Part_I_exploration_template

November 15, 2022

1 Loan Data from Prosper

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1.2 Introduction

This data set contains 113,937 loans with 81 variables on each loan, including loan amount, borrower rate (or interest rate), current loan status, borrower income, and many others.

A description of the variables is as follows: Dataset Description

1.3 Preliminary Wrangling

```
In [93]: # import all packages and set plots to be embedded inline
         import numpy as np
         import pandas as pd
         import matplotlib.pyplot as plt
         import seaborn as sb

         %matplotlib inline
```

```
In [94]: # load dataset into a pandas dataframe
         LoanData = pd.read_csv("prosperLoanData.csv")
```

Data shape and Compostion

```
In [95]: # Data shape
         LoanData.shape
```

```
Out[95]: (113937, 81)
```

```
In [96]: # Composition
         LoanData.dtypes
```

```
Out[96]: ListingKey                              object
         ListingNumber                            int64
         ListingCreationDate                     object
         CreditGrade                             object
         Term                                     int64
```

```
LoanStatus                              object
ClosedDate                              object
BorrowerAPR                            float64
BorrowerRate                           float64
LenderYield                            float64
EstimatedEffectiveYield                float64
EstimatedLoss                          float64
EstimatedReturn                        float64
ProsperRating (numeric)                float64
ProsperRating (Alpha)                   object
ProsperScore                           float64
ListingCategory (numeric)                int64
BorrowerState                           object
Occupation                              object
EmploymentStatus                        object
EmploymentStatusDuration               float64
IsBorrowerHomeowner                       bool
CurrentlyInGroup                          bool
GroupKey                                object
DateCreditPulled                        object
CreditScoreRangeLower                  float64
CreditScoreRangeUpper                  float64
FirstRecordedCreditLine                 object
CurrentCreditLines                     float64
OpenCreditLines                        float64
                                        ...
TotalProsperLoans                      float64
TotalProsperPaymentsBilled             float64
OnTimeProsperPayments                  float64
ProsperPaymentsLessThanOneMonthLate    float64
ProsperPaymentsOneMonthPlusLate        float64
ProsperPrincipalBorrowed               float64
ProsperPrincipalOutstanding            float64
ScorexChangeAtTimeOfListing            float64
LoanCurrentDaysDelinquent                int64
LoanFirstDefaultedCycleNumber          float64
LoanMonthsSinceOrigination               int64
LoanNumber                               int64
LoanOriginalAmount                       int64
LoanOriginationDate                     object
LoanOriginationQuarter                  object
MemberKey                               object
MonthlyLoanPayment                     float64
LP_CustomerPayments                    float64
LP_CustomerPrincipalPayments           float64
LP_InterestandFees                     float64
LP_ServiceFees                         float64
LP_CollectionFees                      float64
```

```
LP_GrossPrincipalLoss                  float64
LP_NetPrincipalLoss                    float64
LP_NonPrincipalRecoverypayments        float64
PercentFunded                          float64
Recommendations                          int64
InvestmentFromFriendsCount               int64
InvestmentFromFriendsAmount            float64
Investors                                int64
Length: 81, dtype: object
```

In [97]:
```
# first five rows
LoanData.head()
```

Out[97]:
```
                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 [98]:
```
# descriptive statitics
LoanData.describe()
```

Out[98]:
```
       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 [99]:
```python
# numerical data (integers)


LoanData.select_dtypes(include = 'int64').head()
```

Out[99]:
```
   ListingNumber  Term  ListingCategory (numeric)  OpenRevolvingAccounts  \
0         193129    36                          0                      1
1        1209647    36                          2                     13
2          81716    36                          0                      0
3         658116    36                         16                      7
4         909464    36                          2                      6

   LoanCurrentDaysDelinquent  LoanMonthsSinceOrigination  LoanNumber  \
0                          0                          78       19141
1                          0                           0      134815
2                          0                          86        6466
3                          0                          16       77296
4                          0                           6      102670

   LoanOriginalAmount  Recommendations  InvestmentFromFriendsCount  Investors
0                9425                0                           0        258
1               10000                0                           0          1
```

```
2              3001                0                             0         41
3             10000                0                             0        158
4             15000                0                             0         20
```

In [100]:
```python
# numerical data (float)


LoanData.select_dtypes(include = 'float64').head()
```

Out[100]:
```
   BorrowerAPR  BorrowerRate  LenderYield  EstimatedEffectiveYield  \
0      0.16516        0.1580       0.1380                      NaN
1      0.12016        0.0920       0.0820                  0.07960
2      0.28269        0.2750       0.2400                      NaN
3      0.12528        0.0974       0.0874                  0.08490
4      0.24614        0.2085       0.1985                  0.18316

   EstimatedLoss  EstimatedReturn  ProsperRating (numeric)  ProsperScore  \
0            NaN              NaN                      NaN           NaN
1         0.0249          0.05470                      6.0           7.0
2            NaN              NaN                      NaN           NaN
3         0.0249          0.06000                      6.0           9.0
4         0.0925          0.09066                      3.0           4.0

   EmploymentStatusDuration  CreditScoreRangeLower  \
0                       2.0                  640.0
1                      44.0                  680.0
2                       NaN                  480.0
3                     113.0                  800.0
4                      44.0                  680.0

               ...              LP_CustomerPayments  \
0              ...                         11396.14
1              ...                             0.00
2              ...                          4186.63
3              ...                          5143.20
4              ...                          2819.85

   LP_CustomerPrincipalPayments  LP_InterestandFees  LP_ServiceFees  \
0                       9425.00             1971.14         -133.18
1                          0.00                0.00            0.00
2                       3001.00             1185.63          -24.20
3                       4091.09             1052.11         -108.01
4                       1563.22             1256.63          -60.27

   LP_CollectionFees  LP_GrossPrincipalLoss  LP_NetPrincipalLoss  \
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

   LP_NonPrincipalRecoverypayments  PercentFunded  InvestmentFromFriendsAmount
0                              0.0            1.0                          0.0
1                              0.0            1.0                          0.0
2                              0.0            1.0                          0.0
3                              0.0            1.0                          0.0
4                              0.0            1.0                          0.0

[5 rows x 50 columns]
```

In [101]:
```
# selecting numerical data (float)


LoanData.select_dtypes(include = 'float64').columns
```

Out[101]:
```
Index(['BorrowerAPR', 'BorrowerRate', 'LenderYield', 'EstimatedEffectiveYield',
       'EstimatedLoss', 'EstimatedReturn', 'ProsperRating (numeric)',
       'ProsperScore', 'EmploymentStatusDuration', 'CreditScoreRangeLower',
       'CreditScoreRangeUpper', 'CurrentCreditLines', 'OpenCreditLines',
       'TotalCreditLinespast7years', 'OpenRevolvingMonthlyPayment',
       'InquiriesLast6Months', 'TotalInquiries', 'CurrentDelinquencies',
       'AmountDelinquent', 'DelinquenciesLast7Years',
       'PublicRecordsLast10Years', 'PublicRecordsLast12Months',
       'RevolvingCreditBalance', 'BankcardUtilization',
       'AvailableBankcardCredit', 'TotalTrades',
       'TradesNeverDelinquent (percentage)', 'TradesOpenedLast6Months',
       'DebtToIncomeRatio', 'StatedMonthlyIncome', 'TotalProsperLoans',
       'TotalProsperPaymentsBilled', 'OnTimeProsperPayments',
       'ProsperPaymentsLessThanOneMonthLate',
       'ProsperPaymentsOneMonthPlusLate', 'ProsperPrincipalBorrowed',
       'ProsperPrincipalOutstanding', 'ScorexChangeAtTimeOfListing',
       'LoanFirstDefaultedCycleNumber', 'MonthlyLoanPayment',
       'LP_CustomerPayments', 'LP_CustomerPrincipalPayments',
       'LP_InterestandFees', 'LP_ServiceFees', 'LP_CollectionFees',
       'LP_GrossPrincipalLoss', 'LP_NetPrincipalLoss',
       'LP_NonPrincipalRecoverypayments', 'PercentFunded',
       'InvestmentFromFriendsAmount'],
      dtype='object')
```

In [102]:
```
# categorical data (object)


LoanData.select_dtypes(include = 'object').head()
```

Out[102]:
```
                ListingKey            ListingCreationDate CreditGrade  \
0  1021339766868145413AB3B  2007-08-26 19:09:29.263000000           C
1  10273602499503308B223C1  2014-02-27 08:28:07.900000000         NaN
```

```
2  0EE9337825851032864889A  2007-01-05 15:00:47.090000000          HR
3  0EF5356002482715299901A  2012-10-22 11:02:35.010000000         NaN
4  0F023589499656230C5E3E2  2013-09-14 18:38:39.097000000         NaN

  LoanStatus           ClosedDate ProsperRating (Alpha) BorrowerState  \
0  Completed  2009-08-14 00:00:00                   NaN            CO
1    Current                  NaN                     A            CO
2  Completed  2009-12-17 00:00:00                   NaN            GA
3    Current                  NaN                     A            GA
4    Current                  NaN                     D            MN

     Occupation EmploymentStatus                 GroupKey  \
0         Other    Self-employed                      NaN
1  Professional         Employed                      NaN
2         Other    Not available  783C3371218786870A73D20
3  Skilled Labor        Employed                      NaN
4     Executive         Employed                      NaN

                 DateCreditPulled FirstRecordedCreditLine     IncomeRange  \
0  2007-08-26 18:41:46.780000000     2001-10-11 00:00:00  $25,000-49,999
1            2014-02-27 08:28:14     1996-03-18 00:00:00  $50,000-74,999
2  2007-01-02 14:09:10.060000000     2002-07-27 00:00:00   Not displayed
3            2012-10-22 11:02:32     1983-02-28 00:00:00  $25,000-49,999
4            2013-09-14 18:38:44     2004-02-20 00:00:00        $100,000+

                   LoanKey  LoanOriginationDate LoanOriginationQuarter  \
0  E33A3400205839220442E84  2007-09-12 00:00:00                Q3 2007
1  9E3B37071505919926B1D82  2014-03-03 00:00:00                Q1 2014
2  6954337960046817851BCB2  2007-01-17 00:00:00                Q1 2007
3  A0393664465886295619C51  2012-11-01 00:00:00                Q4 2012
4  A180369302188889200689E  2013-09-20 00:00:00                Q3 2013

                 MemberKey
0  1F3E3376408759268057EDA
1  1D13370546739025387B2F4
2  5F7033715035555618FA612
3  9ADE356069835475068C6D2
4  36CE356043264555721F06C
```

1.3.1 Variables of Interest

```
In [103]: # variables to use for analysis
          LoanData2 = LoanData[['IncomeRange', 'StatedMonthlyIncome','ListingNumber','LoanStatus
                                'IsBorrowerHomeowner','ProsperRating (Alpha)', 'ProsperScore', 'Li
```

1.4 Assess

```
In [104]: LoanData2.shape
```

Out[104]: (113937, 13)

In [105]: # first five rows

```
LoanData2.head()
```

Out[105]:

```
       IncomeRange  StatedMonthlyIncome  ListingNumber LoanStatus  \
0  $25,000-49,999          3083.333333         193129  Completed
1  $50,000-74,999          6125.000000        1209647    Current
2   Not displayed          2083.333333          81716  Completed
3  $25,000-49,999          2875.000000         658116    Current
4        $100,000+          9583.333333         909464    Current

      Occupation EmploymentStatus  LoanOriginalAmount  Investors  \
0          Other    Self-employed                9425        258
1   Professional         Employed               10000          1
2          Other    Not available                3001         41
3  Skilled Labor         Employed               10000        158
4      Executive         Employed               15000         20

  IsBorrowerHomeowner ProsperRating (Alpha)  ProsperScore  \
0                True                   NaN           NaN
1               False                     A           7.0
2               False                   NaN           NaN
3                True                     A           9.0
4                True                     D           4.0

  ListingCategory (numeric)  Recommendations
0                         0                0
1                         2                0
2                         0                0
3                        16                0
4                         2                0
```

In [106]: # concise summary

```
LoanData2.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 113937 entries, 0 to 113936
Data columns (total 13 columns):
IncomeRange                  113937 non-null object
StatedMonthlyIncome          113937 non-null float64
ListingNumber                113937 non-null int64
LoanStatus                   113937 non-null object
Occupation                   110349 non-null object
EmploymentStatus             111682 non-null object
LoanOriginalAmount           113937 non-null int64
Investors                    113937 non-null int64
IsBorrowerHomeowner          113937 non-null bool
```

```
ProsperRating (Alpha)        84853 non-null object
ProsperScore                 84853 non-null float64
ListingCategory (numeric)    113937 non-null int64
Recommendations              113937 non-null int64
dtypes: bool(1), float64(2), int64(5), object(5)
memory usage: 10.5+ MB
```

In [107]:
```
# check for null values

LoanData2.isnull().sum()
```

Out[107]:
```
IncomeRange                      0
StatedMonthlyIncome              0
ListingNumber                    0
LoanStatus                       0
Occupation                    3588
EmploymentStatus              2255
LoanOriginalAmount               0
Investors                        0
IsBorrowerHomeowner              0
ProsperRating (Alpha)        29084
ProsperScore                 29084
ListingCategory (numeric)        0
Recommendations                  0
dtype: int64
```

In [108]:
```
# check for duplicates

LoanData2.duplicated().sum()
```

Out[108]:
```
0
```

Check unique values for some variables of interest

In [109]:
```
LoanData2['Occupation'].unique()
```

Out[109]:
```
array(['Other', 'Professional', 'Skilled Labor', 'Executive',
       'Sales - Retail', 'Laborer', 'Food Service', 'Fireman',
       'Waiter/Waitress', 'Construction', 'Computer Programmer',
       'Sales - Commission', 'Retail Management', 'Engineer - Mechanical',
       'Military Enlisted', 'Clerical', nan, 'Teacher', 'Clergy',
       'Accountant/CPA', 'Attorney', 'Nurse (RN)', 'Analyst',
       "Nurse's Aide", 'Investor', 'Realtor', 'Flight Attendant',
       'Nurse (LPN)', 'Military Officer', 'Food Service Management',
       'Truck Driver', 'Administrative Assistant',
       'Police Officer/Correction Officer', 'Social Worker',
       'Tradesman - Mechanic', 'Medical Technician', 'Professor',
       'Postal Service', 'Civil Service', 'Pharmacist',
```

```
                'Tradesman - Electrician', 'Scientist', 'Dentist',
                'Engineer - Electrical', 'Architect', 'Landscaping',
                'Tradesman - Carpenter', 'Bus Driver', 'Tradesman - Plumber',
                'Engineer - Chemical', 'Doctor', 'Chemist',
                'Student - College Senior', 'Principal', "Teacher's Aide",
                'Pilot - Private/Commercial', 'Religious', 'Homemaker',
                'Student - College Graduate Student', 'Student - Technical School',
                'Psychologist', 'Biologist', 'Student - College Sophomore', 'Judge',
                'Student - College Junior', 'Car Dealer',
                'Student - Community College', 'Student - College Freshman'], dtype=object)
```

```
In [110]: LoanData2['EmploymentStatus'].unique()
```

```
Out[110]: array(['Self-employed', 'Employed', 'Not available', 'Full-time', 'Other',
                 nan, 'Not employed', 'Part-time', 'Retired'], dtype=object)
```

```
In [111]: LoanData2['Recommendations'].unique()
```

```
Out[111]: array([ 0,  2,  1,  4,  3,  9,  5, 16, 39, 21,  7, 14,  8,  6, 24, 19, 18])
```

```
In [112]: LoanData2['ProsperScore'].unique()
```

```
Out[112]: array([ nan,   7.,   9.,   4.,  10.,   2.,  11.,   8.,   5.,   3.,   6.,
                   1.])
```

```
In [113]: LoanData2['ProsperRating (Alpha)'].unique()
```

```
Out[113]: array([nan, 'A', 'D', 'B', 'E', 'C', 'AA', 'HR'], dtype=object)
```

1.4.1 Issues

1. Missing values in Occupation, EmploymentStatus, CreditGrade, ProsperRating (Alpha), ProsperScore variables

1.5 Clean

```
In [114]: LoanData_clean = LoanData2.copy()
```

```
In [115]: LoanData_clean.head()
```

```
Out[115]:       IncomeRange  StatedMonthlyIncome  ListingNumber LoanStatus  \
          0  $25,000-49,999          3083.333333         193129  Completed
          1  $50,000-74,999          6125.000000        1209647    Current
          2   Not displayed          2083.333333          81716  Completed
          3  $25,000-49,999          2875.000000         658116    Current
          4        $100,000+          9583.333333         909464    Current

                Occupation EmploymentStatus  LoanOriginalAmount  Investors  \
          0          Other    Self-employed                9425        258
          1   Professional         Employed               10000          1
```

```
2          Other    Not available                3001         41
3  Skilled Labor         Employed               10000        158
4      Executive         Employed               15000         20

   IsBorrowerHomeowner ProsperRating (Alpha)  ProsperScore  \
0                 True                   NaN           NaN
1                False                     A           7.0
2                False                   NaN           NaN
3                 True                     A           9.0
4                 True                     D           4.0

   ListingCategory (numeric)  Recommendations
0                          0                0
1                          2                0
2                          0                0
3                         16                0
4                          2                0
```

In [116]:
```python
LoanData_clean.isnull().sum()
```

Out[116]:
```
IncomeRange                      0
StatedMonthlyIncome              0
ListingNumber                    0
LoanStatus                       0
Occupation                    3588
EmploymentStatus              2255
LoanOriginalAmount               0
Investors                        0
IsBorrowerHomeowner              0
ProsperRating (Alpha)        29084
ProsperScore                 29084
ListingCategory (numeric)        0
Recommendations                  0
dtype: int64
```

In [117]:
```python
# filter out null values

LoanData_clean = LoanData_clean[LoanData_clean['Occupation'].notnull()]
```

In [118]:
```python
LoanData_clean = LoanData_clean[LoanData_clean['ProsperRating (Alpha)'].notnull()]
```

In [119]:
```python
LoanData_clean = LoanData_clean[LoanData_clean['ProsperScore'].notnull()]
```

In [120]:
```python
LoanData_clean.head()
```

Out[120]:
```
     IncomeRange  StatedMonthlyIncome  ListingNumber LoanStatus  \
1  $50,000-74,999          6125.000000        1209647    Current
3  $25,000-49,999          2875.000000         658116    Current
4       $100,000+          9583.333333         909464    Current
```

```
5       $100,000+          8333.333333        1074836    Current
6  $25,000-49,999          2083.333333         750899    Current

       Occupation EmploymentStatus  LoanOriginalAmount  Investors  \
1    Professional         Employed               10000          1
3   Skilled Labor         Employed               10000        158
4       Executive         Employed               15000         20
5    Professional         Employed               15000          1
6  Sales - Retail         Employed                3000          1

   IsBorrowerHomeowner ProsperRating (Alpha)  ProsperScore  \
1                False                     A           7.0
3                 True                     A           9.0
4                 True                     D           4.0
5                 True                     B          10.0
6                False                     E           2.0

   ListingCategory (numeric)  Recommendations
1                          2                0
3                         16                0
4                          2                0
5                          1                0
6                          1                0
```

Test

In [121]:
```
LoanData_clean.isnull().sum()
```

Out[121]:
```
IncomeRange                  0
StatedMonthlyIncome          0
ListingNumber                0
LoanStatus                   0
Occupation                   0
EmploymentStatus             0
LoanOriginalAmount           0
Investors                    0
IsBorrowerHomeowner          0
ProsperRating (Alpha)        0
ProsperScore                 0
ListingCategory (numeric)    0
Recommendations              0
dtype: int64
```

1.5.1 What is the structure of your dataset?

This data set contains 113,937 loans with 81 variables on each loan, including loan amount, borrower rate (or interest rate), current loan status, borrower income, and many others. Specific variables of interest were chosen for analysis and include a few highlighted below:

- ListingNumber: The number that uniquely identifies the listing to the public as displayed on the website. (Numerical)
- LoanOriginalAmount: The origination amount of the loan.

- LoanStatus: The current status of the loan: Cancelled, Chargedoff, Completed, Current, Defaulted, FinalPaymentInProgress, PastDue. The PastDue status will be accompanied by a delinquency bucket. (Categorical)
- Occupation: The Occupation selected by the Borrower at the time they created the listing (Categorical)
- EmploymentStatus: The employment status of the borrower at the time they posted the listing.
- StatedMonthlyIncome: The monthly income the borrower stated at the time the listing was created.

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

The main features of interest are variables that would be best for determing the loan original amount

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

I believe IncomeRange, Recomendations, Occupation, EmploymentStatus, Stated Monthly Income will help support my investigation

1.6 Univariate Exploration

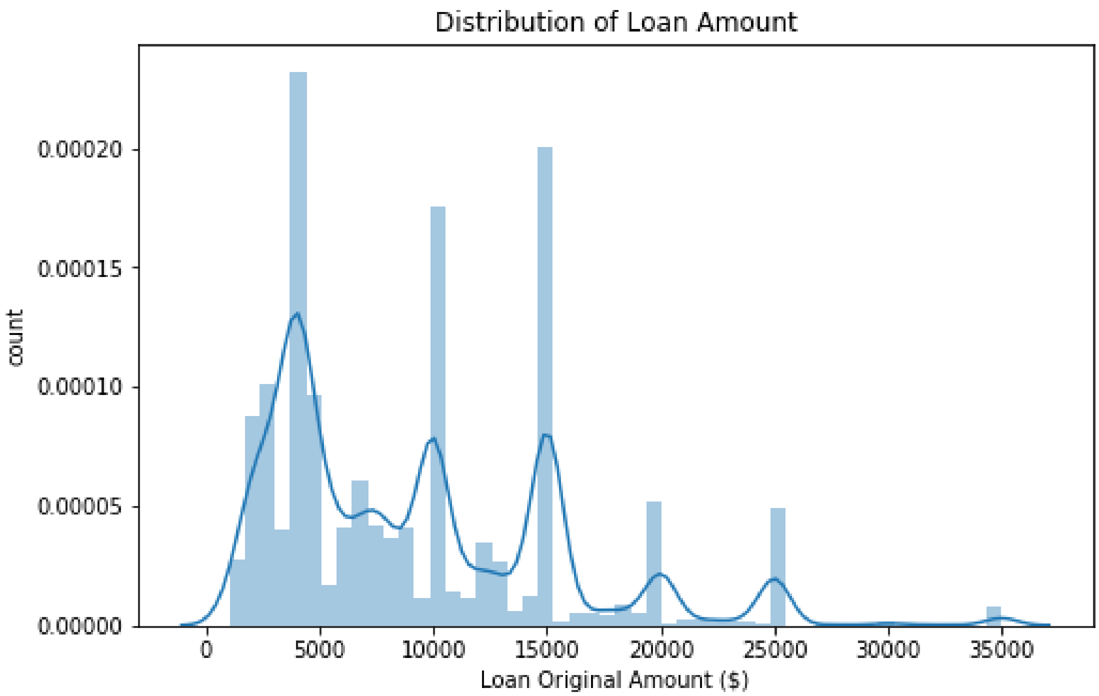
In this section, investigation of distributions of individual variables will be conducted

1.6.1 Question 1

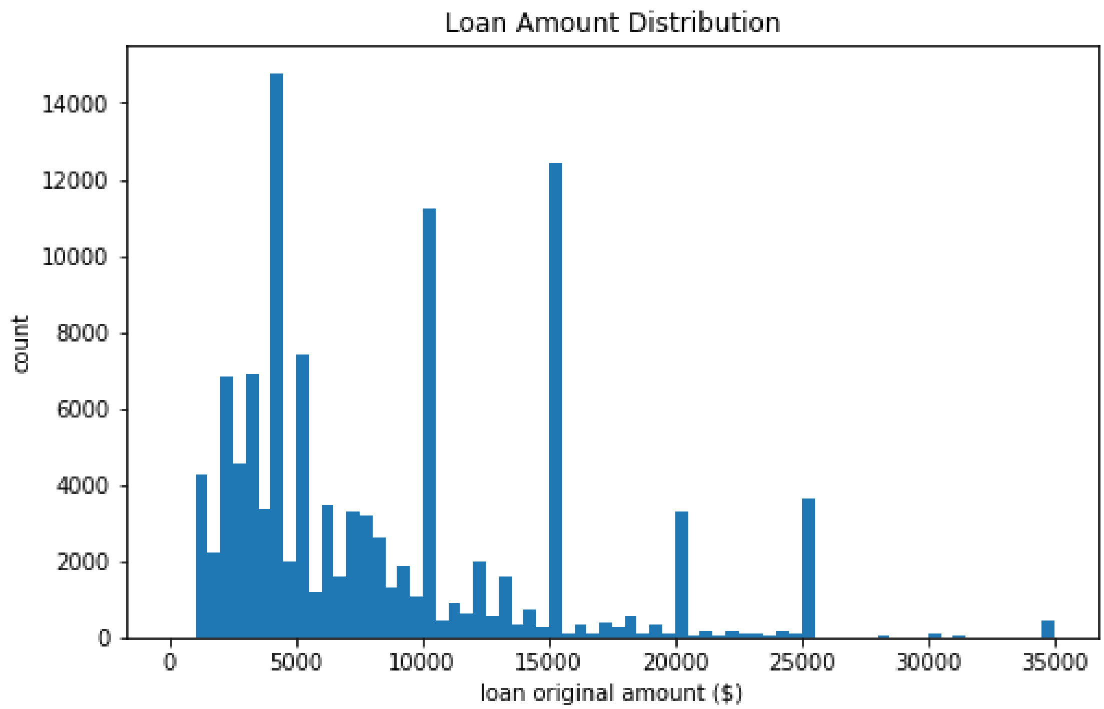
What is the distribution of original loan amount like?

1.6.2 Visualization

```
In [122]: # histogram plot of LoanOriginalAmount feature using seaborn
          plt.figure(figsize=[8, 5])
          sb.distplot(LoanData_clean['LoanOriginalAmount'], hist = True);
          plt.xlabel('Loan Original Amount ($)');
          plt.ylabel('count');
          plt.title('Distribution of Loan Amount');
```




```
In [123]: # i'll start with the distribution of LoanOriginalAmount

          # With a standard-scaled plot
          binsize = 500
          bins = np.arange(0, LoanData2['LoanOriginalAmount'].max()+binsize, binsize)

          plt.figure(figsize=[8, 5])
          plt.hist(data = LoanData2, x = 'LoanOriginalAmount', bins = bins)
          plt.xlabel('loan original amount ($)')
          plt.ylabel('count')
          plt.title('Loan Amount Distribution')
          plt.show()
```



1.6.3 Observation

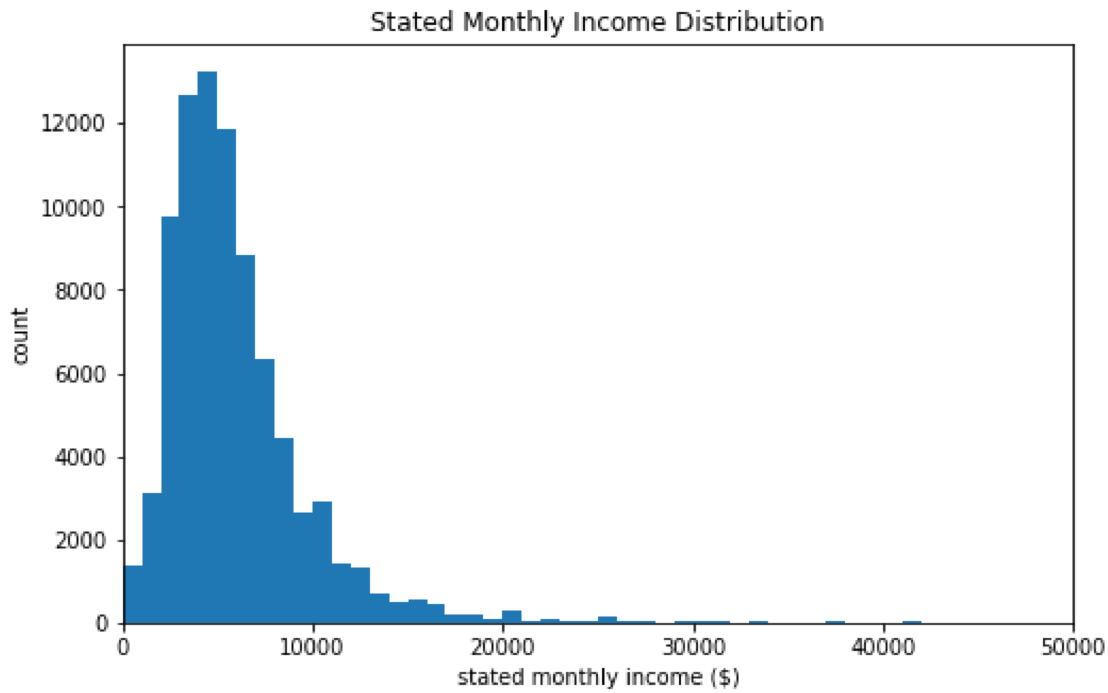
The distribution indicates tri-modality with most given loan amounts at 4000, 10000, 15000 US dollars

1.6.4 Question 2

What is the distribution of StatedMonthlyIncome like?

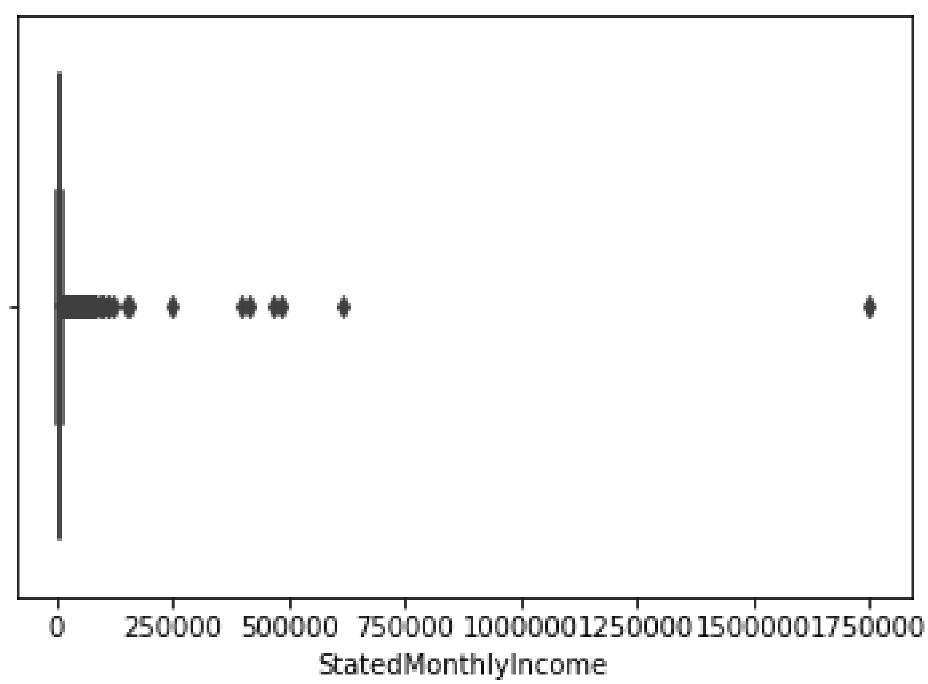
1.6.5 Visualization

```
In [124]: # distribution of StatedMonthlyIncome

          # start with a standard-scaled plot
          binsize = 1000
          bins = np.arange(0, LoanData_clean['StatedMonthlyIncome'].max()+binsize, binsize)

          plt.figure(figsize=[8, 5])
          plt.hist(data = LoanData_clean, x = 'StatedMonthlyIncome', bins = bins)
          plt.xlabel('stated monthly income ($)')
          plt.ylabel('count')
          plt.xlim(0, 50000)
          plt.title('Stated Monthly Income Distribution')
          plt.show()
```



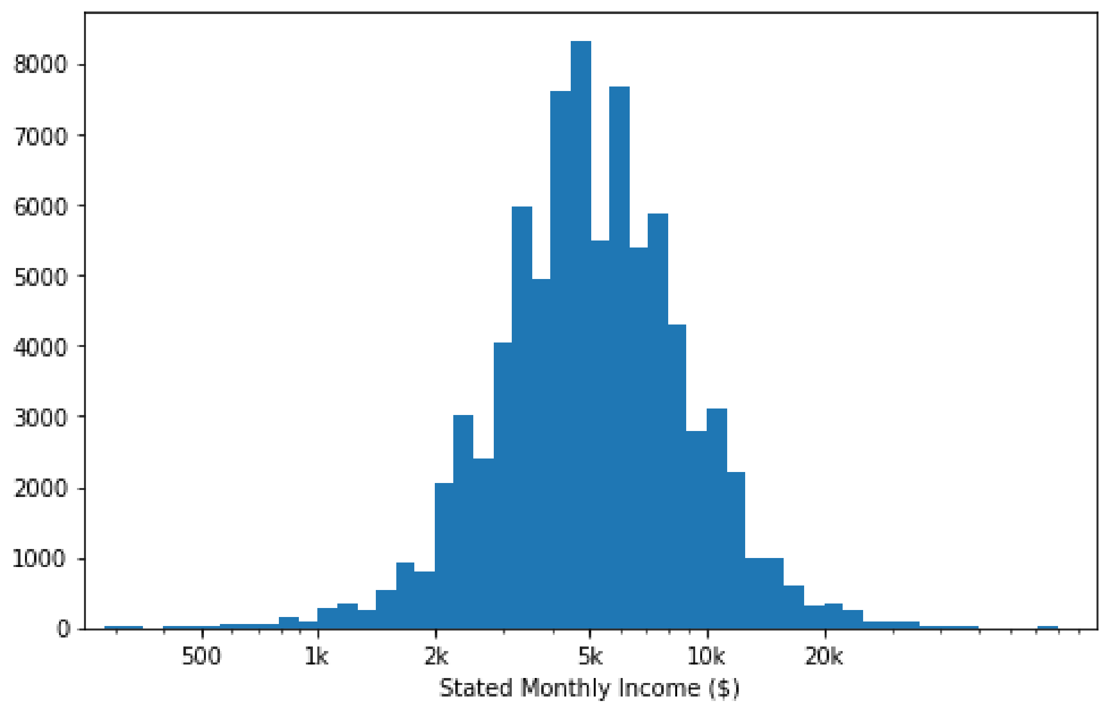
The presence of a long tail is an indication of outliers

```
In [125]: # checking for outliers
          sb.boxplot(LoanData_clean['StatedMonthlyIncome']);
```



```
In [126]: # there's a long tail in the distribution, so let's put it on a log scale instead
          log_binsize = 0.05
          bins = 10 ** np.arange(2.4, np.log10(LoanData_clean['StatedMonthlyIncome'].max())+log_

          plt.figure(figsize=[8, 5])
          plt.hist(data = LoanData_clean, x = 'StatedMonthlyIncome', bins = bins)
          plt.xscale('log')
          plt.xticks([500, 1e3, 2e3, 5e3, 1e4, 2e4], [500, '1k', '2k', '5k', '10k', '20k'])
          plt.xlim(0, 100000)
          plt.xlabel('Stated Monthly Income ($)')
          plt.show()
```

```
/opt/conda/lib/python3.6/site-packages/matplotlib/axes/_base.py:2923: UserWarning: Attempted to
  'Attempted to set non-positive xlimits for log-scale axis; '
```



1.6.6 Observation

The distribution indicates that majority of the custormers have a monthly income between 2000 and 10000 US dollars with a noticable peak monthly income around 5000 dollars which would likely be the median monthly income

```
In [127]: # summary statistics of StatedMonthlyIncome
          LoanData_clean['StatedMonthlyIncome'].describe()
```

```
Out[127]: count    8.352000e+04
          mean     5.966707e+03
          std      8.296751e+03
          min      0.000000e+00
          25%      3.500000e+03
          50%      5.000000e+03
          75%      7.166667e+03
          max      1.750003e+06
          Name: StatedMonthlyIncome, dtype: float64
```

1.6.7 Question 3

What Occupation get the most Loans?

1.6.8 Visualization

```
In [128]: # checking for unique occupations in the data

          LoanData_clean['Occupation'].unique()
```

```
Out[128]: array(['Professional', 'Skilled Labor', 'Executive', 'Sales - Retail',
                 'Laborer', 'Food Service', 'Fireman', 'Construction',
                 'Computer Programmer', 'Other', 'Sales - Commission',
                 'Retail Management', 'Engineer - Mechanical', 'Military Enlisted',
                 'Clerical', 'Teacher', 'Clergy', 'Attorney', 'Nurse (RN)',
                 'Accountant/CPA', 'Analyst', 'Investor', 'Flight Attendant',
                 'Nurse (LPN)', 'Military Officer', 'Truck Driver',
                 'Administrative Assistant', 'Police Officer/Correction Officer',
                 'Social Worker', 'Food Service Management', 'Tradesman - Mechanic',
                 'Medical Technician', 'Professor', 'Postal Service',
                 'Waiter/Waitress', 'Civil Service', 'Pharmacist',
                 'Tradesman - Electrician', 'Scientist', 'Dentist',
                 'Engineer - Electrical', 'Architect', 'Landscaping', 'Bus Driver',
                 'Engineer - Chemical', 'Doctor', 'Chemist', "Teacher's Aide",
                 'Pilot - Private/Commercial', "Nurse's Aide", 'Religious',
                 'Homemaker', 'Realtor', 'Student - College Senior', 'Principal',
                 'Psychologist', 'Biologist', 'Tradesman - Carpenter', 'Judge',
                 'Car Dealer', 'Student - College Graduate Student',
                 'Student - College Freshman', 'Student - College Junior',
                 'Tradesman - Plumber', 'Student - College Sophomore',
                 'Student - Community College', 'Student - Technical School'], dtype=object)
```

```
In [129]: # frequency count for each occupation in the data

          (LoanData_clean.Occupation.value_counts())
```

```
Out[129]: Other                                   21317
          Professional                            10542
          Executive                                3468
          Computer Programmer                      3236
          Teacher                                  2888
          Analyst                                  2735
          Administrative Assistant                 2708
          Accountant/CPA                           2574
          Sales - Commission                       2350
          Skilled Labor                            2180
          Nurse (RN)                               2159
          Clerical                                 2116
          Sales - Retail                           2029
          Retail Management                        2001
          Truck Driver                             1366
          Construction                             1326
          Police Officer/Correction Officer        1277
          Laborer                                  1217
          Civil Service                            1139
          Engineer - Mechanical                    1135
          Food Service Management                  1005
          Engineer - Electrical                     900
          Medical Technician                        891
          Attorney                                  866
          Food Service                              837
          Military Enlisted                         824
          Tradesman - Mechanic                      797
          Social Worker                             575
          Postal Service                            487
          Professor                                 452
                                                  ...
          Principal                                 262
          Realtor                                   252
          Military Officer                          252
          Bus Driver                                250
          Pharmacist                                225
          Investor                                  201
          Teacher's Aide                            200
          Engineer - Chemical                       176
          Landscaping                               172
          Clergy                                    157
          Pilot - Private/Commercial                153
          Architect                                 149
          Car Dealer                                143
          Psychologist                              118
          Student - College Graduate Student        112
          Chemist                                   109
          Biologist                                  95
```

```
Religious                                  93
Flight Attendant                           87
Tradesman - Carpenter                      85
Tradesman - Plumber                        74
Student - College Senior                   70
Homemaker                                  57
Dentist                                    56
Student - College Junior                   27
Judge                                      22
Student - College Freshman                 17
Student - College Sophomore                16
Student - Community College                10
Student - Technical School                  2
Name: Occupation, Length: 67, dtype: int64
```

let us filter by cut off of atleast 500 records to be consider as an occupation for visualization

In [130]:
```
# OccupationCount = LoanData_clean.Occupation.value_counts().to_frame().reset_index()

# OccupationCount.rename(columns = {'index':'Occupation','Occupation':'Count'}, inplac
```

In [131]:
```
(LoanData_clean.Occupation.value_counts()>500)
```

Out[131]:
```
Other                                    True
Professional                             True
Executive                                True
Computer Programmer                      True
Teacher                                  True
Analyst                                  True
Administrative Assistant                 True
Accountant/CPA                           True
Sales - Commission                       True
Skilled Labor                            True
Nurse (RN)                               True
Clerical                                 True
Sales - Retail                           True
Retail Management                        True
Truck Driver                             True
Construction                             True
Police Officer/Correction Officer        True
Laborer                                  True
Civil Service                            True
Engineer - Mechanical                    True
Food Service Management                  True
Engineer - Electrical                    True
Medical Technician                       True
Attorney                                 True
Food Service                             True
```

```
Military Enlisted                      True
Tradesman - Mechanic                   True
Social Worker                          True
Postal Service                        False
Professor                             False
                                      ...
Principal                             False
Realtor                               False
Military Officer                      False
Bus Driver                            False
Pharmacist                            False
Investor                              False
Teacher's Aide                        False
Engineer - Chemical                   False
Landscaping                           False
Clergy                                False
Pilot - Private/Commercial            False
Architect                             False
Car Dealer                            False
Psychologist                          False
Student - College Graduate Student    False
Chemist                               False
Biologist                             False
Religious                             False
Flight Attendant                      False
Tradesman - Carpenter                 False
Tradesman - Plumber                   False
Student - College Senior              False
Homemaker                             False
Dentist                               False
Student - College Junior              False
Judge                                 False
Student - College Freshman            False
Student - College Sophomore           False
Student - Community College           False
Student - Technical School            False
Name: Occupation, Length: 67, dtype: bool
```

In [132]:
```
#InterestedOccupation.Occupation.unique()
```

In [133]:
```
# occupations of interest
OccupationList = ['Other', 'Professional', 'Executive', 'Computer Programmer',
       'Teacher', 'Analyst', 'Administrative Assistant', 'Accountant/CPA',
       'Sales - Commission', 'Skilled Labor', 'Nurse (RN)', 'Clerical',
       'Sales - Retail', 'Retail Management', 'Truck Driver',
       'Construction', 'Police Officer/Correction Officer', 'Laborer',
       'Civil Service', 'Engineer - Mechanical', 'Food Service Management',
       'Engineer - Electrical', 'Medical Technician', 'Attorney',
```

```
        'Food Service', 'Military Enlisted', 'Tradesman - Mechanic',
        'Social Worker']
```

In [134]:
```
InterestedOccupation = LoanData_clean.loc[LoanData_clean.Occupation.isin(OccupationLis
```

In [135]:
```
InterestedOccupation.head()
```

Out[135]:
```
      IncomeRange  StatedMonthlyIncome  ListingNumber LoanStatus  \
1  $50,000-74,999          6125.000000        1209647    Current
3  $25,000-49,999          2875.000000         658116    Current
4        $100,000+          9583.333333         909464    Current
5        $100,000+          8333.333333        1074836    Current
6  $25,000-49,999          2083.333333         750899    Current

       Occupation EmploymentStatus  LoanOriginalAmount  Investors  \
1    Professional         Employed               10000          1
3   Skilled Labor         Employed               10000        158
4       Executive         Employed               15000         20
5    Professional         Employed               15000          1
6  Sales - Retail         Employed                3000          1

  IsBorrowerHomeowner ProsperRating (Alpha)  ProsperScore  \
1               False                     A           7.0
3                True                     A           9.0
4                True                     D           4.0
5                True                     B          10.0
6               False                     E           2.0

  ListingCategory (numeric)  Recommendations
1                         2                0
3                        16                0
4                         2                0
5                         1                0
6                         1                0
```

In [136]:
```
InterestedOccupation[InterestedOccupation.Occupation == 'Other']
```

Out[136]:
```
          IncomeRange  StatedMonthlyIncome  ListingNumber  \
15     $50,000-74,999          5500.000000         577164
22          $1-24,999           118.333333         706927
24     $25,000-49,999          2333.333333        1046345
29          $100,000+         10416.666667        1051243
30     $25,000-49,999          3750.000000         555213
31     $25,000-49,999          2250.000000         643927
33          $100,000+         13083.333333         478891
38     $50,000-74,999          6000.000000         869272
40          $100,000+         12750.000000        1167746
41          $100,000+          9000.000000         594297
52     $75,000-99,999          8166.666667         733454
```

65	$50,000-74,999	4666.666667	1233194
71	$25,000-49,999	2916.666667	658787
72	$100,000+	8333.333333	503744
73	$50,000-74,999	6000.000000	842723
80	$1-24,999	1061.500000	1144712
82	$50,000-74,999	4166.666667	843206
85	$25,000-49,999	2916.666667	1070092
91	$25,000-49,999	2250.000000	487757
99	$25,000-49,999	3750.000000	886064
100	Not employed	0.000000	704916
104	$50,000-74,999	4916.666667	1027861
106	$50,000-74,999	4699.000000	538122
125	Not employed	0.000000	506130
133	$25,000-49,999	2750.000000	621421
139	$1-24,999	1835.416667	571141
163	$50,000-74,999	4166.666667	671952
165	$50,000-74,999	5250.000000	451142
170	Not employed	0.000000	578652
180	$25,000-49,999	2841.916667	1068929
...	...	...	...
113761	Not employed	0.000000	580125
113762	$100,000+	9083.333333	1040844
113766	Not employed	0.000000	579432
113773	$25,000-49,999	2720.833333	1056749
113784	$100,000+	8583.333333	1021056
113807	$75,000-99,999	8166.666667	545906
113808	$50,000-74,999	5000.000000	503406
113816	$25,000-49,999	3333.333333	1131469
113817	$25,000-49,999	3416.666667	671443
113821	$50,000-74,999	5216.666667	1115217
113822	$75,000-99,999	7483.333333	835549
113824	$75,000-99,999	6666.666667	1184645
113828	$50,000-74,999	5083.333333	738520
113844	$50,000-74,999	4631.250000	996813
113845	$50,000-74,999	4333.333333	1022349
113846	$25,000-49,999	3750.000000	536612
113851	$100,000+	10416.666667	538084
113856	$25,000-49,999	2466.250000	594390
113862	$75,000-99,999	8000.000000	586434
113876	$100,000+	8666.666667	647703
113877	$75,000-99,999	7000.000000	503829
113882	$25,000-49,999	3333.333333	448077
113885	$50,000-74,999	4375.000000	815386
113888	$1-24,999	1000.000000	1214654
113905	$25,000-49,999	3250.000000	539189
113911	$25,000-49,999	3333.333333	996496
113919	$25,000-49,999	2500.000000	772509
113924	$25,000-49,999	3208.333333	657862

```
113928  $25,000-49,999          2333.333333         510097
113934  $25,000-49,999          2875.000000        1069178

                    LoanStatus Occupation EmploymentStatus  LoanOriginalAmount  \
15                   Defaulted      Other            Other                4000
22                     Current      Other            Other                4000
24                     Current      Other         Employed                4000
29                     Current      Other         Employed               35000
30                   Completed      Other         Employed               10000
31                     Current      Other            Other                2000
33                   Completed      Other         Employed               16000
38                     Current      Other            Other                7000
40                     Current      Other    Self-employed               15000
41                     Current      Other         Employed               13000
52                     Current      Other         Employed                7000
65                     Current      Other            Other               15000
71                     Current      Other         Employed                2774
72                   Completed      Other         Employed                4500
73                     Current      Other         Employed                4000
80                     Current      Other         Employed                4000
82        Past Due (16-30 days)      Other         Employed                4000
85                     Current      Other         Employed               10000
91                   Completed      Other         Employed                3500
99                     Current      Other            Other               10000
100                 Chargedoff      Other     Not employed                4000
104                    Current      Other         Employed               15000
106                    Current      Other         Employed               10000
125                    Current      Other     Not employed                5000
133                    Current      Other         Employed                5000
139        Past Due (1-15 days)      Other            Other                2500
163                    Current      Other            Other               12500
165                  Completed      Other        Full-time                9000
170                  Completed      Other     Not employed               10000
180                    Current      Other         Employed                7500
...                        ...        ...              ...                 ...
113761                 Current      Other     Not employed                7000
113762                 Current      Other         Employed               25000
113766                 Current      Other     Not employed                4500
113773                 Current      Other         Employed               10000
113784                 Current      Other         Employed               15000
113807                 Current      Other         Employed               10000
113808              Chargedoff      Other         Employed                4000
113816                 Current      Other         Employed                9000
113817                 Current      Other            Other               15000
113821                 Current      Other         Employed               13200
113822                 Current      Other         Employed               15000
113824                 Current      Other         Employed               25000
113828                 Current      Other         Employed               12400
```

113844	Current	Other	Employed	15000
113845	Current	Other	Employed	10000
113846	Completed	Other	Employed	7000
113851	Current	Other	Employed	3000
113856	Current	Other	Other	2500
113862	Current	Other	Employed	15000
113876	Chargedoff	Other	Other	18500
113877	Current	Other	Employed	10000
113882	Completed	Other	Full-time	1500
113885	Current	Other	Employed	15000
113888	Current	Other	Employed	3000
113905	Chargedoff	Other	Employed	4000
113911	Current	Other	Employed	10000
113919	Current	Other	Other	4000
113924	Current	Other	Employed	5000
113928	Completed	Other	Full-time	2000
113934	Current	Other	Employed	10000

	Investors	IsBorrowerHomeowner	ProsperRating (Alpha)	ProsperScore \
15	10	True	HR	5.0
22	94	False	HR	2.0
24	1	True	C	5.0
29	1	True	A	6.0
30	30	False	A	9.0
31	24	False	HR	5.0
33	326	False	AA	10.0
38	151	True	AA	9.0
40	3	False	C	4.0
41	181	True	B	8.0
52	87	True	A	6.0
65	1	True	C	4.0
71	49	True	HR	4.0
72	49	False	D	6.0
73	40	True	D	3.0
80	25	False	D	4.0
82	1	False	E	2.0
85	1	True	C	4.0
91	54	False	E	5.0
99	184	False	AA	10.0
100	73	False	HR	3.0
104	1	False	C	5.0
106	188	False	B	6.0
125	92	False	E	5.0
133	31	False	A	8.0
139	25	False	E	3.0
163	134	True	AA	8.0
165	413	True	AA	8.0
170	161	True	D	5.0

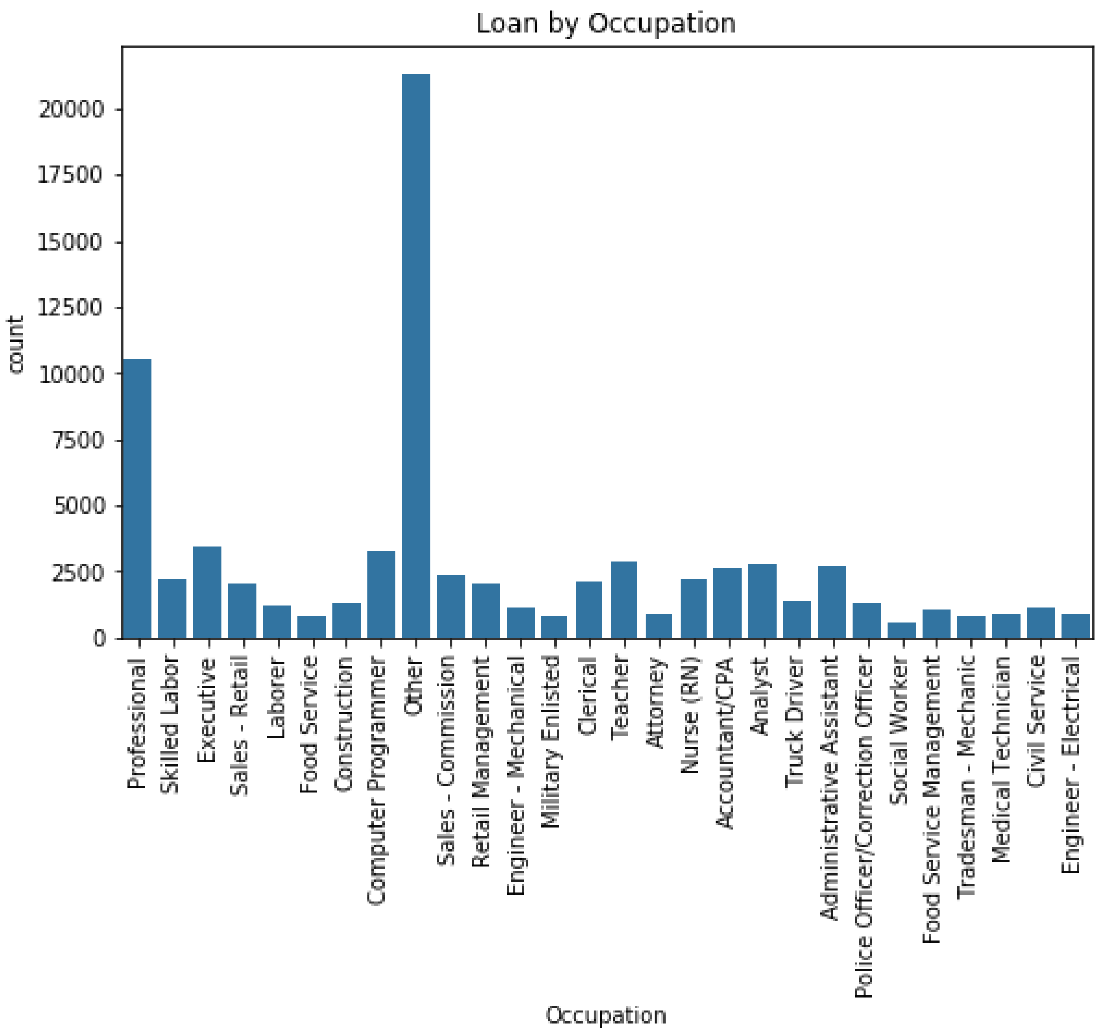
180	1	False	C	3.0
...	...	...	...	...
113761	9	False	A	8.0
113762	149	True	A	11.0
113766	71	False	A	8.0
113773	1	True	B	6.0
113784	1	True	A	11.0
113807	124	False	B	8.0
113808	45	True	HR	5.0
113816	1	False	E	3.0
113817	181	True	B	8.0
113821	1	False	C	6.0
113822	1	True	C	3.0
113824	1	True	A	10.0
113828	118	False	D	3.0
113844	1	False	A	10.0
113845	1	True	B	3.0
113846	34	True	E	4.0
113851	30	True	E	4.0
113856	14	True	D	6.0
113862	274	True	B	8.0
113876	245	False	B	8.0
113877	225	False	A	9.0
113882	56	True	AA	10.0
113885	119	False	B	5.0
113888	1	False	A	5.0
113905	69	True	HR	2.0
113911	1	False	D	3.0
113919	1	True	D	3.0
113924	83	False	A	8.0
113928	25	False	C	6.0
113934	119	True	D	3.0

	ListingCategory (numeric)	Recommendations
15	13	0
22	1	0
24	1	0
29	1	0
30	20	0
31	2	0
33	7	0
38	1	0
40	1	0
41	7	0
52	1	0
65	1	0
71	13	0
72	7	0

73	1	0
80	1	0
82	7	0
85	1	0
91	1	0
99	2	0
100	13	0
104	1	0
106	1	0
125	7	0
133	11	0
139	2	0
163	1	0
165	3	0
170	7	0
180	1	0
...	...	...
113761	1	0
113762	20	0
113766	19	0
113773	1	0
113784	1	0
113807	7	0
113808	2	0
113816	1	0
113817	1	0
113821	1	0
113822	7	0
113824	1	0
113828	1	0
113844	7	0
113845	1	0
113846	1	0
113851	1	0
113856	1	0
113862	3	0
113876	1	0
113877	2	0
113882	7	0
113885	2	0
113888	7	0
113905	1	0
113911	14	0
113919	2	0
113924	13	1
113928	3	0
113934	1	0

```
[21317 rows x 13 columns]
```

In [137]:
```
# Occupation distribution

plt.figure(figsize=[8, 5])

base_color = sb.color_palette()[0]
sb.countplot(data = InterestedOccupation, x= 'Occupation', color=base_color)
plt.title('Loan by Occupation')
plt.xlabel('Occupation')
plt.xticks(rotation=90);
```



1.6.9 Observation

From the visualization above we see that the occupation category with the most loans given is 'Other' with 'Professional' following it.

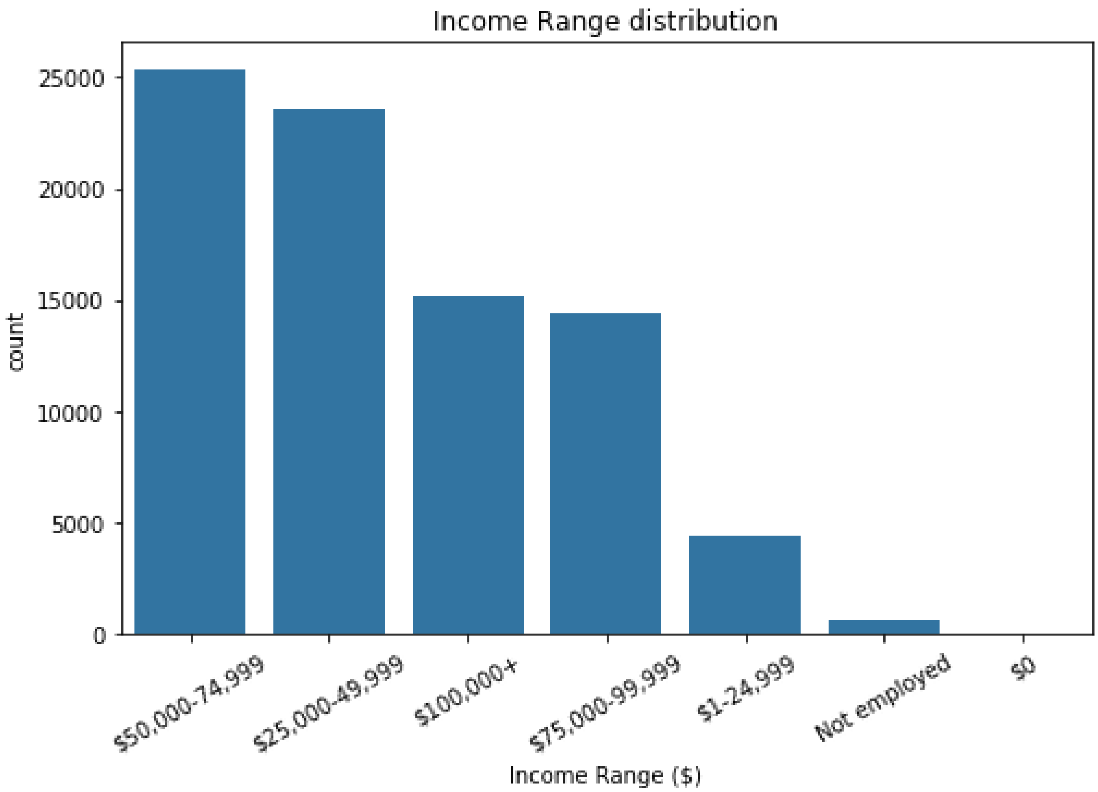
it can also be seen from the value_counts series for occupation that the occupation category with the least loans given are 'Student"

1.6.10 Question 4

How many loans are given per income range

1.6.11 Visualization

In [138]:
```
plt.figure(figsize=[8, 5])
sb.countplot(LoanData_clean['IncomeRange'], color=base_color)
plt.title('Income Range distribution')
plt.xlabel('Income Range ($)')
plt.xticks(rotation=30);
```



1.6.12 Observation

From the above barplot we see that custormers with the income range ($) 50,000 - 74,999 get the most loans while the income range category of 'Not employed' get the least loans

1.6.13 Question 5

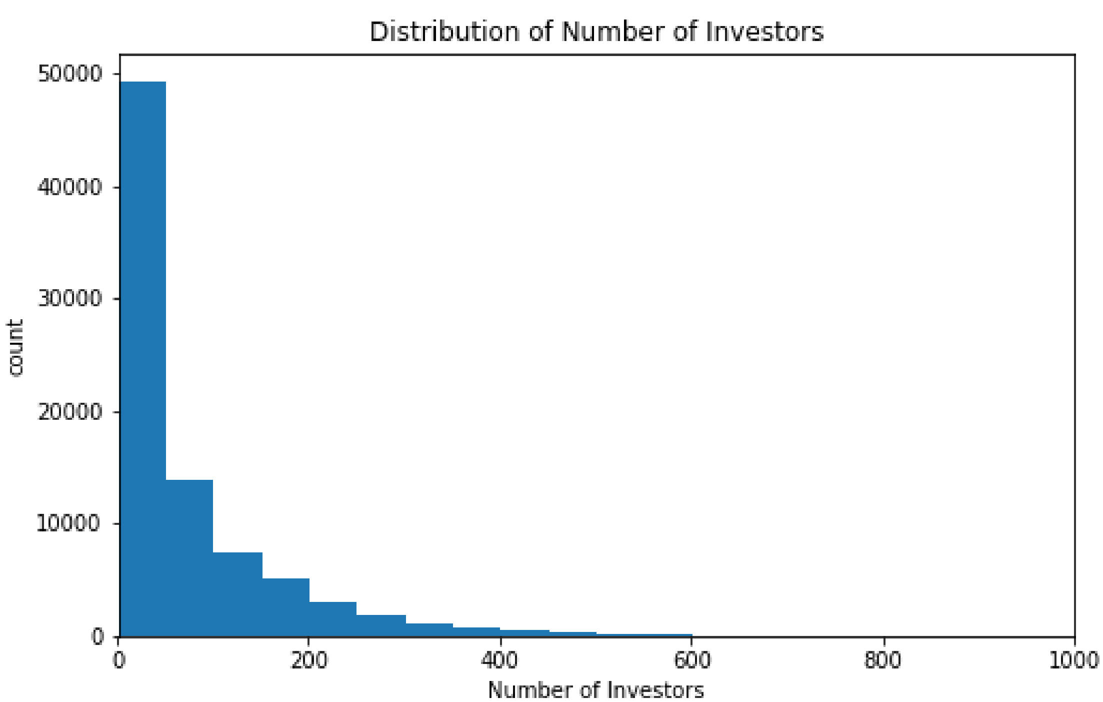
What is the distribution for the Investors variable, it shows the number of The number of investors that funded the loan.

1.6.14 Visualization

In [139]:
```
LoanData_clean.Investors.describe()
```

Out[139]:
```
count    83520.000000
mean        68.955759
std         95.511709
min          1.000000
25%          1.000000
50%         33.000000
75%         98.000000
max       1189.000000
Name: Investors, dtype: float64
```

In [140]:
```
binsize = 50
bins = np.arange(1, LoanData_clean.Investors.max()+binsize, binsize)


plt.figure(figsize=[8, 5])
plt.hist(data=LoanData_clean, x = 'Investors', bins = bins)
plt.xlabel('Number of Investors')
plt.xlim(1, 1000)
plt.ylabel('count')
plt.title('Distribution of Number of Investors');
```



1.6.15 Observation

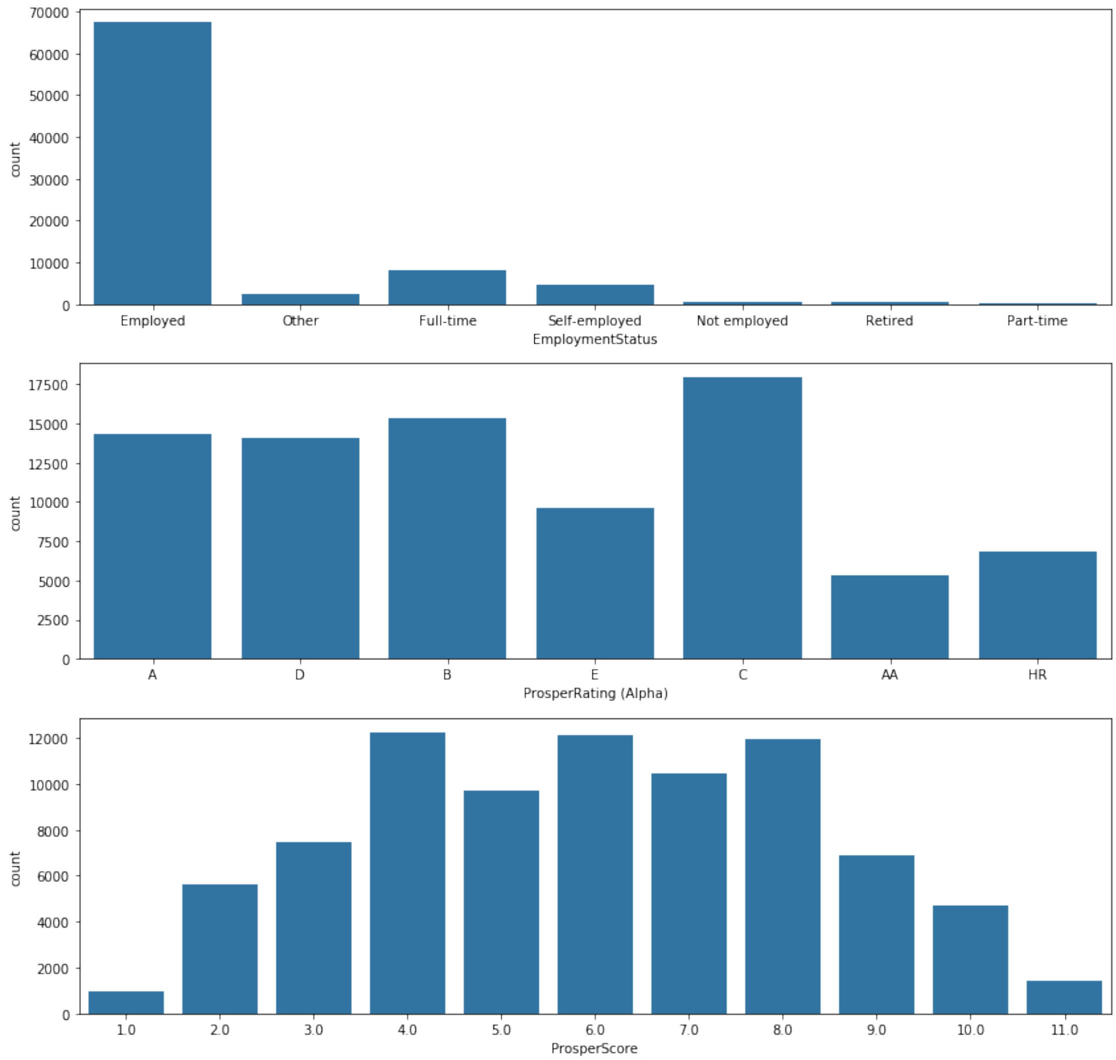
It can be observed that the number of investors that funded most of the loans range from 1 to about 200 in number

1.6.16 Question 6

Visualization for some ordinal categorical variables

1.6.17 Visualization

In [141]:
```
# let's plot all three together to get an idea of each ordinal variable's distribution

fig, ax = plt.subplots(nrows=3, figsize = [14,14])

default_color = sb.color_palette()[0]
sb.countplot(data = LoanData_clean, x = 'EmploymentStatus', color = default_color, ax
sb.countplot(data = LoanData_clean, x = 'ProsperRating (Alpha)', color = default_color
sb.countplot(data = LoanData_clean, x = 'ProsperScore', color = default_color, ax = ax

plt.show()
```



1.6.18 Observation

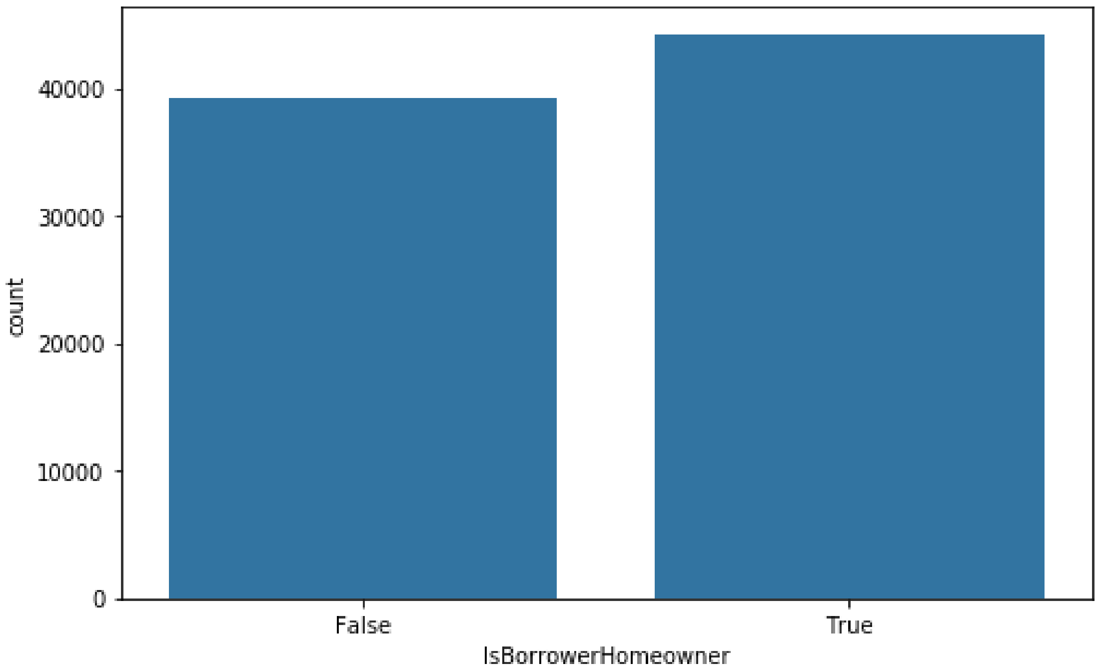
- For EmploymentStatus it is observed that most loans were given to customers who are employed while the least given to Students (Part-time)
- For ProsperRating, it is observed the majority of the loans given were to customers with ProsperRating of 'C' while the least amount of loans was given to customers with ProsperRating of 'AA'
- For ProsperScore we observe some form of trimodality at scores of 4,6, and 7 risk levels

1.6.19 Question 7

What is the distribution of custormers who are house owners?

1.6.20 Visualization

```
In [142]: plt.figure(figsize = [8,5])

          default_color = sb.color_palette()[0]
          sb.countplot(data = LoanData_clean, x = 'IsBorrowerHomeowner', color = default_color);
```



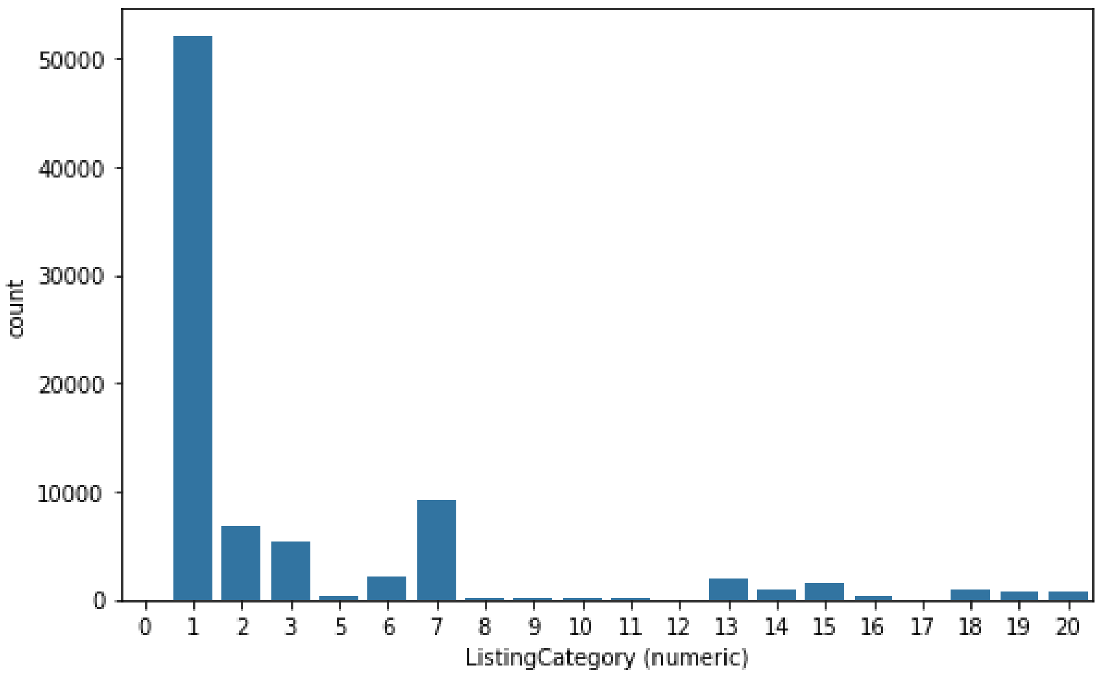
1.6.21 Question 8

How is the ListingCategory (numeric) distributed

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

1.6.22 Visualization

```
In [143]: plt.figure(figsize = [8,5])

          default_color = sb.color_palette()[0]
          sb.countplot(data = LoanData_clean, x = 'ListingCategory (numeric)', color = default_c
```



1.6.23 Observation

It is observed that more loans were given to custormers/borrowers who chose listing category 1 (Debt Consolidation)

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

For LoanOriginalAmount, The distribution indicates tri-modality with most given loan amounts at 4000, 10000, 15000 US dollars, no unusual points were obsereved.

1.6.25 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?

On investigating the StatedMonthlyIncome Variable, it was observed that it was a long tail distribution, indicative of the presence of outliers, a log scale transformation was done on the data to cater for outliers and the distribution re-plotted.

1.7 Bivariate Exploration

Here we'll be looking at relationships between pairs of variables choosen for analysis

1.7.1 Question 9

How are the features correlated? Let us look at pairwise correlations between features in the data.

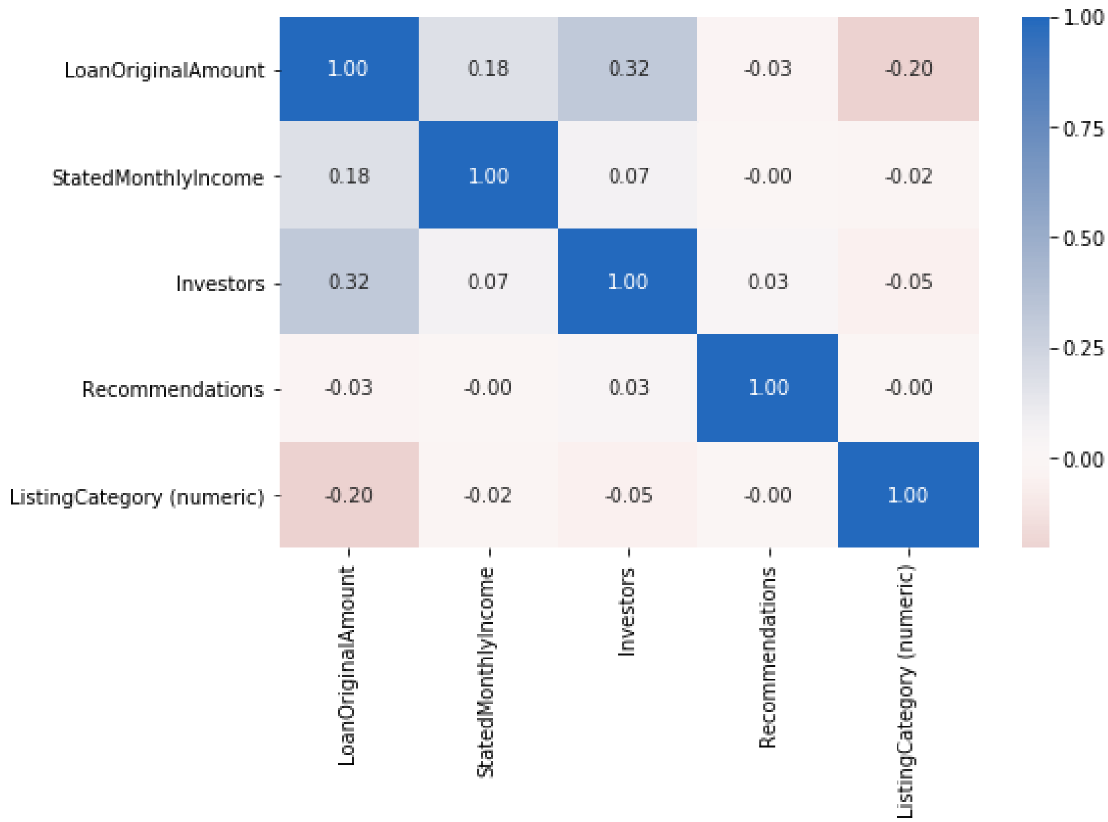
```
In [144]: # concise summary of data
          LoanData_clean.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 83520 entries, 1 to 113936
Data columns (total 13 columns):
IncomeRange                  83520 non-null object
StatedMonthlyIncome          83520 non-null float64
ListingNumber                83520 non-null int64
LoanStatus                   83520 non-null object
Occupation                   83520 non-null object
EmploymentStatus             83520 non-null object
LoanOriginalAmount           83520 non-null int64
Investors                    83520 non-null int64
IsBorrowerHomeowner          83520 non-null bool
ProsperRating (Alpha)        83520 non-null object
ProsperScore                 83520 non-null float64
ListingCategory (numeric)    83520 non-null int64
Recommendations              83520 non-null int64
dtypes: bool(1), float64(2), int64(5), object(5)
memory usage: 10.9+ MB
```

```
In [145]: #grouping both numerical and categorical features

          numerical_vars = ['LoanOriginalAmount','StatedMonthlyIncome','Investors','Recommendati

          categorical_vars = ['ProsperRating (Alpha)','IsBorrowerHomeowner','EmploymentStatus','
```

1.7.2 Visualization

```
In [146]: # correlation plot
          plt.figure(figsize = [8, 5])
          sb.heatmap(LoanData_clean[numerical_vars].corr(), annot = True, fmt = '.2f', cmap = 'v
          plt.show()
```



1.7.3 Observation

from the heat map we can observe that a minute positive relationship exist between Investors and LoanOriginalAmount(0.32), we can also observe that some form of relationship exist between StatedMonthlyIncome and LoanOriginalAmount(0.18) further inverstigation with more records and features is required to be certain.

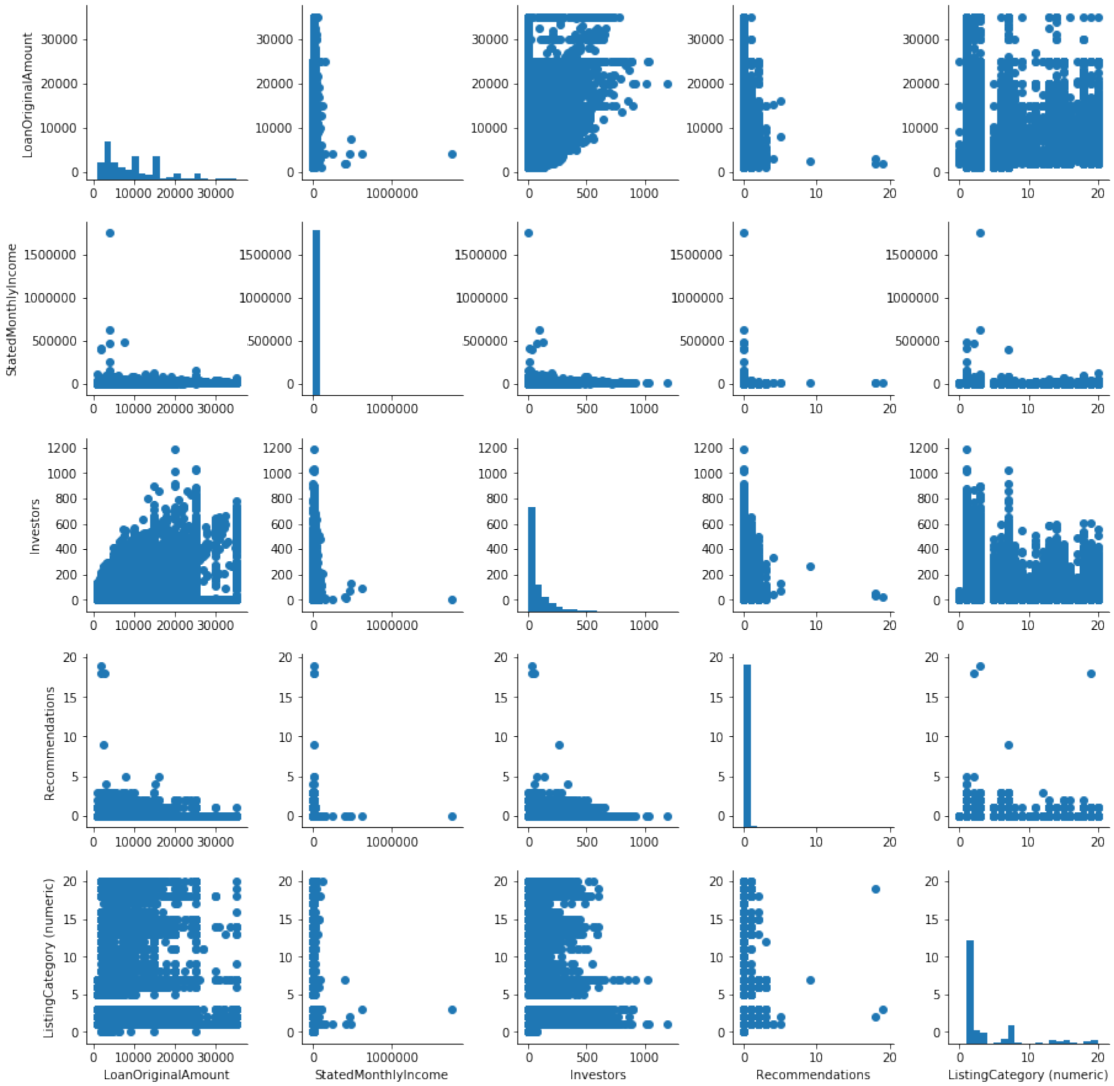
1.7.4 Question 10

Lets look at correlations between variables using a scatter plot

1.7.5 Visualization

```
In [147]: # plot matrix: sample 500 diamonds so that plots are clearer and they render faster
          print("LoanData_clean.shape=",LoanData_clean.shape)
          LoanData_clean_samp = LoanData_clean.sample(n=500, replace = False)
          print("LoanData_clean.shape=",LoanData_clean_samp.shape)

          g = sb.PairGrid(data = LoanData_clean, vars = numerical_vars)
          g = g.map_diag(plt.hist, bins = 20);
          g.map_offdiag(plt.scatter);
```

```
LoanData_clean.shape= (83520, 13)
LoanData_clean.shape= (500, 13)
```



1.7.6 Observation

Some form of relationship can be seen in the scatter plot between Inverstors and LoanOriginalAmount

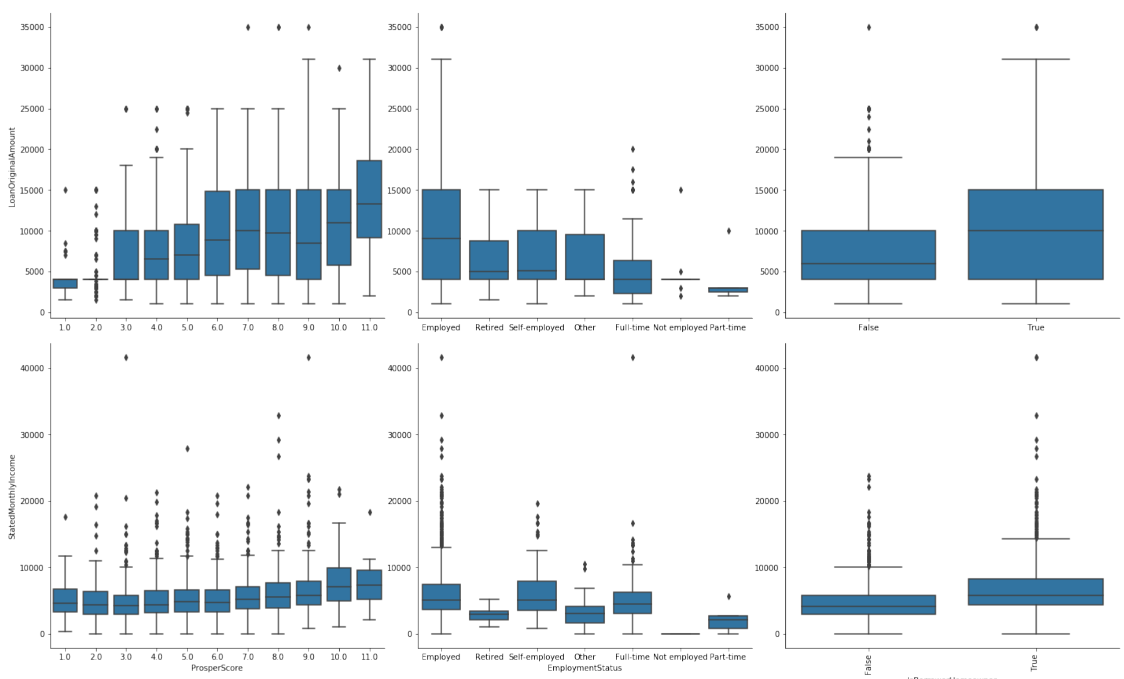
1.7.7 Question 11

How does LoanOriginalAmount and StatedMonthly correlated with the categorical variables?

1.7.8 Visualization

```
In [148]: # plot matrix of numeric features against categorical features.
          # can use a larger sample since there are fewer plots and they're simpler in nature.



          LoanData_clean_samp = LoanData_clean.sample(n=2000, replace = False)
          categoric_vars = ['ProsperScore', 'EmploymentStatus', 'IsBorrowerHomeowner']

          def boxgrid(x, y, **kwargs):
              default_color = sb.color_palette()[0]
              sb.boxplot(x=x, y=y, color=default_color)

          plt.figure(figsize = [10, 10])
          g = sb.PairGrid(data = LoanData_clean_samp, y_vars = ['LoanOriginalAmount', 'StatedMon
          g.map(boxgrid)
          plt.xticks(rotation = 90)
          plt.show();
```

```
<matplotlib.figure.Figure at 0x7fe5e2c29d30>
```



1.7.9 Obsrvation

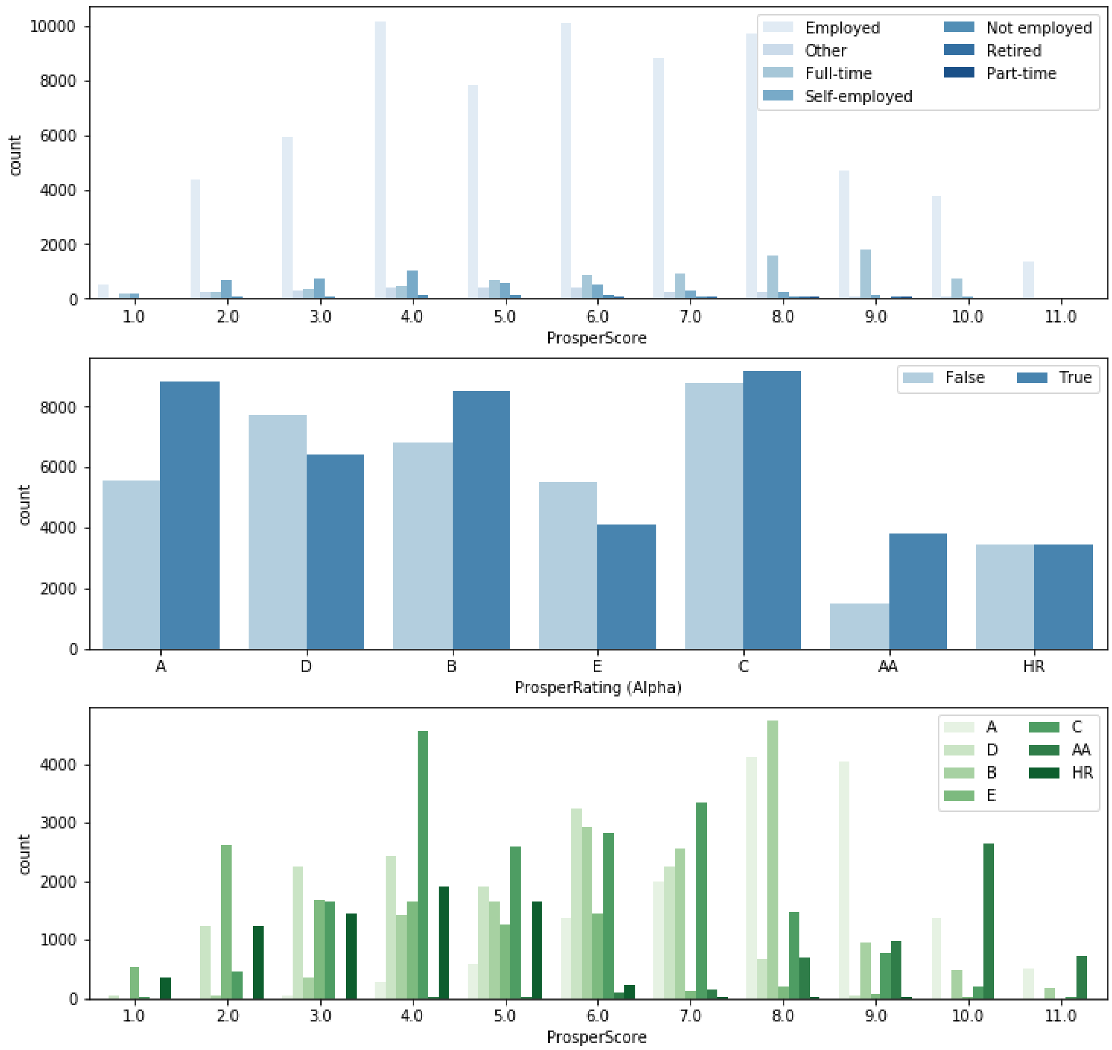
Custormers with ProsperScore of 11, are selfemployed and are home owners seem to get the most loan amounts, while custormers with ProsperScore of 1 are full time employed and not home owners seem to get the least loan amounts, Which should be subject to further investigation.

1.7.10 Question 12

What kind of relationship exist between the categorical variables

1.7.11 Visualization

In [149]:
```
# since there's only three subplots to create, using the full data should be fine.
plt.figure(figsize = [12, 12])

# subplot 1: color vs cut
plt.subplot(3, 1, 1)
sb.countplot(data = LoanData_clean, x = 'ProsperScore', hue = 'EmploymentStatus', pale
plt.legend(loc = 1, ncol = 2)
# subplot 2: clarity vs. cut
ax = plt.subplot(3, 1, 2)
sb.countplot(data = LoanData_clean, x = 'ProsperRating (Alpha)', hue = 'IsBorrowerHome
ax.legend(ncol = 2) # re-arrange legend to reduce overlapping

# subplot 3: clarity vs. color, use different color palette
ax = plt.subplot(3, 1, 3)
sb.countplot(data = LoanData_clean, x = 'ProsperScore', hue = 'ProsperRating (Alpha)',
ax.legend(loc = 1, ncol = 2) # re-arrange legend to remove overlapping

plt.show()
```



1.7.12 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?

- Some form of relationship can be seen in the scatter plot between Inverstors and LoanOriginalAmount
- Custormers with ProsperScore of 11, are selfemployed and are home owners seem to get the most loan amounts, while custormers with ProsperScore of 1 are full time students and not home owners seem to get the least loan amounts, Which should be subject to further investigation.
-

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

It was observed that custormbers with ProsperRating A, B and C and are home owners seem to get the most loans

1.8 Multivariate Exploration

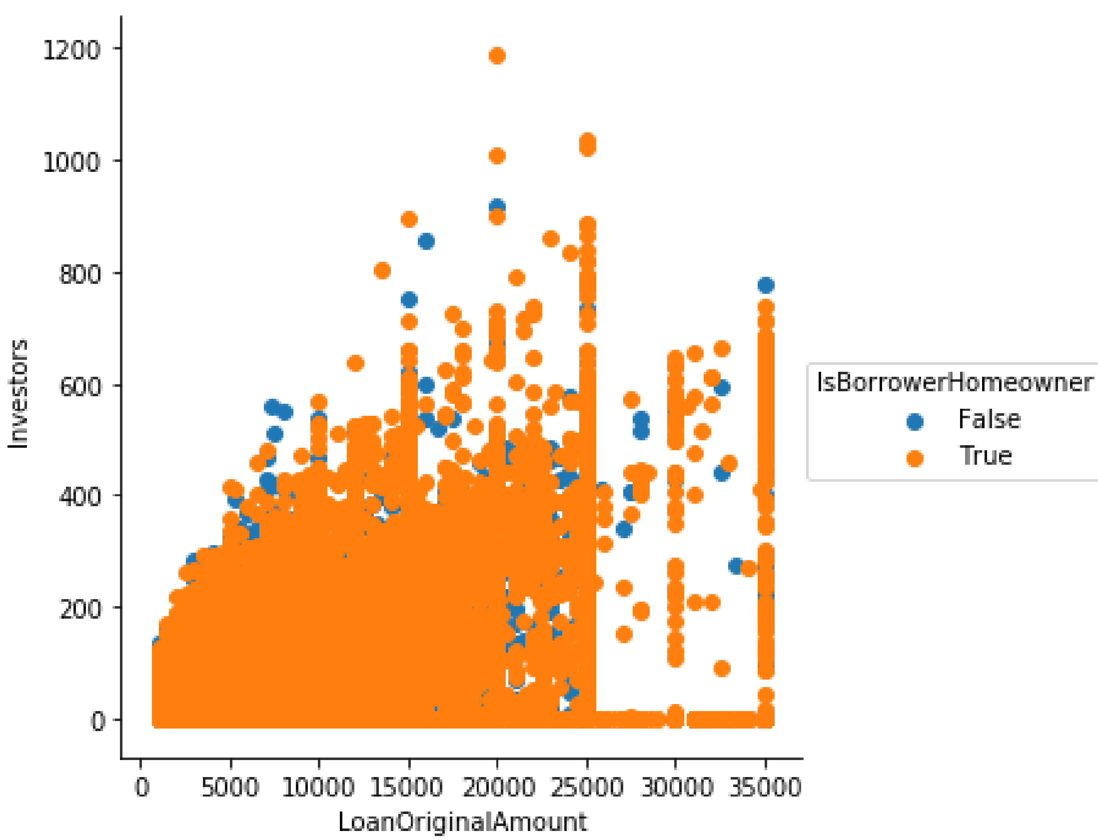
Here we would explore how some categorical measures play into the relationship between LoanOriginalAmount and Investors

1.8.1 Question 13

How does the IsBorrwerHomeowner feature affect LoanOriginalAmount and Investors

1.8.2 Visualization

```
In [150]: g = sb.FacetGrid(data = LoanData_clean, hue = 'IsBorrowerHomeowner', size = 5);
          g.map(plt.scatter,'LoanOriginalAmount', 'Investors');

          g.add_legend();
```



1.8.3 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?

There was some form of slight correlation between Investors and LoanOriginalAmount, although it is uncertain if there are features that strengthen each other. Perhaps on investigation with more features, we can be certain.

1.8.4 Were there any interesting or surprising interactions between features?

it is uncertain, further investigation with more features is recommended.

1.9 Conclusions

The follow Steps highlight the operations taken for the data exploration:

- Data Importation
- Data Preprocessing
- Univariate Analysis
- Bivariate Analysis
- Multivariate Analysis

In [151]:
```
## Saving LoanData_clean to a CSV

LoanData_clean.to_csv('LoanData_clean.csv')
```

In [ ]: