In [ ]:

Analyzing Loan Data from Prosper

Flow of the notebook

- Introduction
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Introduction

This dataset is financial dataset and this is related to the loan, borrowers, lenders, interest rates and stuffs like that. Prosper or Prosper Marketplace Inc. is a San Francisco, California based company specializing in loans at low interest rates to the borrowers. In this dataset, we are using the data from the Posper to analyse it and trying to find the pattern in the Prosper data. This may be tedious because of the sheer size of the dataset and the complicated nature of all the financial datasets. We are using Python libraries to plot some visualizations.

Our investigation will focus on analyzing the factors that affect borrower's APR and What type of loan has been taken by what kind of borrower.

In [2]:
```
# Let us import all the packages and libraries that will be required in this analysis.

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import datetime

%matplotlib inline
```

In [6]:
```
from IPython.display import display

pd.set_option('display.max_column', None)
pd.set_option('display.max_rows', None)
```

Gathering Data

We have downloaded the data from the link given by Udacity. It is downloaded in 'csv' format and we will start by importing it.

In [15]:
```
df_loan = pd.read_csv('prosperLoanData.csv')
df_loan.head()
```

Out[15]:

	ListingKey	ListingNumber	ListingCreationDate	CreditGrade	Term	LoanStatus
0	1021339766868145413AB3B	193129	2007-08-26 19:09:29.263000000	C	36	Completed
1	10273602499503308B223C1	1209647	2014-02-27 08:28:07.900000000	NaN	36	Current
2	0EE9337825851032864889A	81716	2007-01-05 15:00:47.090000000	HR	36	Completed
3	0EF5356002482715299901A	658116	2012-10-22 11:02:35.010000000	NaN	36	Current
4	0F023589499656230C5E3E2	909464	2013-09-14 18:38:39.097000000	NaN	36	Current

In [16]:
```
df_loan.shape
```

Out[16]: (113937, 81)

Using .shape we can deduce the information about number of rows and columns in the dataset. We see that there are 81 attributes with 113,937 entries.

In [17]:
```
df_loan.dtypes
```

Out[17]:
```
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
TotalCreditLinespast7years             float64
OpenRevolvingAccounts                    int64
OpenRevolvingMonthlyPayment            float64
InquiriesLast6Months                   float64
TotalInquiries                         float64
CurrentDelinquencies                   float64
AmountDelinquent                       float64
DelinquenciesLast7Years                float64
PublicRecordsLast10Years               float64
PublicRecordsLast12Months              float64
RevolvingCreditBalance                 float64
BankcardUtilization                    float64
AvailableBankcardCredit                float64
TotalTrades                            float64
TradesNeverDelinquent (percentage)     float64
TradesOpenedLast6Months                float64
DebtToIncomeRatio                      float64
IncomeRange                             object
IncomeVerifiable                          bool
StatedMonthlyIncome                    float64
LoanKey                                 object
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
dtype: object
```

Assessing and Cleaning Data

1) What is the structure of Data?

```
- The data consist of a total 81 attributes and accounts for 113,937 entrie
s. Each entry gives us idea about the borrower and it's background and the d
etails of the loan associated with them.
```

2) What are the main features of your analysis?

```
- The above question is answered by keeping the attributes of concern and re
moving the others. Done below.
```

3) Does all the entries have a prosper score associated with it?

4) What feature(s) do I think will help most in the analysis of my interest?

```
- I assume that 'Borrower's APR', 'Prosper Rating', and 'Occupation' will pl
ay a major role in determining the result of analysis. The answer to this qu
estion will be answered in detail by visualization.
```

Question 3

In [18]:
```
df_loan = df_loan[df_loan['ProsperScore'].isnull()==False]

df_loan.shape
```

Out[18]:
```
(84853, 81)
```

```
We can realize that once we get rid of the data that is not associated with
 prosper score, number of entries gets reduced by a significant number.
```

Question 2: What are the main features of your analysis?

In [19]:
```
'''
There are 2 ways to go about doing this. 1) we select only that we want,
& 2) we unselect the ones that we dont want
we will take the second route of unselecting the not-required columns.

 we can check from above the columns that have large amount of null valu
es and remove them since getting that lost
data is not a possible and become redundant while we analyze.
'''

df_loan_copy = df_loan.copy()

df_loan_copy.drop(['ListingKey', 'ListingNumber', 'ListingCreationDate',
'CreditGrade', \
                'ClosedDate', 'CurrentlyInGroup', 'GroupKey', 'DateCredi
tPulled', 'FirstRecordedCreditLine',\
                'LoanKey', 'TotalProsperLoans', 'TotalProsperPaymentsBil
led', 'OnTimeProsperPayments',\
                'ProsperPaymentsLessThanOneMonthLate', 'ProsperPaymentsO
neMonthPlusLate',\
                'ProsperPrincipalBorrowed', 'ProsperPrincipalOutstandin
g', 'ScorexChangeAtTimeOfListing',\
                'LoanCurrentDaysDelinquent', 'LoanFirstDefaultedCycleNum
ber'], axis=1, inplace = True)
```

In [20]:
```
df_loan_copy.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 84853 entries, 1 to 113936
Data columns (total 61 columns):
 #   Column                               Non-Null Count  Dtype  
---  ------                               --------------  -----  
 0   Term                                 84853 non-null  int64  
 1   LoanStatus                           84853 non-null  object 
 2   BorrowerAPR                          84853 non-null  float64
 3   BorrowerRate                         84853 non-null  float64
 4   LenderYield                          84853 non-null  float64
 5   EstimatedEffectiveYield              84853 non-null  float64
 6   EstimatedLoss                        84853 non-null  float64
 7   EstimatedReturn                      84853 non-null  float64
 8   ProsperRating (numeric)              84853 non-null  float64
 9   ProsperRating (Alpha)                84853 non-null  object 
 10  ProsperScore                         84853 non-null  float64
 11  ListingCategory (numeric)            84853 non-null  int64  
 12  BorrowerState                        84853 non-null  object 
 13  Occupation                           83520 non-null  object 
 14  EmploymentStatus                     84853 non-null  object 
 15  EmploymentStatusDuration             84834 non-null  float64
 16  IsBorrowerHomeowner                  84853 non-null  bool   
 17  CreditScoreRangeLower                84853 non-null  float64
 18  CreditScoreRangeUpper                84853 non-null  float64
 19  CurrentCreditLines                   84853 non-null  float64
 20  OpenCreditLines                      84853 non-null  float64
 21  TotalCreditLinespast7years           84853 non-null  float64
 22  OpenRevolvingAccounts                84853 non-null  int64  
 23  OpenRevolvingMonthlyPayment          84853 non-null  float64
 24  InquiriesLast6Months                 84853 non-null  float64
 25  TotalInquiries                       84853 non-null  float64
 26  CurrentDelinquencies                 84853 non-null  float64
 27  AmountDelinquent                     84853 non-null  float64
 28  DelinquenciesLast7Years              84853 non-null  float64
 29  PublicRecordsLast10Years             84853 non-null  float64
 30  PublicRecordsLast12Months            84853 non-null  float64
 31  RevolvingCreditBalance               84853 non-null  float64
 32  BankcardUtilization                  84853 non-null  float64
 33  AvailableBankcardCredit              84853 non-null  float64
 34  TotalTrades                          84853 non-null  float64
 35  TradesNeverDelinquent (percentage)   84853 non-null  float64
 36  TradesOpenedLast6Months              84853 non-null  float64
 37  DebtToIncomeRatio                    77557 non-null  float64
 38  IncomeRange                          84853 non-null  object 
 39  IncomeVerifiable                     84853 non-null  bool   
 40  StatedMonthlyIncome                  84853 non-null  float64
 41  LoanMonthsSinceOrigination           84853 non-null  int64  
 42  LoanNumber                           84853 non-null  int64  
 43  LoanOriginalAmount                   84853 non-null  int64  
 44  LoanOriginationDate                  84853 non-null  object 
 45  LoanOriginationQuarter               84853 non-null  object 
 46  MemberKey                            84853 non-null  object 
 47  MonthlyLoanPayment                   84853 non-null  float64
 48  LP_CustomerPayments                  84853 non-null  float64
 49  LP_CustomerPrincipalPayments         84853 non-null  float64
 50  LP_InterestandFees                   84853 non-null  float64
 51  LP_ServiceFees                       84853 non-null  float64
```

```
 52  LP_CollectionFees                    84853 non-null  float64
 53  LP_GrossPrincipalLoss                84853 non-null  float64
 54  LP_NetPrincipalLoss                  84853 non-null  float64
 55  LP_NonPrincipalRecoverypayments      84853 non-null  float64
 56  PercentFunded                        84853 non-null  float64
 57  Recommendations                      84853 non-null  int64
 58  InvestmentFromFriendsCount           84853 non-null  int64
 59  InvestmentFromFriendsAmount          84853 non-null  float64
 60  Investors                            84853 non-null  int64
dtypes: bool(2), float64(41), int64(9), object(9)
memory usage: 39.0+ MB
```

```
We see that the dimensions of our copied dataset has reduced in terms of num
ber of attributes since we removed unnecessary columns.
```

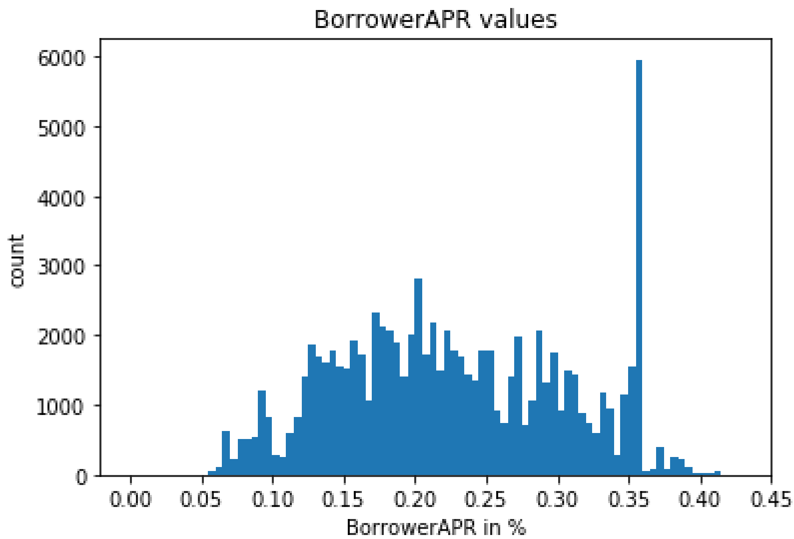
Univariate Exploration

- Which values of APR are most occuring?

In [21]:
```
df_loan_copy.BorrowerAPR.value_counts().head(10)
```

Out[21]:
```
0.35797    3672
0.35643    1644
0.30532     902
0.29510     747
0.35356     721
0.15833     651
0.24246     605
0.24758     601
0.12528     559
0.17359     547
Name: BorrowerAPR, dtype: int64
```

In [22]:
```
# Lets plot different values of BorrowerAPR

bins = np.arange(0, df_loan_copy['BorrowerAPR'].max(), 0.005)
plt.hist(data = df_loan_copy, x='BorrowerAPR', bins = bins)
plt.title('BorrowerAPR values')
plt.xlabel('BorrowerAPR in %')
plt.ylabel('count')
plt.xticks(np.arange(0, df_loan_copy['BorrowerAPR'].max()+0.05, 0.05));
```

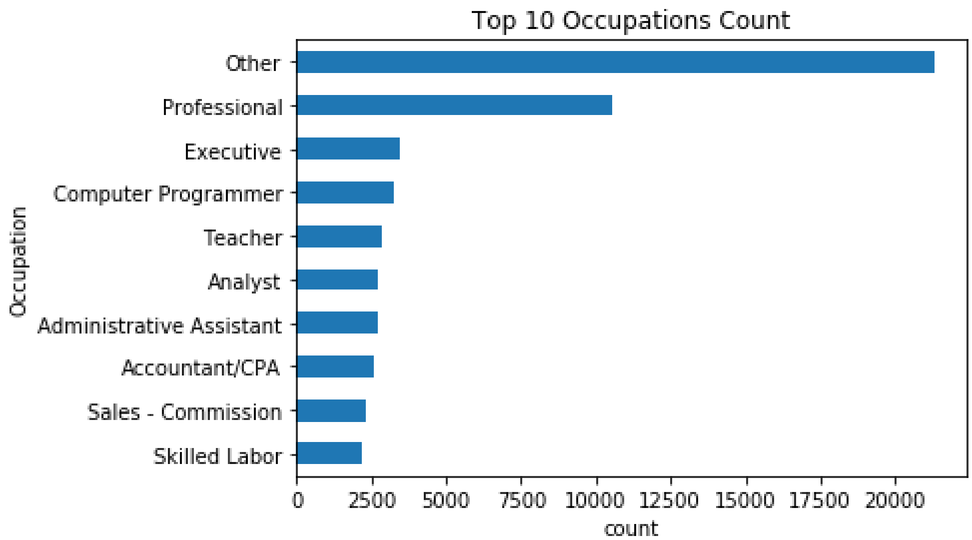


BorrowerAPR distribution seems fairly normal with mean around ~0.19, with an exception of value ~0.35 which is surprisingly high and this needs to be probed.

- What are the most pursued occupation in our dataset?

Lets see the types of occupation that our borrower are involved in

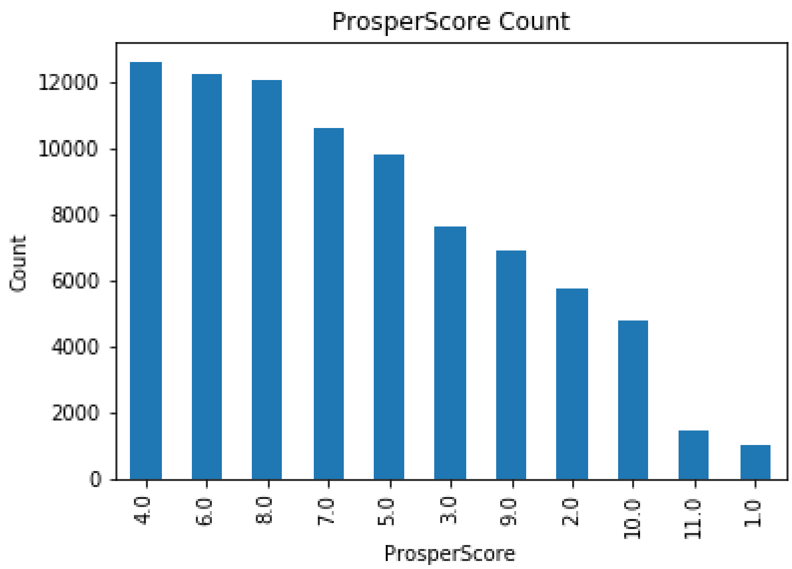
In [24]:
```
df_loan_copy['Occupation'].value_counts()[9::-1].plot(kind='barh')
plt.title('Top 10 Occupations Count')
plt.xlabel('count')
plt.ylabel('Occupation')
plt.fontsize = 10
plt.figsize=(14,14);
```



Occupations: We see a huge number of entries as 'Other' and 'Professional', we can deduce that these people are relectant in disclosing their actual professions. The rest of occupation categories are evenly distributed.

- What Prosper scored occurs the most?

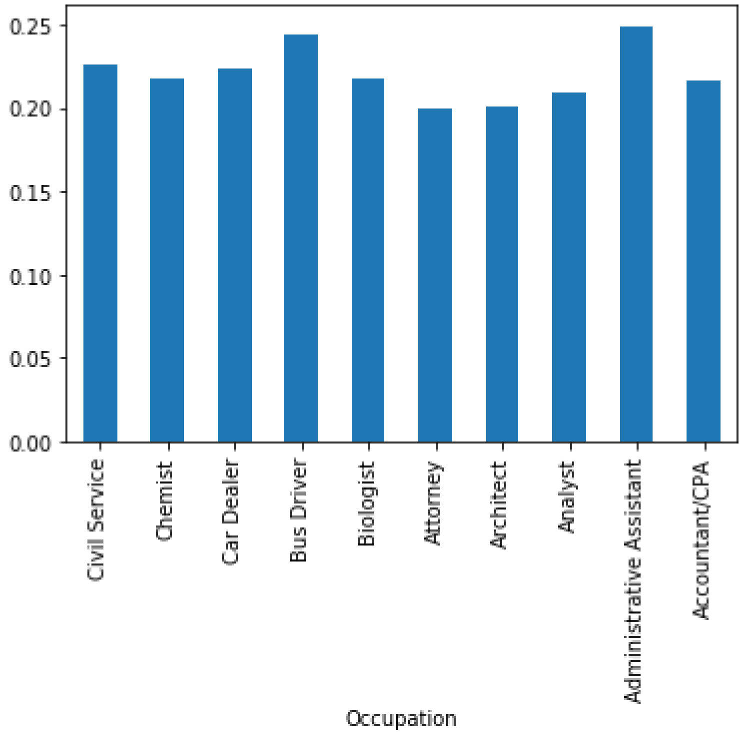
In [26]:
```
# see which ProsperScore borrowers received the most

df_loan_copy['ProsperScore'].value_counts().plot(kind='bar')
plt.title('ProsperScore Count')
plt.xlabel('ProsperScore')
plt.ylabel('Count')
plt.fontsize = 10
plt.figsize=(14,14);
```



ProsperScore : Upon inspection we can say that more the money you borrow, the lesser ProsperScore you get.

- Let us explore the mean values of ProsperScore by each occupation.

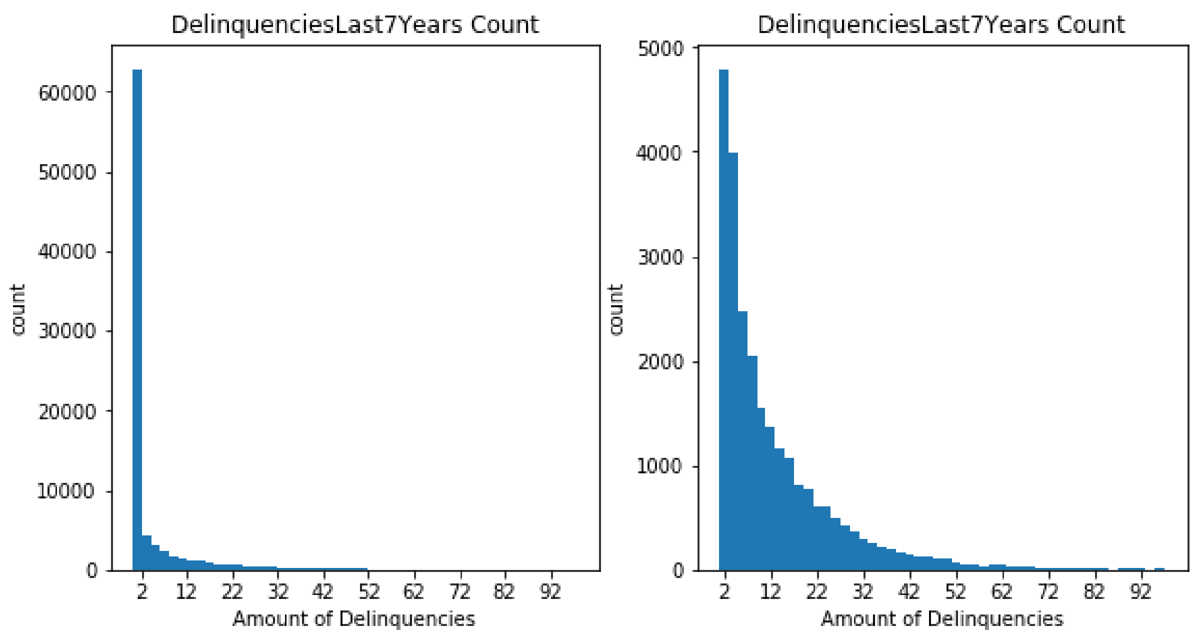
In [27]:
```
# bar plot for APR means of top 10 occupations.

top_10 = df_loan_copy.groupby('Occupation').BorrowerAPR.mean()[9::-1]
top_10.plot(kind='bar');
```



We can observe that there is negligible difference between mean APR scores of top 10 occupations. Hence this exploration is not substantial. We can consider that Occupation might not be the most appropriate attribute in our analysis.

- Lets put some light on delinquencies from past.

In [44]:
```
plt.figure(figsize = [10, 5])


plt.subplot(1, 2, 1)
bins = np.arange(0, df_loan_copy['DelinquenciesLast7Years'].max(), 2)
plt.hist(data = df_loan_copy, x = 'DelinquenciesLast7Years', bins = bins
)
plt.xticks(np.arange(2, 100+1, 10))
plt.title('DelinquenciesLast7Years Count')
plt.xlabel('Amount of Delinquencies')
plt.ylabel('count');

plt.subplot(1, 2, 2)
bins = np.arange(1, df_loan_copy['DelinquenciesLast7Years'].max(), 2)
plt.hist(data = df_loan_copy, x = 'DelinquenciesLast7Years', bins = bins
)
plt.xticks(np.arange(2, 100+1, 10))
plt.title('DelinquenciesLast7Years Count')
plt.xlabel('Amount of Delinquencies')
plt.ylabel('count');
```

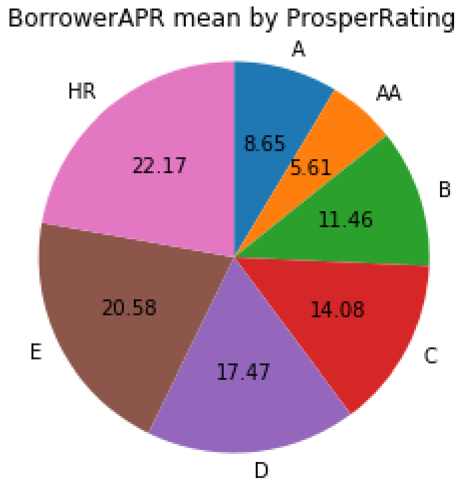


DelinquenciesLast7Years : The first plot shows overall delinquencies and we can infer that most of the borrowers dont have any delinquency. But, as we remove those records where there is no delinquency, the spread becomes more distributed and the decrease is gradual.

Bivariate Exploration

- Let us check for BorrowerAPR mean by ProsperRating mean

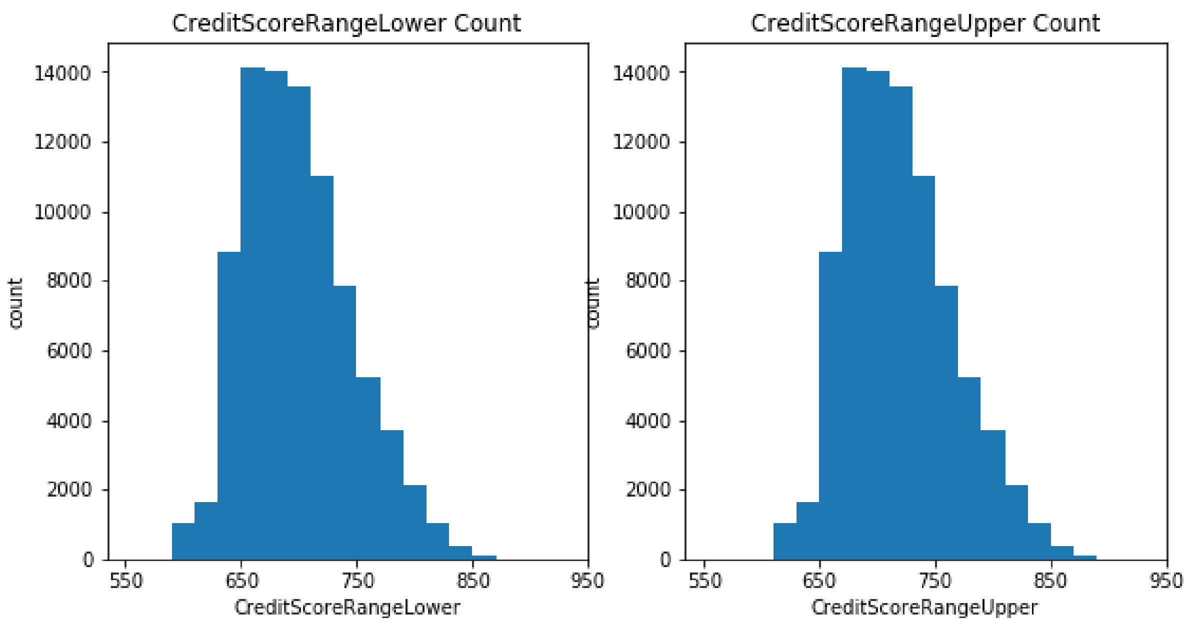
In [30]:
```
# lets try and plot a Pie-plot

ProsperRating_mean = df_loan_copy.groupby('ProsperRating (Alpha)').Borro
werAPR.mean()
ProsperRating_mean

plt.pie(ProsperRating_mean, labels = ProsperRating_mean.index, startangl
e = 90,
    counterclock = False, autopct='%1.2f')
plt.axis('square')
plt.title('BorrowerAPR mean by ProsperRating');
```



BorrowerAPR mean by ProsperRating : The ProsperRating categories have been labelled from highest to lowest manner (i.e. AA, A, B, C, D, E, HR). We can observe that the highest rating of AA has received lowest mean APR and vice-versa, i.e. lowest ratings have received highest mean APR. This is somewhat intuitive because better ratings induce more trust in customer and hence in case of any default also, the punishment in terms of APR is low.

- Comparing CreditScoreRangeLower & CreditScoreRangeUpper

In [45]:
```
plt.figure(figsize = [10, 5])


plt.subplot(1, 2, 1)
bins = np.arange(550, df_loan_copy['CreditScoreRangeLower'].max(), 20)
plt.hist(data = df_loan_copy, x = 'CreditScoreRangeLower', bins = bins)
plt.xticks(np.arange(550, 1000, 100))
plt.title('CreditScoreRangeLower Count')
plt.xlabel('CreditScoreRangeLower')
plt.ylabel('count');

plt.subplot(1, 2, 2)
bins = np.arange(550, df_loan_copy['CreditScoreRangeUpper'].max(), 20)
plt.hist(data = df_loan_copy, x = 'CreditScoreRangeUpper', bins = bins)
plt.xticks(np.arange(550, 1000, 100))
plt.title('CreditScoreRangeUpper Count')
plt.xlabel('CreditScoreRangeUpper')
plt.ylabel('count');
```



In [32]:
```
display(df_loan_copy.CreditScoreRangeLower.describe())
```

```
count    84853.000000
mean       699.390240
std         47.095937
min        600.000000
25%        660.000000
50%        700.000000
75%        720.000000
max        880.000000
Name: CreditScoreRangeLower, dtype: float64
```

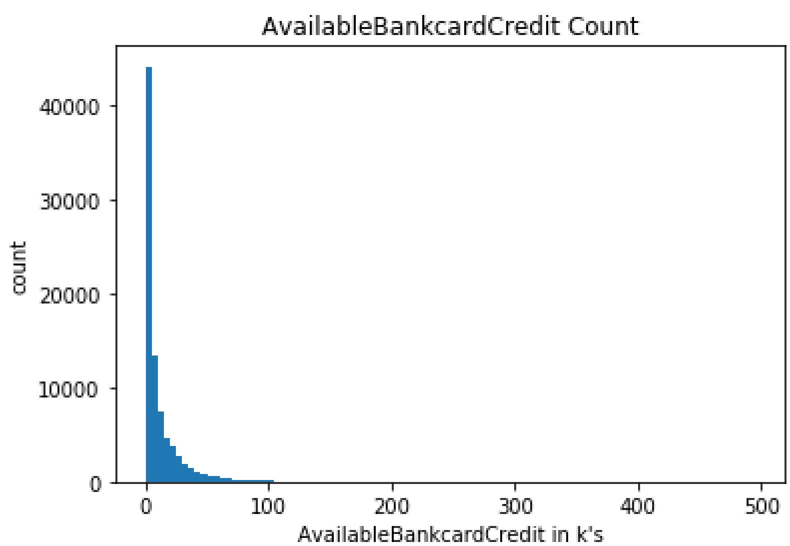
In [33]:
```
display(df_loan_copy.CreditScoreRangeUpper.describe())
```

```
count    84853.000000
mean       718.390240
std         47.095937
min        619.000000
25%        679.000000
50%        719.000000
75%        739.000000
max        899.000000
Name: CreditScoreRangeUpper, dtype: float64
```

CreditScoreRangeLower & CreditScoreRangeLower : The plots are quiet similar and nothing substantial to differentiate.

- Let's see how the AvailableBankcardCredit is distributed.

In [34]:
```
bins = np.arange(0, df_loan_copy['AvailableBankcardCredit'].max(), 5000)
plt.hist(data = df_loan_copy, x = 'AvailableBankcardCredit', bins = bins
)
plt.xticks([0, 1e5, 2e5, 3e5, 4e5, 5e5], [0, '100', '200', '300', '400',
'500'])
plt.title('AvailableBankcardCredit Count')
plt.xlabel("AvailableBankcardCredit in k's")
plt.ylabel('count');
```



We can see that the plot above is not so informative. We can improve upon the filters and then try to re-plot so as to get a better glimps of the distribution.

In [36]:
```
# let us set a baseline of 150,000
High_Creditavailible = df_loan_copy[df_loan_copy['AvailableBankcardCredi
t'] > 150000]
High_Creditavailible.AvailableBankcardCredit.sort_values(ascending = Fal
se)
```

Out[36]:
```
80178     498374.0
92406     432613.0
98518     413367.0
99673     412785.0
64246     406125.0
41112     403880.0
86383     403534.0
45212     395500.0
58930     373348.0
38163     364284.0
56942     360000.0
39963     360000.0
43607     360000.0
61020     360000.0
76296     360000.0
1801      360000.0
32553     350777.0
99273     305996.0
43998     302928.0
8352      285475.0
69640     273978.0
84947     267126.0
49365     265757.0
68191     264939.0
80379     256031.0
24958     246231.0
27990     241928.0
41929     238114.0
44416     237704.0
64323     228829.0
31141     227347.0
85922     225413.0
54325     223896.0
73613     217557.0
54038     217349.0
18457     217218.0
111386    215434.0
23693     213800.0
106726    212800.0
49261     212613.0
7337      210764.0
94729     206964.0
63908     206000.0
74369     204322.0
40041     203472.0
7448      202528.0
65874     202397.0
17455     201674.0
24493     200395.0
62779     195685.0
110598    194405.0
87618     190480.0
73521     186042.0
86793     184487.0
48988     183218.0
47705     182687.0
24801     182559.0
```

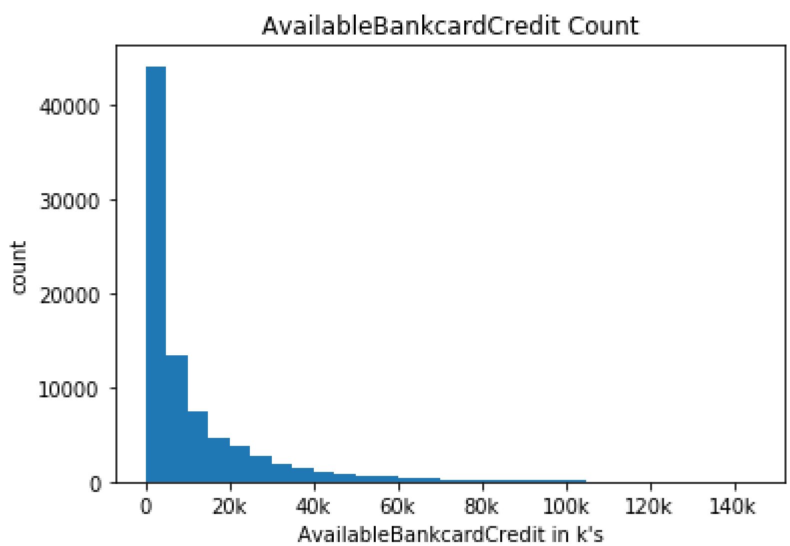
```
99839     182040.0
107135    181721.0
32006     181025.0
95456     179413.0
42512     178850.0
54923     178248.0
28818     177994.0
80370     175625.0
6820      175523.0
52120     172366.0
102543    171786.0
22767     171446.0
68558     171135.0
28947     169405.0
29096     169266.0
79516     169213.0
97515     169006.0
74596     168426.0
31618     167952.0
79652     167852.0
15152     166467.0
94372     166438.0
13912     165764.0
81937     164971.0
89996     163568.0
10075     163531.0
32159     163393.0
88033     163089.0
29229     163069.0
109758    162995.0
85176     162873.0
25880     162506.0
25662     162368.0
84993     161989.0
33347     161218.0
54112     161183.0
55107     160560.0
60923     159880.0
53134     159738.0
4784      158941.0
68405     158745.0
79568     158607.0
94367     156591.0
25696     155880.0
64324     155734.0
66035     154790.0
18028     154752.0
75012     153327.0
50574     153288.0
102225    153214.0
85524     152236.0
2970      151424.0
82691     151069.0
8570      150853.0
7875      150528.0
95998     150114.0
Name: AvailableBankcardCredit, dtype: float64
```

In [37]:
```
print(len(High_Creditavailible['AvailableBankcardCredit']))

# remove fewer people who has high Creditavailible
df_loan_1 = df_loan_copy.drop(High_Creditavailible.index)

# check
print(len(df_loan_1[df_loan_1['AvailableBankcardCredit'] > 150000]))
```

```
113
0
```

Now that we have removed all the entries beyond the bracket and hence we can go on to plot again

In [38]:
```
bins = np.arange(0, df_loan_1['AvailableBankcardCredit'].max(), 5000)
plt.hist(data = df_loan_1, x = 'AvailableBankcardCredit', bins = bins)
plt.xticks([0, 2e4, 4e4, 6e4, 8e4, 1e5, 1.2e5, 1.4e5],
           [0, '20k', '40k', '60k', '80k', '100k', '120k', '140k'])
plt.title('AvailableBankcardCredit Count')
plt.xlabel("AvailableBankcardCredit in k's")
plt.ylabel('count');
```



We can clearly see that the above plot now shows how the Available Bankcard Credit is distributed in more detail.

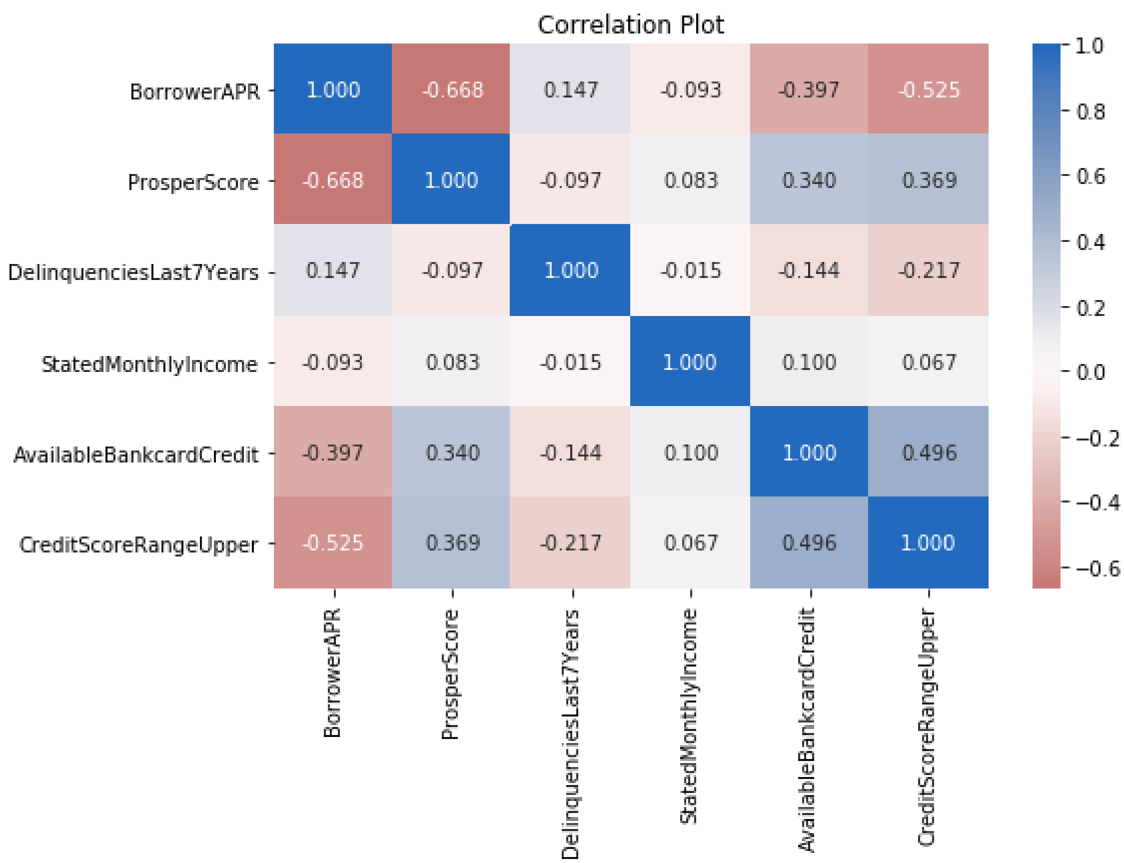
While performing this basic analysis, did you find any feature or attribute to be behaving unusually?

```
Yes, features like Occupation truned out to give no significant idea about h
ow it is affecting Borrower's APR. In real, occupation can be generalized to
give a sense of background and income which indirectly affects APR but from
 the above preliminary analysis, we cannot say so.
```

Multivariate Exploration

- Lets see how the attributes are influencing each other and also how are they correlated using the Correlation plot.

In [41]:
```
col_cor = ['BorrowerAPR', 'ProsperScore', 'DelinquenciesLast7Years', \
           'StatedMonthlyIncome', 'AvailableBankcardCredit', 'CreditScore
RangeUpper']

plt.figure(figsize = [8, 5])
sns.heatmap(df_loan_1[col_cor].corr(), annot = True, fmt = '.3f',
           cmap = 'vlag_r', center = 0)
plt.title('Correlation Plot')
plt.show();
```

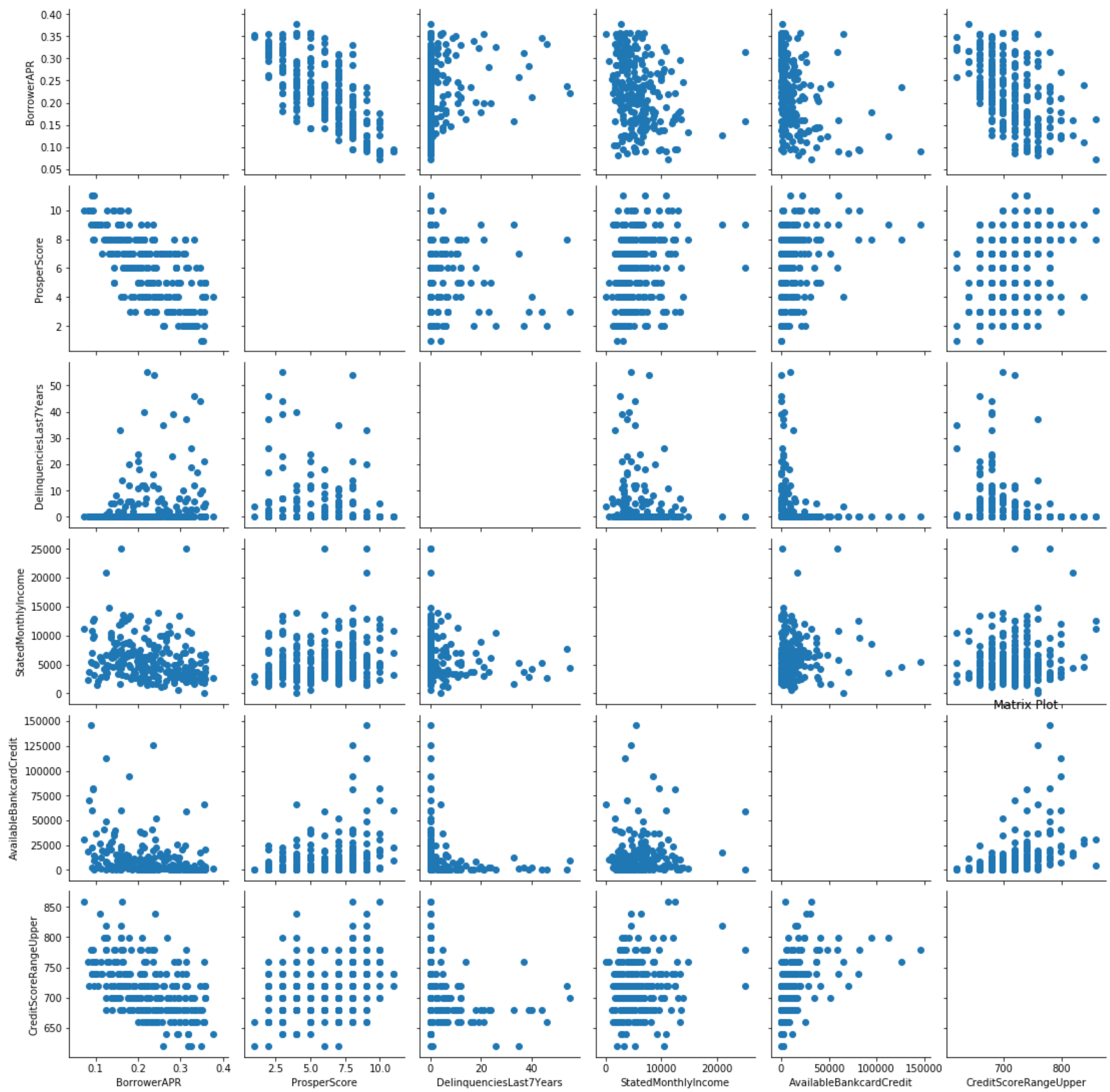


The correlations are mostly negative and that can be understood and also is justified. The highest negative correlation is between 'ProsperScore' and 'BorrowerAPR', which should be true because higher the prosperscore, higher will be the trust in customer and his ability to repay the dues hence they are inversely proportional or negatively correlated. Same relation can be seen in Credit Score and BorrowerAPR also.

- lets have a look at scatter plots for these variables.

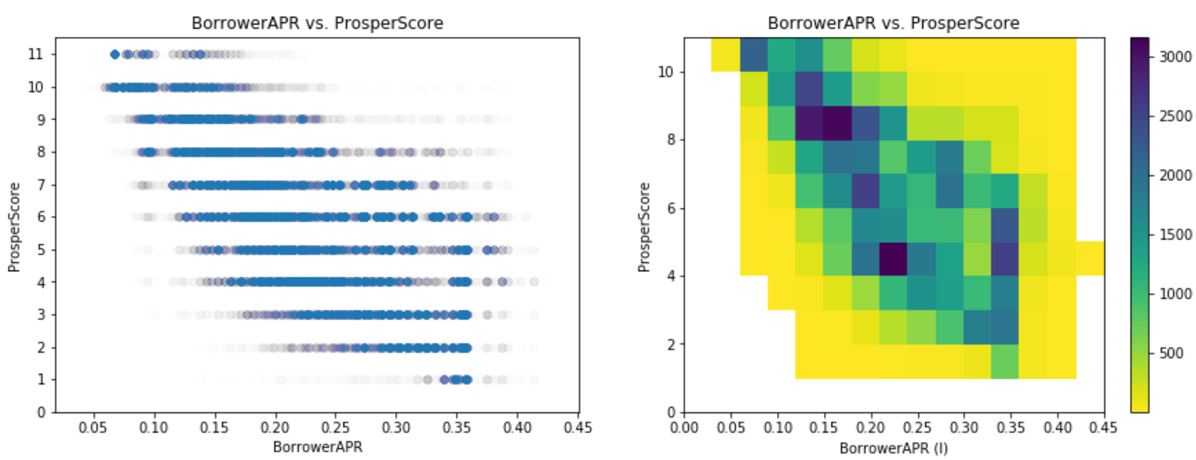
In [47]:
```
# plot matrix: only 250 random loans are used to see the pattern more cl
earer
plt.figure(figsize = [10, 5])


col_cor = ['BorrowerAPR', 'ProsperScore', 'DelinquenciesLast7Years',
           'StatedMonthlyIncome', 'AvailableBankcardCredit', 'CreditSco
reRangeUpper']

sample = np.random.choice(df_loan_1.shape[0], 250, replace = False)
loan_samp = df_loan_1.iloc[sample,:]

g = sns.PairGrid(data = loan_samp, vars = col_cor)
g.map_offdiag(plt.scatter)
plt.title('Matrix Plot')
```

Out[47]:
```
Text(0.5, 1, 'Matrix Plot')

<Figure size 720x360 with 0 Axes>
```



The Matrix plot also turns out to be similar to the correlation plot in determining which attributes have positive and which attributes have negative correlation. We can deduce that ProsperScore has most negative correlation with BorrowerAPR, we can try and analyze it better by explicitely plotting them in different and more informative manner.

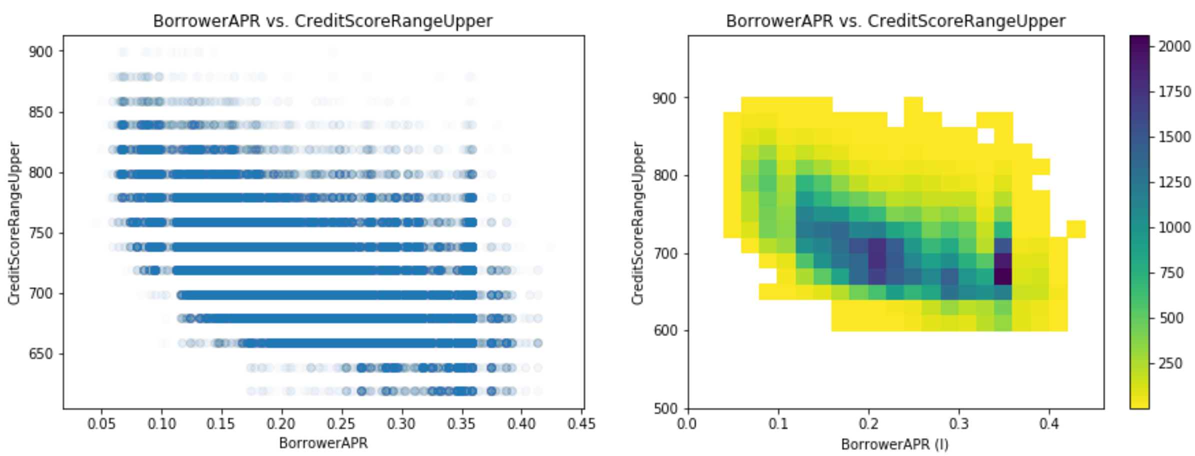
In [48]:
```
# scatter and heat plot for comparing ProsperScore and BorrowerAPR.
plt.figure(figsize = [15, 5])

plt.subplot(1, 2, 1)
plt.scatter(data = df_loan_1, x = 'BorrowerAPR', y = 'ProsperScore', alp
ha =  0.005)
plt.yticks(np.arange(0, 12, 1))
plt.title('BorrowerAPR vs. ProsperScore')
plt.xlabel('BorrowerAPR')
plt.ylabel('ProsperScore')


plt.subplot(1, 2, 2)
bins_x = np.arange(0, df_loan_1['BorrowerAPR'].max()+0.05, 0.03)
bins_y = np.arange(0, df_loan_1['ProsperScore'].max()+1, 1)
plt.hist2d(data = df_loan_1, x = 'BorrowerAPR', y = 'ProsperScore', bins
= [bins_x, bins_y],
               cmap = 'viridis_r', cmin = 0.5)
plt.colorbar()
plt.title('BorrowerAPR vs. ProsperScore')
plt.xlabel('BorrowerAPR (l)')
plt.ylabel('ProsperScore');
```



Our assumtion is likely to be true about both of these variables being Negatively correlated.

- Let us plot a similar scatter plot and heat map for other 2 variable i.e. BorrowerAPR and CreditScoreRangeUpper

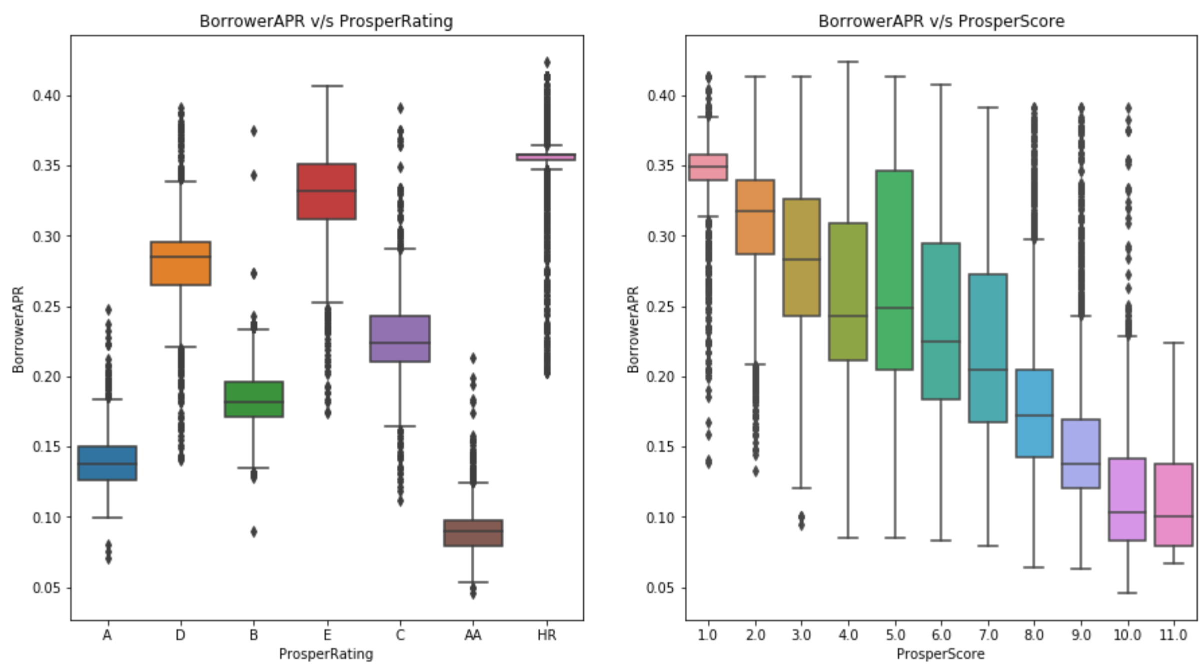
In [58]:
```
plt.figure(figsize = [15, 5])

plt.subplot(1, 2, 1)
plt.scatter(data = df_loan_1, y = 'CreditScoreRangeUpper', x = 'Borrower
APR', alpha = 0.01)
plt.title('BorrowerAPR vs. CreditScoreRangeUpper')
plt.xlabel('BorrowerAPR')
plt.ylabel('CreditScoreRangeUpper');


plt.subplot(1, 2, 2)
bins_x = np.arange(0, df_loan_copy['BorrowerAPR'].max()+0.05, 0.02)
bins_y = np.arange(500, df_loan_copy['CreditScoreRangeUpper'].max()+100,
20)
plt.hist2d(data = df_loan_1, x = 'BorrowerAPR', y = 'CreditScoreRangeUpp
er', bins = [bins_x, bins_y],
               cmap = 'viridis_r', cmin = 0.5)
plt.colorbar()
plt.title('BorrowerAPR vs. CreditScoreRangeUpper')
plt.xlabel('BorrowerAPR (l)')
plt.ylabel('CreditScoreRangeUpper');
```



The above plot makes sense because the higher the Credit Score, the lower will be the BorrowerAPR. The Credit Score also is positively correlated with the ProsperScore.

- Lets try to plot relation between BorrowerAPR and ProsperScore & ProsperRating. The primary focus while doing this viz is to uncover some information that might not be visible using the above plotted plots.

In [57]:
```
plt.figure(figsize = [20, 10])

plt.subplot(1, 2, 1)
sns.boxplot(data = df_loan_copy, x = 'ProsperRating (Alpha)', y = 'Borro
werAPR')
plt.gcf().set_size_inches(15, 8)
plt.title('BorrowerAPR v/s ProsperRating')
plt.xlabel('ProsperRating')
plt.ylabel('BorrowerAPR')

plt.subplot(1, 2, 2)
sns.boxplot(data = df_loan_copy, x = 'ProsperScore', y = 'BorrowerAPR')
plt.gcf().set_size_inches(15, 8)
plt.title('BorrowerAPR v/s ProsperScore')
plt.xlabel('ProsperScore')
plt.ylabel('BorrowerAPR');
```



The Violin plot for BorrowerAPR and ProsperRating & ProsperScore gives us the idea that ProsperRating cannot substantially help in seeing how it affects the BorrowerAPR. ProsperScore plot clearly shows a negative correlation with the BorrowerAPR.

What are some of the relationships of our interest and what is their nature?

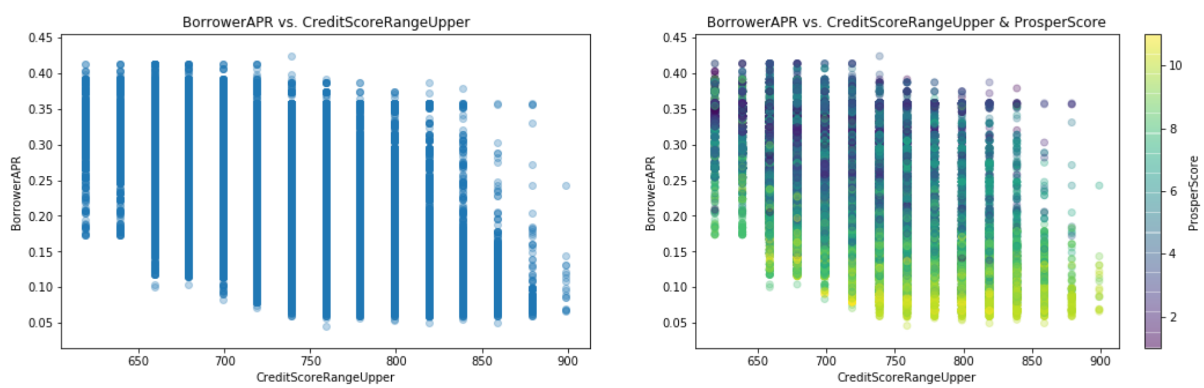
```
- The plots above have revealed 2 features / attributes having a relationshi
p of our interest and should be probed for further insights.
- We can say that ProsperScore and CreditScoreRangeUpper, both, have a negat
ive correlation to the BorrowerAPR. A probable reason for such behavior are
 mentioned below each of the plots.
```

- We will utilize these variables to try 2 kinds of plot and try and implement Multivariate Visualization

Multivariate Exploration

In [63]:

```
# Lets us try and implement these 3 variables together.

plt.figure(figsize = [18, 5])

plt.subplot(1, 2, 1)
plt.scatter(data = df_loan_1, x = 'CreditScoreRangeUpper', y = 'Borrower
APR', alpha = 0.3)
plt.title('BorrowerAPR vs. CreditScoreRangeUpper')
plt.ylabel('BorrowerAPR')
plt.xlabel('CreditScoreRangeUpper');


plt.subplot(1, 2, 2)
plt.scatter(data = df_loan_1, x = 'CreditScoreRangeUpper', y = 'Borrower
APR', c ='ProsperScore', alpha = 0.3)
plt.colorbar(label = 'ProsperScore')
plt.title('BorrowerAPR vs. CreditScoreRangeUpper & ProsperScore')
plt.ylabel('BorrowerAPR')
plt.xlabel('CreditScoreRangeUpper');
```

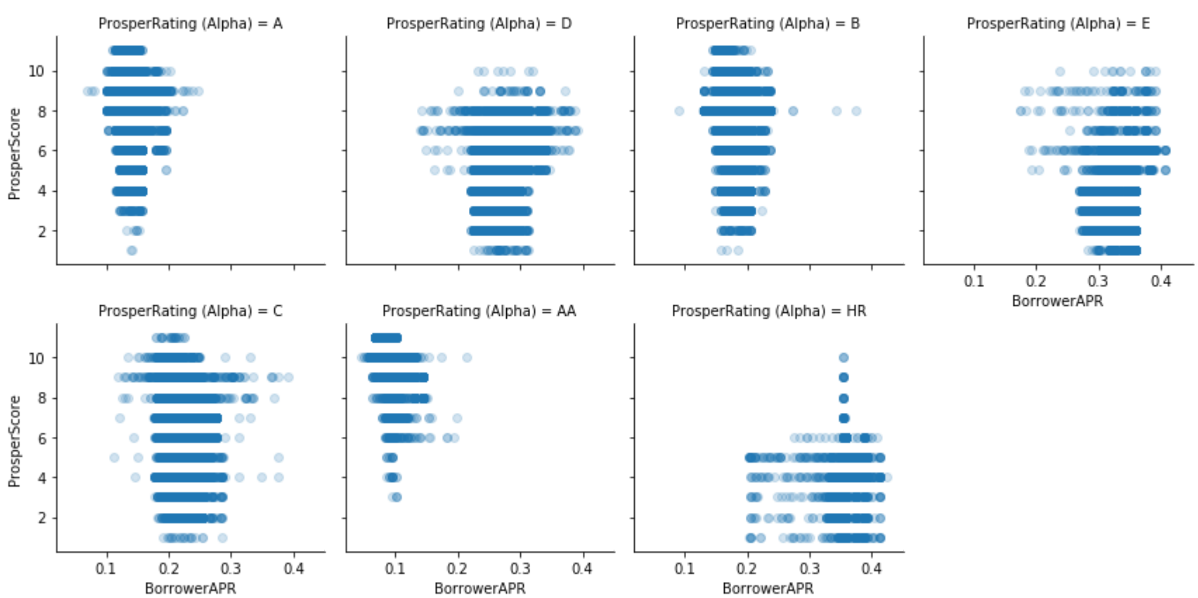


- Here we start by plotting two variables at first and then try to include third variable in the same plot to get a multivariate visualization
- The negative correlations (BorrowerAPR and ProsperScore & BorrowerAPR and CreditScoreRangeUpper) is visible from second plot itself.
- As the Credit Score Range goes higher, the BorrowerAPR can be seen decreasing.
- Similarly, with lower ProsperScore (i.e. bluish dots) the BorrowerAPR stays higher or on top of the plot unlike the yellow dots including lower BorrowerAPR and at the same time also some positive correlation with Credit Score.

```
Let's try and use FacetGrid() to do a similar multivariate visual
```

In [64]:
```
viz = sns.FacetGrid(data= df_loan_1, col='ProsperRating (Alpha)', col_wr
ap=4, size=3)
viz.map(plt.scatter, 'BorrowerAPR', 'ProsperScore', alpha= 0.2)
viz.set_xlabels('BorrowerAPR')
viz.set_ylabels('ProsperScore')

plt.show();
```

```
/Users/parthpatel/opt/anaconda3/lib/python3.7/site-packages/seaborn/axi
sgrid.py:243: UserWarning: The `size` parameter has been renamed to `he
ight`; please update your code.
  warnings.warn(msg, UserWarning)
```



This plot shows us the correlation between BorrowerAPR and ProsperScore for each of the ProsperRating individually. We can deduce that the ProsperRating categories would not have any pattern of correlation with BorrowerAPR. But we can deduce that the people with lower ratings usually tend to have a higher APR and which can be true in real world too.

In [ ]: