Part_I_exploration_template

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1 Part I - Borrower's Annual Percentage Rate (BAPR) Exploration

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1.1 Introduction

This document explores a dataset containing loans and attributes for approximately 113937 individuals. The Borrower's Annual Percentage Rate (APR) for the loans is of particular interest for this analysis.

1.2 Preliminary Wrangling

1.2.1 Load Required Modules

```
In [1]: # 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
```

1.2.2 Load Prosper csv data

```
In [2]: #load prosper loan into a dataframe
        prosper_loan_data = pd.read_csv('prosperLoanData.csv')
```

1.2.3 Checking Data Properties

Check data Shape
Check Data Types
View Some Rows
View Observations per column

```
In [3]: print(prosper_loan_data.shape)
        print(prosper_loan_data.dtypes)
        print(prosper_loan_data.head(10))
        print(prosper_loan_data.count())
```

```
(113937, 81)
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
                ListingKey  ListingNumber            ListingCreationDate  \
0  1021339766868145413AB3B         193129  2007-08-26 19:09:29.263000000
1  10273602499503308B223C1        1209647  2014-02-27 08:28:07.900000000
2  0EE9337825851032864889A          81716  2007-01-05 15:00:47.090000000
3  0EF5356002482715299901A         658116  2012-10-22 11:02:35.010000000
4  0F023589499656230C5E3E2         909464  2013-09-14 18:38:39.097000000
5  0F05359734824199381F61D        1074836  2013-12-14 08:26:37.093000000
6  0F0A3576754255009D63151         750899  2013-04-12 09:52:56.147000000
7  0F1035772717087366F9EA7         768193  2013-05-05 06:49:27.493000000
8  0F043596202561788EA13D5        1023355  2013-12-02 10:43:39.117000000
9  0F043596202561788EA13D5        1023355  2013-12-02 10:43:39.117000000

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

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

```
8       0.0629       0.0529    ...             -16.77                0.0
9       0.0629       0.0529    ...             -16.77                0.0

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

   PercentFunded  Recommendations InvestmentFromFriendsCount  \
0            1.0                0                           0
1            1.0                0                           0
2            1.0                0                           0
3            1.0                0                           0
4            1.0                0                           0
5            1.0                0                           0
6            1.0                0                           0
7            1.0                0                           0
8            1.0                0                           0
9            1.0                0                           0

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

[10 rows x 81 columns]
ListingKey                             113937
ListingNumber                          113937
ListingCreationDate                    113937
CreditGrade                             28953
Term                                   113937
LoanStatus                             113937
ClosedDate                              55089
BorrowerAPR                            113912
```

```
BorrowerRate                          113937
LenderYield                           113937
EstimatedEffectiveYield                84853
EstimatedLoss                          84853
EstimatedReturn                        84853
ProsperRating (numeric)                84853
ProsperRating (Alpha)                  84853
ProsperScore                           84853
ListingCategory (numeric)             113937
BorrowerState                         108422
Occupation                            110349
EmploymentStatus                      111682
EmploymentStatusDuration              106312
IsBorrowerHomeowner                   113937
CurrentlyInGroup                      113937
GroupKey                               13341
DateCreditPulled                      113937
CreditScoreRangeLower                 113346
CreditScoreRangeUpper                 113346
FirstRecordedCreditLine               113240
CurrentCreditLines                    106333
OpenCreditLines                       106333
                                       ...
TotalProsperLoans                      22085
TotalProsperPaymentsBilled             22085
OnTimeProsperPayments                  22085
ProsperPaymentsLessThanOneMonthLate    22085
ProsperPaymentsOneMonthPlusLate        22085
ProsperPrincipalBorrowed               22085
ProsperPrincipalOutstanding            22085
ScorexChangeAtTimeOfListing            18928
LoanCurrentDaysDelinquent             113937
LoanFirstDefaultedCycleNumber          16952
LoanMonthsSinceOrigination            113937
LoanNumber                            113937
LoanOriginalAmount                    113937
LoanOriginationDate                   113937
LoanOriginationQuarter                113937
MemberKey                             113937
MonthlyLoanPayment                    113937
LP_CustomerPayments                   113937
LP_CustomerPrincipalPayments          113937
LP_InterestandFees                    113937
LP_ServiceFees                        113937
LP_CollectionFees                     113937
LP_GrossPrincipalLoss                 113937
LP_NetPrincipalLoss                   113937
LP_NonPrincipalRecoverypayments       113937
```

```
PercentFunded                       113937
Recommendations                     113937
InvestmentFromFriendsCount          113937
InvestmentFromFriendsAmount         113937
Investors                           113937
Length: 81, dtype: int64
```

1.2.4 Tidy up Data

Filtering the data **Attributes** - For the purpose of this data analysis a subset of the entire attributes has been selected. The proceeding section deal with tidying up the data for analysis.

Selection Attributes

```
In [4]: prosper_filter_data=prosper_loan_data[['Term','LoanStatus','BorrowerAPR','ProsperRating
```

Data Subset Selection *The main interest are those borrowers that have/had Prosper Loan*

```
In [5]: previous_borrowers = prosper_filter_data[prosper_filter_data.TotalProsperLoans.isnull()
```

```
In [6]: previous_borrowers.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 22085 entries, 4 to 113935
Data columns (total 11 columns):
Term                     22085 non-null int64
LoanStatus               22085 non-null object
BorrowerAPR              22085 non-null float64
ProsperRating (Alpha)    19797 non-null object
Occupation               22059 non-null object
CreditScoreRangeLower    22085 non-null float64
CreditScoreRangeUpper    22085 non-null float64
CurrentCreditLines       22085 non-null float64
BankcardUtilization      22085 non-null float64
IncomeRange              22085 non-null object
TotalProsperLoans        22085 non-null float64
dtypes: float64(6), int64(1), object(4)
memory usage: 2.0+ MB
```

Correcting Missing Records & Tidy Up Names

```
In [7]: ## The 2 attributes below have missing data, anything that is null will be removed so we
        previous_borrowers = previous_borrowers[previous_borrowers['ProsperRating (Alpha)'].isnu
        previous_borrowers = previous_borrowers[previous_borrowers.Occupation.isnull()==False]
```

```
In [8]: ## Set ProsperRating (Alpha) to ProsperRating
        names = ['Term', 'LoanStatus', 'BorrowerAPR', 'ProsperRating','Occupation','CreditScoreR
        previous_borrowers.columns = names
```

Recheck data properties **Check data Shape**
Check Data Types
View Some Rows
View Observations per column

In [9]:
```
#Shape, get observations and attributes
previous_borrowers.shape
```

Out[9]:
```
(19771, 11)
```

In [10]:
```
#Head, get few rows to observe the data Structure
previous_borrowers.head()
```

Out[10]:
```
    Term LoanStatus  BorrowerAPR ProsperRating   Occupation  \
4     36    Current      0.24614             D    Executive
16    60    Current      0.30748             E  Professional
19    60    Current      0.24754             D      Laborer
33    36  Completed      0.08191            AA        Other
47    36    Current      0.15833             A  Professional

    CreditScoreRangeLower  CreditScoreRangeUpper  CurrentCreditLines  \
4                   680.0                  699.0                19.0
16                  640.0                  659.0                 6.0
19                  680.0                  699.0                15.0
33                  760.0                  779.0                 6.0
47                  680.0                  699.0                15.0

    BankcardUtilization     IncomeRange  TotalProsperLoans
4                  0.81        $100,000+                1.0
16                 1.00  $75,000-99,999                 3.0
19                 0.60  $25,000-49,999                 1.0
33                 0.01        $100,000+                1.0
47                 0.84  $50,000-74,999                 3.0
```

In [11]:
```
previous_borrowers.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 19771 entries, 4 to 113935
Data columns (total 11 columns):
Term                     19771 non-null int64
LoanStatus               19771 non-null object
BorrowerAPR              19771 non-null float64
ProsperRating            19771 non-null object
Occupation               19771 non-null object
CreditScoreRangeLower    19771 non-null float64
CreditScoreRangeUpper    19771 non-null float64
CurrentCreditLines       19771 non-null float64
BankcardUtilization      19771 non-null float64
IncomeRange              19771 non-null object
```

```
TotalProsperLoans        19771 non-null float64
dtypes: float64(6), int64(1), object(4)
memory usage: 1.8+ MB
```

In [12]:
```
previous_borrowers.CurrentCreditLines = previous_borrowers.CurrentCreditLines.astype('i
```

In [13]:
```
previous_borrowers.describe()
```

Out[13]:

	Term	BorrowerAPR	CreditScoreRangeLower
count	19771.000000	19771.000000	19771.000000
mean	42.245511	0.220972	686.843356
std	11.754228	0.082770	52.017707
min	12.000000	0.045830	600.000000
25%	36.000000	0.153240	640.000000
50%	36.000000	0.214740	680.000000
75%	60.000000	0.287040	720.000000
max	60.000000	0.413550	880.000000

	CreditScoreRangeUpper	CurrentCreditLines	BankcardUtilization
count	19771.000000	19771.000000	19771.000000
mean	705.843356	11.022002	0.569269
std	52.017707	5.515708	0.321402
min	619.000000	0.000000	0.000000
25%	659.000000	7.000000	0.300000
50%	699.000000	10.000000	0.620000
75%	739.000000	14.000000	0.860000
max	899.000000	59.000000	2.500000

	TotalProsperLoans
count	19771.000000
mean	1.460118
std	0.788810
min	0.000000
25%	1.000000
50%	1.000000
75%	2.000000
max	8.000000

In [14]:
```
previous_borrowers.describe()
```

Out[14]:

	Term	BorrowerAPR	CreditScoreRangeLower
count	19771.000000	19771.000000	19771.000000
mean	42.245511	0.220972	686.843356
std	11.754228	0.082770	52.017707
min	12.000000	0.045830	600.000000
25%	36.000000	0.153240	640.000000
50%	36.000000	0.214740	680.000000
75%	60.000000	0.287040	720.000000

```
max       60.000000      0.413550            880.000000

       CreditScoreRangeUpper  CurrentCreditLines  BankcardUtilization  \
count           19771.000000        19771.000000         19771.000000
mean              705.843356           11.022002             0.569269
std                52.017707            5.515708             0.321402
min               619.000000            0.000000             0.000000
25%               659.000000            7.000000             0.300000
50%               699.000000           10.000000             0.620000
75%               739.000000           14.000000             0.860000
max               899.000000           59.000000             2.500000

       TotalProsperLoans
count       19771.000000
mean            1.460118
std             0.788810
min             0.000000
25%             1.000000
50%             1.000000
75%             2.000000
max             8.000000
```

Convert float types to Percentage as they produce more understandable values

In [15]:
```
previous_borrowers["BorrowerAPR"]=previous_borrowers["BorrowerAPR"]*100
previous_borrowers["BankcardUtilization"]=previous_borrowers["BankcardUtilization"]*100
```

In [16]:
```
previous_borrowers.head(1)
```

Out[16]:
```
   Term LoanStatus  BorrowerAPR ProsperRating Occupation  \
4    36    Current       24.614             D  Executive

   CreditScoreRangeLower  CreditScoreRangeUpper  CurrentCreditLines  \
4                  680.0                  699.0                  19

   BankcardUtilization IncomeRange  TotalProsperLoans
4                 81.0   $100,000+                1.0
```

Ordinal Data Types

ProsperRating - Order ordinal data type and set type to category

IncomeRange - Order ordinal data type and set type to category

In [17]:
```
print(previous_borrowers.ProsperRating.value_counts())
rating_classes = ['HR','E','D','C','B','A','AA']

ProsperRating = pd.api.types.CategoricalDtype(ordered = True, categories = rating_class
previous_borrowers['ProsperRating'] = previous_borrowers['ProsperRating'].astype(Prospe
```

```
A     4408
C     3513
D     3359
B     3278
E     2567
AA    1363
HR    1283
Name: ProsperRating, dtype: int64
```

In [18]:
```
print(previous_borrowers.LoanStatus.value_counts())
```

```
Current                   10856
Completed                  6494
Chargedoff                 1466
Defaulted                   291
Past Due (1-15 days)        247
Past Due (61-90 days)        98
Past Due (91-120 days)       93
Past Due (31-60 days)        86
Past Due (16-30 days)        74
FinalPaymentInProgress       61
Past Due (>120 days)          5
Name: LoanStatus, dtype: int64
```

In [19]:
```
previous_borrowers.IncomeRange.value_counts()
```

Out[19]:
```
$50,000-74,999    5883
$25,000-49,999    5591
$100,000+         3702
$75,000-99,999    3413
$1-24,999         1040
Not employed       116
$0                  26
Name: IncomeRange, dtype: int64
```

In [20]:
```
income_range_class = ["Not employed","$0","$1-24,999", "$25,000-49,999","$50,000-74,999
IncomeRange = pd.api.types.CategoricalDtype(ordered = True, categories = income_range_c
previous_borrowers['IncomeRange'] = previous_borrowers['IncomeRange'].astype(IncomeRang
```

1.2.5 What is the structure of your dataset?

The original dataset has 113937 observations with 81 attributes, it has been filtered to only include the people that have had/have loans with prosper before. The subset of the dataset now has 19771 observations and 11 attributes.

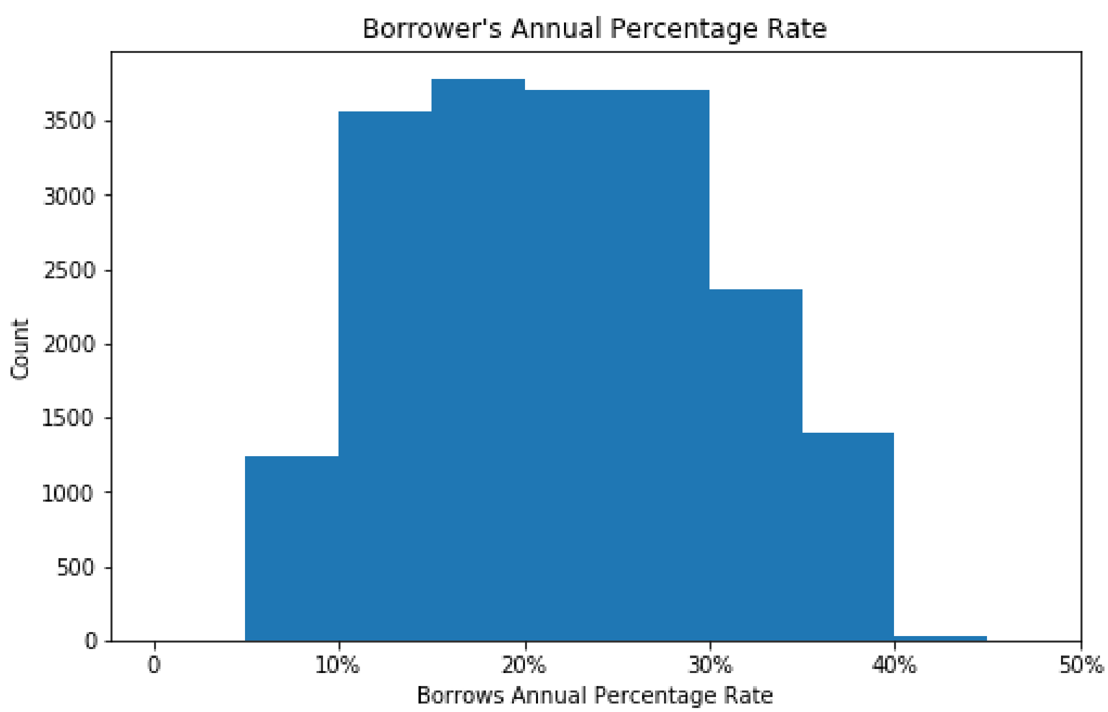
1.2.6 What is/are the main feature(s) of interest in your dataset?

I am interested in the cost of borrowing for people who have had/have prior loans with Prosper. ### What features in the dataset do you think will help support your investigation into your feature(s) of interest? - Term - LoanStatus - BorrowerAPR - ProsperRating (Alpha), renamed to ProsperRating - Occupation - CreditScoreRangeUpper - CreditScoreRangeLower - CurrentCreditLines - BankcardUtilization - IncomeRange - TotalProsperLoans

1.3 Univariate Exploration

In this section, distributions of individual variables are investigated. To see any unusual points or outliers and a deeper look is under take to clean things up and preparation to identify relationships between variables.

In [21]:
```
# Plotting the main variable of interest BorrowerAPR
binsize = 5
bins = np.arange(0, previous_borrowers['BorrowerAPR'].max()+binsize, binsize)
#print(bins)
plt.figure(figsize=[8, 5])
plt.hist(data = previous_borrowers, x = 'BorrowerAPR', bins=bins)
plt.xlabel('Borrows Annual Percentage Rate')
plt.xticks([0,10,20,30,40,50],["0","10%","20%","30%","40%","50%"])
plt.ylabel('Count')
plt.title("Borrower's Annual Percentage Rate")
plt.show()
```



1.3.1 Borrower's Annual Percentage Rate

The Borrower's APR is the annual interest rate charged on a loan. The graph depicts peak Borrower's APR lies between 12% to around 30%. The bin size shows this distribution is unimodal. There is a small number of borrowers with APR that is greater than 40%. I would like to see the raw data for this because is comparatively as oppose to the other APR percentages.

```
In [22]: previous_borrowers[previous_borrowers.BorrowerAPR>40]
```

```
Out[22]:         Term  LoanStatus  BorrowerAPR ProsperRating  \
        2294      36   Completed       40.243            HR
        18473     36   Completed       41.355            HR
        20467     36   Completed       41.355            HR
        28838     36   Completed       41.355            HR
        31732     36   Completed       41.355            HR
        34027     36  Chargedoff       41.355            HR
        36015     36   Completed       41.355            HR
        38573     36   Completed       40.243            HR
        53012     36   Completed       40.315            HR
        54181     36   Completed       40.679             E
        56449     36  Chargedoff       41.355            HR
        58811     36   Completed       41.355            HR
        63447     36   Completed       40.243            HR
        76082     36   Completed       40.243            HR
        81889     36   Defaulted       40.243            HR
        84502     36   Completed       41.355            HR
        86115     36  Chargedoff       40.429            HR
        87372     36   Completed       40.304            HR
        88478     36   Completed       41.355            HR
        94636     36  Chargedoff       40.243            HR
        99888     36   Completed       40.679             E
        101039    36  Chargedoff       41.355            HR
        111463    36   Completed       41.355            HR

                                 Occupation  CreditScoreRangeLower  \
        2294                   Professional                  620.0
        18473                  Professional                  660.0
        20467                Sales - Retail                  640.0
        28838                         Other                  620.0
        31732                     Executive                  600.0
        34027                     Executive                  620.0
        36015                  Professional                  640.0
        38573                  Professional                  620.0
        53012                Sales - Retail                  660.0
        54181                         Other                  660.0
        56449                  Professional                  640.0
        58811                         Other                  640.0
        63447  Student - College Graduate Student             620.0
        76082                         Other                  620.0
```

81889	Other	600.0
84502	Realtor	640.0
86115	Military Enlisted	640.0
87372	Sales - Retail	600.0
88478	Computer Programmer	620.0
94636	Food Service	600.0
99888	Analyst	680.0
101039	Other	600.0
111463	Truck Driver	620.0

	CreditScoreRangeUpper	CurrentCreditLines	BankcardUtilization \
2294	639.0	9	30.0
18473	679.0	9	0.0
20467	659.0	5	88.0
28838	639.0	14	68.0
31732	619.0	18	100.0
34027	639.0	7	0.0
36015	659.0	7	98.0
38573	639.0	17	91.0
53012	679.0	17	25.0
54181	679.0	4	96.0
56449	659.0	16	80.0
58811	659.0	13	116.0
63447	639.0	8	51.0
76082	639.0	4	99.0
81889	619.0	6	0.0
84502	659.0	5	88.0
86115	659.0	10	85.0
87372	619.0	11	81.0
88478	639.0	11	68.0
94636	619.0	5	21.0
99888	699.0	12	86.0
101039	619.0	9	103.0
111463	639.0	3	39.0

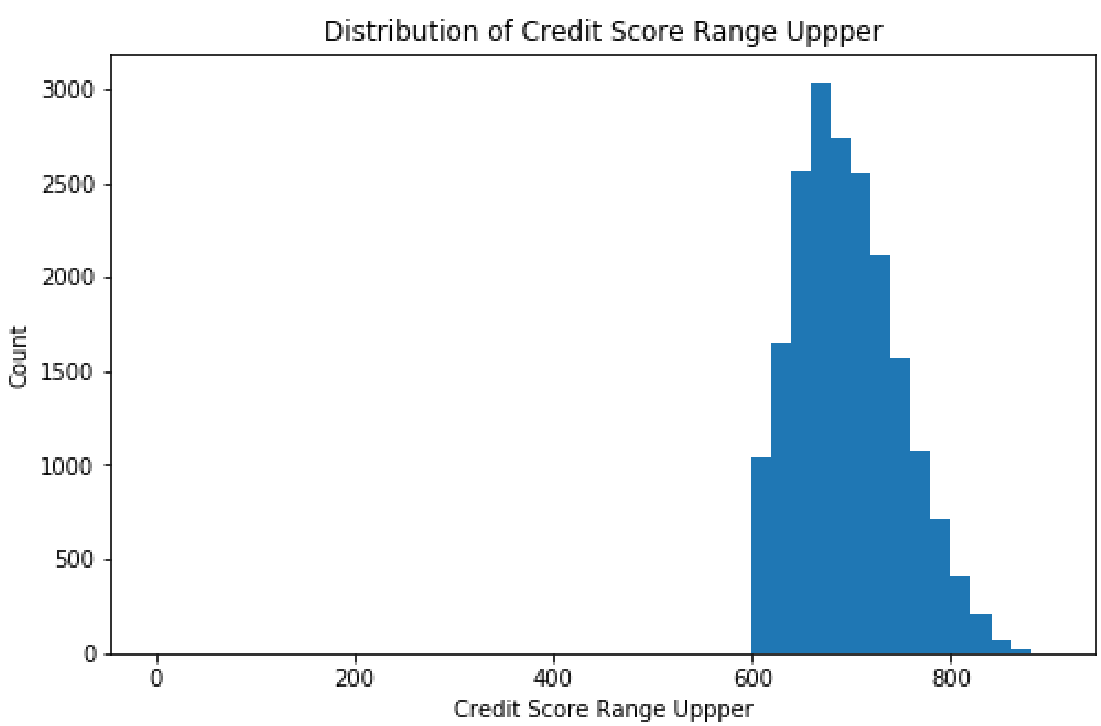
	IncomeRange	TotalProsperLoans
2294	$25,000-49,999	1.0
18473	$100,000+	1.0
20467	$1-24,999	1.0
28838	$25,000-49,999	1.0
31732	$75,000-99,999	1.0
34027	$50,000-74,999	1.0
36015	$50,000-74,999	3.0
38573	$50,000-74,999	1.0
53012	$25,000-49,999	1.0
54181	Not employed	2.0
56449	$50,000-74,999	2.0
58811	$50,000-74,999	1.0

```
63447          $1-24,999                  1.0
76082     $25,000-49,999                  2.0
81889     $25,000-49,999                  2.0
84502          $1-24,999                  1.0
86115     $50,000-74,999                  1.0
87372     $50,000-74,999                  3.0
88478     $50,000-74,999                  2.0
94636     $25,000-49,999                  1.0
99888     $50,000-74,999                  1.0
101039    $25,000-49,999                  1.0
111463         $1-24,999                  2.0
```

1.3.2 Borrower's APR

There are no notable anonmalies in the data but the outliers in this case will aid in investigating other features. Particularly, the prosper rating, for those above 40%, it is on the low end.

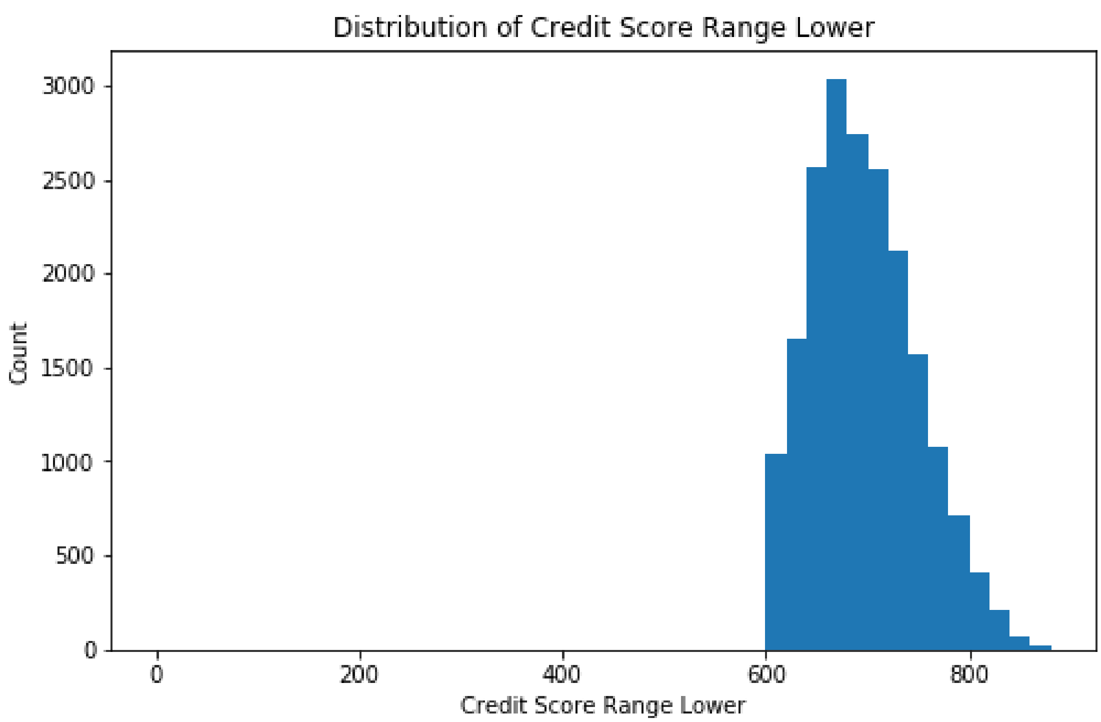
In [23]:
```
# Plot of Credit Score Range Upper
binsize = 20
bins = np.arange(0, previous_borrowers['CreditScoreRangeUpper'].max()+binsize, binsize)
plt.figure(figsize=[8, 5])
plt.hist(data = previous_borrowers, x = 'CreditScoreRangeUpper', bins=bins)
plt.xlabel('Credit Score Range Uppper')
plt.title('Distribution of Credit Score Range Uppper')
plt.ylabel('Count')
plt.show()
```



1.3.3 Credit Score Range Upper

The credit score appears to be unimodal as well. Similarly the vast majority of the lie in a particular range 680 to 730, with the extreme ends having fewer numbers.

```
In [24]: # Plot of Credit Score Range Upper
         binsize = 20
         bins = np.arange(0, previous_borrowers['CreditScoreRangeLower'].max()+binsize, binsize)
         plt.figure(figsize=[8, 5])
         plt.hist(data = previous_borrowers, x = 'CreditScoreRangeLower', bins=bins)
         plt.xlabel('Credit Score Range Lower')
         plt.title('Distribution of Credit Score Range Lower')
         plt.ylabel('Count')
         plt.show()
```

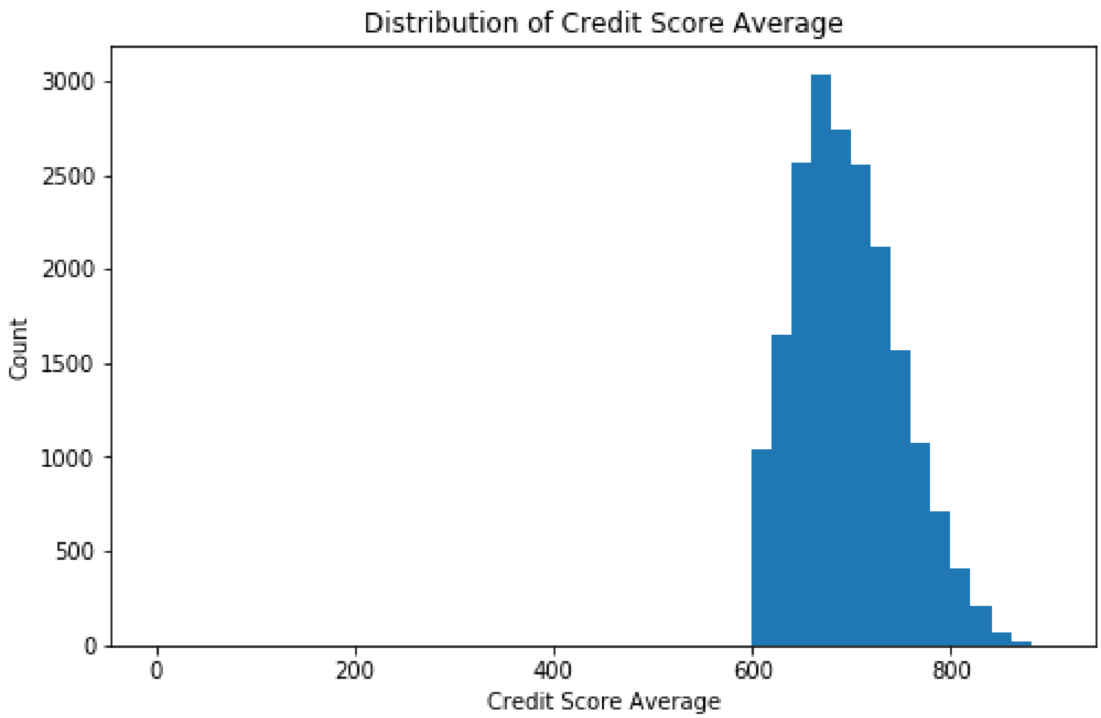


1.3.4 Credit Score Range Lower

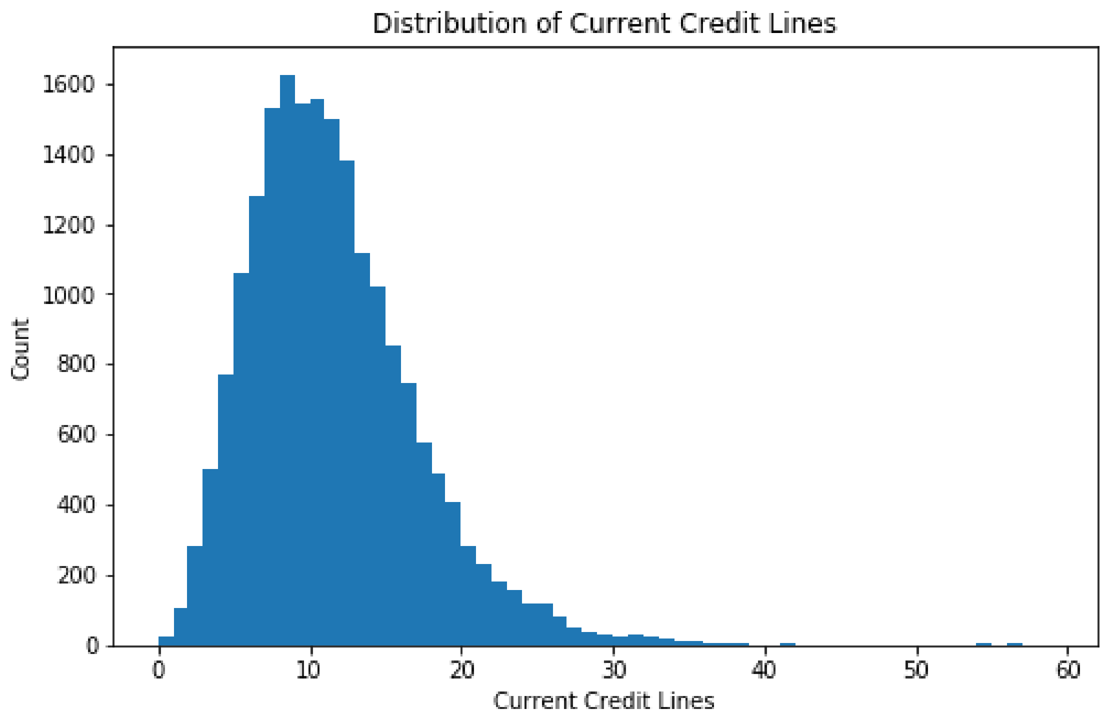
The distriubtion of both Credit Score Range Lower and Credit Score Range Upper is an identical unimodal distribution. For further analysis will consider final that is the average of Credit Scores.

```
In [25]: previous_borrowers['CreditScoreAvg'] = (previous_borrowers['CreditScoreRangeLower'] + p
```

In [26]:
```python
# Plot of Credit Score Average
binsize = 20
bins = np.arange(0, previous_borrowers['CreditScoreAvg'].max()+binsize, binsize)
plt.figure(figsize=[8, 5])
plt.hist(data = previous_borrowers, x = 'CreditScoreAvg', bins=bins)
plt.xlabel('Credit Score Average')
plt.title('Distribution of Credit Score Average')
plt.ylabel('Count')
plt.show()
```



In [27]:
```python
# Plot of Current Credit Lines
binsize = 1
bins = np.arange(0, previous_borrowers['CurrentCreditLines'].max()+binsize, binsize)
plt.figure(figsize=[8, 5])
plt.hist(data = previous_borrowers, x = 'CurrentCreditLines', bins=bins)
plt.xlabel('Current Credit Lines')
plt.title('Distribution of Current Credit Lines')
plt.ylabel('Count')
plt.show()
```



1.3.5 Current Credit Lines

The majority of the credit lines are around 10. This is a unimodal graph skewed to the right like the Borrower's APR graph. It tails off to right with values around 25 to 50, a log transform will give a better picture of the distribution for values greater than 25 to 28.

In [28]:
```
previous_borrowers.CurrentCreditLines.describe()
```

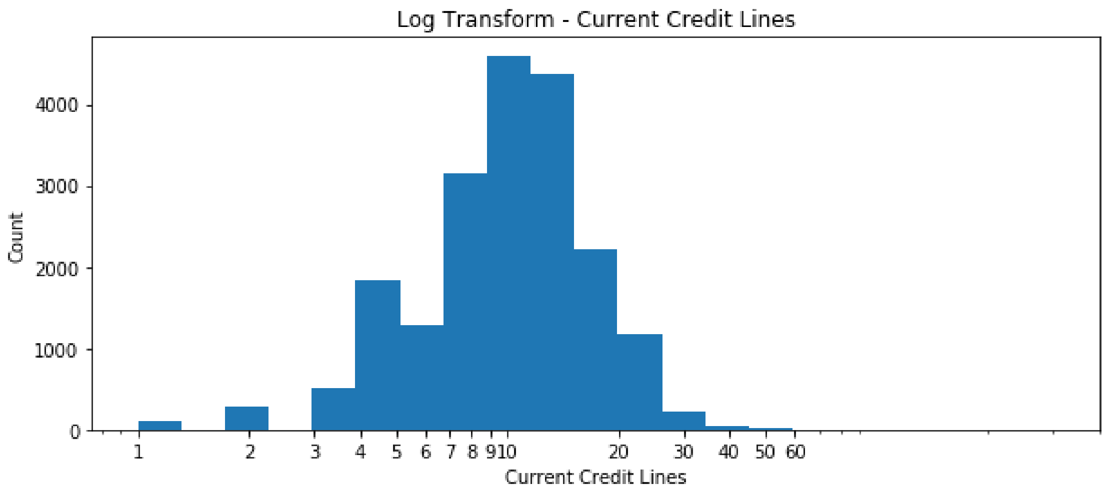
Out[28]:
```
count    19771.000000
mean        11.022002
std          5.515708
min          0.000000
25%          7.000000
50%         10.000000
75%         14.000000
max         59.000000
Name: CurrentCreditLines, dtype: float64
```

In [29]:
```
np.log(previous_borrowers.CurrentCreditLines[previous_borrowers.CurrentCreditLines > 0]
```

Out[29]:
```
count    9.890807
mean     2.401057
std      1.705851
min      0.000000
```

```
25%      1.945910
50%      2.302585
75%      2.639057
max      4.077537
Name: CurrentCreditLines, dtype: float64
```

In [30]:
```
# start with a standard-scaled plot
bins = 30 ** np.arange(0, 1.6+0.1, 0.08)
plt.figure(figsize=[10, 4])
plt.hist(data = previous_borrowers[previous_borrowers.CurrentCreditLines > 0], x = 'Cur
ticks = [1,2,3,4,5,6,7,8,9,10,20,30,40,50,60]
labels = ['{}'.format(v) for v in ticks]
plt.xlabel('Current Credit Lines')
plt.title('Log Transform - Current Credit Lines')
plt.ylabel('Count')
plt.xscale('log')
plt.xticks(ticks, labels)
plt.show()
```

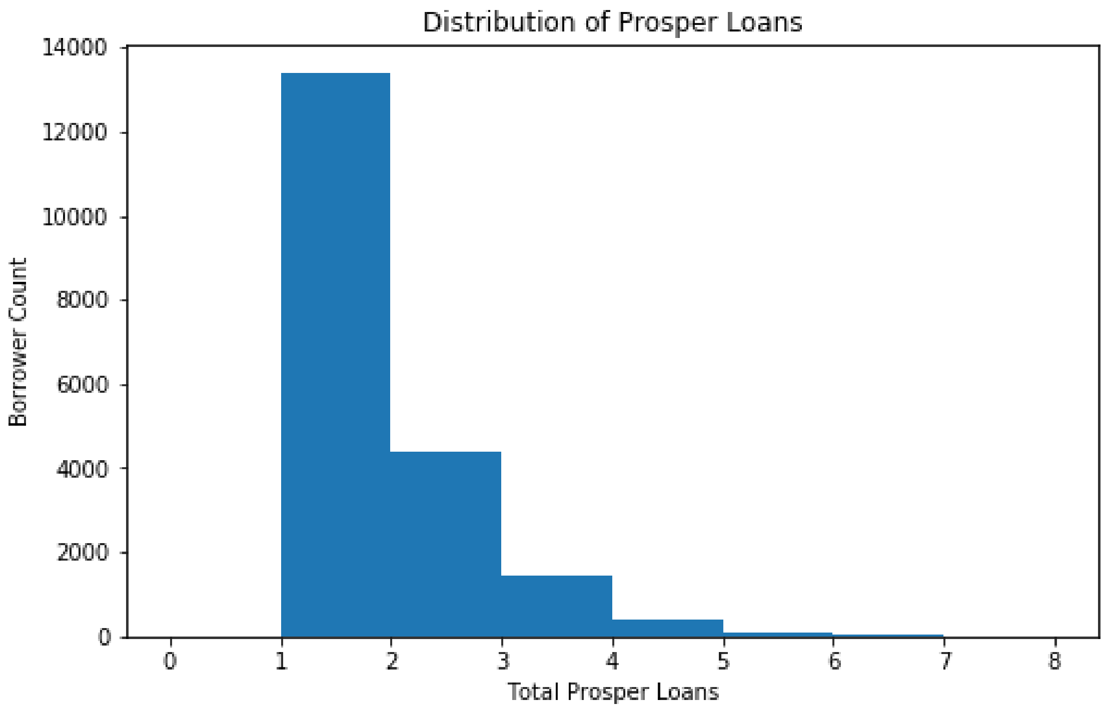


1.3.6 Current Credit Lines

Transformed graph shows a steady increase of credit from 1 to 4, a dip at around 5 and 6, increase from 8 to 10 and peaks at around 15. This shows most borrowers are in the range 8 to 15 credit lines.

In [31]:
```
# Plotting Total Prosper Loans
binsize = 1
bins = np.arange(0, previous_borrowers['TotalProsperLoans'].max()+binsize, binsize)
#print(bins)
plt.figure(figsize=[8, 5])
plt.hist(data = previous_borrowers, x = 'TotalProsperLoans', bins=bins)
```

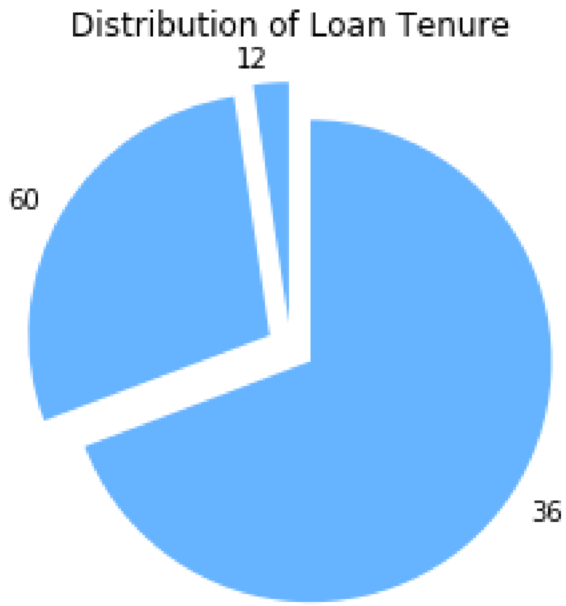
```
plt.xlabel('Total Prosper Loans')
plt.title('Distribution of Prosper Loans')
plt.ylabel('Borrower Count')
#plt.xticks([0.0,0.1,0.2,0.3,0.4],["0","10%","20%","30%","40%"])
plt.show()
```



1.3.7 Total Prosper Loans

The total prosper loans distribution amongst borrowers. This shows that most borrowers only have 1 loan with prosper.

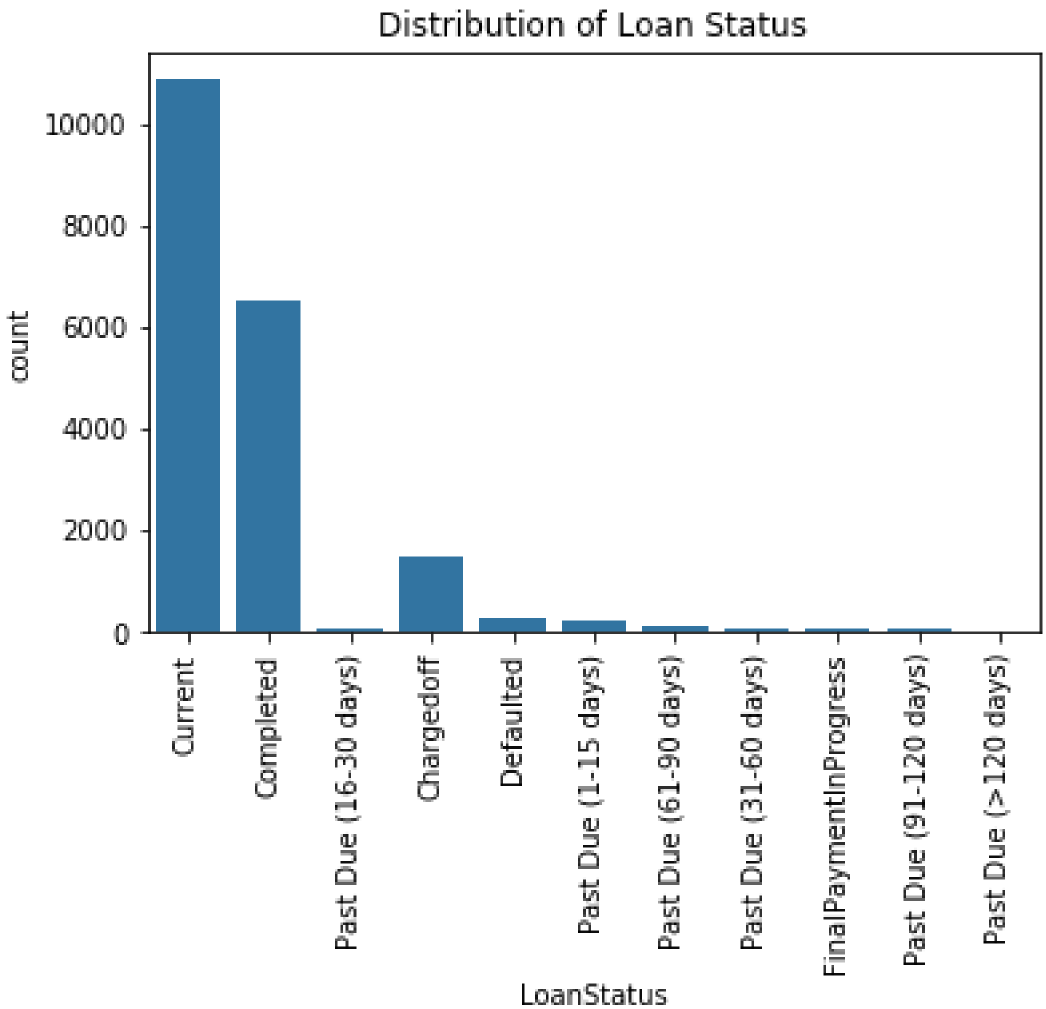
```
In [32]: #Plot of Long Duration using the Term attribute
         base_color = sb.color_palette()[0]
         colors = ['#66b3ff','#66b3ff','#66b3ff']
         explode = (0.1, 0.1, 0.1)
         sorted_counts = previous_borrowers['Term'].value_counts()
         plt.pie(sorted_counts,explode=explode, labels = sorted_counts.index, startangle = 90, c
         plt.axis('square')
         plt.title("Distribution of Loan Tenure");
```



1.3.8 Loan Term

The distribution of loan tenure, the large majority of borrower have loans runing for a duration of 3 years. Followed by 5 years and the least is 1 year. The distribution is in months.

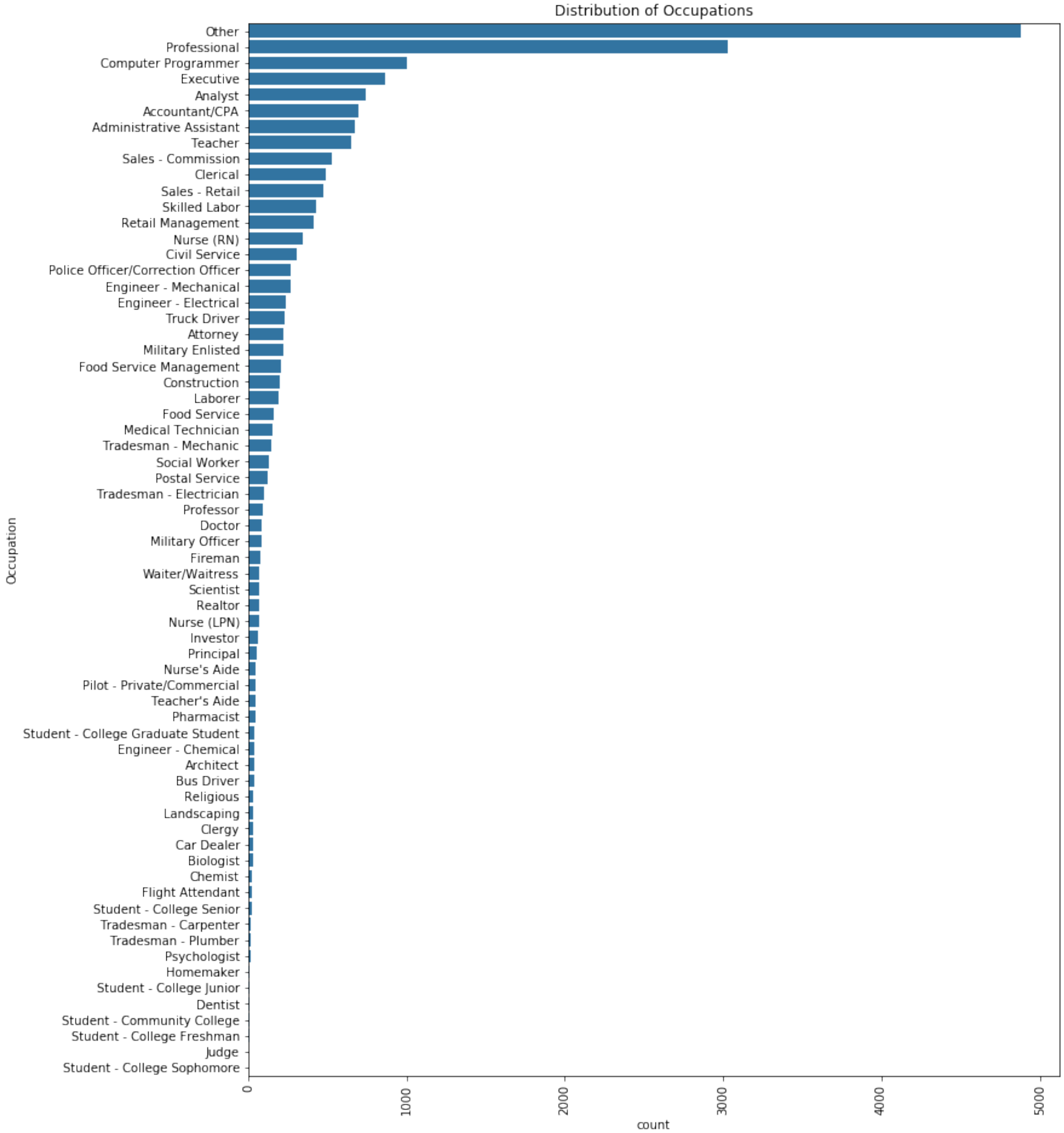
```
In [33]: base_color = sb.color_palette()[0]
         sb.countplot(data=previous_borrowers, x='LoanStatus',color=base_color);
         plt.xticks(rotation=90)
         plt.title("Distribution of Loan Status");
```



1.3.9 Loan Status

The distribution of loans shows the majority are current followed by completed & charged off. The rest are thinly distributed over 7 categories.

```
In [34]: occupation = previous_borrowers.Occupation.value_counts().index #previous_borrowers.Occ
         plt.figure(figsize=[12, 16])
         base_color = sb.color_palette()[0]
         sb.countplot(data=previous_borrowers, y='Occupation', color = base_color, order=occupat
         plt.xticks(rotation=90)
         plt.title("Distribution of Occupations");
```



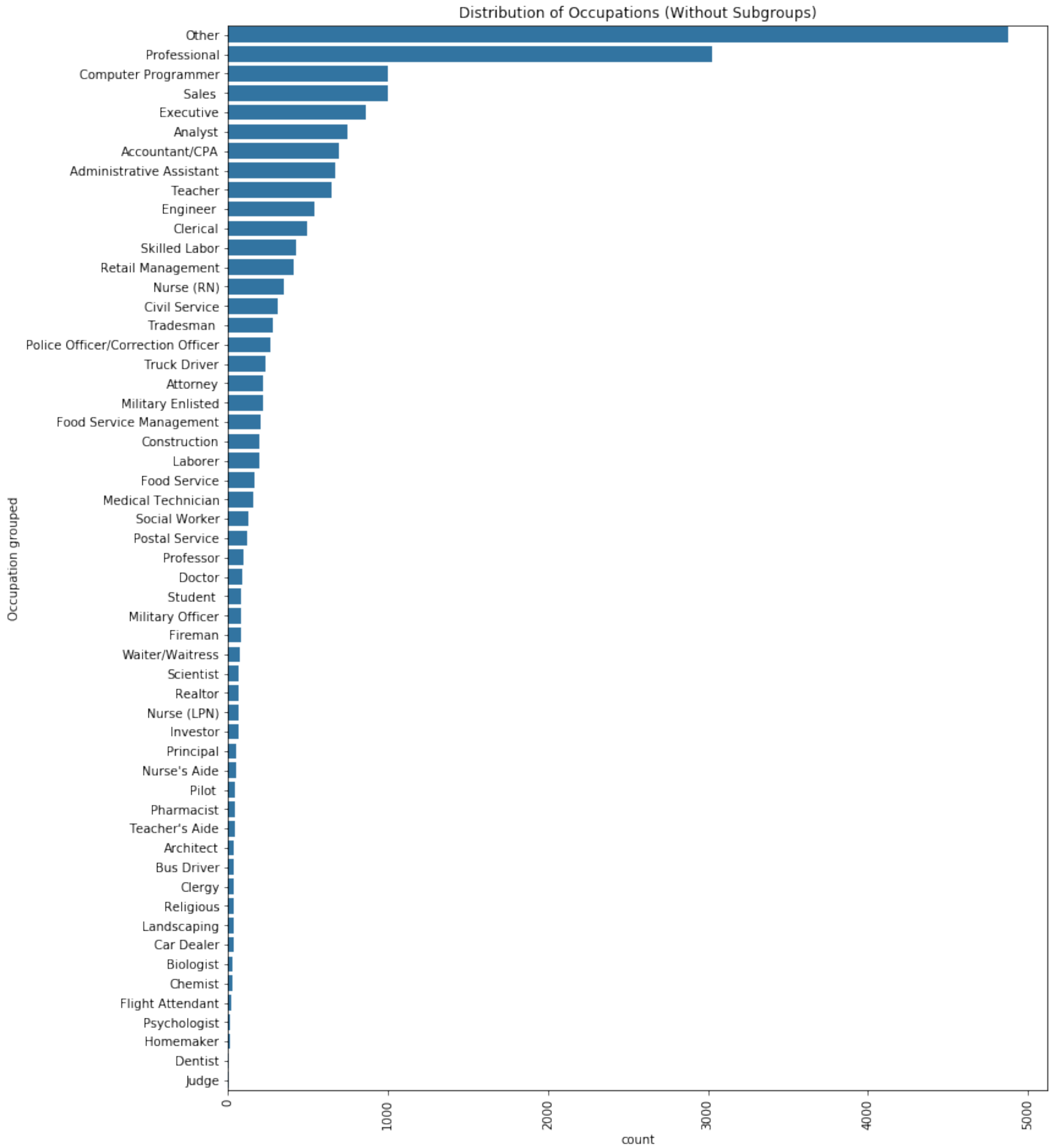
1.3.10 Occupation

There are a few occupations in this list that appear to be subgroups of one occupation for example Tradesman - Carpenter and Tradesman - Plumber. For the purpose of this analysis broad larger groups are better. These will be transformed using the function below.

```
In [35]: def transform_occupation(occupation_name):
             if occupation_name.find("-") > 0:
                 return occupation_name.split("-")[0]
             else:
                 return occupation_name
```

```
previous_borrowers['Occupation_grouped']=previous_borrowers.Occupation.apply(transform_
```

In [36]:
```
occupation_grouped = previous_borrowers.Occupation_grouped.value_counts().index
#occupation_order = pd.api.types.CategoricalDtype(ordered = True, categories = occupati
#previous_borrowers['Occupation'] = previous_borrowers['Occupation'].astype(occupation_
#previous_borrowers.Occupation.astype()
plt.figure(figsize=[12, 16])
base_color = sb.color_palette()[0]
sb.countplot(data=previous_borrowers, y='Occupation_grouped', color = base_color, order
plt.ylabel('Occupation grouped')
plt.title("Distribution of Occupations (Without Subgroups)");
plt.xticks(rotation=90);
```

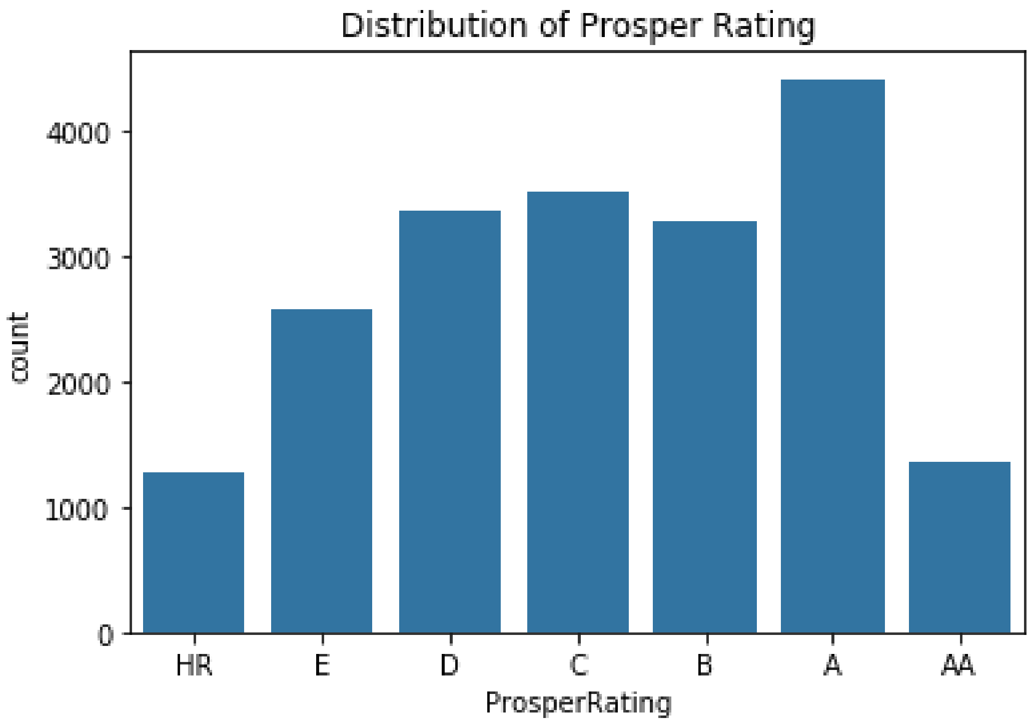


1.3.11 Occupation

The distribtion of occupation is interesting, here is ordered from the highest to the lowest. Since occupation other & professional are the highest, these make occupation a bit doubtful in terms of it's usefulness to the analysis, other would mean the borrowers couldn't find a fitting option for what they do. Professional is ambigious in a way as the remaining occupations consists professional jobs. The quality of this attribute is doubtful.

```
In [37]: # Plot of Prosper Rating - BarChart
         base_color = sb.color_palette()[0]
```

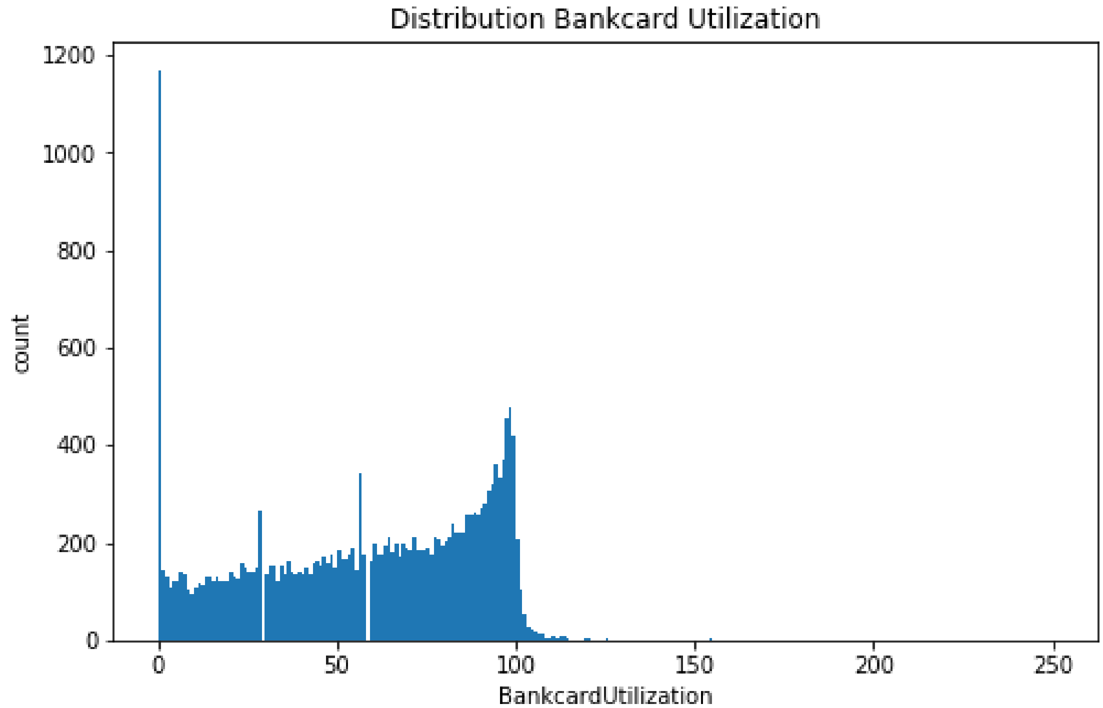
```
plt.title("Distribution of Prosper Rating")
sb.countplot(data=previous_borrowers, x='ProsperRating',color=base_color);
```



1.3.12 Prosper Rating

The distribution here is unimodal and skewed to the right opposite of Borrower's APR graph. From what has been observed some far, the HR rating featured alot in the loans with a BAPR greater than 40%. The behavior of this feature with BAPR needs to be analysed.

```
In [38]: # Plotting Total Prosper Loans
         binsize = 1
         bins = np.arange(0, previous_borrowers['BankcardUtilization'].max()+binsize, binsize)
         #print(bins)
         plt.figure(figsize=[8, 5])
         plt.hist(data = previous_borrowers, x = 'BankcardUtilization', bins=bins)
         plt.xlabel('BankcardUtilization')
         plt.title('Distribution Bankcard Utilization')
         plt.ylabel('count')
         plt.show()
```



1.3.13 Bank Card Utilization

The distribution of Bank Card utilization above 100% are outliers as compared to the spread of the other utilization values.

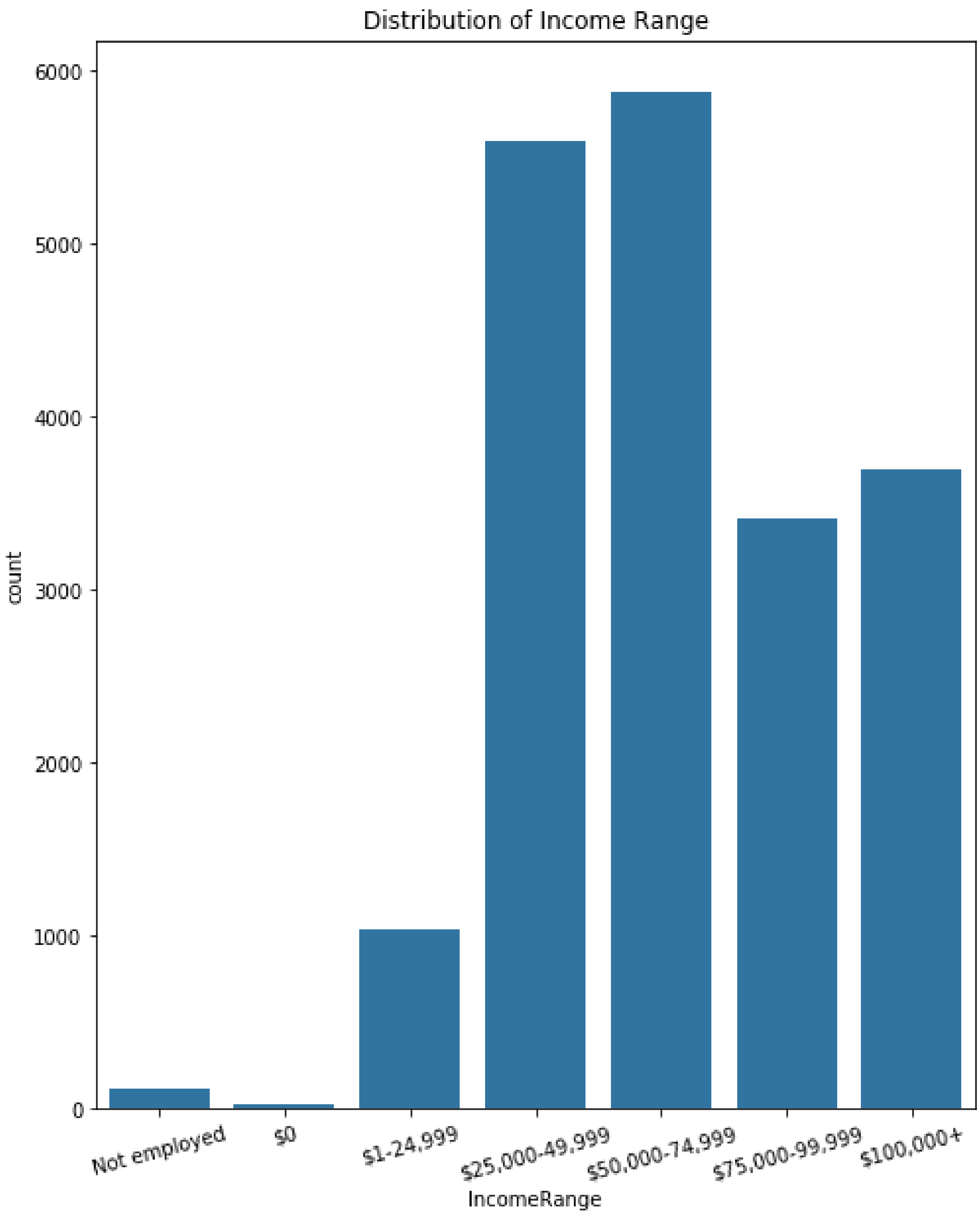
In [39]:
```
#There are not a lot of observations above 100%
#In this case value of Bank Card Utilization above 100% should be normal based the valu
print(previous_borrowers["BankcardUtilization"][previous_borrowers.BankcardUtilization>
print(previous_borrowers.BankcardUtilization.max())
```

```
397      103.0
462      110.0
1319     102.0
1522     113.0
2506     101.0
2558     107.0
2851     101.0
3240     102.0
3357     120.0
3752     122.0
3766     105.0
4664     110.0
5087     108.0
5882     125.0
```

```
6180      103.0
6284      101.0
6356      101.0
6506      101.0
6753      101.0
6930      101.0
7051      104.0
7121      101.0
7194      102.0
7486      101.0
7602      102.0
8778      101.0
8832      109.0
8970      105.0
9085      101.0
9107      102.0
          ...
102282    103.0
102411    101.0
102892    105.0
103053    102.0
103151    120.0
103444    101.0
103848    102.0
104538    101.0
104682    101.0
106031    107.0
106204    109.0
106217    103.0
106294    106.0
106383    101.0
106904    104.0
107037    102.0
107614    154.0
108474    101.0
108994    101.0
109239    120.0
109465    106.0
109608    102.0
109744    102.0
110174    105.0
110731    111.0
110942    101.0
111685    103.0
113200    103.0
113483    102.0
113653    104.0
Name: BankcardUtilization, Length: 302, dtype: float64
```

```
250.0
```

In [40]:
```
plt.figure(figsize=[8, 10])
plt.title("Distribution of Income Range")
base_color = sb.color_palette()[0]
sb.countplot(data=previous_borrowers, x='IncomeRange', color = base_color);
plt.xticks(rotation=15);
```



1.3.14 Income Range

The Income Range highlights the median distribution for most borrowers around 25,000 to 74,999. It will be interesting to see what kind BAPR these categories have.

```
In [41]: # Save Previous Borrowers to CSV
         previous_borrowers.to_csv('previous_borrowers.csv')
```

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

The **Borrower's Annaual Percentage Rate (BAPR)** is a unimodal distribution. With a small percentage of borrowers greater than 40%. Easily identifiable for all these loans was the lower rating for the Proper rating attribute.

The **Credit Score Range Upper and Lower** was averaged to get an average picture of the Credit Score rating. The distribution for the **Credit Score Avg** was similar to the visualization of the two attributes it was drived from, which was unimodal.

Prosper Rating - is a unimodal graph that is skewed to the right, a large mumber of borrowers in category A and minority group are in HR and AA. HR represents lowest score and AA highest score. This behaviour is opposite of what we see in BAPR which is skewed to the left.

Bank Card Utilization has values great than 100%, these are at least 300 observations. The histogram show that peaks are zero, around 40%, 50% and 100%. The distribution is rather different from what has observed so far it will interesting to see what the colleration is like with BAPR.

The **Income Range** show a unimodal distribution, it will be interesting to how income distributed along side BAPR, that could provide further insight into our investigation.

1.3.16 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?

Occupation has an unusal distributions with most groups falling into Other and Professional. There is a potential that these two groups fit into more meaning groups. Additionally, the first graph provide occupations that had subgroups these where transformed into main growth to really focus on granular groups rather than fine groups.

BankCardUtilization and **BorrowerAPR** were transformed to percentage for easier interpretations.

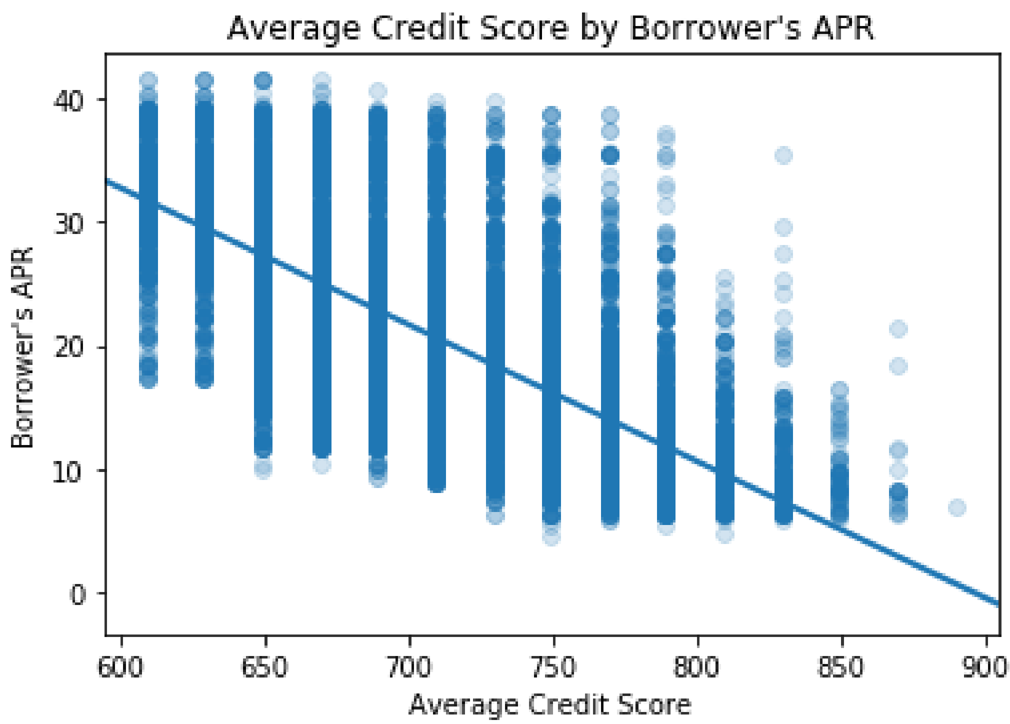
ProsperRating and **IncomeRange** have been transformed into Category type with Order. (Ordinal data types)

CreditScoreAvg is a new column with that is an average of **Credit Score Range Upper and Lower Current Credit lines** produced a unimodal graph, as well, however, the values on the far right where not easily observable, a log transformation was done to have a better understanding of the distribution of how value abouve 40 current credit line where distributed.

1.4 Bivariate Exploration

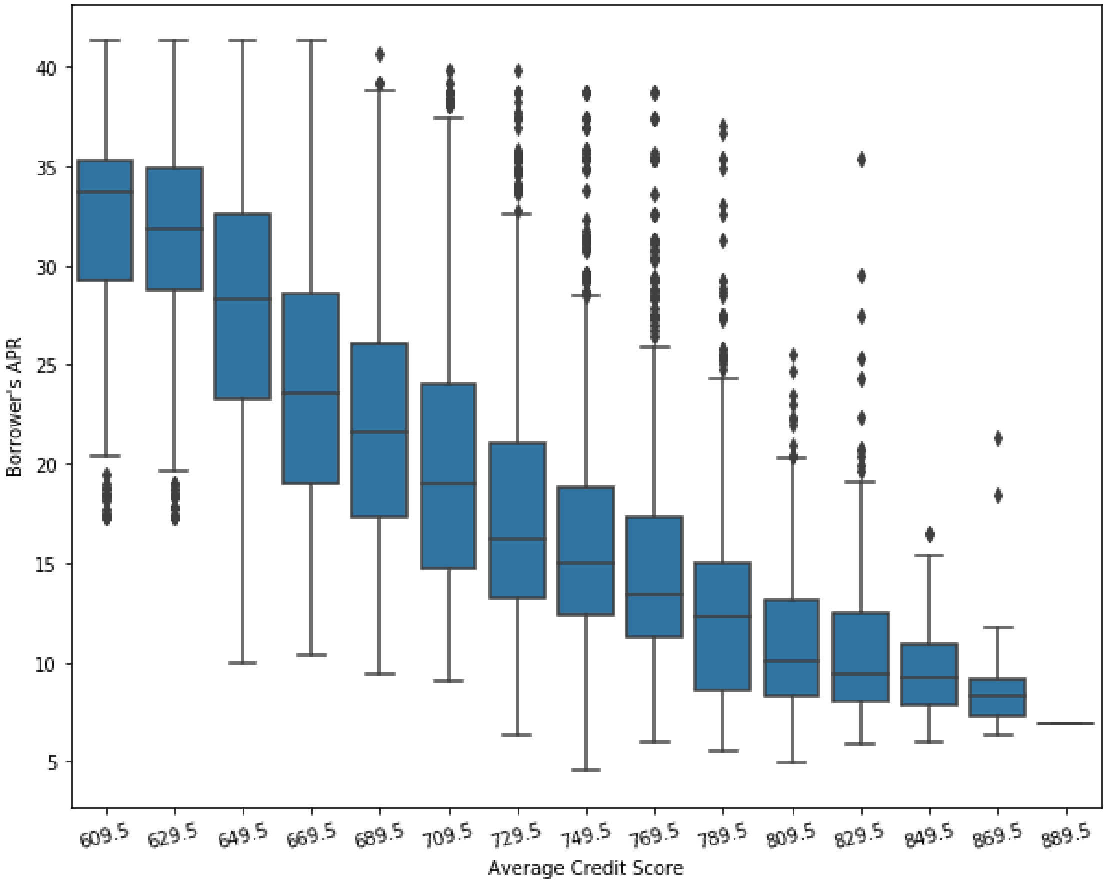
Investigate relationships between pairs of variables, our variable of interest is **BorrowerAPR**.

In [42]:
```
# Scatter plot for CreditScoreAvg and BorrowerAPR
sb.regplot(data = previous_borrowers, x = 'CreditScoreAvg', y = 'BorrowerAPR',truncate=
plt.xlabel('Average Credit Score')
plt.ylabel("Borrower's APR")
plt.title("Average Credit Score by Borrower's APR");
```



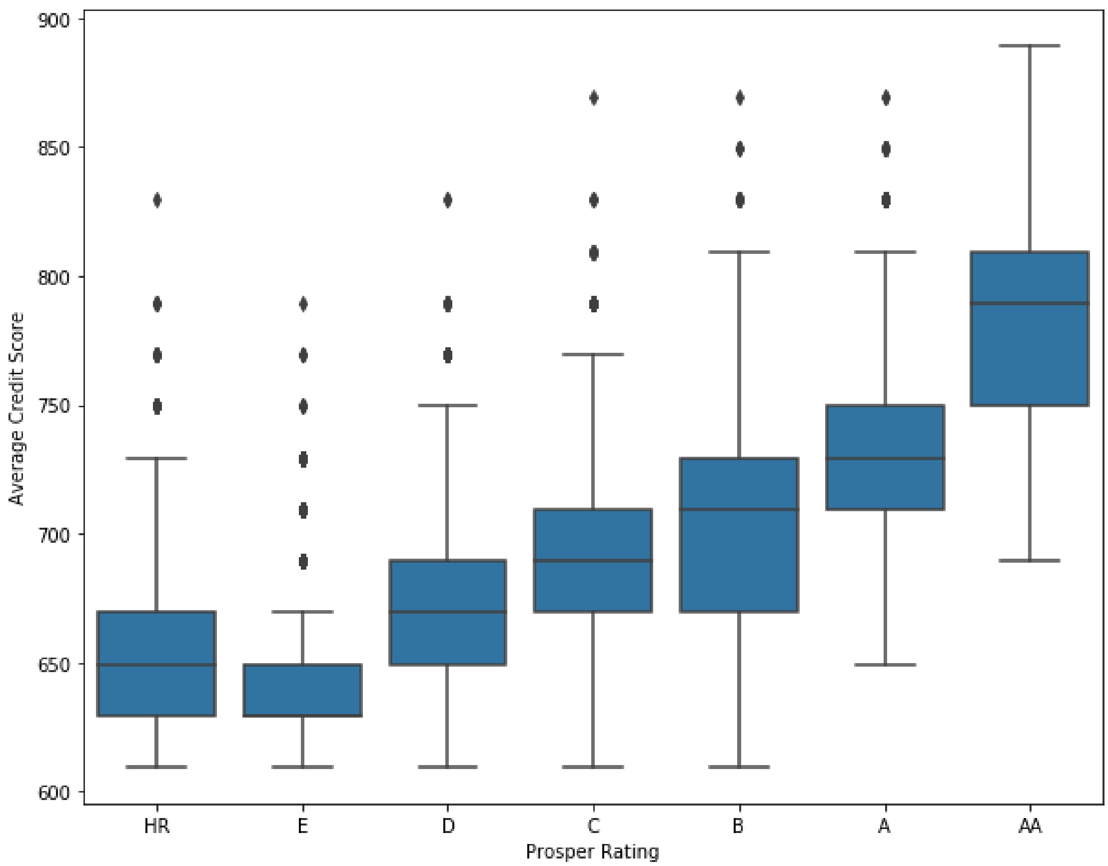
CreditScoreAvg and BorrowerAPR A scatter plot of CreditScoreAvg and BorrowerAPR, shows there is negative relationship between the attributes.

In [43]:
```
#Box Plot of Credit Score Avg and BorrowerAPR
plt.figure(figsize=[10, 8])
base_color = sb.color_palette()[0]
sb.boxplot(data=previous_borrowers, x='CreditScoreAvg', y='BorrowerAPR', color=base_col
plt.xticks(rotation=15)
plt.xlabel('Average Credit Score')
plt.ylabel("Borrower's APR");
```



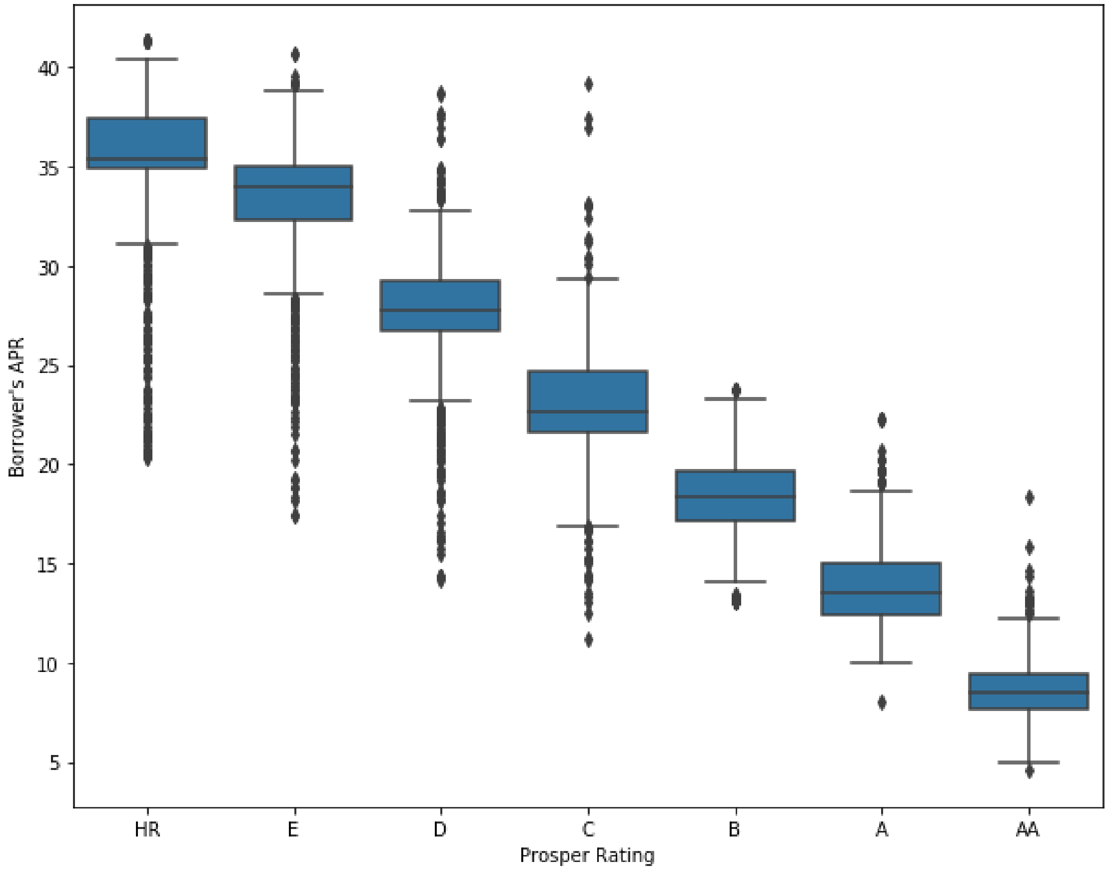
Box Plot of Credit Score Avg and BorrowerAPR A Box Plot show the negative relationship more clearly, outling the ranges and outliners for CreditScoreAvg.

```
In [44]: ##Box Plot for ProsperRating and Credit Score Average
         plt.figure(figsize=[10, 8])
         base_color = sb.color_palette()[0]
         sb.boxplot(data = previous_borrowers, x = 'ProsperRating', y = 'CreditScoreAvg',color=b
         plt.xlabel('Prosper Rating')
         plt.ylabel("Average Credit Score");
```



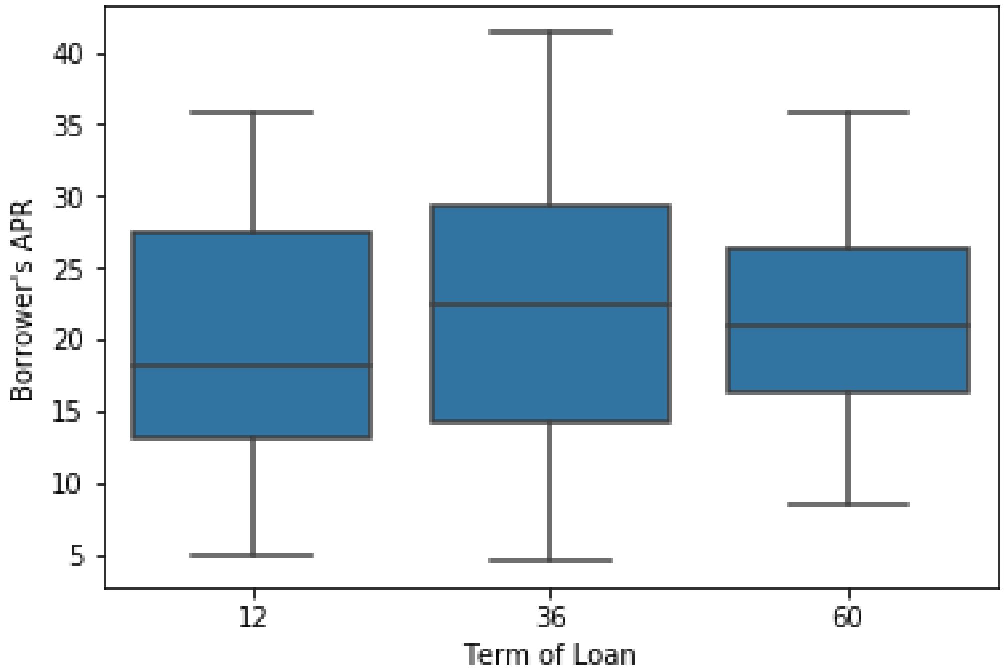
Box Plot for ProsperRating and Credit Score Average ProsperRating and Credit Score Average are postively collerated. However, there is a difference in rating especially if you inspect Rating E from Prosper, this category is lower and has the most outliers. Credit Score Average overlaps in most instance with Prosper ratings.

```
In [45]: #Box Plot of Prosper Rating and BorrowerAPR
         plt.figure(figsize=[10, 8])
         base_color = sb.color_palette()[0]
         sb.boxplot(data=previous_borrowers, x='ProsperRating', y='BorrowerAPR', color=base_colo
         plt.xlabel('Prosper Rating')
         plt.ylabel("Borrower's APR");
```



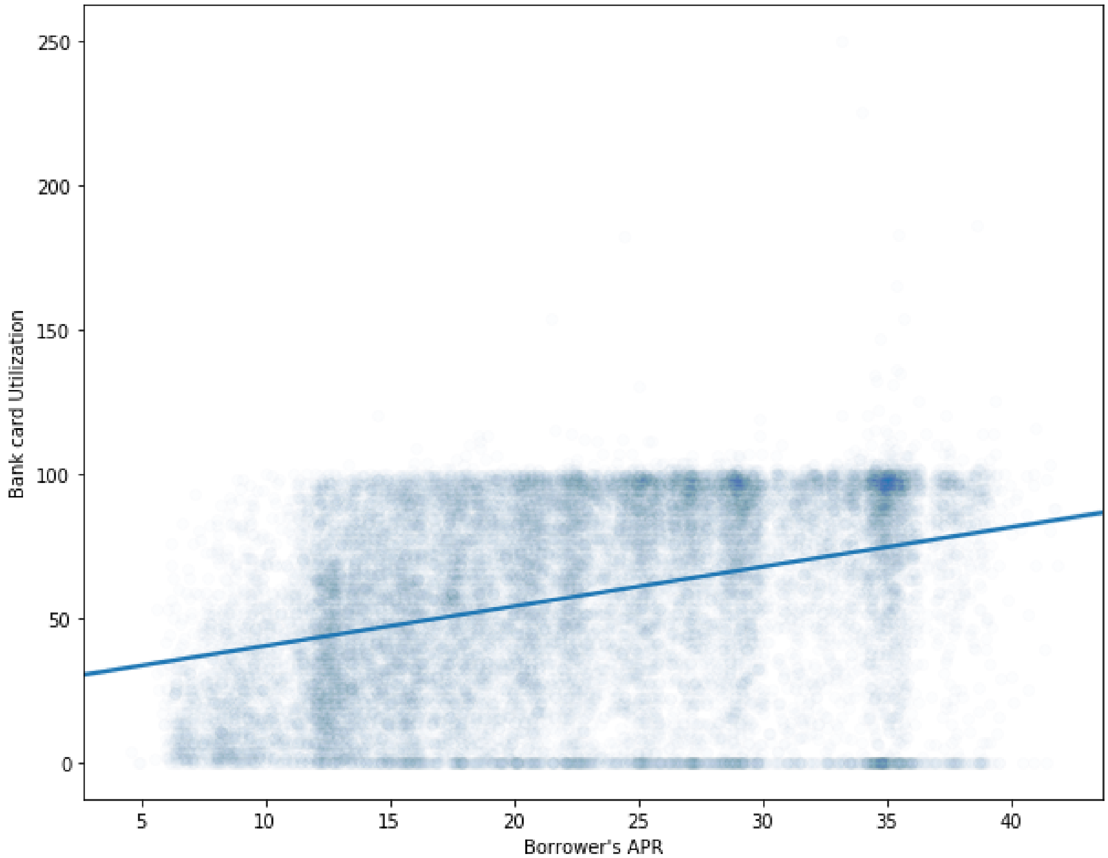
Box Plot of Prosper Rating and BorrowerAPR Prosper rating produces a similar result to what we have with the credit score. However, they are more outliers for each prosper category.

```
In [46]: #Box plot for CreditScoreAvg and BorrowerAPR
         base_color = sb.color_palette()[0]
         sb.boxplot(data = previous_borrowers, x = 'Term', y = 'BorrowerAPR',color=base_color);
         plt.xlabel('Term of Loan')
         plt.ylabel("Borrower's APR");
```



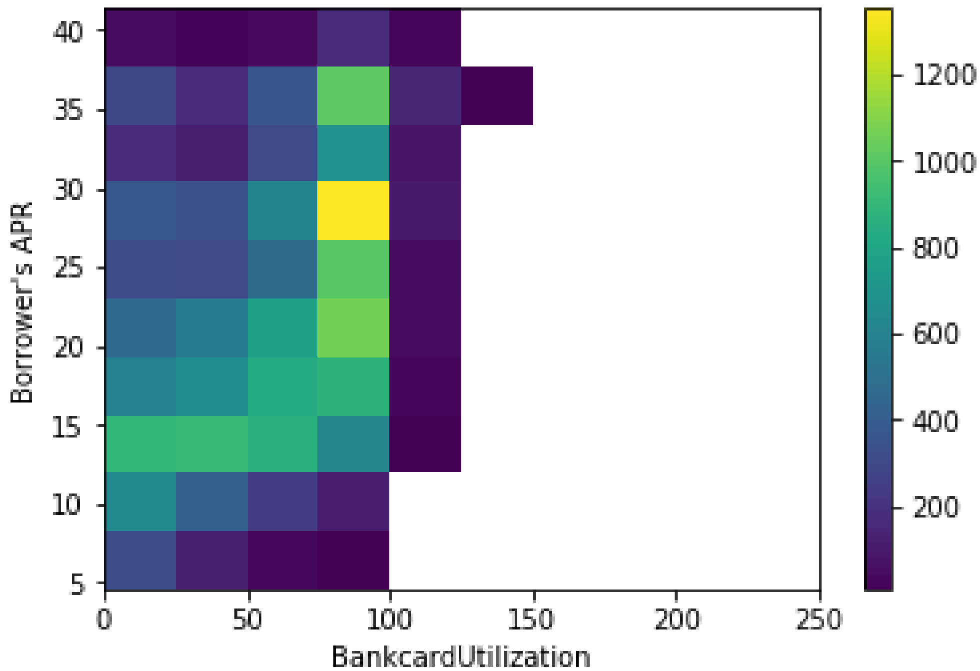
Scatter plot for CreditScoreAvg and BorrowerAPR Loans with a duration of 36 months have the highest average BorrowerAPR. The expectation would be the longer the duration the less costly a loan is per year.

```
In [47]: #Scatter plot BankcardUtilization and BorrowerAPR
         plt.figure(figsize=[10, 8])
         sb.regplot(data = previous_borrowers, y = 'BankcardUtilization', x= 'BorrowerAPR', x_ji
         plt.xlabel("Borrower's APR")
         plt.ylabel("Bank card Utilization");
```



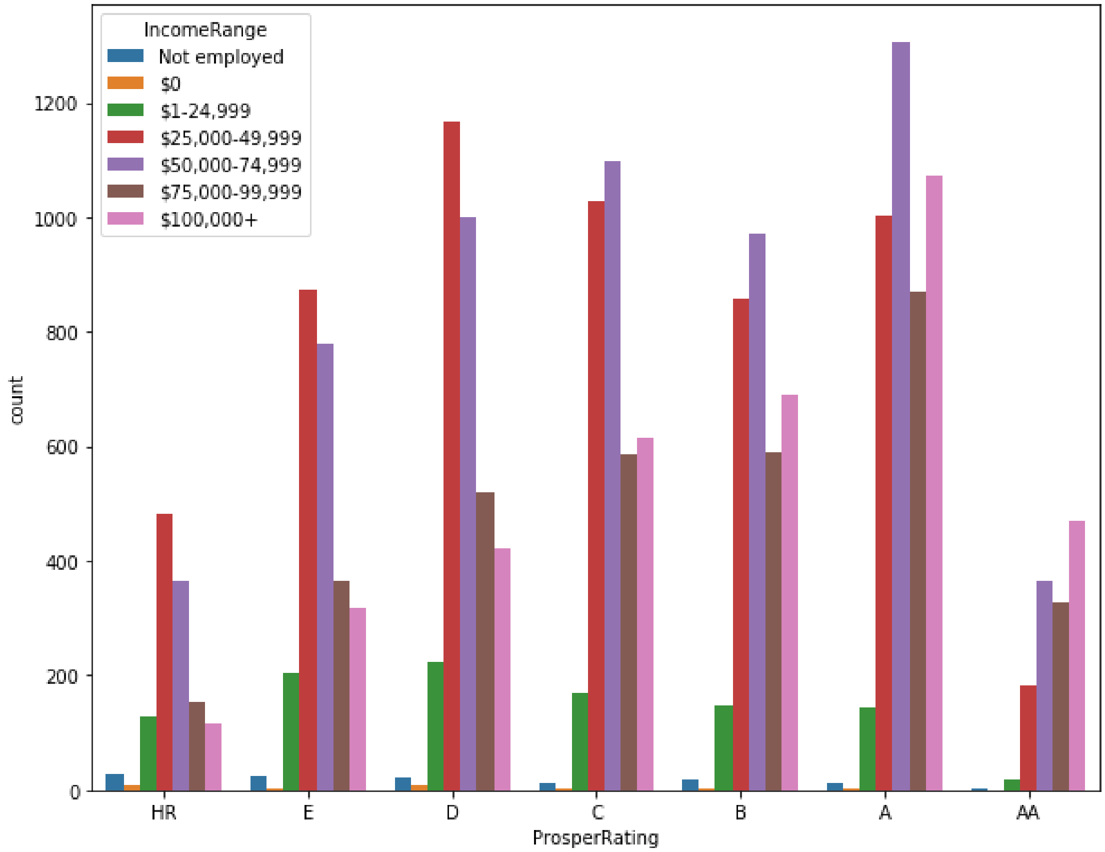
Scatter plot BankcardUtilization and BorrowerAPR Bank Card Utilization show a positive correlation with Borrower's APR, however the distribution is not completely positive for all values of the BankcardUtilization. An additionally plot should provide a clearer picture.

```
In [48]: #Heat map plot of BankCardUtilization and BorrowerAPR
         plt.hist2d(data = previous_borrowers, x = 'BankcardUtilization', y = 'BorrowerAPR', cmi
         plt.colorbar()
         plt.xlabel('BankcardUtilization')
         plt.ylabel("Borrower's APR");
```



Heat map plot of BankCardUtilization and BorrowerAPR The Heat map shows the largely a high Bank Card Utilization is likely going to have a higher APR, with most borrower's in the 20% to 35% representing the borrowers with the highest utilization.

```
In [49]: plt.figure(figsize=[10, 8])
         sb.countplot(data = previous_borrowers, x = 'ProsperRating', hue = 'IncomeRange');
```



Clustered Bar Char Income Range and Prosper Rating Prosper Rating is negatively collerated with our main feature of interest. How it relates to Prosper Rating may also provide an indication of the BAPR based on income range. Higher income range show strong presence where there is a better Prosper Rating.

1.4.1 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?

The main feature of interest the Borrower's APR (BAPR) shows a strong negative correlation with credit score average and Prosper Rating. The prosper rating and credit score average are related but when credit score is compared to prosper rating there are generally more overlaps with credit score average. The box plots were use to outline the relationship in a more visual way.

Bank Card Utilization reflected that there is more of likelihood that customer with higher card utilization would also have a high BAPR.

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

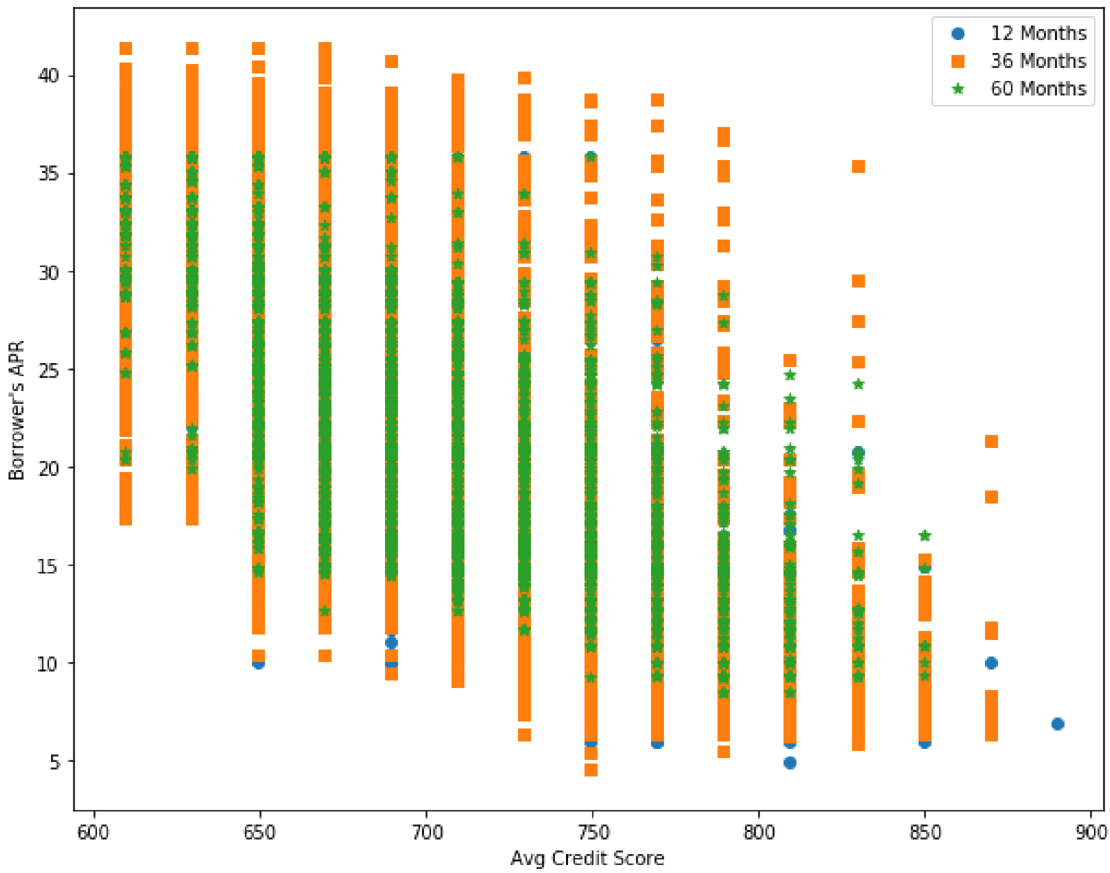
Interesting relationships observed are with loan tenure/term, that showed medium term loans costing more as compared to short (12 months) and long(60 months) term loans.

There is a relationship between prosper rating and Income range. This relationship show that the high income groups are more strong represented in better proper rating groups.

1.5 Multivariate Exploration

Create plots of three or more variables to investigate your data even further. Make sure that your investigations are justified, and follow from your work in the previous sections.

```
In [50]: cat_markers = [[12, 'o'],
                        [36, 's'],
                        [60, '*']]
         plt.figure(figsize=[10, 8])
         for cat, marker in cat_markers:
             previous_borrowers_cat = previous_borrowers[previous_borrowers['Term'] == cat]
             plt.scatter(data = previous_borrowers_cat, x = 'CreditScoreAvg', y = 'BorrowerAPR',
         plt.xlabel('Avg Credit Score')
         plt.ylabel("Borrower's APR")
         plt.legend(['12 Months','36 Months','60 Months']);
```



Avg Credit Score V Borrower's APR and loan term

The graph provides value data, it 12 Months largely have low BAPR, is not affected by the score as much as the other loan terms. On average 36 months loan are more costly, but the provide better cost over the rang of Average Credit Score. The Score affect 60 months loan, the better the score the lower the cost of borrowing but on average is it the better choice.

1.5.1 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?

The addition of Term to the graph for Borrower's APR against Average Credit Score has showed has strengthened the fact that loans of 12 Month in length are the least expensive and has added another angle. The credit score does not affected the cost borrowing as much as the it does when the loan tenure increases to 36 or 60 months. On average the 60 months have more favourable rates as compared to loan that are 36 months long.

1.5.2 Were there any interesting or surprising interactions between features?

The features interacted as predicted independently although the cost of loans that 12 months appears to not be affected by the credit score.

1.6 Conclusions

The investigation focused on the borrowers in the dataset that had loans with prosper in the dataset. The effort began with the wrangling of data. To get an understanding of the data, the shape, data types, observation count, and features were examined. Having extracted the subset of the data with the features of interested selected, tidying up of data was carried out. The cleanup focused on removing attributes with nulls and assigning the correct data types. As part of the tidying up percentage values represented as float values were converted into percentages.

The investigation started with univariate exploration. All the features were visualized to gain an understanding of the distribution and identified unusual data points and outliers. The main variable of interest was BorrowerAPR, which is the Borrower's Annual Percentage Rate (BAPR) the percentage of the annual cost of borrowing to the borrower. The graph of BAPR was unimodal and highlighted that there are few results that are above 40%. The data above 40% all had a poor Prosper Rating and a below-average Credit Score Range Upper and Lower score. Similarly, the rest of the features were explored. The Current Credit Lines (CurrentCreditLines) required a log-transformed histogram for the readability of the graph. The Credit Score Lower & Upper were averaged to create a new feature CreditScoreAvg. Occupation required transformation to eliminate job subgroups. The majority of the plots produced were unimodal. This factored in the reason for picking variables for focus in the bivariate plots.

Bivariate plots strongly indicated the Credit Score Average (CreditScoreAvg) and Prosper Rating (ProsperRating - Prosper's internal rating) were negatively correlated. Using Box & Violin plots made this relationship, after an initial scatter plot of CreditScore against BAPR. Bank Card Utilization (BankCardUtilization) heat map showed a high card utilization matched with a high BAPR but this was not very strong. Interestingly, the tenure of a loan given by the attribute term in months 12, 36, and 60 reflected on average the shortest loan duration had the lowest BAPR. Followed by 60-month-long loans. The loan tenure, Credit Score and BAPR formed the investigation for the multivariate exploration phase.

The multivariate exploration strengthened the fact that loans of 12-month tenure are the least expensive but in addition to this these loans were not affected by a poor credit score. On average the multivariate plot showed that 36-month tenure had the highest BAPR but also had a better range of BAPR values. On average the 60 months have more favorable rates as compared to loans that are 36 months long.

Further investigation can be done by including the loan amount and breaking down the occupation's other and professional values.