Part_I_exploration_template

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1 Part I - (Analysis of Loan Data from Prosper)

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1.2 Introduction

The dataset I will be exploring and visualizing for this project is the Loan Data from Prosper gotten from Udacity's curated datasets. This dataset contains 113,937 loans with 81 variables on each loan, including loan amount, borrower rate (or interest rate), current loan status, borrower income, and many others.

1.3 Preliminary Wrangling

This notebook explores the dataset for the purpose of Exploratory Data Analysis and Explanatory Data Analysis.

[1]:
```python
# 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
sns.set_theme(style='white')

%matplotlib inline
```

Loading the dataset and describing its properties.

[2]:
```python
df = pd.read_csv('prosperLoanData.csv')
df.head(10)
```

[2]:
```
                ListingKey  ListingNumber            ListingCreationDate  \
0  1021339766868145413AB3B         193129  2007-08-26 19:09:29.263000000
1  10273602499503308B223C1        1209647  2014-02-27 08:28:07.900000000
2  0EE9337825851032864889A          81716  2007-01-05 15:00:47.090000000
3  0EF5356002482715299901A         658116  2012-10-22 11:02:35.010000000
4  0F023589499656230C5E3E2         909464  2013-09-14 18:38:39.097000000
5  0F05359734824199381F61D        1074836  2013-12-14 08:26:37.093000000
6  0F0A3576754255009D63151         750899  2013-04-12 09:52:56.147000000
7  0F1035772717087366F9EA7         768193  2013-05-05 06:49:27.493000000
8  0F043596202561788EA13D5        1023355  2013-12-02 10:43:39.117000000
```

```
9  0F043596202561788EA13D5        1023355  2013-12-02 10:43:39.117000000

  CreditGrade  Term LoanStatus           ClosedDate  BorrowerAPR  \
0           C    36  Completed  2009-08-14 00:00:00      0.16516
1         NaN    36    Current                  NaN      0.12016
2          HR    36  Completed  2009-12-17 00:00:00      0.28269
3         NaN    36    Current                  NaN      0.12528
4         NaN    36    Current                  NaN      0.24614
5         NaN    60    Current                  NaN      0.15425
6         NaN    36    Current                  NaN      0.31032
7         NaN    36    Current                  NaN      0.23939
8         NaN    36    Current                  NaN      0.07620
9         NaN    36    Current                  NaN      0.07620

   BorrowerRate  LenderYield  …  LP_ServiceFees  LP_CollectionFees  \
0        0.1580       0.1380  …         -133.18                0.0
1        0.0920       0.0820  …            0.00                0.0
2        0.2750       0.2400  …          -24.20                0.0
3        0.0974       0.0874  …         -108.01                0.0
4        0.2085       0.1985  …          -60.27                0.0
5        0.1314       0.1214  …          -25.33                0.0
6        0.2712       0.2612  …          -22.95                0.0
7        0.2019       0.1919  …          -69.21                0.0
8        0.0629       0.0529  …          -16.77                0.0
9        0.0629       0.0529  …          -16.77                0.0

   LP_GrossPrincipalLoss  LP_NetPrincipalLoss LP_NonPrincipalRecoverypayments  \
0                    0.0                  0.0                              0.0
1                    0.0                  0.0                              0.0
2                    0.0                  0.0                              0.0
3                    0.0                  0.0                              0.0
4                    0.0                  0.0                              0.0
5                    0.0                  0.0                              0.0
6                    0.0                  0.0                              0.0
7                    0.0                  0.0                              0.0
8                    0.0                  0.0                              0.0
9                    0.0                  0.0                              0.0

   PercentFunded  Recommendations InvestmentFromFriendsCount  \
0            1.0                0                          0
1            1.0                0                          0
2            1.0                0                          0
3            1.0                0                          0
4            1.0                0                          0
5            1.0                0                          0
6            1.0                0                          0
7            1.0                0                          0
```

```
8           1.0               0                          0
9           1.0               0                          0

  InvestmentFromFriendsAmount Investors
0                         0.0       258
1                         0.0         1
2                         0.0        41
3                         0.0       158
4                         0.0        20
5                         0.0         1
6                         0.0         1
7                         0.0         1
8                         0.0         1
9                         0.0         1

[10 rows x 81 columns]
```

[3]:
```python
df.shape
```

[3]:
```
(113937, 81)
```

[4]:
```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 113937 entries, 0 to 113936
Data columns (total 81 columns):
 #   Column                               Non-Null Count   Dtype
---  ------                               --------------   -----
 0   ListingKey                           113937 non-null  object
 1   ListingNumber                        113937 non-null  int64
 2   ListingCreationDate                  113937 non-null  object
 3   CreditGrade                          28953 non-null   object
 4   Term                                 113937 non-null  int64
 5   LoanStatus                           113937 non-null  object
 6   ClosedDate                           55089 non-null   object
 7   BorrowerAPR                          113912 non-null  float64
 8   BorrowerRate                         113937 non-null  float64
 9   LenderYield                          113937 non-null  float64
 10  EstimatedEffectiveYield              84853 non-null   float64
 11  EstimatedLoss                        84853 non-null   float64
 12  EstimatedReturn                      84853 non-null   float64
 13  ProsperRating (numeric)              84853 non-null   float64
 14  ProsperRating (Alpha)                84853 non-null   object
 15  ProsperScore                         84853 non-null   float64
 16  ListingCategory (numeric)            113937 non-null  int64
 17  BorrowerState                        108422 non-null  object
 18  Occupation                           110349 non-null  object
 19  EmploymentStatus                     111682 non-null  object
```

```
20  EmploymentStatusDuration             106312 non-null  float64
21  IsBorrowerHomeowner                  113937 non-null  bool
22  CurrentlyInGroup                     113937 non-null  bool
23  GroupKey                             13341 non-null   object
24  DateCreditPulled                     113937 non-null  object
25  CreditScoreRangeLower                113346 non-null  float64
26  CreditScoreRangeUpper                113346 non-null  float64
27  FirstRecordedCreditLine              113240 non-null  object
28  CurrentCreditLines                   106333 non-null  float64
29  OpenCreditLines                      106333 non-null  float64
30  TotalCreditLinespast7years           113240 non-null  float64
31  OpenRevolvingAccounts                113937 non-null  int64
32  OpenRevolvingMonthlyPayment          113937 non-null  float64
33  InquiriesLast6Months                 113240 non-null  float64
34  TotalInquiries                       112778 non-null  float64
35  CurrentDelinquencies                 113240 non-null  float64
36  AmountDelinquent                     106315 non-null  float64
37  DelinquenciesLast7Years              112947 non-null  float64
38  PublicRecordsLast10Years             113240 non-null  float64
39  PublicRecordsLast12Months            106333 non-null  float64
40  RevolvingCreditBalance               106333 non-null  float64
41  BankcardUtilization                  106333 non-null  float64
42  AvailableBankcardCredit              106393 non-null  float64
43  TotalTrades                          106393 non-null  float64
44  TradesNeverDelinquent (percentage)   106393 non-null  float64
45  TradesOpenedLast6Months              106393 non-null  float64
46  DebtToIncomeRatio                    105383 non-null  float64
47  IncomeRange                          113937 non-null  object
48  IncomeVerifiable                     113937 non-null  bool
49  StatedMonthlyIncome                  113937 non-null  float64
50  LoanKey                              113937 non-null  object
51  TotalProsperLoans                    22085 non-null   float64
52  TotalProsperPaymentsBilled           22085 non-null   float64
53  OnTimeProsperPayments                22085 non-null   float64
54  ProsperPaymentsLessThanOneMonthLate  22085 non-null   float64
55  ProsperPaymentsOneMonthPlusLate      22085 non-null   float64
56  ProsperPrincipalBorrowed             22085 non-null   float64
57  ProsperPrincipalOutstanding          22085 non-null   float64
58  ScorexChangeAtTimeOfListing          18928 non-null   float64
59  LoanCurrentDaysDelinquent            113937 non-null  int64
60  LoanFirstDefaultedCycleNumber        16952 non-null   float64
61  LoanMonthsSinceOrigination           113937 non-null  int64
62  LoanNumber                           113937 non-null  int64
63  LoanOriginalAmount                   113937 non-null  int64
64  LoanOriginationDate                  113937 non-null  object
65  LoanOriginationQuarter               113937 non-null  object
66  MemberKey                            113937 non-null  object
67  MonthlyLoanPayment                   113937 non-null  float64
```

```
 68  LP_CustomerPayments                  113937 non-null  float64
 69  LP_CustomerPrincipalPayments         113937 non-null  float64
 70  LP_InterestandFees                   113937 non-null  float64
 71  LP_ServiceFees                       113937 non-null  float64
 72  LP_CollectionFees                    113937 non-null  float64
 73  LP_GrossPrincipalLoss                113937 non-null  float64
 74  LP_NetPrincipalLoss                  113937 non-null  float64
 75  LP_NonPrincipalRecoverypayments      113937 non-null  float64
 76  PercentFunded                        113937 non-null  float64
 77  Recommendations                      113937 non-null  int64
 78  InvestmentFromFriendsCount           113937 non-null  int64
 79  InvestmentFromFriendsAmount          113937 non-null  float64
 80  Investors                            113937 non-null  int64
dtypes: bool(3), float64(50), int64(11), object(17)
memory usage: 68.1+ MB
```

[5]:
```
df.describe()
```

[5]:
```
       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]
```

1.3.1 What is the structure of your dataset?

The dataset contains 113,937 rows with 81 features. Most of the variables are numeric in nature while others are ordered factor variables such as `EmploymentStatus`, `IncomeRange`, `ListingCategory`, `Loan Status`, etc.

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

I'm most interested in finding out the features related to the borrowers and the loans they took.

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

Of the many features available in the dataset, I expect the following to be of great help in my exploration; - `Term`: The length of the loan expressed in months - `LoanStatus`: The current status of the loan: Cancelled, Chargedoff, Completed, Current, Defaulted, FinalPaymentInProgress, PastDue. The PastDue status will be accompanied by a delinquency bucket. - `StatedMonthlyIncome`: The monthly income the borrower stated at the time the listing was created. - `BorrowerAPR`: The Borrower's Annual Percentage Rate (APR) for the loan. - `BorrowerRate`: The Borrower's interest rate for this loan. - `BorrowerState`: The two letter abbreviation of the state of the address of the borrower at the time the Listing was created. - `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. Applicable for loans originated after July 2009. - `ListingCategory (numeric)`: The category of the listing that the borrower selected when posting their listing: 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. - `EmploymentStatus`: The employment status of the borrower at the time they posted the listing. - `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. - `IncomeRange`: The income range of the borrower at the time the listing was created. - `Occupation`: The Occupation selected by the Borrower at the time they created the listing. - `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%). - `TotalProsperLoans`: Number of Prosper loans the borrower at the time they created this listing. This value will be null if the borrower had no prior loans. - `LoanOriginalAmount`: The origination amount of the loan. - `Investors`: The number of investors that funded the loan. - `LoanOriginationDate`: The date the loan was originated.

1.3.4 Selecting the features of interest.

[6]:
```
to_use = ['Term', 'LoanStatus', 'StatedMonthlyIncome', 'BorrowerAPR',␣
 ↪'BorrowerRate', 'BorrowerState', 'ProsperScore',
          'ListingCategory (numeric)', 'EmploymentStatus',␣
 ↪'IsBorrowerHomeowner', 'IncomeRange', 'Occupation', 'DebtToIncomeRatio',
          'TotalProsperLoans', 'LoanOriginalAmount', 'Investors',␣
 ↪'LoanOriginationDate']
```

[7]:
```
loans = df[to_use]
loans.head()
```

[7]:
```
   Term LoanStatus  StatedMonthlyIncome  BorrowerAPR  BorrowerRate  \
0    36  Completed          3083.333333      0.16516        0.1580
1    36    Current          6125.000000      0.12016        0.0920
```

```
2    36  Completed          2083.333333      0.28269        0.2750
3    36    Current          2875.000000      0.12528        0.0974
4    36    Current          9583.333333      0.24614        0.2085

  BorrowerState  ProsperScore  ListingCategory (numeric) EmploymentStatus  \
0            CO           NaN                          0    Self-employed
1            CO           7.0                          2         Employed
2            GA           NaN                          0    Not available
3            GA           9.0                         16         Employed
4            MN           4.0                          2         Employed

   IsBorrowerHomeowner     IncomeRange     Occupation  DebtToIncomeRatio  \
0                 True  $25,000-49,999          Other               0.17
1                False  $50,000-74,999   Professional               0.18
2                False   Not displayed          Other               0.06
3                 True  $25,000-49,999  Skilled Labor               0.15
4                 True        $100,000+      Executive               0.26

   TotalProsperLoans  LoanOriginalAmount  Investors  LoanOriginationDate
0                NaN                9425        258  2007-09-12 00:00:00
1                NaN               10000          1  2014-03-03 00:00:00
2                NaN                3001         41  2007-01-17 00:00:00
3                NaN               10000        158  2012-11-01 00:00:00
4                1.0               15000         20  2013-09-20 00:00:00
```

[8]:

```
import warnings;warnings.filterwarnings('ignore')
# convert 'LoanOriginationDate' data type to datetime and extract year, month␣
↪and week from it
loans.LoanOriginationDate = pd.to_datetime(loans.LoanOriginationDate)
loans['Year'] = loans.LoanOriginationDate.dt.year
loans['Month'] = loans.LoanOriginationDate.dt.strftime('%B')
loans['Week'] = loans.LoanOriginationDate.dt.week

#convert the numeric values in the Listing Category to object and change the␣
↪column data type.
mapping = {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: 'Enagement Ring', 12: 'Green Loans',
          13: 'Household Expenses', 14: 'Large Purchases', 15: 'Medical/
↪Dental', 16: 'Motorcycle', 17: 'RV', 18: 'Taxes', 19: 'Vacation',
           20: 'Wedding Loans'}

loans['ListingCategory (numeric)'] = loans['ListingCategory (numeric)'].
↪replace(mapping)
loans['ListingCategory (numeric)'] = loans['ListingCategory (numeric)'].
↪astype(object)
```

```python
loans = loans.rename(columns={'ListingCategory (numeric)': 'Listing Category'})
```

[9]:
```python
loans.head(1)
```

[9]:
```
   Term LoanStatus  StatedMonthlyIncome  BorrowerAPR  BorrowerRate  \
0    36  Completed          3083.333333      0.16516         0.158

  BorrowerState  ProsperScore Listing Category EmploymentStatus  \
0            CO           NaN    Not available    Self-employed

   IsBorrowerHomeowner     IncomeRange Occupation  DebtToIncomeRatio  \
0                 True  $25,000-49,999      Other               0.17

   TotalProsperLoans  LoanOriginalAmount  Investors LoanOriginationDate  Year  \
0                NaN                9425        258          2007-09-12  2007

       Month  Week
0  September    37
```

[10]:
```python
print(loans.shape)
print(loans.dtypes)
```

```
(113937, 20)
Term                            int64
LoanStatus                     object
StatedMonthlyIncome           float64
BorrowerAPR                   float64
BorrowerRate                  float64
BorrowerState                  object
ProsperScore                  float64
Listing Category               object
EmploymentStatus               object
IsBorrowerHomeowner              bool
IncomeRange                    object
Occupation                     object
DebtToIncomeRatio             float64
TotalProsperLoans             float64
LoanOriginalAmount              int64
Investors                       int64
LoanOriginationDate    datetime64[ns]
Year                            int64
Month                          object
Week                            int64
dtype: object
```

[11]:
```python
loans.describe()
```

[11]:
```
                Term  StatedMonthlyIncome    BorrowerAPR   BorrowerRate  \
count  113937.000000         1.139370e+05  113912.000000  113937.000000
mean       40.830248         5.608026e+03       0.218828       0.192764
std        10.436212         7.478497e+03       0.080364       0.074818
min        12.000000         0.000000e+00       0.006530       0.000000
25%        36.000000         3.200333e+03       0.156290       0.134000
50%        36.000000         4.666667e+03       0.209760       0.184000
75%        36.000000         6.825000e+03       0.283810       0.250000
max        60.000000         1.750003e+06       0.512290       0.497500

       ProsperScore  DebtToIncomeRatio  TotalProsperLoans  LoanOriginalAmount  \
count  84853.000000      105383.000000       22085.000000        113937.00000
mean       5.950067           0.275947           1.421100          8337.01385
std        2.376501           0.551759           0.764042          6245.80058
min        1.000000           0.000000           0.000000          1000.00000
25%        4.000000           0.140000           1.000000          4000.00000
50%        6.000000           0.220000           1.000000          6500.00000
75%        8.000000           0.320000           2.000000         12000.00000
max       11.000000          10.010000           8.000000         35000.00000

           Investors           Year           Week
count  113937.000000  113937.000000  113937.000000
mean       80.475228    2011.042611      26.953860
std       103.239020       2.506634      15.520827
min         1.000000    2005.000000       1.000000
25%         2.000000    2008.000000      13.000000
50%        44.000000    2012.000000      28.000000
75%       115.000000    2013.000000      41.000000
max      1189.000000    2014.000000      53.000000
```

[12]:
```python
for i, col in enumerate(loans.columns):
    print('Value counts for {}: '.format(col))
    print(loans[col].value_counts())
    if i < len(loans.columns) - 1:
        print('-' * 100)
```

```
Value counts for Term:
36    87778
60    24545
12     1614
Name: Term, dtype: int64
--------------------------------------------------------------------------------
--------------------
Value counts for LoanStatus:
Current                   56576
Completed                 38074
Chargedoff                11992
Defaulted                  5018
```

```
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
Cancelled                     5
Name: LoanStatus, dtype: int64
--------------------------------------------------------------------------------
--------------------
Value counts for StatedMonthlyIncome:
4166.666667     3526
5000.000000     3389
3333.333333     2917
3750.000000     2428
5416.666667     2374
                …
7069.916667        1
4266.333333        1
2211.750000        1
7032.916667        1
18756.000000       1
Name: StatedMonthlyIncome, Length: 13502, dtype: int64
--------------------------------------------------------------------------------
--------------------
Value counts for BorrowerAPR:
0.35797    3672
0.35643    1644
0.37453    1260
0.30532     902
0.29510     747
           …
0.37266       1
0.27518       1
0.18477       1
0.29961       1
0.19543       1
Name: BorrowerAPR, Length: 6677, dtype: int64
--------------------------------------------------------------------------------
--------------------
Value counts for BorrowerRate:
0.3177    3672
0.3500    1905
0.3199    1651
0.2900    1508
0.2699    1319
          …
```

```
0.2201       1
0.0752       1
0.1416       1
0.2812       1
0.0739       1
Name: BorrowerRate, Length: 2294, dtype: int64
--------------------------------------------------------------------------------
--------------------
Value counts for BorrowerState:
CA    14717
TX     6842
NY     6729
FL     6720
IL     5921
GA     5008
OH     4197
MI     3593
VA     3278
NJ     3097
NC     3084
WA     3048
PA     2972
MD     2821
MO     2615
MN     2318
MA     2242
CO     2210
IN     2078
AZ     1901
WI     1842
OR     1817
TN     1737
AL     1679
CT     1627
SC     1122
NV     1090
KS     1062
KY      983
OK      971
LA      954
UT      877
AR      855
MS      787
NE      674
ID      599
NH      551
NM      472
RI      435
```

```
HI      409
WV      391
DC      382
MT      330
DE      300
VT      207
AK      200
SD      189
IA      186
WY      150
ME      101
ND       52
Name: BorrowerState, dtype: int64
--------------------------------------------------------------------------------
--------------------
Value counts for ProsperScore:
4.0     12595
6.0     12278
8.0     12053
7.0     10597
5.0      9813
3.0      7642
9.0      6911
2.0      5766
10.0     4750
11.0     1456
1.0       992
Name: ProsperScore, dtype: int64
--------------------------------------------------------------------------------
--------------------
Value counts for Listing Category:
Debt Consolidation    58308
Not available         16965
Other                 10494
Home Improvement       7433
Business               7189
Auto                   2572
Personal Loan          2395
Household Expenses     1996
Medical/Dental         1522
Taxes                   885
Large Purchases         876
Wedding Loans           771
Vacation                768
Student Use             756
Motorcycle              304
Enagement Ring          217
Baby&Adoption           199
```

```
Cosmetic Procedure       91
Boat                     85
Green Loans              59
RV                       52
Name: Listing Category, dtype: int64
--------------------------------------------------------------------------------
--------------------
Value counts for EmploymentStatus:
Employed         67322
Full-time        26355
Self-employed     6134
Not available     5347
Other             3806
Part-time         1088
Not employed       835
Retired            795
Name: EmploymentStatus, dtype: int64
--------------------------------------------------------------------------------
--------------------
Value counts for IsBorrowerHomeowner:
True     57478
False    56459
Name: IsBorrowerHomeowner, dtype: int64
--------------------------------------------------------------------------------
--------------------
Value counts for IncomeRange:
$25,000-49,999    32192
$50,000-74,999    31050
$100,000+         17337
$75,000-99,999    16916
Not displayed      7741
$1-24,999          7274
Not employed        806
$0                  621
Name: IncomeRange, dtype: int64
--------------------------------------------------------------------------------
--------------------
Value counts for Occupation:
Other                          28617
Professional                   13628
Computer Programmer             4478
Executive                       4311
Teacher                         3759
                               …
Dentist                           68
Student - College Freshman        41
Student - Community College       28
Judge                             22
```

```
Student - Technical School        16
Name: Occupation, Length: 67, dtype: int64
--------------------------------------------------------------------------------
--------------------
Value counts for DebtToIncomeRatio:
0.18000    4132
0.22000    3687
0.17000    3616
0.14000    3553
0.20000    3481
           …
0.06375       1
0.06281       1
0.19960       1
0.17775       1
0.23284       1
Name: DebtToIncomeRatio, Length: 1207, dtype: int64
--------------------------------------------------------------------------------
--------------------
Value counts for TotalProsperLoans:
1.0    15538
2.0     4540
3.0     1447
4.0      417
5.0      104
6.0       29
7.0        8
8.0        1
0.0        1
Name: TotalProsperLoans, dtype: int64
--------------------------------------------------------------------------------
--------------------
Value counts for LoanOriginalAmount:
4000     14333
15000    12407
10000    11106
5000      6990
2000      6067
         …
5284         1
7936         1
1201         1
10593        1
4292         1
Name: LoanOriginalAmount, Length: 2468, dtype: int64
--------------------------------------------------------------------------------
--------------------
Value counts for Investors:
```

```
1      27814
2       1386
3        991
4        827
5        753
       …
665        1
634        1
555        1
752        1
754        1
Name: Investors, Length: 751, dtype: int64
--------------------------------------------------------------------------------
--------------------
Value counts for LoanOriginationDate:
2014-01-22    491
2013-11-13    490
2014-02-19    439
2013-10-16    434
2014-01-28    339
             …
2006-02-03      1
2006-01-24      1
2005-11-18      1
2009-07-20      1
2005-11-15      1
Name: LoanOriginationDate, Length: 1873, dtype: int64
--------------------------------------------------------------------------------
--------------------
Value counts for Year:
2013    34345
2012    19553
2014    12172
2008    11552
2007    11460
2011    11228
2006     5906
2010     5652
2009     2047
2005       22
Name: Year, dtype: int64
--------------------------------------------------------------------------------
--------------------
Value counts for Month:
January      11395
October      11043
December     10708
February      9728
```

```
November      9635
August        9592
September     9221
July          9154
June          8847
March         8555
May           8500
April         7559
Name: Month, dtype: int64
--------------------------------------------------------------------------------
--------------------
Value counts for Week:
39    3145
4     2813
51    2801
9     2777
50    2664
3     2599
10    2598
43    2592
35    2591
2     2578
5     2532
42    2468
30    2454
26    2452
8     2441
48    2409
41    2404
7     2399
46    2379
44    2372
38    2294
49    2269
45    2247
34    2240
40    2232
25    2210
29    2201
31    2180
21    2178
52    2156
6     2151
17    2096
11    2088
33    2033
47    2032
20    2013
```

```
23    1968
24    1959
32    1911
28    1864
19    1847
37    1842
13    1812
16    1804
1     1750
18    1701
12    1694
22    1645
15    1615
36    1467
14    1428
27    1373
53     169
Name: Week, dtype: int64
```

[13]:

```
import warnings;warnings.simplefilter(action='ignore')

# convert LoanStatus, EmploymentStatus, and IncomeRange into ordered␣
↪categorical types
ordinal_var_dict = {
                    'LoanStatus': ['Cancelled', 'Defaulted', 'Past Due (>120␣
↪days)', 'Past Due (91-120 days)', 'Past Due (61-90 days)',
                                   'Past Due (31-60 days)', 'Past Due (16-30␣
↪days)', 'Past Due (1-15 days)', 'Chargedoff',
                                  'Current', 'FinalPaymentInProgress',␣
↪'Completed'],
                    'EmploymentStatus': ['Not available', 'Not employed',␣
↪'Self-employed', 'Part-time',
                                         'Employed', 'Full-time', 'Retired',␣
↪'Other'],
                    'IncomeRange': ['Not employed', 'Not displayed', '$0',␣
↪'$1-24,999', '$25,000-49,999', '$50,000-74,999',
                                   '$75,000-99,999', '$100,000+']
}

for var in ordinal_var_dict:
    ordered_var = pd.api.types.CategoricalDtype(ordered = True, categories =␣
↪ordinal_var_dict[var])
    loans[var] = loans[var].astype(ordered_var)
```

[14]:

```
cats = loans[ordinal_var_dict]
for i, col in enumerate(cats.columns):
    print('Unique values for {}: '.format(col))
```

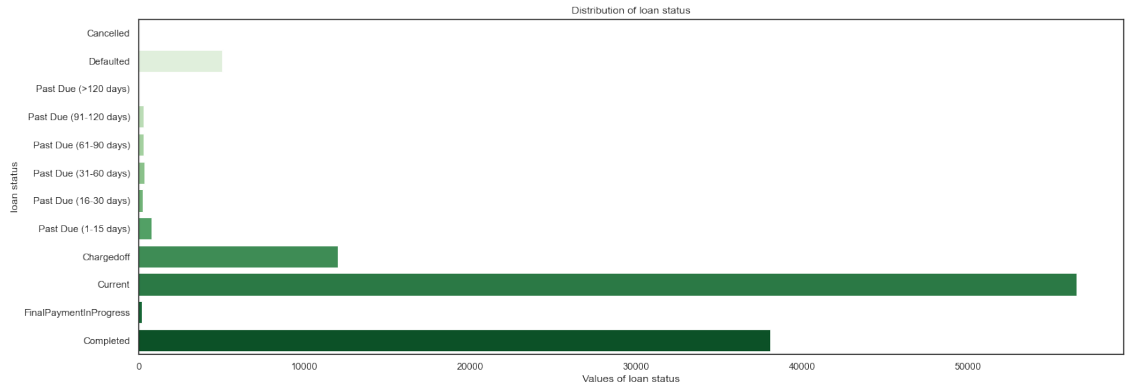
```
    print(cats[col].unique())
    if i < len(cats.columns) - 1:
        print('-' * 328)
```

```
Unique values for LoanStatus:
['Completed', 'Current', 'Past Due (1-15 days)', 'Defaulted', 'Chargedoff', …,
'Past Due (61-90 days)', 'Past Due (31-60 days)', 'Past Due (91-120 days)',
'FinalPaymentInProgress', 'Past Due (>120 days)']
Length: 12
Categories (12, object): ['Cancelled' < 'Defaulted' < 'Past Due (>120 days)' <
'Past Due (91-120 days)' … 'Chargedoff' < 'Current' < 'FinalPaymentInProgress'
< 'Completed']
--------------------------------------------------------------------------------
--------------------------------------------------------------------------------
--------------------------------------------------------------------------------
--------------------------------------------------------------------------------
--------
Unique values for EmploymentStatus:
['Self-employed', 'Employed', 'Not available', 'Full-time', 'Other', NaN, 'Not
employed', 'Part-time', 'Retired']
Categories (8, object): ['Not available' < 'Not employed' < 'Self-employed' <
'Part-time' < 'Employed' < 'Full-time' < 'Retired' < 'Other']
--------------------------------------------------------------------------------
--------------------------------------------------------------------------------
--------------------------------------------------------------------------------
--------------------------------------------------------------------------------
--------
Unique values for IncomeRange:
['$25,000-49,999', '$50,000-74,999', 'Not displayed', '$100,000+',
'$75,000-99,999', '$1-24,999', 'Not employed', '$0']
Categories (8, object): ['Not employed' < 'Not displayed' < '$0' < '$1-24,999' <
'$25,000-49,999' < '$50,000-74,999' < '$75,000-99,999' < '$100,000+']
```

1.4 Univariate Exploration

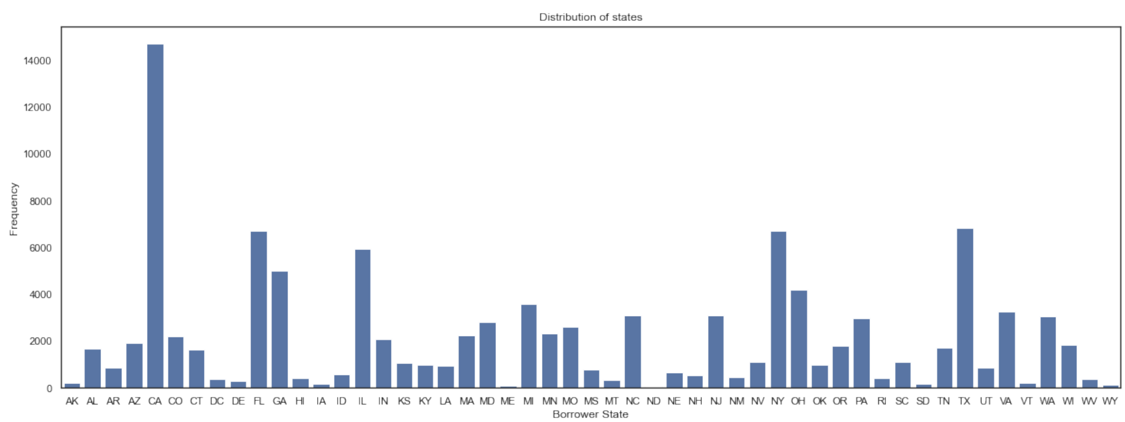
Exploring the distributions of individual features.

[15]:
```
# exploring the statuses of loans that were took.
plot = loans.LoanStatus.value_counts()
x = plot.index
y = plot.values
plt.figure(figsize=[20,7])
sns.barplot(y=plot.index, x=plot.values, palette='Greens').set(xlabel='Values␣
 ↪of loan status',
                                                               ylabel='loan␣
 ↪status', title='Distribution of loan status')
plt.show();
```



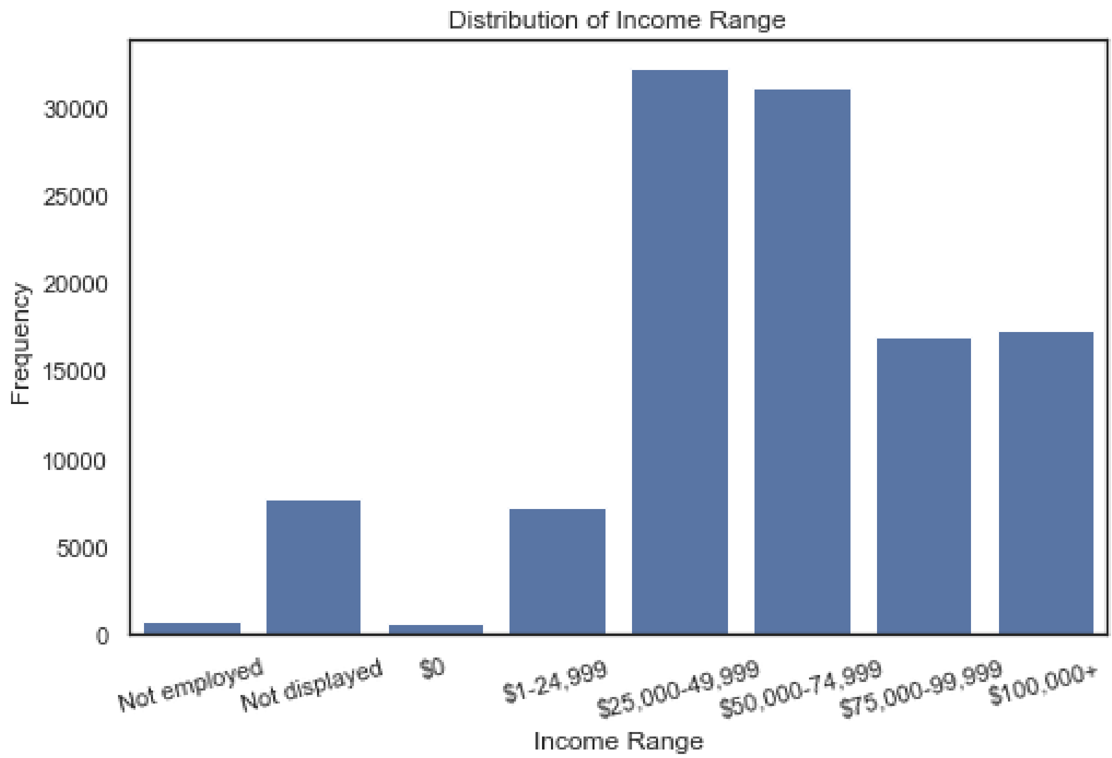
The most common loan status amongst the borrowers is **Current**.

[16]:
```
# exploring the distribution of states.
plot = loans.BorrowerState
plot = plot.sort_values(ascending=True)
color = sns.color_palette()[0]
plt.figure(figsize=[20,7])
sns.countplot(plot, color=color).set(xlabel='Borrower State',␣
↪ylabel='Frequency', title='Distribution of states');
```



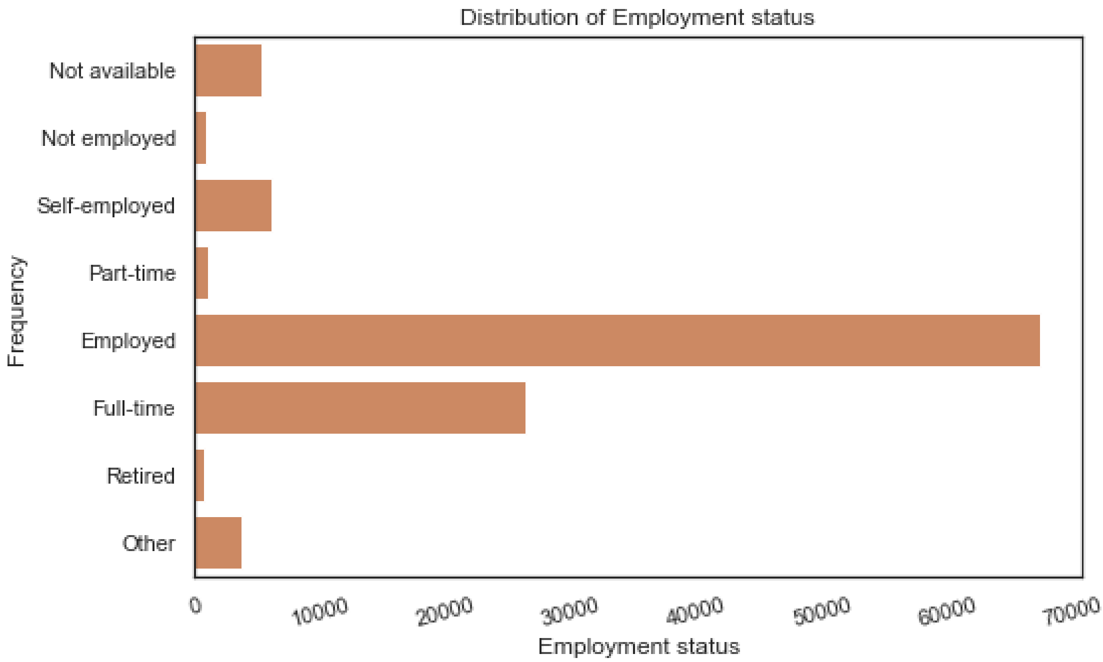
Majority of the borrowers originated from **California (CA)**

[17]:
```
# exploring the Income range of the borrowers
plot = loans.IncomeRange
color = sns.color_palette()[0]
plt.figure(figsize=[8,5])
sns.countplot(plot, color=color).set(xlabel='Income Range', ylabel='Frequency',␣
↪title='Distribution of Income Range')
plt.xticks(rotation=15);
```



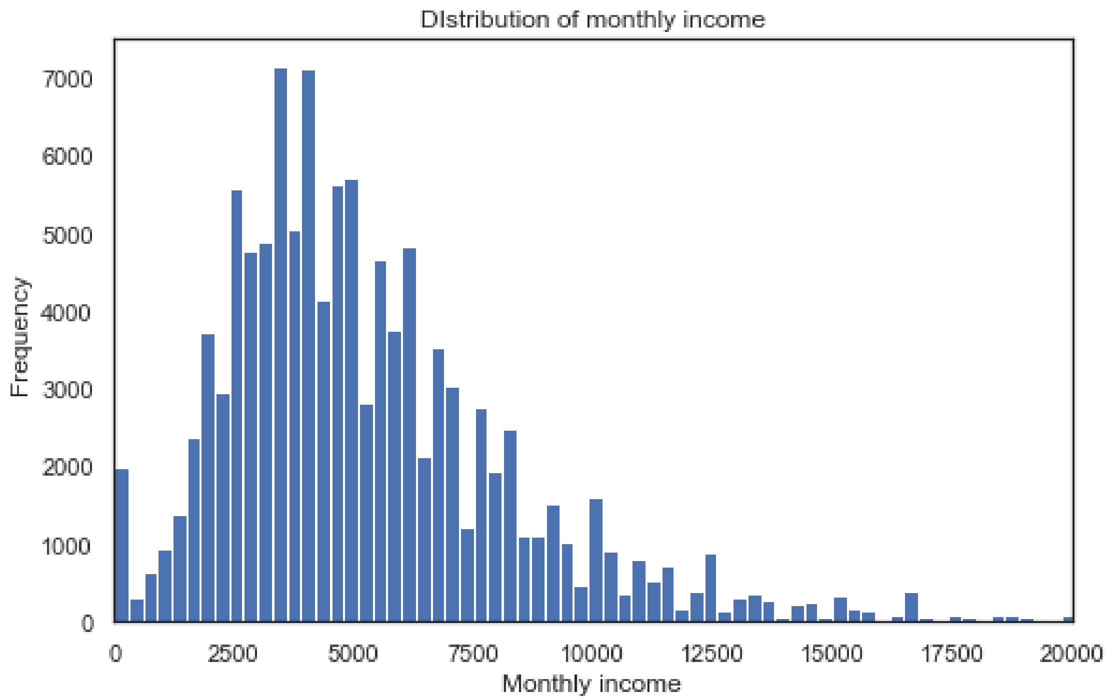
Majority of the borrowers had an income range between $25,000-$50,000.

[18]:
```
# employment status of the borrowers
plot = loans.EmploymentStatus.value_counts()
x = plot.values
y = plot.index
plt.figure(figsize=[8,5])
color = sns.color_palette()[1]
sns.barplot(x=x, y=y, color=color).set(xlabel='Employment status',
                                       ylabel='Frequency', title='Distribution␣
 ↪of Employment status')
plt.xticks(rotation=15);
```



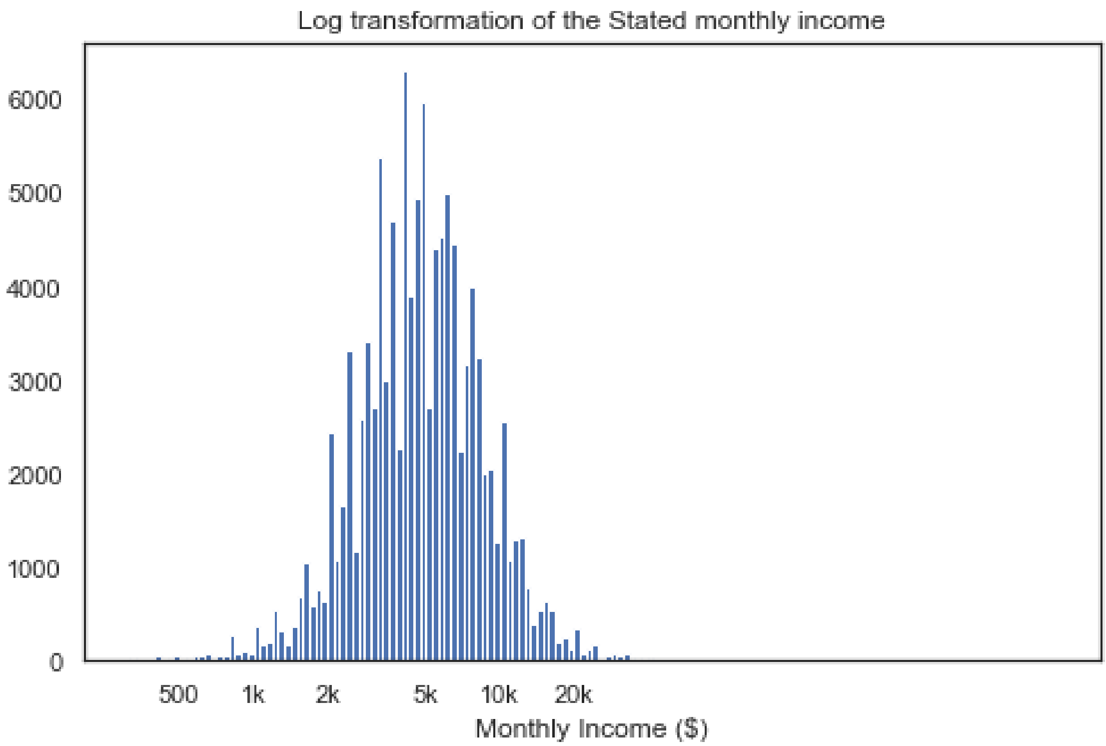
The majority of the borrowers are **Employed and Full-time**

[19]:
```
# distribution of monthly income plotted with more bins
bins = np.arange(0, loans.StatedMonthlyIncome.max()+300, 300)
plt.figure(figsize=[8,5])
plt.hist(x=loans.StatedMonthlyIncome, bins=bins)
plt.title('DIstribution of monthly income')
plt.xlabel('Monthly income')
plt.ylabel('Frequency')
plt.xlim(0, 20000);
```



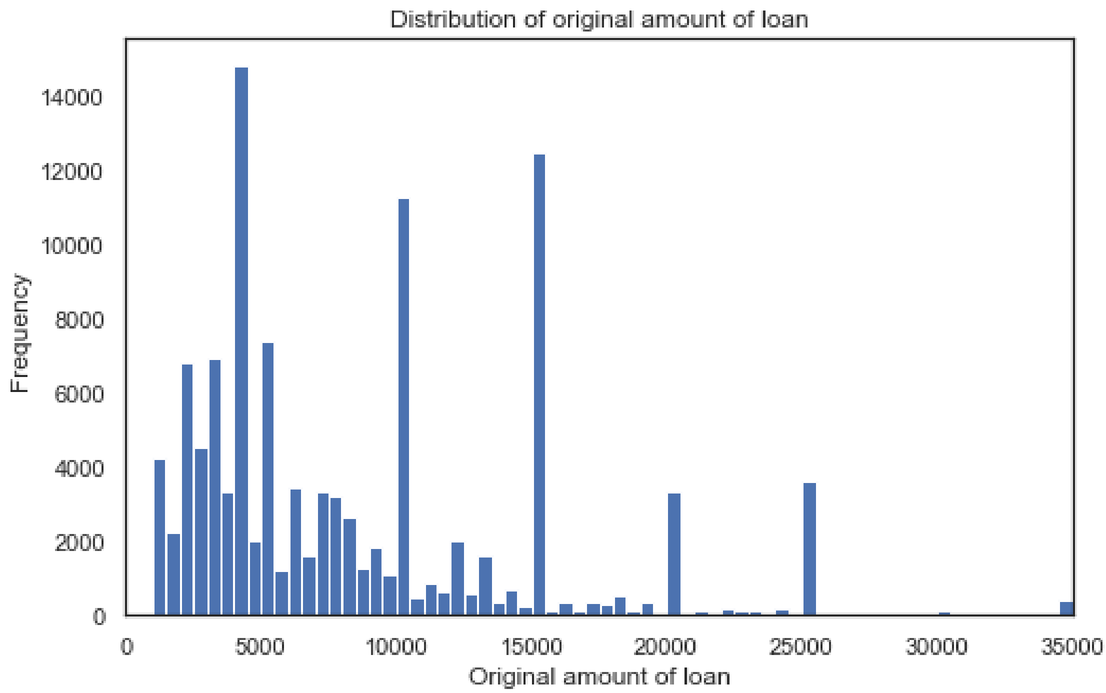
The monthly income of the borrowers is positively skewed with majority of the borrowers having an income less than $5,000

[20]:
```
# using a log transformation for the stated monthly income viz
log_binsize = 0.025
bins = 10 ** np.arange(2.5, np.log10(loans['StatedMonthlyIncome'].
 ↪max())+log_binsize, log_binsize)

plt.figure(figsize=[8,5])
plt.hist(data = loans, x = 'StatedMonthlyIncome', bins = bins)
plt.xscale('log')
plt.xticks([500, 1e3, 2e3, 5e3, 1e4, 2e4], [500, '1k', '2k', '5k', '10k',␣
 ↪'20k'])
plt.title('Log transformation of the Stated monthly income')
plt.xlabel('Monthly Income ($)')
plt.show();
```



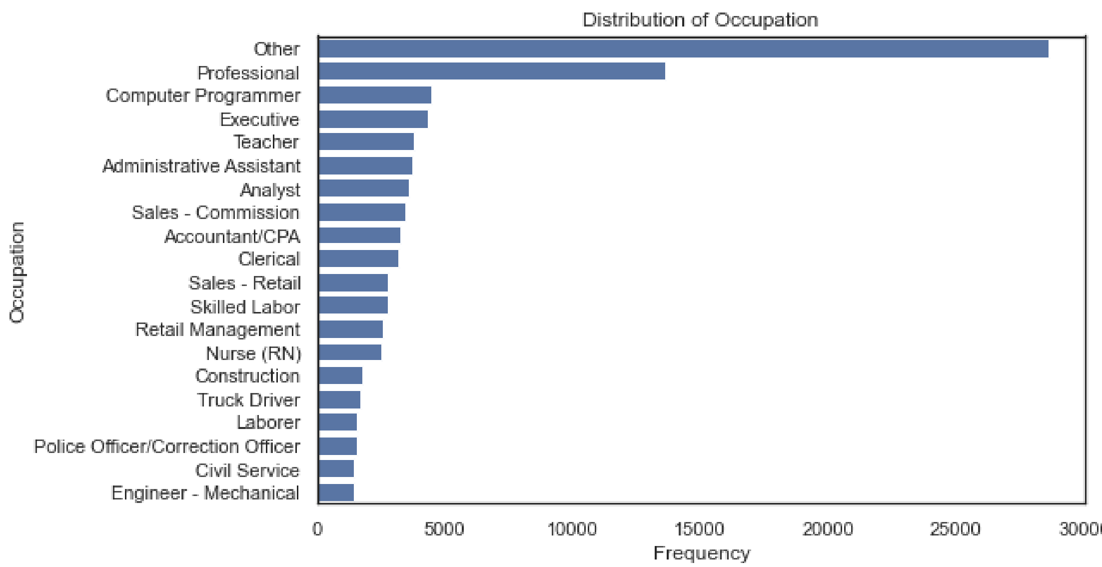
Became much more skewed to the right

[21]:
```
# Distribution of the original amount of loan taken
plot = loans.LoanOriginalAmount
bins = np.arange(0, loans.LoanOriginalAmount.max()+500, 500)
plt.figure(figsize=[8,5])
plt.hist(plot, bins=bins)
plt.title('Distribution of original amount of loan')
plt.xlabel('Original amount of loan')
plt.ylabel('Frequency')
plt.xlim([0, 35000]);
```



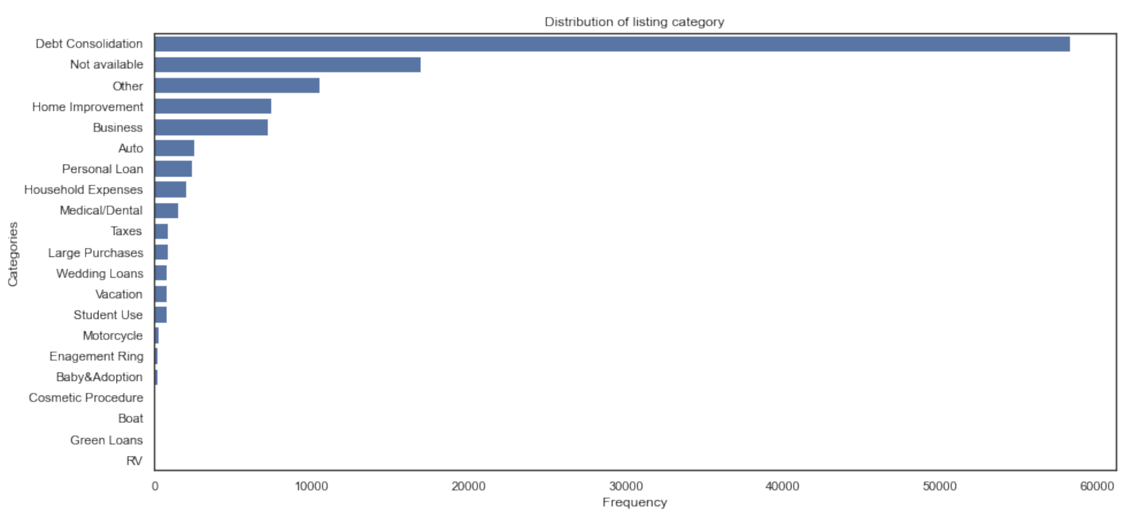
Most borrowers took about $5,000 as loan.

[22]:
```
# occupation of borrowers
plot = loans.Occupation.value_counts()[:20]
plt.figure(figsize=[8,5])
x = plot.index
y = plot.values
color = sns.color_palette()[0]
sns.barplot(x=y, y=x, order=x, color=color).set(title='Distribution of␣
↪Occupation', xlabel='Frequency', ylabel='Occupation')
plt.show();
```



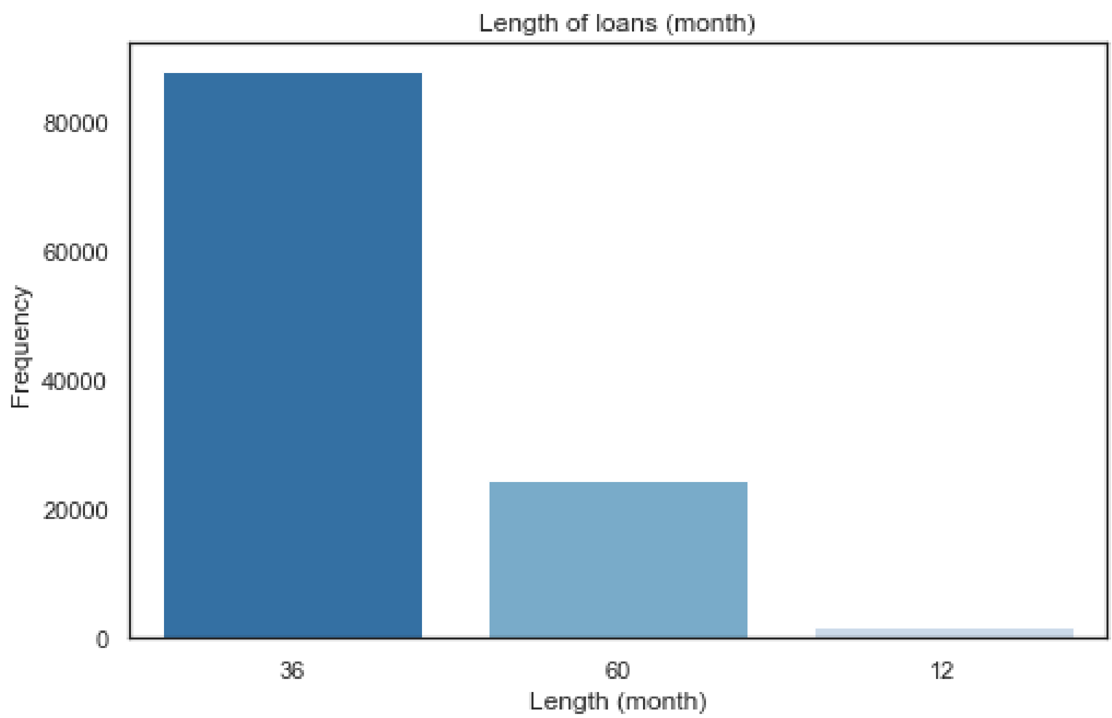
Most borrowers had other occupations apart from the ones provided in the listing. Professionals are also common among the borrowers

[23]:
```
# listing category
plot = loans['Listing Category'].value_counts()
x = plot.index
y = plot.values
color = sns.color_palette()[0]
plt.figure(figsize=[15,7])
sns.barplot(x=y, y=x, color=color, order=x).set(
    title='Distribution of listing category', xlabel='Frequency',␣
  ↪ylabel='Categories')
plt.show();
```



A vast majority applied for debt consolidation loans while 16965 borrowers didn't have their listing available.

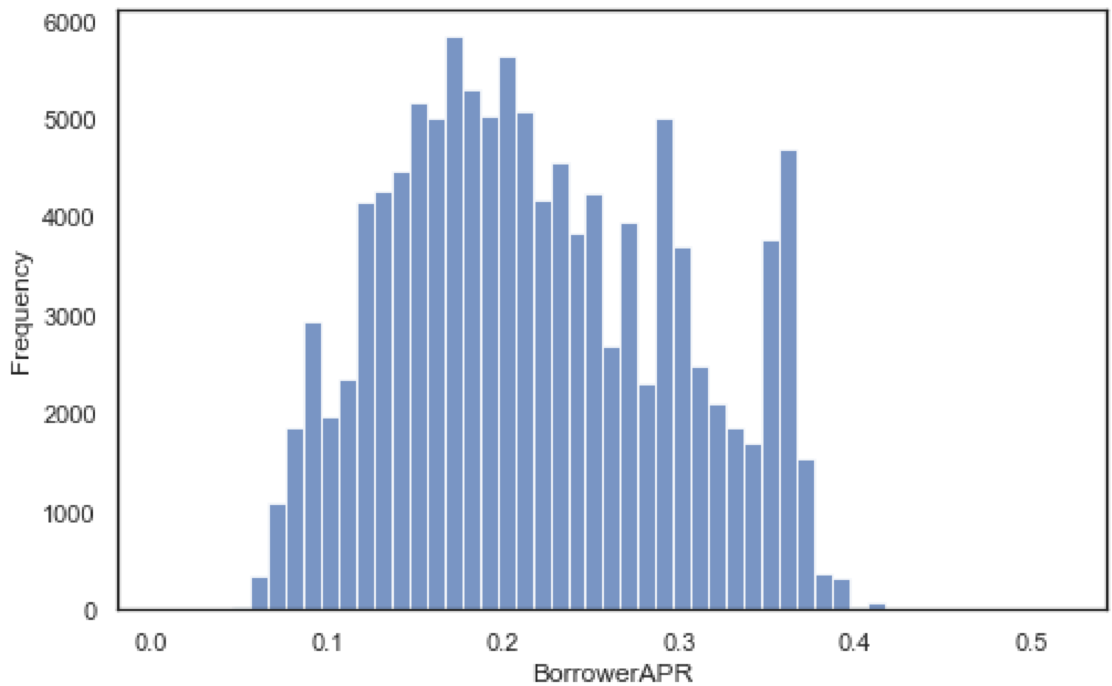
[24]:
```
# term distribution
plot = loans.Term
plt.figure(figsize=[8,5])
sns.countplot(plot, order=loans.Term.value_counts().index, palette='Blues_r').
 ↪set(title='Length of loans (month)',
                                                                 xlabel='Length␣
 ↪(month)', ylabel='Frequency')
plt.show();
```



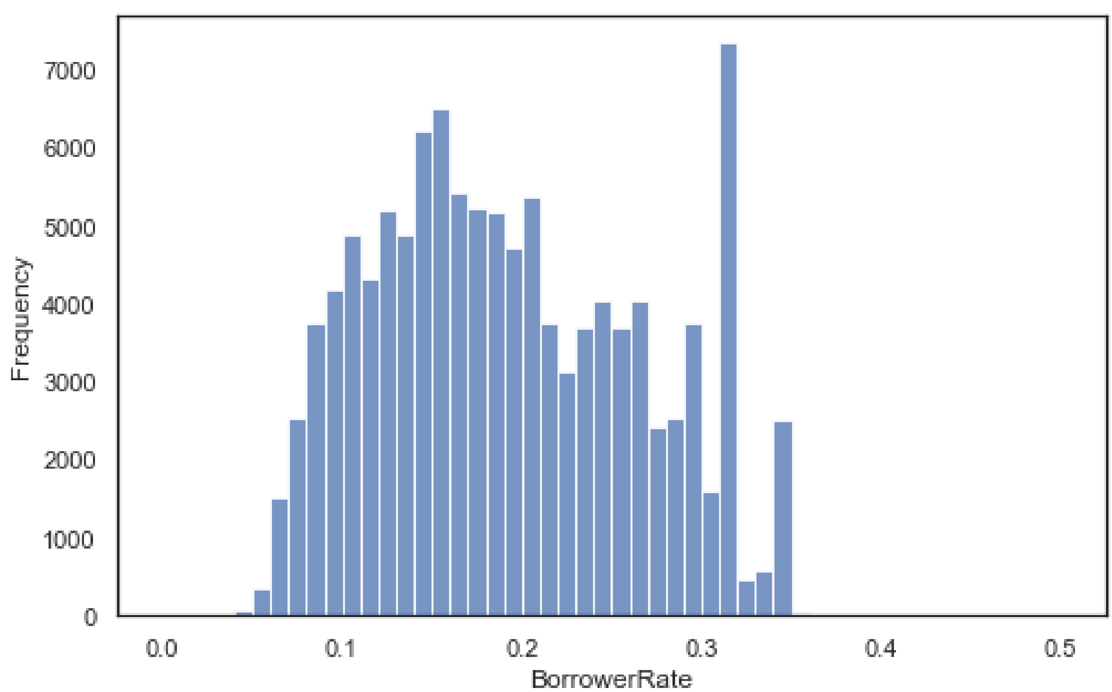
A large bloc of borrowers applied for a loan for 36 months while a very small number applied for the shortest loan term -12 months.

[25]:
```
# borrower APR and Interest Rate
review = loans[['BorrowerAPR', 'BorrowerRate']]
for i in review:
    plt.figure(figsize=[8,5])
    bins = np.arange(min(loans[i].values), max(loans[i].values)+0.01, 0.01)
    sns.histplot(review[i], bins=bins).set(xlabel='{}'.format(i),␣
 ↪ylabel='Frequency')
```

```
plt.show();
```



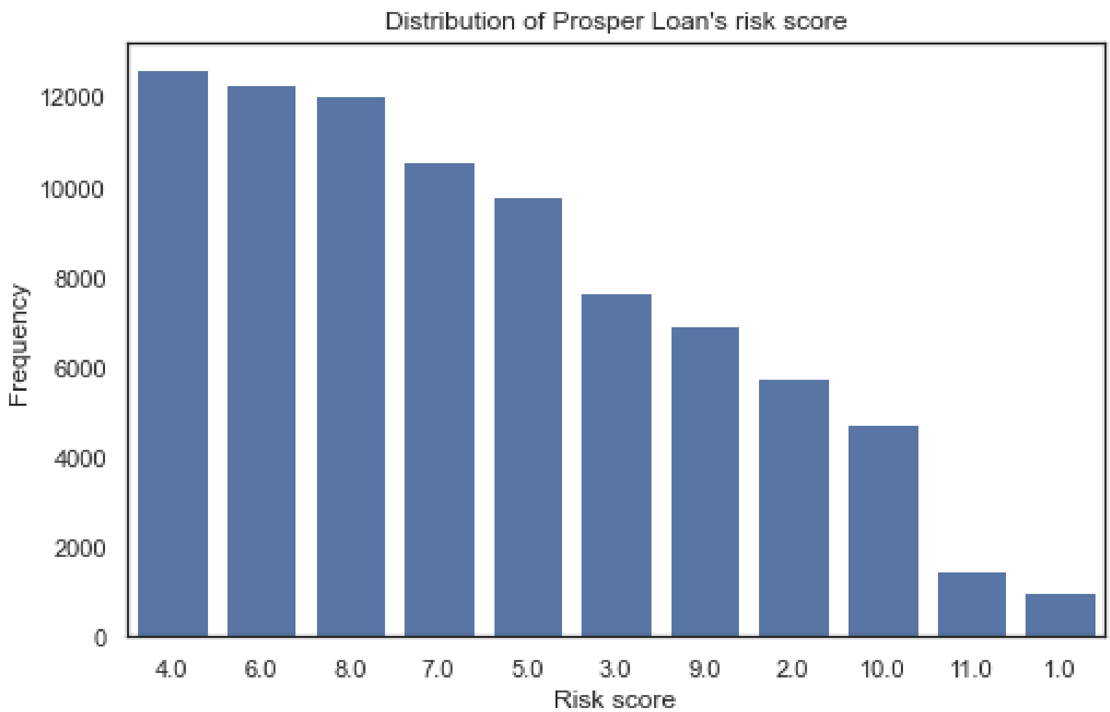
6000
5000
4000
3000
2000
1000
0
Frequency
0.0
0.1
0.2
0.3
0.4
0.5
BorrowerAPR



7000
6000
5000
4000
3000
2000
1000
0
Frequency
0.0
0.1
0.2
0.3
0.4
0.5
BorrowerRate

The Borrowers's APR and Interest rates distributions are very similar which may indicate that the two features are highly correlated.

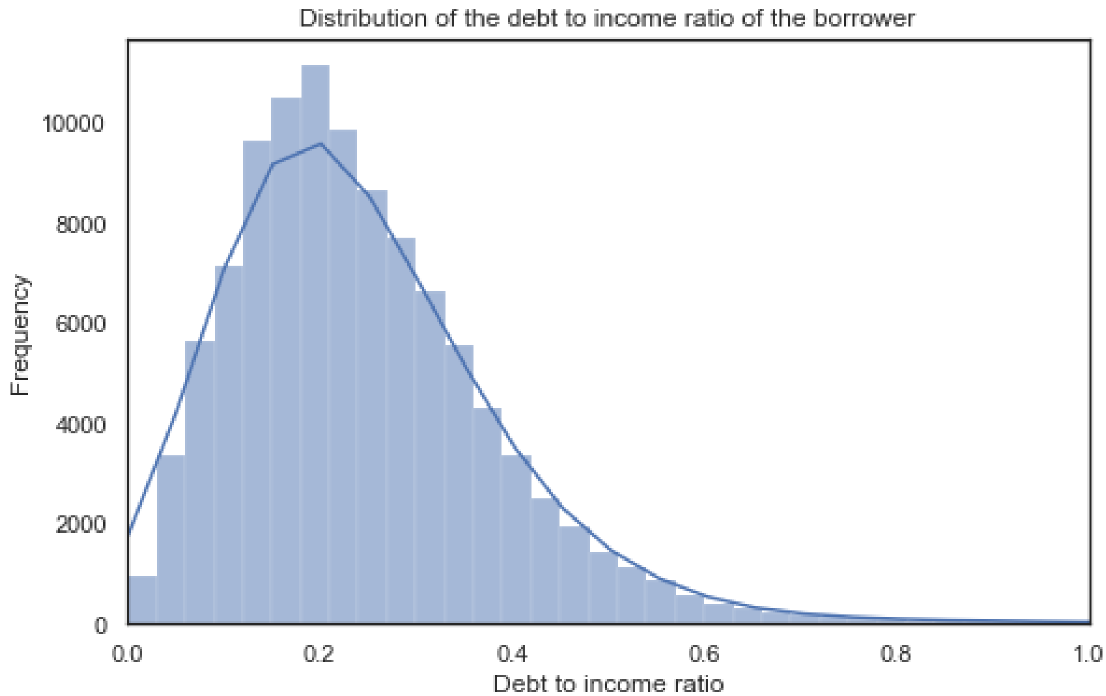
[26]:
```
# prosper loan risk score
plot = loans.ProsperScore
color = sns.color_palette()[0]
plt.figure(figsize=[8,5])
sns.countplot(plot, order=plot.value_counts().index, color=color).set(
    title='Distribution of Prosper Loan\'s risk score', xlabel='Risk score',␣
  ↪ylabel='Frequency')
plt.show();
```



Most borrowers have a risk score of 4.0 which is very close to bad while about 5000 borrowers had a perfect risk score.

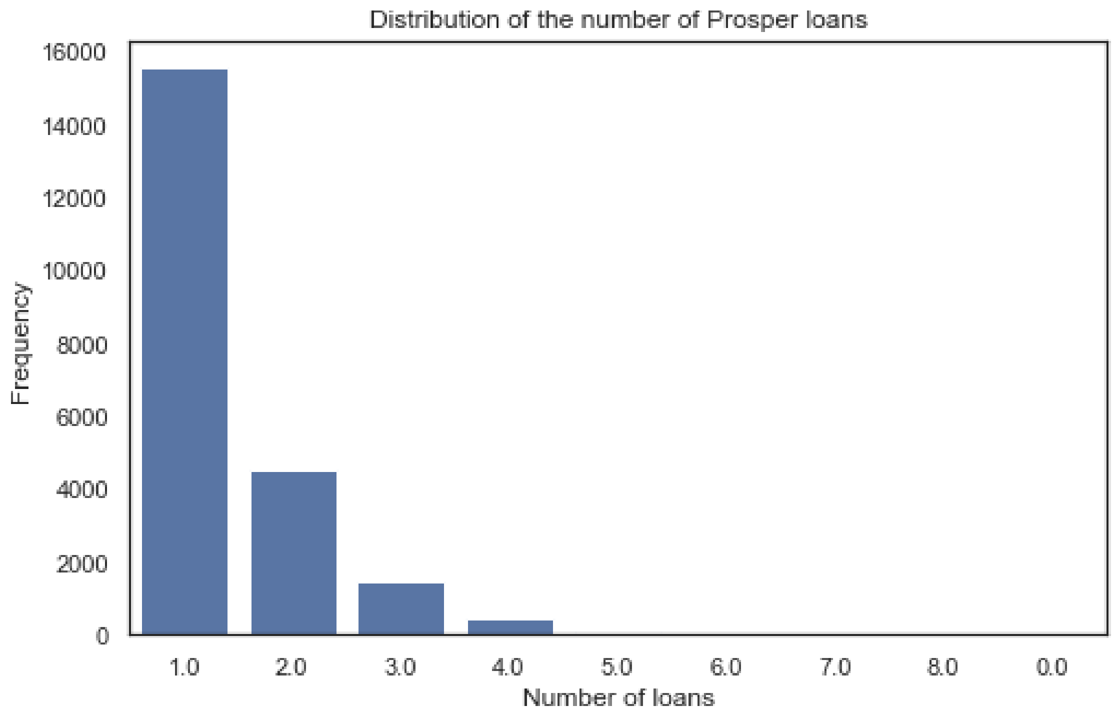
[27]:
```
# debt to income ratio
bins = (np.arange(0, loans.DebtToIncomeRatio.max()+0.03, 0.03))
plt.figure(figsize=[8,5])
color = sns.color_palette()[0]
sns.histplot(data= loans, x='DebtToIncomeRatio', bins=bins, kde=True,␣
  ↪color=color).set(
title='Distribution of the debt to income ratio of the borrower', xlabel='Debt␣
  ↪to income ratio', ylabel='Frequency')
plt.xlim([0, 1])
```

```
plt.show();
```



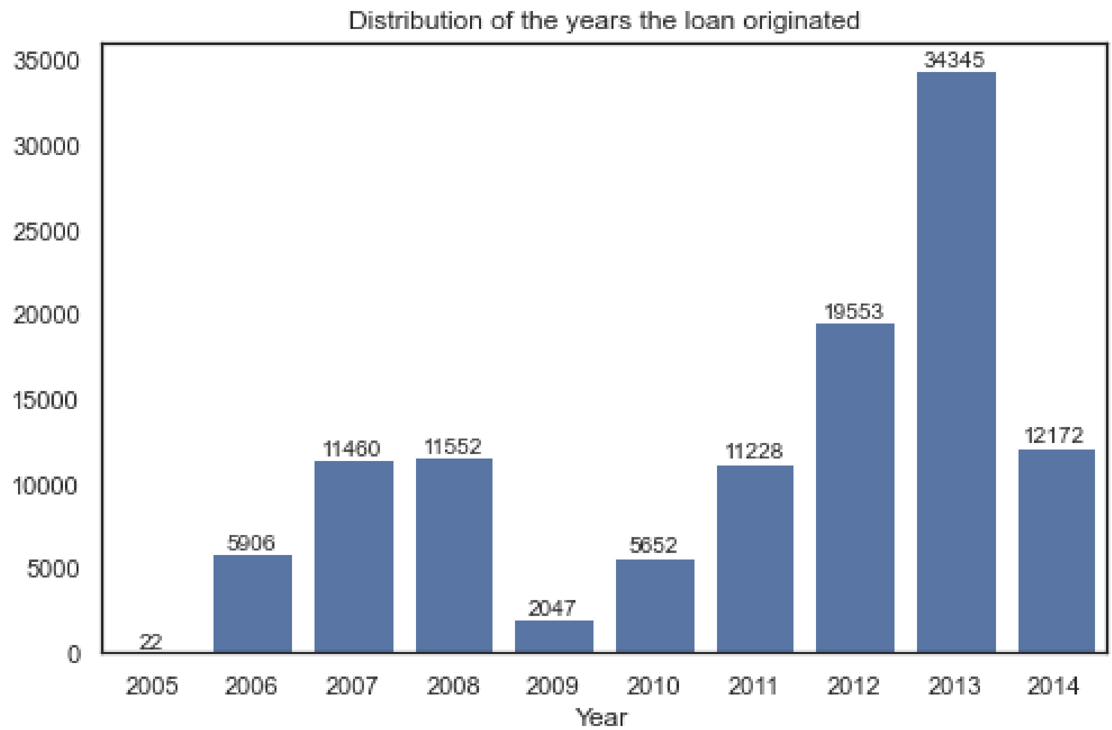
The debt to income ratio distribution is highly skewed to the right and hence highly positively skewed

[28]:
```
# number of prosper loans
plot = loans.TotalProsperLoans
color = sns.color_palette()[0]
plt.figure(figsize=[8,5])
sns.countplot(plot, order=plot.value_counts().index, color=color).set(
    title='Distribution of the number of Prosper loans', xlabel='Number of␣
 ↪loans', ylabel='Frequency')
plt.show();
```



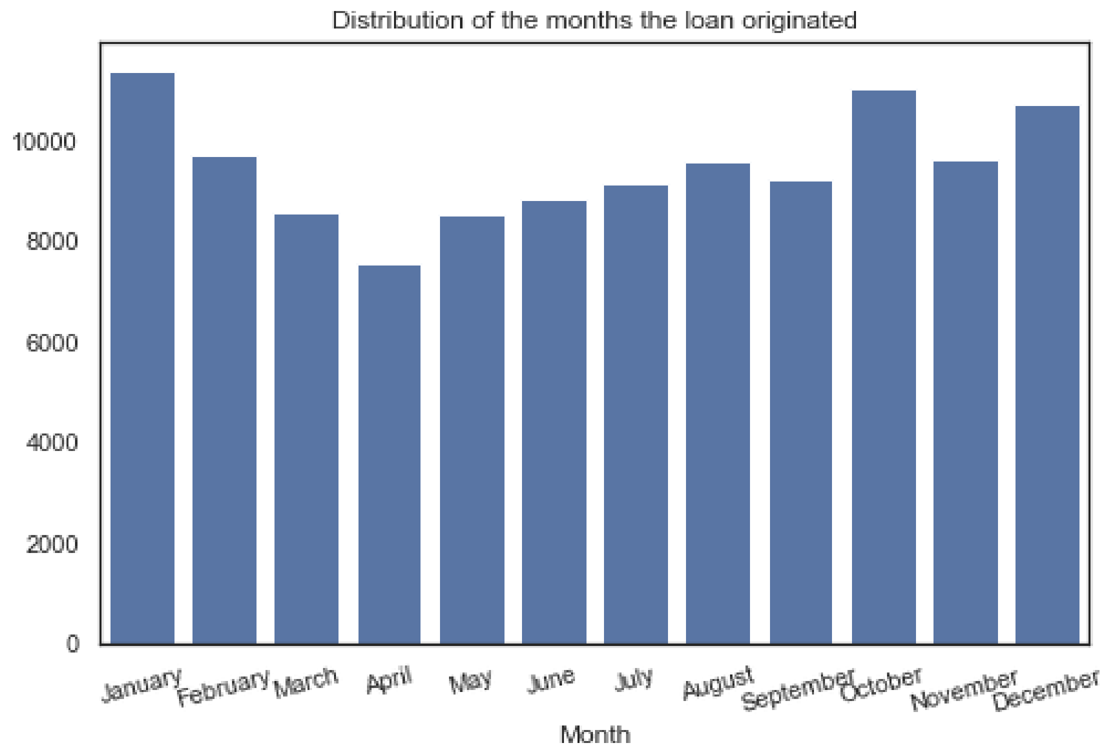
A large bloc of the borrowers had only one prosper loan and a single borrower took the highest loan -8.

[30]:
```
# year loans originated
plot = loans.Year.value_counts().sort_index()
x = plot.index
y = plot.values
color = sns.color_palette()[0]
plt.figure(figsize=[8,5])
sns.barplot(x=x, y=y, color=color, order=x).set(
    title='Distribution of the years the loan originated', xlabel='Year')
for i, v in enumerate(plot):
    plt.annotate(str(v), xy=(i, v), ha='center', va='bottom')
plt.show();
```



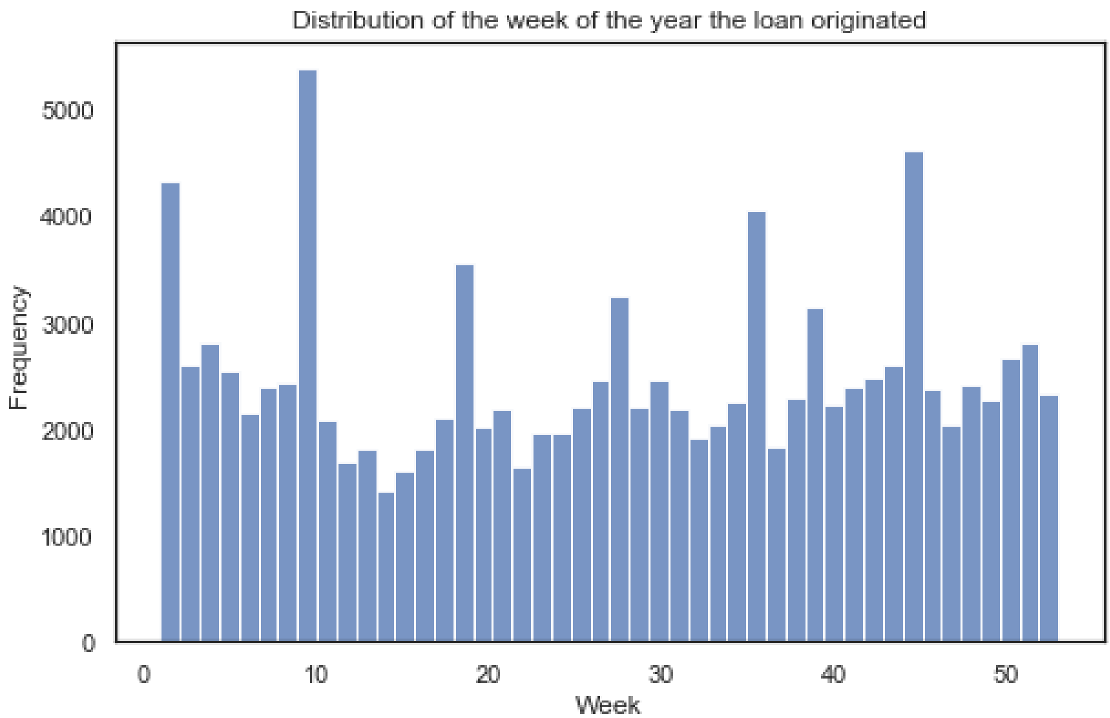
About 34,500 loans originated in the year 2013 which is the highest of any year while the fewest occurred in 2005.

[32]:
```
# months loans originated
month_order = ['January', 'February', 'March', 'April', 'May', 'June', 'July',␣
↪'August', 'September', 'October', 'November', 'December']
plot = loans.Month.value_counts()
x = plot.index
y = plot.values
color = sns.color_palette()[0]
plt.figure(figsize=[8,5])
sns.barplot(x=x, y=y, color=color, order=month_order).set(
    title='Distribution of the months the loan originated', xlabel='Month')
plt.xticks(rotation=15)
plt.show();
```



Most borrowers took a loan at the beginning of the year while fewer borrowers took loans around the spring.

[33]:
```
# week of loan origin
plot = loans.Week
color = sns.color_palette()[0]
bins = np.arange(0, loans.Week.max()+2, 1)
plt.figure(figsize=[8,5])
sns.histplot(plot).set(
    title='Distribution of the week of the year the loan originated',␣
 ↪xlabel='Week', ylabel='Frequency')
plt.show();
```



Most borrowers took loans in the 10th week of the year

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

Yeah. I had to make some transformations. The `LoanOriginationDate` variable had to be transformed into years, months and weeks of the year to enable me gain more insights into the time people started taking Prosper loans. Apart from others that didn't have their occupation listed, professionals were the most common borrowers at Prosper loans. Majority of the borrowers have their loan status at current and are employed or either Full-time. The term of most loans was pegged at 36 months while a small minority took a loan of a year. A large faction of borrowers originated from California and took their loans at the beginning of the year with the most loans also originating from 2013. The listing category of a majority of the loans was for Debt consolidation purposes. Again, most borrowers have a not so good risk score of 4.0.

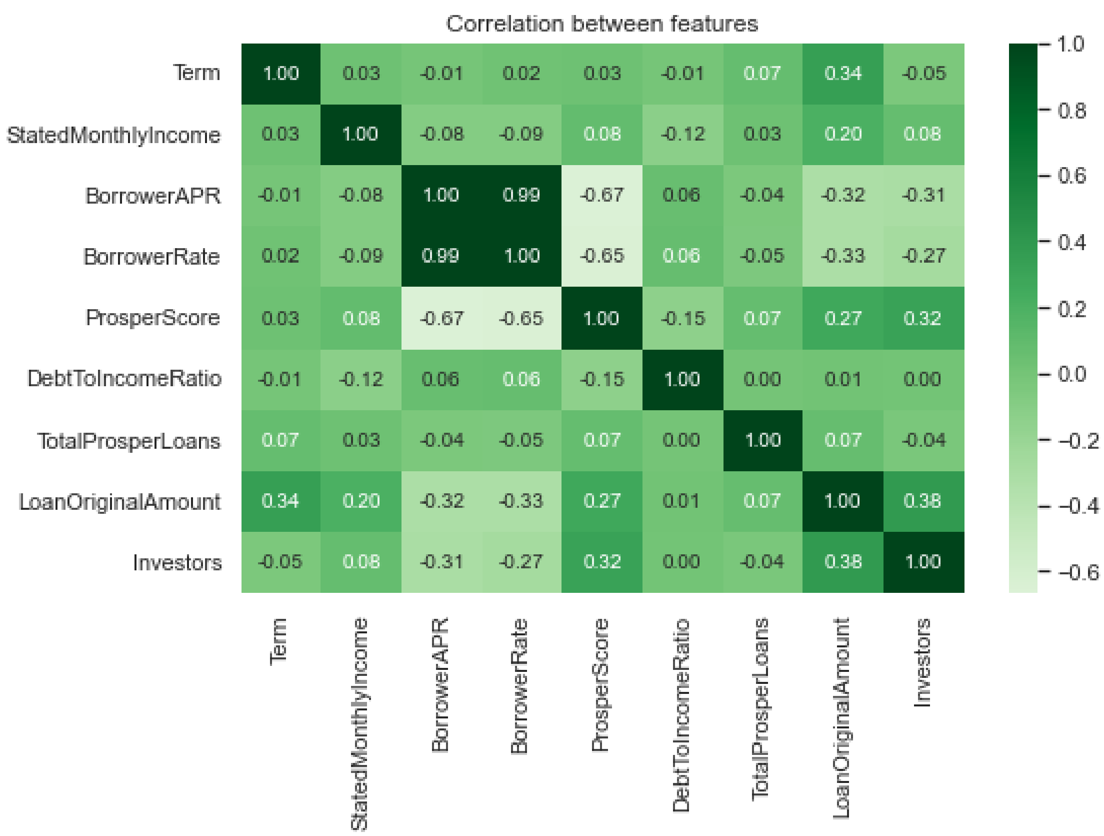
1.4.2 Of the features you investigated, were there any unusual distributions? Did you perform any operations on the data to tidy, adjust, or change the form of the data? If so, why did you do this?

The `LoanOriginationDate` variable was originally recorded as an object type variable instead of a datetime. Again, the Listing category variable was an integer which I also had to map onto the alpha equivalent which I sourced from the internet. I also converted the data type to an object data type.

1.5 Bivariate Exploration

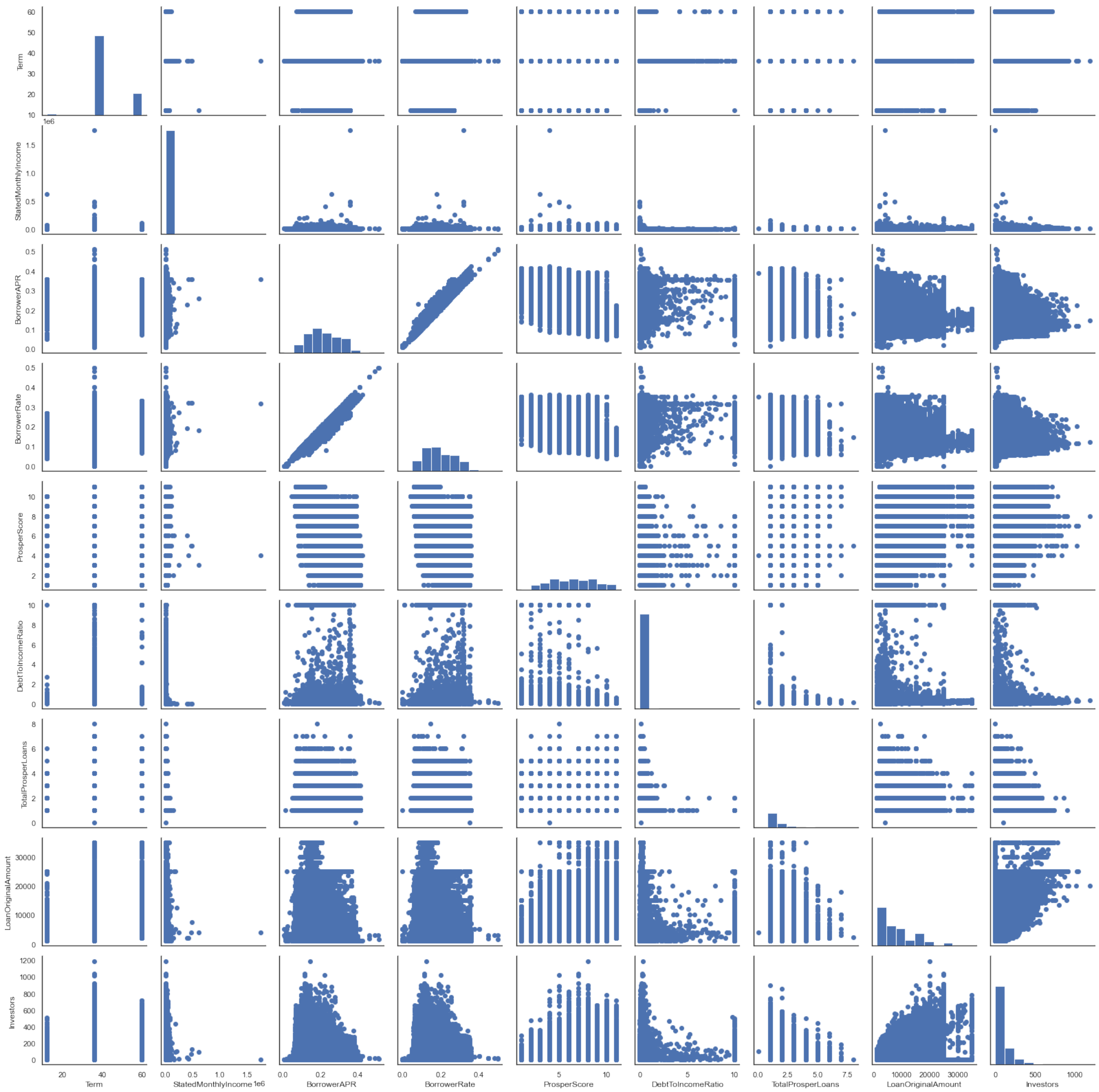
In this section, I investigated relationships between pairs of variables in the data.

[34]:
```
# correlation matrix of numeric variables
numeric_vars = ['Term', 'StatedMonthlyIncome', 'BorrowerAPR', 'BorrowerRate',␣
↪'ProsperScore',
                'DebtToIncomeRatio', 'TotalProsperLoans', 'LoanOriginalAmount',␣
↪'Investors']

plt.figure(figsize=[8,5])
sns.heatmap(loans[numeric_vars].corr(), fmt='.2f', annot=True, cmap='Greens',␣
↪center=0).set(title='Correlation between features');
```

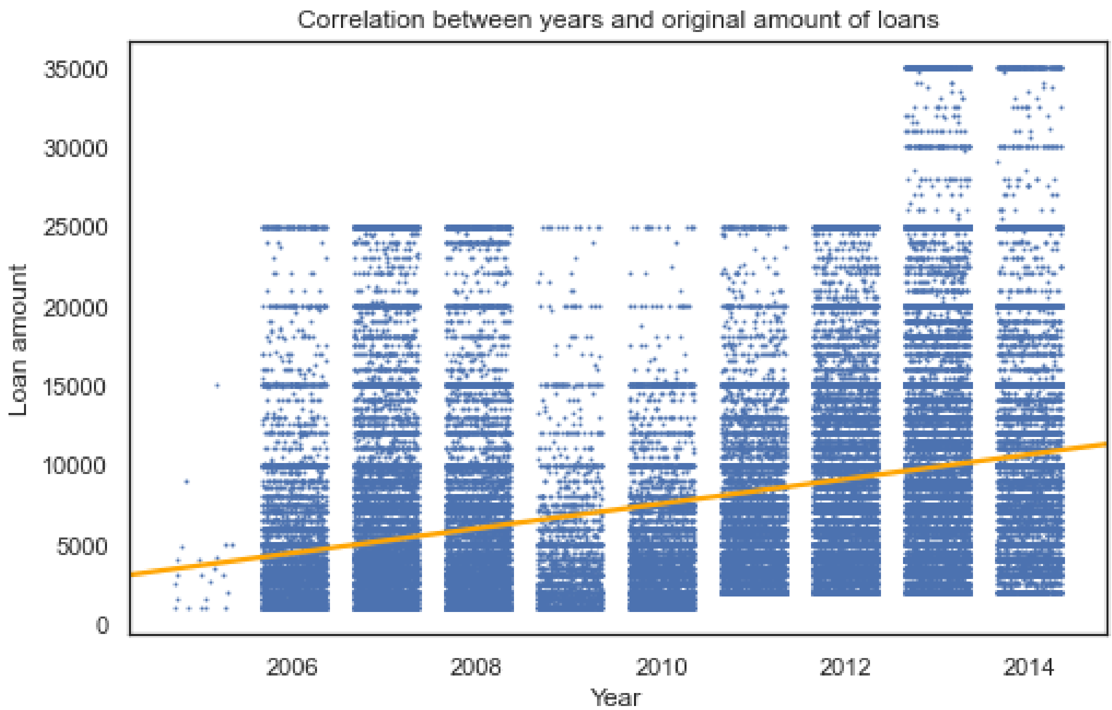


As can be seen above, `BorrowerAPR` and `BorrowerRate` have a very high correlation. `Investors` also have a correlation of 0.38 with `LoanOriginalAMount`.

[35]:
```
plot_sample = np.random.choice(loans[numeric_vars].shape[0], 500, replace=False)
loans_plot_sample =  loans[numeric_vars].loc[plot_sample]
g = sns.PairGrid(data=loans, vars=loans_plot_sample)
g = g.map_diag(plt.hist)
g.map_offdiag(plt.scatter);
```

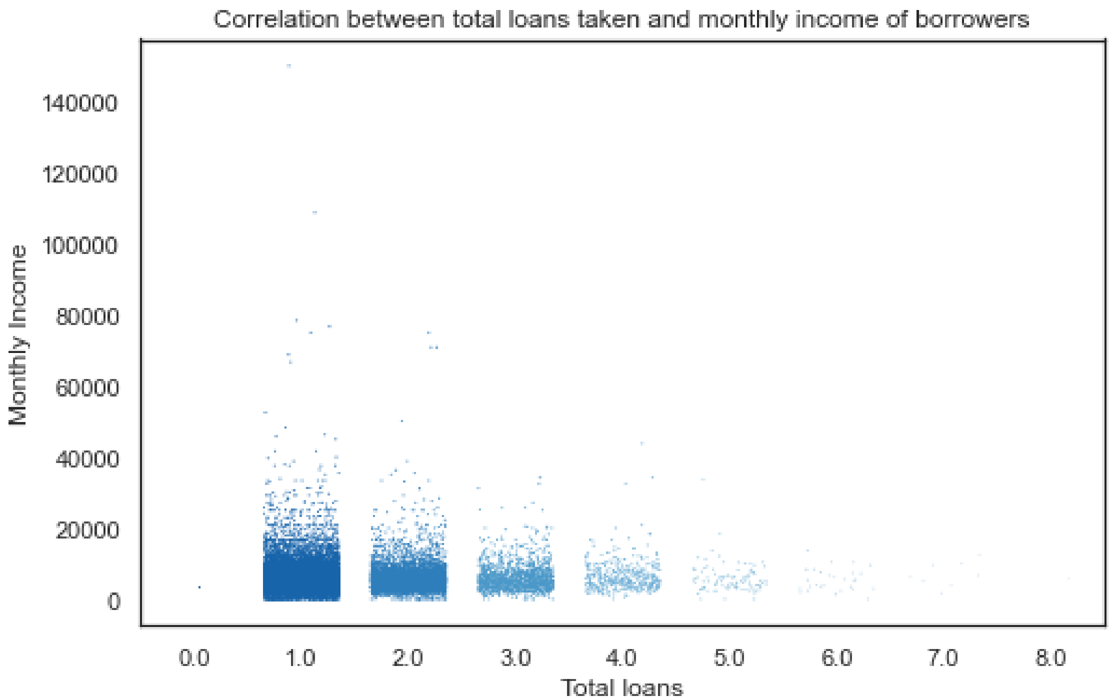


[46]:
```python
# Correlation between years and original amount of loans
plt.figure(figsize=[8,5])
sns.regplot(data=loans, x='Year', y='LoanOriginalAmount', truncate=False, x_jitter=0.35, scatter_kws={'s': 1}, line_kws={'color': 'orange'}).set(
    title='Correlation between years and original amount of loans', xlabel='Year', ylabel='Loan amount');
```



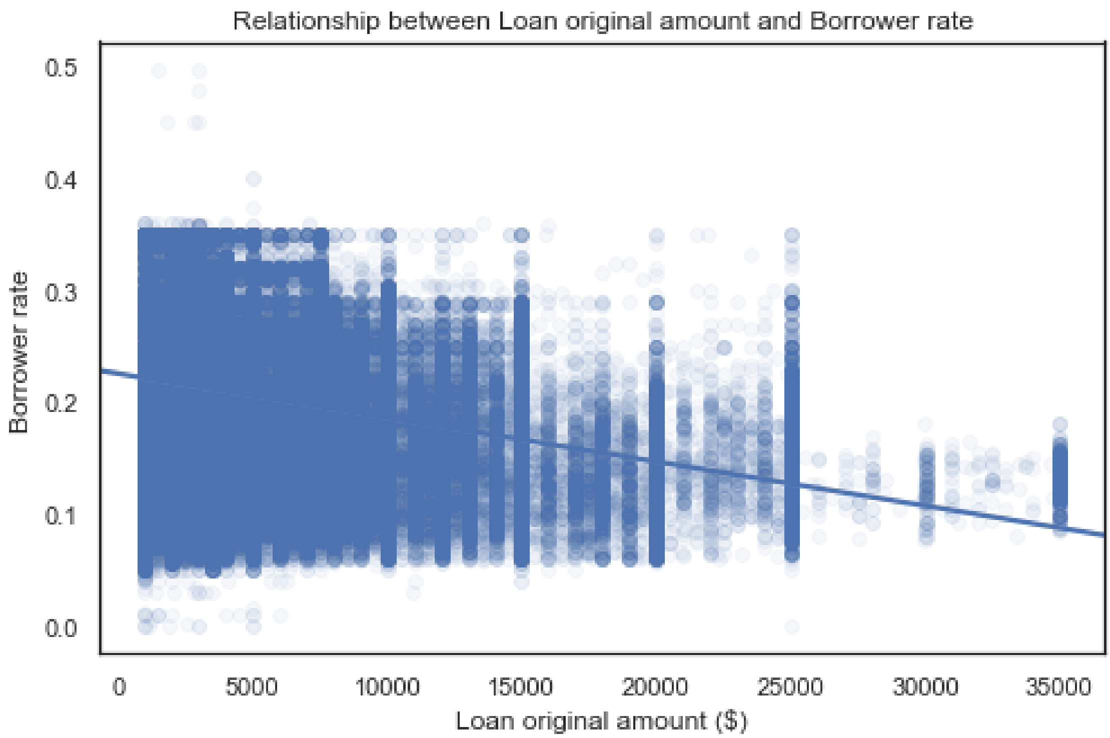
There is a positive correlation between `Year` and `LoanOriginalAmount`.

[45]:
```
# Correlation between total loans taken and monthly income of borrowers
plt.figure(figsize = [8,5])
sns.stripplot(data=loans, x='TotalProsperLoans', y='StatedMonthlyIncome',␣
↪size=1, jitter=0.35, palette='Blues_r').set(
title='Correlation between total loans taken and monthly income of borrowers',␣
↪xlabel='Total loans', ylabel='Monthly Income')
plt.show();
```



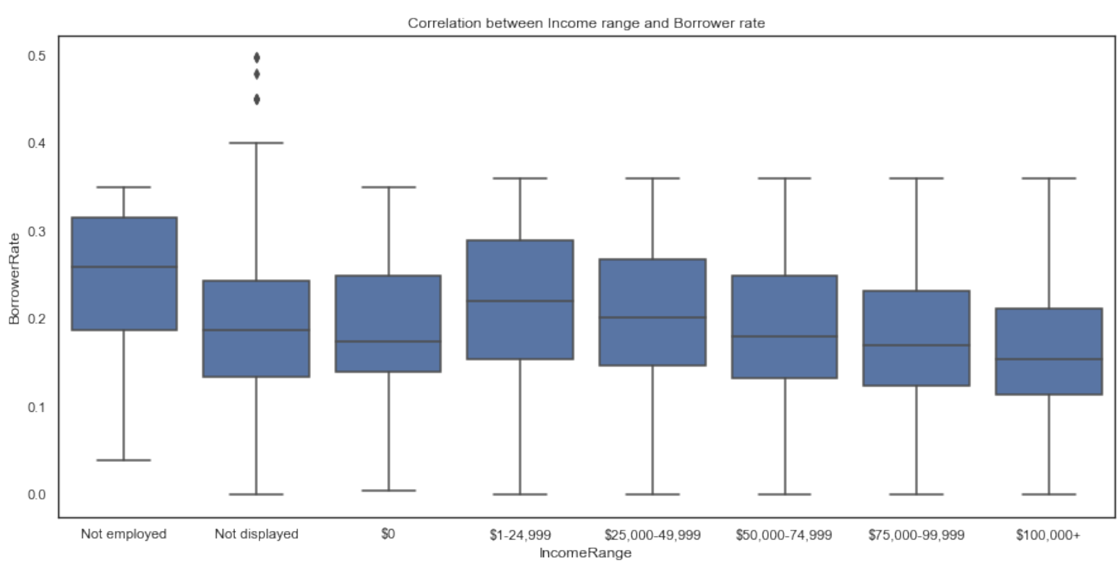
The borrowers with the highest monthly income took the least number of loans while those with the most loans taken are the low income earners. It can be noted that `TotalProsperLoans` is negatively correlated with `StatedMonthlyIncome`

[25]:
```
# regplot of BorrowerRate and LoanOriginalAmount
plt.figure(figsize=[8,5])
sns.regplot(data=loans, x='LoanOriginalAmount', y='BorrowerRate',␣
 ↪truncate=False, x_jitter=0.3, scatter_kws={'alpha':1/20})
plt.title('Relationship between Loan original amount and Borrower rate')
plt.xlabel('Loan original amount ($)')
plt.ylabel('Borrower rate');
```



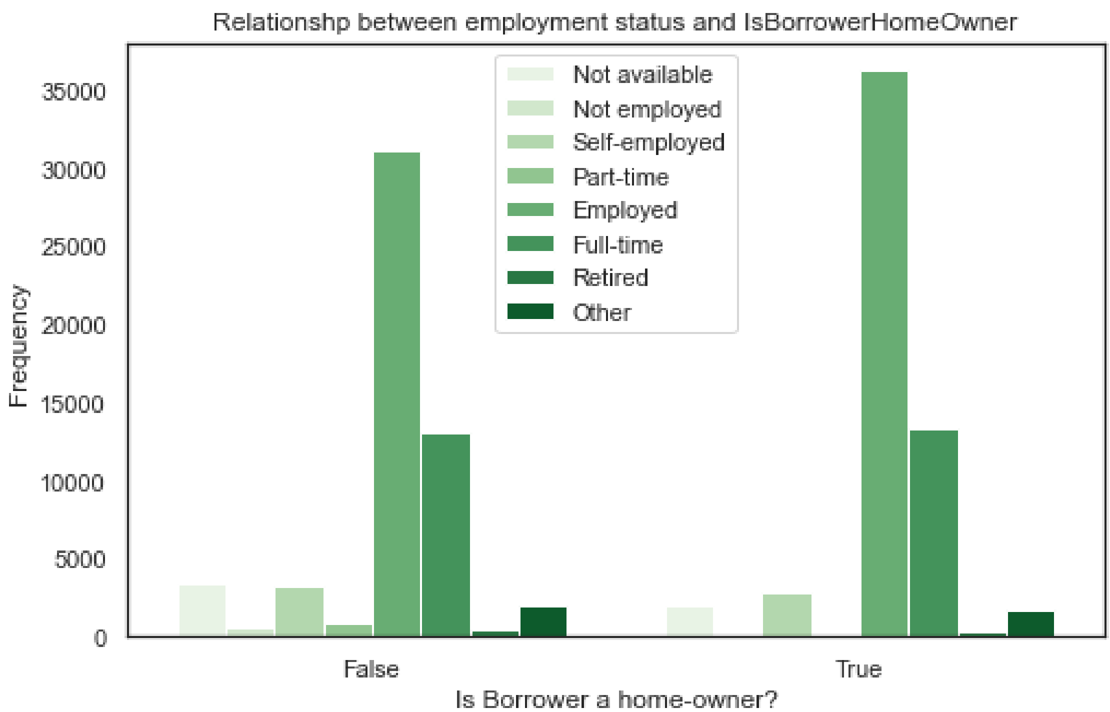
Range of BorrowerRate decreases with an increase of loan amount.

[39]:
```
# boxplot of IncomeRange vs BorrowerRate
plt.figure(figsize=[15,7])
color = sns.color_palette()[0]
sns.boxplot(data=loans, x='IncomeRange', y='BorrowerRate', color=color).
 ↪set(title='Correlation between Income range and Borrower rate');
```



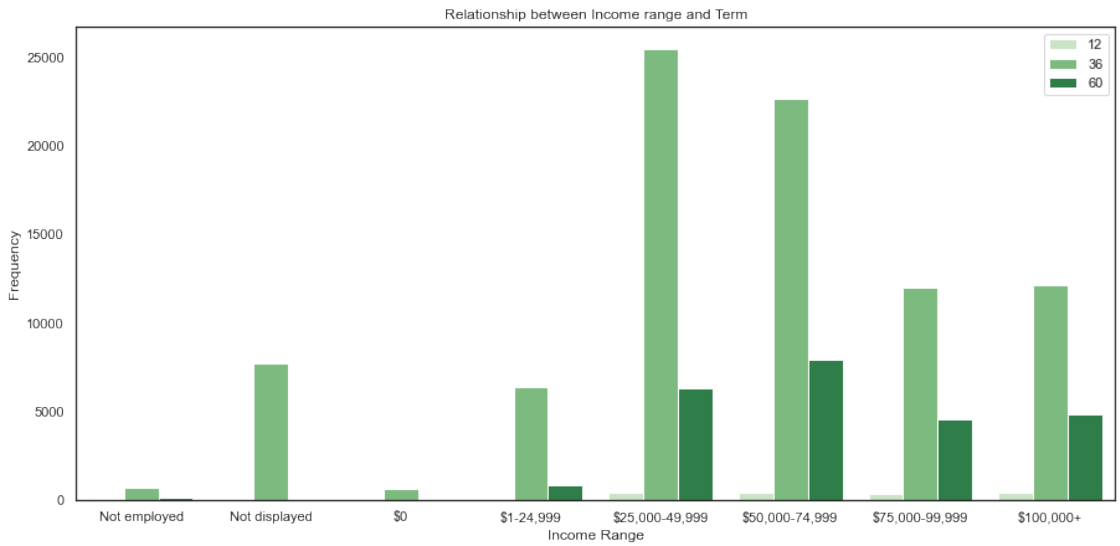
The **not displayed** IncomeRange has a sizeable number of outliers. It also has the highest value of interest rate.

[40]:
```
# relationship between employment status and IsBorrowerHomeOwner
plt.figure(figsize=[8,5])
sns.countplot(data=loans, x='IsBorrowerHomeowner', hue='EmploymentStatus',␣
 ↪palette='Greens')
plt.legend(ncol=1)
plt.title('Relationshp between employment status and IsBorrowerHomeOwner')
plt.xlabel('Is Borrower a home-owner?')
plt.ylabel('Frequency');
```



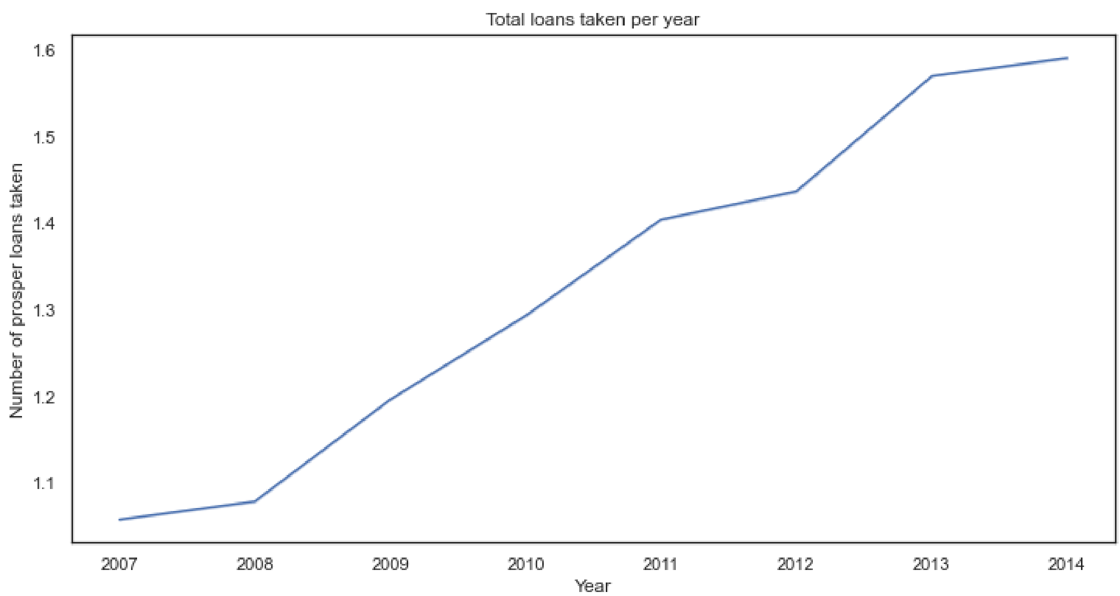
Employed folks make up the majority of borrowers that own a home. Interestingly, it's also the same for borrowers that don't own any.

[41]:
```
# term vs IncomeRange relationship
plt.figure(figsize=[15,7])
sns.countplot(data=loans, x='IncomeRange', hue='Term', palette='Greens')
plt.legend(ncol=1)
plt.title('Relationship between Income range and Term')
plt.xlabel('Income Range')
plt.ylabel('Frequency');
```



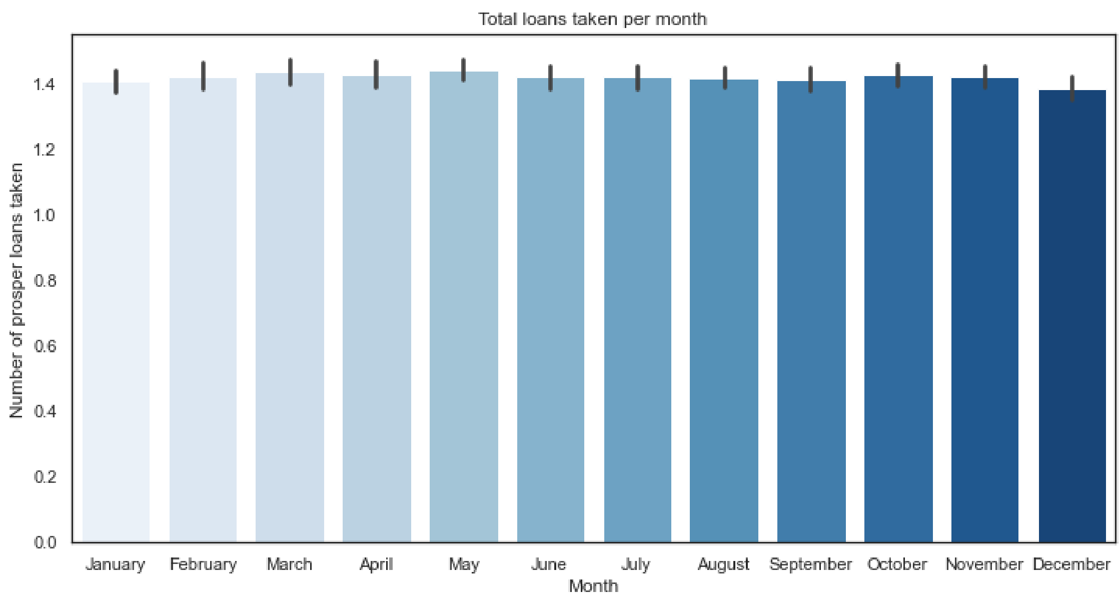
Majority of borrowers who took the shortest loan term have an income range between 25k and 100k dollars. It shows that the higher earning borrowers took the shortest loan term available.

[42]:
```
# Relationship between TotalProsperLoans Vs Year
plt.figure(figsize=[12,6])
sns.lineplot(data=loans, x='Year', y='TotalProsperLoans', palette='Blues', ci=0)
plt.title('Total loans taken per year')
plt.xlabel('Year')
plt.ylabel('Number of prosper loans taken');
```



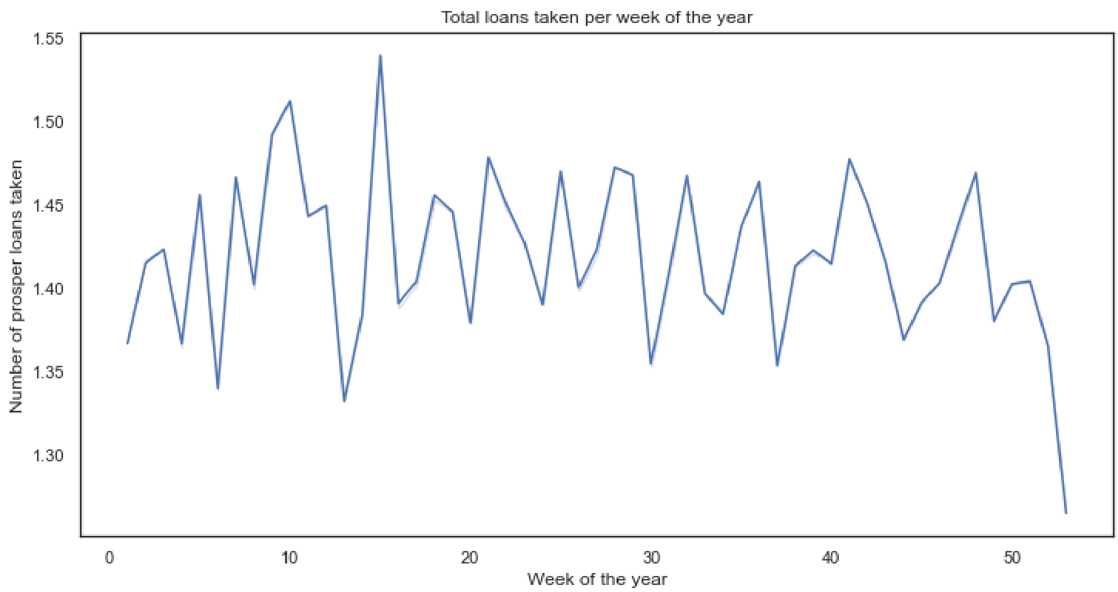
Generally, a positive correlation exists between `TotalProsperLoans` and `Year`. The number of loans taken decreased from 2008 to 2009 before going up again in 2012 thereafter with 2014 becoming the year with the highest number of loans taken.

[43]:
```
# Relationship between TotalProsperLoans Vs Month
month_order = ['January', 'February', 'March', 'April', 'May', 'June', 'July',␣
↪'August', 'September', 'October', 'November', 'December']
plt.figure(figsize=[12,6])
sns.barplot(data=loans, x='Month', y='TotalProsperLoans', palette='Blues',␣
↪order=month_order)
plt.title('Total loans taken per month')
plt.xlabel('Month')
plt.ylabel('Number of prosper loans taken');
```



May is the month with the highest number of loans that were taken while borrowers seldom take loans at the end of the year.

[44]:
```
# Relationship between TotalProsperLoans Vs Week
plt.figure(figsize=[12,6])
sns.lineplot(data=loans, x='Week', y='TotalProsperLoans', palette='Blues', ci=0)
plt.title('Total loans taken per week of the year')
plt.xlabel('Week of the year')
plt.ylabel('Number of prosper loans taken');
```



The least number of loans was taken during the last weeks of the year.

1.5.1 Talk about some of the relationships you observed in this part of the investigation. How did the feature(s) of interest vary with other features in the dataset?

- BorrowerAPR and BorrowerRate have a very high correlation.
- Investors have a correlation of 0.38 with LoanOriginalAMount.
- There is a positive correlation between Year and LoanOriginalAmount.
- The borrowers with the highest monthly income took the least number of loans while those with the most loans taken are the low income earners.
- It can also be noted that TotalProsperLoans is negatively correlated with StatedMonthlyIncome.
- The not displayed IncomeRange has a sizeable number of outliers
- Majority of borrowers who took the shortest loan term have an income range between 25k and 100k dollars. It shows that the higher earning borrowers took the shortest loan term available.
- Generally, a positive correlation exists between TotalProsperLoans and Year.
- May is the month with the highest number of loans that were taken while borrowers seldom take loans at the end of the year.
- The least number of loans was taken during the last weeks of the year.

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

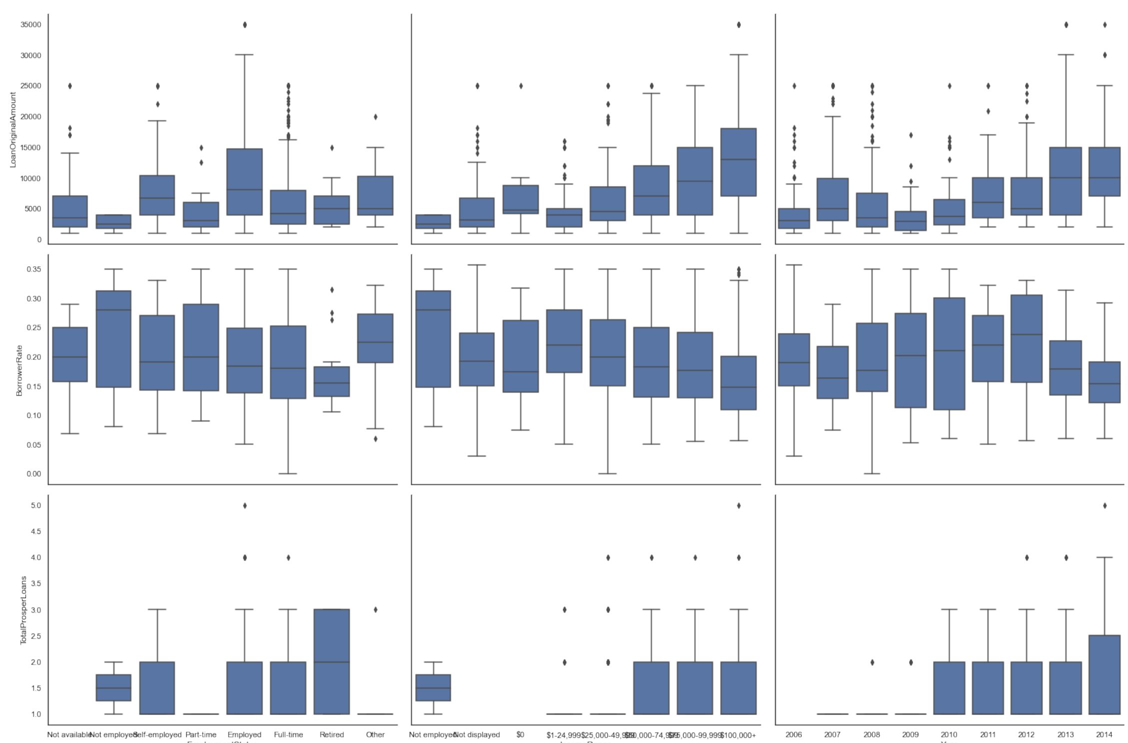
- Employed folks make up the majority of borrowers that own a home.
- The higher earning borrowers took the shortest loan term available.

1.6 Multivariate Exploration

Creating plots of three or more variables to investigate the data even further.

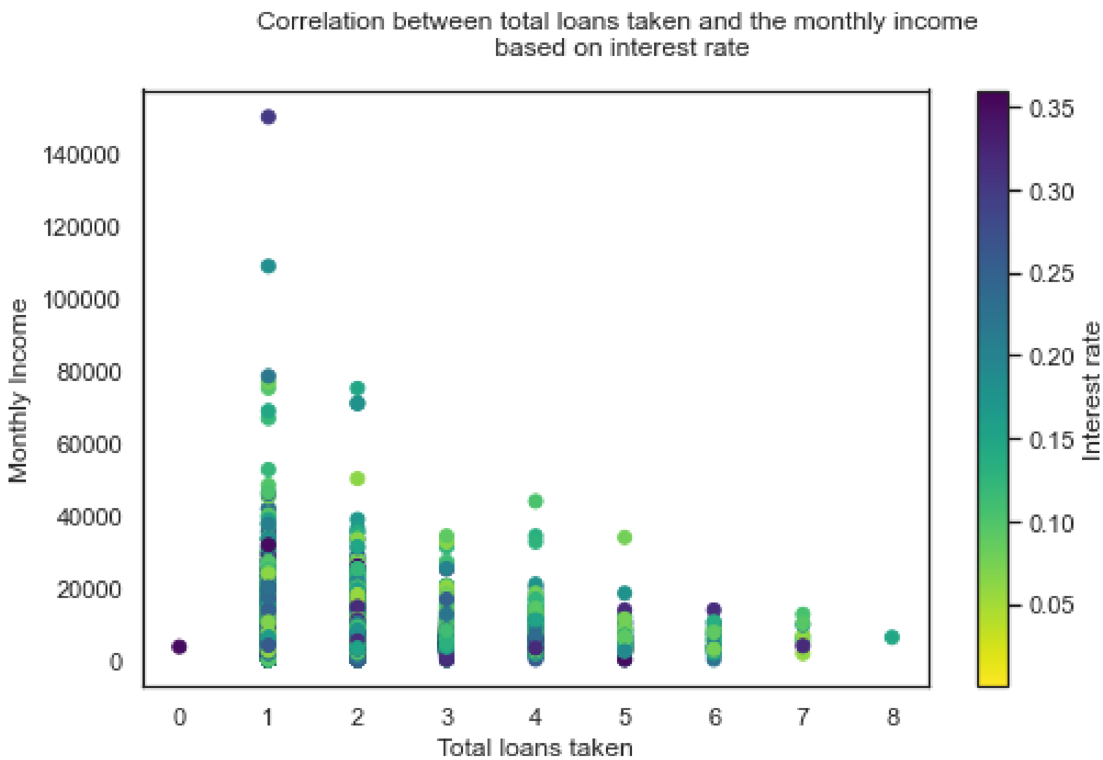
[82]:
```python
# plot matrix of numeric features against categorical features with only 2000 random samples taken
samples = np.random.choice(loans.shape[0], 2000, replace = False)
loans_samp = loans.loc[samples,:]
cat_vars = ['EmploymentStatus', 'IncomeRange', 'Year']

def boxgrid(x, y, **kwargs):
    """ Quick hack for creating box plots with seaborn's PairGrid. """
    default_color = sns.color_palette()[0]
    sns.boxplot(x, y, color = default_color)

plt.figure(figsize = [20, 20])
g = sns.PairGrid(data = loans_samp, y_vars = ['LoanOriginalAmount', 'BorrowerRate', 'TotalProsperLoans'], x_vars = cat_vars, size=5, aspect=1.5, height=5)
g.map(boxgrid)
plt.show();
```

```
<Figure size 1440x1440 with 0 Axes>
```



It can be noted that IncomeRange and LoanOriginalAMount are positively correlated.

[83]:
```
# relationship between TotalProsperLoans and StatedMonthlyIncome based on
↪BorrowerRate
plt.figure(figsize = [8,5])
plt.scatter(data=loans, x='TotalProsperLoans', y='StatedMonthlyIncome',
↪c='BorrowerRate', cmap='viridis_r')
plt.suptitle('Correlation between total loans taken and the monthly income\n
↪based on interest rate')
plt.xlabel('Total loans taken')
plt.ylabel('Monthly Income')
plt.colorbar(label='Interest rate')
plt.show();
```

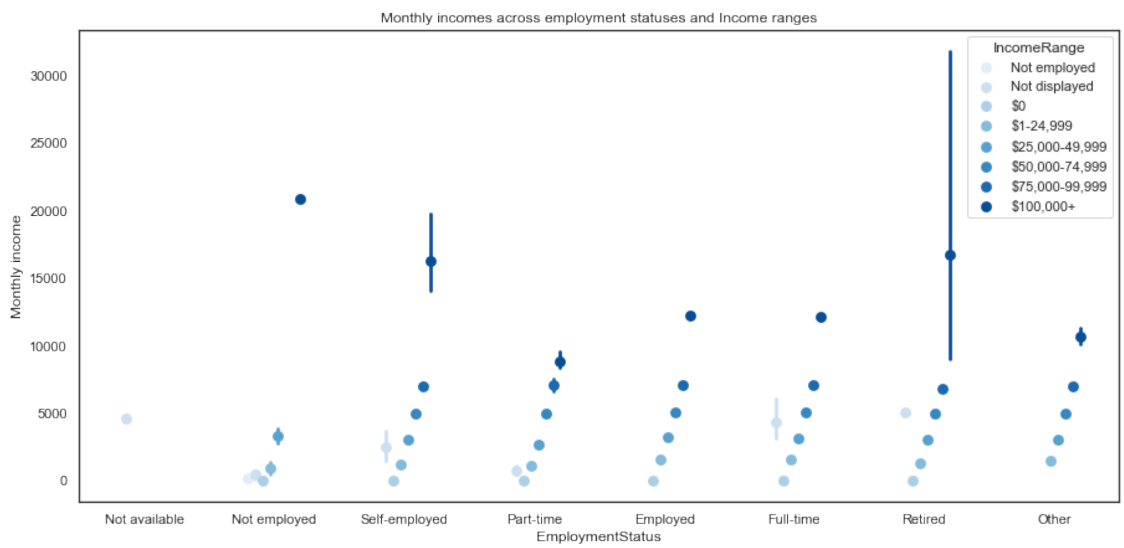


Borrowers with the least number of loans taken are the highest earners and they also have the highest interest rate (BorrowerRate). Generally, it can be observed that the more you take loans, the higher your interest rate(safe for the borrowers who took a single loan). This category of borrowers also have the lowest monthly income.

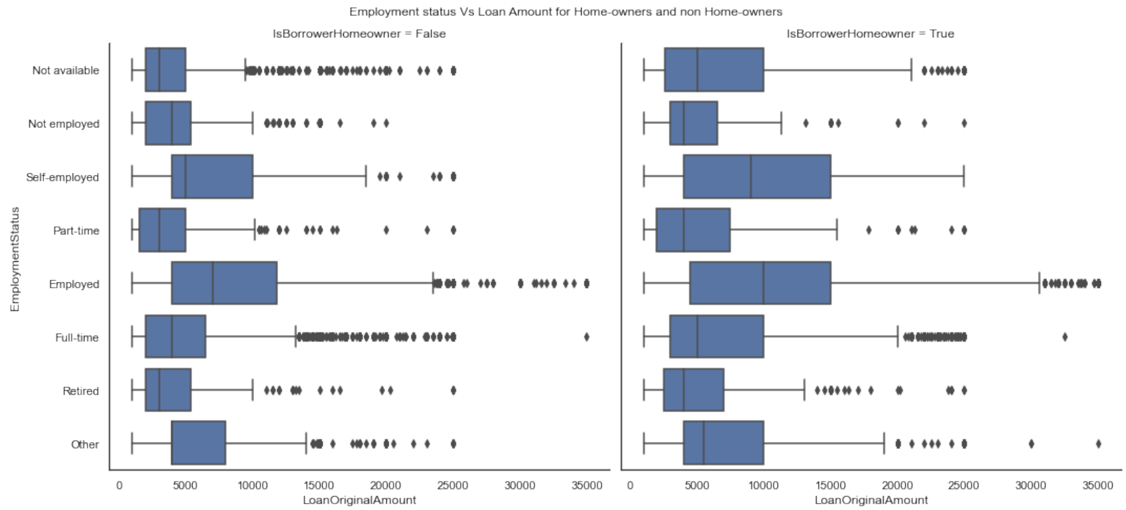
[87]:
```
# fig = plt.figure(figsize = [15,7])
# ax = sns.pointplot(data = loans, y = 'Listing Category', x =
↪'StatedMonthlyIncome', hue = 'EmploymentStatus',
#             palette = 'Blues', linestyles = '', dodge = 0.4)
# plt.title('Monthly incomes across employment statuses and Income ranges')
```

```
# plt.ylabel('Monthly income')
# plt.show();
```

[88]:
```
# Monthly incomes across employment statuses and Income ranges
fig = plt.figure(figsize = [15,7])
ax = sns.pointplot(data = loans, x = 'EmploymentStatus', y =␣
↪'StatedMonthlyIncome', hue = 'IncomeRange',
            palette = 'Blues', linestyles = '', dodge = 0.4)
plt.title('Monthly incomes across employment statuses and Income ranges')
plt.ylabel('Monthly income')
plt.show();
```



[89]:
```
# Employment status Vs Loan Amount for Home-owners and non Home-owners
g = sns.FacetGrid(data=loans, col='IsBorrowerHomeowner', height=5, aspect=1.5,␣
↪size=5)
g.map(sns.boxplot, 'LoanOriginalAmount', 'EmploymentStatus')
g.fig.set_size_inches(15, 7)
plt.suptitle('Employment status Vs Loan Amount for Home-owners and non␣
↪Home-owners', y=1)
plt.show();
```



Borrowers who are either employed or Full-time and are home-owners tend to have more loan original amount. Also, self-employed borrowers who are home owners tend to have much loan original amount.

1.6.1 Talk about some of the relationships you observed in this part of the investigation. Were there features that strengthened each other in terms of looking at your feature(s) of interest?

- It can be noted that IncomeRange and LoanOriginalAMount are positively correlated.
- Borrowers who are either employed or Full-time and are home-owners tend to have more loan original amount. Also, self-employed borrowers who are home owners tend to have much loan original amount.
- Generally, it can be observed that the more you take loans, the larger your interest rate.

1.6.2 Were there any interesting or surprising interactions between features?

I noticed that folks who have a larger Income range tend to have the larger amount of loan original amount.

1.7 Conclusions

For this project, my main task was to explore the features related to the borrowers and how it relates to the loans they took. I started off with the univariate exploration where I explored the distribution of individual features. I got some notable insights from this exploration such as the majority of borrowers originating from California. I also observed that most borrowers are either employed or Full-time. A little minority took their loans for a year while most took their for 36 months.Exploring the Listing Category further, majority of the loans was tajen for Debt consolidation. Taking a look at the ProsperLoans score, it can be seen that most borrowers have a not so good risk score of 4.0. Next I moved on to the Bivariate exploration where I investigated relationships between pairs of variables in the dataset. Using a heatmap, I explored the correlation of all numeric variables in the data and found out that BorrowerAPR and BorrowerRate are highly correlated. Looking down the chart, I observed Investors have a correlation of 0.38 with LoanOriginalAmount. I also observed that borrowers with the highest monthly income took the least number of loans while those with the most loans taken are the low income earners. Exploring further, TotalProsperLoans is negatively correlated with StatedMonthlyIncome. Most borrowers also took loans in the month of May while very few loans were taken at the end of the year. Next, I moved on to the Multivariate exploration where I created plots of three or more variables to investigate the data even further. I used plot matrices to investigate the relationship between numeric features and categorical features in the data. I noted that IncomeRange and LoanOriginalAMount are positively correlated. I then checked the relationship between TotalProsperLoans and StatedMonthlyIncome based on BorrowerRate. Here, I observed that borrowers with the least number of loans taken are the highest earners and they also have the highest interest rate (BorrowerRate). I also noted that the more you take loans, the higher your interest rate(safe for the borrowers who took a single loan). Exploring the data further, I reviewed the relationship between Employment status and Loan Amount for Home-owners and non Home-owners. I found out that Borrowers who are either employed or Full-time and are home-owners tend to have more loan original amount. Also, self-employed borrowers who are home owners tend to have much loan original amount. An interesting interaction I noticed was that folks who have a larger Income range tend to have the larger amount of loan original amount. Finally, it was fun making this analysis and applying what I have learnt from the Data Visualization course of the Data Analyst Nanodegree to this exciting project. One issue I faced though was picking the best features from the many variables in the dataset for this analysis.