount', bins = bins);
         plt.xlabel('Original Loan Amount ($)');
         plt.title('Distribution of Loan Original Amount');
```



- The distribution of Loan Original Amounts is multimodal, with big peaks at around USD 5000, USD 10000, and USD 15000
- The distribution is also right skewed, with the majority of the Loan Original Amounts being lower than USD 30,000

Plot 4: What is the Distribution of Borrowers according to Income Range? Definition: **IncomeRange** * The income range of the borrower at the time the listing was created.

```
In [20]: df_column = loans_df['IncomeRange']
         title = 'Income Range of Borrowers'

         # calling horizontal bar function
         draw_horizontal_bar(df_column, title)
```



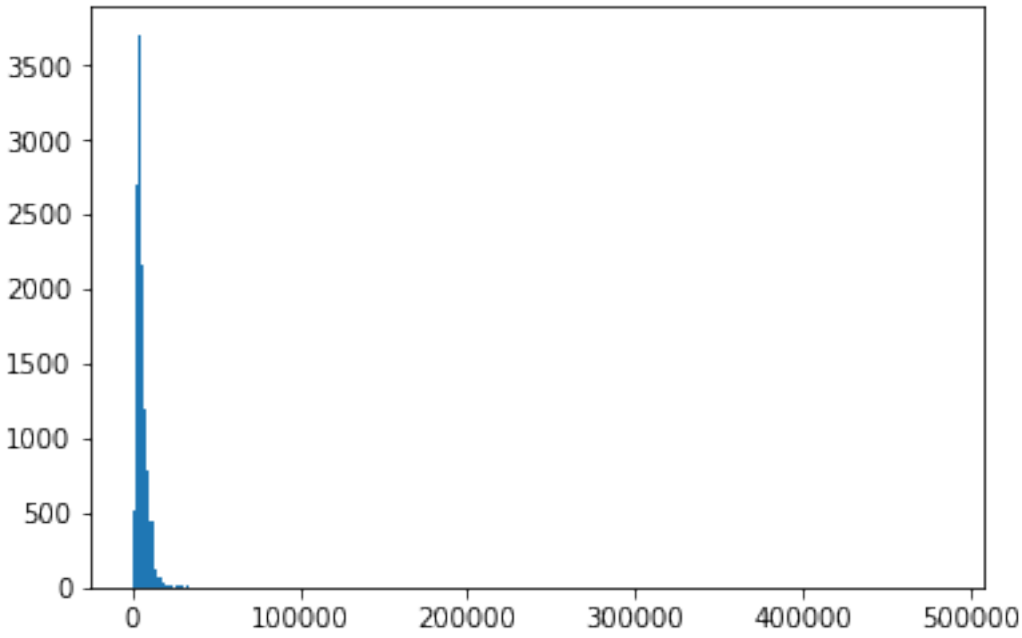
- Majority of the borrowers have an Income Range of USD 25k - 50k and USD 50k - 75k (Middle Class). This implies that Middle Class group are the greatest loan takers
- The least of the borrowers are in the group of USD 1 - 25k, "Not Employed", and USD 0
- This implies that the Unemployed and Low Income earners are at a lesser chance of being given loans; as compared to the Middle Class earner's

Plot 5: What is the Distribution of Stated Monthly Income? Definition: **StatedMonthlyIncome**
* The monthly income the borrower stated at the time the listing was created

```
In [21]: # Defining min and max of IncomeRange Column
         min = loans_df['StatedMonthlyIncome'].min()
         max = loans_df['StatedMonthlyIncome'].max()

         print("Min:", min)
         print("Max:", max)
```

```
Min: 1.416667
Max: 483333.333333
```

```
In [22]: # Distribution of stated monthly income
         bins = np.arange(min, max + 1000, 500)
         plt.hist(data = loans_df, x = 'StatedMonthlyIncome', bins=bins);
```



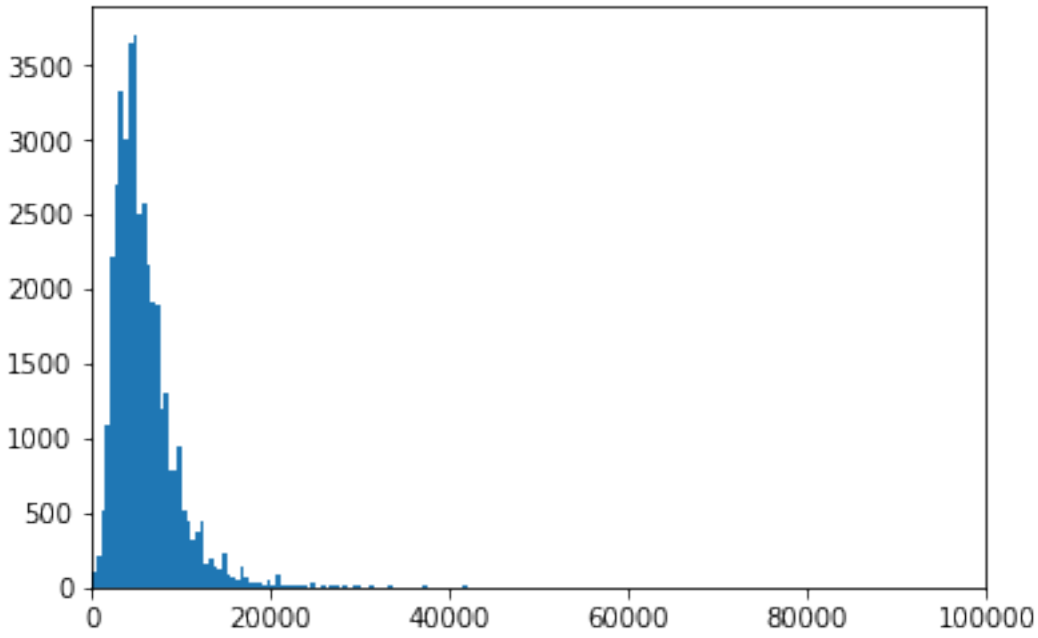
- There seems to be outliers around max, hence the no detail histogram produced
- We will proceed to do a more intuitive analysis below:

```
In [23]: # Checking basic statistics of 'StatedMonthlyIncome' column
         loans_df['StatedMonthlyIncome'].describe()
```

```
Out[23]: count     40481.000000
         mean       5955.758885
         std        5522.692870
         min           1.416667
         25%        3500.000000
         50%        5000.000000
         75%        7133.333333
         max      483333.333333
         Name: StatedMonthlyIncome, dtype: float64
```

- The value of max seems to be an outlier (exponent power of 6 as compared to other values with exponent power of 3)
- We will limit our max to values of power 5; when plotting the histogram

```
In [24]: # Distribution of stated monthly income: With X-axis Limits

         bins = np.arange(min, max + 1000, 500)
         plt.hist(data = loans_df, x = 'StatedMonthlyIncome', bins=bins);
         plt.xlim(0, 100000);
```



- The distribution of Stated Monthly Income is greatly skewed to the right
- The greater proportion of Stated Monthly Income is below USD 20,000

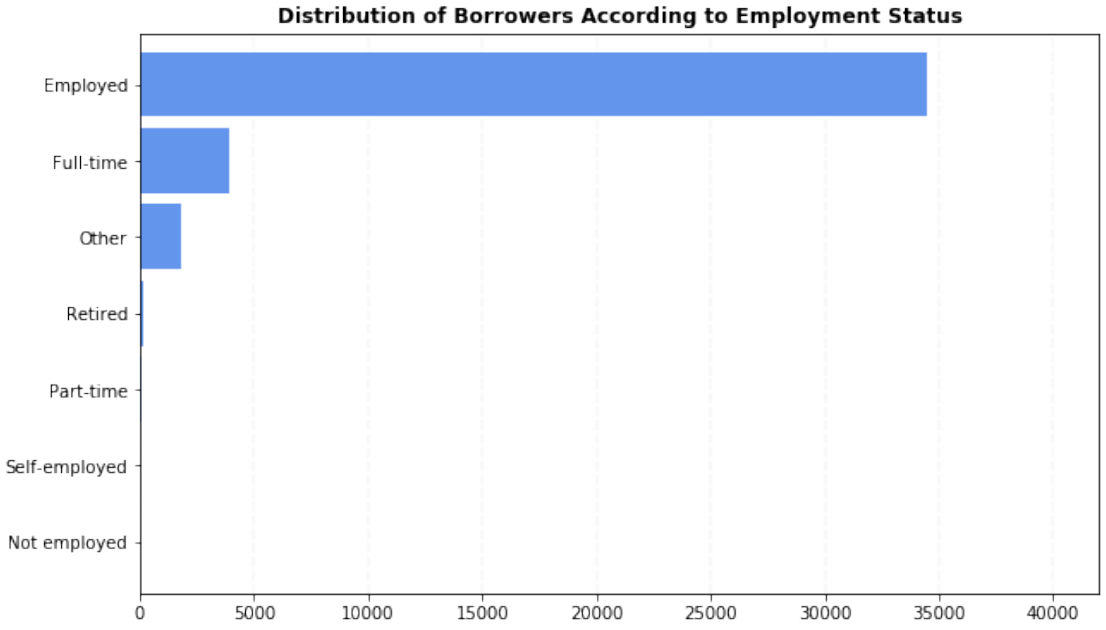
```
In [25]: a = loans_df[loans_df['StatedMonthlyIncome'] == 0]
         a.shape
```

```
Out[25]: (0, 81)
```

- The above statistic shows that many of the borrowers may have not stated their monthly income (that's why it is zero)

Plot 6: What is the Distribution of the Employment Status of the Borrowers? Definition: **EmploymentStatus** * The employment status of the borrower at the time they posted the listing

```
In [26]: column = loans_df['EmploymentStatus']
         title = 'Distribution of Borrowers According to Employment Status'

         # Calling Horizontal Bar Chart Drawing Function
         draw_horizontal_bar(column, title)
```



- The majority of the Borrowers have an Employment Status of "Employed"
- Conversely, the least proportion of Borrowers are in the "Other",, "Part-time", "Not employed", and "Retired" employment statuses
- This implies that lenders are more likely to give loans to employed persons, due to the security associated with employment

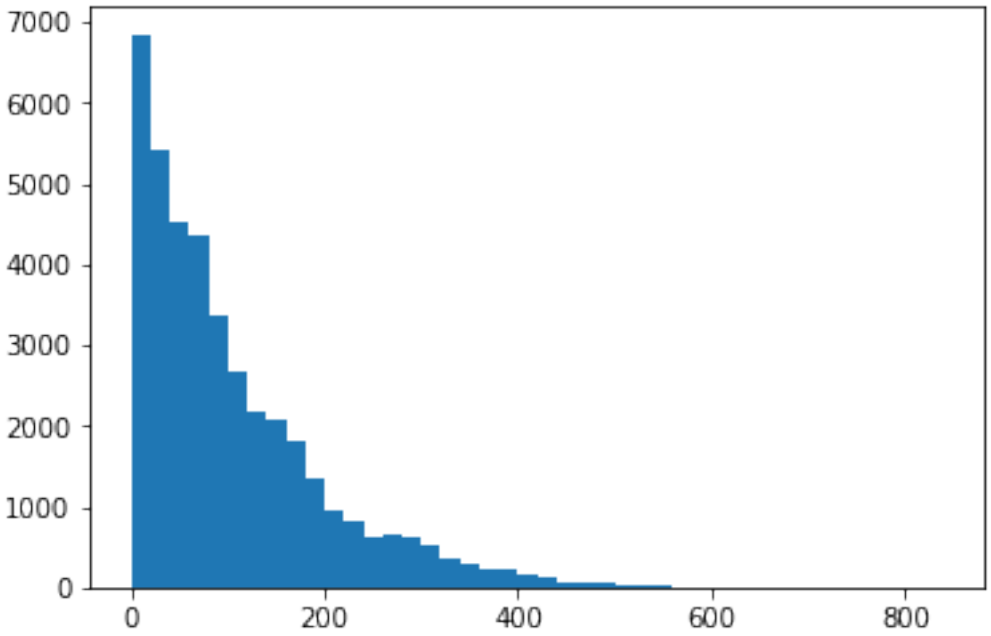
Plot 7: What is the Distribution of Employment Status Duration of the Borrowers? Definition: **EmploymentStatusDuration**

- The length in months of the employment status at the time the listing was created

```
In [27]: # Defining min and max of IncomeRange Column
         min = loans_df['EmploymentStatusDuration'].min()
         max = loans_df['EmploymentStatusDuration'].max()

         print("Min:", min)
         print("Max:", max)
```

```
Min: 0.0
Max: 755.0
```

```
In [28]: # Plotting histogram

         bins = np.arange(min, max + 100, 20)
         plt.hist(data = loans_df, x = 'EmploymentStatusDuration', bins=bins);
```



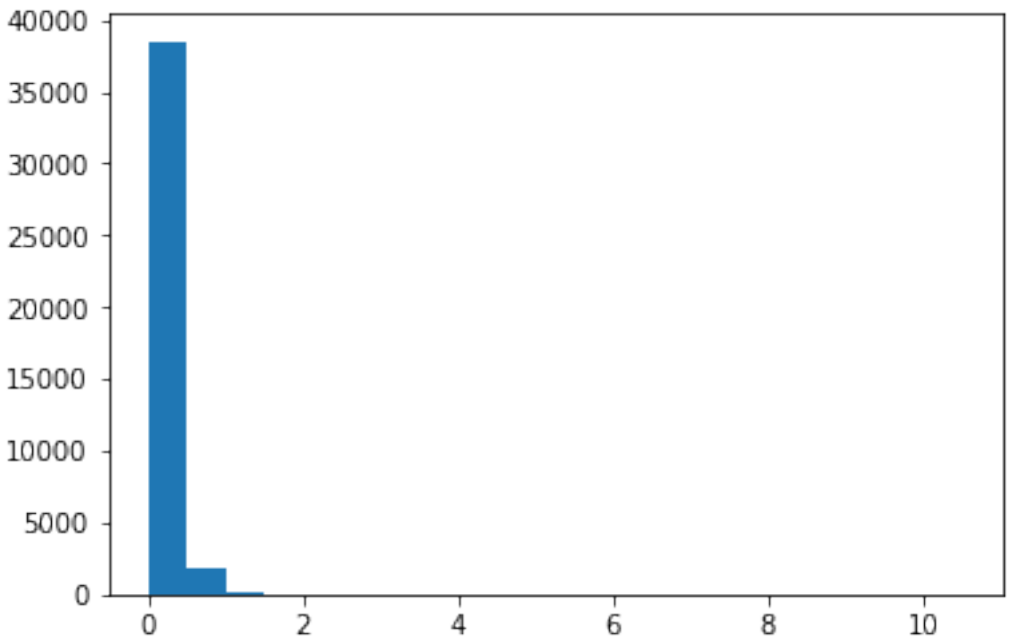
- The distribution of Employment Status Duration of the borrowers is unimodal, with one peak at around 0 months
- The distribution is also right skewed, with majority of the borrowers having an Employment Status Duration of less than 400 months

Plot 8: What is the Distribution of Debt-to-Income Ratio? Definition: **DebtToIncomeRatio** * The debt to income ratio of the borrower at the time the credit profile was pulled. * This value is Null if the debt to income ratio is not available. * This value is capped at 10.01 (any debt to income ratio larger than 1000% will be returned as 1001%).

```
In [29]: # Defining min and max of Debt to Income Ratio Column
         min = loans_df['DebtToIncomeRatio'].min()
         max = loans_df['DebtToIncomeRatio'].max()

         print("Min:", min)
         print("Max:", max)
```

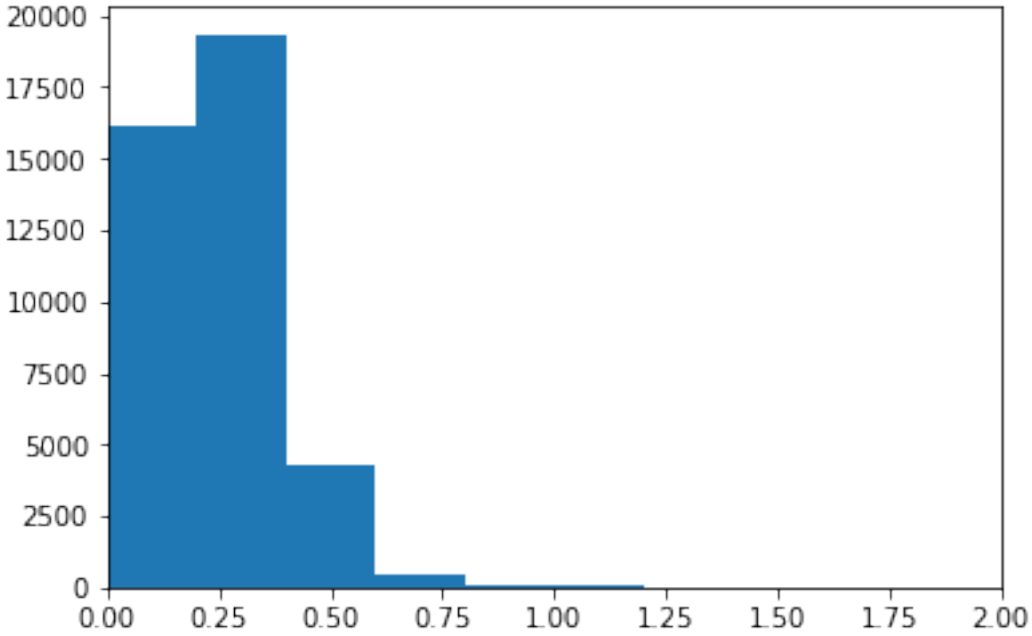
```
Min: 0.0
Max: 10.01
```

```
In [30]: # Basic histogram: Bins with Interval of 0.5
         bins = np.arange(min, max + 0.5, 0.5)
         plt.hist(data = loans_df, x = 'DebtToIncomeRatio', bins = bins);
```

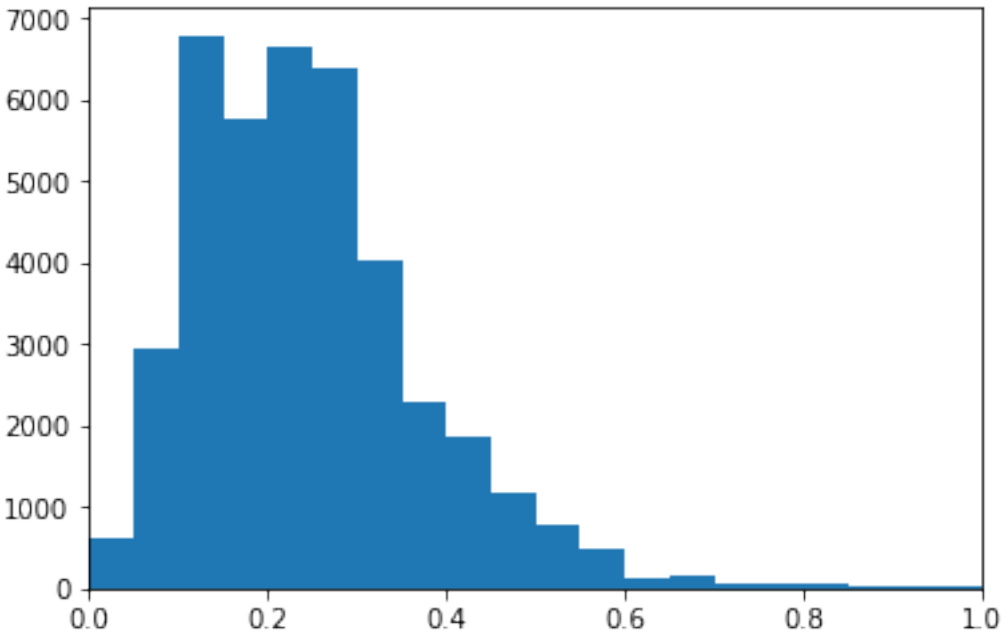


- The values between 9 and 10 (outliers) obscure the majority of the values, making viewing the distribution difficult
- We create a new histogram with modified X-axis limits to examine the distribution of the bulk of the values

```
In [31]: # New histogram with axis limits (0,2), Interval of 0.2
         bins = np.arange(min, max + 0.2, 0.2)
         plt.hist(data = loans_df, x = 'DebtToIncomeRatio', bins = bins);
         plt.xlim((0,2)); #axis limits
```



In [32]:
```
# New histogram with axis limits (0,1), Interval of 0.05
bins = np.arange(min, max + 0.05, 0.05)
plt.hist(data = loans_df, x = 'DebtToIncomeRatio', bins = bins);
plt.xlim((0,1));
```



- The histogram is skewed right, implying that the majority of the debt to income ratios lay between 0 and 0.4
- This implies that lenders pay keen attention to ensure a borrower can service the loan, by ensuring that their debt-to-income ratio is low

Plot 9: Which Quarter of the Year has the highest number of Loans by Origin? Definition: **LoanOriginationQuarter** * The quarter in which the loan was originated

Data Transformation: Splitting one Column into 2 Columns * We need to split the LoanOriginationQuarter into two columns: LoanQuarter, LoanYear

```
In [33]: # Splitting 'LoanOriginationQuarter' column into two columns: 'LoanQuarter','LoanYear'

         loans_df[['LoanQuarter','LoanYear']] = loans_df['LoanOriginationQuarter'].str.split(exp
```

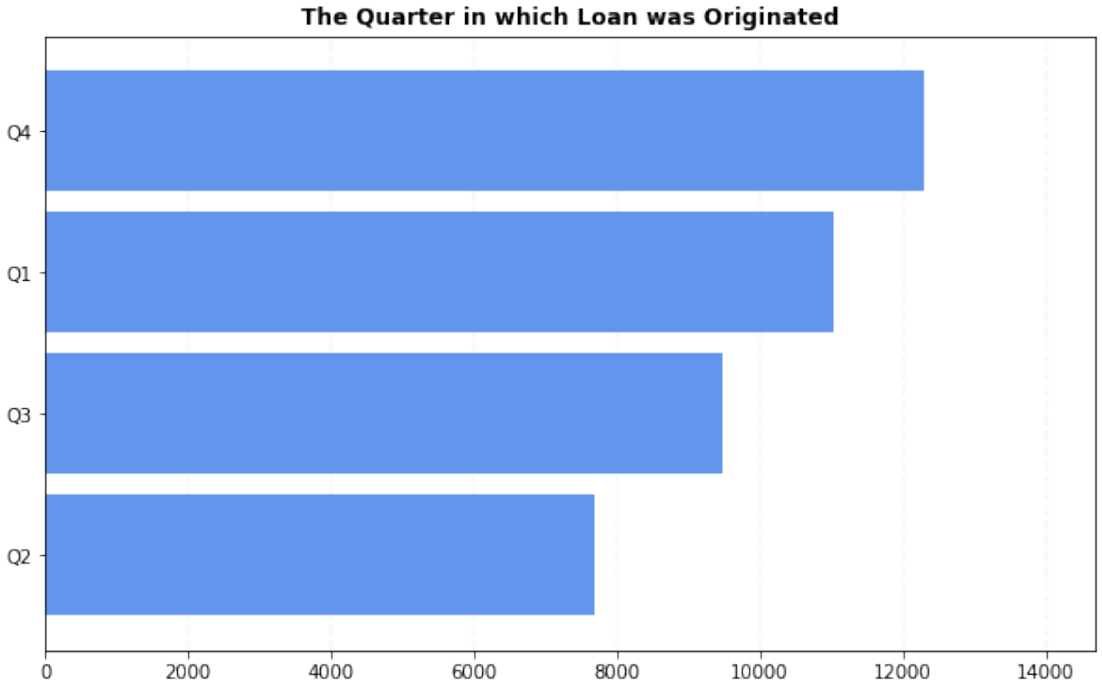
```
In [34]: # Checking sample of df
         loans_df.sample(3)
```

Out[34]:

	ListingKey	ListingNumber	ListingCreationDate	CreditGrade	Term	LoanStatus	ClosedDate	BorrowerAPR	BorrowerRate	LenderYield	...	LP_GrossPrincipalLoss	LP_NetPrincipalLoss	LP_NonPrincipalRecoverypayments	PercentFunded	Recommendations	InvestmentFromFriendsCount	InvestmentFromFriendsAmount	Investors	LoanQuarter	LoanYear
2435	358B360083740637998CDCD	1170686	2014-01-28 08:34:24.973000000	NaN	36	Current	NaN	0.09030	0.0769	0.0669	...	0.0	0.0	0.0	1.0	0	0.0	0.0	144.0	Q1	2014
20027	16BA35827045609239877CC	827889	2013-07-03 14:57:08.197000000	NaN	36	Current	NaN	0.13697	0.1089	0.0989	...	0.0	0.0	0.0	1.0	0	0.0	0.0	209.0	Q3	2013
4628	696B360463984945609D03B	1245219	2014-03-06 12:26:11.600000000	NaN	60	Current	NaN	0.19860	0.1745	0.1645	...	0.0	0.0	0.0	1.0	0	0.0	0.0	1.0	Q1	2014

[3 rows x 83 columns]

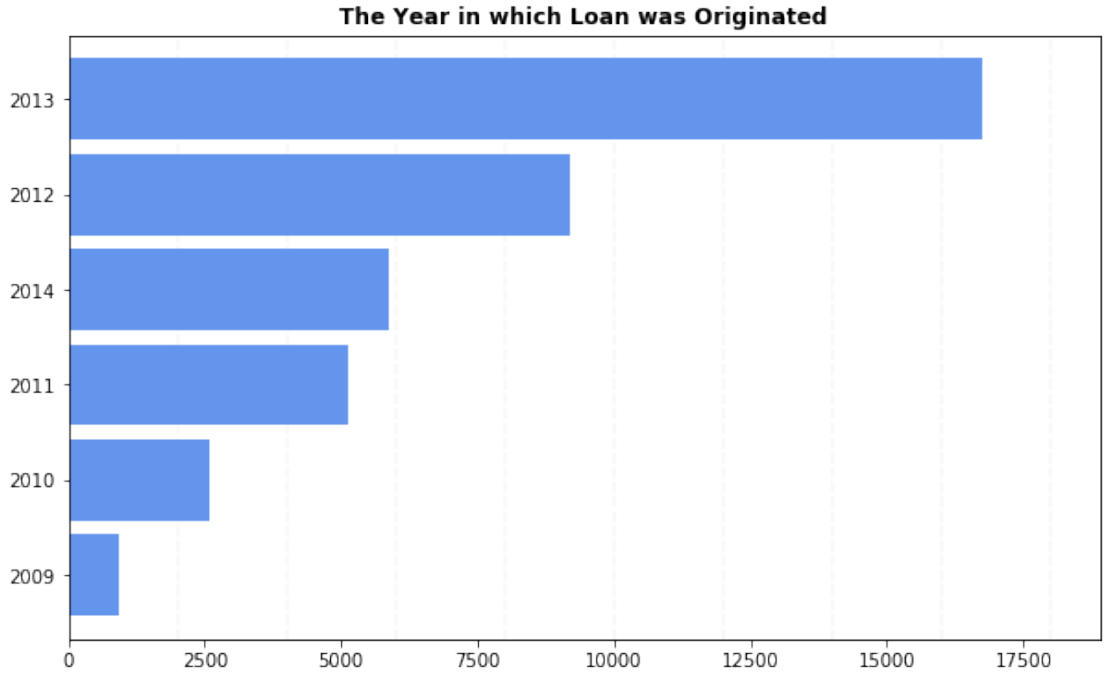
```
In [35]: df_column = loans_df['LoanQuarter']
         title = 'The Quarter in which Loan was Originated'

         # Calling Horizontal Bar Function
         draw_horizontal_bar(df_column, title)
```



- The plot shows that Quarter 4 is the leading quarter by loan origination
- This can point out that majority of loans are taken towards the end of the year; possibly owing to the buzz of festivities and increase in expenditures surrounding that period

Plot 10: What is the Distribution of Loans per Year of Origin? Definition: **LoanYear** * The year in which the loan was originated

```
In [36]: df_column = loans_df['LoanYear']
         title = 'The Year in which Loan was Originated'

         # Calling Horizontal Bar Function
         draw_horizontal_bar(df_column, title)
```



- There is a tremendous increase in the number of loans originated from 2013,as compared to other years
- This can be attributed to the low interest rates imposed in that year; as compared to other years. Hence, the favourable interest rates spurred extensive borrowing
- Reference: U.S. regional banks see loan growth in 2013

1.3.3 Discussion on Univariate Exploration

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 Borrower APR is largely multimodal, with small peaks around 0.1 and 0.3. There is a large peak around 0.2
- The unusual points noted in the Borrower APR are the big steep peak around 0.35
- To explore the distribution of loans according to loan year and loan-year quarter; I split the split the LoanOriginationQuarter into two columns: > * LoanQuarter > * LoanYear

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 unusual distributions I noted include: * There is a small irrecognizable difference between distributions of loan takers who are home-owners and those who are not. > * This is contrary to the fact that home-owners are more likely to be given loans as compared to those who are not; as there is more security assured with the lending * There is also a great discrepancy between the distributions of Stated Monthly Income and Income Range. > * Majority of the borrowers have an Income Range of USD 25k - 50k; while majority of borrowers have a Stated Monthly Income of

below USD 20k. > * The two variables are closely related, hence their distributions should not be counter-intuitive

The operation I undertook that changed the form of the data is the splitting of the LoanOriginationQuarter into two columns: LoanQuarter, and LoanYear * The transformation is to facilitate an exploration of the column on a deeper scale; as compared to as just a single variable

1.4 Bivariate Exploration

- In this section, I will investigate relationships between two variables. I have split the exploration into two parts: > * Part 1: Relationships between Quantitative Variables > * Part 2: Relationships of Quantitative Vs. Qualitative Variables

1.4.1 Part 1: Relationships between Quantitative Variables

Some Basic Data Preparation from Insights gotten in Univariate Exploration

```
In [37]: loans_df.shape
```

```
Out[37]: (40481, 83)
```

- Records of loans which have Stated Monthly Income greater than USD 30,000 are outliers (Refer to Plot 5 above)
- We preprocess the data by removing the outliers

```
In [38]: # filtering data to remove outliers
         loans_final_df = loans_df[loans_df['StatedMonthlyIncome'] <= 30000]
         loans_final_df.shape
```

```
Out[38]: (40373, 83)
```

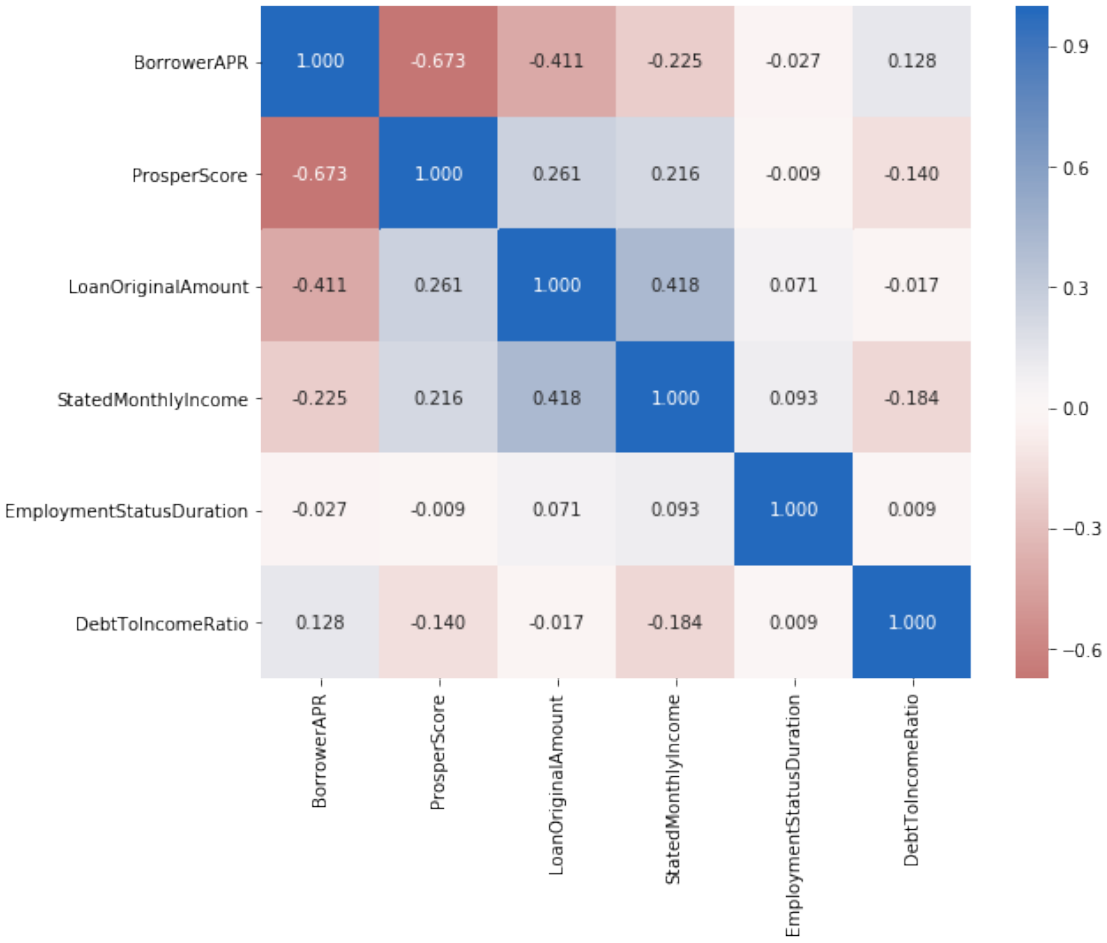
Plot 11: What is the correlation between the features of interest?

```
In [39]: # Function to draw Correlation Matrix as Heatmap
         def plot_correlation(features):
           features = features
           plt.figure(figsize = [9, 7])
           sb.heatmap(loans_final_df[features].corr(), annot = True, fmt = '.3f',
                      cmap = 'vlag_r', center = 0);
```

```
In [40]: # Function to draw Scatter Plots
         def plot_scatter(df, features):
           g = sb.PairGrid(data = df, vars = features)
           g = g.map_diag(plt.hist, bins=20)
           g.map_offdiag(plt.scatter, alpha=0.2);
```

```
In [41]: # defining numerical features of interest
         features = ['BorrowerAPR', 'ProsperScore', 'LoanOriginalAmount', 'StatedMonthlyIncome',
```

```
In [42]: # Calling Correlation Function with Features
         plot_correlation(features)
```

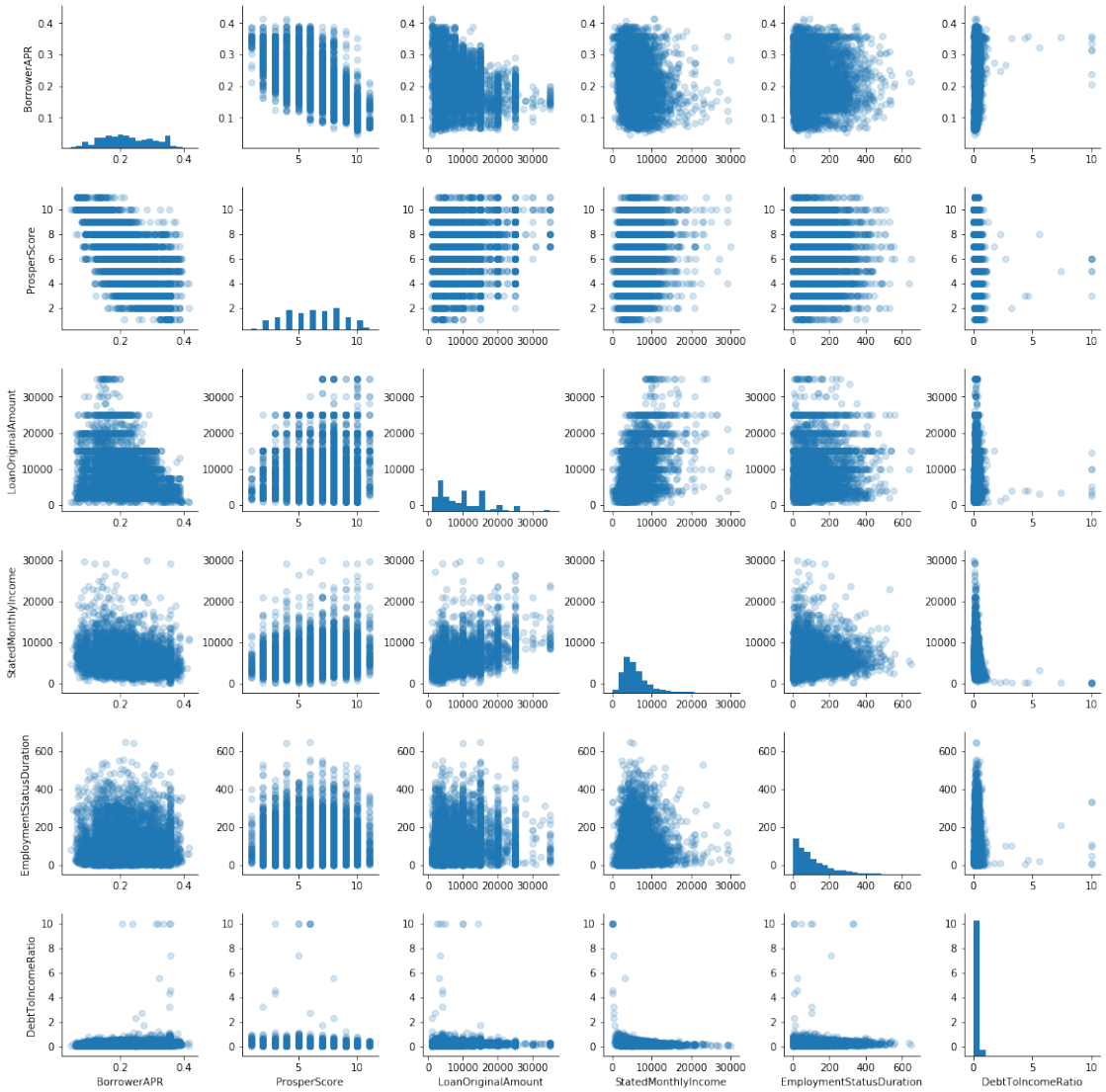


- The correlation matrix heatmap shows that there is a weak positive correlation (0.404) between the Loan Original Amount and the Stated Monthly Income. > This is in tandem with basic knowledge that the more a borrower earns, the more they can borrow (greater loan limit)
- Conversely, there is a weak negative correlation (-0.323) between the Loan Original Amount and the Borrower APR > This implies that the more the loan amount borrowed, the lower the APR (interest) charged for the loan
- There is a strong negative correlation (-0.668) between the Prosper Score and the Borrower APR > This shows that as the borrower's Prosper Score increases (as risk reduces), the APR decreases. By convention, less risk loans have less APR
- There is a weak negative correlation (-0.164) between Stated Monthly Income and Debt to Income Ratio > This implies that as the Stated Monthly Income increases, then the Debt to Income Ratio reduces

```
In [43]: # Sample few loans for faster correlation plotting
         loans_sampled_df = loans_final_df.sample(6000)
         loans_sampled_df.shape
```

```
Out[43]: (6000, 83)
```

```
In [44]: # Plotting Scatter Plots of Features
         plot_scatter(loans_sampled_df, features)
```



- The above scatter plots confirm the results obtained from the correlation matrix above
- While "Correlation is not Causation", the above results show some interesting patterns between the features

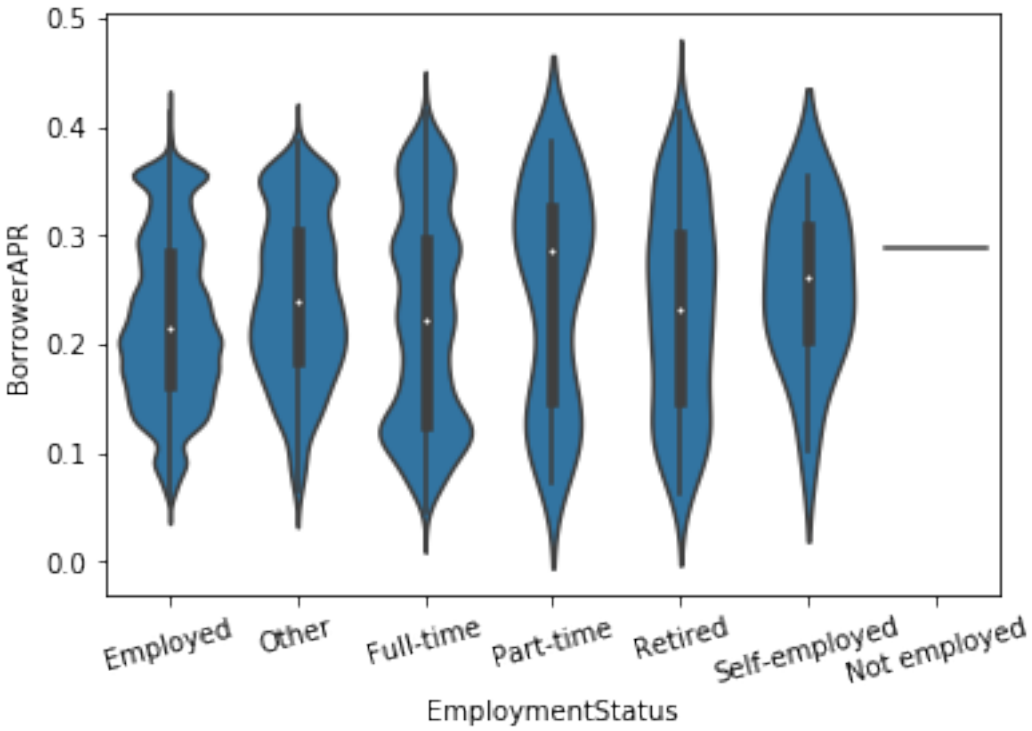
1.4.2 Part 2: Relationships of Quantitative Vs. Qualitative Variables

Defining Function for Drawing Violin Plot

```
In [45]: def draw_violin_plot(df, x_column, y_column):

             base_color = sb.color_palette()[0]

             sb.violinplot(data=df, x=x_column, y=y_column, color=base_color)
             plt.xticks(rotation=15);
```

Plot 12: What is the effect of Employment Status on Borrower APR?

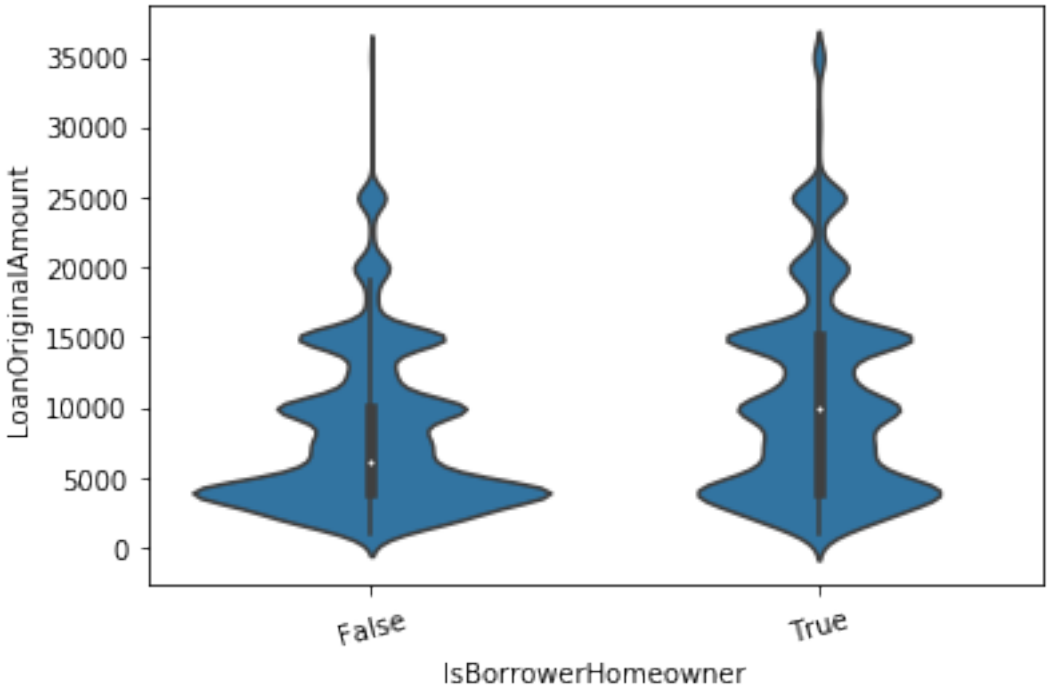
```
In [46]: # Calling violin plot drawing function

         draw_violin_plot(loans_final_df, 'EmploymentStatus', 'BorrowerAPR')
```



- Borrowers who have "Part-time", "Retired", and "Other" as their Employment Statuses have the highest Borrower APR's. This can be attributed to the increased risk of lending such people money; which has to be countered by increasing the APR

Plot 13: What is the Relationship Between Home-owners and Loan Original Amount

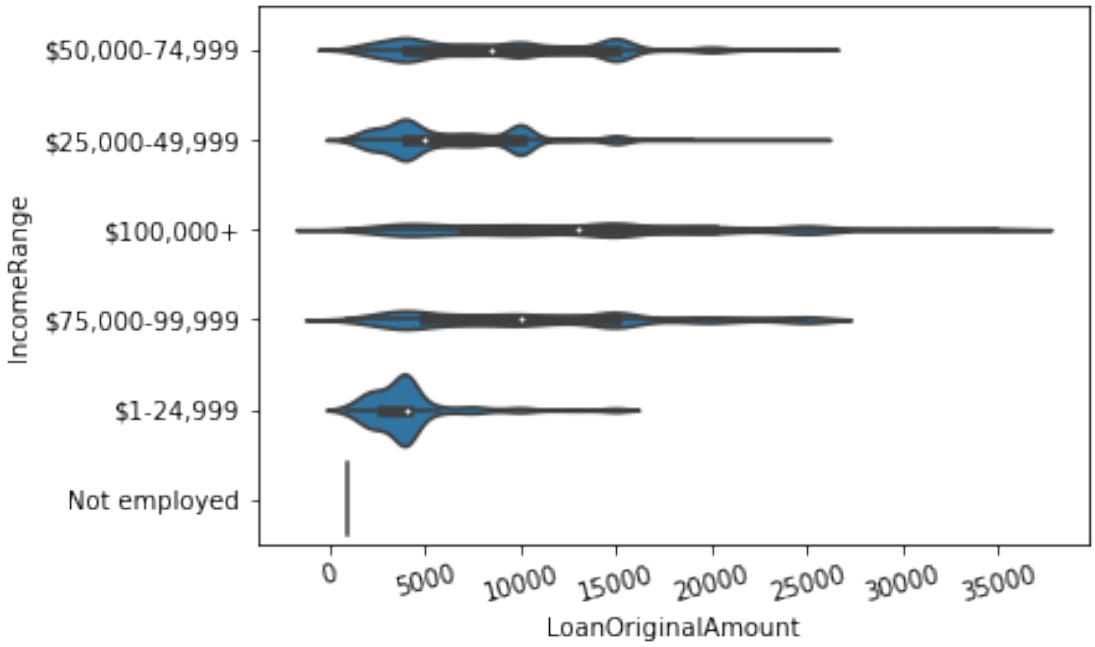
```
In [47]: # Calling violin plot drawing function

         draw_violin_plot(loans_final_df, 'IsBorrowerHomeowner', 'LoanOriginalAmount')
```



- The plot shows that people who are home-owners are able to borrow more; as compared to people who are not home-owners.
- This can be explained in part by the security associated with having a home; which can be used as collateral in the loan

Plot 14: How does the Income Range compare with the Loan Original Amount?

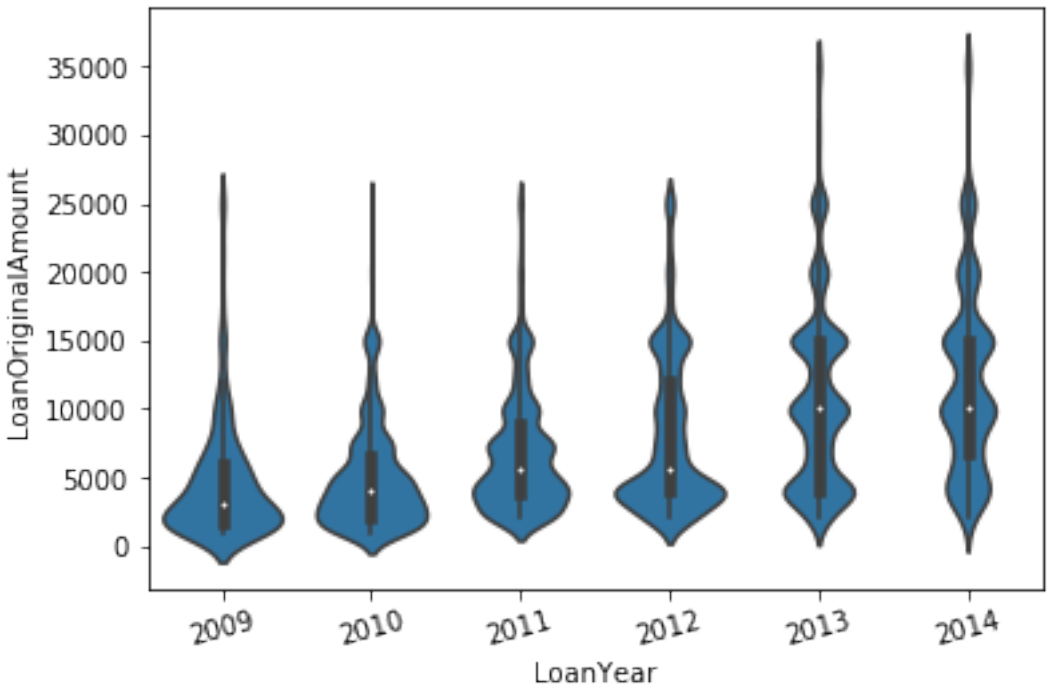
```
In [48]: # Calling violin plot drawing function

         draw_violin_plot(loans_final_df, 'LoanOriginalAmount', 'IncomeRange')
```



- The plot shows that the people with the highest loan original amount are borrowers in the income range of USD 100,000+; and the least are in the income ranges of "Not employed", and "USD 1 - 25,000"
- This implies that the more you earn, the more you can borrow

Plot 15: How does the Loan Original Amount compare with the Year of Loan Origin?

```
In [49]: # Calling violin plot drawing function

         draw_violin_plot(loans_final_df, 'LoanYear', 'LoanOriginalAmount')
```



- The highest proportion of Loan Original Amounts are in the years of 2013 and 2014
- This result is an addition to the observation in Plot 10 above; which lays out that there was a surge in the number of loans borrowed between 2013 - 2014; due to the favorable interest rates in that period
- Reference: U.S. regional banks see loan growth in 2013

1.4.3 Discussion on Bivariate Exploration

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?

- Borrower APR vs. Loan Original Amount > * There is a weak negative correlation (-0.323) between the Loan Original Amount and the Borrower APR > * This implies that the more the loan amount borrowed, the lower the APR (interest) charged for the loan

- Borrower APR vs. Employment Status > * Borrowers who have "Not Employed" and "Other" as their Employment Statuses have the highest Borrower APR's. > * This can be attributed to the increased risk of lending such people money; which has to be countered by increasing the APR

- Debt to Income Ratio vs. Stated Monthly Income > * There is a weak negative correlation (-0.164) between Stated Monthly Income and Debt to Income Ratio > * This implies that as the Stated Monthly Income increases, then the Debt to Income Ratio reduces

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

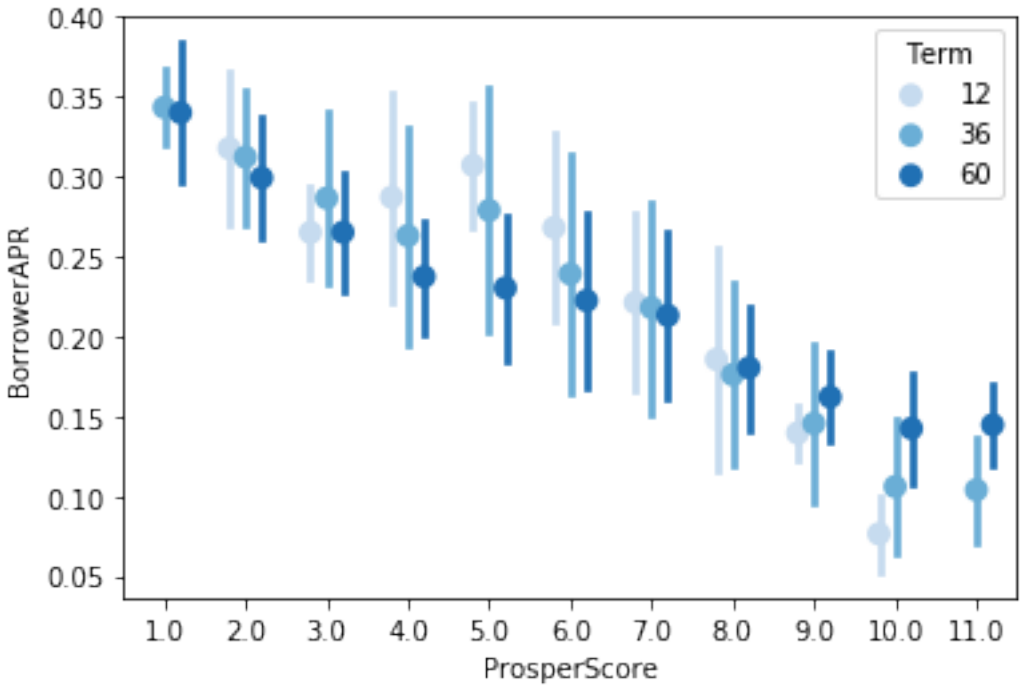
- Loan Original Amount vs. Is Home-owners: > * People who are home-owners are able to borrow more; as compared to people who are not home-owners. > *This can be explained in part by the security associated with having a home; which can be used as collateral in the loan
- Loan Original Amount vs. Income Range: > * There is a positive relationship between the Income Range and the Loan Original Amount. > * This implies that the more you earn, the more you can borrow

1.5 Multivariate Exploration

Here, I will create plots of three or more variables to ensure a more in-depth exploration of the features

Plot 16: How does the Loan Term and the Prosper Score affect the Borrower APR?

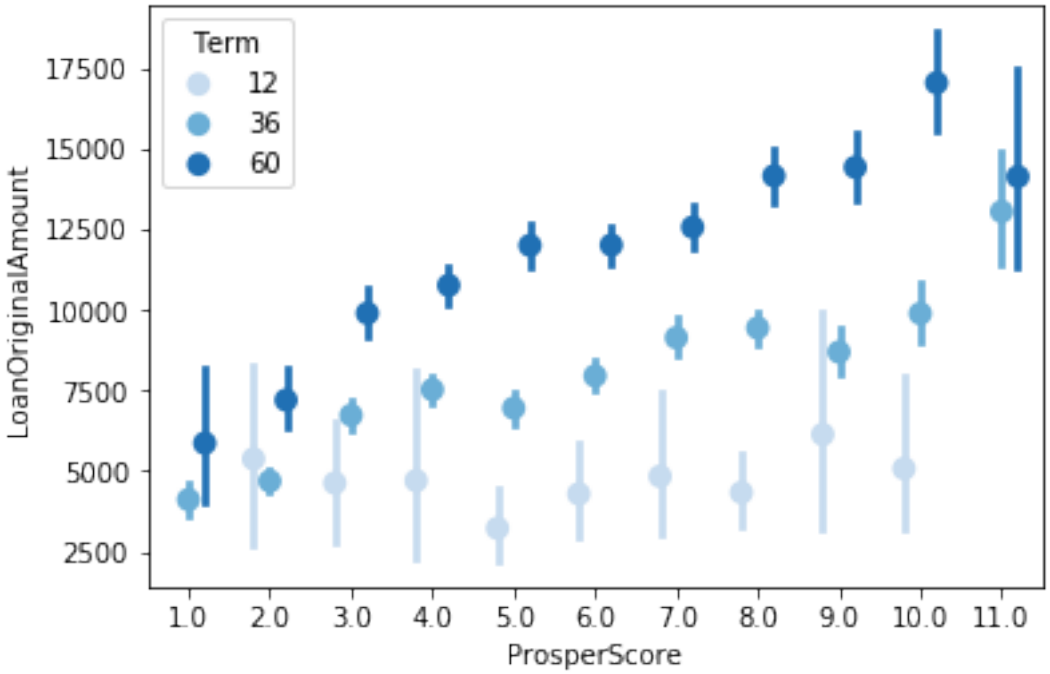
```
In [50]: sb.pointplot(data = loans_sampled_df, x = 'ProsperScore', y = 'BorrowerAPR', hue = 'Ter
                     palette = 'Blues', linestyles = '', dodge = 0.4, ci='sd');
```



- The plot shows that there is an inverse relationship between Borrower APR; and Term and Prosper Score
- Thus, Borrower APR decreases as the Loan Term and Prosper Score increase

Plot 17: How does the Loan Term and the Prosper Score affect the Loan Original Amount?

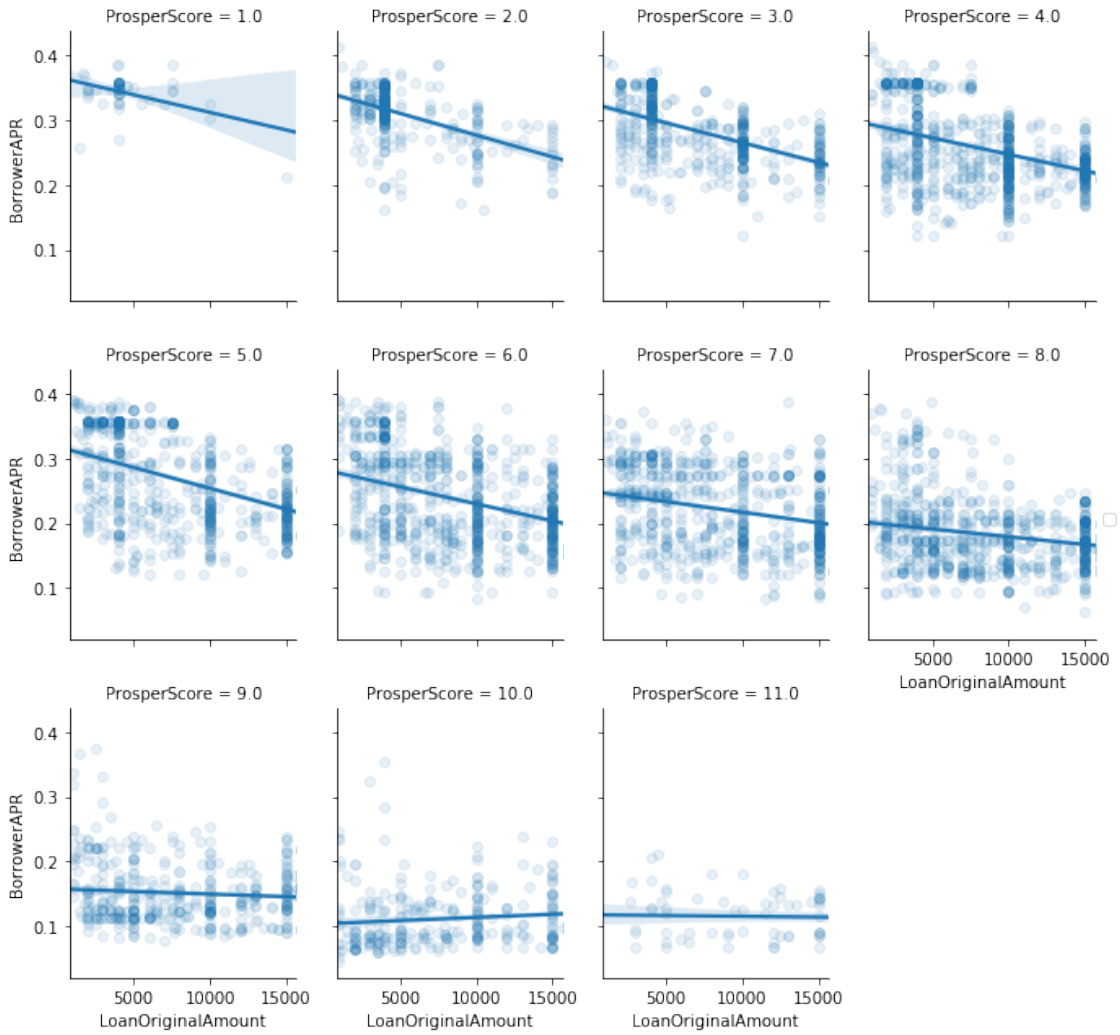
```
In [51]: # drawing visualization
         sb.pointplot(data = loans_sampled_df, x = 'ProsperScore', y = 'LoanOriginalAmount', hue
                      palette = 'Blues', linestyles = '', dodge = 0.4);
```



- The key observation from the plot above is that Loan Original Amount; and Prosper Score and Term share a positive relationship
- The plot shows that the Loan Original Amount increases as the Prosper Score increases, and also as the Loan Term increases

Plot 18: What is the effect of Prosper Score on Borrower APR and Loan Original Amount?

```
In [52]: # Prosper Score effect on relationship of APR and loan amount

         g=sb.FacetGrid(data=loans_sampled_df, aspect=0.8, col='ProsperScore', col_wrap=4)
         g.map(sb.regplot, 'LoanOriginalAmount', 'BorrowerAPR', x_jitter=0.04, scatter_kws={'alp
         g.add_legend();
```



- The plots show that the Loan Original Amount increase with an increase in the Prosper Score and a decrease in Borrower APR
- However, when the Prosper Score is above 9 (best Prosper Scores) and the Loan Original Amount increases; there is an abnormal behaviour of the Borrower APR increasing
- This can be explained in part by the propensity of people with better Prosper Scores borrowing bigger loans; which creates a high demand for the loans; and a corresponding increase in Borrower APR
- This is to maximize on profits, going by the Law of Supply and Demand

1.5.1 Discussion on Multivariate Exploration

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?

- Borrower APR vs. Loan Term and Prosper Score > * There is an inverse relationship between Borrower APR; and Term and Prosper Score. Thus, Borrower APR decreases as the Loan Term and Prosper Score increase

- Loan Original Amount vs. Loan Term and Prosper Score > * The Loan Original Amount; and Prosper Score and Term share a positive relationship. Hence, the Loan Original Amount increases as the Prosper Score increases, and also as the Loan Term increases

Were there any interesting or surprising interactions between features?

- Prosper Score vs. Borrower APR and Loan Original Amount > * The plots show that the Loan Original Amount increase with an increase in the Prosper Score and a decrease in Borrower APR > * However, there is an interesting and surprising observation from the three features > * When the Prosper Score is above 9 (top ratings) and the Loan Original Amount increases; there is an abnormal behaviour of the Borrower APR increasing > * This can be explained in part by the propensity of people with better Prosper Scores borrowing bigger loans; which creates a high demand for the loans; and a corresponding increase in Borrower APR > * The anomalous observation can be attributed to the maximizing on loan profits by the lenders, going by the Law of Supply and Demand

1.6 Conclusions

- This notebook is an exploration of the Loan Data from Prosper dataset
- The analysis employs univariate, bivariate and multivariate exploratory data visualizations to draw insights from the data
- Notable insights gotten from the analysis include: > * There is a weak negative correlation (-0.323) between the Loan Original Amount and the Borrower APR >> Hence, the more the loan amount borrowed, the lower the APR (interest) charged for the loan > * Borrowers who have "Not Employed" and "Other" as their Employment Statuses have the highest Borrower APR's. >> This is due to the increased risk of lending money to people with those statuses; which has to be countered by increasing the APR > * People who are home-owners are able to borrow more; as compared to people who are not home-owners. >> This can be attributed to the security associated with having a home; which can be used as collateral in the loan > * There is a positive relationship between the Income Range and the Loan Original Amount >> Thus, the more you earn, the more you can borrow > * There is an inverse relationship between Borrower APR; and Term and Prosper Score >> This implies that the Borrower APR decreases as the Loan Term and Prosper Score increase > * The Loan Original Amount; and Prosper Score and Term share a positive relationship. >> Therefore, the Loan Original Amount increases as the Prosper Score increases, and also as the Loan Term increases > * The Loan Original Amount increases with an increase in the Prosper Score and a decrease in Borrower APR (which is expected by convention) > * However, when the Prosper Score is above 9 (top ratings) and the Loan Original Amount increases; there is an abnormal behaviour of the Borrower APR increasing >> This can be expounded by the increase in the demand of bigger loans from borrowers with best Prosper Scores; which leads to an increase in Borrower APR to heighten loan profits (Law of Demand and Supply)