Part_I_exploration_template

March 15, 2023

1 Part I - (Prosper Loan Dataset Exploration)

1.1 by (Sussan Omeruah)

1.2 Introduction

Prosper is a lending platform in the U.S. that offers a variety of resources people can use to try and improve their financial health, regardless of their financial situation. Users can consolidate debt, improve their home, or finance healthcare costs with personal loans among many other purposes. Investors who may be looking for new opportunities to diversify their portfolio can invest in personal loans.

This data set contains 113,937 loans with 81 variables on each loan, with duration between november 2005 to march 2014, including loan amount, borrower rate (or interest rate), current loan status, borrower income, and many others. See this data dictionary to understand the dataset's variables.

1.3 Preliminary Wrangling

```
In [16]: # 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 sns

         %matplotlib inline
```

```
In [17]: # Upgrade seaborn
         !pip install seaborn --upgrade
```

```
Requirement already up-to-date: seaborn in /opt/conda/lib/python3.6/site-packages (0.11.2)
Requirement already satisfied, skipping upgrade: matplotlib>=2.2 in /opt/conda/lib/python3.6/sit
Requirement already satisfied, skipping upgrade: scipy>=1.0 in /opt/conda/lib/python3.6/site-pac
Requirement already satisfied, skipping upgrade: numpy>=1.15 in /opt/conda/lib/python3.6/site-pa
Requirement already satisfied, skipping upgrade: pandas>=0.23 in /opt/conda/lib/python3.6/site-p
Requirement already satisfied, skipping upgrade: pyparsing!=2.0.4,!=2.1.2,!=2.1.6,>=2.0.3 in /op
Requirement already satisfied, skipping upgrade: cycler>=0.10 in /opt/conda/lib/python3.6/site-p
Requirement already satisfied, skipping upgrade: kiwisolver>=1.0.1 in /opt/conda/lib/python3.6/s
```

```
Requirement already satisfied, skipping upgrade: python-dateutil>=2.1 in /opt/conda/lib/python3.
Requirement already satisfied, skipping upgrade: pillow>=6.2.0 in /opt/conda/lib/python3.6/site-
Requirement already satisfied, skipping upgrade: pytz>=2011k in /opt/conda/lib/python3.6/site-pa
Requirement already satisfied, skipping upgrade: six in /opt/conda/lib/python3.6/site-packages (
```

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

```
In [82]: # import dataset
         loans = pd.read_csv('prosperLoanData.csv')
```

1.3.1 View/explore dataset

```
In [19]: #view data
         loans.head()
```

```
Out[19]:                 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 [20]:
```python
# View columns and data types
loans.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 [21]:
```
# View data summary statistics
loans.describe()
```

Out[21]:
```
       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 [22]:
```
print(loans.ListingCreationDate.min())
```

```
2005-11-09 20:44:28.847000000
```

In [23]:
```
print(loans.ListingCreationDate.max())
```

```
2014-03-10 12:20:53.760000000
```

In [24]:
```
# Checking for missing data
loans.isna().sum()
```

Out[24]:
```
ListingKey                                 0
ListingNumber                              0
ListingCreationDate                        0
CreditGrade                            84984
Term                                       0
LoanStatus                                 0
ClosedDate                             58848
BorrowerAPR                               25
BorrowerRate                               0
LenderYield                                0
EstimatedEffectiveYield                29084
EstimatedLoss                          29084
```

```
EstimatedReturn                         29084
ProsperRating (numeric)                 29084
ProsperRating (Alpha)                   29084
ProsperScore                            29084
ListingCategory (numeric)                   0
BorrowerState                            5515
Occupation                               3588
EmploymentStatus                         2255
EmploymentStatusDuration                 7625
IsBorrowerHomeowner                         0
CurrentlyInGroup                            0
GroupKey                               100596
DateCreditPulled                            0
CreditScoreRangeLower                     591
CreditScoreRangeUpper                     591
FirstRecordedCreditLine                   697
CurrentCreditLines                       7604
OpenCreditLines                          7604
                                        ...
TotalProsperLoans                       91852
TotalProsperPaymentsBilled              91852
OnTimeProsperPayments                   91852
ProsperPaymentsLessThanOneMonthLate     91852
ProsperPaymentsOneMonthPlusLate         91852
ProsperPrincipalBorrowed                91852
ProsperPrincipalOutstanding             91852
ScorexChangeAtTimeOfListing             95009
LoanCurrentDaysDelinquent                   0
LoanFirstDefaultedCycleNumber           96985
LoanMonthsSinceOrigination                  0
LoanNumber                                  0
LoanOriginalAmount                          0
LoanOriginationDate                         0
LoanOriginationQuarter                      0
MemberKey                                   0
MonthlyLoanPayment                          0
LP_CustomerPayments                         0
LP_CustomerPrincipalPayments                0
LP_InterestandFees                          0
LP_ServiceFees                              0
LP_CollectionFees                           0
LP_GrossPrincipalLoss                       0
LP_NetPrincipalLoss                         0
LP_NonPrincipalRecoverypayments             0
PercentFunded                               0
Recommendations                             0
InvestmentFromFriendsCount                  0
InvestmentFromFriendsAmount                 0
```

```
Investors                                    0
Length: 81, dtype: int64
```

In [25]:
```
#copy dataset before wrangling
df = loans.copy()
```

In [26]:
```
# Select necessary columns

columns=['ListingNumber','ListingCreationDate','Term','LoanStatus','BorrowerRate','Borr
         'EmploymentStatus','IncomeRange','MonthlyLoanPayment','Investors','CurrentDeli
df=df[columns]
```

In [27]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 113937 entries, 0 to 113936
Data columns (total 21 columns):
ListingNumber                113937 non-null int64
ListingCreationDate          113937 non-null object
Term                         113937 non-null int64
LoanStatus                   113937 non-null object
BorrowerRate                 113937 non-null float64
BorrowerState                108422 non-null object
IsBorrowerHomeowner          113937 non-null bool
LoanOriginationDate          113937 non-null object
LenderYield                  113937 non-null float64
LoanOriginalAmount           113937 non-null int64
ListingCategory (numeric)    113937 non-null int64
StatedMonthlyIncome          113937 non-null float64
ProsperRating (Alpha)        84853 non-null object
ProsperRating (numeric)      84853 non-null float64
DebtToIncomeRatio            105383 non-null float64
EmploymentStatus             111682 non-null object
IncomeRange                  113937 non-null object
MonthlyLoanPayment           113937 non-null float64
Investors                    113937 non-null int64
CurrentDelinquencies         113240 non-null float64
AmountDelinquent             106315 non-null float64
dtypes: bool(1), float64(8), int64(5), object(7)
memory usage: 17.5+ MB
```

In [30]:
```
# Check for missing data
df.isna().sum()
```

Out[30]:
```
ListingNumber              0
ListingCreationDate        0
Term                       0
LoanStatus                 0
```

```
BorrowerRate                    0
BorrowerState                5515
IsBorrowerHomeowner             0
LoanOriginationDate             0
LenderYield                     0
LoanOriginalAmount              0
ListingCategory (numeric)       0
StatedMonthlyIncome             0
ProsperRating (Alpha)       29084
ProsperRating (numeric)     29084
DebtToIncomeRatio               0
EmploymentStatus             2255
IncomeRange                     0
MonthlyLoanPayment              0
Investors                       0
CurrentDelinquencies          697
AmountDelinquent             7622
dtype: int64
```

1.3.2 Handling Missing Data

```
In [31]: #fill the missing values of DebttoIncomeRatio with the mean
         df.DebtToIncomeRatio = df.DebtToIncomeRatio.fillna(df.DebtToIncomeRatio.mean())
```

```
In [32]: #drop rows of missing data in ProsperRating
         df = df[df['ProsperRating (Alpha)'].notnull()]
```

```
In [33]: # Test for missing data
         df.isna().sum()
```

```
Out[33]: ListingNumber                0
         ListingCreationDate          0
         Term                         0
         LoanStatus                   0
         BorrowerRate                 0
         BorrowerState                0
         IsBorrowerHomeowner          0
         LoanOriginationDate          0
         LenderYield                  0
         LoanOriginalAmount           0
         ListingCategory (numeric)    0
         StatedMonthlyIncome          0
         ProsperRating (Alpha)        0
         ProsperRating (numeric)      0
         DebtToIncomeRatio            0
         EmploymentStatus             0
         IncomeRange                  0
         MonthlyLoanPayment           0
         Investors                    0
```

```
CurrentDelinquencies        0
AmountDelinquent            0
dtype: int64
```

```
In [34]: #Adjust Datetime columns
         df['ListingCreationDate'] = pd.to_datetime(df['ListingCreationDate'])
         df['LoanOriginationDate'] = pd.to_datetime(df['LoanOriginationDate'])
         df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 84853 entries, 1 to 113936
Data columns (total 21 columns):
ListingNumber                84853 non-null int64
ListingCreationDate          84853 non-null datetime64[ns]
Term                         84853 non-null int64
LoanStatus                   84853 non-null object
BorrowerRate                 84853 non-null float64
BorrowerState                84853 non-null object
IsBorrowerHomeowner          84853 non-null bool
LoanOriginationDate          84853 non-null datetime64[ns]
LenderYield                  84853 non-null float64
LoanOriginalAmount           84853 non-null int64
ListingCategory (numeric)    84853 non-null int64
StatedMonthlyIncome          84853 non-null float64
ProsperRating (Alpha)        84853 non-null object
ProsperRating (numeric)      84853 non-null float64
DebtToIncomeRatio            84853 non-null float64
EmploymentStatus             84853 non-null object
IncomeRange                  84853 non-null object
MonthlyLoanPayment           84853 non-null float64
Investors                    84853 non-null int64
CurrentDelinquencies         84853 non-null float64
AmountDelinquent             84853 non-null float64
dtypes: bool(1), datetime64[ns](2), float64(8), int64(5), object(5)
memory usage: 13.7+ MB
```

```
In [35]: # Extract year and month from ListingCreationDate
         df["ListingYear"] = df["ListingCreationDate"].dt.year
         df["ListingMonth"] = df["ListingCreationDate"].dt.month
```

```
In [36]: # Convert ProsperRating & IncomeRange to ordinal categorical
         var_dict = {'ProsperRating (Alpha)': ['HR','E','D','C', 'B', 'A', 'AA'],
                              'IncomeRange':['$1-24,999','$25,000-49,999','$50,000-74,999','$75,0
                     'EmploymentStatus':['Employed','Self-employed','Full-time','Part-time','Ret
         for var in var_dict:
             ordered_var = pd.api.types.CategoricalDtype(ordered = True, categories = var_dict[v
             df[var] = df[var].astype(ordered_var)
```

```
In [79]: #Adjust datatype for all other categorical columns
         df['BorrowerState'] = df['BorrowerState'].astype('category')
         df['LoanStatus'] = df['LoanStatus'].astype('category')
         df['ListingCategory (numeric)'] = df['ListingCategory (numeric)'].astype('category')
```

```
In [80]: # Check size of df
         df.shape
```

```
Out[80]: (84853, 25)
```

1.3.3 What is the structure of your dataset?

The dataset contains columns with information on date, purpose, amount, rates and status of loans. The size is (84853, 28)

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

I am interested in exploring the factors that affect loan outcome

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

I am guessing that loan amount, borrower rate and loan status will help my investigation. I also think that some borrower characteristics like loan purpose(ListingCategory) and Loan Term will affect the outcome of a loan

1.4 Univariate Exploration

I will start from Loan Amount

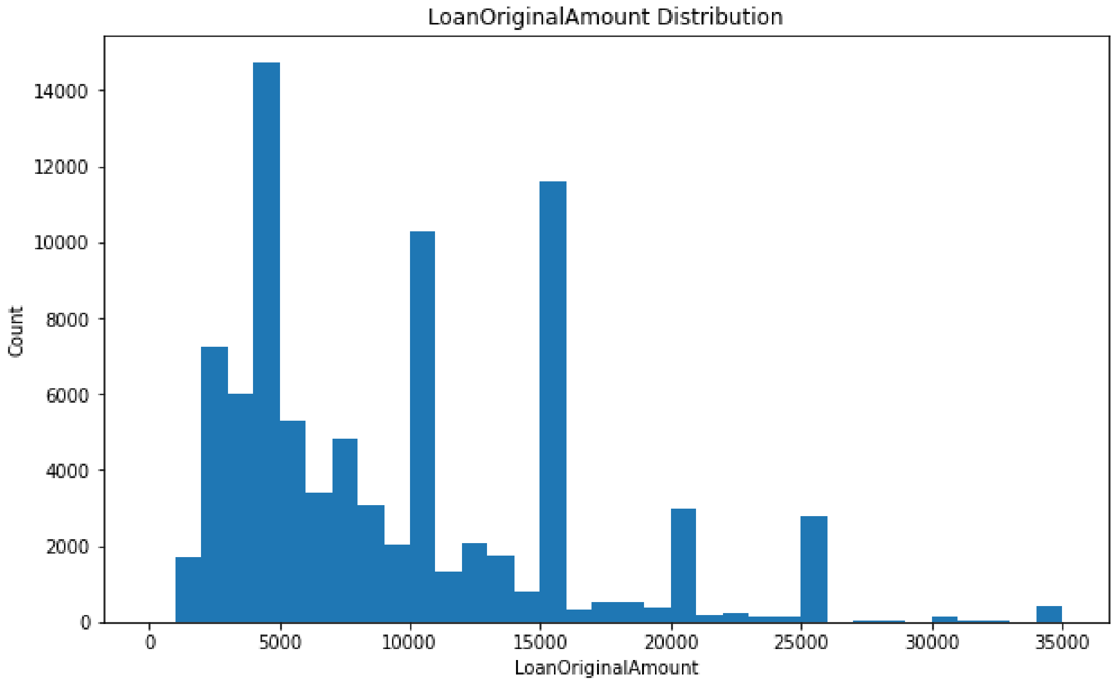
1.4.1 Question

What is the distribution of loan amounts?

1.4.2 Visualization

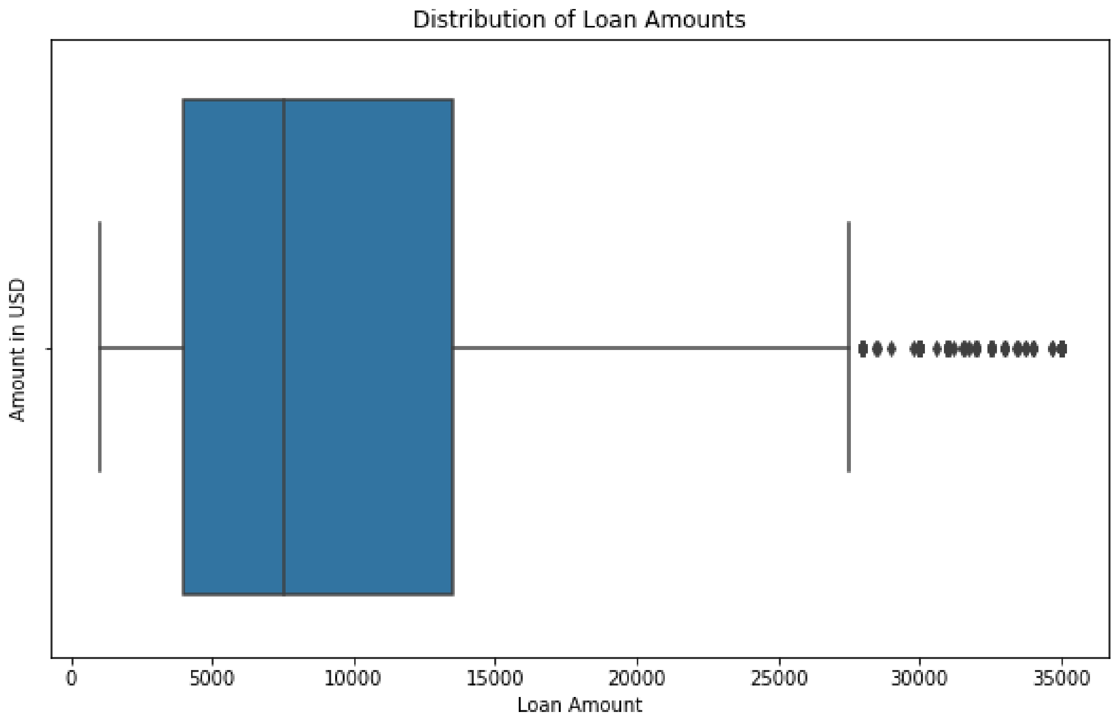
```
In [39]: def plot_histogram(df, column, bin_size):
             # Create bins using specified bin size
             bins = np.arange(0, df[column].max()+bin_size, bin_size)

             # Create a histogram of the specified column
             base_color = sns.color_palette()[0]
             fig, ax = plt.subplots(figsize=(10, 6))
             ax.hist(df[column], bins=bins, color= base_color)

             # Set the chart title and axes labels
             ax.set_title(f'{column} Distribution')
             ax.set_xlabel(column)
             ax.set_ylabel('Count')
```

In [40]:
```
plot_histogram(df,'LoanOriginalAmount',1000)
```



In [41]:
```
# Create a boxplot to examine outliers
fig, ax = plt.subplots(figsize=(10, 6))
sns.boxplot(df["LoanOriginalAmount"])

# Add labels and title
plt.xlabel("Loan Amount")
plt.ylabel("Amount in USD")
plt.title("Distribution of Loan Amounts");
```

```
/opt/conda/lib/python3.6/site-packages/seaborn/_decorators.py:43: FutureWarning: Pass the follow
  FutureWarning
```



1.4.3 Observation

The loan original Amount is multimodal with various peaks,with loan amount of about 5000 having the most peak

The histogram appears to be positively skewed, meaning that there are relatively more loans with lower amounts and fewer loans with higher amounts. The long tail towards higher loan amounts suggests that there are some loans with very high amounts that are considered outliers.

1.4.4 Observation

The median loan amount is around $7500, which is represented by the line in the middle of the box.

The height of the box indicates that half of the loan amounts in the dataset fall between approximately $4000 and 14000

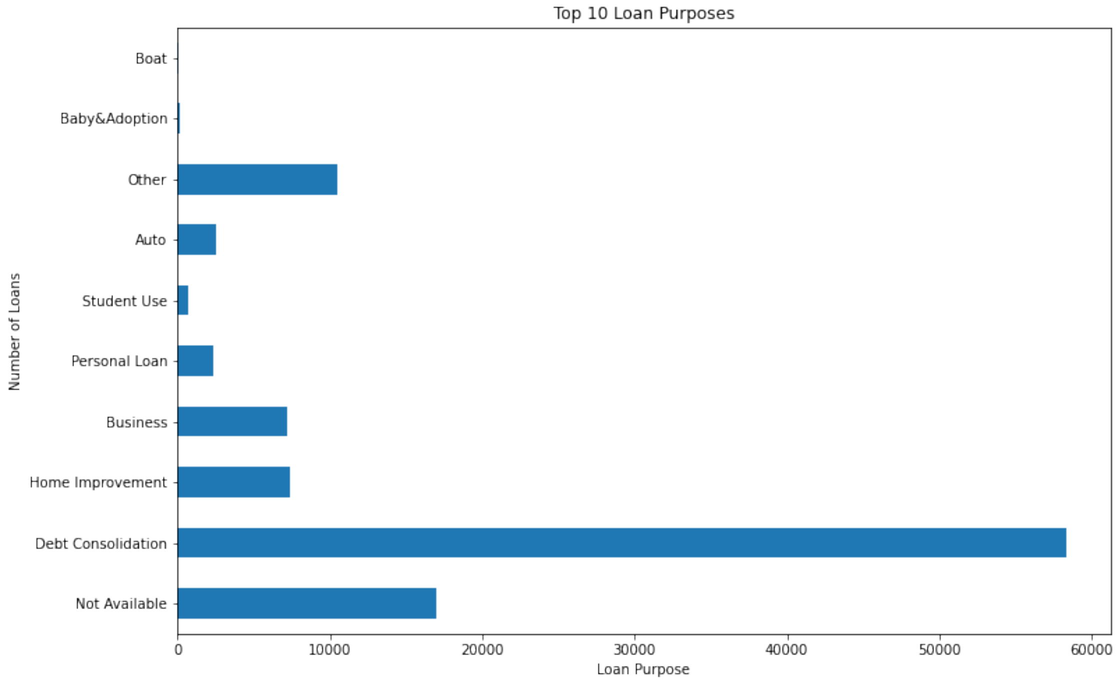
From the boxplot, we can also see that the distribution of loan amounts in the dataset is positively skewed, with a long tail towards higher values, but the highest loan amounts in the dataset are much higher than the median loan amount.

1.4.5 Question

What are the common reasons for taking loans?

1.4.6 Visualization

In [42]:
```
# Count the number of loans for each purpose
purpose_counts = loans['ListingCategory (numeric)'].value_counts().sort_index()

# Map the numeric categories to their corresponding string values

listing_category = {
    0: 'Not Available',
    1: 'Debt Consolidation',
    2: 'Home Improvement',
    3: 'Business',
    4: 'Personal Loan',
    5: 'Student Use',
    6: 'Auto',
    7: 'Other',
    8: 'Baby&Adoption',
    9: 'Boat',
    10: 'Cosmetic Procedure',
    11: 'Engagement Ring',
    12: 'Green Loans',
    13: 'Household Expenses',
    14: 'Large Purchases',
    15: 'Medical/Dental',
    16: 'Motorcycle',
    17: 'RV',
    18: 'Taxes',
    19: 'Vacation',
    20: 'Wedding Loans'
}

purpose_counts.index = purpose_counts.index.map(listing_category)

# Create a bar chart of the loan purposes
base_color = sns.color_palette()[0]
fig, ax = plt.subplots(figsize=(12, 8))
purpose_counts.head(10).plot(kind='barh', color= base_color)

# Set the chart title and axes labels
ax.set_title('Top 10 Loan Purposes')
ax.set_xlabel('Loan Purpose')
ax.set_ylabel('Number of Loans');
```



1.4.7 Observation

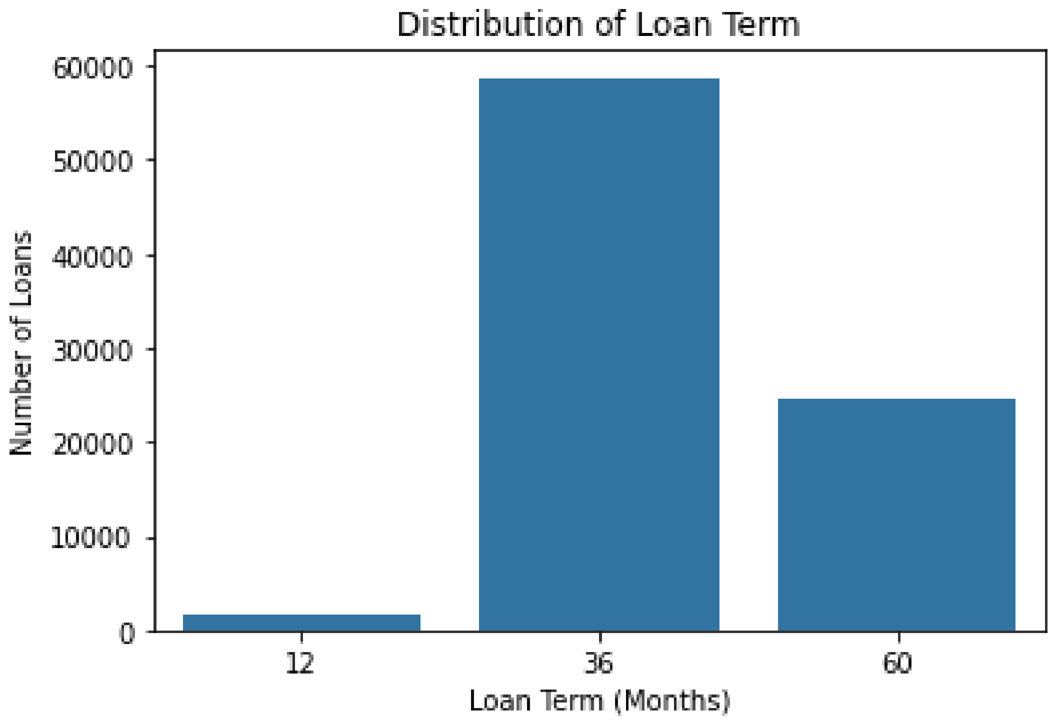
The most common loan purpose is debt consolidation

1.4.8 Question

What is the common duration for loans?

1.4.9 Visualization

In [43]:
```
# Set figsize
plt.figure(figsize=[6, 4])

#plot barchart
sns.countplot(x='Term', data=df, color = base_color)

# Add labels and title
plt.xlabel('Loan Term (Months)')
plt.ylabel('Number of Loans')
plt.title('Distribution of Loan Term');
```



1.4.10 Observation

Most of the loan duration is 3years and 2years

1.4.11 Question

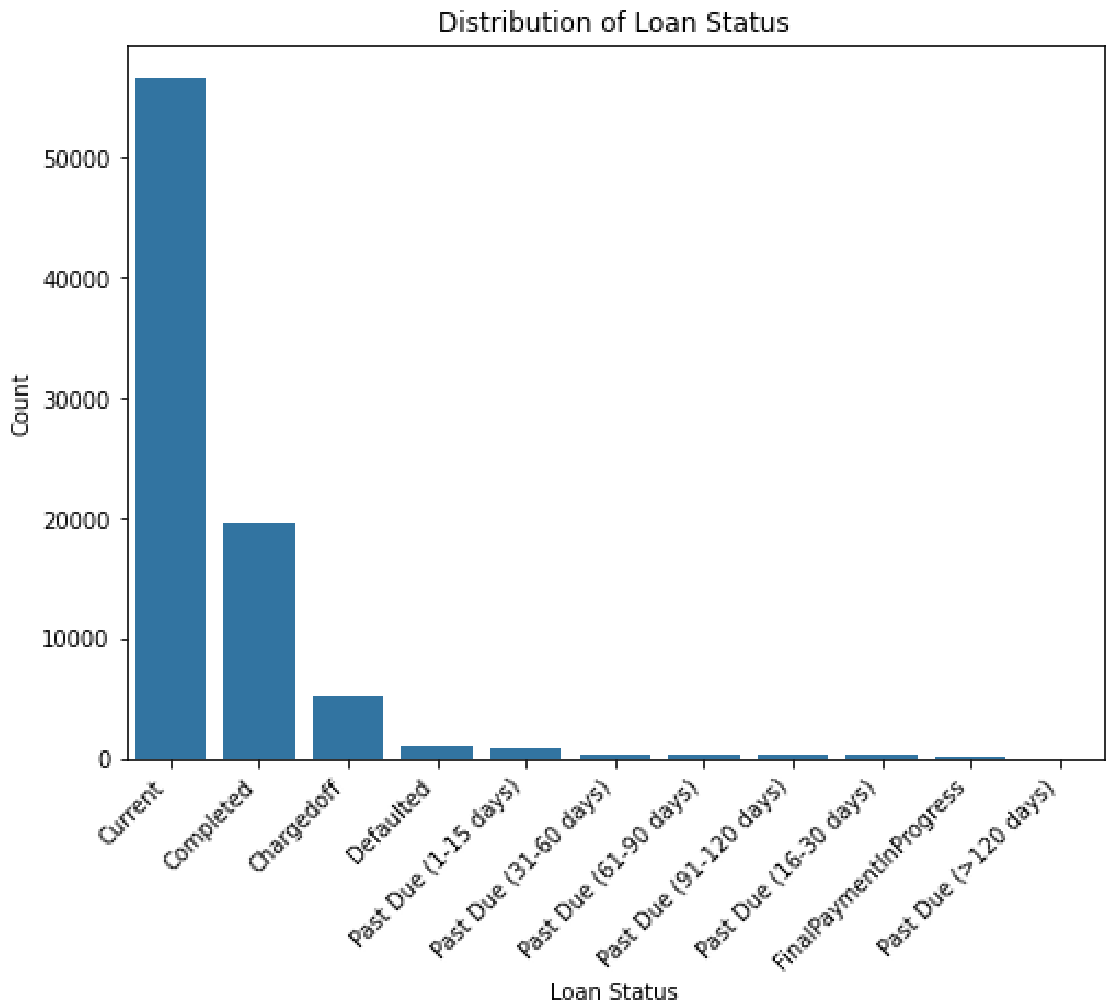
What is the distribution of LoanStatus?

1.4.12 Visualization

```
In [44]: df["LoanStatus"].value_counts()
```

```
Out[44]: Current                   56576
         Completed                 19664
         Chargedoff                 5336
         Defaulted                  1005
         Past Due (1-15 days)        806
         Past Due (31-60 days)       363
         Past Due (61-90 days)       313
         Past Due (91-120 days)      304
         Past Due (16-30 days)       265
         FinalPaymentInProgress      205
         Past Due (>120 days)         16
         Name: LoanStatus, dtype: int64
```

```
In [45]: # Create countplot
         plt.figure(figsize=(8, 6))
         sns.countplot(x='LoanStatus', data=df, order=df['LoanStatus'].value_counts().index, col
         plt.xticks(rotation=45, ha='right')
         plt.title('Distribution of Loan Status')
         plt.xlabel('Loan Status')
         plt.ylabel('Count');
```



1.4.13 Observation

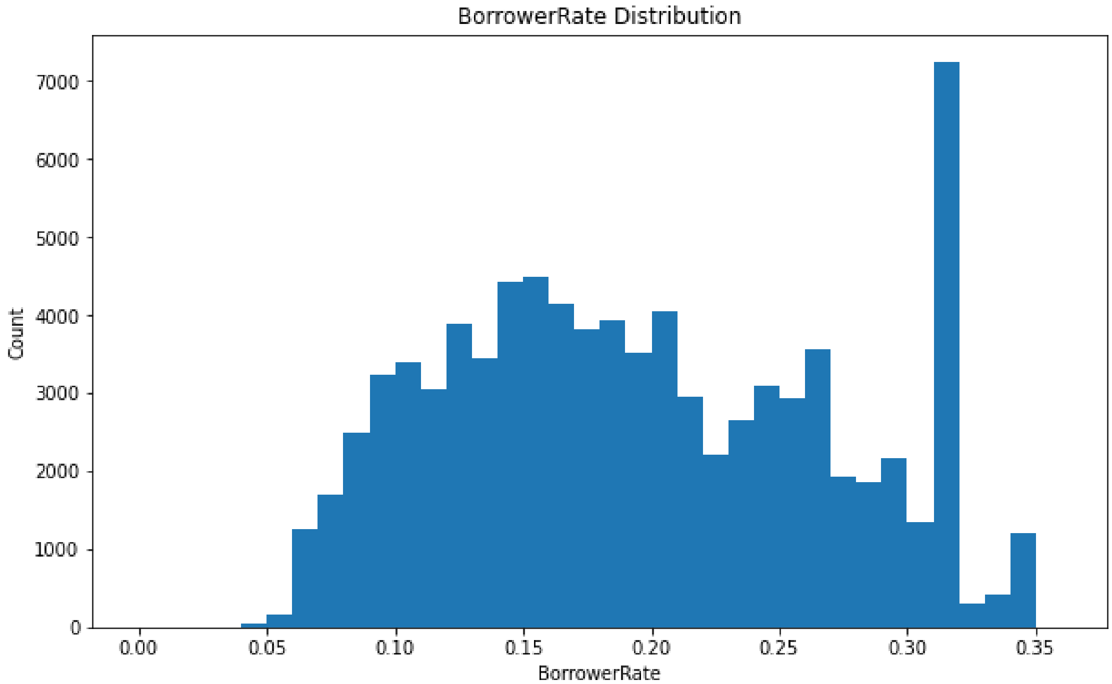
Majority of the loans fall under 'Current' status

1.4.14 Question

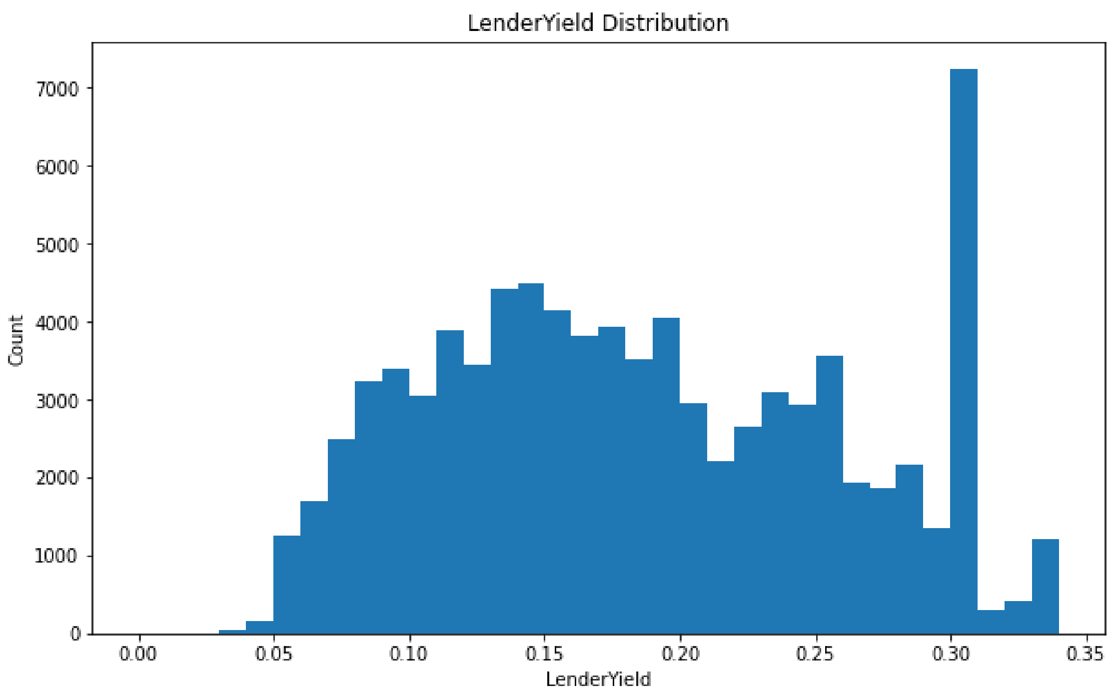
What is the distribution of BorrowerRate, LenderYield?

1.4.15 Visualization

```
In [46]: plot_histogram(df,'BorrowerRate', 0.01)
```




```
In [47]: plot_histogram(df, 'LenderYield',0.01)
```



1.4.16 Observation

Borrower Rate distribution is multimodal. The majority of loans have APRs between approximately 0.05 and 0.25. There are also some loans with APRs greater than 0.3 but they are relatively few compared to those in the lower APR ranges. We have a shape peak between 0.15 and 0.2 and outlier in 0.3

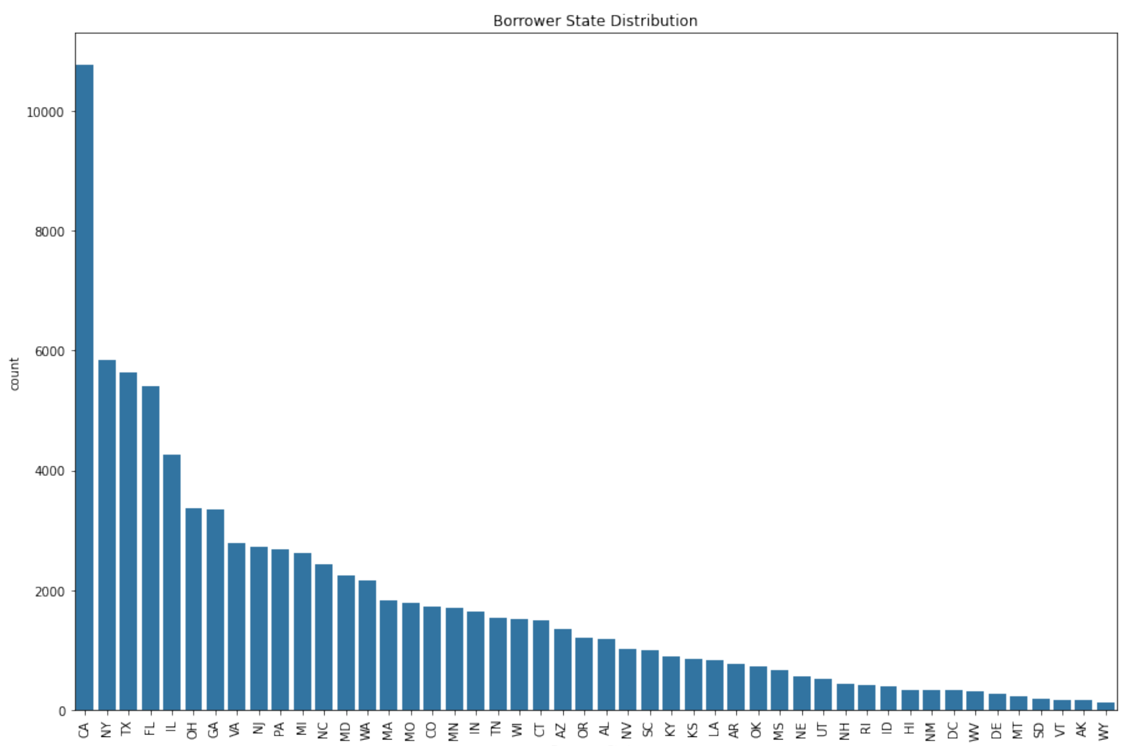
Lender Yield follows the same distribution as borrower rate

1.4.17 Question

What are the distributions of borrower characteristics like State, employment status, income range, prosper rating, homeowner?

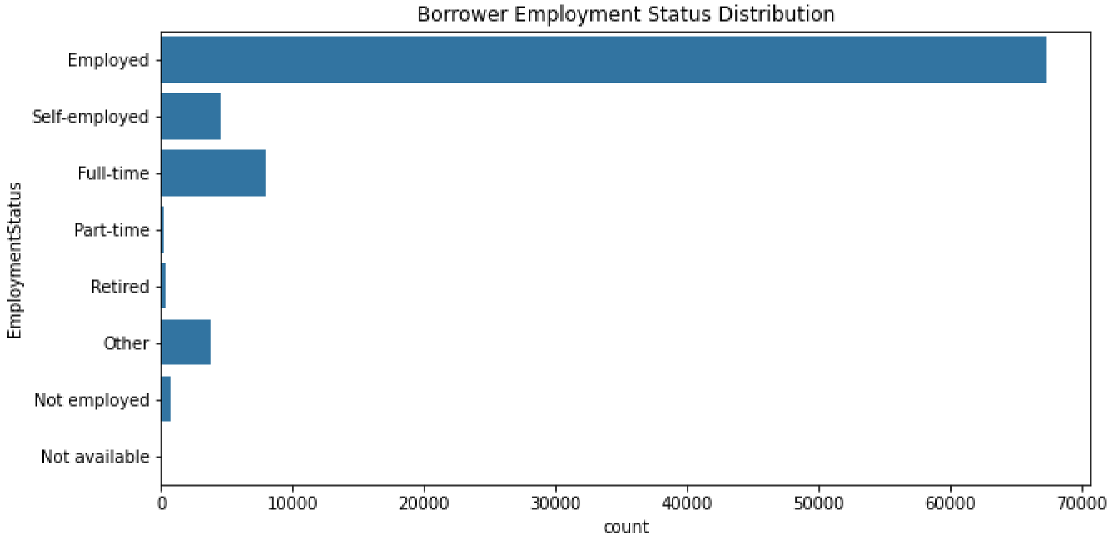
1.4.18 Visualization

In [48]:
```
#Borrower State Distribution

state_order = df['BorrowerState'].value_counts().index

base_color = sns.color_palette()[0]
plt.figure(figsize=[15, 10])
sns.countplot(data=df, x='BorrowerState', color=base_color, order=state_order);
plt.title('Borrower State Distribution');
plt.xticks(rotation=90);
```



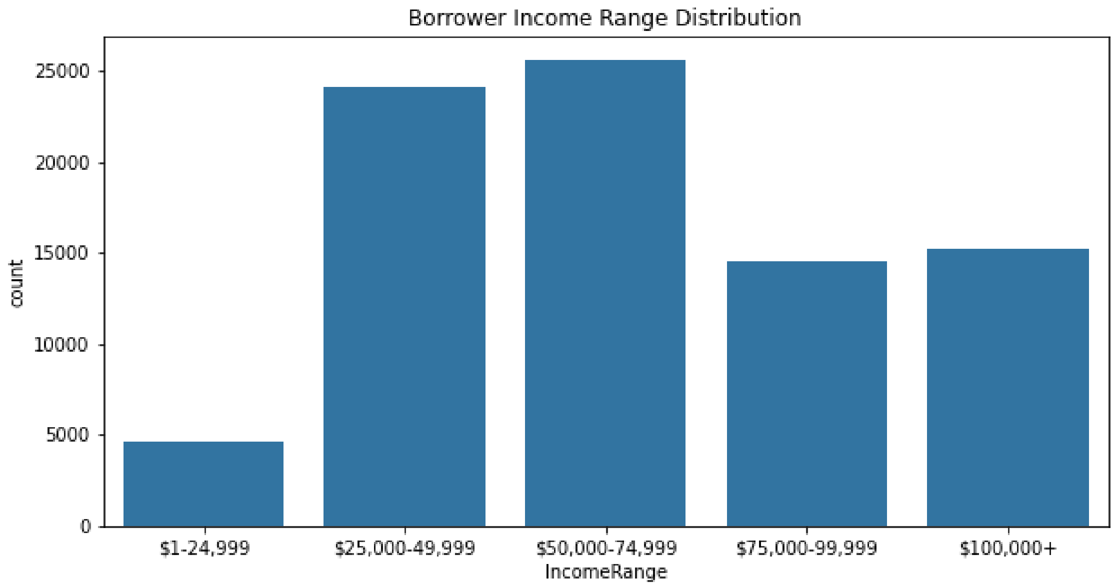
In [49]: # Borrower Employment Status Distribution

```
plt.figure(figsize=[10, 5])
sns.countplot(data = df, y = 'EmploymentStatus', color = base_color)
plt.title('Borrower Employment Status Distribution');
```

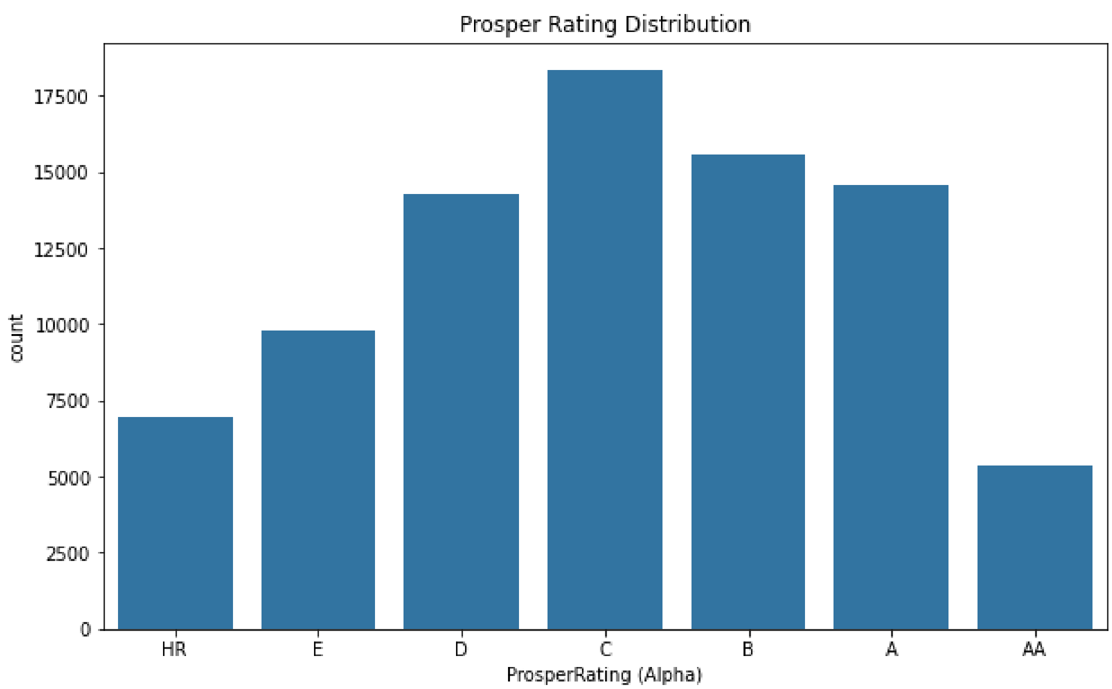


In [50]: #Borrower Income Range Distrobution

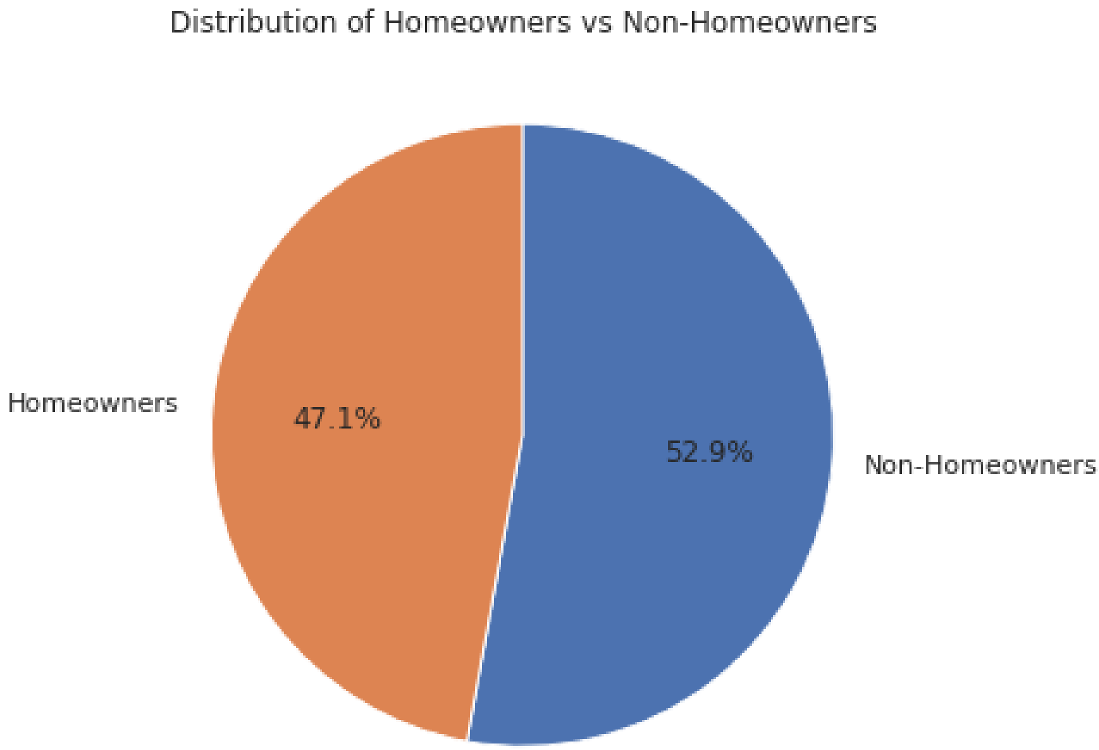
```
plt.figure(figsize=[10, 5])
sns.countplot(data=df,x='IncomeRange',color=base_color);
plt.title('Borrower Income Range Distribution');
```



In [51]:
```
# Prosper Rating Distribution

plt.figure(figsize=[10, 6]);
sns.countplot(data=df, x='ProsperRating (Alpha)', color=base_color);
plt.title('Prosper Rating Distribution');
```



```
In [85]: # Create a pie chart of IsBorrowerHomeowner
         plt.figure(figsize=[10, 6])
         plt.pie(df['IsBorrowerHomeowner'].value_counts(), labels=['Non-Homeowners', 'Homeowners
                 autopct='%1.1f%%', startangle = 90,
                 counterclock = False)
         plt.title('Distribution of Homeowners vs Non-Homeowners');
```



1.4.19 Observation

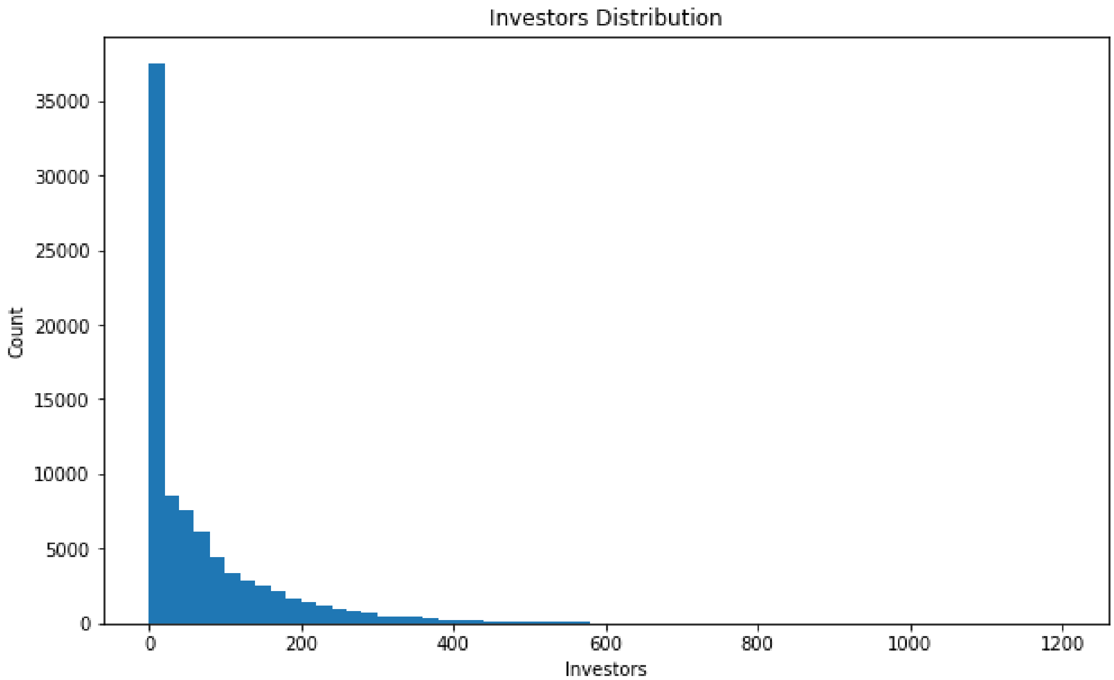
Majority of the borrowers come from California(CA), they're employed, earn between 25,000 to 74,000 dollars, have a 'C' Prosper rating and often own a house

1.4.20 Question

How are Investors spread out across loans?

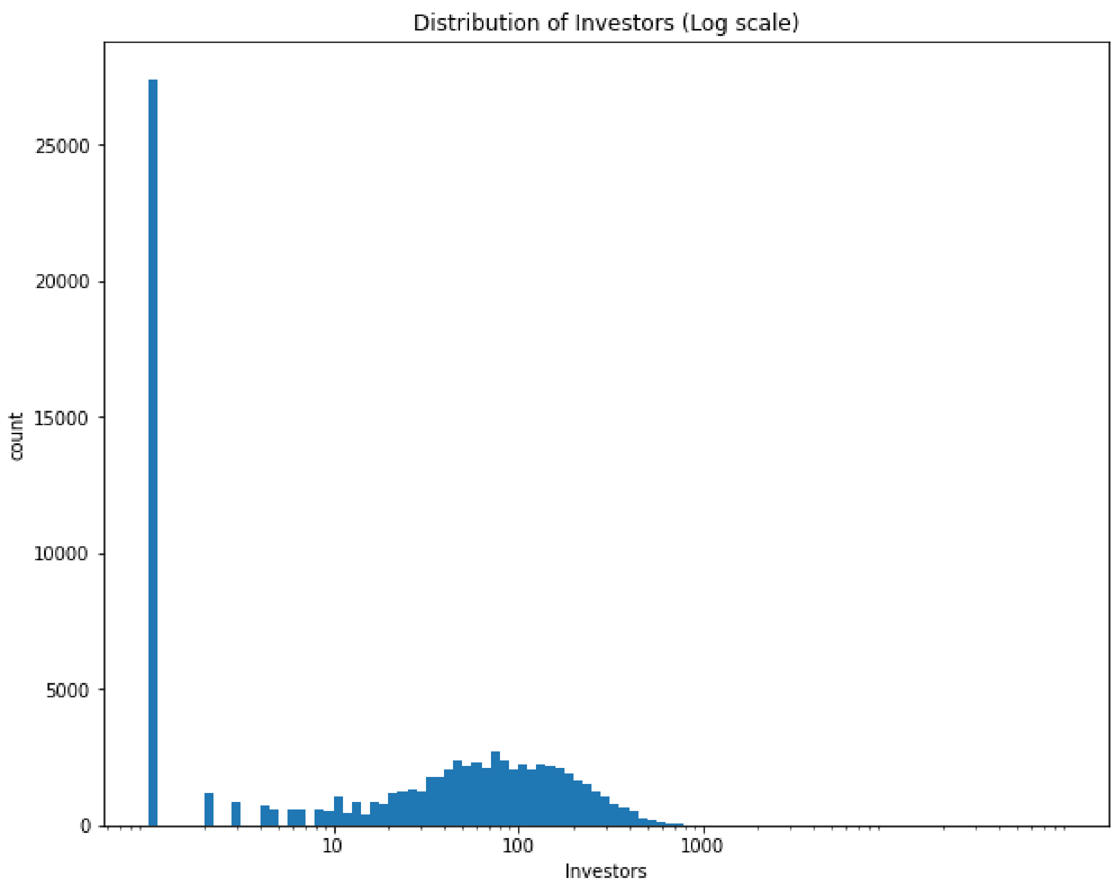
1.4.21 Visualization

```
In [53]: plot_histogram(df, 'Investors', 20)
```



This chart is not very informative. Using a logarithmic scale would help to display the smaller values in more detail

In [54]:
```
# create histogram of Investors using log scale
log_binsize = 0.05
bins = 10 ** np.arange(0, 5, log_binsize)

plt.figure(figsize=[10, 8])
plt.hist(data = df, x = 'Investors', bins = bins)
plt.title('Distribution of Investors (Log scale)')
plt.xscale('log')
plt.xticks([1e1, 1e2, 1e3], ['10', '100', '1000'])
plt.xlabel('Investors')
plt.ylabel('count');
```



1.4.22 Observation

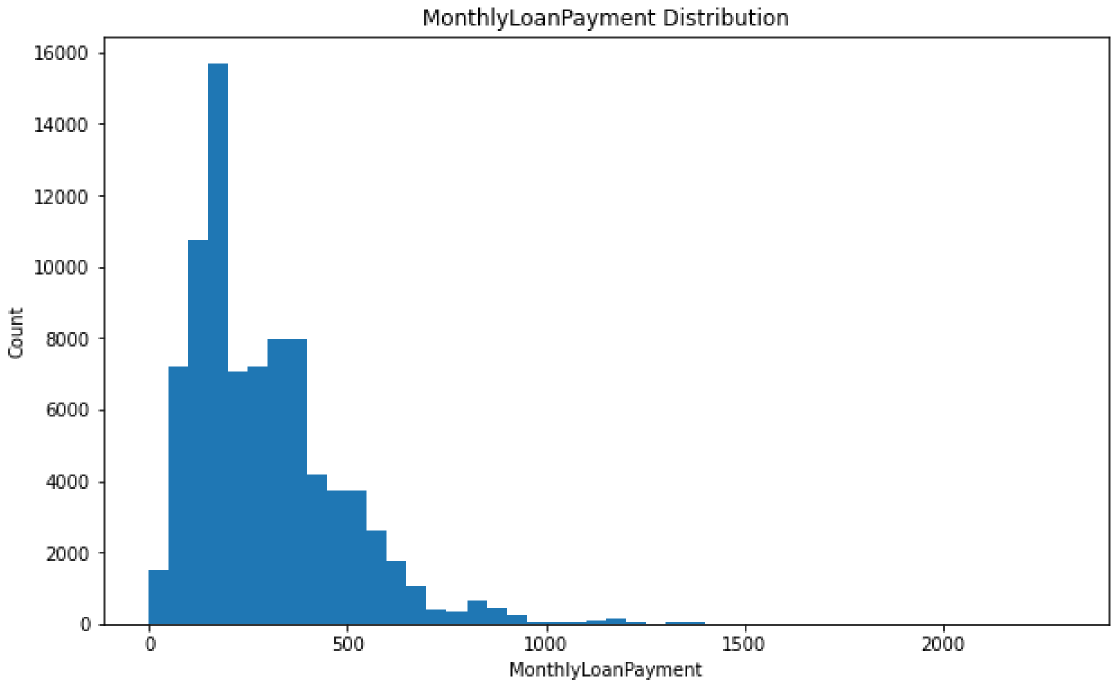
we can see that the majority of the loans have less than 10 investors, with a peak at around 90-100 investors.

1.4.23 Question

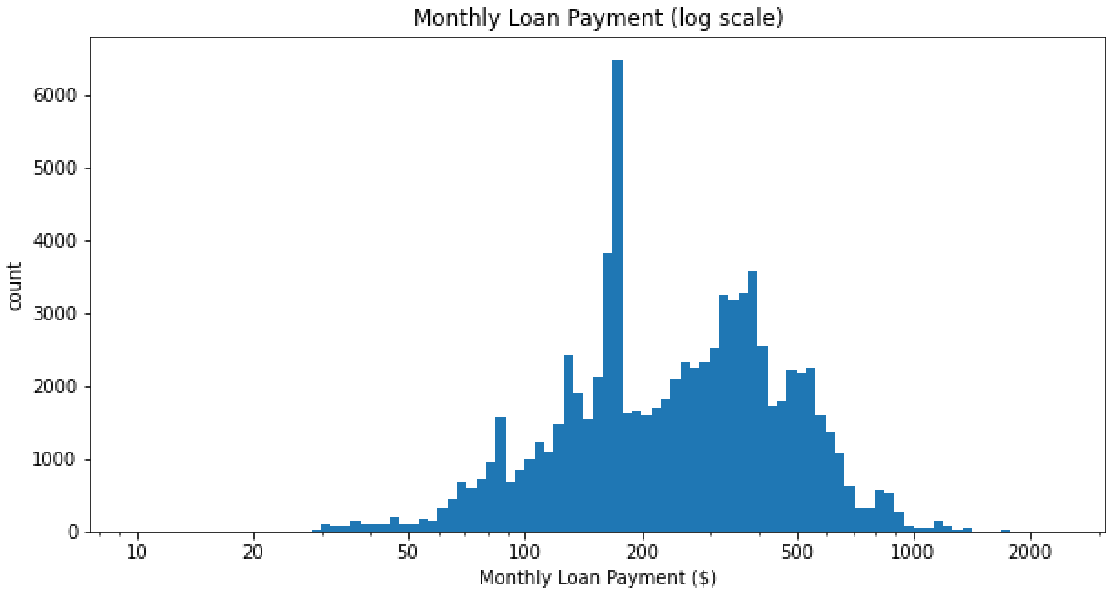
What is the distribution of loan monthly payments?

1.4.24 Visualization

```
In [55]: plot_histogram(df,'MonthlyLoanPayment', 50)
```



In [56]:
```
# Taking a closer look using log-scale
log_binsize = 0.025
bins = 10 ** np.arange(1, np.log10(df['MonthlyLoanPayment'].max())+log_binsize, log_bin

plt.figure(figsize=[10, 5])
plt.hist(data = df, x = 'MonthlyLoanPayment', bins = bins)
plt.xscale('log')
plt.xticks([10, 20, 50, 100, 200, 500, 1e3, 2e3], ['10', '20','50', '100', '200', '500'
plt.xlabel('Monthly Loan Payment ($)')
plt.ylabel('count')
plt.title('Monthly Loan Payment (log scale)');
```



1.4.25 Observation

Most of the borrowers are scheduled to pay about $180 monthly, although a considerable amount are also scheduled to pay between 300 to 500 dollars monthly

1.4.26 Question

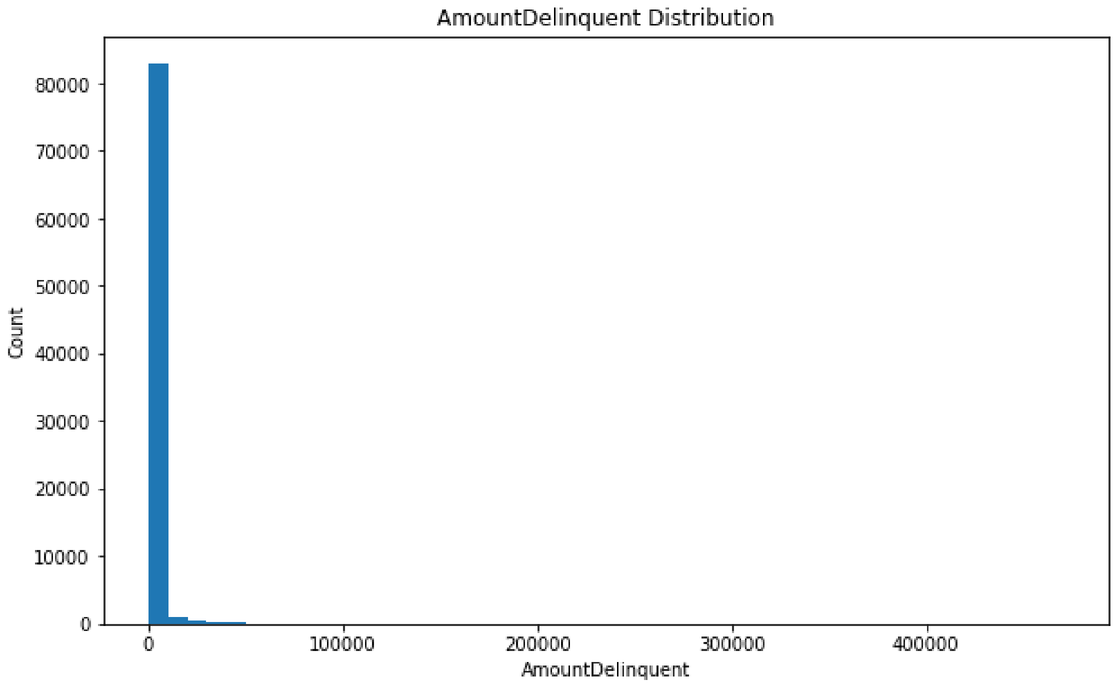
What is the distribution of delinquent loans?

1.4.27 Visualization

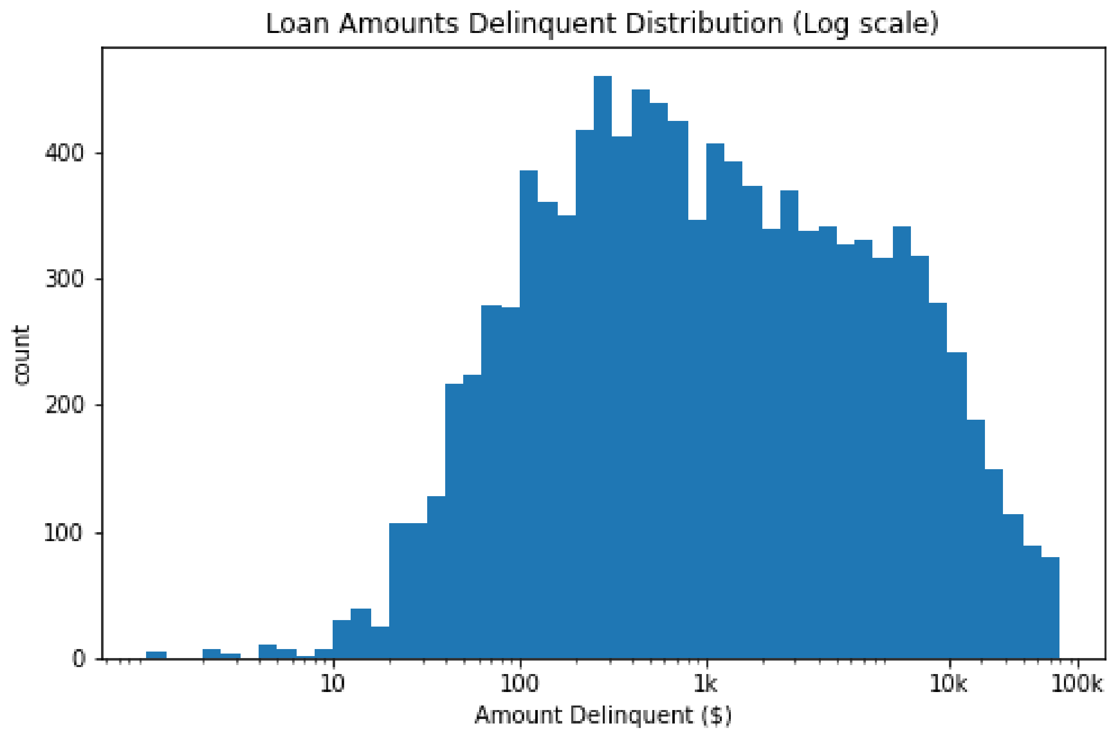
```
In [57]: df['AmountDelinquent'].describe()
```

```
Out[57]: count     84853.000000
         mean        950.773797
         std        7419.574684
         min           0.000000
         25%           0.000000
         50%           0.000000
         75%           0.000000
         max      463881.000000
         Name: AmountDelinquent, dtype: float64
```

```
In [58]: plot_histogram(df,'AmountDelinquent', 10000)
```



In [59]:
```
#Amount Delinquent Distribution on a log scale

log_binsize = 0.1
bins = 10 ** np.arange(0,5, log_binsize)

plt.figure(figsize=[8, 5])
plt.hist(data = df, x = 'AmountDelinquent', bins = bins)
plt.title('Loan Amounts Delinquent Distribution (Log scale)')
plt.xscale('log')
plt.xticks([1e1, 1e2, 1e3, 2e4, 1e5], ['10', '100', '1k', '10k', '100k'])
plt.xlabel('Amount Delinquent ($)')
plt.ylabel('count');
```



1.4.28 Observation

Most loan amounts delinquent falls around $950 and it is normally distibuted

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

Loan Original Amount distribution is right skewed and Borrower Rate distribution is multimodal

1.4.30 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 performed log transformation on the Investors, MonthlyLoanPayments and Amount-Delinquent columns in order to take a closer look at the smaller values and interpret the visualization

1.5 Bivariate Exploration

I'd start by looking at the relationships between Numerical variables

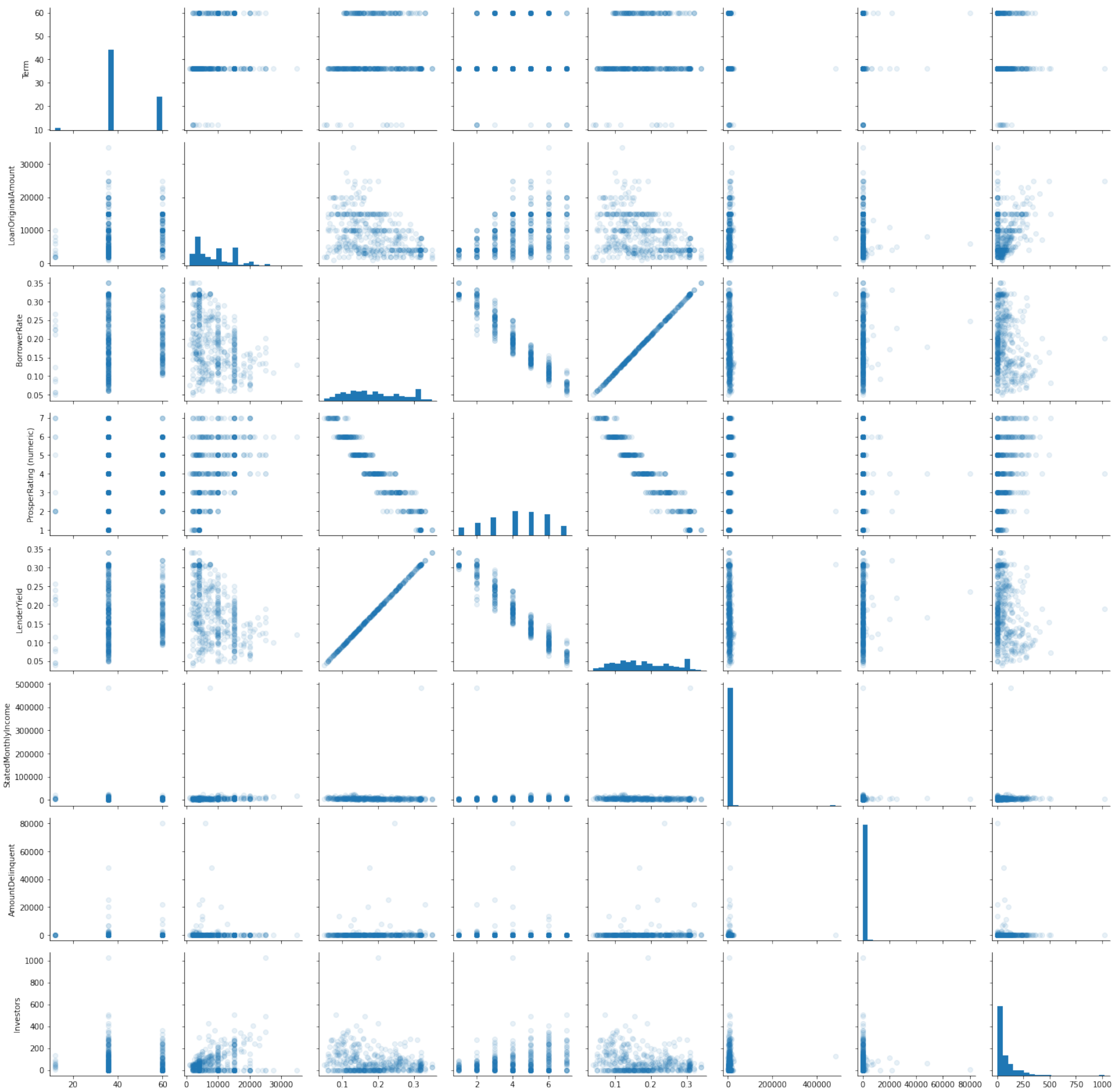
```
In [60]: numerical_vars = ['Term', 'LoanOriginalAmount', 'BorrowerRate', 'ProsperRating (numeric
                           'LenderYield', 'StatedMonthlyIncome', 'AmountDelinquent','Investors']
```

```
categorical_vars = ['Term','ProsperRating (Alpha)', 'EmploymentStatus','Occupation',
                    'IncomeRange','LoanStatus','BorrowerState','ListingCategory (numeri
```

```
In [61]: plt.figure(figsize = [12, 10])
         sns.heatmap(df[numerical_vars].corr(), annot = True, fmt = '.3f',
                     cmap = 'rocket', center = 0)
         plt.title('Correlation Heat Map');
```


```
In [62]: # plot matrix: sample of 600
         print("df.shape=",df.shape)
         df_samp = df.sample(n=500, replace = False)
         print("df_samp.shape=",df_samp.shape)

         g = sns.PairGrid(data = df_samp, vars = numerical_vars)
         g = g.map_diag(plt.hist, bins = 20);
         g.map_offdiag(plt.scatter,alpha=0.1);
```

```
df.shape= (84853, 23)
df_samp.shape= (500, 23)
```



1.5.1 Observation

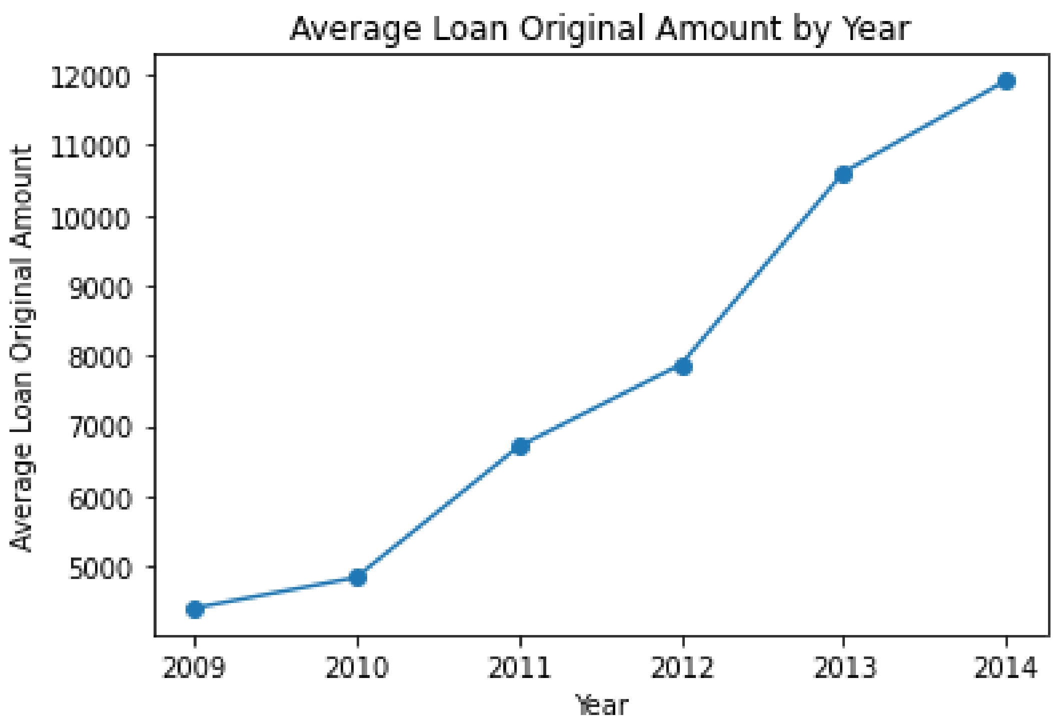
- LoanOriginalAmount and BorrowerRate are negatively correlated with coefficient of -0.413 which suggests that larger loans have lower borrower rate compared to lesser loans
- Strong positive correlations between Lender yield and Borrower Rate which is logical, higher borrower rates should result in higher lender yield
- Strong negative correlation between Prosper rating and borrower rate, which suggests that high prosper ratings have lower borrower rates

1.5.2 Question

How has Loan amount changed over time?

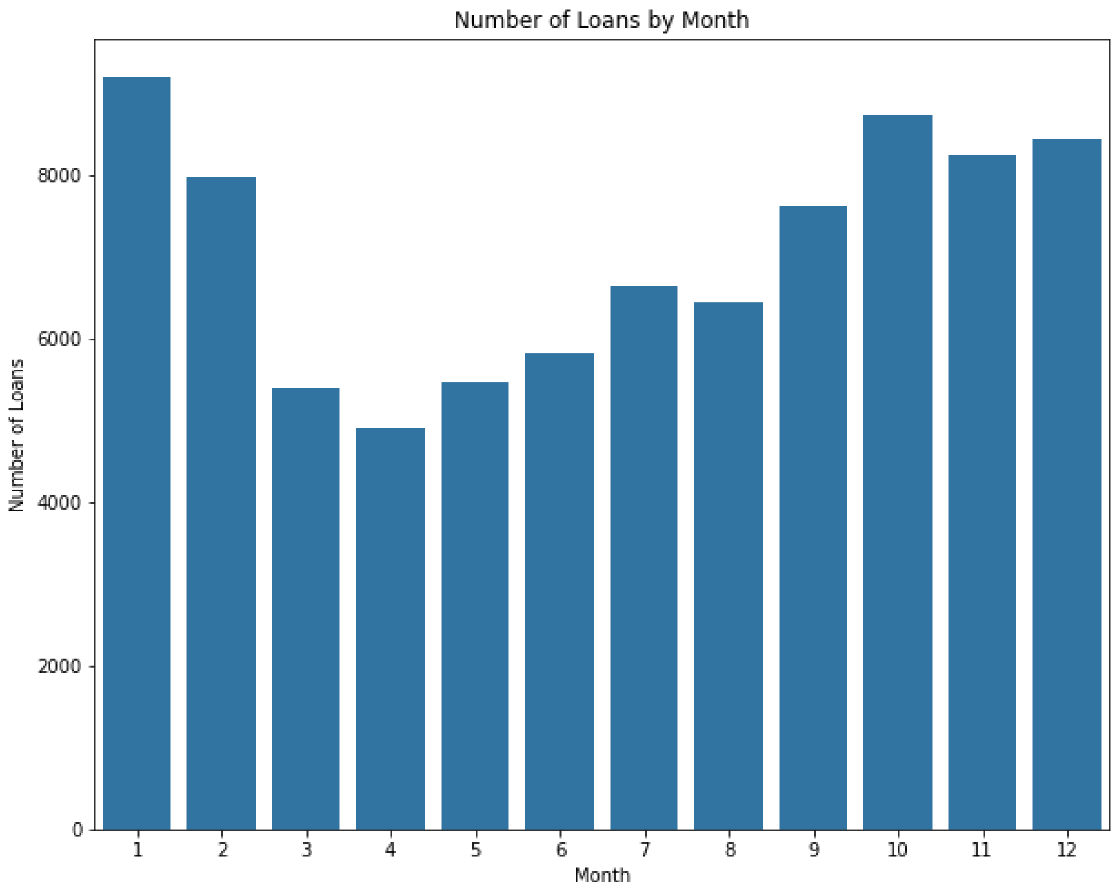
1.5.3 Visualization

In [63]:
```python
# Calculate the average loan original amount by year
avg_loan_by_year = df.groupby('ListingYear')['LoanOriginalAmount'].mean()

# Create a line plot of the average loan original amount by year
plt.plot(avg_loan_by_year.index, avg_loan_by_year.values, marker='o')
plt.xlabel('Year')
plt.ylabel('Average Loan Original Amount')
plt.title('Average Loan Original Amount by Year');
```



In [64]:
```python
# How are loans distributed across each month?

# Count the number of loans in each month
month_counts = df["ListingMonth"].value_counts()

# set figsize
fig, ax = plt.subplots(figsize=(10, 8))

# Create the bar chart
```

```
sns.barplot(x=month_counts.index, y=month_counts.values, color = base_color)

# Add labels and title
plt.xlabel("Month")
plt.ylabel("Number of Loans")
plt.title("Number of Loans by Month");
```



1.5.4 Observation

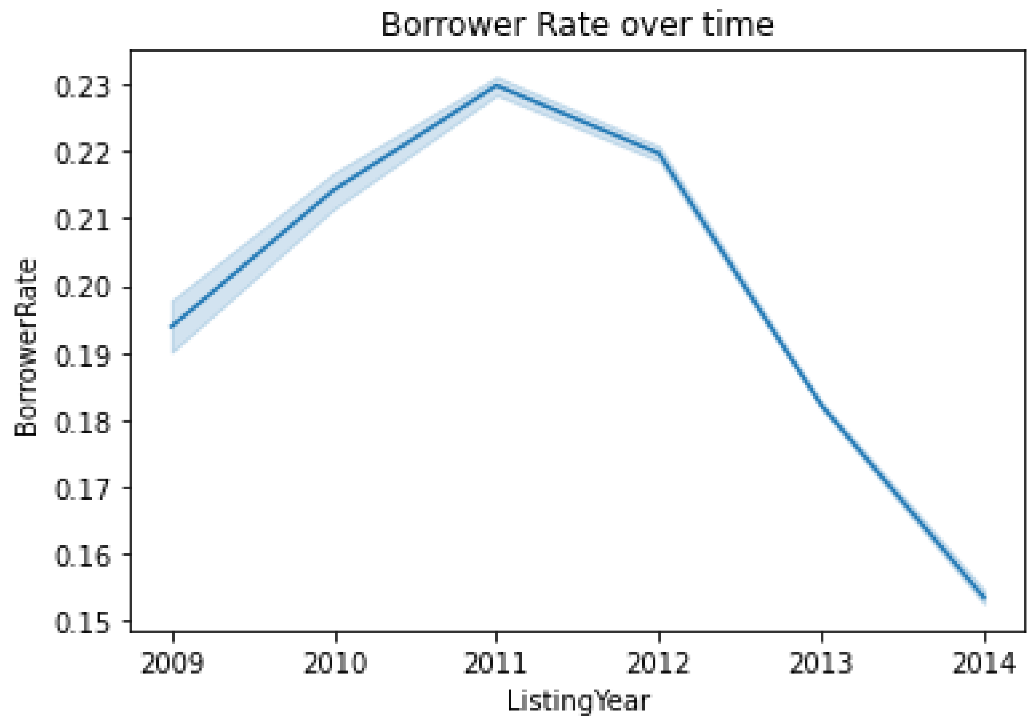
- Loan amount has been on a continuous uptrend over the years
- January has the most number of loans

1.5.5 Question

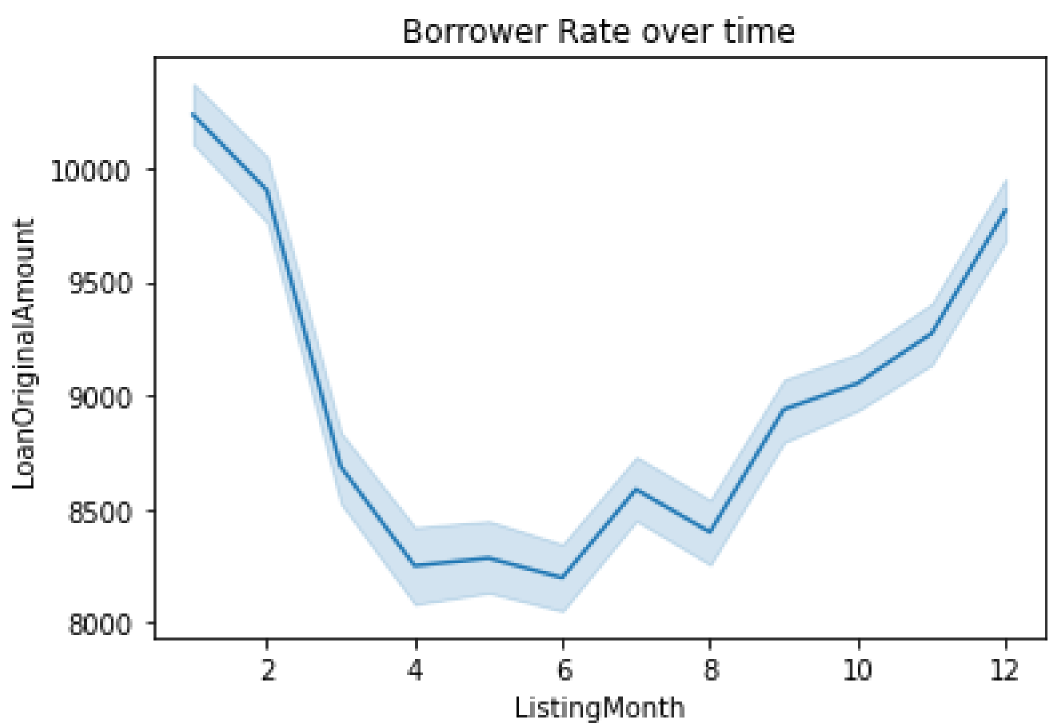
How has borrower rate changed over time?

1.5.6 Visualization

```
In [65]: sns.lineplot(x="ListingYear", y="BorrowerRate", data=df).set(title='Borrower Rate over
```




```
In [66]: # Taking a closer look at the borrower rate over months

         sns.lineplot(x="ListingMonth", y="LoanOriginalAmount", data=df).set(title='Borrower Rat
```



1.5.7 Observation

On yearly timeframe, Borrower rate peaked at 2011 and has been on a downtrend since then

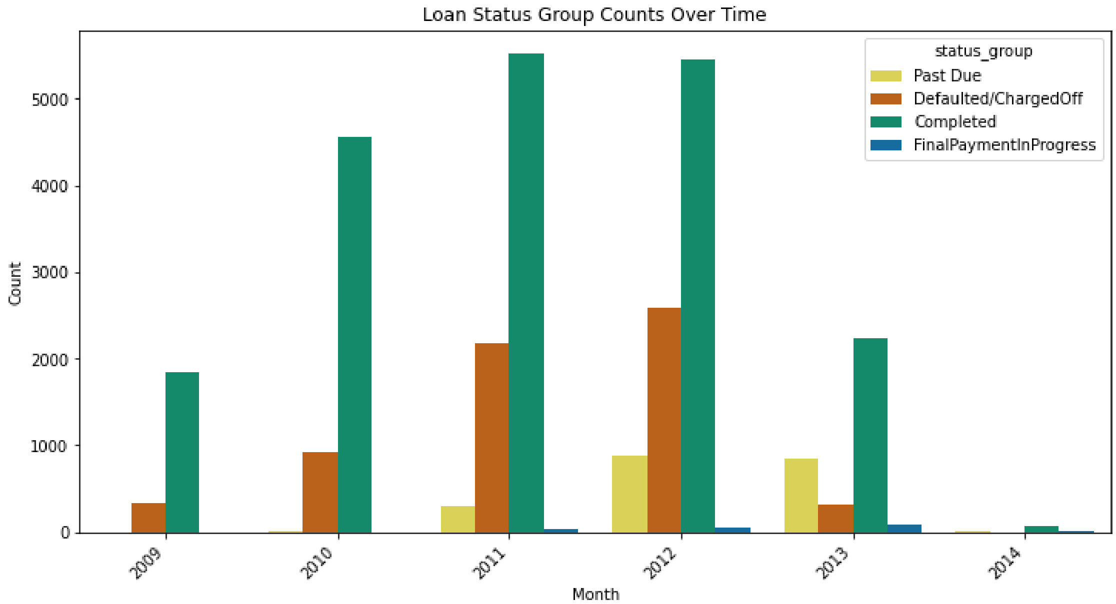
On monthly timeframe, rates are highest during january and february(which might be because the most number of loans are taken in january) but drop towards April to june

1.5.8 Question

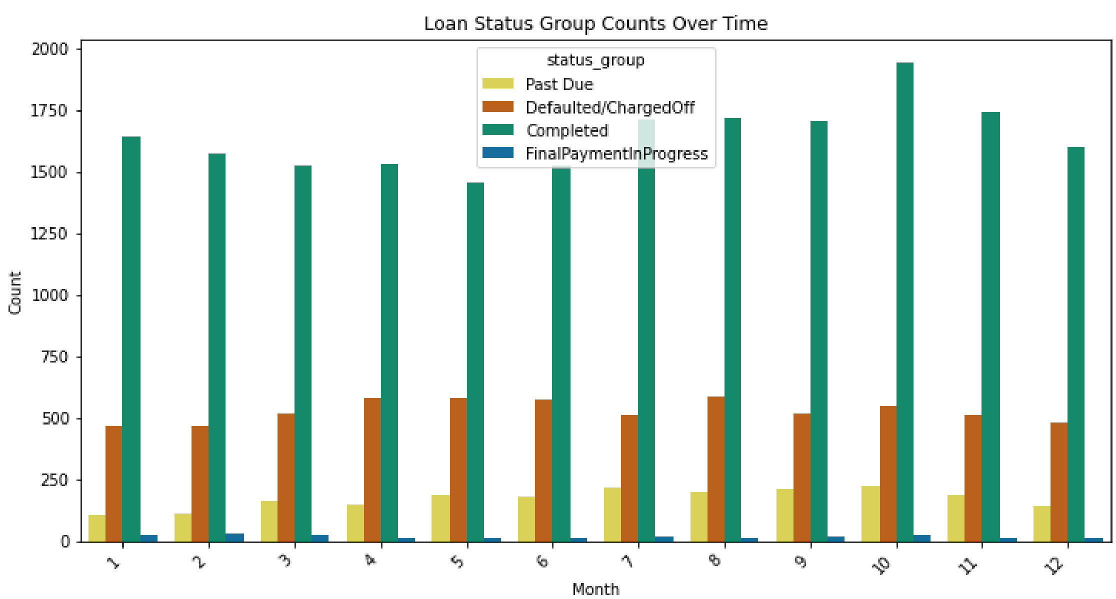
How has loan status changed over time?

1.5.9 Visualization

In [67]:
```
# create a dictionary to map loan statuses to their corresponding group
status_groups = {
    'Completed': 'Completed',
    'Defaulted': 'Defaulted/ChargedOff',
    'Chargedoff': 'Defaulted/ChargedOff',
    'Past Due (1-15 days)': 'Past Due',
    'Past Due (16-30 days)': 'Past Due',
    'Past Due (31-60 days)': 'Past Due',
    'Past Due (61-90 days)': 'Past Due',
    'Past Due (91-120 days)': 'Past Due',
    'Past Due (>120 days)': 'Past Due',
    'FinalPaymentInProgress': 'FinalPaymentInProgress'
}

# create a new column for the loan status group
df['status_group'] = df['LoanStatus'].map(status_groups)


# plot the loan status group counts over the years
colored = ['#F0E442','#D55E00','#009E73','#0072B2']

plt.figure(figsize=(12, 6))
sns.countplot(data=df, x='ListingYear', hue='status_group', palette=colored)
plt.title('Loan Status Group Counts Over Time')
plt.xlabel('Month')
plt.ylabel('Count')
plt.xticks(rotation=45, ha='right');
```



In [68]:
```
# Taking a closer look on a monthly timeframe

# plot the loan status group counts over months
plt.figure(figsize=(12, 6))
sns.countplot(data=df, x='ListingMonth', hue='status_group', palette=colored)
plt.title('Loan Status Group Counts Over Time')
plt.xlabel('Month')
plt.ylabel('Count')
plt.xticks(rotation=45, ha='right');
```



1.5.10 Observation

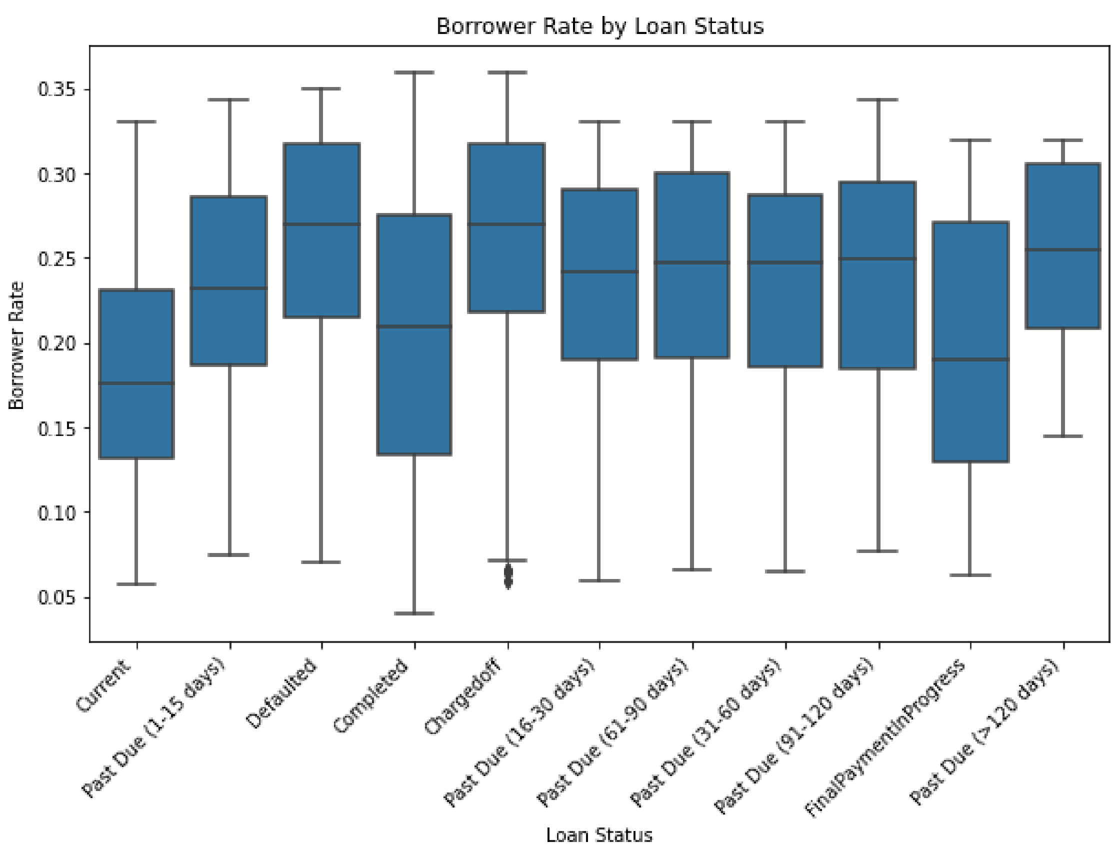
- 2011 has the highest number of completed loans
- The year with the highest delinqent loans is 2012
- October has the highest completed loans

1.5.11 Question

What is the relationship between Borrower Rate and Loan Status?

1.5.12 Visualization

In [69]:
```python
# create a box plot of borrower rate by loan status

plt.figure(figsize=(10, 6))
sns.boxplot(data=df, x='LoanStatus', y='BorrowerRate', color = base_color)
plt.xticks(rotation=45, ha='right')
plt.title('Borrower Rate by Loan Status')
plt.xlabel('Loan Status')
plt.ylabel('Borrower Rate')
plt.show()
```



1.5.13 Observation

We can see that the median borrower rate is generally higher for loans that are defaulted, charged-off or past due compared to completed loans. Completed and current loans have median borrower rate of 0.22 and 0.18 respectively.

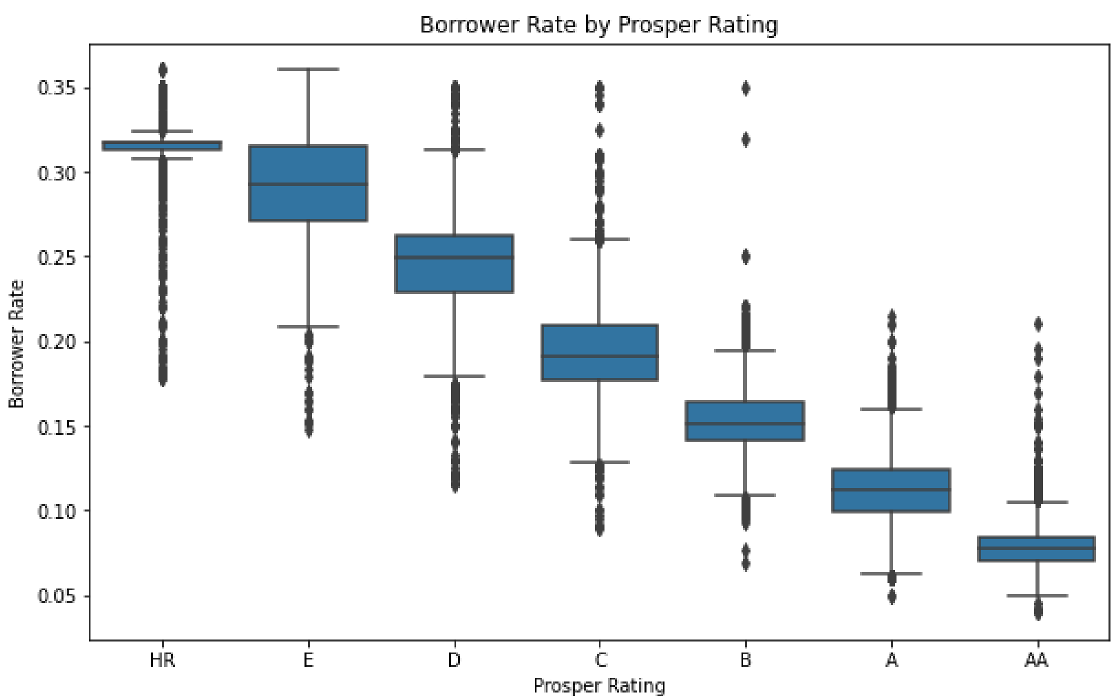
This suggests that lower borrower rates are associated with higher completion rates, while higher borrower rates are associated with higher rates of default, charge off, and past due status.

1.5.14 Question

What is the relationship between Borrower rate and Prosper rating?

1.5.15 Visualization

```
In [70]: # Create box plot
         plt.figure(figsize=(10, 6))
         sns.boxplot(x='ProsperRating (Alpha)', y='BorrowerRate', data=df, color = base_color)
         plt.title('Borrower Rate by Prosper Rating')
         plt.xlabel('Prosper Rating')
         plt.ylabel('Borrower Rate');
```



1.5.16 Observation

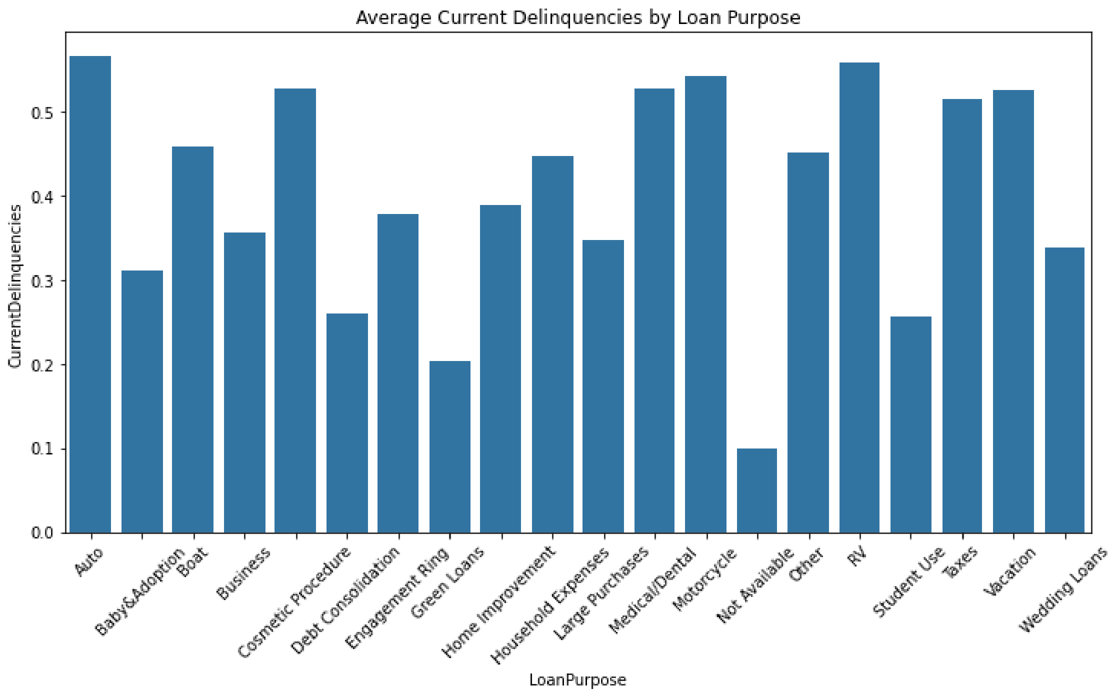
Borrower rates are highest for HR(High risk) Prosper rating and lowest for the highest Prosper rating AA This shows that borrowers with better Prosper rating get lower rates

1.5.17 Question

What listing category is likely to (1) default (2) Be Completed

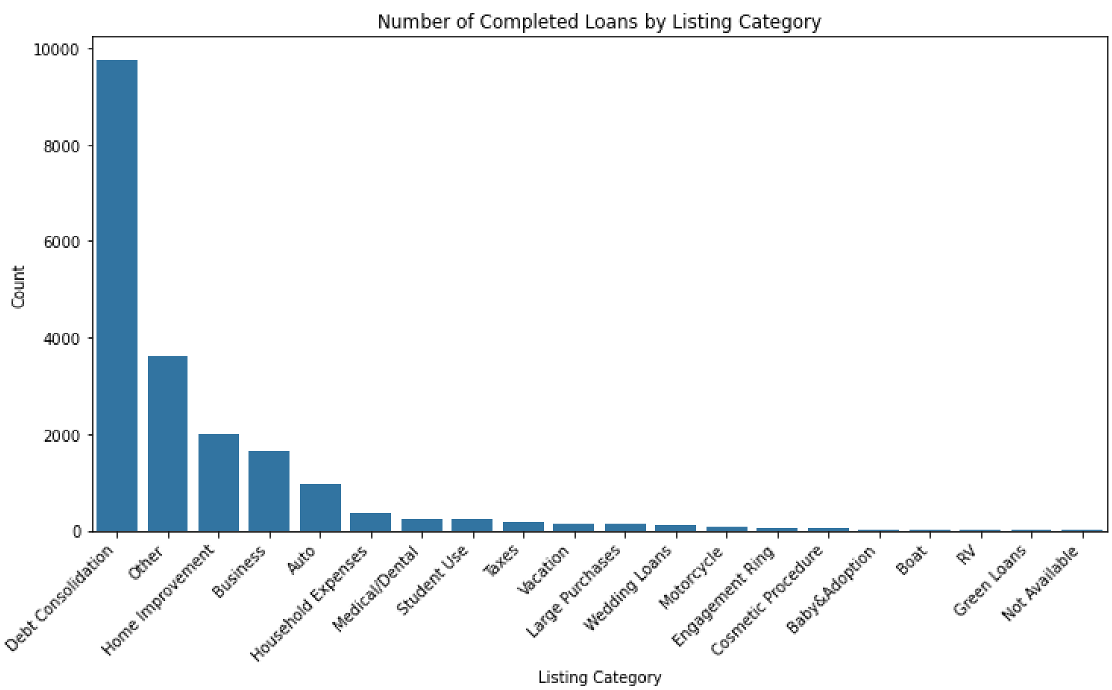
1.5.18 Visualization

```
In [71]: # create a new column with the loan purposes
         df['LoanPurpose'] = df['ListingCategory (numeric)'].map(listing_category)

         # group the data by loan purpose and calculate the mean current delinquencies
         delinquencies_by_purpose = df.groupby('LoanPurpose')['CurrentDelinquencies'].mean().res

         # create a barplot of loan purposes and current delinquencies
         plt.figure(figsize=(12, 6))
         sns.barplot(x='LoanPurpose', y='CurrentDelinquencies', data=delinquencies_by_purpose, c
         plt.title('Average Current Delinquencies by Loan Purpose')
         plt.xticks(rotation=45);
```




```
In [72]: # create a subset dataframe with only completed loans
         completed_loans = df[df['LoanStatus'] == 'Completed']
```

```python
# count the number of completed loans for each listing category
listing_counts = completed_loans['ListingCategory (numeric)'].value_counts()

# map the numeric listing categories to their corresponding names
listing_counts.index = listing_counts.index.map(listing_category)

# create a bar plot of completed loans by listing category
plt.figure(figsize=(12, 6))
sns.barplot(x=listing_counts.index, y=listing_counts.values, color= base_color)
plt.title('Number of Completed Loans by Listing Category')
plt.xlabel('Listing Category')
plt.ylabel('Count')
plt.xticks(rotation=45, ha='right');
```



1.5.19 Observation

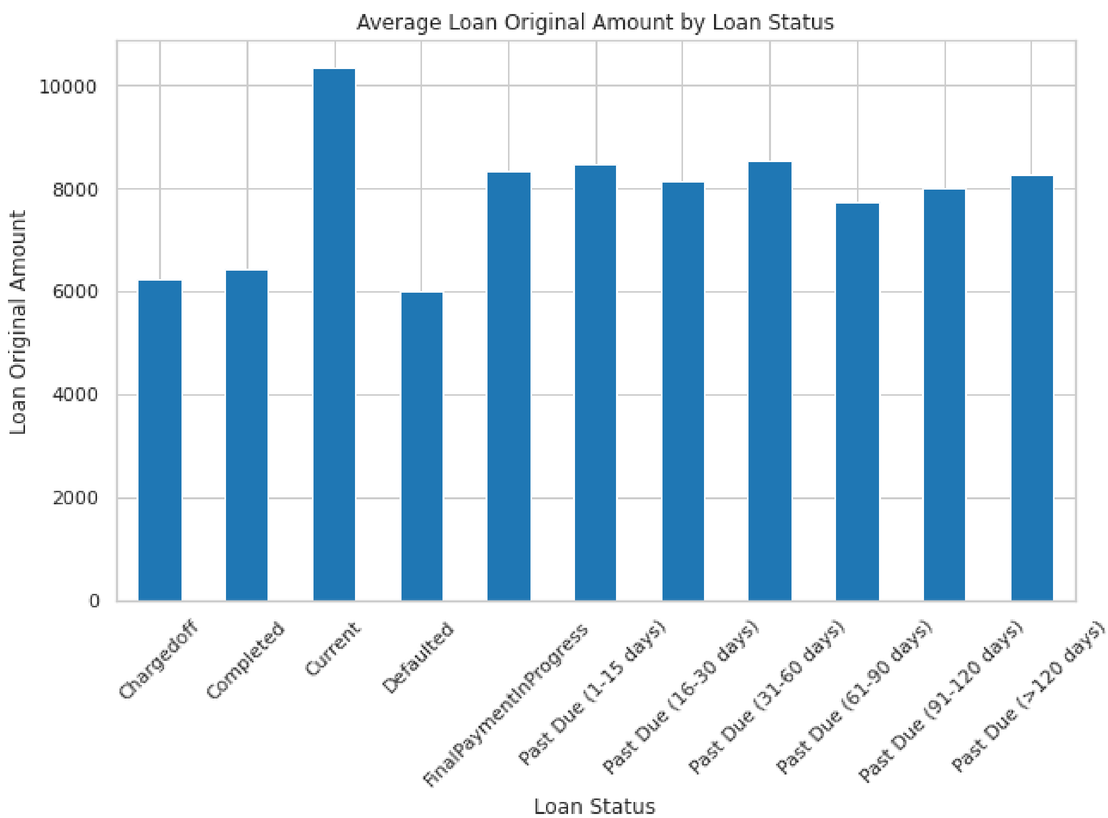
- Loans requested for the purpose of Auto have the highest delinquencies It suggests that loans for Auto, Business, Large purchases, Medical/dental and RV may be riskier than other purposes like debt consolidation and student use.
- Loans taken for debt consolidation are most likely to be completed

1.5.20 Question

What is the relationship between LoanOriginalAmount and LoanStatus?

1.5.21 Visualization

```
In [86]: # Group the dataset by LoanStatus and calculate the mean loan original amount for each
         grouped = df.groupby('LoanStatus')['LoanOriginalAmount'].mean()

         # Create a bar chart of the mean loan original amount for each loan status
         grouped.plot(kind='bar', figsize=(10,6), color = base_color)
         plt.title('Average Loan Original Amount by Loan Status')
         plt.xlabel('Loan Status')
         plt.xticks(rotation=45)
         plt.ylabel('Loan Original Amount');
```



1.5.22 Observation

Larger loans are more likely to be in the "Current" status, while smaller loans are more likely to be in the "Defaulted" and "Chargedoff" categories.

1.5.23 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?

Strong positive correlations between Lender yield and Borrower Rate which is logical, higher borrower rates should result in higher lender yield

Strong negative correlation between Prosper rating and borrower rate, which suggests that high prosper ratings have lower borrower rates

2011 had the highest borrower rates and highest completed loans
Loans taken for debt consolidation are most likely to be completed

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

Loans taken for the purpose of Auto have the highest delinquency

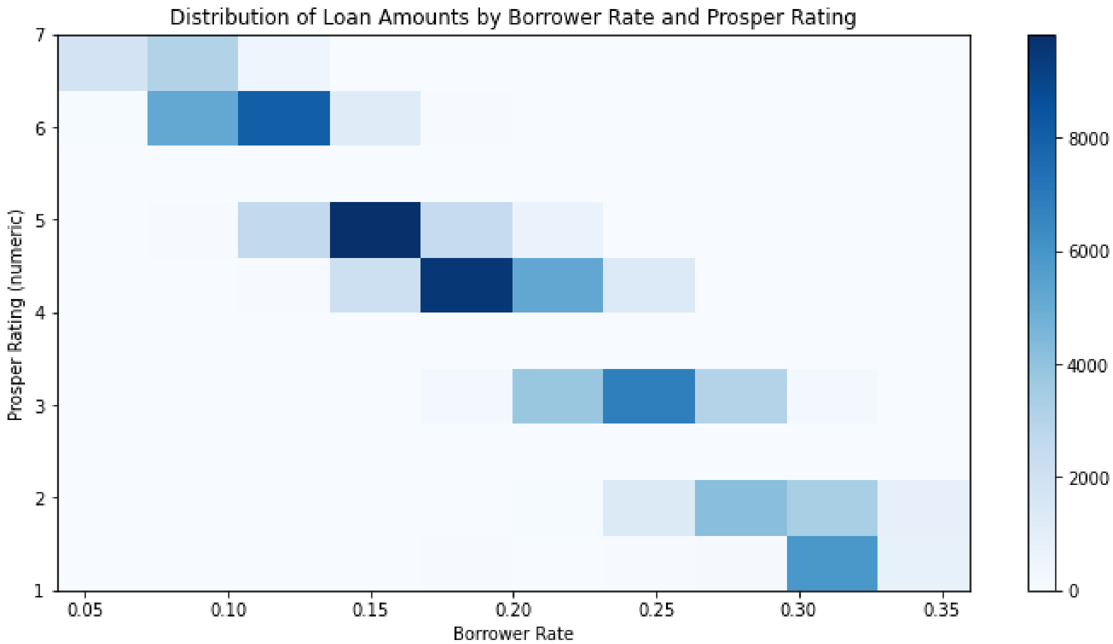
1.6 Multivariate Exploration

1.6.1 Question

What is the distribution of Loan amounts by Borrower rate and Prosper rating?

1.6.2 Visualization

```
In [74]: median_loan_by_rating_rate = df.pivot_table(index='BorrowerRate', columns='ProsperRatin

         # plot 2D histogram
         plt.figure(figsize=(12, 6))
         plt.hist2d(x=df['BorrowerRate'], y=df['ProsperRating (numeric)'], bins=(10,10), cmap=pl

         # add a colorbar
         plt.colorbar()

         # set the title and axis labels

         plt.title('Distribution of Loan Amounts by Borrower Rate and Prosper Rating')
         plt.xlabel('Borrower Rate')
         plt.ylabel('Prosper Rating (numeric)');
```



1.6.3 Observation

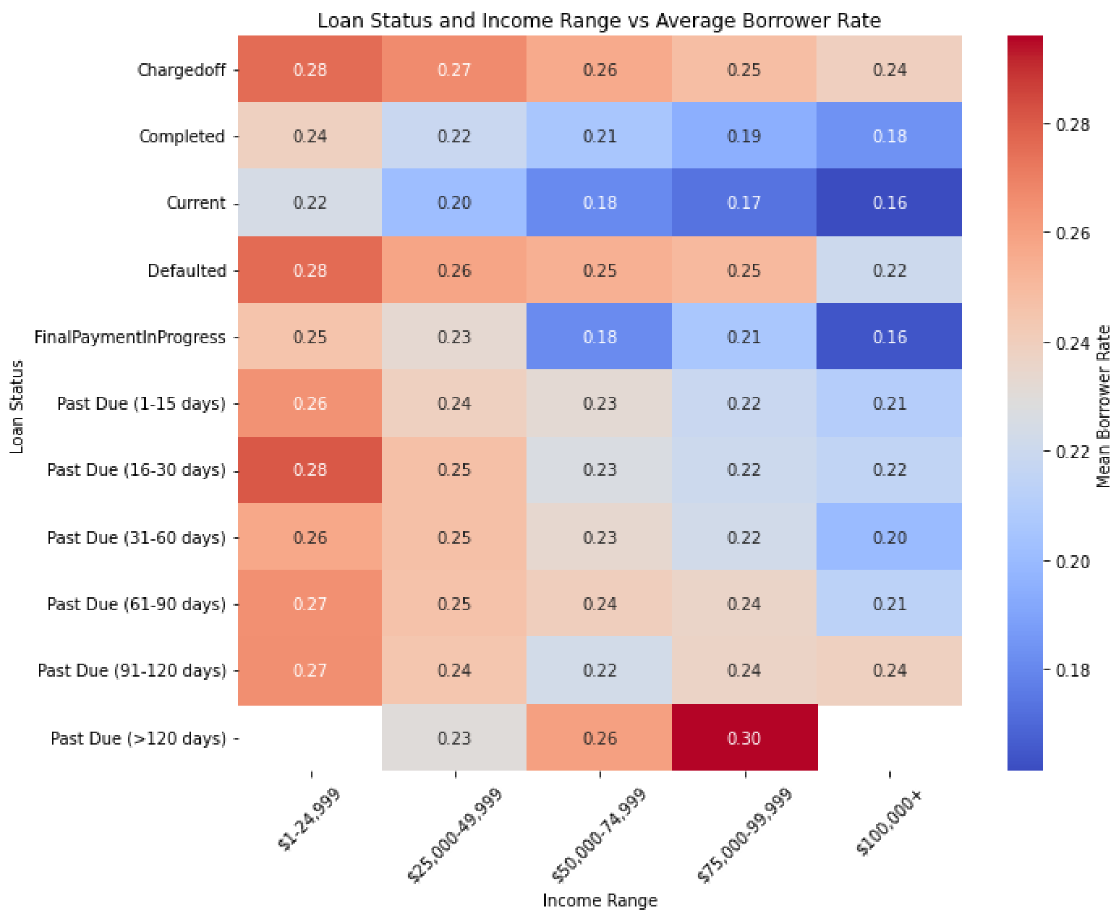
We can see that prosper ratings of 4 (same as C- rating) and above have the largest Loan amounts but lowest borrower rates

1.6.4 Question

What is the average borrower rate across Loan status and income range?

1.6.5 Visualization

In [75]:
```
# create heatmap of Mean Borrower rate across Loan status and Income Range

plt.figure(figsize=(10, 8))
pivot_table = pd.pivot_table(df, values='BorrowerRate', index='LoanStatus', columns='In
sns.heatmap(pivot_table, cmap='coolwarm', annot=True, fmt='.2f', cbar_kws={'label': 'Me
plt.title('Loan Status and Income Range vs Average Borrower Rate')
plt.xlabel('Income Range')
plt.xticks(rotation=45)
plt.ylabel('Loan Status')
plt.tight_layout();
```



1.6.6 Observation

- borrowers in higher income ranges tend to have lower rates across all loan statuses, with the lowest rates concentrated in the $100,000+ income range
- Loans that are charged off or defaulted tend to have higher rates across all income ranges, while completed loans tend to have the lowest rates

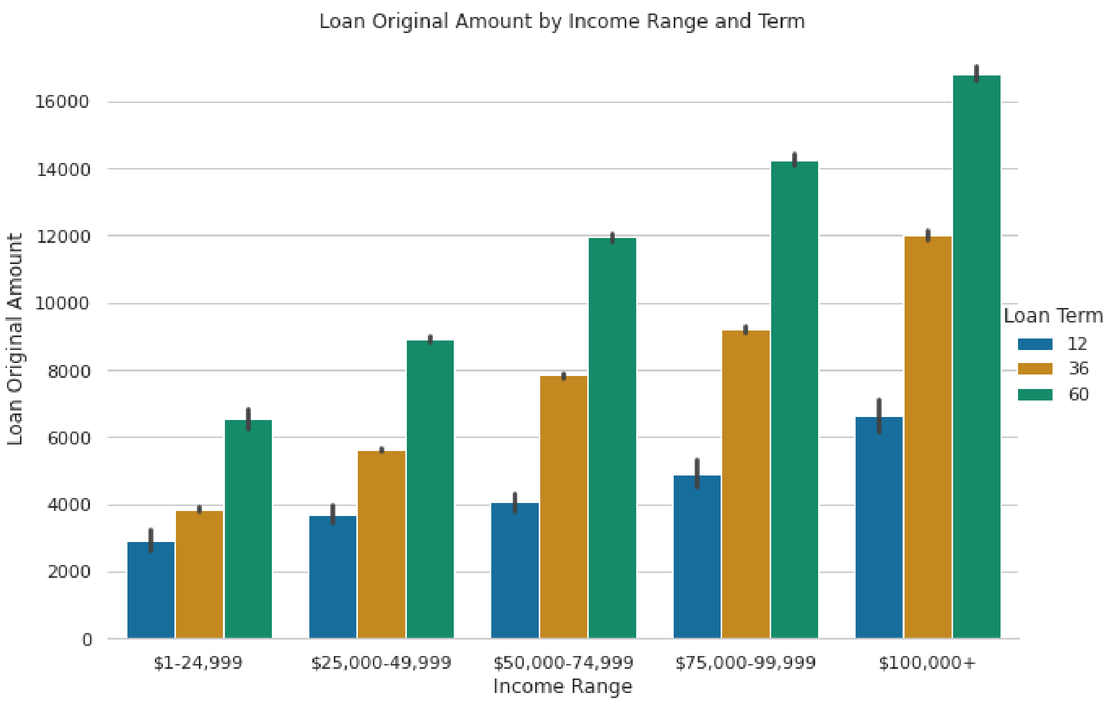
1.6.7 Question

How does Loan amount interact with Income range and Loan Term?

1.6.8 Visualization

In [76]:
```
# create a stacked bar chart of LoanOriginalAmount by IncomeRange and Term
sns.set(style="whitegrid")
g = sns.catplot(x="IncomeRange", y="LoanOriginalAmount", hue="Term", data=df,
                kind="bar", palette="colorblind", height=6, aspect=1.5)
g.despine(left=True)
```

```
g.set_axis_labels("Income Range", "Loan Original Amount")
g.legend.set_title("Loan Term")
plt.title('Loan Original Amount by Income Range and Term');
```



1.6.9 Observation

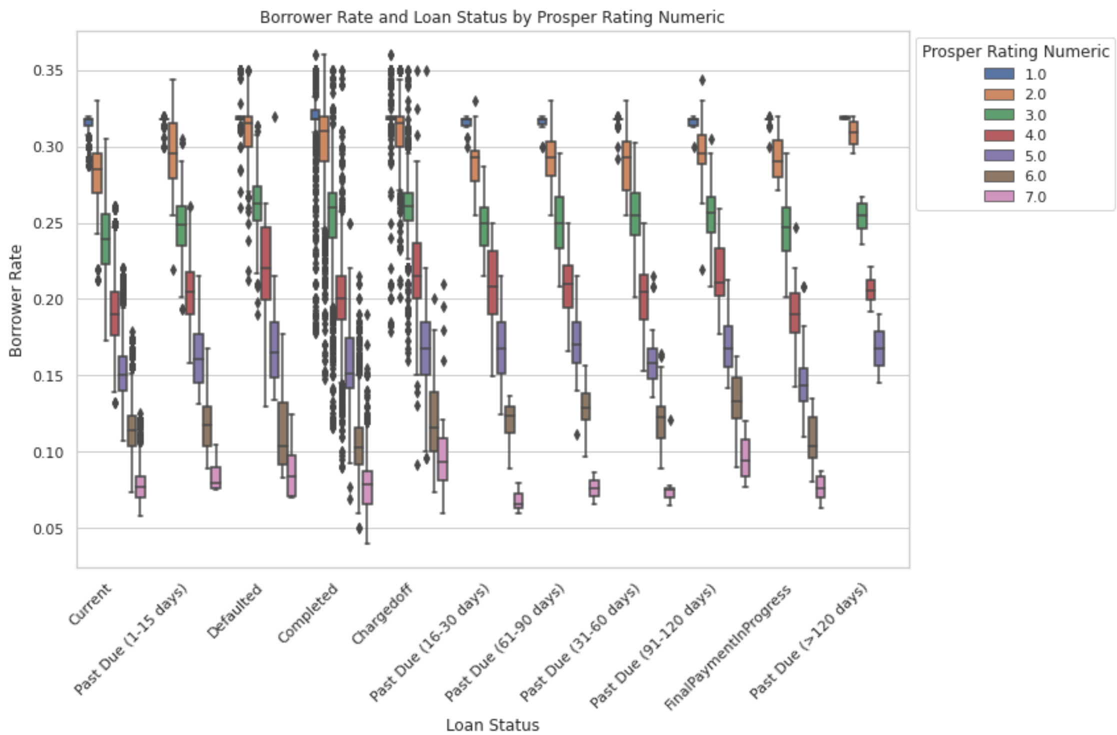
- The amount of loans increases as income range increases
- The chart suggests that Prosper tends to give larger loans to individuals with higher incomes and the 60-month term is the most popular among borrowers.

1.6.10 Question

What is the distribution of Borrower rate by Loan status and Prosper rating?

1.6.11 Visualization

```
In [77]: # create a box plot to show the distribution of borrower rate by loan status and prospe
         plt.figure(figsize=(12, 8))
         sns.boxplot(data=df, x='LoanStatus', y='BorrowerRate', hue='ProsperRating (numeric)')
         plt.title('Borrower Rate and Loan Status by Prosper Rating Numeric')
         plt.xlabel('Loan Status')
         plt.ylabel('Borrower Rate')
         plt.xticks(rotation=45, ha='right')
         plt.legend(title='Prosper Rating Numeric', bbox_to_anchor=(1, 1))
         plt.tight_layout()
```



1.6.12 Observation

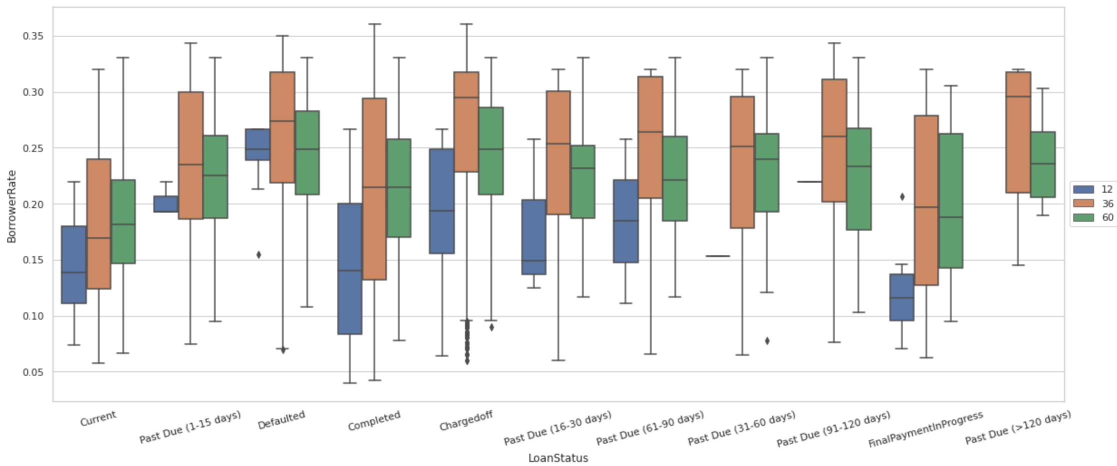
- Borrower rate tends to be higher for loans that are charged off or defaulted compared to loans that are current or have been paid off.
- The borrower rate tends to decrease as the Prosper rating increases, with lower ratings associated with higher rates
- Borrower rate is also lower for completed loans

1.6.13 Question

How does Borrower rate and Loan status interact with loan term?

1.6.14 Visualization

```
In [78]: #Creating a boxplot for BorrowerRate, LoanStatus, and Term with the Term as color encod
         plt.figure(figsize=[20,8])
         sns.boxplot(data = df, y = 'BorrowerRate', x = 'LoanStatus', hue = 'Term')
         plt.legend(loc = 6, bbox_to_anchor = (1.0, 0.5)) # legend to right of figure
         plt.xticks(rotation = 15);
```



1.6.15 Observation

- The median borrower rate is generally higher for loans that have defaulted or charged off compared to loans that are current or completed
- The median borrower rate tends to increase as the loan term gets longer, with the 60-month term having the highest median rate.

1.6.16 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?

Prosper rating increased borrower amount but had negative relationship with borrower rates

Borrower amount increased with income range

As the Loan term increased, borrower rates generally increased

Borrowers in higher income ranges tend to have lower rates across all loan statuses

1.6.17 Were there any interesting or surprising interactions between features?

Loan Amount increased over the years while borrower rate reduced over the years

1.7 Conclusions

1.7.1 Steps Taken

I started by exploring the distrubution of the various variables including the main variables of interest which include distribution of Loan amount, Listing Category, Term, Loan status, borrower rate and lender yield.

I looked at some borrower characteristics which are Borrower state, employment status, Income range, prosper rating and homeowners. I also viewed the distribution of investors, monthly loan payments and amount delinquent.

Some of the charts(Investors, MonthlyLoanPayments and AmountDelinquent) were not informative at first hence I visualized on a log-scale for a more detailed look.

Next I created a heatmap and plot matrix to visualize numerical variables before proceeding to check for the relationship between various variables

In the Multivariate section, I visualized how a combination of some of the main variables (Loan Amount, Borrower rate and Loan status) interacted with other variables like Prosper rating, Term, Income range,

1.8 Main Findings

- Average loan amount is about 5000 dollars and there are relatively more loans with lower amounts and fewer loans with higher amounts with an average borrower rate of 0.2
- Majority of the borrowers come from California(CA), they're employed, earn between 25,000 to 74,000 dollars, have a 'C' Prosper rating and often own a house
- LoanOriginalAmount and BorrowerRate are negatively correlated which suggests that larger loans have lower borrower rate compared to lesser loans
- Strong positive correlations between Lender yield and Borrower Rate which is logical, higher borrower rates should result in higher lender yield
- Strong negative correlation between Prosper rating and borrower rate, which suggests that high prosper ratings have lower borrower rates
- Loan amounts increased over the years with january recording the most loans while borrower rates dropped over the years
- Lower borrower rates are associated with higher completion rates, while higher borrower rates are associated with higher rates of default, charge off, and past due status
- Borrower rates are highest for HR(High risk) Prosper rating and lowest for the highest Prosper rating AA This shows that borrowers with better Prosper rating get lower rates
- Loans for Auto, Business, Large purchases, Medical/dental and RV may be riskier than other purposes like debt consolidation and student use. Loans taken for debt consolidation are most likely to be completed
- We can see that prosper ratings of 4 (same as C- rating) and above have the largest Loan amounts but lowest borrower rates
- Borrowers in higher income ranges tend to have lower rates across all loan statuses, with the lowest rates concentrated in the $100,000+ income range
- Prosper tends to give larger loans to individuals with higher incomes and the 60-month term is the most popular among borrowers

- Borrower rate tends to be higher for loans that are charged off or defaulted compared to loans that are current or have been paid off.

```
In [ ]:
```