exploration

August 22, 2020

1 Prosper Loan Dataset Exploration

1.1 by Noaman Mangera

1.1.1 Preliminary Wrangling

This document explores a dataset containing attributes for approximately 110,00 loans made with the p2p lending firm Prosper.

[1]:
```
# import packages
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sb

#set plots within notebook environment
%matplotlib inline
```

[2]:
```
#read in dataset
df = pd.read_csv(r'C:\Users\noama\prosperLoanData.csv')
```

[3]:
```
#view first five rows of the dataset
df.head(5)
```

[3]:
```
                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]
```

[4]:
```
# view number of rows and columns
df.shape
```

[4]:
```
(113937, 81)
```

Observations:

The entire dataset contains 113,937 rows (loans) and 81 variables (features). The focus for this project will be a subset of these variables.

[5]:
```
#isolate variables of interest
columns = ['MemberKey', 'BorrowerAPR', 'CreditGrade', 'Term', 'ProsperScore',␣
↪'EmploymentStatus', 'EmploymentStatusDuration'
           , 'OpenRevolvingAccounts', 'CurrentDelinquencies',␣
↪'AmountDelinquent', 'DebtToIncomeRatio', 'Recommendations',␣
↪'InvestmentFromFriendsCount'
           , 'InvestmentFromFriendsAmount', 'PercentFunded', 'Investors']

#create a new df with subset of variables
```

```
sub_df = df.loc[:, columns]
sub_df.head()
```

[5]:
```
                 MemberKey  BorrowerAPR CreditGrade  Term  ProsperScore  \
0  1F3E3376408759268057EDA      0.16516           C    36           NaN
1  1D13370546739025387B2F4      0.12016         NaN    36           7.0
2  5F7033715035555618FA612      0.28269          HR    36           NaN
3  9ADE356069835475068C6D2      0.12528         NaN    36           9.0
4  36CE356043264555721F06C      0.24614         NaN    36           4.0

  EmploymentStatus  EmploymentStatusDuration  OpenRevolvingAccounts  \
0    Self-employed                       2.0                      1
1         Employed                      44.0                     13
2    Not available                       NaN                      0
3         Employed                     113.0                      7
4         Employed                      44.0                      6

   CurrentDelinquencies  AmountDelinquent  DebtToIncomeRatio  Recommendations  \
0                   2.0             472.0               0.17                0
1                   0.0               0.0               0.18                0
2                   1.0               NaN               0.06                0
3                   4.0           10056.0               0.15                0
4                   0.0               0.0               0.26                0

   InvestmentFromFriendsCount  InvestmentFromFriendsAmount  PercentFunded  \
0                           0                          0.0            1.0
1                           0                          0.0            1.0
2                           0                          0.0            1.0
3                           0                          0.0            1.0
4                           0                          0.0            1.0

   Investors
0        258
1          1
2         41
3        158
4         20
```

[6]:
```
# view number of rows and columns in subset
sub_df.shape
```

[6]: (113937, 16)

[7]:
```
# view columns names and data types in subset
sub_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
```

```
RangeIndex: 113937 entries, 0 to 113936
Data columns (total 16 columns):
 #   Column                       Non-Null Count   Dtype
---  ------                       --------------   -----
 0   MemberKey                    113937 non-null  object
 1   BorrowerAPR                  113912 non-null  float64
 2   CreditGrade                  28953 non-null   object
 3   Term                         113937 non-null  int64
 4   ProsperScore                 84853 non-null   float64
 5   EmploymentStatus             111682 non-null  object
 6   EmploymentStatusDuration     106312 non-null  float64
 7   OpenRevolvingAccounts        113937 non-null  int64
 8   CurrentDelinquencies         113240 non-null  float64
 9   AmountDelinquent             106315 non-null  float64
 10  DebtToIncomeRatio            105383 non-null  float64
 11  Recommendations              113937 non-null  int64
 12  InvestmentFromFriendsCount   113937 non-null  int64
 13  InvestmentFromFriendsAmount  113937 non-null  float64
 14  PercentFunded                113937 non-null  float64
 15  Investors                    113937 non-null  int64
dtypes: float64(8), int64(5), object(3)
memory usage: 13.9+ MB
```

[8]:
```
# convert Credit Grade and Prosper Score variables into ordered categorical␣
↪types
ordinal_var_dict = {'CreditGrade': ['AA', 'A', 'B', 'C', 'D', 'E', 'HR', 'NC'],
                    'ProsperScore': [11.0, 10.0, 9.0, 8.0, 7.0, 6.0, 5.0, 4.0,␣
↪3.0, 2.0, 1.0],
                    'Term': [12, 36, 60],
                    'EmploymentStatus': ['Employed', 'Full-time',␣
↪'Self-employed', 'Not available', 'Other',
                                         'Part-time', 'Not employed',␣
↪'Retired']}

#loop over dictionary of variables and convert to categorical data type
for var in ordinal_var_dict:
    ordered_var = pd.api.types.CategoricalDtype(ordered = True,
                                                categories =␣
↪ordinal_var_dict[var])
    sub_df[var] = sub_df[var].astype(ordered_var)
sub_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 113937 entries, 0 to 113936
Data columns (total 16 columns):
 #   Column                       Non-Null Count   Dtype
---  ------                       --------------   -----
```

```
 0   MemberKey                     113937 non-null  object
 1   BorrowerAPR                   113912 non-null  float64
 2   CreditGrade                   28953 non-null   category
 3   Term                          113937 non-null  category
 4   ProsperScore                  84853 non-null   category
 5   EmploymentStatus              111682 non-null  category
 6   EmploymentStatusDuration      106312 non-null  float64
 7   OpenRevolvingAccounts         113937 non-null  int64
 8   CurrentDelinquencies          113240 non-null  float64
 9   AmountDelinquent              106315 non-null  float64
 10  DebtToIncomeRatio             105383 non-null  float64
 11  Recommendations               113937 non-null  int64
 12  InvestmentFromFriendsCount    113937 non-null  int64
 13  InvestmentFromFriendsAmount   113937 non-null  float64
 14  PercentFunded                 113937 non-null  float64
 15  Investors                     113937 non-null  int64
dtypes: category(4), float64(7), int64(4), object(1)
memory usage: 10.9+ MB
```

[9]:
```python
#user defined function to calculate missing values
def missing_values_table(df):
        mis_val = df.isnull().sum()
        mis_val_percent = 100 * (df.isnull().sum() / len(df))
        mis_val_table = pd.concat([mis_val, mis_val_percent], axis=1)
        mis_val_table_ren_columns = mis_val_table.rename(
        columns = {0 : 'Missing Values', 1 : '% of Total Values'})
        mis_val_table_ren_columns = mis_val_table_ren_columns[
            mis_val_table_ren_columns.iloc[:,1] != 0].sort_values(
        '% of Total Values', ascending=False).round(1)
        print ("Your selected dataframe has " + str(df.shape[1]) + " columns.\n"
            "There are " + str(mis_val_table_ren_columns.shape[0]) +
              " columns that have missing values.")
        return mis_val_table_ren_columns
```

[10]:
```python
#apply user defined function over subset of data
missing_values_table(sub_df)
```

```
Your selected dataframe has 16 columns.
There are 8 columns that have missing values.
```

[10]:

	Missing Values	% of Total Values
CreditGrade	84984	74.6
ProsperScore	29084	25.5
DebtToIncomeRatio	8554	7.5
EmploymentStatusDuration	7625	6.7
AmountDelinquent	7622	6.7
EmploymentStatus	2255	2.0

```
CurrentDelinquencies                     697                 0.6
BorrowerAPR                               25                 0.0
```

Observations:

Credit Grade and Prosper Score have a significant portion of "missing" values. From the documentation, it appears Credit Grade was used prior to 2009, while Prosper Score was applied subsequently. The two variables can thus be considered one metric. Feature engineering to merge the two is an option. Another is to consider each on its own merit, and compare the efficacy of each against each other.

[11]:
```python
# Check for duplicates
sub_df.duplicated().sum()
```

[11]:
```
0
```

1.1.2 What is the structure of your dataset?

There are 113,937 loans. Most variables are numeric, but the variables CreditGrade and ProsperScore are ordered factor variables with the following levels.

(best) ——> (worst)

CreditGrade: AA, A, B, C, D, E, NC

ProsperScore: 11, 10, 9, 8, 7, 6, 5, 4, 3, 2, 1

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

The main feature considered here is the Borrower's Annual Percentage Rate (APR) for a loan. The main research question can be stated as:

> What affects a borrower's APR or interest rate?

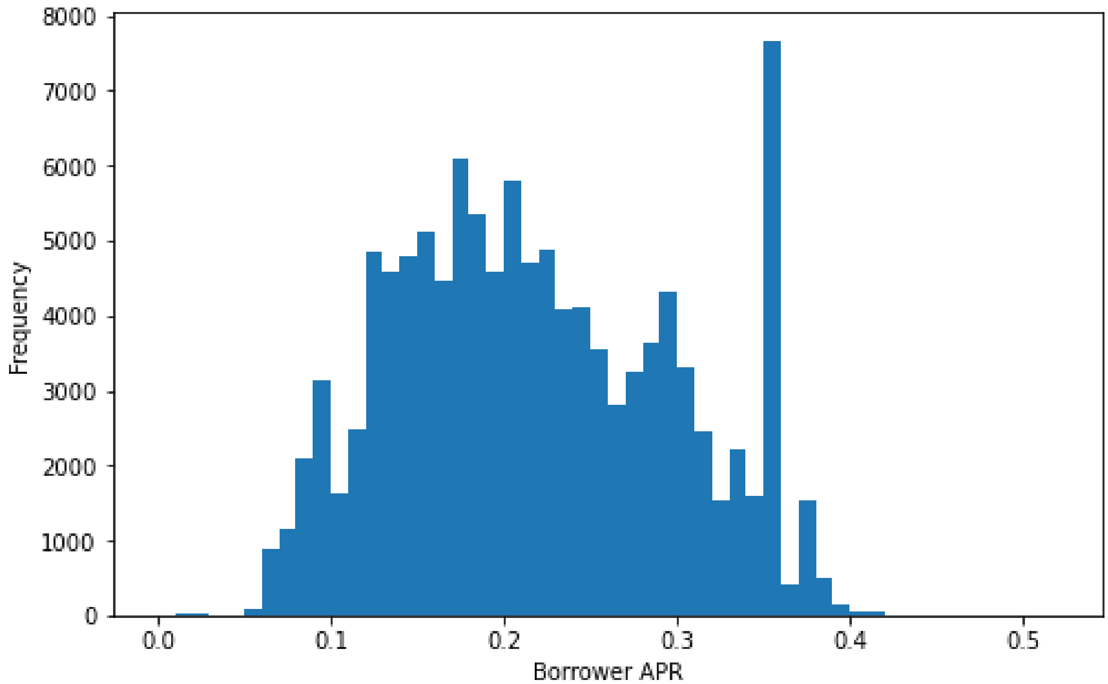
1.1.4 What features in the dataset do you think will help support your investigation into your feature(s) of interest?

1. CreditGrade: The Credit rating that was assigned at the time the listing went live. Applicable for listings pre-2009 period and will only be populated for those listings.
2. Term: The length of the loan expressed in months.
3. ProsperScore: A custom risk score built using historical Prosper data. The score ranges from 1-10, with 10 being the best, or lowest risk score. Applicable for loans originated after July 2009.
4. EmploymentStatus: The employment status of the borrower at the time they posted the listing.
5. EmploymentStatusDuration: The length in months of the employment status at the time the listing was created.
6. OpenRevolvingAccounts: Number of open revolving accounts at the time the credit profile was pulled.

7. CurrentDelinquencies: Number of accounts delinquent at the time the credit profile was pulled.
8. AmountDelinquent: Dollars delinquent at the time the credit profile was pulled.
9. DebtToIncomeRatio: The debt to income ratio of the borrower at the time the credit profile was pulled. This value is Null if the debt to income ratio is not available.
10. MemberKey: The unique key that is associated with the borrower. This is the same identifier that is used in the API member object.
11. Recommendations: Number of recommendations the borrower had at the time the listing was created.
12. InvestmentFromFriendsCount: Number of friends that made an investment in the loan.
13. InvestmentFromFriendsAmount: Dollar amount of investments that were made by friends.
14. PercentFunded: Percent the listing was funded.
15. Investors: The number of investors that funded the loan.

1.2 Univariate Exploration

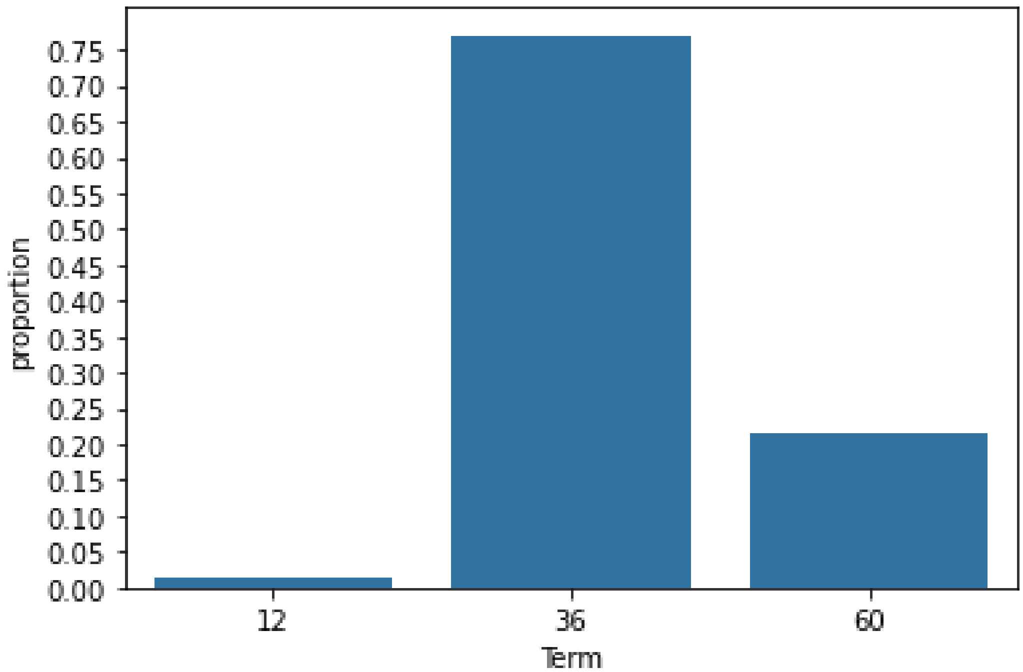
[12]:
```
# create bin width
binsize = 0.01
bins = np.arange(0, sub_df['BorrowerAPR'].max()+binsize, binsize)

# plot distribution of main variable of interest
plt.figure(figsize=[8, 5])
plt.hist(data = sub_df, x = 'BorrowerAPR', bins = bins)

#give x and y axis labels
plt.xlabel('Borrower APR')
plt.ylabel('Frequency');
```



Observations

- Distribution appears normal with a spike at around 0.36 APR. This probably represents a standard rate loan.

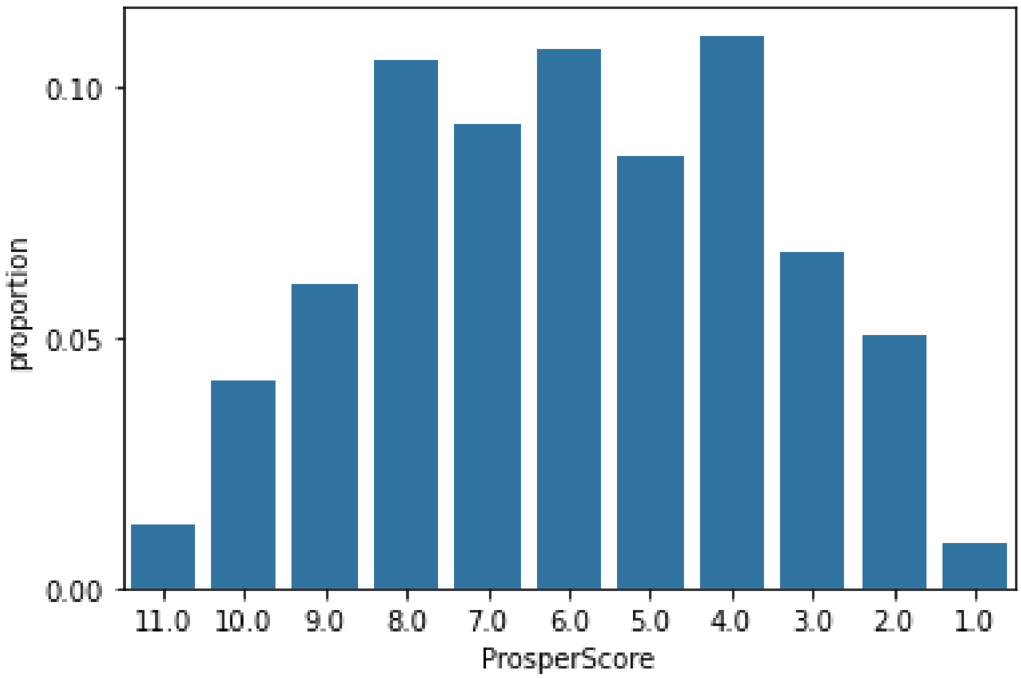
[13]:
```
#use number of observations and total oberservations to calculate proportion
n_points = sub_df.shape[0]
max_count = sub_df['Term'].value_counts().max()
max_prop = max_count / n_points

# tick mark locations and names to 2 d.p
tick_props = np.arange(0, max_prop, 0.05)
tick_names = ['{:0.2f}'.format(v) for v in tick_props]

#uniform color for visualisation
base_color = sb.color_palette()[0]

# create and display  plot
sb.countplot(data = sub_df, x = 'Term', color = base_color)

#y ticks marks and labels
plt.yticks(tick_props * n_points, tick_names)
plt.ylabel('proportion');
```



Observations

- The most common type of loan in this dataset has a duration of 36 months, followed by 60 and 12.

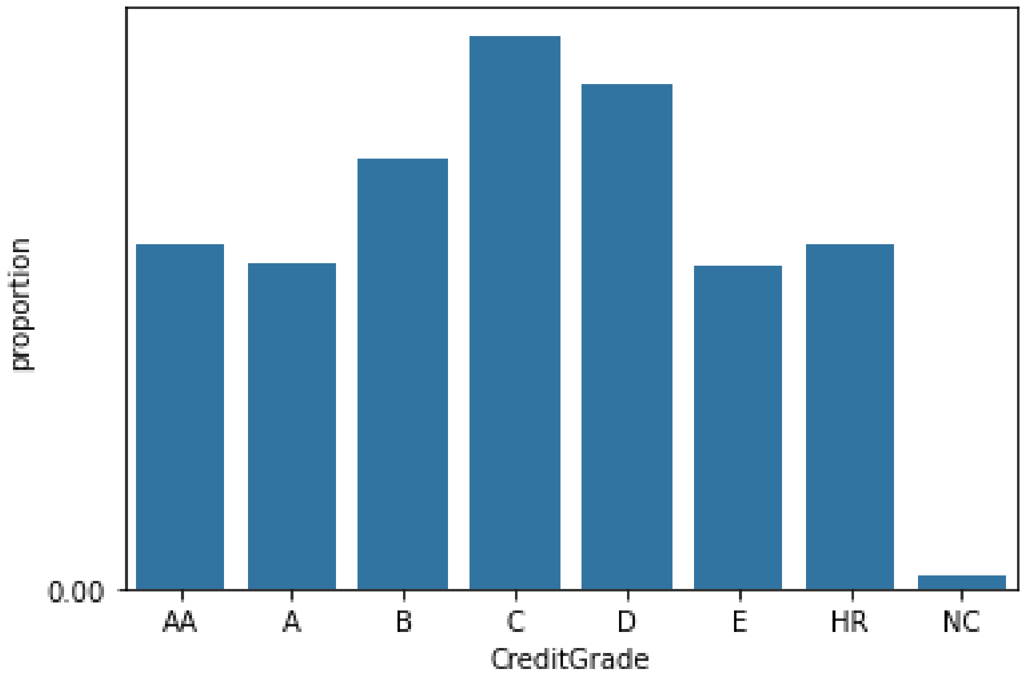
[14]:
```
#use number of observations and total oberservations to calculate proportion
n_points = sub_df.shape[0]
max_count = sub_df['ProsperScore'].value_counts().max()
max_prop = max_count / n_points

# tick mark locations and names to 2 d.p
tick_props = np.arange(0, max_prop, 0.05)
tick_names = ['{:0.2f}'.format(v) for v in tick_props]

#uniform color
base_color = sb.color_palette()[0]

# create and display plot
sb.countplot(data = sub_df, x = 'ProsperScore', color = base_color)

#y ticks marks and labels
plt.yticks(tick_props * n_points, tick_names)
plt.ylabel('proportion');
```



Observations:

- normal distribution, with a median ProsperScore of around 6. In other words, a "middling" rating.

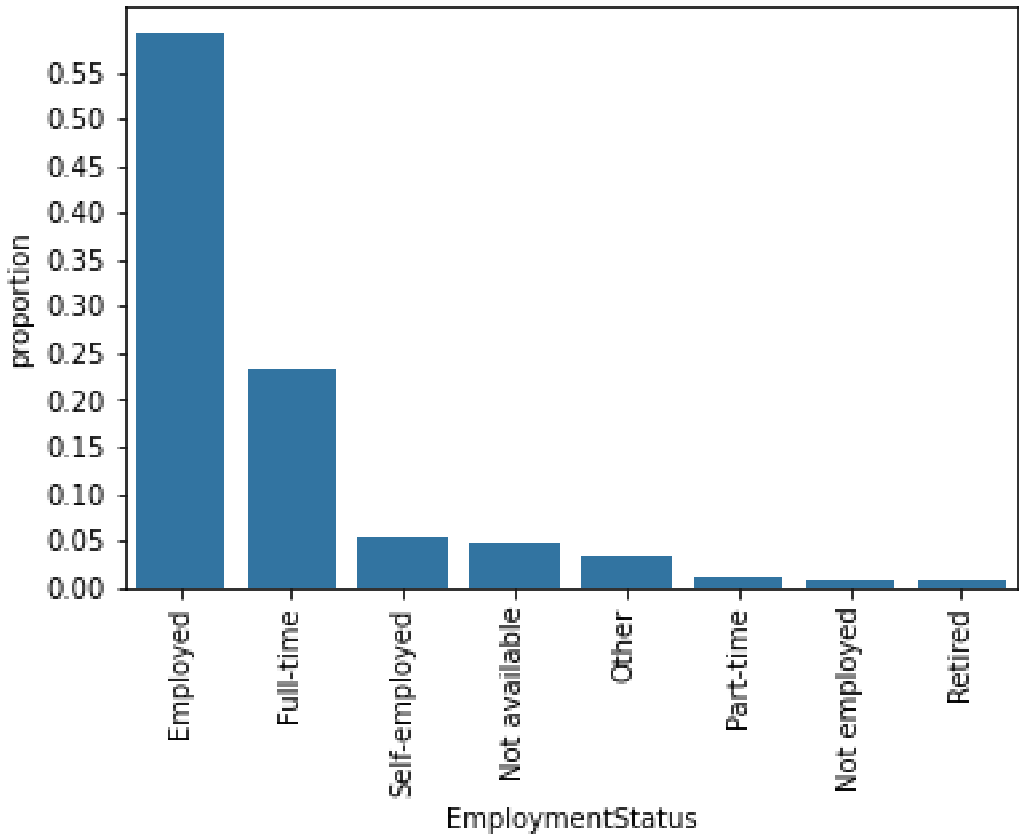
[15]:
```
#use number of observations and total oberservations to calculate proportion
n_points = sub_df.shape[0]
max_count = sub_df['CreditGrade'].value_counts().max()
max_prop = max_count / n_points

# tick mark locations and names to 2 d.p
tick_props = np.arange(0, max_prop, 0.05)
tick_names = ['{:0.2f}'.format(v) for v in tick_props]

#uniform color
base_color = sb.color_palette()[0]

# create and display plot
sb.countplot(data = sub_df, x = 'CreditGrade', color = base_color)

#y ticks marks and labels
plt.yticks(tick_props * n_points, tick_names)
plt.ylabel('proportion');
```



Observations:

- normal distribution, with a median CreditGrade C. In other words, a “middling” rating.

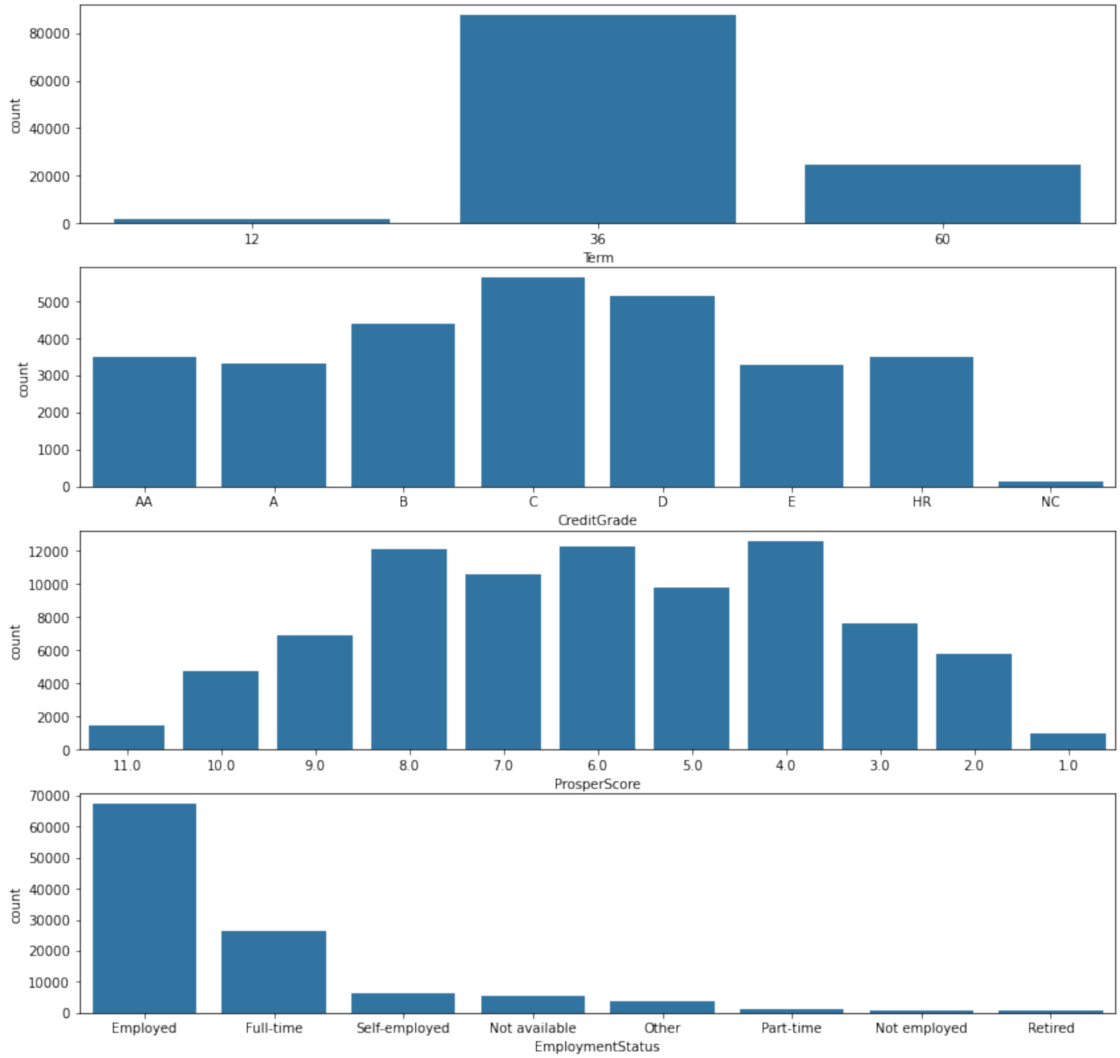
[16]:
```
#use number of observations and total oberservations to calculate proportion
n_points = sub_df.shape[0]
max_count = sub_df['EmploymentStatus'].value_counts().max()
max_prop = max_count / n_points

# tick mark locations and names to 2 d.p
tick_props = np.arange(0, max_prop, 0.05)
tick_names = ['{:0.2f}'.format(v) for v in tick_props]

#uniform color
base_color = sb.color_palette()[0]

# create the plot
sb.countplot(data = sub_df, x = 'EmploymentStatus', color = base_color)

# shift labels to avoid overlap
plt.xticks(rotation=90)

#y ticks marks and labels
plt.yticks(tick_props * n_points, tick_names)
plt.ylabel('proportion');
```



Observations:

- most applicants are in some form of employment.

[17]:
```
#create figure and axis objects
fig, ax = plt.subplots(nrows=4, figsize = [14,14])

#uniform color
default_color = sb.color_palette()[0]

#all four catergorical plots together
sb.countplot(data = sub_df, x = 'Term', color = default_color, ax = ax[0])
sb.countplot(data = sub_df, x = 'CreditGrade', color = default_color, ax =␣
 ↪ax[1])
sb.countplot(data = sub_df, x = 'ProsperScore', color = default_color, ax =␣
 ↪ax[2])
sb.countplot(data = sub_df, x = 'EmploymentStatus', color = default_color, ax =␣
 ↪ax[3]);
```

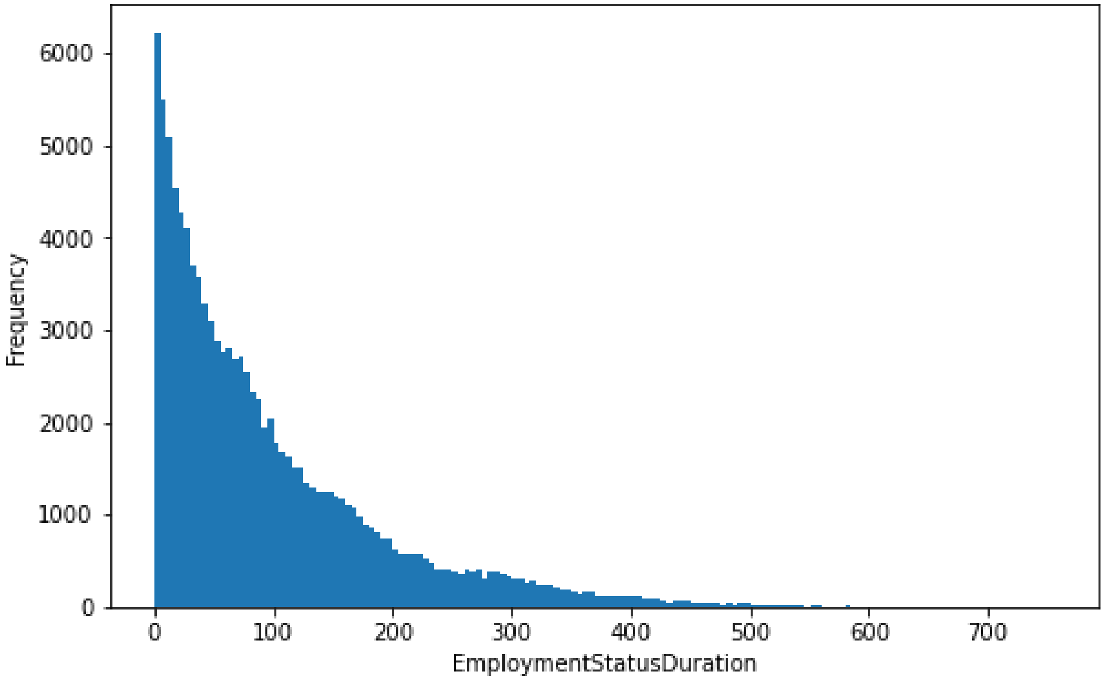


Observations:

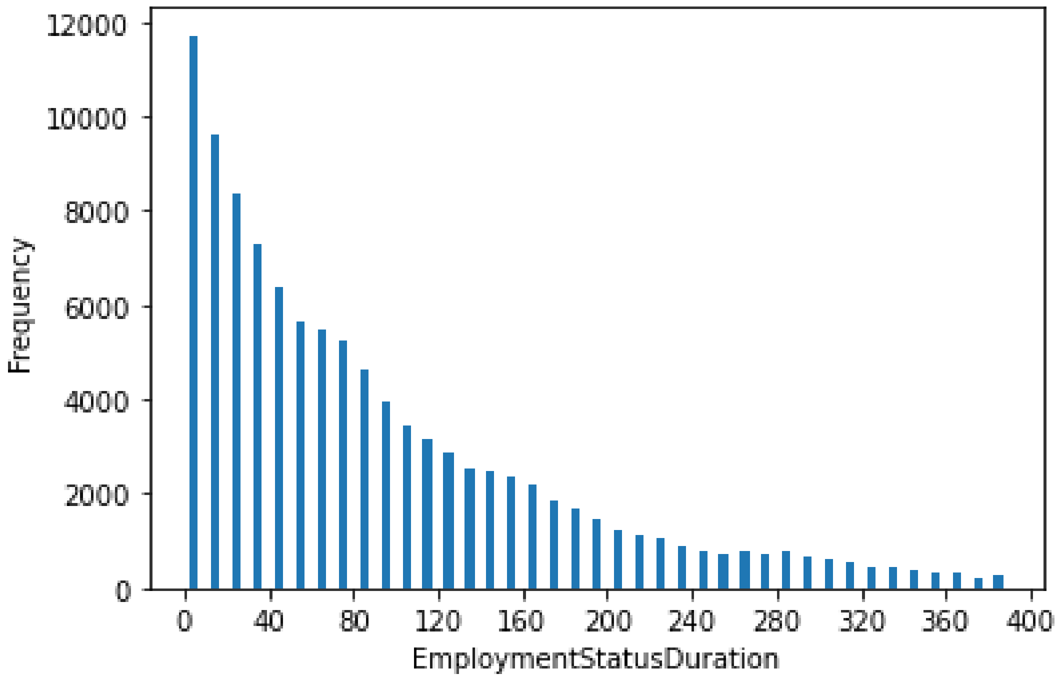
Profile of a "standard" loan application: - 36 Month Term - C/4 Credit Grade/ProsperScore - Employed Status

[18]:
```
# create bin width
binsize = 5
bins = np.arange(0, sub_df['EmploymentStatusDuration'].max()+binsize, binsize)

# plot distribution of variable
plt.figure(figsize=[8, 5])
plt.hist(data = sub_df, x = 'EmploymentStatusDuration', bins = bins)

#give x and y axis labels
plt.xlabel('EmploymentStatusDuration')
```

```
plt.ylabel('Frequency');
```



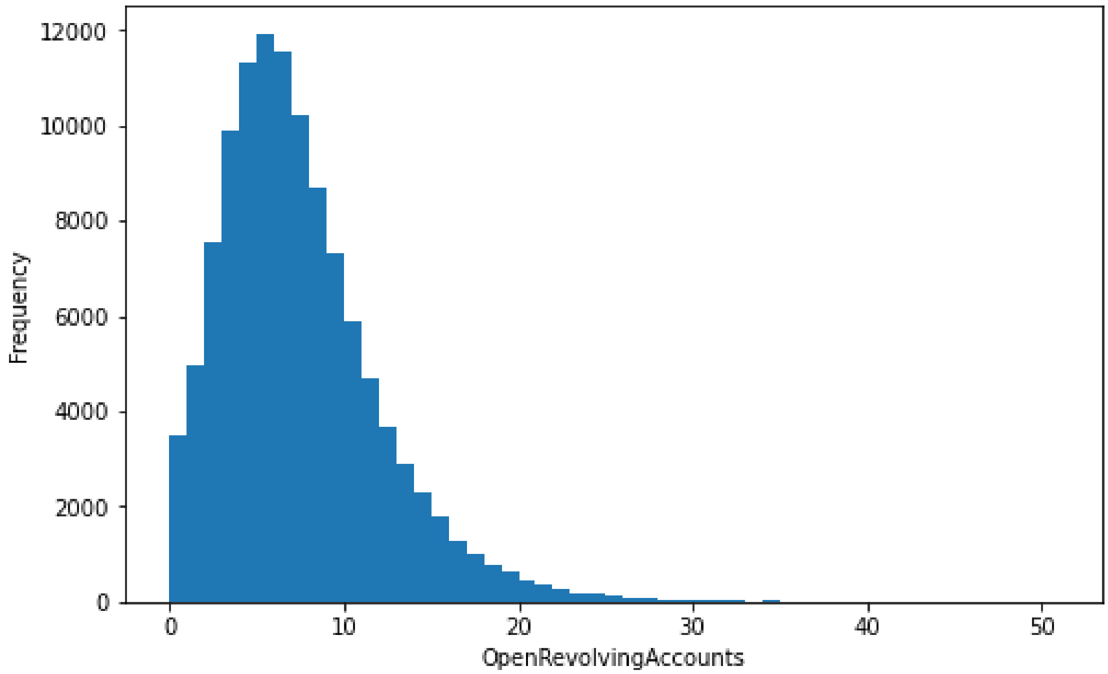
[19]:
```
# create bin width
bin_edges = np.arange(0, 400, 10)

# plot distribution of variable as discrete
plt.hist(sub_df['EmploymentStatusDuration'], bins = bin_edges, rwidth = 0.4)

#x axis ticks and labels
plt.xticks(np.arange(0, 400+10, 40))
plt.xlabel('EmploymentStatusDuration')
plt.ylabel('Frequency');
```



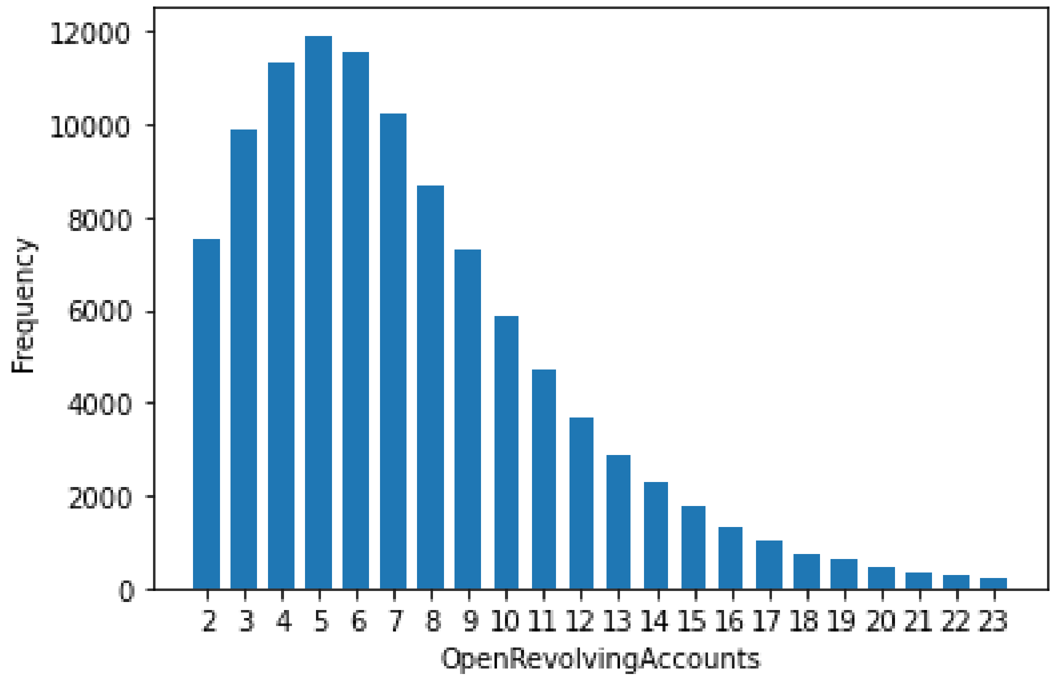
Observations:

- Right tailed distribution, with the bulk of observations for employment duration at the low end, and few at the high end.

[20]:
```
# create bin width
binsize = 1
bins = np.arange(0, sub_df['OpenRevolvingAccounts'].max()+binsize, binsize)

# plot distribution of variable
plt.figure(figsize=[8, 5])
plt.hist(data = sub_df, x = 'OpenRevolvingAccounts', bins = bins)

#give x and y axis labels
plt.xlabel('OpenRevolvingAccounts')
plt.ylabel('Frequency');
```



[21]:
```
# create bin width
bin_edges = np.arange(1.5, 23.5+1, 1)

# plot distribution of variable as discrete
plt.hist(sub_df['OpenRevolvingAccounts'], bins = bin_edges, rwidth = 0.7)

#x axis ticks and labels
plt.xticks(np.arange(2, 23+1, 1))
plt.xlabel('OpenRevolvingAccounts')
plt.ylabel('Frequency');
```



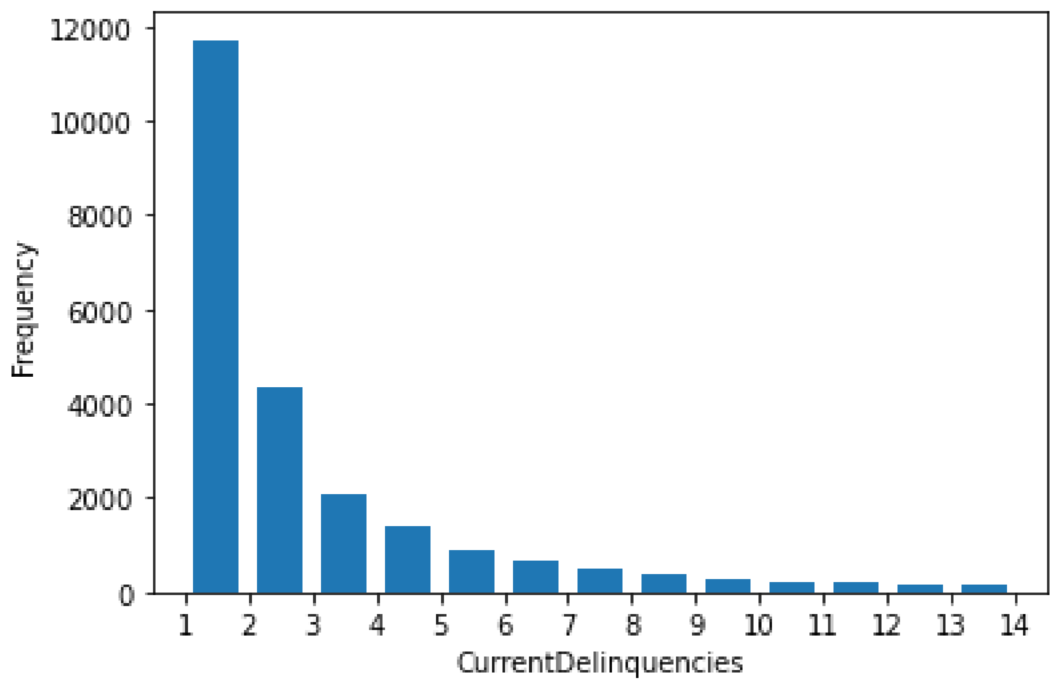
Observations:

- right tailed, unimodal with peak at 5.

[22]:
```
#raw count of unique observations (top 5)
sub_df['CurrentDelinquencies'].value_counts().head()
```

[22]:
```
0.0    89742
1.0    11716
2.0     4357
3.0     2098
4.0     1379
Name: CurrentDelinquencies, dtype: int64
```

[23]:
```
# create bin width
bin_edges = np.arange(1, 15, 1)

# plot distribution of variable as discrete
plt.hist(sub_df['CurrentDelinquencies'], bins = bin_edges, rwidth = 0.7)

#x axis ticks and labels
plt.xticks(np.arange(1, 15, 1))
plt.xlabel('CurrentDelinquencies')
plt.ylabel('Frequency');
```



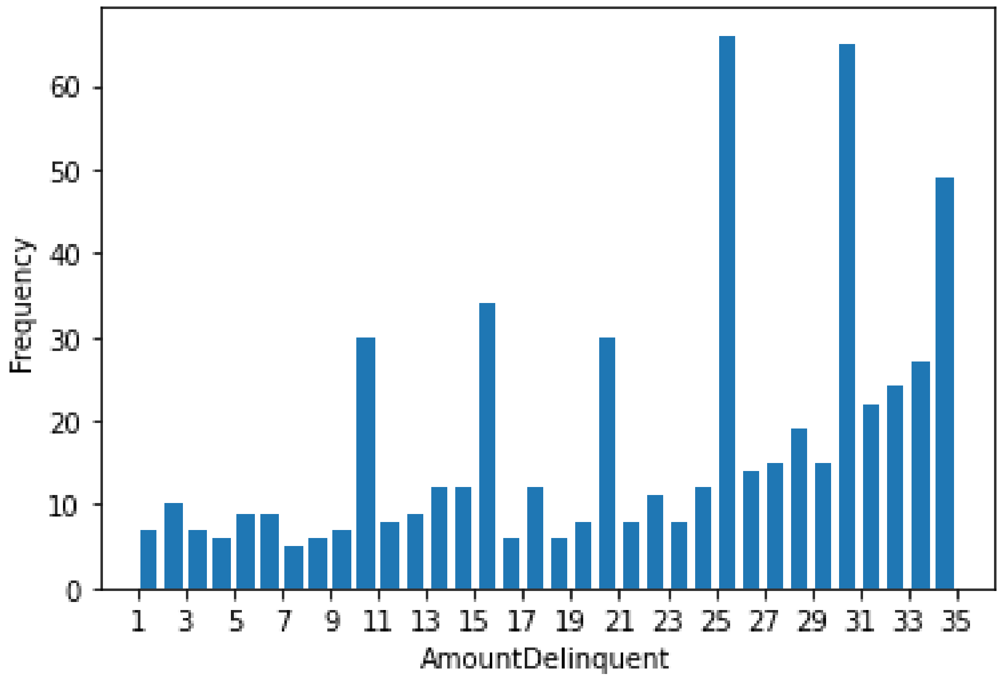
Observations:

- ~80% of loan applicants have zero delinquencies. The above therefore excludes this "extreme" value to focus on the remaining data.

[24]:
```
#raw count of unique observations (top 5)
sub_df['AmountDelinquent'].value_counts().head()
```

[24]:
```
0.0      89818
50.0        73
100.0       67
25.0        66
30.0        65
Name: AmountDelinquent, dtype: int64
```

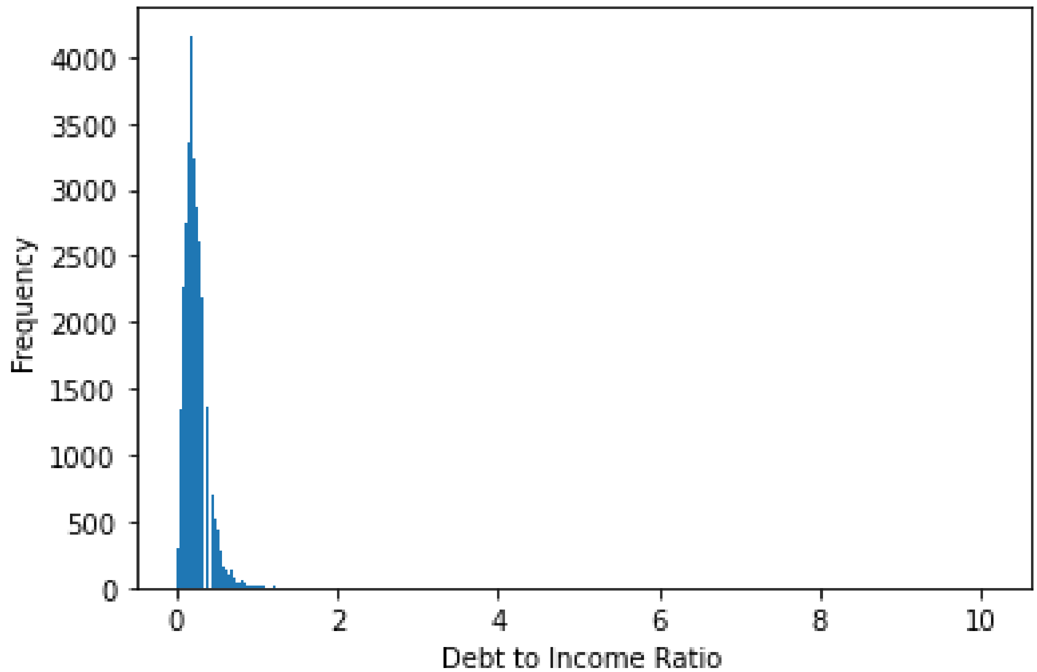
[25]:
```
# create bin width
bin_edges = np.arange(1, 35+1, 1)

# plot distribution of variable as discrete
plt.hist(sub_df['AmountDelinquent'], bins = bin_edges, rwidth = 0.7)

#x axis ticks and labels
plt.xticks(np.arange(1, 35+1, 2))
plt.xlabel('AmountDelinquent')
plt.ylabel('Frequency');
```



Oberservation:

- ~80% of loan applciactions are those with a zero balance outstanding (delinquencies). After stripping these out the distrubtion of the variable is left tail, with the higher count of observations made for applciations with greater amount outstanding.
- Also periodic spikes at regular intervals.

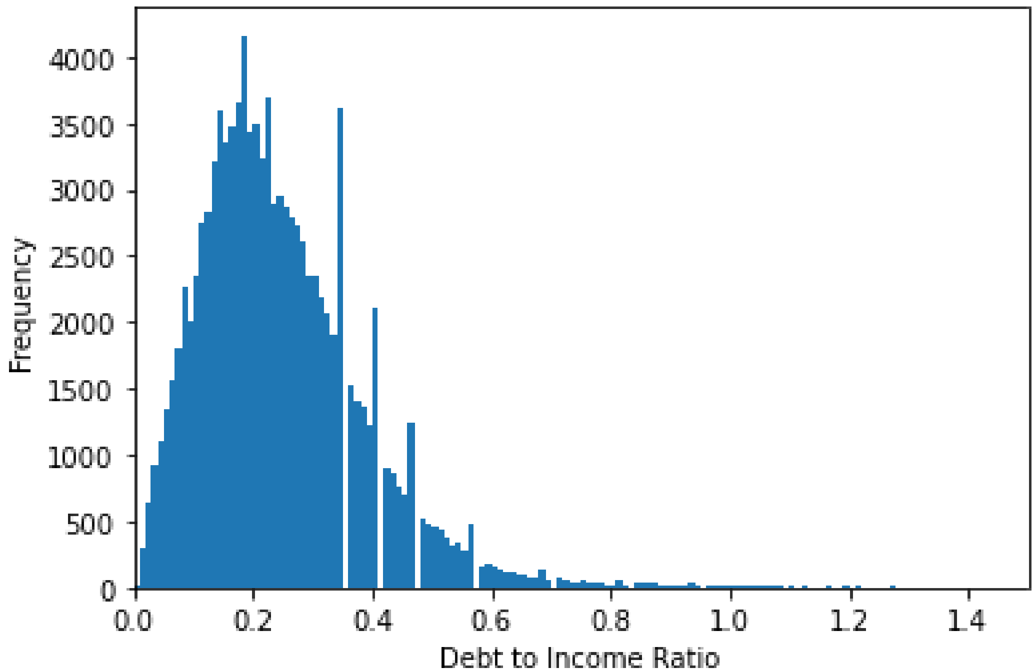
[26]:
```
# create bin width
bins_edges = np.arange(sub_df.DebtToIncomeRatio.min(), sub_df.DebtToIncomeRatio.
 ↪max()+0.1, 0.01)

# plot distribution of variable
plt.hist(data=sub_df, x='DebtToIncomeRatio', bins=bins_edges)

#x axis ticks and labels
plt.xlabel('Debt to Income Ratio')
plt.ylabel('Frequency');
```



[27]:
```
#numerical summary of variable
sub_df['DebtToIncomeRatio'].describe()
```

[27]:
```
count    105383.000000
mean          0.275947
std           0.551759
min           0.000000
25%           0.140000
50%           0.220000
75%           0.320000
max          10.010000
Name: DebtToIncomeRatio, dtype: float64
```

[28]:
```
# plot distribution of variable
plt.hist(data=sub_df, x='DebtToIncomeRatio', bins=bins_edges)

#limit x axis to bulk of distruction and label axis
plt.xlim(0,1.5);
plt.xlabel('Debt to Income Ratio')
plt.ylabel('Frequency');
```



Oberservations:

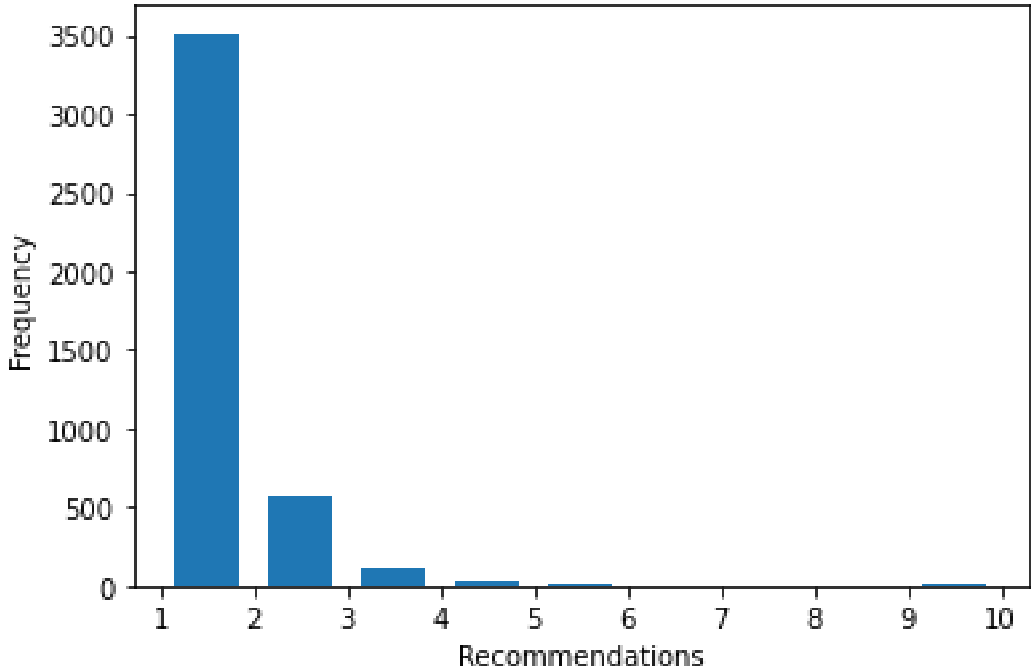
- Outliers, with a mean greater than the median. The resulting distribution is skewed to the right.
- Also periodic spikes at regular intervals.

[29]:
```
#raw count of unique obsevations (top 5)
sub_df['Recommendations'].value_counts().head()
```

[29]:
```
0    109678
1      3516
2       568
3       108
4        26
Name: Recommendations, dtype: int64
```

[30]:
```
# create bin width
bin_edges = np.arange(1, 10+1, 1)

# plot distribution of variable as discrete
plt.hist(sub_df['Recommendations'], bins = bin_edges, rwidth = 0.7)

#x axis ticks and labels
plt.xticks(np.arange(1, 10+1, 1))
plt.xlabel('Recommendations')
```

```
plt.ylabel('Frequency');
```



Observations:

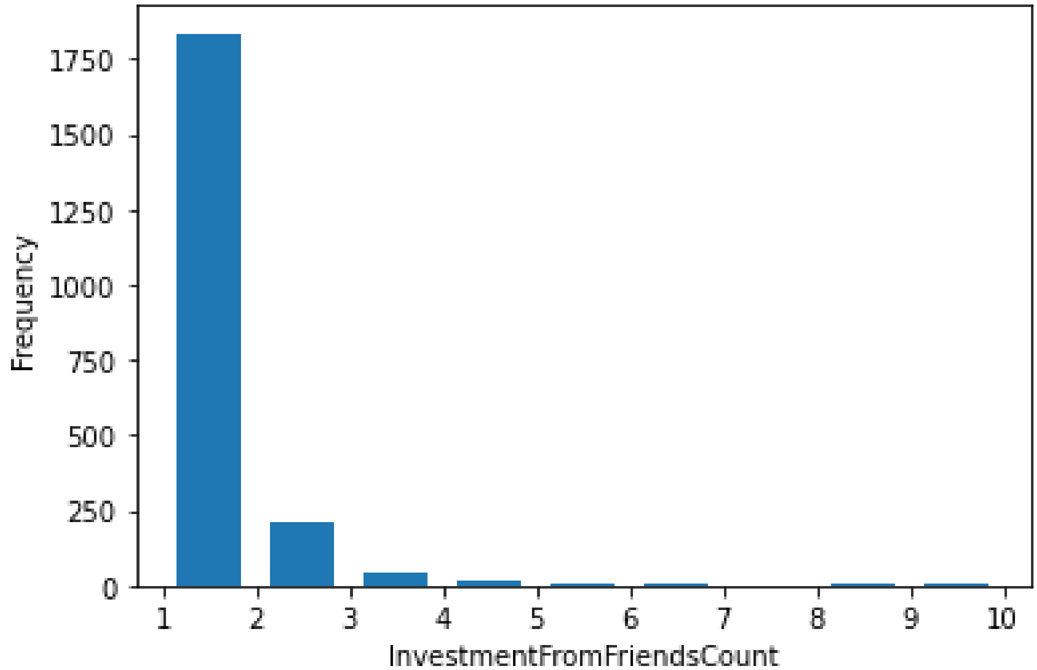
- ~90% of records have zero recommendations.

[31]:
```
#raw count of unique observations (top 5)
sub_df['InvestmentFromFriendsCount'].value_counts().head()
```

[31]:
```
0    111806
1      1835
2       215
3        40
4        15
Name: InvestmentFromFriendsCount, dtype: int64
```

[32]:
```
# create bin width
bin_edges = np.arange(1, 10+1, 1)

# plot distribution of variable as discrete
plt.hist(sub_df['InvestmentFromFriendsCount'], bins = bin_edges, rwidth = 0.7)

#x axis ticks and labels
plt.xticks(np.arange(1, 10+1, 1))
plt.xlabel('InvestmentFromFriendsCount')
```

```
plt.ylabel('Frequency');
```



Observations:

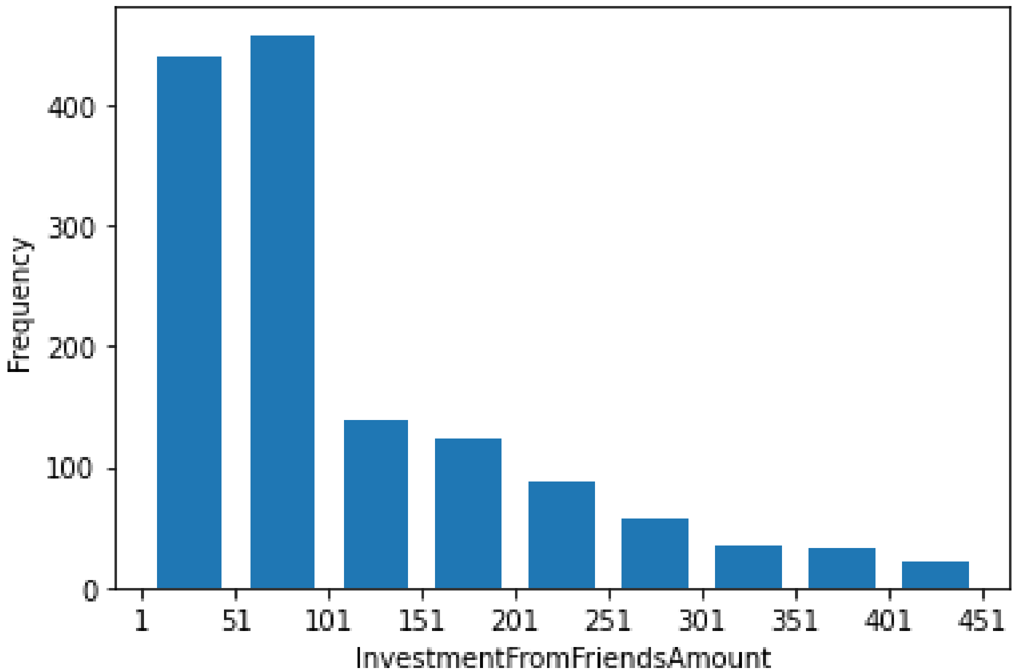
- ~99% of records have zero InvestmentFromFriendsCount.

[33]:
```
#raw count of unique observations
sub_df['InvestmentFromFriendsAmount'].value_counts()
```

[33]:
```
0.00       111806
50.00         323
100.00        242
1000.00       100
500.00         97
            …
48.51           1
102.34          1
53.27           1
953.33          1
501.99          1
Name: InvestmentFromFriendsAmount, Length: 726, dtype: int64
```

[34]:
```
# create bin width
bin_edges = np.arange(1, 500+1, 50)
```

```python
# plot distribution of variable as discrete
plt.hist(sub_df['InvestmentFromFriendsAmount'], bins = bin_edges, rwidth = 0.7)

#x axis ticks and labels
plt.xticks(np.arange(1, 500+1, 50))
plt.xlabel('InvestmentFromFriendsAmount')
plt.ylabel('Frequency');
```



Observations:

- ~99% of records have zero InvestmentFromFriendsAmount, congruent with the above variable.

[35]:
```python
sub_df['PercentFunded'].value_counts()
```

[35]:
```
1.0000    113067
0.9998         5
0.7000         4
0.8087         4
0.7784         3
           …
0.8167         1
0.7854         1
0.7903         1
0.7167         1
0.9575         1
```

```
Name: PercentFunded, Length: 719, dtype: int64
```

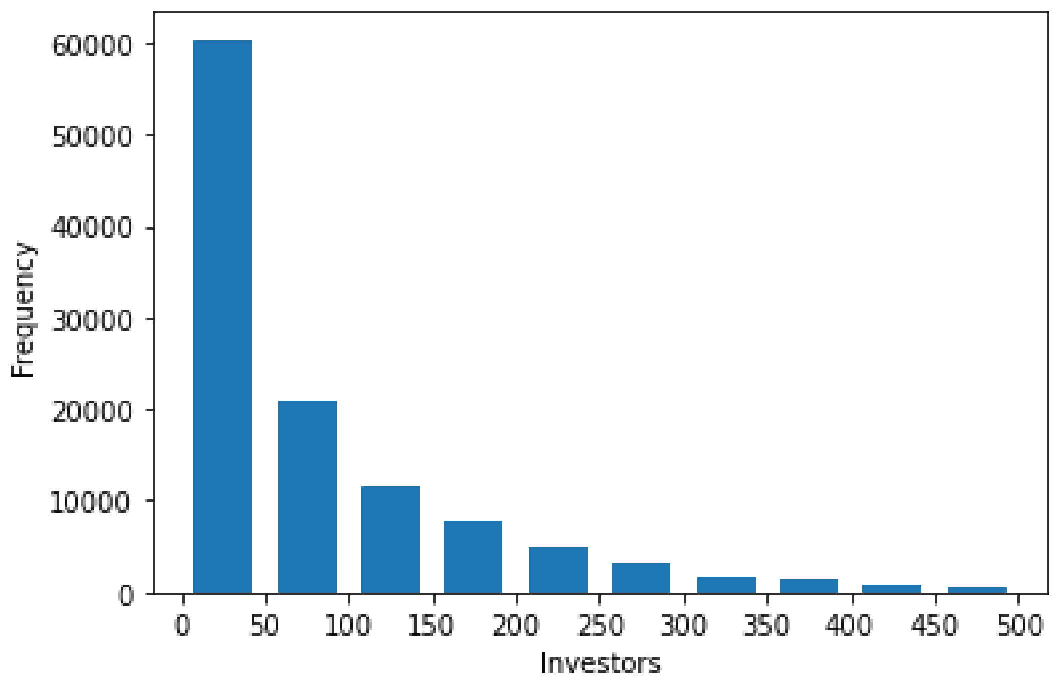
Observations:

- ~99% of records are fully funded.

[36]:
```python
#raw count of unique observations
sub_df['Investors'].value_counts()
```

[36]:
```
1      27814
2       1386
3        991
4        827
5        753
       …
881        1
801        1
752        1
715        1
831        1
Name: Investors, Length: 751, dtype: int64
```

[37]:
```python
# create bin width
bin_edges = np.arange(0, 500+1, 50)

# plot distribution of variable as discrete
plt.hist(sub_df['Investors'], bins = bin_edges, rwidth = 0.7)

#x axis ticks and labels
plt.xticks(np.arange(0, 500+1, 50))
plt.xlabel('Investors')
plt.ylabel('Frequency');
```



Observations:

- Congruent with the findings on Percent Funded.

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

1. Large spike at 0.36 APR. This probably represent a rate offered for standard loans.
2. AmountDelinquent and DebttoIncomeRatio have periodic spikes at regular intervals.
3. Over 80% of the oberservations for CurrentDelinquencies and Amount Delinquent contain a value of zero. These are probably valid as applicants are likely to be first time borrowers.
4. DebtToIncome contains outliers

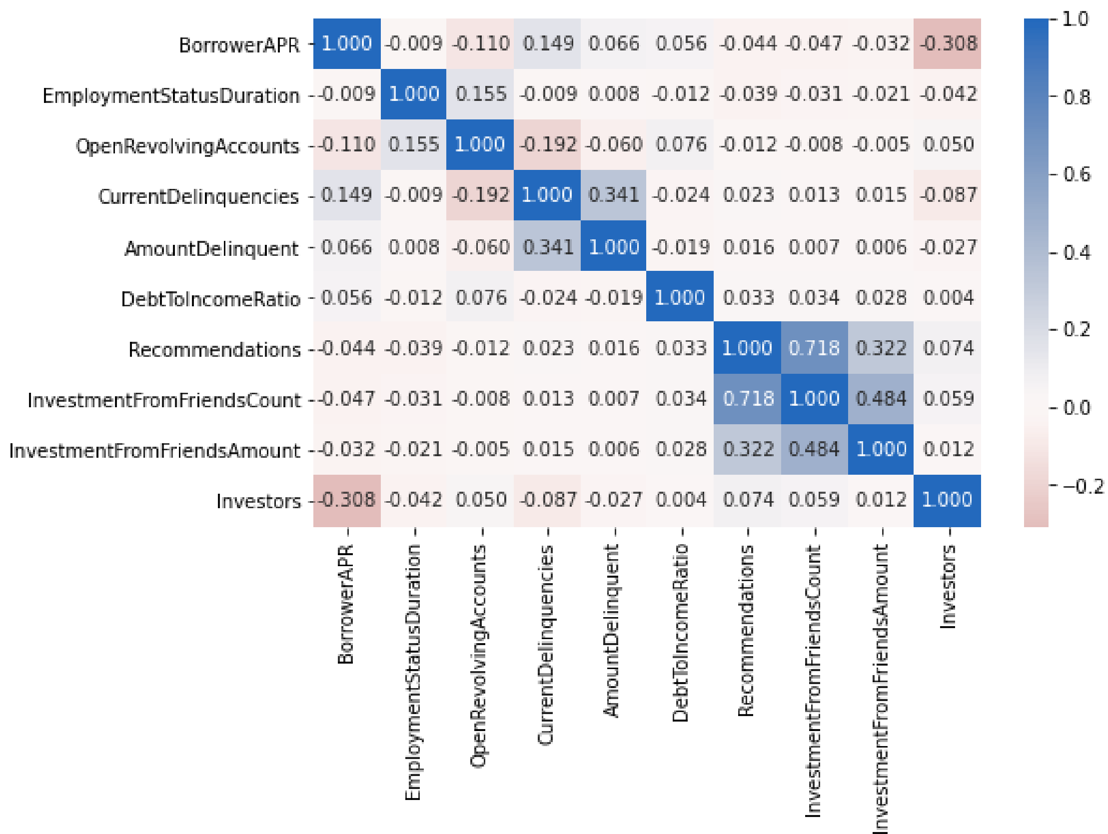
1.2.2 Of the features you investigated, were there any unusual distributions? Did you perform any operations on the data to tidy, adjust, or change the form of the data? If so, why did you do this?

1. To make visible the remaining distribution the value of zero is omitted from the visualisations for CurrentDelinquincies, AmountDelinquent, Recommendations, InvestmentFromFriendsAmount, InvestmentFromFriendsCount.
2. DebtToIncome ratio contains outlier value(s) far from the bulk of the distribution. The x-axis is truncated to magnify the bulk of the distribution.

1.3 Bivariate Exploration

[38]:
```
#isolate numeric variables
numeric_vars = ['BorrowerAPR', 'EmploymentStatusDuration' ,␣
↪'OpenRevolvingAccounts', 'CurrentDelinquencies',
                'AmountDelinquent', 'DebtToIncomeRatio', 'Recommendations',␣
↪'InvestmentFromFriendsCount'
                , 'InvestmentFromFriendsAmount', 'Investors']

#isolate categorical variables
categoric_vars = ['CreditGrade', 'Term', 'EmploymentStatus', 'ProsperScore']
```

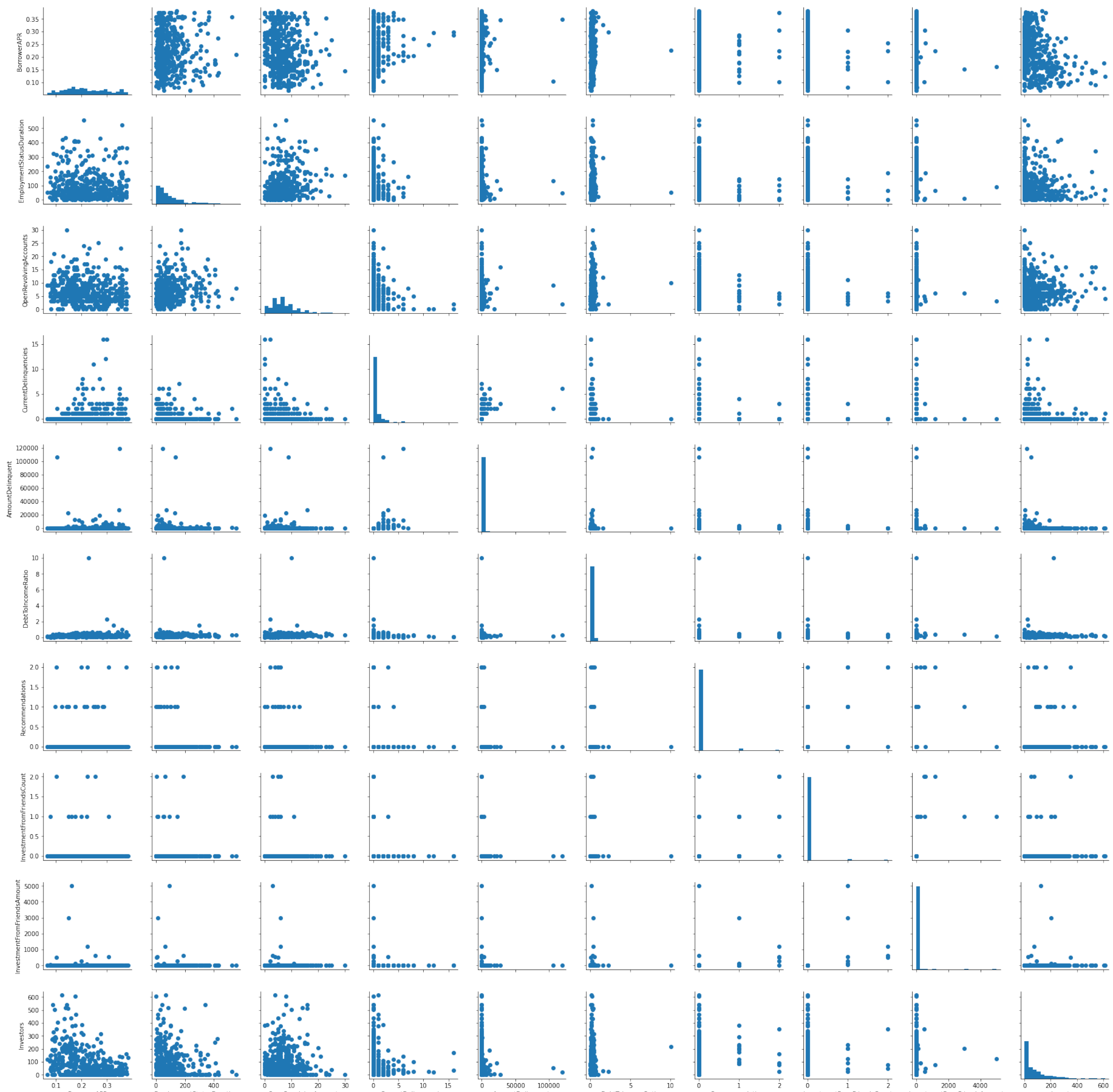
[39]:
```
# correlation plot of numeric variables
plt.figure(figsize = [8, 5])
sb.heatmap(sub_df[numeric_vars].corr(), annot = True, fmt = '.3f',
           cmap = 'vlag_r', center = 0);
```



[40]:
```
#draw random sample of 500 observations
samples = np.random.choice(sub_df.shape[0], 500, replace = False)
loans_samp = sub_df.loc[samples,:]
```

```
#pairwise scatter plots of variables using sample
g = sb.PairGrid(data = loans_samp, vars = numeric_vars)
g = g.map_diag(plt.hist, bins = 20);
g.map_offdiag(plt.scatter)
```

[40]: <seaborn.axisgrid.PairGrid at 0x1a580471488>



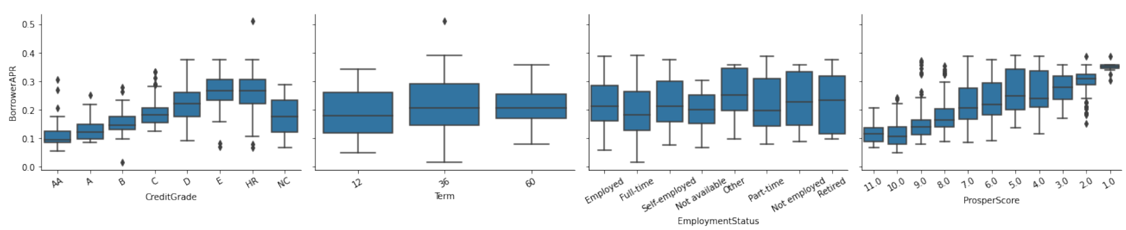
Observations:

- Borrower APR does not appear to be strongly correlated with any of the numeric variables.
- Weak/Mild pairwise correlations between AmountDelinquent & CurrentDelinquencies, InvestmentFromFriends & Recommendations, InvestmentFromFriendsCount & InvestmentFromFirendsAmount

[41]:
```
#draw random sample of 500 observations
samples = np.random.choice(sub_df.shape[0], 2000, replace = False)
loans_samp = sub_df.loc[samples,:]

#user defined function to plot multiple boxplots of categorical variables
def boxgrid(x, y, **kwargs):
    default_color = sb.color_palette()[0]
    sb.boxplot(x, y, color = default_color)
    plt.xticks(rotation=30) ;

#boxplot of categorical variables using sample
plt.figure(figsize = [10, 10])
g = sb.PairGrid(data = loans_samp, y_vars = ['BorrowerAPR'], x_vars =␣
↪categoric_vars,
                size = 3, aspect = 1.5)
g.map(boxgrid);
```

```
C:\Users\noama\anaconda3\lib\site-packages\seaborn\axisgrid.py:1264:
UserWarning: The `size` parameter has been renamed to `height`; please update
your code.
  warnings.warn(UserWarning(msg))
```

```
<Figure size 720x720 with 0 Axes>
```



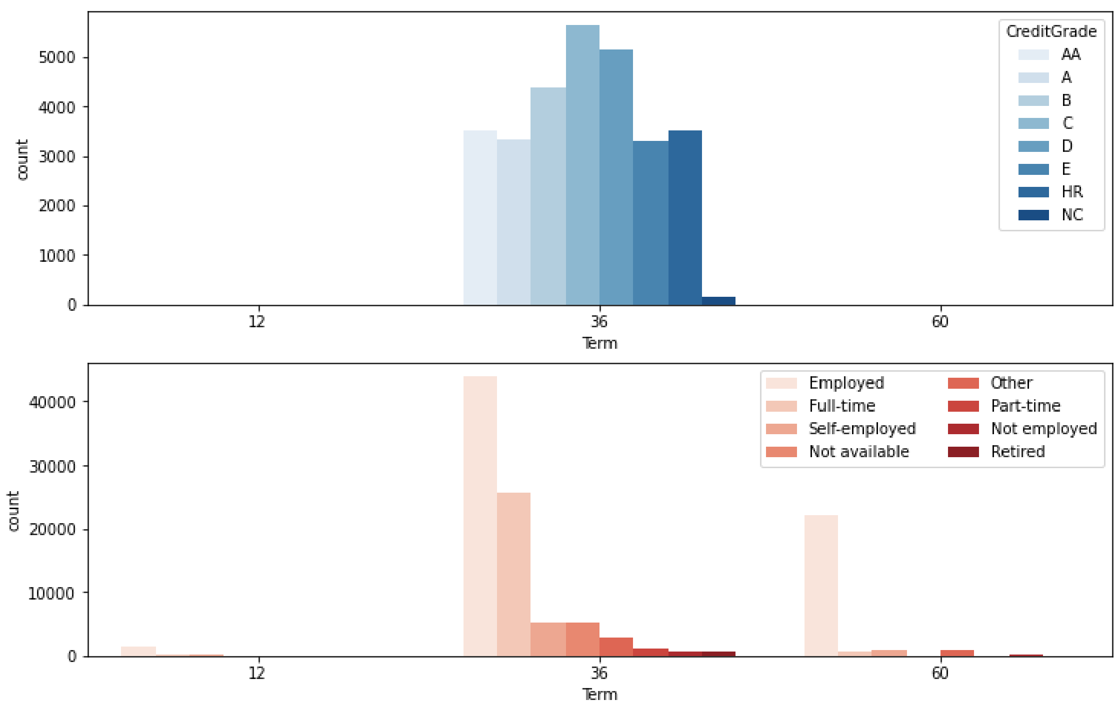
Observations:

- As expected, CreditGrade and ProsperScore have a clear effect on the rate of Borrower APR, with lower ratings correlated with higher rates of interest.
- The IQR for Term is largest for shorter term loans suggesting other variables also play a role in determining the rate of APR.
- The employment status "employed" does not appear to have a significant difference (vis-vis most of the other categories), to the implied rate of APR. The exceptions to this are the categories Part-time and Not employed.

[42]:
```
# create figure object
plt.figure(figsize = [12, 12])

# subplot 1: CreditGrade vs Term
```

```
plt.subplot(3, 1, 1)
sb.countplot(data = sub_df, x = 'Term', hue = 'CreditGrade', palette = 'Blues')

# subplot 2: Term vs. EmploymentStatus
ax = plt.subplot(3, 1, 2)
sb.countplot(data = sub_df, x = 'Term', hue = 'EmploymentStatus', palette =␣
↪'Reds')

# re-arrange legend to remove overlapping
ax.legend(ncol = 2)

# re-arrange legend to remove overlapping
ax.legend(loc = 1, ncol = 2)
```

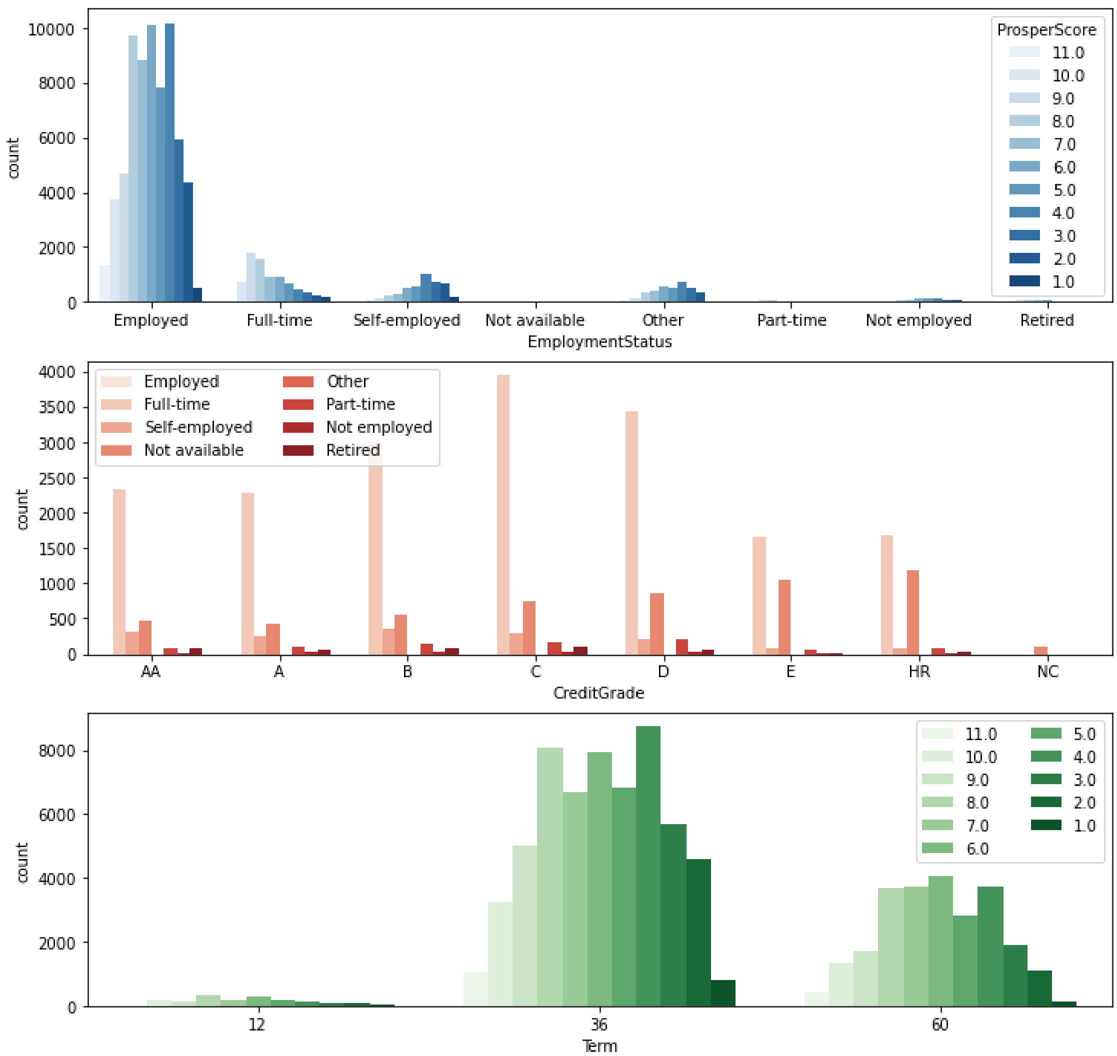
[42]: <matplotlib.legend.Legend at 0x1a583e9ce48>



[43]:
```
# create figure object
plt.figure(figsize = [12, 12])

# subplot 1: EmploymentStatus vs ProsperScore
plt.subplot(3, 1, 1)
sb.countplot(data = sub_df, x = 'EmploymentStatus', hue = 'ProsperScore',␣
↪palette = 'Blues')
```

```python
# subplot 2: CreditGrade vs. EmploymentStatus
ax = plt.subplot(3, 1, 2)
sb.countplot(data = sub_df, x = 'CreditGrade', hue = 'EmploymentStatus', palette = 'Reds')

# re-arrange legend to reduce overlapping
ax.legend(ncol = 2)

# subplot 3: ProsperScore vs. EmploymentStatus
ax = plt.subplot(3, 1, 3)
sb.countplot(data = sub_df, x = 'Term', hue = 'ProsperScore', palette = 'Greens')

# re-arrange legend to reduce overlapping
ax.legend(loc = 1, ncol = 2)
```

[43]: <matplotlib.legend.Legend at 0x1a584444e08>



Observations:

1. The imbalance of observations among the categories
2. CreditGrade and ProsperScore display a normal distribution along all of the Terms
3. The distribution of Full-time against ProsperScore is right-tailed, suggesting applicants are evaluated favourably in this category. The reverse is true for the self-employed.

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

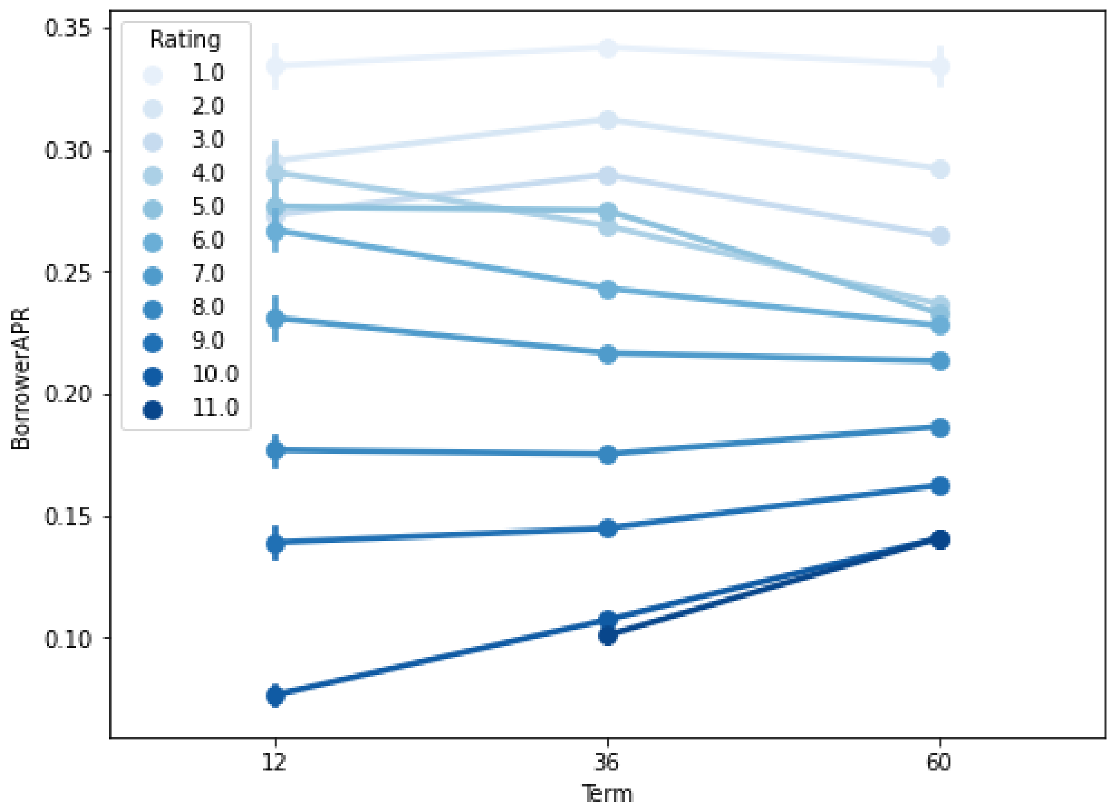
1. Borrower APR did not appear to be strongly correlated with any single numerical feature.
2. Relationships were observed between the main feature of interest (Borrower APR) and the categorical features. CreditGrade and ProsperScore were found to have a clear relationship with Borrwer APR, with rates of interest offered in according with the ranking of the application. Said otherwise, applicants with a "better" rating were offfered lower rates of interest. This chimes with offering competitive terms to applicants assessed as a lower credit risk.
3. Interestingly, the term of a loan is correlated with Borrower APR, with longer terms displaying less variation (as measured by the IQR) than shorter term loans.

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

1. Some form of income (Employed, Full-time, Self-employed) is correlated with higher ranked CreditGrade and ProsperScore.
2. The self-employed however tend to have a lower ProsperScore than the Full-time and employed.

1.4 Multivariate Exploration

[44]:
```
#create figure
fig = plt.figure(figsize=[8,6])

#create pointplot of BorrowerAPR with ProsperScorwe
ax = sb.pointplot(data=df, x='Term', y='BorrowerAPR', hue='ProsperScore',
                  palette='Blues');
plt.legend(loc=2, title='Rating');
```



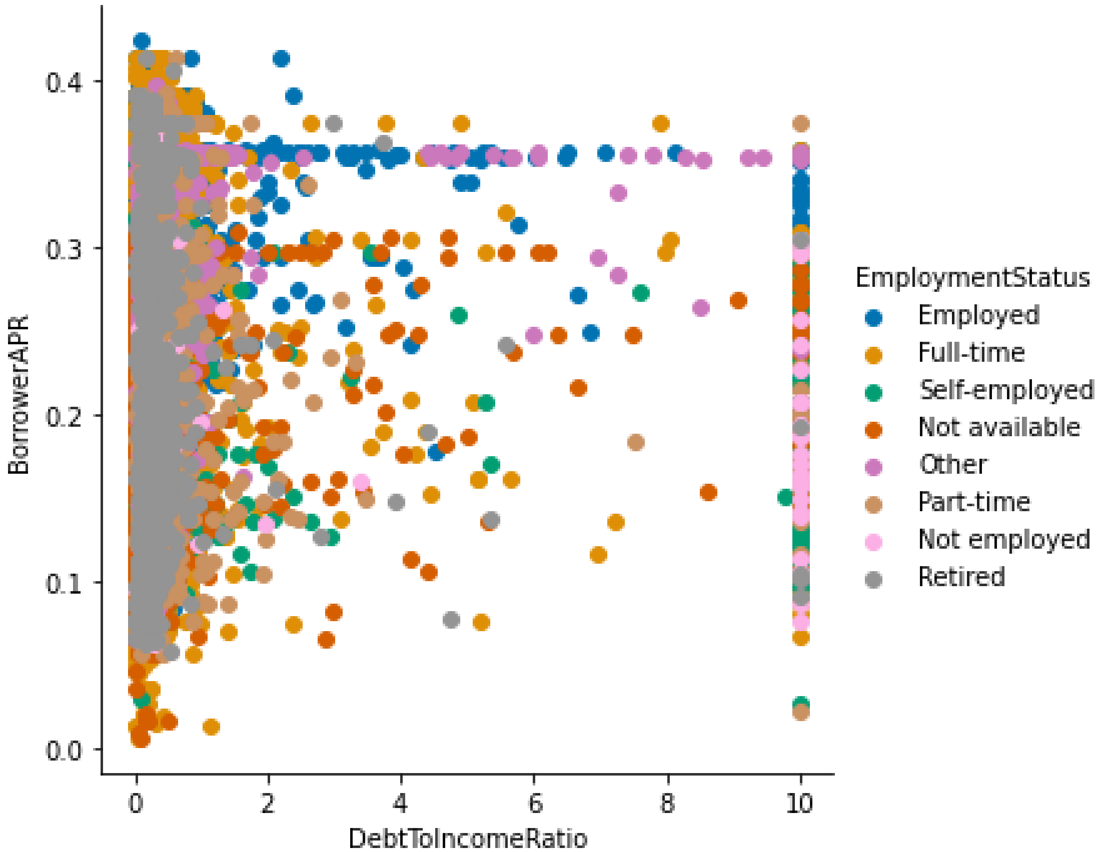
Observations:

- The results appear counter intuitive, with interest rates higher for longer term loans, for some ProsperScore levels.

[45]:
```
#scatter plot with a 3 variable encoded with color
g = sb.FacetGrid(data = sub_df, hue = 'EmploymentStatus', size = 5,
                 palette = 'colorblind')
g.map(plt.scatter, 'DebtToIncomeRatio', 'BorrowerAPR')
g.add_legend()
```

```
C:\Users\noama\anaconda3\lib\site-packages\seaborn\axisgrid.py:243: UserWarning:
The `size` parameter has been renamed to `height`; please update your code.
  warnings.warn(msg, UserWarning)
```

[45]:
```
<seaborn.axisgrid.FacetGrid at 0x1a584ceed48>
```

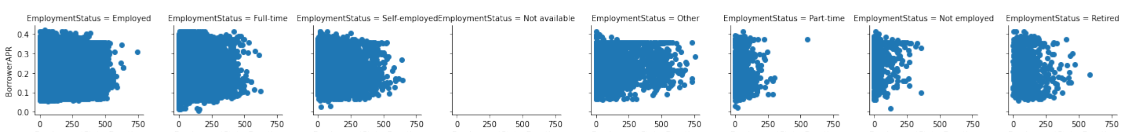


Observations:

- applicants not employed tend to have a higher DebtToIncomeRatio than applicants that are either Employed or Full-time.

[46]:
```python
#scatter plots facetting by employedstatus
g = sb.FacetGrid(data = sub_df, col = 'EmploymentStatus', size = 2.5,
                margin_titles = True)
g.map(plt.scatter, 'EmploymentStatusDuration', 'BorrowerAPR')
```

[46]:
```
<seaborn.axisgrid.FacetGrid at 0x1a584cf8548>
```



Observations:

- No single employment status and duration is strongly correlated with Borrower APR.

1.4.1 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?

1. As noted, longer term loans carry higher rates of interest. This trend is even more pronounced for loan applications with a lower PropserScore rating.

1.4.2 Were there any interesting or surprising interactions between features?

1. Counter intuitively, Borrower APR is not systematically different for applicants with a higher debt to income ratio. This is becuase the relationship may be moderated by other features.
2. BorrowerAPR increases for longer Term loans. The opposite could reasonably be expected with longer term loans generally carrying a lower risk profile as they have a longer time to accrue interest. Perthaps, principal at risk is weighted more heavily than return on loan (interest payments) among the profile of applicants in the dataset.