Exploration_ProsperLoan

October 7, 2020

1 Prosper Loan Data Analysis & Visualization

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1.2 Preliminary Wrangling

The Prosper loan 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. The loan information is spread throughout the United States.

```
In [251]: # 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 [252]: df = pd.read_csv('prosperLoanData.csv')
```

1.2.1 What is the structure of your dataset?

There are 81 columns in this dataset. Here are the columns that I will be using the most.

- ListingKey - Unique key for each listing
- ListingCreationDate - The date the listing was created
- Term - Length of the loan expressed in months
- LoanStatus - Status of the loan - canceled, current, defaulted, etc.
- BorrowerRate - Borrower's annual interest percentage rate
- Listing Category - what type of loan it is
- BorrowerState - the state where the listing was created
- Occupation: The occupation selected by the borrower
- CreditScoreRangeLower - The lower credit score
- CreditScoreRangeHigher - The upper credit score
- DebtToIncomeRatio - Debt to income ratio of borrower
- IncomeRange - Income of the borrower
- LoanOriginalAmount - The amount of the loan

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

Beings this dataset is so large, I have endless opportunities to find relationships. Here are the top most interesting things I'd like to explore.

- The average interest rate of most borrowers.
- What the highest, lowest and average risk scores are.
- What the most common loan types are.
- Which states have the highest borrowers.
- What are the different occupations and how much did they borrow?

I'm interested in the individuals income range compared to how much they borrowed.

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

The features that I'll being using in the dataset the most are: the borrower rate will help me investigate how much each individual was charged for interest rate; the prosper score will allow me to see the average risk scores (based on a scale of 1 to 10, 10 being the

2 Clean

2.0.1 Step 1. Delete all unused columns

```
In [253]: df.drop(columns=['ListingNumber', 'ListingNumber', 'BorrowerAPR', 'LenderYield',
                  'EstimatedEffectiveYield', 'EstimatedLoss', 'EstimatedReturn'], axis=1, inplac

          df.drop(columns=['ProsperRating (numeric)', 'ProsperRating (Alpha)', 'EmploymentStatus
                  'EmploymentStatusDuration', 'IsBorrowerHomeowner', 'CurrentlyInGroup'], axis=1

          df.drop(columns=['GroupKey', 'DateCreditPulled', 'FirstRecordedCreditLine', 'CurrentCr
                  'OpenCreditLines', 'TotalCreditLinespast7years', 'OpenRevolvingAccounts'], axi

          df.drop(columns=['OpenRevolvingMonthlyPayment', 'InquiriesLast6Months', 'TotalInquirie
                  'CurrentDelinquencies', 'AmountDelinquent', 'DelinquenciesLast7Years'], axis=1

          df.drop(columns=['PublicRecordsLast10Years', 'PublicRecordsLast12Months', 'RevolvingCr
                  'BankcardUtilization', 'AvailableBankcardCredit', 'TotalTrades'], axis=1, inpl

          df.drop(columns=['TradesOpenedLast6Months', 'IncomeVerifiable', 'LoanKey', 'TotalProsp
                  'TotalProsperPaymentsBilled', 'OnTimeProsperPayments', 'ProsperPaymentsLessTha

          df.drop(columns=['ProsperPaymentsOneMonthPlusLate', 'ProsperPrincipalBorrowed', 'Prosp
                  'ScorexChangeAtTimeOfListing', 'LoanCurrentDaysDelinquent', 'LoanFirstDefaulte

          df.drop(columns=['LoanMonthsSinceOrigination', 'LoanOriginationDate', 'LoanOrigination
                  'MonthlyLoanPayment', 'LP_CustomerPayments', 'LP_CustomerPrincipalPayments', '
```

```
df.drop(columns=['LP_ServiceFees', 'LP_CollectionFees', 'LP_GrossPrincipalLoss', 'LP_N
       'LP_NonPrincipalRecoverypayments', 'PercentFunded', 'Recommendations', 'Invest

df.drop(columns=['InvestmentFromFriendsAmount', 'Investors', 'LoanNumber', 'TradesNeve

df.head()
```

Out[253]:

```
                ListingKey           ListingCreationDate CreditGrade  Term  \
0  1021339766868145413AB3B  2007-08-26 19:09:29.263000000           C    36
1  10273602499503308B223C1  2014-02-27 08:28:07.900000000         NaN    36
2  0EE9337825851032864889A  2007-01-05 15:00:47.090000000          HR    36
3  0EF5356002482715299901A  2012-10-22 11:02:35.010000000         NaN    36
4  0F023589499656230C5E3E2  2013-09-14 18:38:39.097000000         NaN    36

  LoanStatus           ClosedDate  BorrowerRate  ProsperScore  \
0  Completed  2009-08-14 00:00:00        0.1580           NaN
1    Current                  NaN        0.0920           7.0
2  Completed  2009-12-17 00:00:00        0.2750           NaN
3    Current                  NaN        0.0974           9.0
4    Current                  NaN        0.2085           4.0

   ListingCategory (numeric) BorrowerState    Occupation  \
0                          0            CO         Other
1                          2            CO  Professional
2                          0            GA         Other
3                         16            GA  Skilled Labor
4                          2            MN     Executive

   CreditScoreRangeLower  CreditScoreRangeUpper  DebtToIncomeRatio  \
0                  640.0                  659.0               0.17
1                  680.0                  699.0               0.18
2                  480.0                  499.0               0.06
3                  800.0                  819.0               0.15
4                  680.0                  699.0               0.26

      IncomeRange  StatedMonthlyIncome  LoanOriginalAmount
0  $25,000-49,999          3083.333333                9425
1  $50,000-74,999          6125.000000               10000
2   Not displayed          2083.333333                3001
3  $25,000-49,999          2875.000000               10000
4        $100,000+          9583.333333               15000
```

In [254]:
```
duplicate_df = df[df.duplicated(subset='ListingKey')]
```

Test

In [255]:
```
duplicate_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 871 entries, 9 to 113863
Data columns (total 17 columns):
ListingKey                  871 non-null object
ListingCreationDate         871 non-null object
CreditGrade                 0 non-null object
Term                        871 non-null int64
LoanStatus                  871 non-null object
ClosedDate                  13 non-null object
BorrowerRate                871 non-null float64
ProsperScore                871 non-null float64
ListingCategory (numeric)   871 non-null int64
BorrowerState               871 non-null object
Occupation                  812 non-null object
CreditScoreRangeLower       871 non-null float64
CreditScoreRangeUpper       871 non-null float64
DebtToIncomeRatio           789 non-null float64
IncomeRange                 871 non-null object
StatedMonthlyIncome         871 non-null float64
LoanOriginalAmount          871 non-null int64
dtypes: float64(6), int64(3), object(8)
memory usage: 122.5+ KB
```

In [256]:
```
df.drop_duplicates(subset=['ListingKey'], keep='last', inplace=True)
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 113066 entries, 0 to 113936
Data columns (total 17 columns):
ListingKey                  113066 non-null object
ListingCreationDate         113066 non-null object
CreditGrade                 28953 non-null object
Term                        113066 non-null int64
LoanStatus                  113066 non-null object
ClosedDate                  55076 non-null object
BorrowerRate                113066 non-null float64
ProsperScore                83982 non-null float64
ListingCategory (numeric)   113066 non-null int64
BorrowerState               107551 non-null object
Occupation                  109537 non-null object
CreditScoreRangeLower       112475 non-null float64
CreditScoreRangeUpper       112475 non-null float64
DebtToIncomeRatio           104594 non-null float64
IncomeRange                 113066 non-null object
StatedMonthlyIncome         113066 non-null float64
LoanOriginalAmount          113066 non-null int64
dtypes: float64(6), int64(3), object(8)
```

```
memory usage: 15.5+ MB
```

2.0.2 Step 2. Replace category numbers with the name

```
In [257]: df.replace({'ListingCategory (numeric)': {0: 'Not Available', 1: 'Debt Consolidation',
                                                    3: 'Business', 4: 'Personal Loan', 5: 'Studen
                                                    7: 'Other', 8: 'Baby&Adoption', 9: 'Boat', 10
                                                    11: 'Engagement Ring', 12: 'Green Loans', 13:
                                                    14: 'Large Purchases', 15: 'Medical/Dental',
                                                   17: 'RV', 18: 'Taxes', 19: 'Vacation', 20: 'We
```

Test

```
In [258]: df.head()
```

```
Out[258]:                 ListingKey            ListingCreationDate CreditGrade  Term  \
          0  1021339766868145413AB3B  2007-08-26 19:09:29.263000000           C    36
          1  10273602499503308B223C1  2014-02-27 08:28:07.900000000         NaN    36
          2  0EE9337825851032864889A  2007-01-05 15:00:47.090000000          HR    36
          3  0EF5356002482715299901A  2012-10-22 11:02:35.010000000         NaN    36
          4  0F023589499656230C5E3E2  2013-09-14 18:38:39.097000000         NaN    36

            LoanStatus           ClosedDate  BorrowerRate  ProsperScore  \
          0  Completed  2009-08-14 00:00:00        0.1580           NaN
          1    Current                  NaN        0.0920           7.0
          2  Completed  2009-12-17 00:00:00        0.2750           NaN
          3    Current                  NaN        0.0974           9.0
          4    Current                  NaN        0.2085           4.0

            ListingCategory (numeric) BorrowerState     Occupation  \
          0             Not Available            CO          Other
          1          Home Improvement            CO   Professional
          2             Not Available            GA          Other
          3                Motorcycle            GA  Skilled Labor
          4          Home Improvement            MN      Executive

             CreditScoreRangeLower  CreditScoreRangeUpper  DebtToIncomeRatio  \
          0                  640.0                  659.0               0.17
          1                  680.0                  699.0               0.18
          2                  480.0                  499.0               0.06
          3                  800.0                  819.0               0.15
          4                  680.0                  699.0               0.26

                IncomeRange  StatedMonthlyIncome  LoanOriginalAmount
          0  $25,000-49,999          3083.333333                9425
          1  $50,000-74,999          6125.000000               10000
          2   Not displayed          2083.333333                3001
```

```
3  $25,000-49,999          2875.000000                  10000
4       $100,000+          9583.333333                  15000
```

2.0.3 Step 3. Remove null values from the 'CreditScoreRangeLower' column.

In [259]:
```
df_score = df[df.CreditScoreRangeLower != 0]
```

Test

In [260]:
```
df_score.describe()
```

Out[260]:
```
                Term   BorrowerRate  ProsperScore  CreditScoreRangeLower  \
count  112933.000000  112933.000000  83982.000000          112342.000000
mean       40.805823       0.192907      5.954502             686.336544
std        10.426350       0.074928      2.373520              62.358444
min        12.000000       0.000000      1.000000             360.000000
25%        36.000000       0.134000      4.000000             660.000000
50%        36.000000       0.184000      6.000000             680.000000
75%        36.000000       0.250600      8.000000             720.000000
max        60.000000       0.497500     11.000000             880.000000

       CreditScoreRangeUpper  DebtToIncomeRatio  StatedMonthlyIncome  \
count          112342.000000      104522.000000         1.129330e+05
mean              705.336544           0.276162         5.608873e+03
std                62.358444           0.553864         7.498445e+03
min               379.000000           0.000000         0.000000e+00
25%               679.000000           0.140000         3.204167e+03
50%               699.000000           0.220000         4.666667e+03
75%               739.000000           0.320000         6.833333e+03
max               899.000000          10.010000         1.750003e+06

       LoanOriginalAmount
count       112933.000000
mean          8321.863379
std           6237.048103
min           1000.000000
25%           4000.000000
50%           6350.000000
75%          12000.000000
max          35000.000000
```

2.0.4 Step 4. Change 'CreditScoreRangeLower', 'BorrowerRate' to integar.

In [261]:
```
df.replace({'CreditScoreRangeLower': {None: 0}}, inplace=True )
df.CreditScoreRangeLower
```

Out[261]:
```
0         640.0
1         680.0
2         480.0
```

```
3         800.0
4         680.0
5         740.0
6         680.0
7         700.0
9         820.0
10        640.0
11        640.0
12        680.0
13        740.0
14        740.0
15        700.0
16        640.0
17        760.0
18        740.0
19        680.0
20        660.0
21        620.0
22        700.0
23        680.0
24        660.0
25        680.0
26        660.0
27        700.0
28        720.0
30        740.0
31        680.0
          ...
113907    640.0
113908    700.0
113909    800.0
113910    640.0
113911    660.0
113912    800.0
113913    780.0
113914    520.0
113915    620.0
113916    660.0
113917    660.0
113918    740.0
113919    680.0
113920    740.0
113921      0.0
113922    640.0
113923    700.0
113924    640.0
113925    680.0
113926    540.0
```

```
113927    760.0
113928    740.0
113929    660.0
113930    680.0
113931    800.0
113932    700.0
113933    700.0
113934    700.0
113935    680.0
113936    680.0
Name: CreditScoreRangeLower, Length: 113066, dtype: float64
```

In [262]: df.ListingCreationDate

```
Out[262]: 0         2007-08-26 19:09:29.263000000
          1         2014-02-27 08:28:07.900000000
          2         2007-01-05 15:00:47.090000000
          3         2012-10-22 11:02:35.010000000
          4         2013-09-14 18:38:39.097000000
          5         2013-12-14 08:26:37.093000000
          6         2013-04-12 09:52:56.147000000
          7         2013-05-05 06:49:27.493000000
          9         2013-12-02 10:43:39.117000000
          10        2012-05-10 07:04:01.577000000
          11        2007-10-09 20:28:33.640000000
          12        2013-12-15 20:01:10.757000000
          13        2013-07-15 16:28:28.087000000
          14        2013-04-19 11:17:41.700000000
          15        2012-04-10 09:14:46.297000000
          16        2013-07-16 12:42:48.680000000
          17        2006-08-15 12:21:09.433000000
          18        2013-02-20 03:48:37.470000000
          19        2013-08-21 06:49:02.093000000
          20        2013-11-22 11:35:02.987000000
          21        2007-11-30 20:33:49.227000000
          22        2013-01-30 09:36:13.783000000
          23        2013-04-22 13:29:19.073000000
          24        2013-12-03 11:34:46.127000000
          25        2013-10-02 14:31:09.157000000
          26        2013-02-12 18:07:31.690000000
          27        2010-06-16 16:23:44.533000000
          28        2013-11-02 16:01:28.050000000
          30        2012-01-30 17:59:17.200000000
          31        2012-09-21 13:37:43.210000000
                                  ...
          113907    2013-11-09 06:55:05.690000000
          113908    2010-11-29 10:40:09.730000000
          113909    2012-09-08 10:34:38.837000000
```

```
113910    2014-01-24 19:56:49.960000000
113911    2013-11-15 11:42:47.540000000
113912    2013-12-16 16:36:00.990000000
113913    2010-04-25 15:13:27.963000000
113914    2006-08-09 14:34:40.010000000
113915    2008-07-29 05:22:29.390000000
113916    2012-11-08 20:07:36.600000000
113917    2013-11-23 04:52:50.057000000
113918    2008-06-19 12:02:53.300000000
113919    2013-05-07 18:49:59.750000000
113920    2013-06-11 05:49:40.247000000
113921    2005-11-09 20:44:28.847000000
113922    2008-08-08 16:58:54.760000000
113923    2008-09-10 08:26:30.537000000
113924    2012-10-20 19:15:52.670000000
113925    2013-04-25 13:54:45.017000000
113926    2006-08-01 10:31:31.143000000
113927    2008-04-30 21:25:19.670000000
113928    2011-06-06 19:02:44.443000000
113929    2013-07-06 17:40:01.657000000
113930    2013-07-08 10:24:49.700000000
113931    2014-01-16 20:13:08.040000000
113932    2013-04-14 05:55:02.663000000
113933    2011-11-03 20:42:55.333000000
113934    2013-12-13 05:49:12.703000000
113935    2011-11-14 13:18:26.597000000
113936    2014-01-15 09:27:37.657000000
Name: ListingCreationDate, Length: 113066, dtype: object
```

```
In [263]: df_int = df[df.ProsperScore != 0]
          df_int.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 113066 entries, 0 to 113936
Data columns (total 17 columns):
ListingKey                   113066 non-null object
ListingCreationDate          113066 non-null object
CreditGrade                  28953 non-null object
Term                         113066 non-null int64
LoanStatus                   113066 non-null object
ClosedDate                   55076 non-null object
BorrowerRate                 113066 non-null float64
ProsperScore                 83982 non-null float64
ListingCategory (numeric)    113066 non-null object
BorrowerState                107551 non-null object
Occupation                   109537 non-null object
CreditScoreRangeLower        113066 non-null float64
CreditScoreRangeUpper        112475 non-null float64
```

```
DebtToIncomeRatio            104594 non-null float64
IncomeRange                  113066 non-null object
StatedMonthlyIncome          113066 non-null float64
LoanOriginalAmount           113066 non-null int64
dtypes: float64(6), int64(2), object(9)
memory usage: 15.5+ MB
```

```
In [264]: df_int = df.astype({'CreditScoreRangeLower': 'int', 'BorrowerRate': 'int'})
```

```
In [265]: df_int.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 113066 entries, 0 to 113936
Data columns (total 17 columns):
ListingKey                   113066 non-null object
ListingCreationDate          113066 non-null object
CreditGrade                  28953 non-null object
Term                         113066 non-null int64
LoanStatus                   113066 non-null object
ClosedDate                   55076 non-null object
BorrowerRate                 113066 non-null int64
ProsperScore                 83982 non-null float64
ListingCategory (numeric)    113066 non-null object
BorrowerState                107551 non-null object
Occupation                   109537 non-null object
CreditScoreRangeLower        113066 non-null int64
CreditScoreRangeUpper        112475 non-null float64
DebtToIncomeRatio            104594 non-null float64
IncomeRange                  113066 non-null object
StatedMonthlyIncome          113066 non-null float64
LoanOriginalAmount           113066 non-null int64
dtypes: float64(4), int64(4), object(9)
memory usage: 15.5+ MB
```

2.0.5 Step 5. Remove values from 'Occupation' like "None", "Other", and null values

```
In [266]: df.dropna(subset=['Occupation'], inplace=True)
```

```
In [267]: df_occupation = df[(df['Occupation'] == 'Other')].index
          df.drop(df_occupation , inplace=True)
```

Test

```
In [268]: df.Occupation
```

```
Out[268]: 1                     Professional
          3                    Skilled Labor
```

```
4                      Executive
5                   Professional
6                 Sales - Retail
7                        Laborer
9                   Food Service
10                       Fireman
11              Waiter/Waitress
12                Sales - Retail
13                  Construction
14           Computer Programmer
16                  Professional
17                  Professional
18            Sales - Commission
19                       Laborer
20             Retail Management
21                  Professional
23                 Skilled Labor
25         Engineer - Mechanical
26            Sales - Commission
27                     Executive
28             Military Enlisted
32                      Clerical
35             Retail Management
36                  Professional
37                       Teacher
43                        Clergy
44                  Professional
45                     Executive
                    ...
113895     Engineer - Mechanical
113896              Food Service
113897                    Doctor
113898            Sales - Retail
113899         Military Enlisted
113900            Accountant/CPA
113901                 Executive
113903               Landscaping
113904               Nurse (LPN)
113906              Professional
113907            Sales - Retail
113908        Sales - Commission
113909                  Clerical
113910                 Executive
113912                 Scientist
113913                   Analyst
113916              Professional
113917                  Clerical
113918             Social Worker
```

```
113920         Retail Management
113923                    Clergy
113925                 Homemaker
113927                 Executive
113929            Accountant/CPA
113930              Professional
113931                   Analyst
113932   Food Service Management
113933              Professional
113935              Food Service
113936                 Professor
Name: Occupation, Length: 81115, dtype: object
```

2.0.6 Step 6: Create a random dataset

```
In [269]: np.random.seed(2018)
          sample = np.random.choice(df.shape[0], 300, replace = False)
          df_random2 = df.loc[sample]
```

```
/opt/conda/lib/python3.6/site-packages/ipykernel_launcher.py:3: FutureWarning:
Passing list-likes to .loc or [] with any missing label will raise
KeyError in the future, you can use .reindex() as an alternative.

See the documentation here:
https://pandas.pydata.org/pandas-docs/stable/indexing.html#deprecate-loc-reindex-listlike
  This is separate from the ipykernel package so we can avoid doing imports until
```

```
In [270]: np.random.seed(2018)
          sample = np.random.choice(df.shape[0], 500, replace = False)
          df_random = df.loc[sample]
```

```
/opt/conda/lib/python3.6/site-packages/ipykernel_launcher.py:3: FutureWarning:
Passing list-likes to .loc or [] with any missing label will raise
KeyError in the future, you can use .reindex() as an alternative.

See the documentation here:
https://pandas.pydata.org/pandas-docs/stable/indexing.html#deprecate-loc-reindex-listlike
  This is separate from the ipykernel package so we can avoid doing imports until
```

3 Analyze

3.1 Univariate Exploration

3.1.1 Average interest rate of most Borrowers

```
In [271]: df.describe()
```

```
Out[271]:                Term  BorrowerRate  ProsperScore  CreditScoreRangeLower  \
          count  81115.000000  81115.000000  61586.000000           81115.000000
          mean      40.929594      0.191218      6.037720             687.528324
          std       10.568458      0.075064      2.388946              64.839848
          min       12.000000      0.000000      1.000000               0.000000
          25%       36.000000      0.131400      4.000000             660.000000
          50%       36.000000      0.181400      6.000000             680.000000
          75%       36.000000      0.249900      8.000000             720.000000
          max       60.000000      0.360000     11.000000             880.000000

                 CreditScoreRangeUpper  DebtToIncomeRatio  StatedMonthlyIncome  \
          count           81114.000000       75977.000000         8.111500e+04
          mean              706.536800           0.262449         5.970960e+03
          std                64.795293           0.461642         7.858231e+03
          min                19.000000           0.000000         0.000000e+00
          25%               679.000000           0.140000         3.416667e+03
          50%               699.000000           0.220000         5.000000e+03
          75%               739.000000           0.310000         7.166667e+03
          max               899.000000          10.010000         1.750003e+06

                 LoanOriginalAmount
          count        81115.000000
          mean          8612.301633
          std           6377.056491
          min           1000.000000
          25%           4000.000000
          50%           7000.000000
          75%          12500.000000
          max          35000.000000
```

This chart shows that the average interest rate in this data set is just about 19 percent, whereas, some people have 0 percent interest rates and some have up to 50 percent interest rates but those are pretty rare. It would be interesting to see the correlation between the income range and interest rate

3.1.2 Correlation between Stated Monthly Income and the Borrower Rate

3.1.3 The correlation between interest rate and credit score

```
In [272]: df.describe()
```

```
Out[272]:                Term  BorrowerRate  ProsperScore  CreditScoreRangeLower  \
          count  81115.000000  81115.000000  61586.000000           81115.000000
          mean      40.929594      0.191218      6.037720             687.528324
          std       10.568458      0.075064      2.388946              64.839848
          min       12.000000      0.000000      1.000000               0.000000
          25%       36.000000      0.131400      4.000000             660.000000
          50%       36.000000      0.181400      6.000000             680.000000
          75%       36.000000      0.249900      8.000000             720.000000
```

```
max        60.000000       0.360000      11.000000              880.000000

       CreditScoreRangeUpper  DebtToIncomeRatio  StatedMonthlyIncome  \
count           81114.000000       75977.000000         8.111500e+04
mean              706.536800           0.262449         5.970960e+03
std                64.795293           0.461642         7.858231e+03
min                19.000000           0.000000         0.000000e+00
25%               679.000000           0.140000         3.416667e+03
50%               699.000000           0.220000         5.000000e+03
75%               739.000000           0.310000         7.166667e+03
max               899.000000          10.010000         1.750003e+06

       LoanOriginalAmount
count        81115.000000
mean          8612.301633
std           6377.056491
min           1000.000000
25%           4000.000000
50%           7000.000000
75%          12500.000000
max          35000.000000
```

When the individual pulled their credit score, they get an upper and lower credit score. On average, the lower credit score was 686 and the lower is 705. I will use this to explore how the lower score correlates with the interest rate.

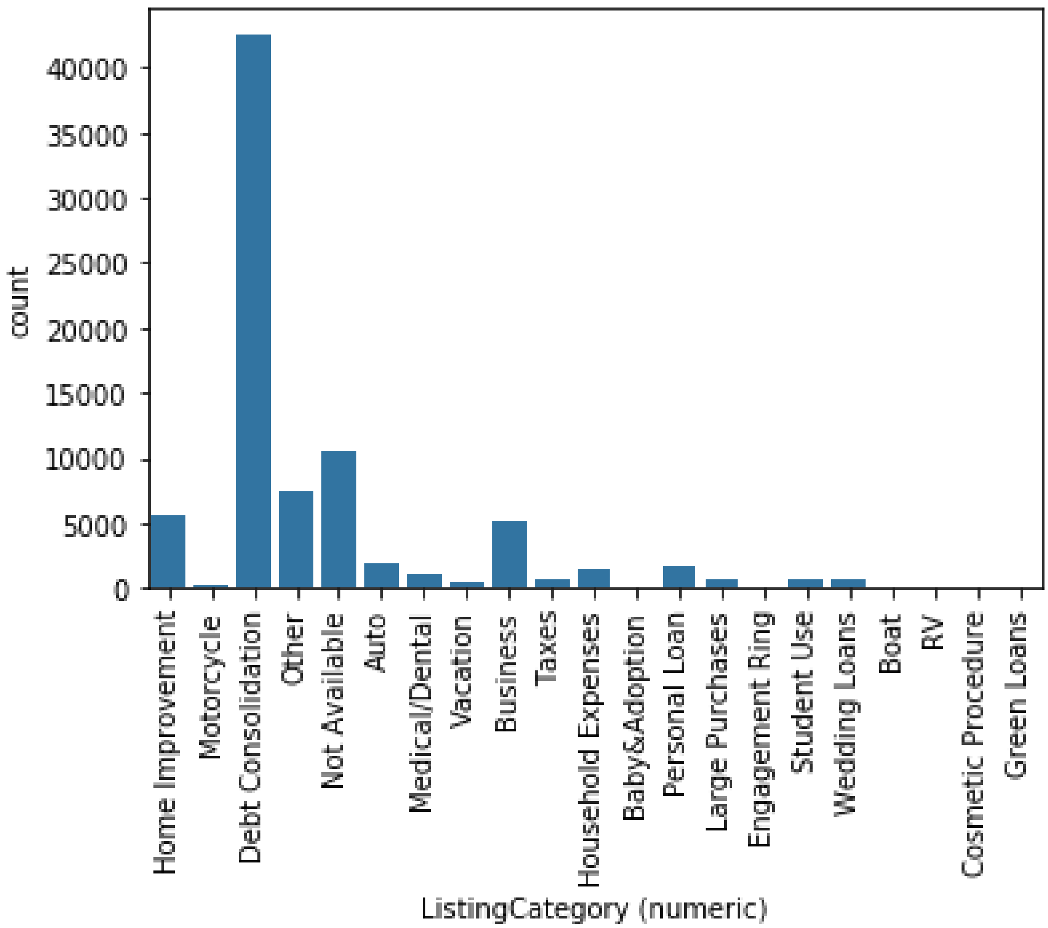
3.1.4 Most common loan types

In [273]:

```python
base_color = sb.color_palette()[0]
ListingCategory = df['ListingCategory (numeric)'].value_counts().index
sb.countplot(data = df, x = 'ListingCategory (numeric)', color = base_color)
plt.xticks(rotation = 90)
```

Out[273]:

```
(array([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11, 12, 13, 14, 15, 16,
        17, 18, 19, 20]), <a list of 21 Text xticklabel objects>)
```



By far, the most common loan type is the debt consolidation loan. It would be interesting to see the correlation between loan categorie and loan amount.

3.1.5 What is the highest, lowest and the average risk scores

In [274]:
```
df.describe()
```

Out[274]:
```
                Term  BorrowerRate  ProsperScore  CreditScoreRangeLower  \
count   81115.000000  81115.000000  61586.000000           81115.000000
mean       40.929594      0.191218      6.037720             687.528324
std        10.568458      0.075064      2.388946              64.839848
min        12.000000      0.000000      1.000000               0.000000
25%        36.000000      0.131400      4.000000             660.000000
50%        36.000000      0.181400      6.000000             680.000000
75%        36.000000      0.249900      8.000000             720.000000
max        60.000000      0.360000     11.000000             880.000000

       CreditScoreRangeUpper  DebtToIncomeRatio  StatedMonthlyIncome  \
```

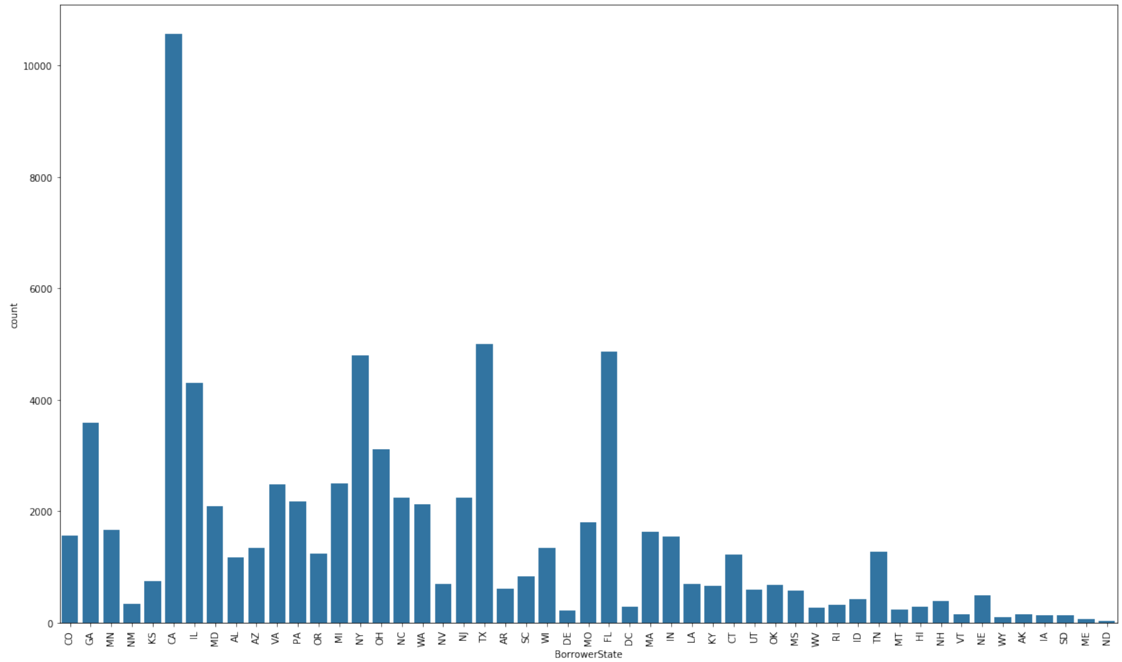
```
count      81114.000000   75977.000000   8.111500e+04
mean         706.536800       0.262449   5.970960e+03
std           64.795293       0.461642   7.858231e+03
min           19.000000       0.000000   0.000000e+00
25%          679.000000       0.140000   3.416667e+03
50%          699.000000       0.220000   5.000000e+03
75%          739.000000       0.310000   7.166667e+03
max          899.000000      10.010000   1.750003e+06

       LoanOriginalAmount
count        81115.000000
mean          8612.301633
std           6377.056491
min           1000.000000
25%           4000.000000
50%           7000.000000
75%          12500.000000
max          35000.000000
```

The highest risk score is 11 and the lowest score is 1 (out of 10). The average risk score is about 6. It would be interesting to see if there is a correlation between risk score and monthly income.

3.2 Which state has the highest borrowing rate

In [275]:
```python
plt.figure(figsize=(20,12))
base_color = sb.color_palette()[0]
ListingCategory = df['BorrowerState'].value_counts().index
sb.countplot(data = df, x = 'BorrowerState', color = base_color)
plt.xticks(rotation = 90)
```

Out[275]:
```
(array([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11, 12, 13, 14, 15, 16,
        17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33,
        34, 35, 36, 37, 38, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49, 50]),
 <a list of 51 Text xticklabel objects>)
```

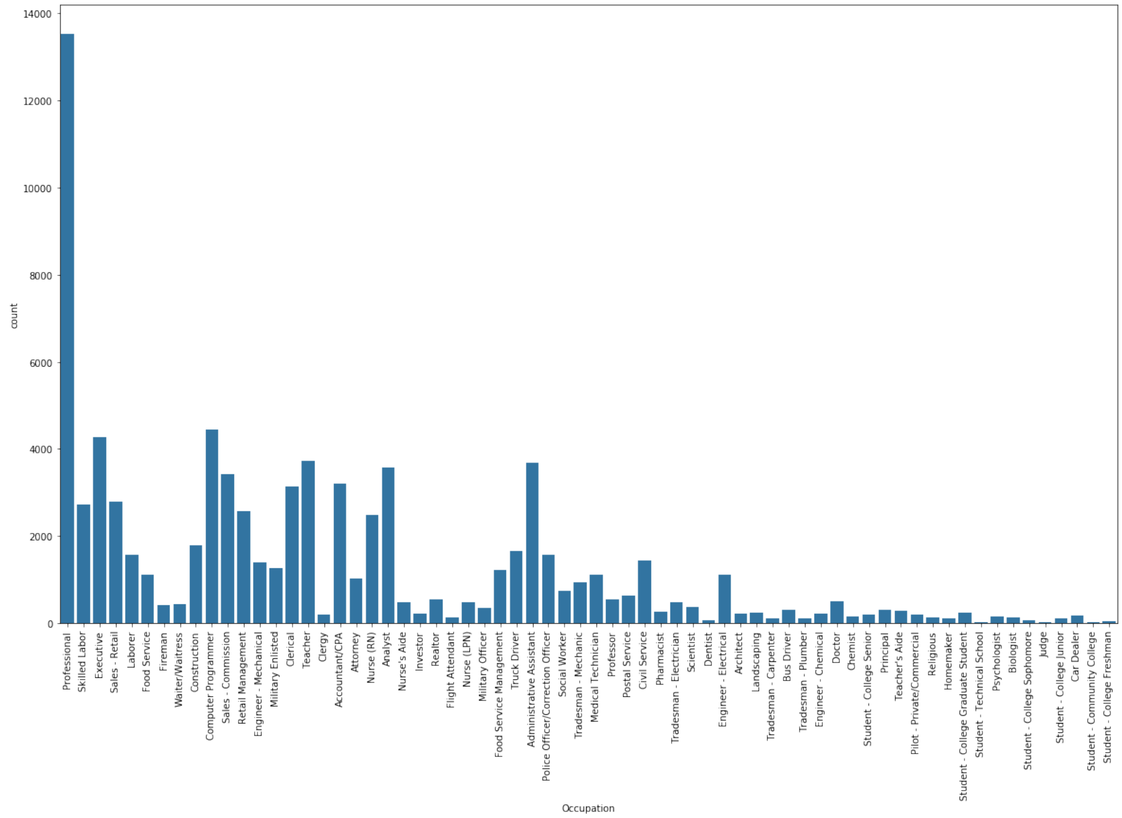


The most popular borrower state is California which is not surprising beings they have a high population. It is not surprising that the other states are higher. Many of the top borrowing states have high population. It would be worth looking at each state versus population.

3.2.1 Difference between occupation and how much they borrowed

```
In [276]: plt.figure(figsize=(20,12))
          base_color = sb.color_palette()[0]
          ListingCategory = df['Occupation'].value_counts().index
          sb.countplot(data = df, x = 'Occupation', color = base_color)
          plt.xticks(rotation = 90)
```

```
Out[276]: (array([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11, 12, 13, 14, 15, 16,
                  17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33,
                  34, 35, 36, 37, 38, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49, 50,
                  51, 52, 53, 54, 55, 56, 57, 58, 59, 60, 61, 62, 63, 64, 65]),
           <a list of 66 Text xticklabel objects>)
```



The most common occupation for borrowers is "Professional". Since this is so vague, I would like to remove this term and look more into the correlation between occupation and loan amount.

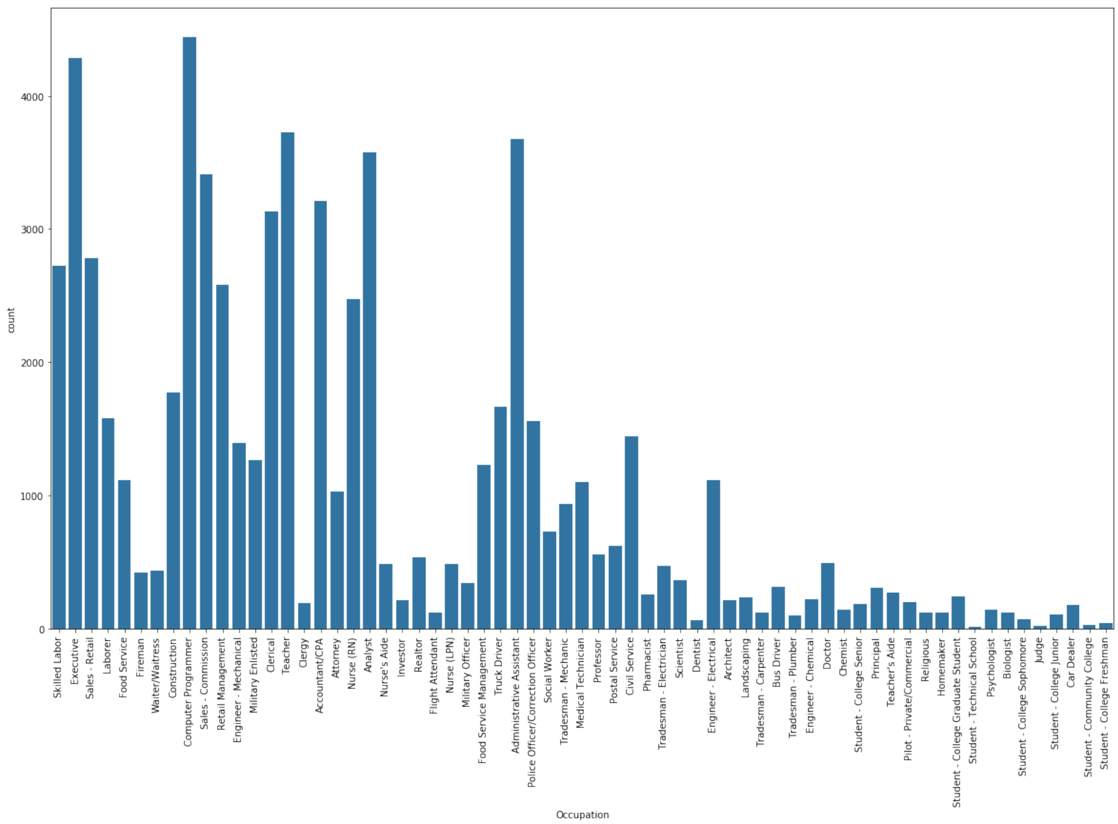
In [277]:
```
df_occupation = df[(df['Occupation'] == 'Professional')].index
df.drop(df_occupation , inplace=True)
df['Occupation'].value_counts()
```

Out[277]:
```
Computer Programmer                    4442
Executive                              4280
Teacher                                3729
Administrative Assistant               3677
Analyst                                3578
Sales - Commission                     3414
Accountant/CPA                         3209
Clerical                               3135
Sales - Retail                         2780
Skilled Labor                          2723
Retail Management                      2579
Nurse (RN)                             2475
Construction                           1777
Truck Driver                           1666
```

```
Laborer                                  1578
Police Officer/Correction Officer        1561
Civil Service                            1445
Engineer - Mechanical                    1397
Military Enlisted                        1265
Food Service Management                  1227
Engineer - Electrical                    1118
Food Service                             1115
Medical Technician                       1105
Attorney                                 1033
Tradesman - Mechanic                      937
Social Worker                             733
Postal Service                            622
Professor                                 556
Realtor                                   535
Doctor                                    492
                                         ...
Scientist                                 367
Military Officer                          341
Bus Driver                                314
Principal                                 307
Teacher's Aide                            275
Pharmacist                                255
Student - College Graduate Student        245
Landscaping                               234
Engineer - Chemical                       222
Investor                                  213
Architect                                 212
Pilot - Private/Commercial                198
Clergy                                    195
Student - College Senior                  187
Car Dealer                                177
Chemist                                   144
Psychologist                              143
Biologist                                 125
Religious                                 124
Flight Attendant                          122
Tradesman - Carpenter                     119
Homemaker                                 119
Student - College Junior                  111
Tradesman - Plumber                       102
Student - College Sophomore                69
Dentist                                    67
Student - College Freshman                 41
Student - Community College                28
Judge                                      22
Student - Technical School                 16
Name: Occupation, Length: 65, dtype: int64
```

```
In [278]: plt.figure(figsize=(20,12))
          base_color = sb.color_palette()[0]
          ListingCategory = df['Occupation'].value_counts().index
          sb.countplot(data = df, x = 'Occupation', color = base_color)
          plt.xticks(rotation = 90)
```

```
Out[278]: (array([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11, 12, 13, 14, 15, 16,
                  17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33,
                  34, 35, 36, 37, 38, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49, 50,
                  51, 52, 53, 54, 55, 56, 57, 58, 59, 60, 61, 62, 63, 64]),
           <a list of 65 Text xticklabel objects>)
```



In this graph, computer programmers, executives, teachers and administrative assistants borrow the most frequently.

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

There were a few changes that needed to be made throughout the exploring process. Personally, I find it easier to complete these cleaning tasks (besides the major ones) as I go. Cleaning steps 3 through 5 were completed after the analysis began.

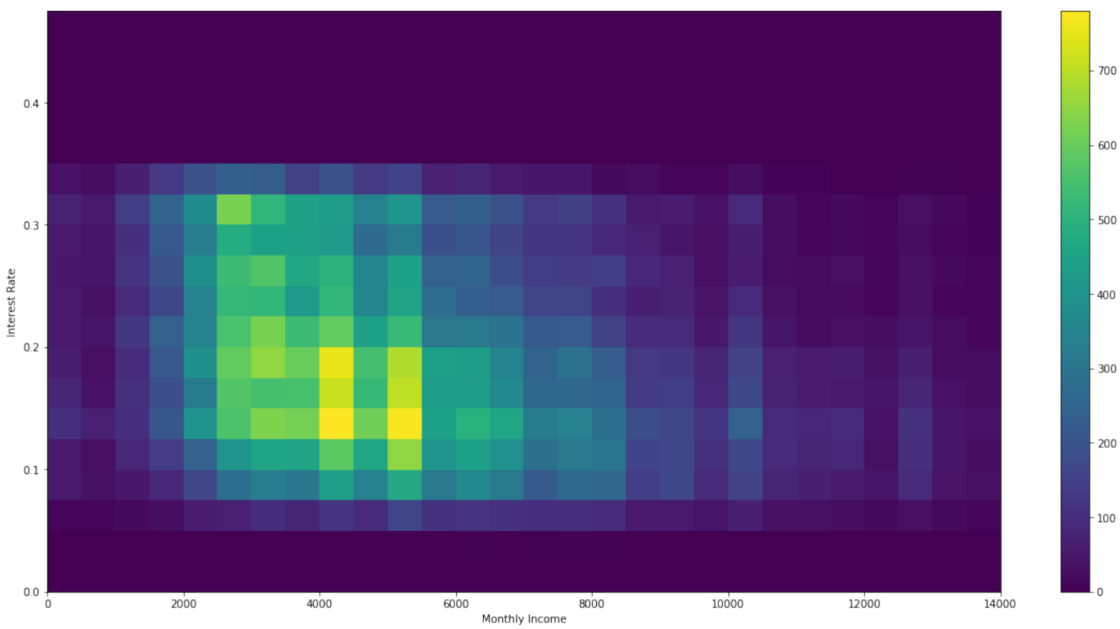
3.2.3 Of the features you investigated, were there any unusual distributions? Did you perform any operations on the data to tidy, adjust, or change the form of the data? If so, why did you do this?

There were a few instances where I believed that the data would've been more defined if values were removed. In the 'difference between occupation and how much they borrowed' portion of the assessment, I found that the occupation "Professional" was wildly used. Beings this isn't specific, I believe it would be best to remove so you can clearly see which occupations were the most popular.

3.3 Bivariate Exploration

In this section, I will investigate relationships between pairs of variables in your data.

In [279]:
```
plt.figure(figsize = [20, 10])

bins_x = np.arange(0, 14000.5+1, 500)
bins_y = np.arange(0, 0.4+.1, .025)

plt.hist2d(data = df, x = 'StatedMonthlyIncome', y = 'BorrowerRate', bins = [bins_x, b
plt.xlabel('Monthly Income')
plt.ylabel('Interest Rate')
plt.colorbar();
```

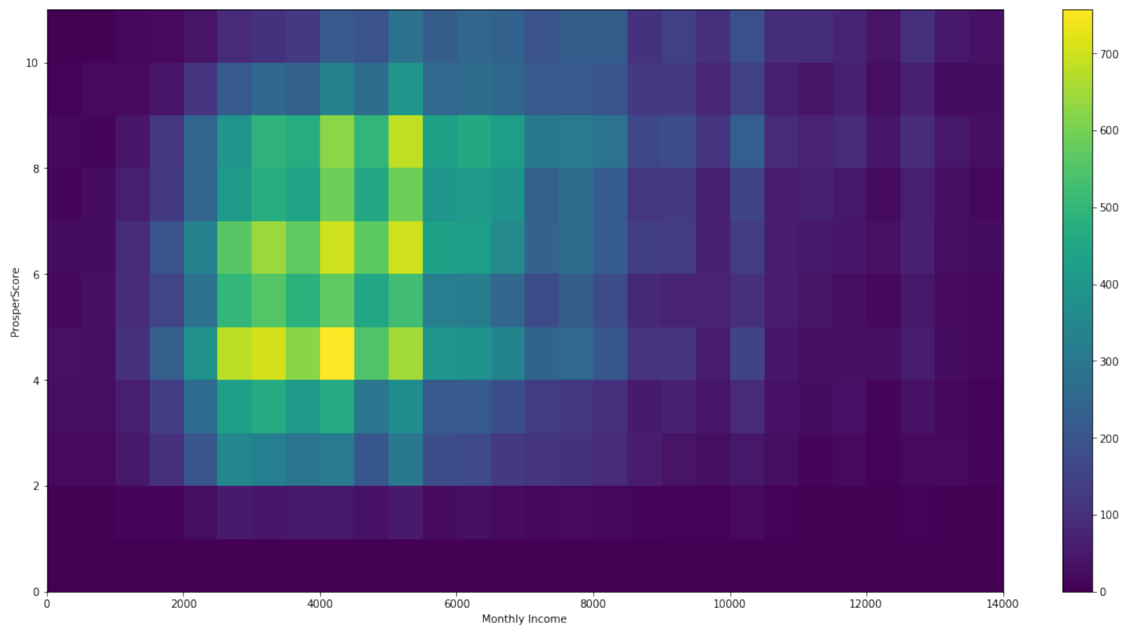


The graph shows that the majority of borrowers make between 4,000 and 4,500 dollars monthly and have an interest rate between 15 and 20 percent. The majority of borrowers make between 2,500 and 5,000 dollars monthly.

3.3.1 Correlation between monthly income and prosper score

In [280]:
```
plt.figure(figsize = [20, 10])

bins_x = np.arange(0, 14000.5+1, 500)
bins_y = np.arange(0, 11.0+.1, 1)

plt.hist2d(data = df, x = 'StatedMonthlyIncome', y = 'ProsperScore', bins = [bins_x, b
plt.xlabel('Monthly Income')
plt.ylabel('ProsperScore')
plt.colorbar();
```

```
/opt/conda/lib/python3.6/site-packages/numpy/lib/function_base.py:968: RuntimeWarning: invalid v
  not_smaller_than_edge = (sample[:, i] >= edges[i][-1])
```



There is not a huge correlation between monthly income and prosper score. There is quite a bit of yellow between 3,000 dollars monthly income and 5,500 dollars monthly income and the prosper score ranges from 4 to 9.

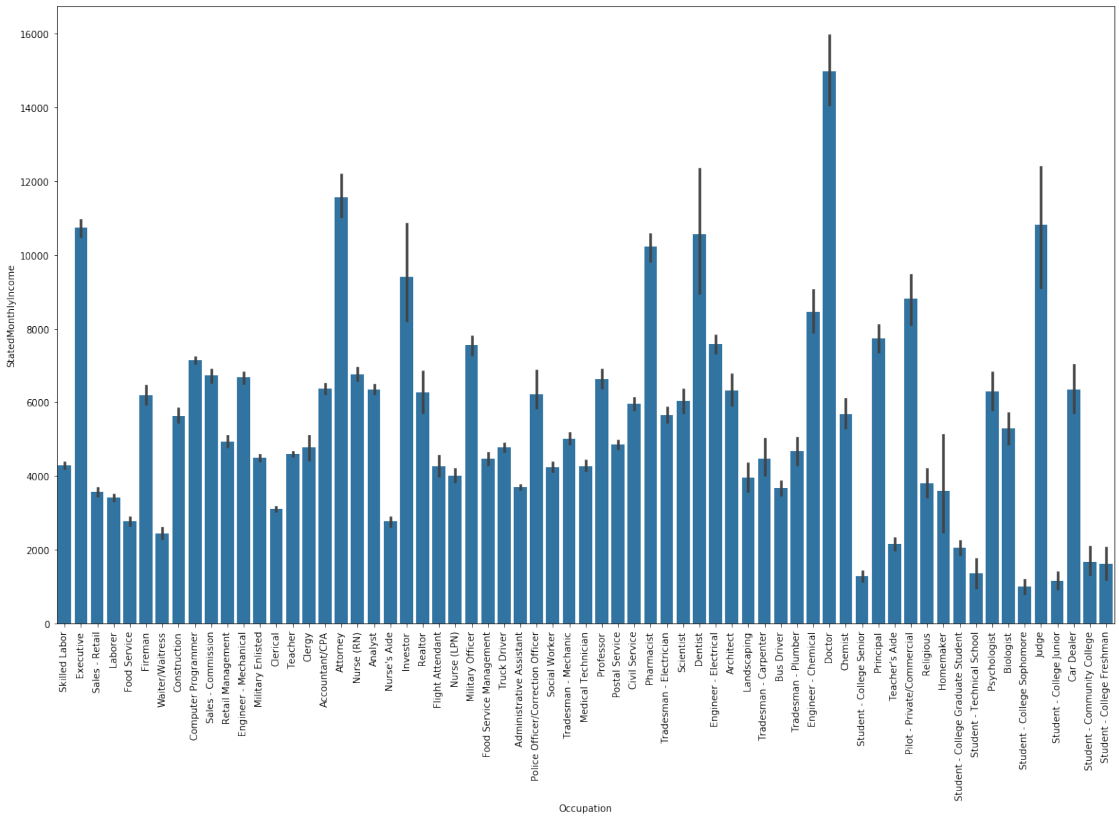
This graph shows that the majority of people have credit scores between 700 and 725. Those credit scores have interest rates between 10 and 15 percent.

3.3.2 Correlation between occupation and how much they borrowed

In [281]:
```
plt.figure(figsize=(20,12))

base_color = sb.color_palette()[0]
```

```
ax = sb.barplot(data = df, x = 'Occupation', y = 'StatedMonthlyIncome', color = base_c
ax.legend(loc = 20, ncol = 3, framealpha = 1, title = 'cat_var2')

plt.xticks(rotation = 90)
```

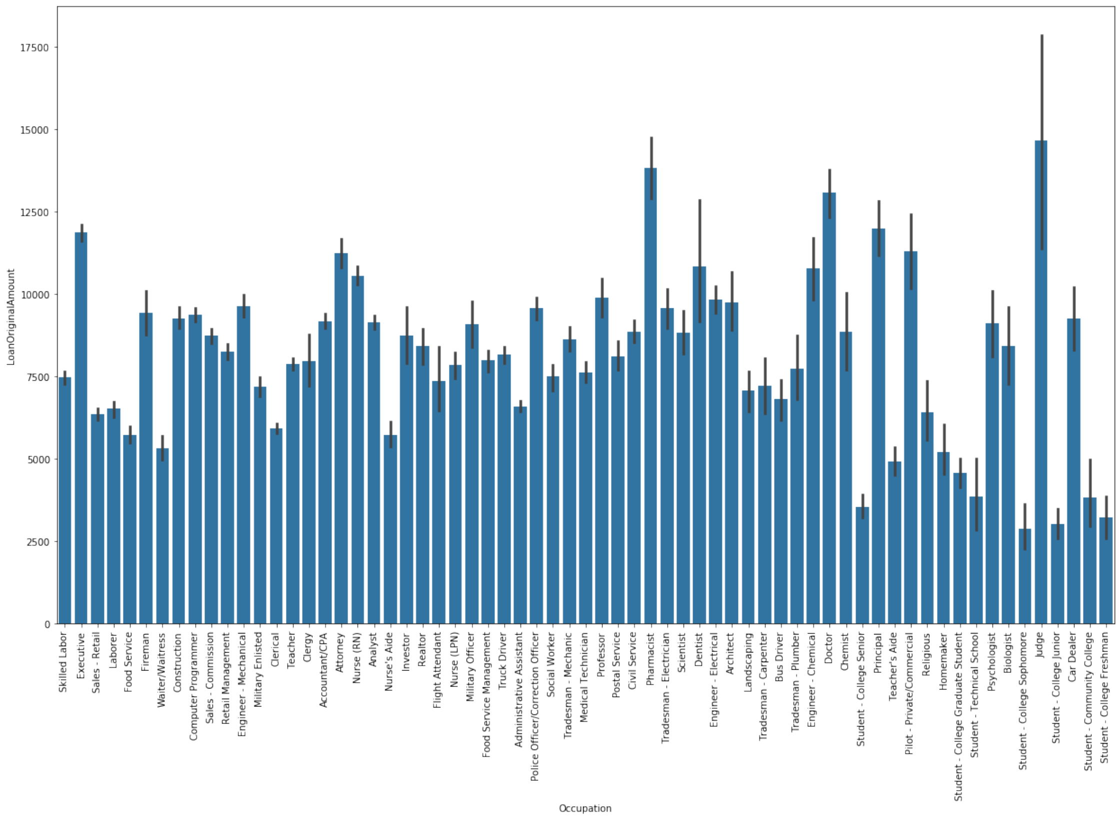
```
Out[281]: (array([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11, 12, 13, 14, 15, 16,
         17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33,
         34, 35, 36, 37, 38, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49, 50,
         51, 52, 53, 54, 55, 56, 57, 58, 59, 60, 61, 62, 63, 64]),
 <a list of 65 Text xticklabel objects>)
```



According to the graph, doctors, attorneys, dentists, judges and executives borrow the most amount of money.

```
In [282]: plt.figure(figsize=(20,12))

base_color = sb.color_palette()[0]

ax = sb.barplot(data = df, x = 'Occupation', y = 'LoanOriginalAmount', color = base_co
ax.legend(loc = 20, ncol = 3, framealpha = 1, title = 'cat_var2')

plt.xticks(rotation = 90)
```

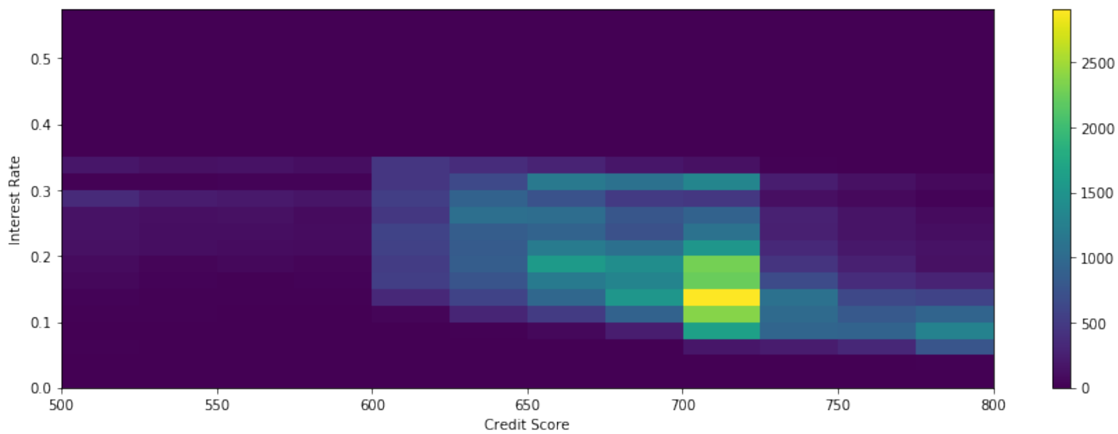
```
Out[282]: (array([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11, 12, 13, 14, 15, 16,
                  17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33,
                  34, 35, 36, 37, 38, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49, 50,
                  51, 52, 53, 54, 55, 56, 57, 58, 59, 60, 61, 62, 63, 64]),
           <a list of 65 Text xticklabel objects>)
```



Judges, pharmacists, doctors and executives make the most amount of money. Whereas, judges, pharmacists, doctors, executives, and pilots borrow the most amount of money. It makes sense, if you have a lot of money, you have more money to borrow.

3.3.3 The correlation between interest rate and credit score

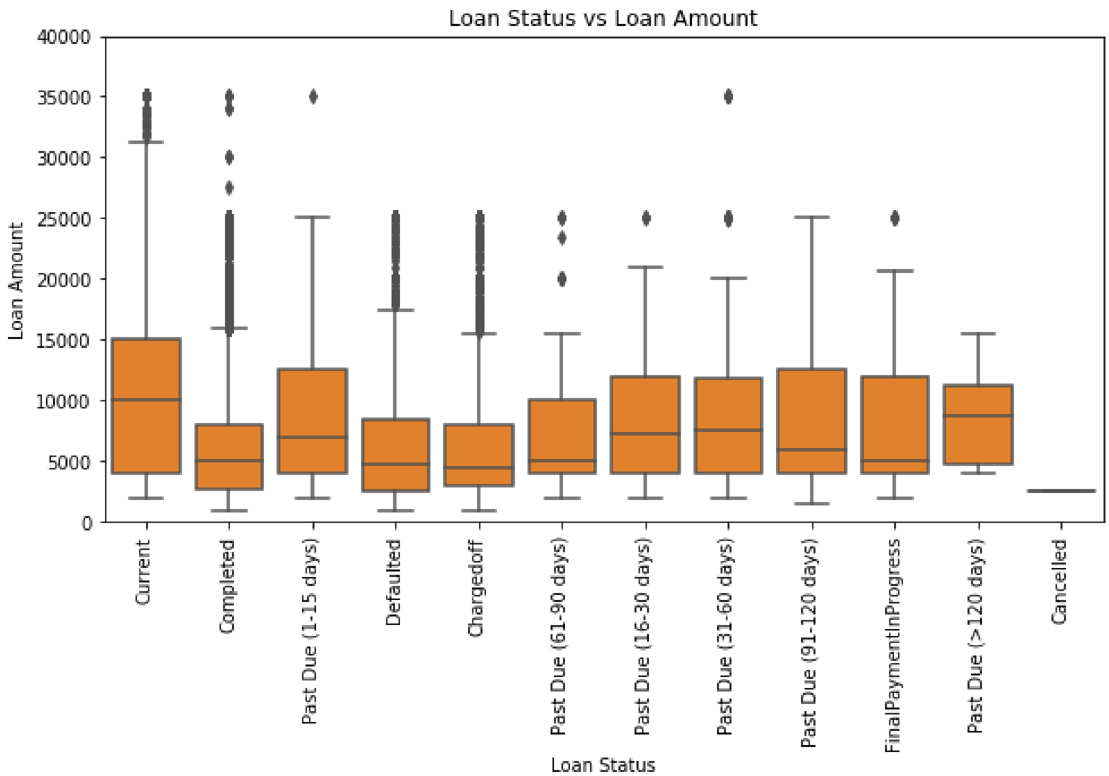
```
In [283]: plt.figure(figsize = [15, 5])

          bins_x = np.arange(500, 800.5+1, 25)
          bins_y = np.arange(0, 0.5+.1, .025)

          plt.hist2d(data = df, x = 'CreditScoreRangeLower', y = 'BorrowerRate', bins = [bins_x,
          plt.xlabel('Credit Score')
          plt.ylabel('Interest Rate')
          plt.colorbar();
```



This graph shows that the majority of borrowers had a credit score of between 700 and 725 and their interest rates fell around 15%.

3.3.4 Loan status versus loan amount

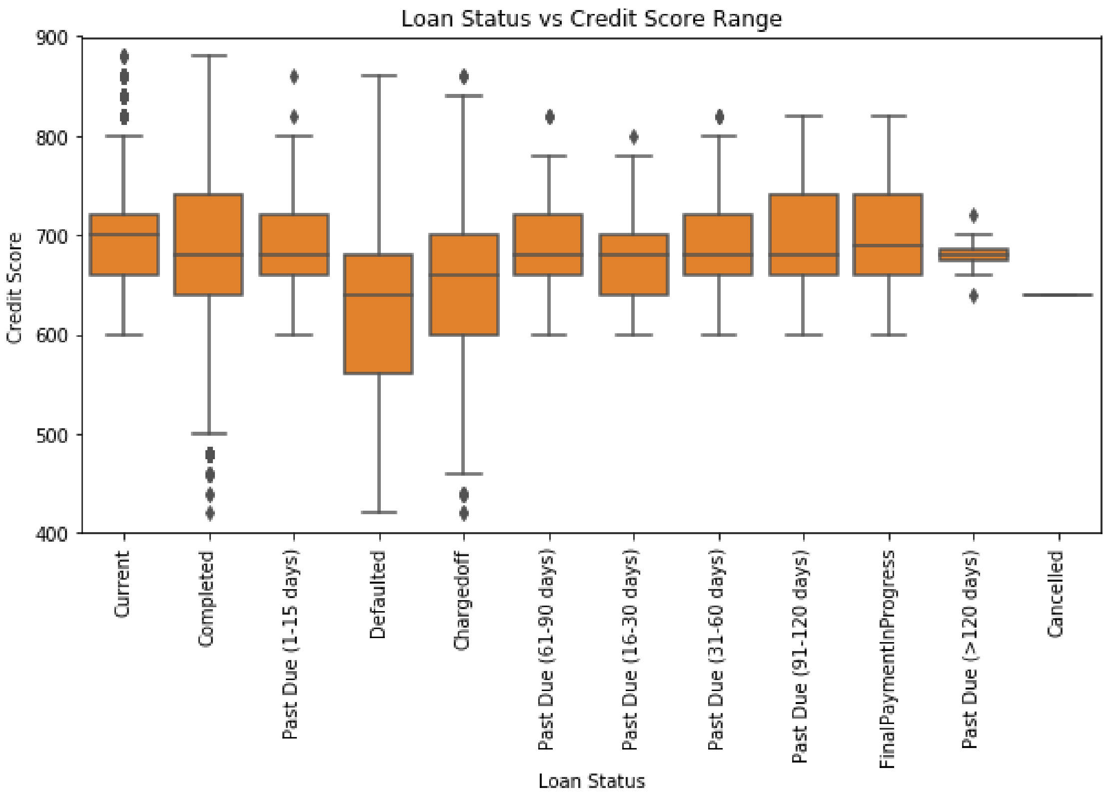
In [284]:
```
plt.figure(figsize = [10, 5])
base_color = sb.color_palette()[1]
sb.boxplot(data = df, x = 'LoanStatus', y = 'LoanOriginalAmount', color = base_color)
plt.ylim([0, 40000])
plt.title('Loan Status vs Loan Amount')
plt.xlabel('Loan Status')
plt.ylabel('Loan Amount')
plt.xticks(rotation = 90)
plt.show()
```



Loans that are in the 10,000 dollar range are more likely to be current, whereas, seriously past due loans (91-120 days) are about 5,000. Many loans that have defaulted are lower loan amounts (on average, about 5,000 dollars).

3.3.5 Loan Status versus credit score

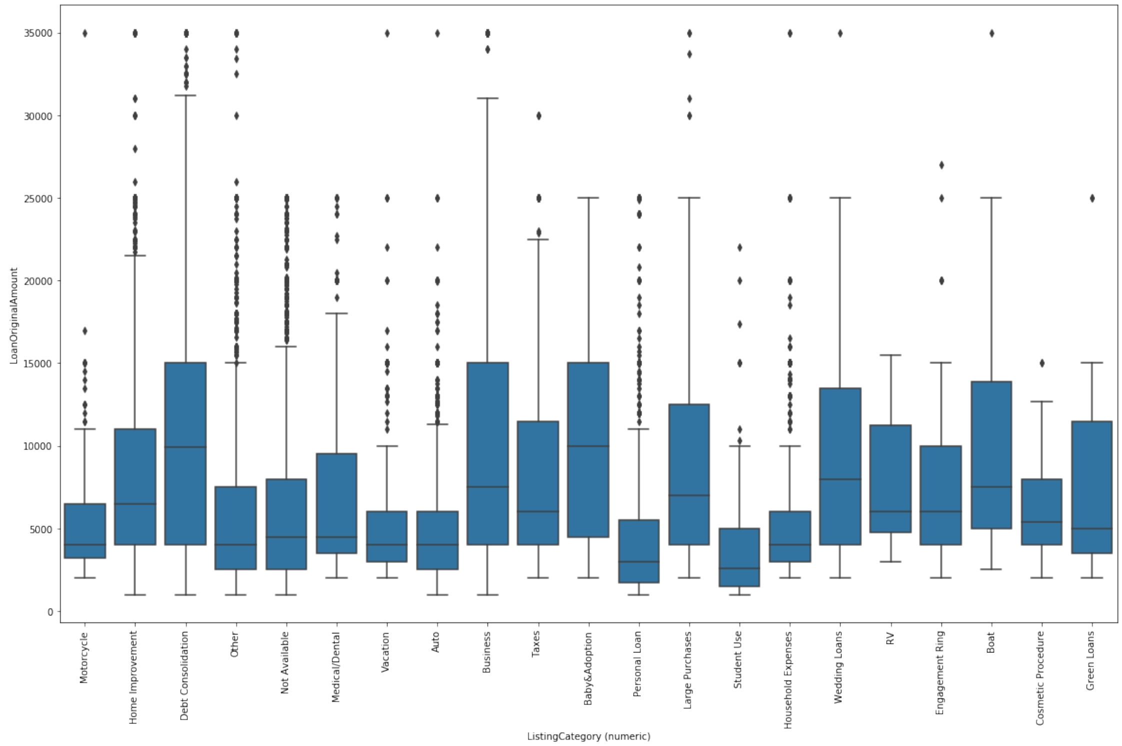
```
In [285]: plt.figure(figsize = [10, 5])
          base_color = sb.color_palette()[1]
          sb.boxplot(data = df, x = 'LoanStatus', y = 'CreditScoreRangeLower', color = base_colo
          plt.ylim([400, 900])
          plt.title('Loan Status vs Credit Score Range')
          plt.xlabel('Loan Status')
          plt.ylabel('Credit Score')
          plt.xticks(rotation = 90)
          plt.show()
```



This graph shows that people with 700 and higher credit scores are much more likely to pay for their loan. This graph also shows that if people have a 650 credit score or lower, they are more likely to default on their loan.

3.3.6 Loan category and the amount of the loan

```
In [286]: plt.figure(figsize=(20,12))
          base_color = sb.color_palette()[0]
          sb.boxplot(data = df, x = 'ListingCategory (numeric)', y = 'LoanOriginalAmount', color
          plt.xticks(rotation = 90)

Out[286]: (array([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11, 12, 13, 14, 15, 16,
                  17, 18, 19, 20]), <a list of 21 Text xticklabel objects>)
```



This graph shows that people that are borrowing for baby & adoption tend to borrow much more than other categories. Debt consolidation is the most popular loan and they are second highest borrower.

3.3.7 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?

There is a strong correlation between interest rate and credit score is high. Most of borrowers fall into a particular interest rate and credit score. Secondly, there is an interesting correlation between occupation and many different factors including how much their monthly income is, the loan amount, etc. The relationship between income, occupation and loan amount was not shocking; the more money someone made, the more they spent. The correlation between interest rate and credit score was the most interesting relationship that I found.

One of the graph shows that the majority of borrowers make between 4,000 and 4,500 dollars monthly and have an interest rate between 15 and 20 percent. The majority of borrowers make between 2,500 and 5,000 dollars monthly.

Another graph shows that people with 700 and higher credit scores are much more likely to pay for their loan. This graph also shows that if people have a 650 credit score or lower, they are more likely to default on their loan.

By far, the most common loan type is the debt consolidation loan.

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

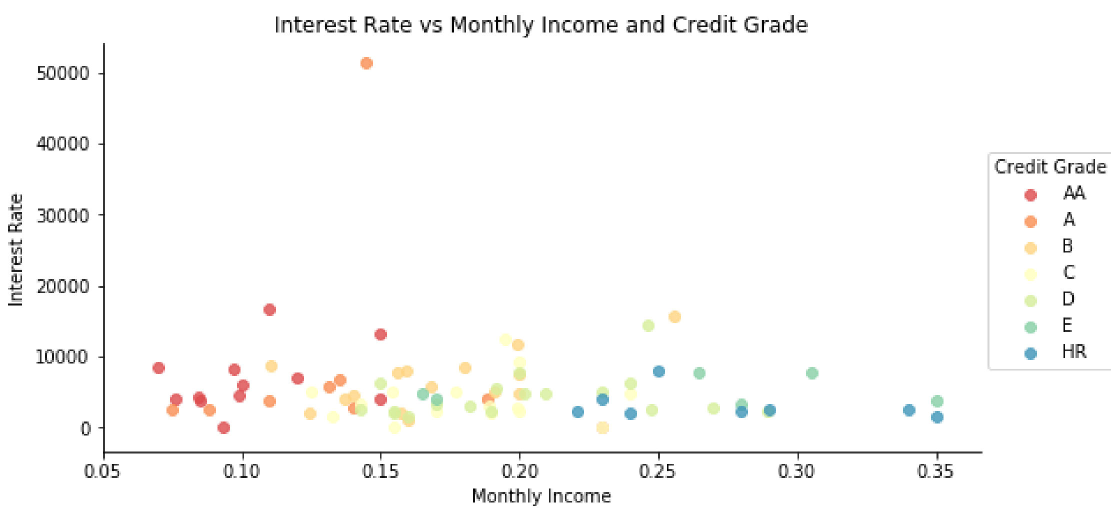
I found some interesting data while exploring how many people work at a certain occupation got loans and also the relationship between occupation and loan amount.

Judges, pharmacists, doctors and executives borrow the most amount of money. Whereas, computer programmers, executives, teachers and administrative assistants borrow more frequently

3.4 Multivariate Exploration

3.4.1 Borrowing Rate versus Monthly Income versus Credit Grade

```
In [287]: g = sb.FacetGrid(data = df_random, hue = "CreditGrade", hue_order = ['AA', 'A', 'B', '
          g.map(sb.regplot,"BorrowerRate", "StatedMonthlyIncome", fit_reg = False);

          new_title = 'Credit Grade'
          g.add_legend(title = 'Credit Grade')
          plt.ylabel('Interest Rate')
          plt.xlabel('Monthly Income')
          plt.title("Interest Rate vs Monthly Income and Credit Grade");
```

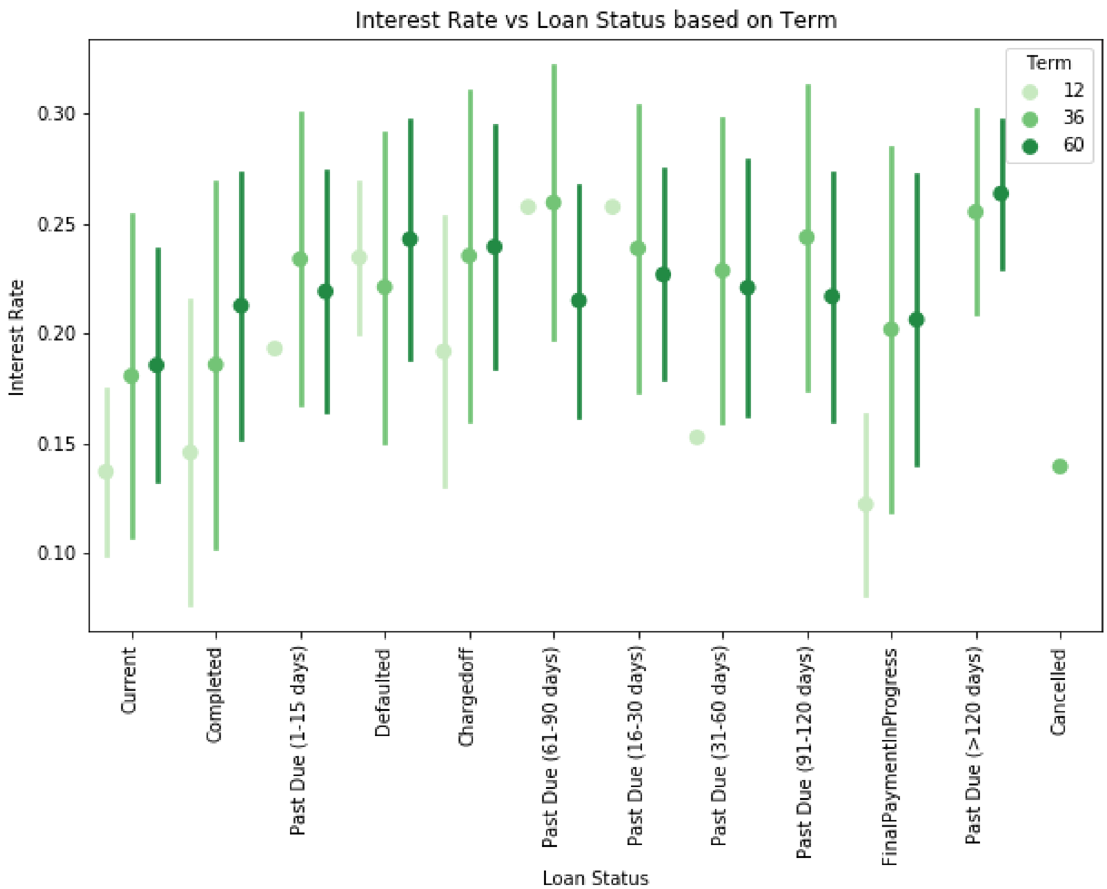


According to the graph, borrowers that had an 'AA' credit score, also had low interest rates and their income ranged anywhere from about 16,000 dollars a month to 0 dollars per month. As you can see, the interest rate and the credit score are directly related and you can see that as the credit interest rate gets higher, the monthly income comes down.

3.5 Interest Rate vs Loan Status based on Term

```
In [288]: fig = plt.figure(figsize = [10,6])
          ax = sb.pointplot(data = df, x = 'LoanStatus', y = 'BorrowerRate', hue = 'Term',
```

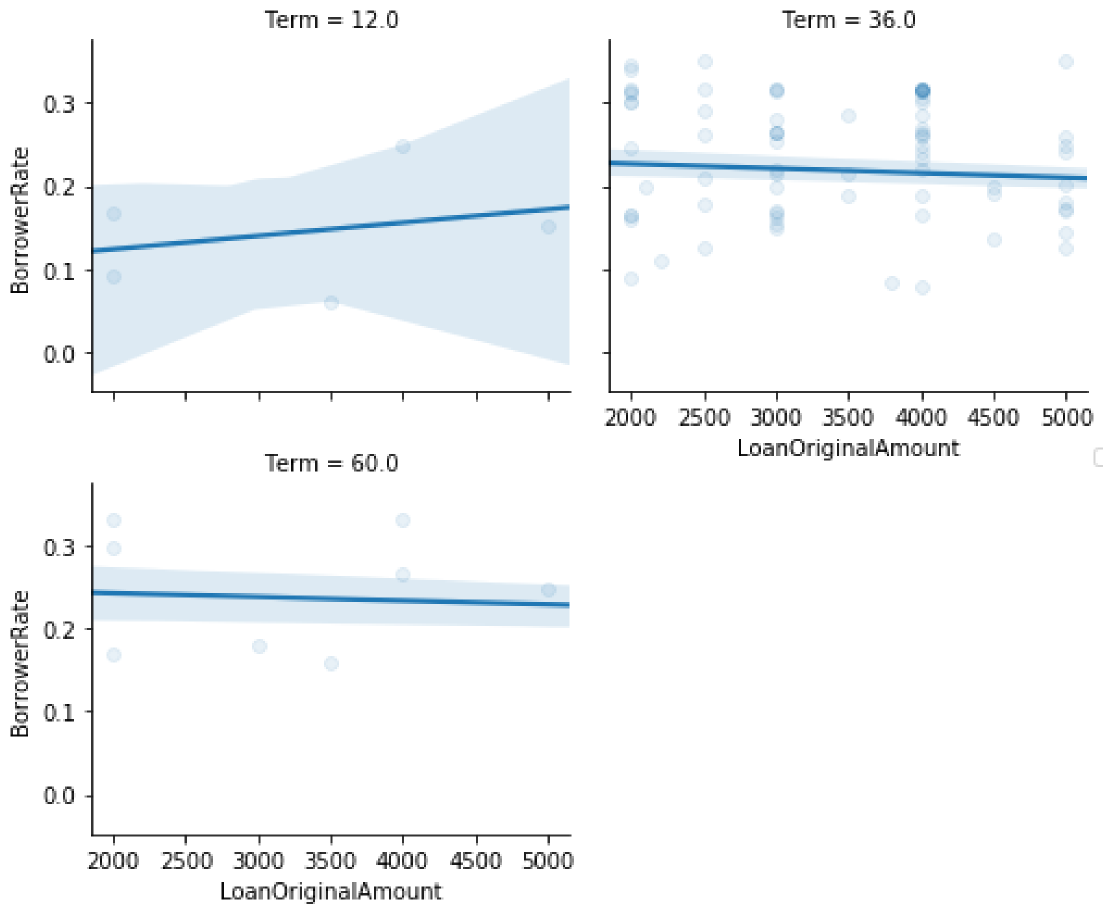
```
                palette = 'Greens', linestyles = '', dodge = .6, ci='sd')
plt.title('Interest Rate vs Loan Status based on Term')
plt.ylabel('Interest Rate')
plt.xlabel('Loan Status')
plt.xticks(rotation = 90)
ax.set_yticklabels([],minor = True);
```



This graph shows that current loans that have a shorter term has less of an interest rate. This is the same for completed. Surprisingly, the past due loan status' typically have higher interest rates. This would make sense - based on my analysis, people that have bad credit scores are at high risk (not paying back their loan). If someone has a high interest rate, they most likely have a bad credit score and thus higher interest rates.

3.5.1 Loan Amount versus Interest Rate and Loan Term

```
In [290]: g=sb.FacetGrid(data=df_random2, aspect=1.2, col='Term', col_wrap=2)
          g.map(sb.regplot, 'LoanOriginalAmount', 'BorrowerRate', x_jitter=0.04, scatter_kws={'a
          g.add_legend();
```

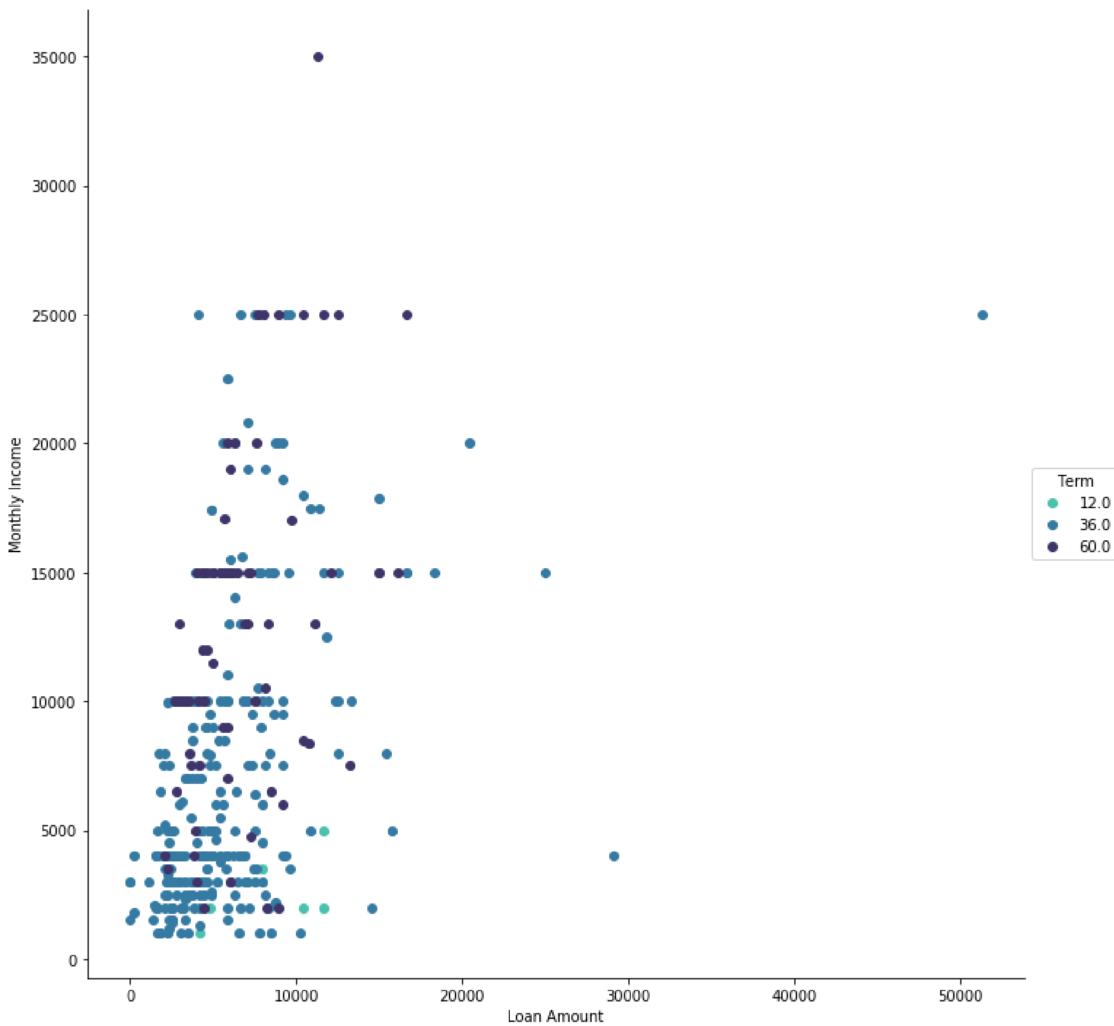


In a 12 month term, it appears that there is a slight increase in interest rate the more the loan is. In a 36 month term, there is a slight (barely noticable) decline in interest rate the more money that was borrowed.

3.6 Loan Amount versus Monthly Income and Term

In [291]:
```
g = sb.FacetGrid(data = df_random, hue = 'Term', size = 10,
                 palette = 'mako_r')
g.map(plt.scatter, 'StatedMonthlyIncome', 'LoanOriginalAmount')
plt.ylabel('Monthly Income')
plt.xlabel('Loan Amount')
g.add_legend()
```

Out[291]: <seaborn.axisgrid.FacetGrid at 0x7f22f01f2c88>



This graph shows that the majority of people making betweeen 1,000 and 10,000 a month that also borrowed between 0 to 8,000 dollars typically have a 36 month loan. It is interesting looking at the 60 month loan because they are typically always either (about) make around 4,000, 1,000 and 15,000 dollars a month. It appears to be lines in the graph right where those income ranges are. Many of the 60 month loans are less than 10,000 dollars. Most of the loans are 12 months.

3.6.1 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?

Current loans that have a shorter term has less of an interest rate. This is the same for completed. Surprisingly, the past due loan status' typically have higher interest rates. This would make sense - based on my analysis, people that have bad credit scores are at high risk (not paying back their loan). If someone has a high interest rate, they most likely have a bad credit score and thus higher interest rates.

Borrowers that had an 'AA' credit score, also had low interest rates and their income ranged anywhere from about 16,000 dollars a month to 0 dollars per month. As you can see, the interest rate and the credit score are directly related and you can see that as the credit interest rate gets higher, the monthly income comes down.

In a 12 month term, it appears that there is a slight increase in interest rate the more the loan is. In a 36 month term, there is a slight (barely noticable) decline in interest rate the more money that was borrowed.

The majority of people making betweeen 1,000 and 10,000 a month that also borrowed between 0 to 8,000 dollars typically have a 36 month loan. It is interesting looking at the 60 month loan because they are typically always either (about) make around 4,000, 1,000 and 15,000 dollars a month. It appears to be lines in the graph right where those income ranges are. Many of the 60 month loans are less than 10,000 dollars. Most of the loans are 12 months.

3.6.2 Were there any interesting or surprising interactions between features?

The most surprising interaction in this dataset is the correlation between borrowing rate versus monthly income versus credit grade because of how clear the graph shows that monthly income, interest rate and the credit grade are directly linked and it shows perfectly on the map.

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