(Loan Data from Prosper)

by (Ahmed Tarek)

Preliminary Wrangling

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

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
```

Assessing data

In [2]:
```
df = pd.read_csv('prosperLoanData.csv')
df
```

Out[2]:

	ListingKey	ListingNumber	ListingCreationDate	CreditGrade	Term	
0	1021339766868145413AB3B	193129	2007-08-26 19:09:29.263000000	C	36	
1	10273602499503308B223C1	1209647	2014-02-27 08:28:07.900000000	NaN	36	
2	0EE9337825851032864889A	81716	2007-01-05 15:00:47.090000000	HR	36	
3	0EF5356002482715299901A	658116	2012-10-22 11:02:35.010000000	NaN	36	
4	0F023589499656230C5E3E2	909464	2013-09-14 18:38:39.097000000	NaN	36	
...	...	...	...	...	...	
113932	E6D9357655724827169606C	753087	2013-04-14 05:55:02.663000000	NaN	36	
113933	E6DB353036033497292EE43	537216	2011-11-03 20:42:55.333000000	NaN	36	FinalPa
113934	E6E13596170052029692BB1	1069178	2013-12-13 05:49:12.703000000	NaN	60	
113935	E6EB3531504622671970D9E	539056	2011-11-14 13:18:26.597000000	NaN	60	
113936	E6ED3600409833199F711B7	1140093	2014-01-15 09:27:37.657000000	NaN	36	

113937 rows × 81 columns

In [3]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 113937 entries, 0 to 113936
Data columns (total 81 columns):
 #   Column                               Non-Null Count   Dtype  
---  ------                               --------------   -----  
 0   ListingKey                           113937 non-null  object 
 1   ListingNumber                        113937 non-null  int64  
 2   ListingCreationDate                  113937 non-null  object 
 3   CreditGrade                          28953 non-null   object 
 4   Term                                 113937 non-null  int64  
 5   LoanStatus                           113937 non-null  object 
 6   ClosedDate                           55089 non-null   object 
 7   BorrowerAPR                          113912 non-null  float64
 8   BorrowerRate                         113937 non-null  float64
 9   LenderYield                          113937 non-null  float64
 10  EstimatedEffectiveYield              84853 non-null   float64
 11  EstimatedLoss                        84853 non-null   float64
 12  EstimatedReturn                      84853 non-null   float64
 13  ProsperRating (numeric)              84853 non-null   float64
 14  ProsperRating (Alpha)                84853 non-null   object 
 15  ProsperScore                         84853 non-null   float64
 16  ListingCategory (numeric)            113937 non-null  int64  
 17  BorrowerState                        108422 non-null  object 
 18  Occupation                           110349 non-null  object 
 19  EmploymentStatus                     111682 non-null  object 
 20  EmploymentStatusDuration             106312 non-null  float64
 21  IsBorrowerHomeowner                  113937 non-null  bool   
 22  CurrentlyInGroup                     113937 non-null  bool   
 23  GroupKey                             13341 non-null   object 
 24  DateCreditPulled                     113937 non-null  object 
 25  CreditScoreRangeLower                113346 non-null  float64
 26  CreditScoreRangeUpper                113346 non-null  float64
 27  FirstRecordedCreditLine              113240 non-null  object 
 28  CurrentCreditLines                   106333 non-null  float64
 29  OpenCreditLines                      106333 non-null  float64
 30  TotalCreditLinespast7years           113240 non-null  float64
 31  OpenRevolvingAccounts                113937 non-null  int64  
 32  OpenRevolvingMonthlyPayment          113937 non-null  float64
 33  InquiriesLast6Months                 113240 non-null  float64
 34  TotalInquiries                       112778 non-null  float64
 35  CurrentDelinquencies                 113240 non-null  float64
 36  AmountDelinquent                     106315 non-null  float64
 37  DelinquenciesLast7Years              112947 non-null  float64
 38  PublicRecordsLast10Years             113240 non-null  float64
 39  PublicRecordsLast12Months            106333 non-null  float64
 40  RevolvingCreditBalance               106333 non-null  float64
 41  BankcardUtilization                  106333 non-null  float64
 42  AvailableBankcardCredit              106393 non-null  float64
 43  TotalTrades                          106393 non-null  float64
 44  TradesNeverDelinquent (percentage)   106393 non-null  float64
 45  TradesOpenedLast6Months              106393 non-null  float64
 46  DebtToIncomeRatio                    105383 non-null  float64
 47  IncomeRange                          113937 non-null  object 
 48  IncomeVerifiable                     113937 non-null  bool   
 49  StatedMonthlyIncome                  113937 non-null  float64
```

```
 50  LoanKey                              113937 non-null  object
 51  TotalProsperLoans                    22085 non-null   float64
 52  TotalProsperPaymentsBilled           22085 non-null   float64
 53  OnTimeProsperPayments                22085 non-null   float64
 54  ProsperPaymentsLessThanOneMonthLate  22085 non-null   float64
 55  ProsperPaymentsOneMonthPlusLate      22085 non-null   float64
 56  ProsperPrincipalBorrowed             22085 non-null   float64
 57  ProsperPrincipalOutstanding          22085 non-null   float64
 58  ScorexChangeAtTimeOfListing          18928 non-null   float64
 59  LoanCurrentDaysDelinquent            113937 non-null  int64
 60  LoanFirstDefaultedCycleNumber        16952 non-null   float64
 61  LoanMonthsSinceOrigination           113937 non-null  int64
 62  LoanNumber                           113937 non-null  int64
 63  LoanOriginalAmount                   113937 non-null  int64
 64  LoanOriginationDate                  113937 non-null  object
 65  LoanOriginationQuarter               113937 non-null  object
 66  MemberKey                            113937 non-null  object
 67  MonthlyLoanPayment                   113937 non-null  float64
 68  LP_CustomerPayments                  113937 non-null  float64
 69  LP_CustomerPrincipalPayments         113937 non-null  float64
 70  LP_InterestandFees                   113937 non-null  float64
 71  LP_ServiceFees                       113937 non-null  float64
 72  LP_CollectionFees                    113937 non-null  float64
 73  LP_GrossPrincipalLoss                113937 non-null  float64
 74  LP_NetPrincipalLoss                  113937 non-null  float64
 75  LP_NonPrincipalRecoverypayments      113937 non-null  float64
 76  PercentFunded                        113937 non-null  float64
 77  Recommendations                      113937 non-null  int64
 78  InvestmentFromFriendsCount           113937 non-null  int64
 79  InvestmentFromFriendsAmount          113937 non-null  float64
 80  Investors                            113937 non-null  int64
dtypes: bool(3), float64(50), int64(11), object(17)
memory usage: 68.1+ MB
```

In [4]:
```
df.describe()
```

Out[4]:

	ListingNumber	Term	BorrowerAPR	BorrowerRate	LenderYield	EstimatedEffect
count	1.139370e+05	113937.000000	113912.000000	113937.000000	113937.000000	84853
mean	6.278857e+05	40.830248	0.218828	0.192764	0.182701	0
std	3.280762e+05	10.436212	0.080364	0.074818	0.074516	0
min	4.000000e+00	12.000000	0.006530	0.000000	-0.010000	-0
25%	4.009190e+05	36.000000	0.156290	0.134000	0.124200	0
50%	6.005540e+05	36.000000	0.209760	0.184000	0.173000	0
75%	8.926340e+05	36.000000	0.283810	0.250000	0.240000	0
max	1.255725e+06	60.000000	0.512290	0.497500	0.492500	0

8 rows × 61 columns

In [5]:
```
# checking if there is duplicated data
sum(df.duplicated())
```

Out[5]:
```
0
```

In [6]:
```
# checking null values
df.isnull().sum()
```

Out[6]:
```
ListingKey                          0
ListingNumber                       0
ListingCreationDate                 0
CreditGrade                     84984
Term                                0
                                ...  
PercentFunded                       0
Recommendations                     0
InvestmentFromFriendsCount          0
InvestmentFromFriendsAmount         0
Investors                           0
Length: 81, dtype: int64
```

In [7]:
```
df.columns
```

Out[7]:
```
Index(['ListingKey', 'ListingNumber', 'ListingCreationDate', 'CreditGrade',
       'Term', 'LoanStatus', 'ClosedDate', 'BorrowerAPR', 'BorrowerRate',
       'LenderYield', 'EstimatedEffectiveYield', 'EstimatedLoss',
       'EstimatedReturn', 'ProsperRating (numeric)', 'ProsperRating (Alpha)',
       'ProsperScore', 'ListingCategory (numeric)', 'BorrowerState',
       'Occupation', 'EmploymentStatus', 'EmploymentStatusDuration',
       'IsBorrowerHomeowner', 'CurrentlyInGroup', 'GroupKey',
       'DateCreditPulled', 'CreditScoreRangeLower', 'CreditScoreRangeUpper',
       'FirstRecordedCreditLine', 'CurrentCreditLines', 'OpenCreditLines',
       'TotalCreditLinespast7years', 'OpenRevolvingAccounts',
       'OpenRevolvingMonthlyPayment', 'InquiriesLast6Months', 'TotalInquiries',
       'CurrentDelinquencies', 'AmountDelinquent', 'DelinquenciesLast7Years',
       'PublicRecordsLast10Years', 'PublicRecordsLast12Months',
       'RevolvingCreditBalance', 'BankcardUtilization',
       'AvailableBankcardCredit', 'TotalTrades',
       'TradesNeverDelinquent (percentage)', 'TradesOpenedLast6Months',
       'DebtToIncomeRatio', 'IncomeRange', 'IncomeVerifiable',
       'StatedMonthlyIncome', 'LoanKey', 'TotalProsperLoans',
       'TotalProsperPaymentsBilled', 'OnTimeProsperPayments',
       'ProsperPaymentsLessThanOneMonthLate',
       'ProsperPaymentsOneMonthPlusLate', 'ProsperPrincipalBorrowed',
       'ProsperPrincipalOutstanding', 'ScorexChangeAtTimeOfListing',
       'LoanCurrentDaysDelinquent', 'LoanFirstDefaultedCycleNumber',
       'LoanMonthsSinceOrigination', 'LoanNumber', 'LoanOriginalAmount',
       'LoanOriginationDate', 'LoanOriginationQuarter', 'MemberKey',
       'MonthlyLoanPayment', 'LP_CustomerPayments',
       'LP_CustomerPrincipalPayments', 'LP_InterestandFees', 'LP_ServiceFees',
       'LP_CollectionFees', 'LP_GrossPrincipalLoss', 'LP_NetPrincipalLoss',
       'LP_NonPrincipalRecoverypayments', 'PercentFunded', 'Recommendations',
       'InvestmentFromFriendsCount', 'InvestmentFromFriendsAmount',
       'Investors'],
      dtype='object')
```

Quality:

- There are null values some can be droped others no

Tidiness:

- Some columns wont be necessary

Cleaning data

In [8]:
```
# droping columns that are not necessary
cols = ['ListingKey', 'ListingNumber', 'ListingCreationDate', 'CreditGrade', 'Clo
        'EstimatedEffectiveYield', 'EstimatedLoss', 'EstimatedReturn', 'ProsperRa
        'BorrowerState', 'EmploymentStatusDuration','IsBorrowerHomeowner', 'Curre
        'FirstRecordedCreditLine', 'CurrentCreditLines', 'OpenCreditLines', 'Tota
        'OpenRevolvingAccounts', 'OpenRevolvingMonthlyPayment', 'InquiriesLast6Mo
        'CurrentDelinquencies', 'AmountDelinquent', 'DelinquenciesLast7Years', 'P
        'PublicRecordsLast12Months','RevolvingCreditBalance', 'BankcardUtilizatio
        'TradesNeverDelinquent (percentage)', 'TradesOpenedLast6Months', 'DebtToI
        'StatedMonthlyIncome', 'LoanKey', 'TotalProsperLoans', 'OnTimeProsperPaym
        'ProsperPaymentsOneMonthPlusLate', 'ProsperPrincipalBorrowed', 'ProsperPr
        'ScorexChangeAtTimeOfListing', 'LoanCurrentDaysDelinquent', 'LoanFirstDef
        'LoanMonthsSinceOrigination', 'LoanNumber', 'LoanOriginationDate', 'LoanO
        'MonthlyLoanPayment', 'LP_CustomerPayments', 'LP_CustomerPrincipalPayment
        'LP_CollectionFees', 'LP_GrossPrincipalLoss', 'LP_NetPrincipalLoss', 'LP_
        'PercentFunded', 'Recommendations', 'InvestmentFromFriendsCount', 'Invest

df.drop(cols, axis =1, inplace=True)
```

In [9]:
```
# replacing null values with 0 in TotalProsperPaymentsBilled because we cant drop
# number of on time payments the borrower made on Prosper loans at the time they
# will be null if the borrower had no prior loans.
df.TotalProsperPaymentsBilled.fillna(0, inplace = True)
```

In [10]:
```
# droping null values
df.dropna(inplace = True)
```

In [11]:
```
df
```

Out[11]:

	Term	LoanStatus	BorrowerAPR	ProsperRating (Alpha)	ProsperScore	Occupation	Em
1	36	Current	0.12016	A	7.0	Professional	
3	36	Current	0.12528	A	9.0	Skilled Labor	
4	36	Current	0.24614	D	4.0	Executive	
5	60	Current	0.15425	B	10.0	Professional	
6	36	Current	0.31032	E	2.0	Sales - Retail	
...	...	...	...	...	...	...	
113932	36	Current	0.22354	C	5.0	Food Service Management	
113933	36	FinalPaymentInProgress	0.13220	A	8.0	Professional	
113934	60	Current	0.23984	D	3.0	Other	
113935	60	Completed	0.28408	C	5.0	Food Service	
113936	36	Current	0.13189	A	7.0	Professor	

83520 rows × 12 columns

In [12]:
```
# check if there are duplicates
sum(df.duplicated())
```

Out[12]: 2461

In [13]:
```
# droping duplicates
df.drop_duplicates(inplace = True)
```

In [14]:
```
df
```

Out[14]:

	Term	LoanStatus	BorrowerAPR	ProsperRating (Alpha)	ProsperScore	Occupation	Em
1	36	Current	0.12016	A	7.0	Professional	
3	36	Current	0.12528	A	9.0	Skilled Labor	
4	36	Current	0.24614	D	4.0	Executive	
5	60	Current	0.15425	B	10.0	Professional	
6	36	Current	0.31032	E	2.0	Sales - Retail	
...	...	...	...	...	...	...	
113931	60	Current	0.15016	B	6.0	Analyst	
113932	36	Current	0.22354	C	5.0	Food Service Management	
113933	36	FinalPaymentInProgress	0.13220	A	8.0	Professional	
113935	60	Completed	0.28408	C	5.0	Food Service	
113936	36	Current	0.13189	A	7.0	Professor	

81059 rows × 12 columns

In [15]:
```
# saving cleaned data to another file
df.to_csv('prosperLoanData_cleaned.csv', encoding='utf-8',index=False)
```

What is the structure of your dataset?

- 113937 loans (rows)
- 81 attributes (columns)

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

- The Borrower's Annual Percentage Rate (APR) for the loan
- The loan statues and what attributes affect it

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

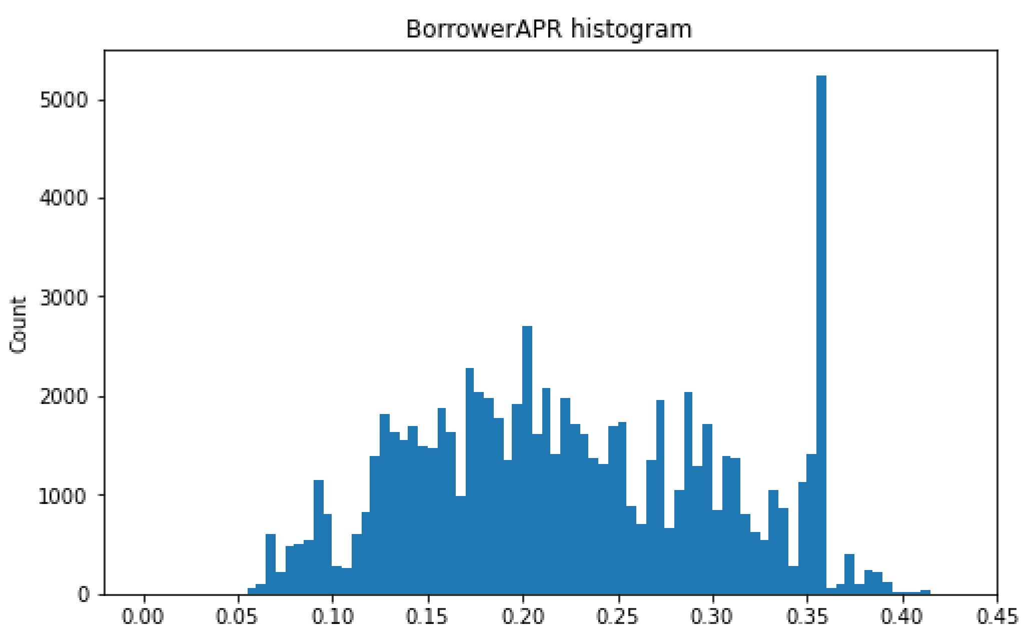
- ProsperScore
- ProsperRating (Alpha)
- Occupation
- CreditScoreRangeLower and CreditScoreRangeUpper
- Term
- LoanOriginalAmount
- TotalProsperPaymentsBilled
- IncomeRange
- EmploymentStatus

Univariate Exploration

Lets take a look at the BorrowerAPR

In [16]:
```
# reading data
df_loans = pd.read_csv('prosperLoanData_cleaned.csv')
```

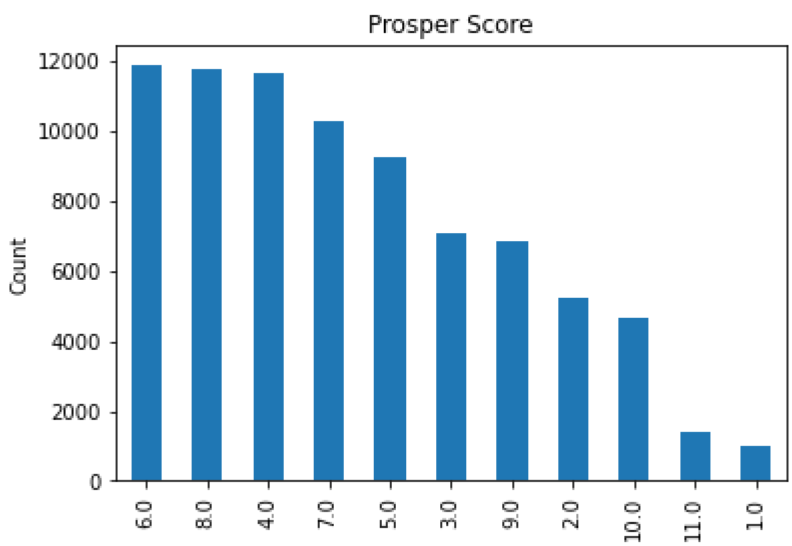
In [17]:
```
# counts for BorrowerAPR values
bins = np.arange(0, df_loans.BorrowerAPR.max(), 0.005)
plt.figure(figsize=[8, 5])
plt.hist(data = df_loans, x = 'BorrowerAPR', bins = bins)
plt.xticks(np.arange(0, df_loans.BorrowerAPR.max()+0.05, 0.05))
plt.ylabel('Count')
plt.title('BorrowerAPR histogram');
```



It appears that this distribution is multimodal with several peaks. A peak at 0.08, 0.2, 0.28, and an exceptionally high peak at 0.36.

Let's look at Prosper Score which is a custom risk score built using historical Prosper data.

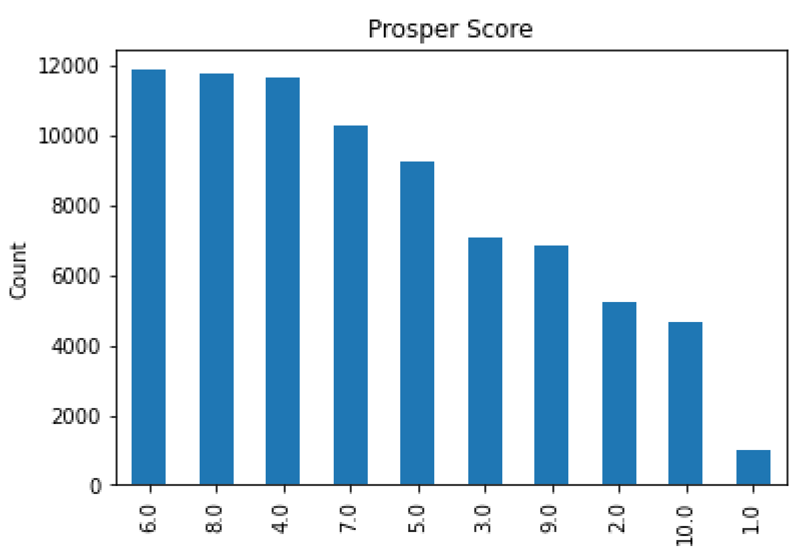
In [18]:
```
# Bar Chart ProsperScore
def plot1():
    df_loans.ProsperScore.value_counts().plot(kind='bar')
    plt.ylabel('Count')
    plt.title('Prosper Score');

plot1()
```



This shows that there are scores above 10 which is not possible since the score is from 1-10. This data must be removed.

In [19]:
```
# excluding all borrowers with a Prosper Score of 11
df_loans = df_loans[df_loans.ProsperScore != 11]
```

In [20]:
```
# ploting the bar chart again
plot1()
```



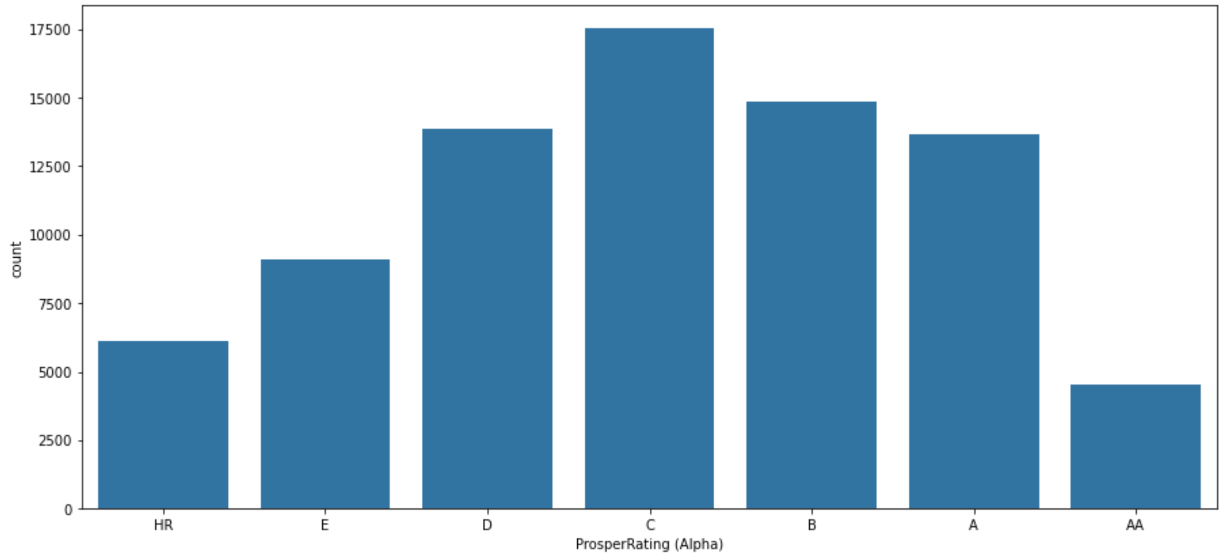
Most of the borrower got Prosper Score of 6 that means they are safe to loan. Notice that even customers with a low risks score of 1 or 2 did get a loan. Not many borrowers received the highest score of 10.

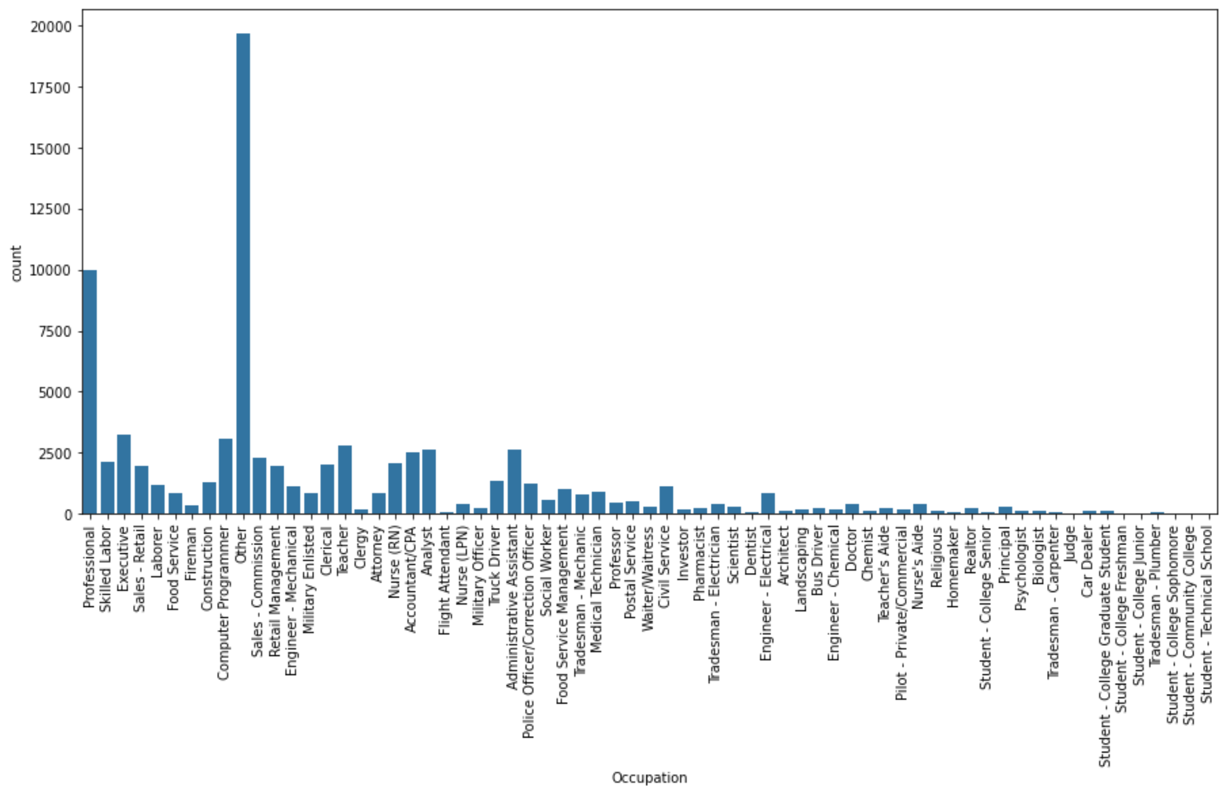
Now lets look at ProsperRating (Alpha) and Occupation

Before plotting, the ProsperRating (Alpha) should be ordered from low to high so there won't be any misleading visualization about the rating order

In [21]:
```
# Convert ProsperRating into ordered categorical types
rate_order = ['HR','E','D','C','B','A','AA']
ordered_var = pd.api.types.CategoricalDtype(ordered = True, categories = rate_orc
df_loans['ProsperRating (Alpha)'] = df_loans['ProsperRating (Alpha)'].astype(orde
```

In [22]:
```
fig, ax = plt.subplots(nrows=2, figsize = [15,15])
default_color = sb.color_palette()[0]
sb.countplot(data = df_loans, x = 'ProsperRating (Alpha)', color = default_color,
sb.countplot(data = df_loans, x = 'Occupation', color = default_color, ax = ax[1]
plt.xticks(rotation=90);
```

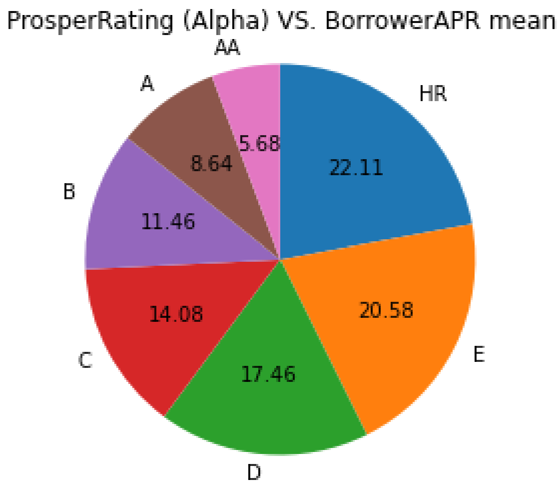




It appears that most borrowers were rated from C to A, and students are the least to take loans

Now, let's compare the Prosper rating (Alpha) mean with the Borrower APR mean

In [23]:
```
# ploting bar chart for ProsperRating vs BorrowerAPR mean
ProsperRatingAlpha_mean = df_loans.groupby('ProsperRating (Alpha)').BorrowerAPR.r

plt.pie(ProsperRatingAlpha_mean, labels = ProsperRatingAlpha_mean.index, startang
plt.axis('square')
plt.title('ProsperRating (Alpha) VS. BorrowerAPR mean');
```



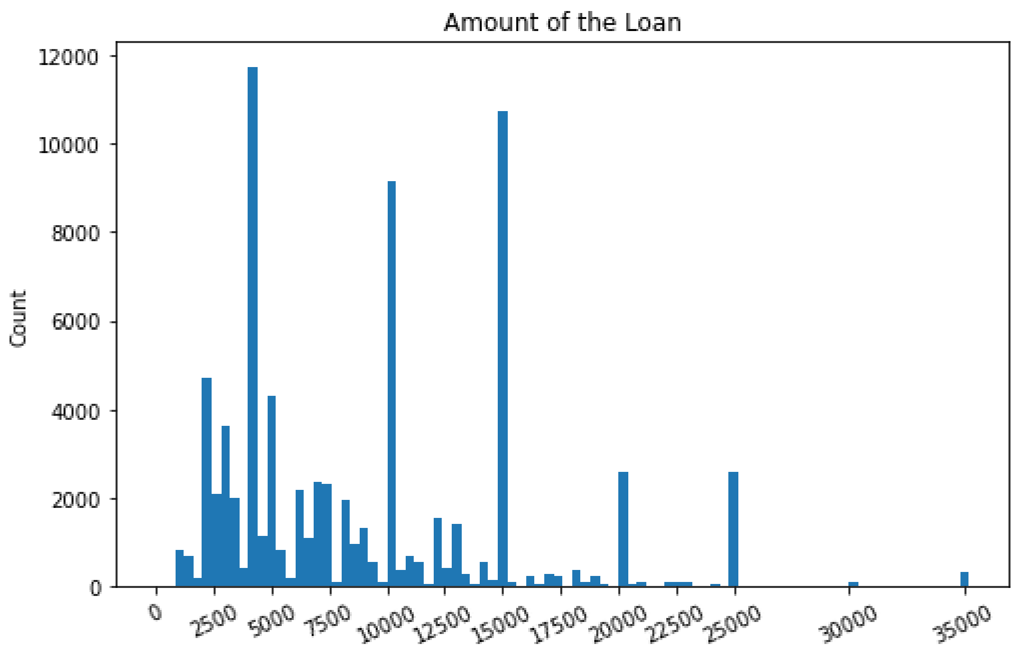
Notice that the highest rating of AA received the lowest BorrowerAPR (5.68), while the lowerest rating of HR received the highest BorrowerAPR (22.11). This shows that borrowers with higher ratings received lower BorrowerAPR.

I am interested in knowing more about the LoanOriginalAmount

In [24]:
```
# getting overview over the Loan amount
df_loans.LoanOriginalAmount.describe()
```

Out[24]:
```
count    79645.000000
mean      9021.664034
std       6203.914172
min       1000.000000
25%       4000.000000
50%       7500.000000
75%      13000.000000
max      35000.000000
Name: LoanOriginalAmount, dtype: float64
```

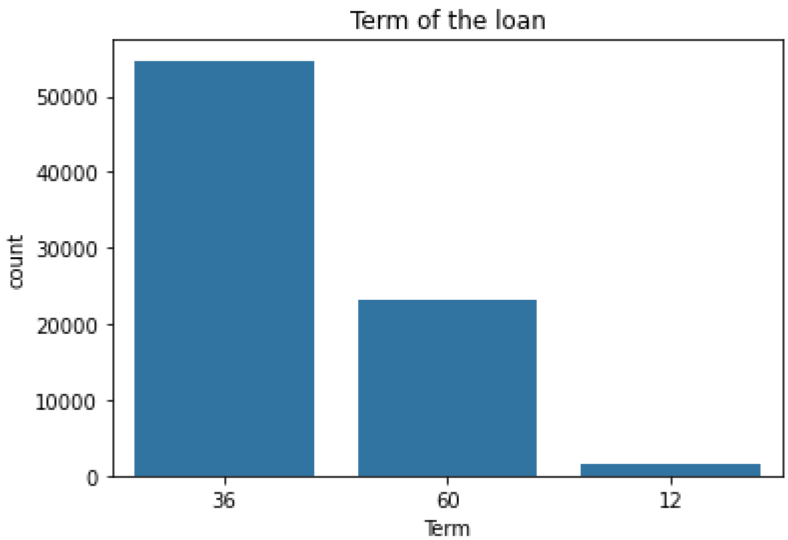
In [25]:
```
# Histogramm for The origination amount of the Loan
binsize = 400
bins = np.arange(0, df_loans.LoanOriginalAmount.max()+binsize, binsize)

plt.figure(figsize=[8, 5])
plt.hist(data = df_loans, x = 'LoanOriginalAmount', bins = bins)
plt.ylabel('Count')
plt.title('Amount of the Loan')
plt.xticks([0,2500,5000,7500,10000,12500,15000,17500,20000,22500,25000,30000,3500
```



The histogram has serval peaks at around 4,000, 10,000, and 15,000. But most of the values are in the lower end between 2500 and 10,000. The most loaned amounts are 4,000 and 15,000.

Now lets see if there is a relation between the LoanOriginalAmount and Term

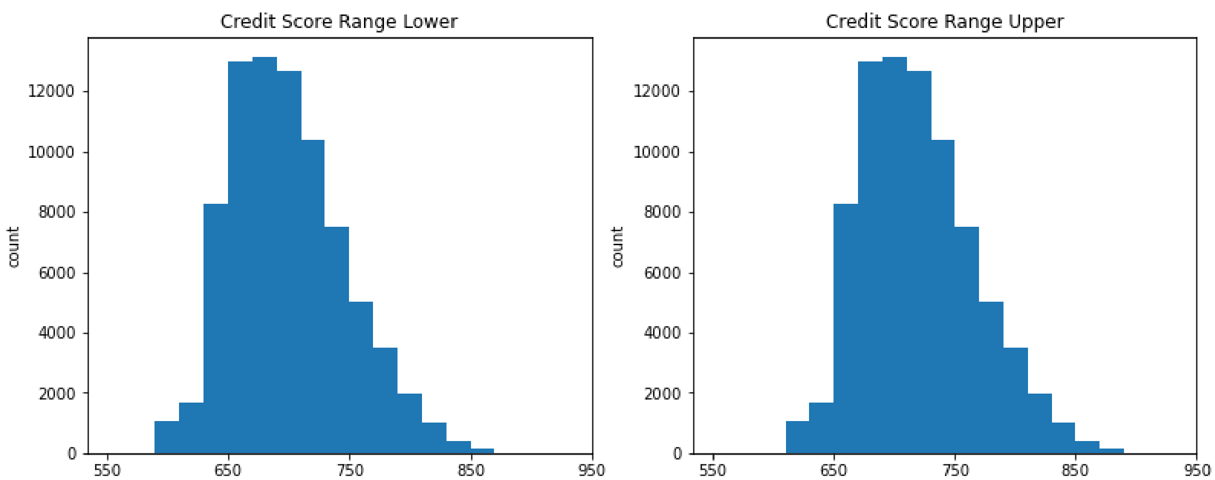
In [26]:
```
# Bar chart of the length of the loan in months
base_color = sb.color_palette()[0]
sb.countplot(data = df_loans, x='Term', color = base_color, order = df_loans.Terr
plt.title('Term of the loan');
```



Most of the loans have a length of 36 months. The fact that most of the loans have a length of just 36 months might be correlated to the fact the average loan amount is around 9000 which can be paid back quickly.

Lets look at the CreditScoreRangeLower and CreditScoreRangeUpper

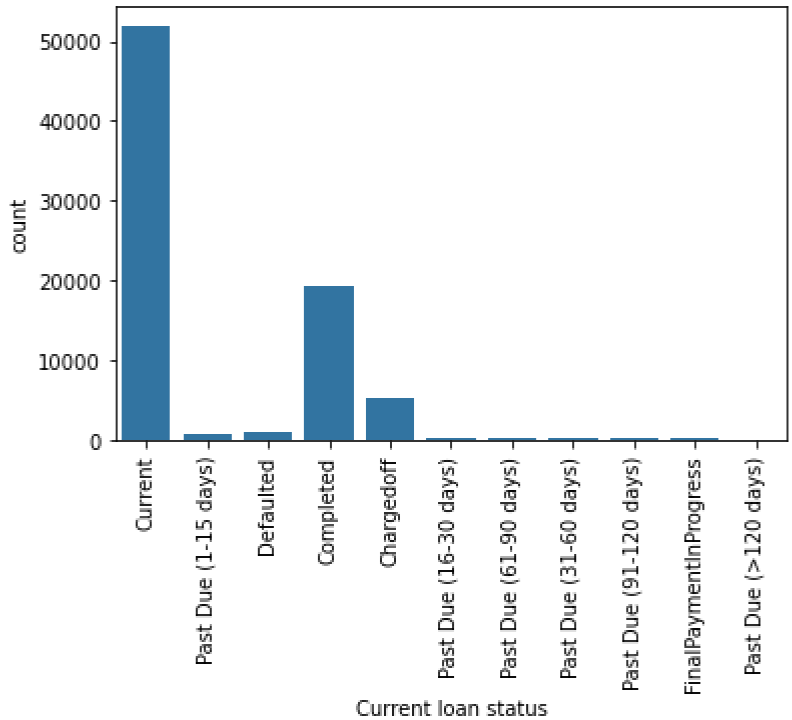
In [27]:
```
# Histogram for CreditScoreRangeLower and CreditScoreRangeUpper
plt.figure(figsize = [13, 5])


plt.subplot(1, 2, 1)
bins = np.arange(550, df_loans.CreditScoreRangeLower.max(), 20)
plt.hist(data = df_loans, x = 'CreditScoreRangeLower', bins = bins)
plt.xticks(np.arange(550, 1000, 100))
plt.title('Credit Score Range Lower')
plt.ylabel('count');

plt.subplot(1, 2, 2)
bins = np.arange(550, df_loans.CreditScoreRangeUpper.max(), 20)
plt.hist(data = df_loans, x = 'CreditScoreRangeUpper', bins = bins)
plt.xticks(np.arange(550, 1000, 100))
plt.title('Credit Score Range Upper')
plt.ylabel('count');
```



The two histograms show similar trends, and there are no outliers that fall out of the range.

Now lets take a look at the loan status

In [28]:
```
# bar chart LoanStatus for the current status of the loan
def plot2():
    base_color = sb.color_palette()[0]
    sb.countplot(data = df_loans, x = 'LoanStatus', color = base_color)
    plt.xlabel('Current loan status')
    plt.xticks(rotation = 90);

plot2()
```

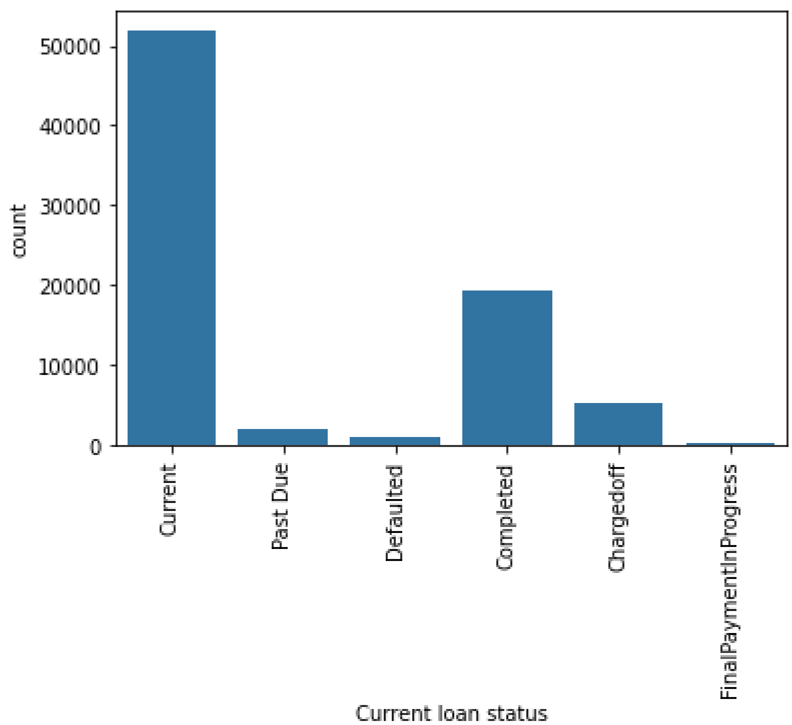


Combining the past dues into one column since it is not important to show that much information

In [29]:
```
# replacing Past Due (1-15 days)etc. with just Past Due
df_loans.LoanStatus = df_loans.LoanStatus.replace(['Past Due (1-15 days)', 'Past
                                                   'Past Due (91-120 days)','Past
                                                   'Past Due (>120 days)'],'Past

df_loans.LoanStatus.value_counts()
```

Out[29]:
```
Current                   51857
Completed                 19355
Chargedoff                 5191
Past Due                   2043
Defaulted                   999
FinalPaymentInProgress      200
Name: LoanStatus, dtype: int64
```

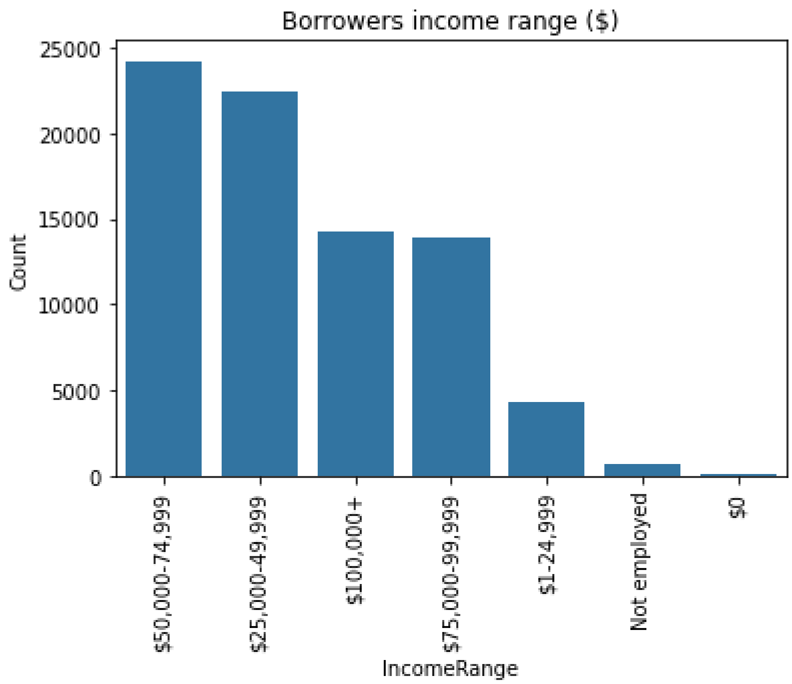
In [30]:
```
# plotting the bar chart of LoanStatus again
plot2()
```



Most of the loans are current or completed.

Now the IncomeRange

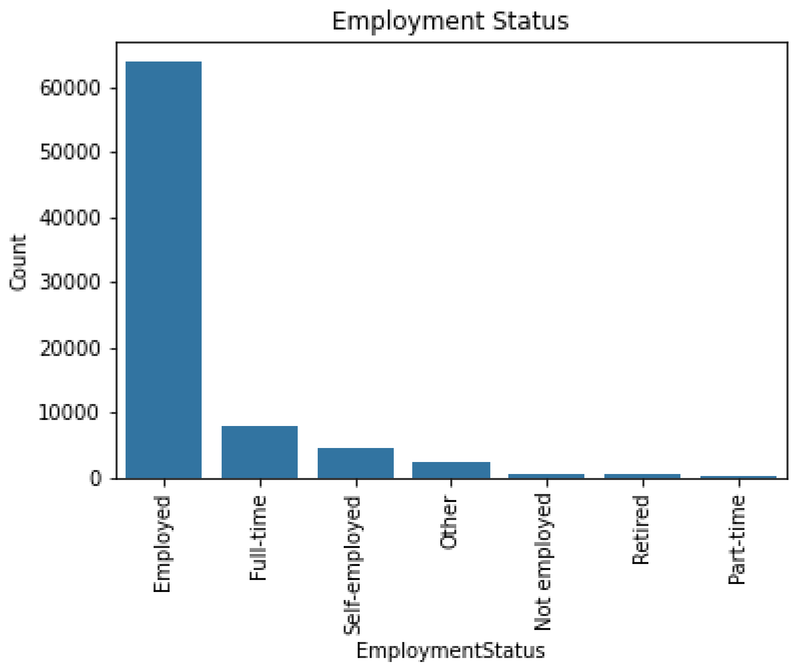
In [31]:
```
# Bar chart of the borrowers income range
sb.countplot(data= df_loans, x= 'IncomeRange', color= base_color, order = df_loar
plt.xticks(rotation=90)
plt.ylabel('Count')
plt.title('Borrowers income range ($)');
```



The income range of the borrowers shows that most of the loans were given to customers with an income between 25,000 and 74,999. Notice that people that are not employed, or have an income of 0 received a loan as well. They might be other criteria than the income that qualifies one to get a loan like being a student.

Lets check the EmploymentStatus to find out

In [32]:
```
# plotting the borrowers employment status
sb.countplot(data= df_loans, x= 'EmploymentStatus', color= base_color, order = df
plt.xticks(rotation=90)
plt.ylabel('Count')
plt.title('Employment Status');
```



Of course, most of the borrowers are employed, but the data shows that retired persons got a loan too.

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

> - The distribution of borrowers' APR most of the values are between 0.05 and 0.4. but there is one value that was higher than the rest there might be a reason that this value is used that much. Therefore, there is no need to perform any transformations.
> - Most of the loans are current or completed. However, there are a fairly significant number of loans that are charged off, defaulted, or past due.
> - The income range of the borrowers shows that most of the loans were to give to customers with an income between 25,000 and 74,999.
> - Most of the borrower got Prosper Score of 6 that means they are safe to loan. Notice that even customers with a low risks score of 1 or 2 did get a loan. Not many borrowers received the highest score of 10.
> - Most of the loans have a length of 36 months. The fact that most of the loans have a length of just 36 months might be correlated to the fact the average loan amount is around 9000 which can be paid back quickly.

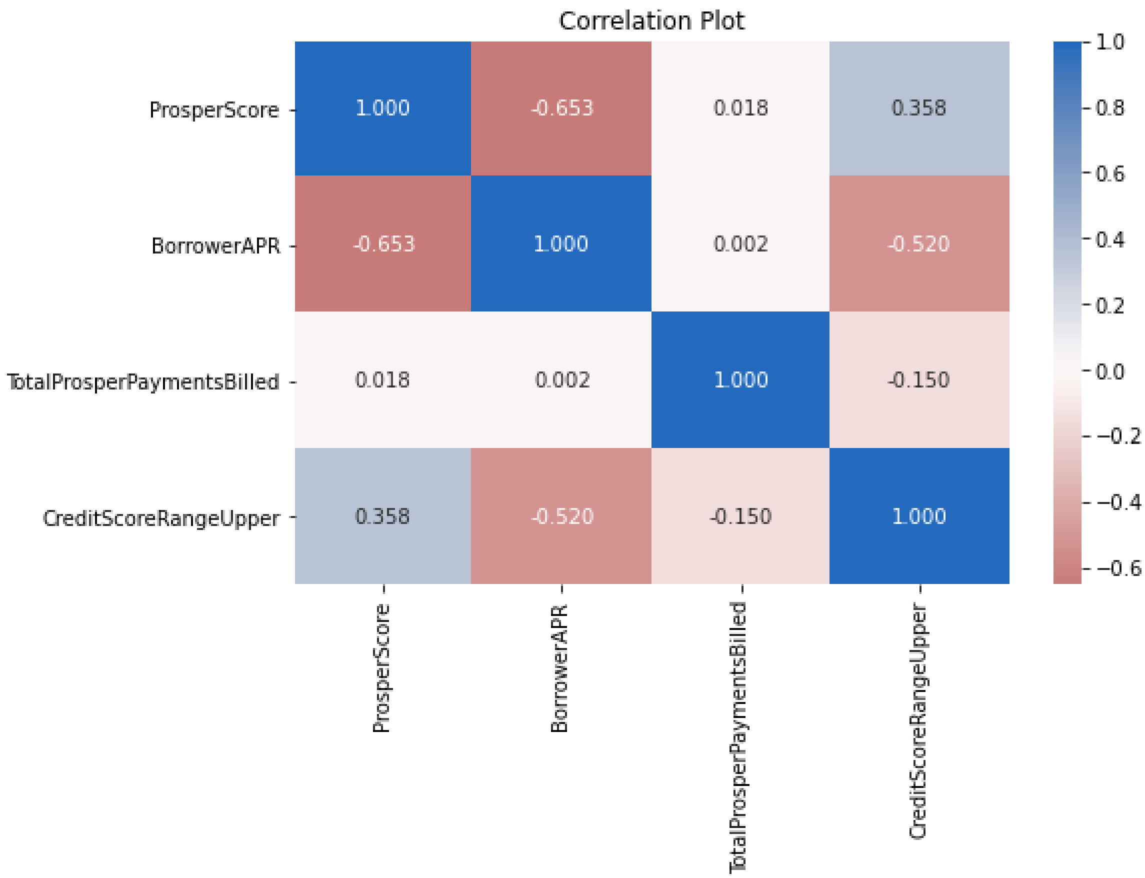
Of the features you investigated, were there any unusual distributions? Did you perform any operations on the data to tidy, adjust, or change the form of the data? If so, why did you do this?

> - Notice in the distribution of the Employment status that people that are not employed, or have an income of 0 received a loan. There might be other criteria than that qualifies one to get a loan like being a student or retired.
> - The bar chart of the Prosper Score showed that there are customers in the data set that have a score of 11 which is not possible since the score is from 1-10, this data was removed.
> - Combining the past dues into one column since it is not important to show that much information.

Bivariate Exploration

Lets look at the numeric variables

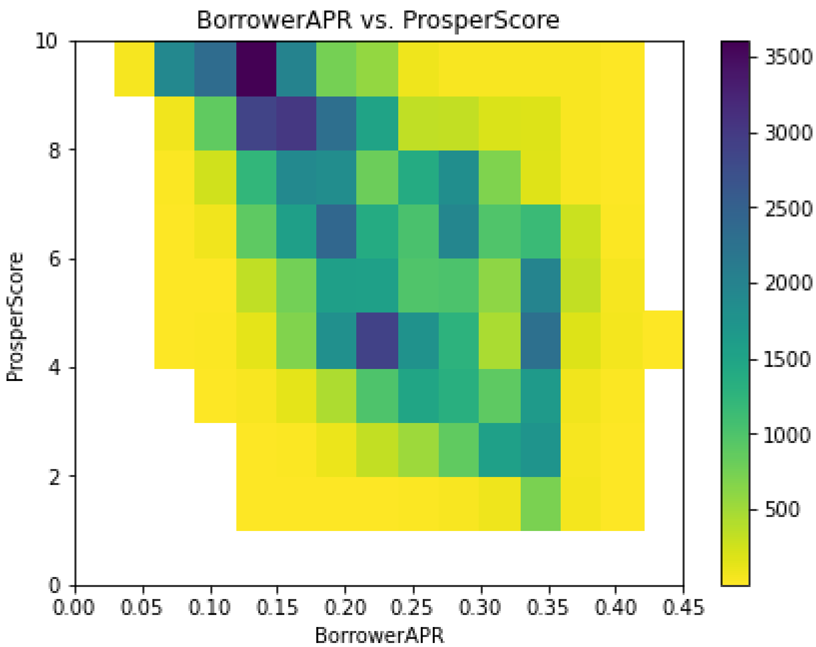
In [33]:
```
# correlation plot for numeric variables
num_var = ['ProsperScore', 'BorrowerAPR', 'TotalProsperPaymentsBilled', 'CreditSc

plt.figure(figsize = [8, 5])
sb.heatmap(df_loans[num_var].corr(), annot = True, fmt = '.3f', cmap = 'vlag_r',
plt.title('Correlation Plot');
```



There are no strong positive relationships between any pairs. BorrowerAPR and ProsperScore are negative because borrowers with a lower score are more likely to pay higher APR. CreditScore and BorrowerAPR are also negative because the higher the borrowers CreditScore the more trustworthy they are, therefore they received lower APR.

Lets look more closely at ProsperScore vs BorrowerAPR

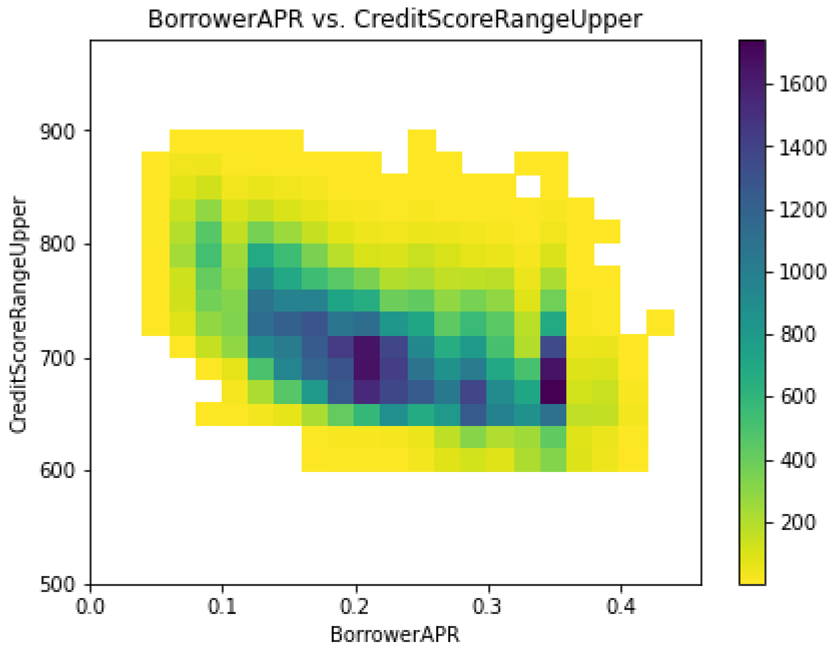
In [34]:
```
# heat plot for comparing ProsperScore and BorrowerAPR
plt.figure(figsize = [15, 5])

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



This also proves that people with higher ratings tend to be more trustworthy and therefore given lower BorrowerAPR.

Now BorrowerAPR vs. CreditScoreRangeUpper

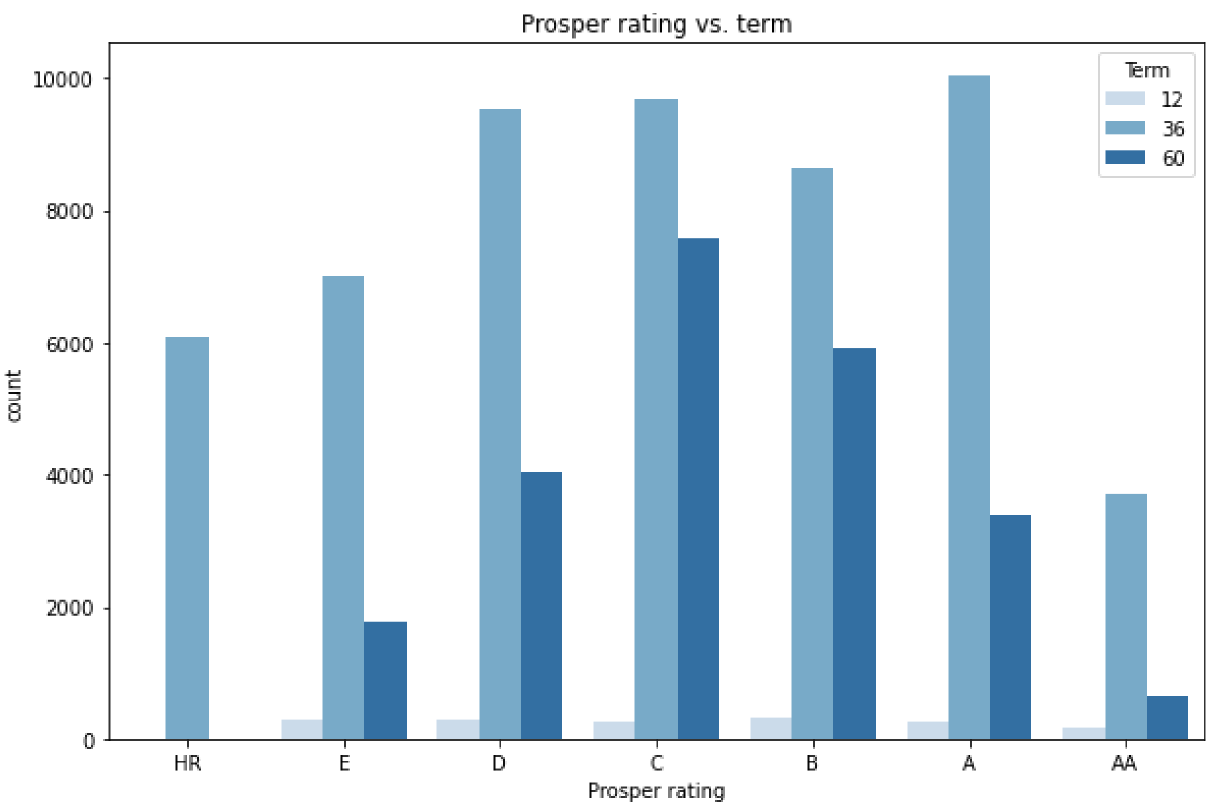
In [35]:
```
# heat plot for comparing ProsperScore and BorrowerAPR
plt.figure(figsize = [15, 5])

plt.subplot(1, 2, 2)
bins_x = np.arange(0, df_loans.BorrowerAPR.max()+0.05, 0.02)
bins_y = np.arange(500, df_loans.CreditScoreRangeUpper.max()+100, 20)
plt.hist2d(data = df_loans, x = 'BorrowerAPR', y = 'CreditScoreRangeUpper', bins
plt.colorbar()
plt.title('BorrowerAPR vs. CreditScoreRangeUpper')
plt.xlabel('BorrowerAPR')
plt.ylabel('CreditScoreRangeUpper');
```

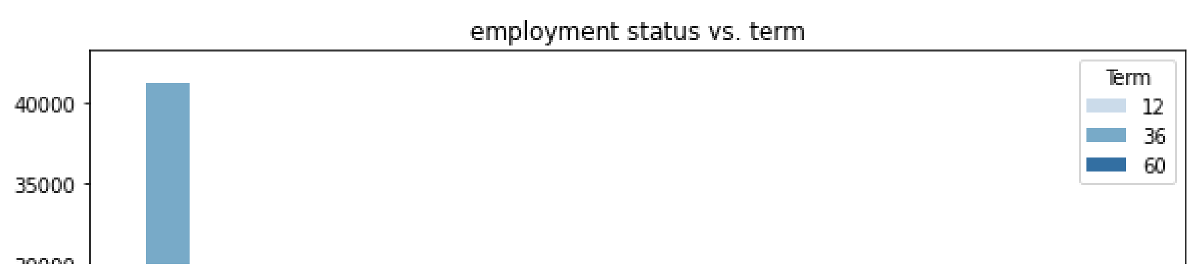


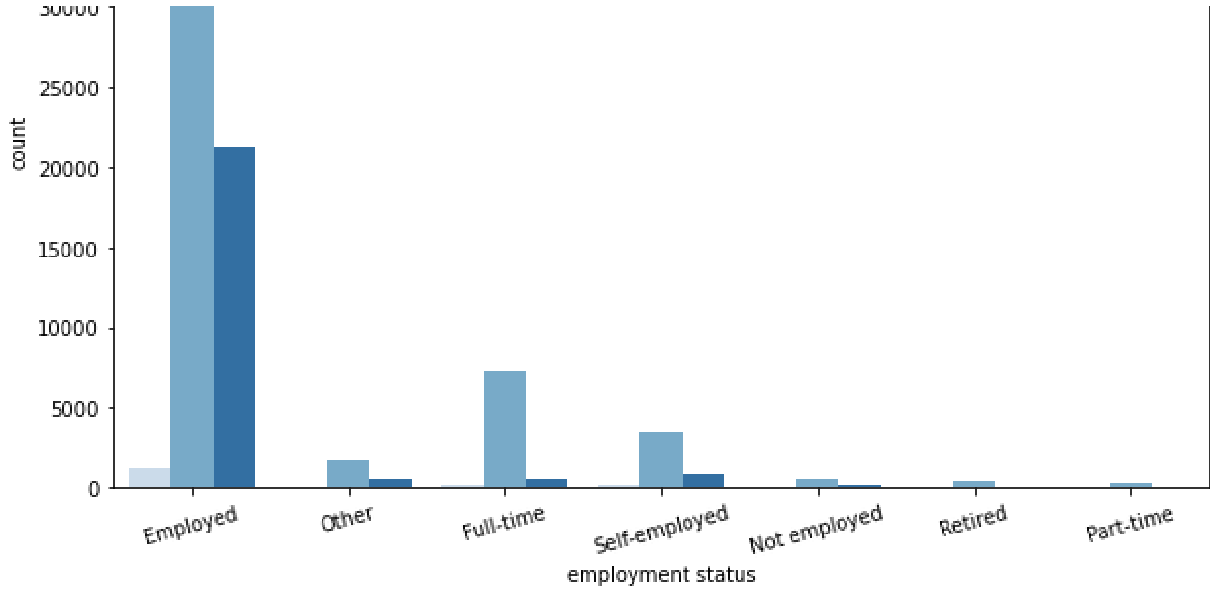
We can see the trend that the higher the CreditScore the lower the APR.

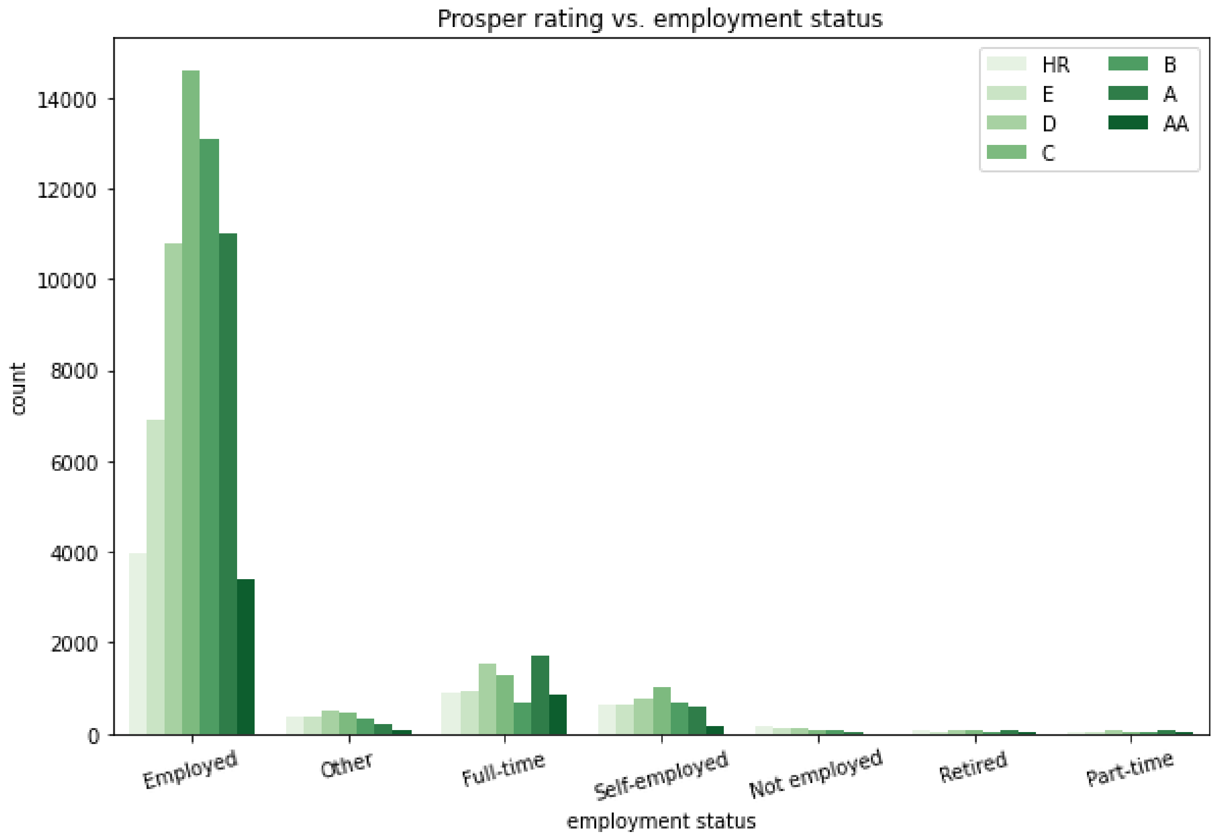
let's look at relationships between the categorical features.

In [36]:
```
plt.figure(figsize = [10, 30])

# Prosper rating vs. term
plt.subplot(4, 1, 1)
sb.countplot(data = df_loans, x = 'ProsperRating (Alpha)', hue = 'Term', palette
plt.xlabel('Prosper rating')
plt.title('Prosper rating vs. term')

# employment status vs. term
ax = plt.subplot(4, 1, 2)
sb.countplot(data = df_loans, x = 'EmploymentStatus', hue = 'Term', palette = 'Bl
plt.xticks(rotation = 15)
plt.xlabel('employment status')
plt.title('employment status vs. term')


# Prosper rating vs. employment status
ax = plt.subplot(4, 1, 3)
sb.countplot(data = df_loans, x = 'EmploymentStatus', hue = 'ProsperRating (Alpha
ax.legend(loc = 1, ncol = 2)
plt.xticks(rotation = 15)
plt.xlabel('employment status')
plt.title('Prosper rating vs. employment status');
```





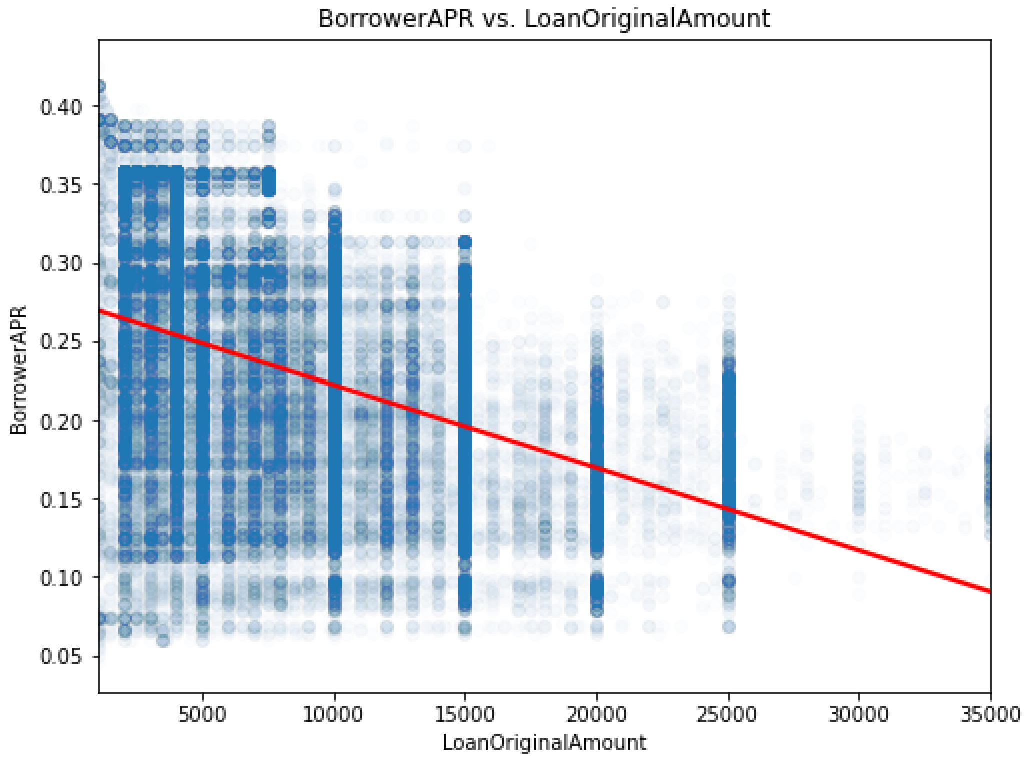




We can see that there is an interaction between term and Prosper rating. The most popular term was 36 and most of the employed especially with full-time jobs took that kind of loan. And of course, the higher proper ratings were given to the employed personnel.

Lets see how borrower APR and loan original amount are related

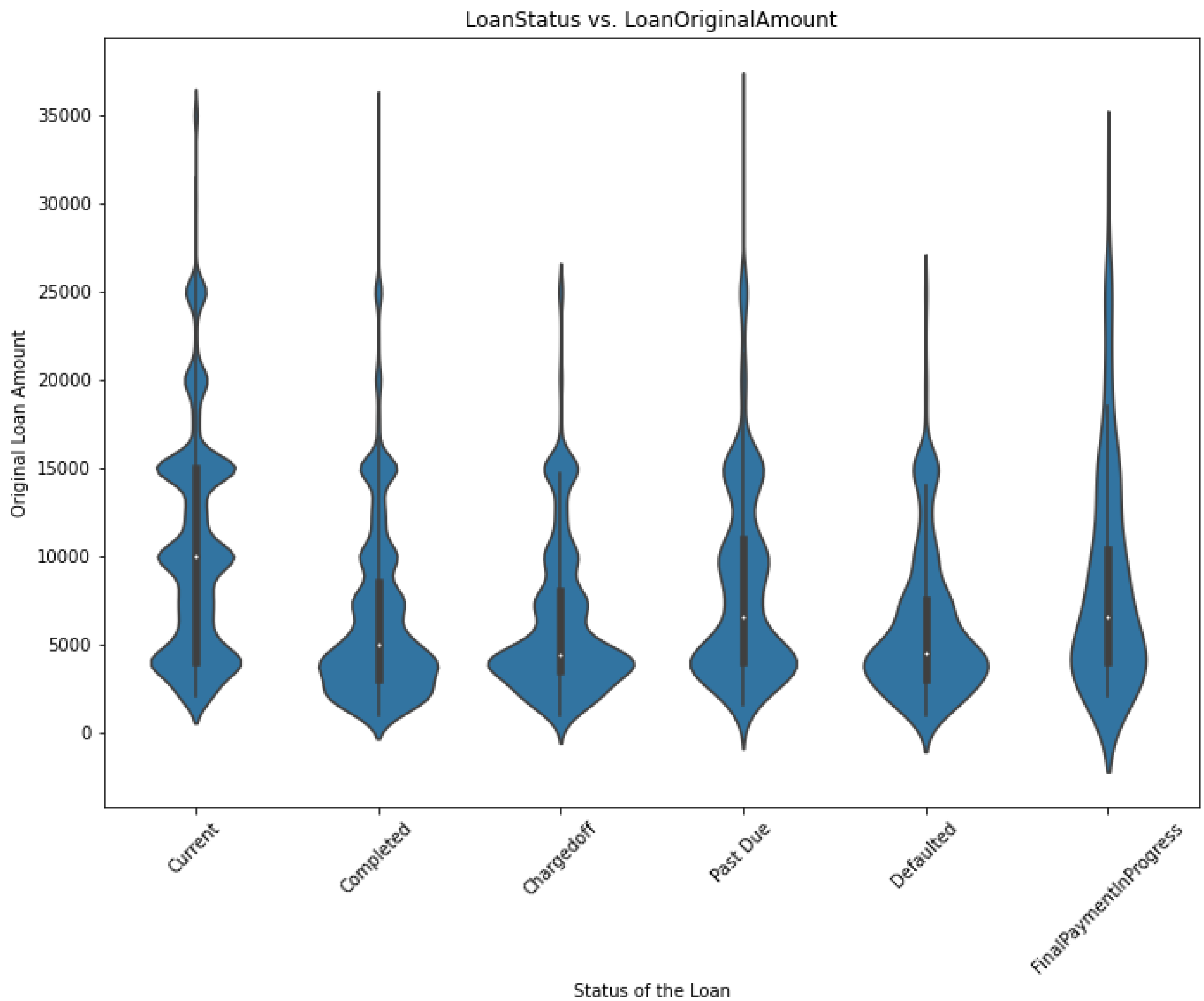
In [37]:
```
# how borrower APR and loan original amount are related
plt.figure(figsize = [8, 6])
sb.regplot(data = df_loans, x = 'LoanOriginalAmount', y = 'BorrowerAPR', scatter_
plt.title('BorrowerAPR vs. LoanOriginalAmount');
```



This relation shows that the range of APR decreases with the increase in the loan amount. Overall, the borrower's APR is negatively correlated with the loan amount.

Now the relation between LoanStatus and LoanOriginalAmount

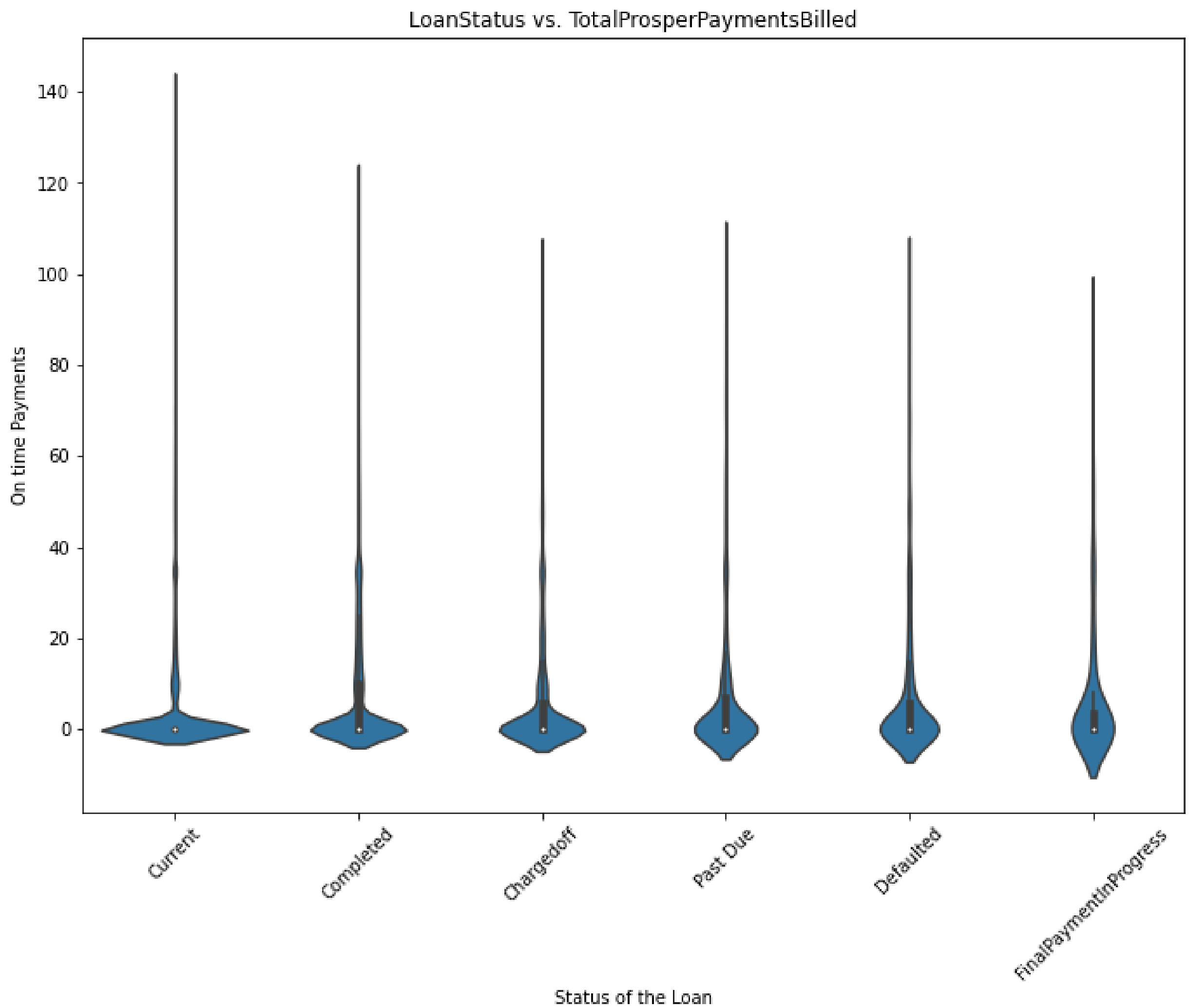
In [38]:
```
# plotting original loan amount with a violinplot against LoanStatus
plt.figure(figsize = [25, 18])

plt.subplot(2, 2, 2)
sb.violinplot(data = df_loans, x = 'LoanStatus', y = 'LoanOriginalAmount', color
plt.xticks(rotation=45)
plt.xlabel('Status of the Loan')
plt.ylabel('Original Loan Amount')
plt.title('LoanStatus vs. LoanOriginalAmount');
```



The original loan amount is about the same on average for loans that are completed, current. However, loans with past due payments have on average a higher original loan amount.

Now the relation between loan status and loan total prosper payments billed

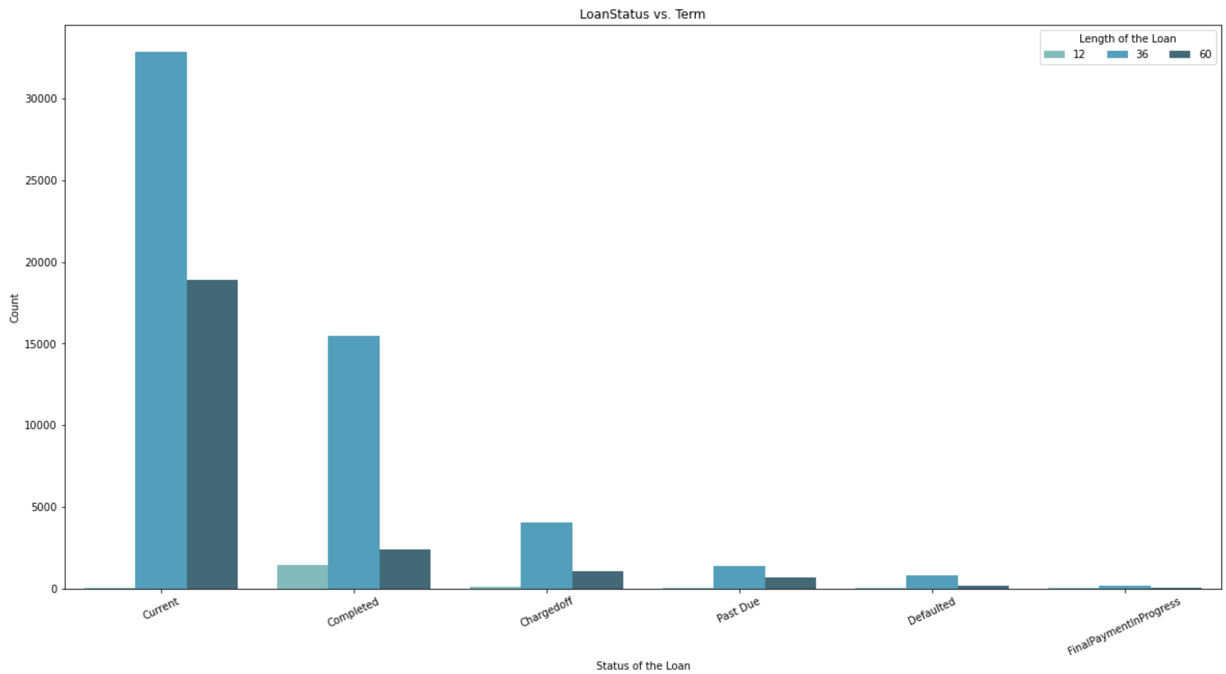
In [39]:
```
# plotting TotalProsperPaymentsBilled (On time Payments) with a violinplot agains
plt.figure(figsize = [25, 18])

plt.subplot(2, 2, 2)
sb.violinplot(data = df_loans, x = 'LoanStatus', y = 'TotalProsperPaymentsBilled'
plt.xticks(rotation=45)
plt.xlabel('Status of the Loan')
plt.ylabel('On time Payments')
plt.title('LoanStatus vs. TotalProsperPaymentsBilled');
```



Current loans have on average the highest number of on time payments while loans with the status charged-off and defaulted have the lowest.

Relation between loan status and term

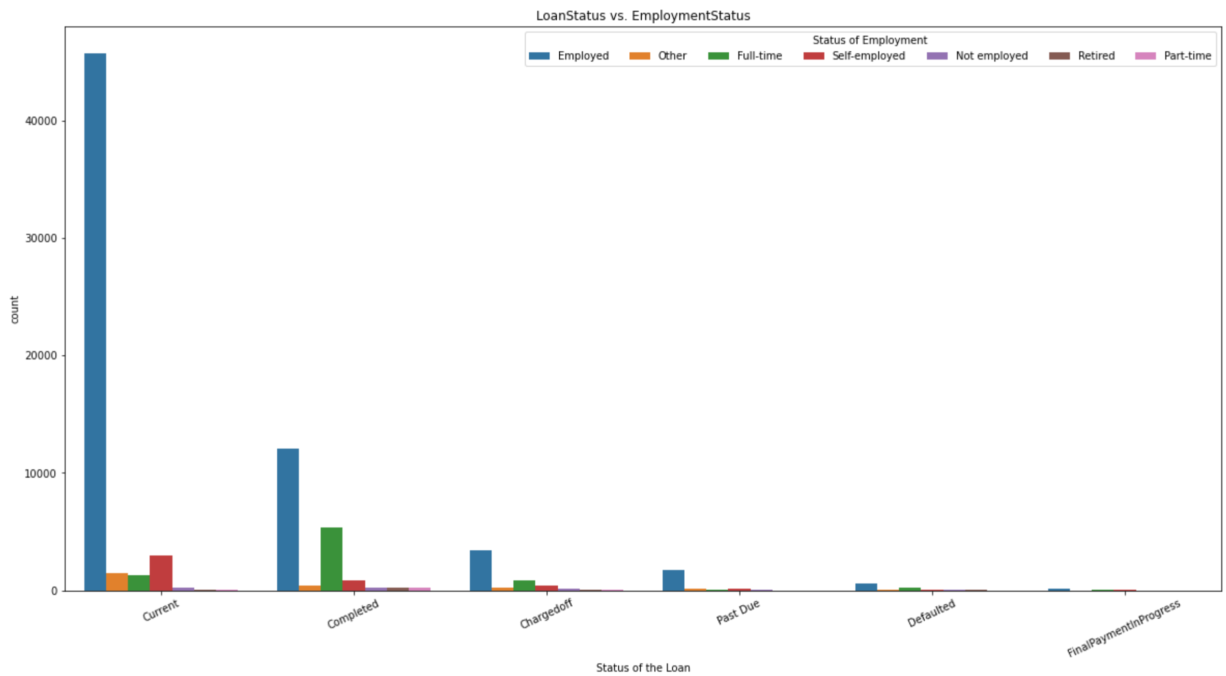
In [40]:
```
# plotting length of the Loans against LoanStatus a clusterd bar chart
plt.figure(figsize = [20,10])

ax = sb.countplot(data = df_loans, x = 'LoanStatus', hue = 'Term', palette = "GnB
plt.legend(loc = 1, ncol = 3, title = 'Length of the Loan')
plt.xticks(rotation = 25)
plt.xlabel('Status of the Loan')
ax.set_ylabel('Count')
plt.title('LoanStatus vs. Term');
```



No matter what status a loan has, the most common length is 36 months and the least common is 60 months.

Relation between loan status and employment status

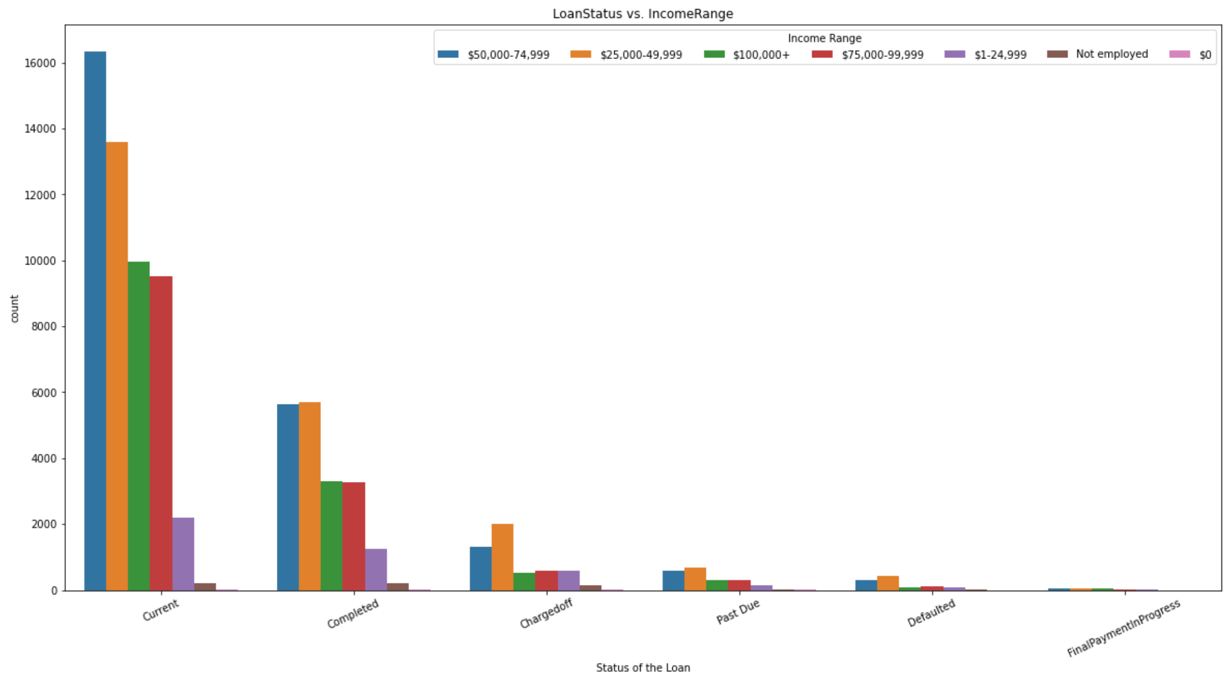
In [41]:
```
# plotting EmploymentStatus against LoanStatus
plt.figure(figsize = [20,10])

sb.countplot(data = df_loans, x = 'LoanStatus', hue = 'EmploymentStatus', order =
plt.legend(loc = 1, ncol = 8, title = 'Status of Employment')
plt.xticks(rotation = 25)
plt.xlabel('Status of the Loan')
plt.title('LoanStatus vs. EmploymentStatus');
```



The status of the employment of the borrower seems not to have an impact on the outcome of the loan. but again the ones who take loans mostly are employed as also the ones who completed their loans are the full-time employed.

Relation between loan status and income range

In [42]:
```
# plotting Income Range against LoanStatus
plt.figure(figsize = [20,10])

sb.countplot(data = df_loans, x = 'LoanStatus', hue = 'IncomeRange', order = df_l
plt.legend(loc = 1, ncol = 8, title = 'Income Range')
plt.xticks(rotation = 25)
plt.xlabel('Status of the Loan')
plt.title('LoanStatus vs. IncomeRange');
```



The borrowers who have an Income Range of (25000 - 74999) seem to be the ones who get more loans and pay them on time.

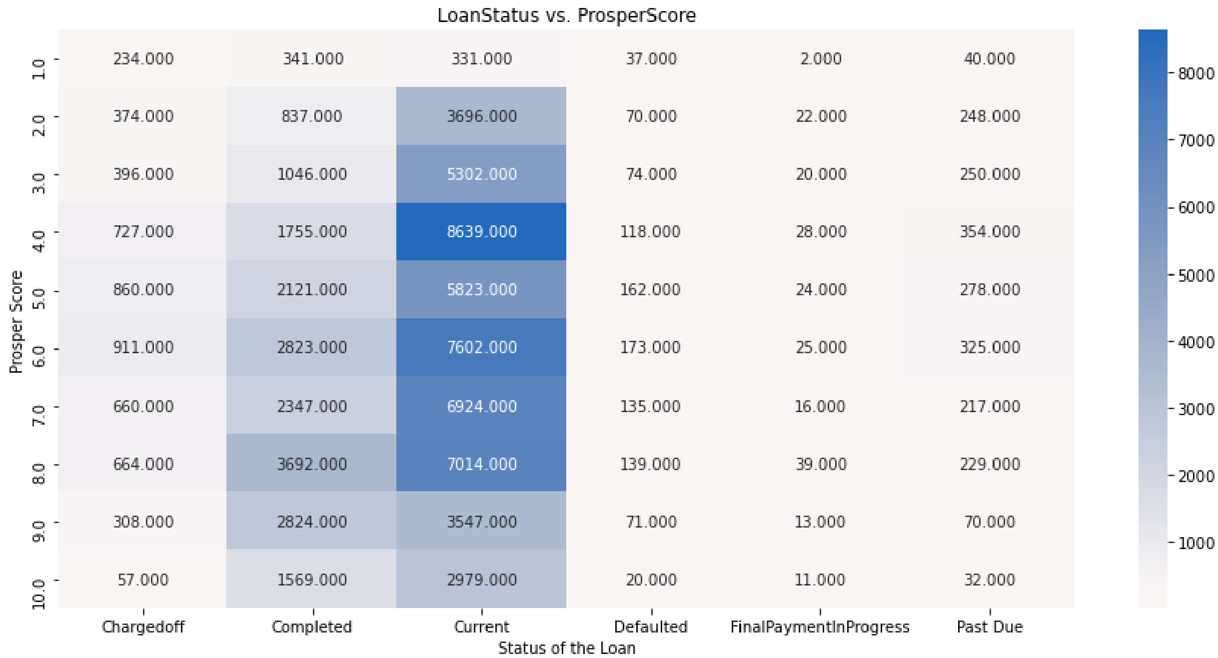
Relation between prosper score and loan status

In [43]:
```
# first I need to reshape the data
reshape = df_loans.groupby(['LoanStatus', 'ProsperScore']).size()
reshape = reshape.reset_index(name = 'count')
reshape = reshape.pivot(index = 'ProsperScore', columns = 'LoanStatus', values =
reshape
```

Out[43]:

LoanStatus	Chargedoff	Completed	Current	Defaulted	FinalPaymentInProgress	Past Due
ProsperScore						
1.0	234	341	331	37	2	40
2.0	374	837	3696	70	22	248
3.0	396	1046	5302	74	20	250
4.0	727	1755	8639	118	28	354
5.0	860	2121	5823	162	24	278
6.0	911	2823	7602	173	25	325
7.0	660	2347	6924	135	16	217
8.0	664	3692	7014	139	39	229
9.0	308	2824	3547	71	13	70
10.0	57	1569	2979	20	11	32

In [44]:
```
# plotting ProsperScore against LoanStatus with a heat map
plt.figure(figsize = [15,7])

sb.heatmap(reshape, annot = True, fmt = '.3f', cmap = 'vlag_r', center = 0)
plt.xlabel('Status of the Loan')
plt.ylabel('Prosper Score')
plt.title('LoanStatus vs. ProsperScore');
```



The Prosper Score seems to affect the outcome of the loan. So the highest number of borrowers with completed loans has a prosper score of 8, while the highest number of borrowers with defaulted and charged-off loans have a prosper score of 6. Notice that the most common prosper score for borrowers with loans that are past due payments is 6.

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?

- BorrowerAPR and ProsperScore are negative because borrowers with a lower score are more likely to pay higher APR. CreditScore and BorrowerAPR are also negative because the higher the borrowers CreditScore the more trustworthy they are, therefore they received lower APR.
- People with higher ratings tend to be more trustworthy and therefore given lower BorrowerAPR.
- We can see the trend that the higher the CreditScore the lower the APR.
- We can see that there is an interaction between term and Prosper rating. The most popular term was 36 and most of the employed especially with full-time jobs took that kind of loan. And of course, the higher proper ratings were given to the employed personnel.
- The range of APR decreases with the increase of loan amount. Overall, the borrower's APR is negatively correlated with the loan amount. This means the more the loan amount the lower the APR
- The original loan amount is about the same on average for loans that are completed, current. However, loans with past due payments have on average a higher original loan amount.
- Current loans have on average the highest number of on time payments while loans with the status charged-off and defaulted have the lowest.
- No matter what status a loan has, the most common length is 36 months, and the least common is 60 months.
- The status of the employment of the borrower seems not to have an impact on the outcome of the loan. but again the ones who take loans mostly are employed as also the ones who completed their loans are the full-time employed.
- The Prosper Score seems to affect the outcome of the loan. So the highest number of borrowers with completed loans has a prosper score of 8, while the highest number of borrowers with defaulted and charged-off loans have a prosper score of 6. Notice that the most common prosper score for borrowers with loans that are past due payments is 6.
- The borrowers who have an Income Range of (25000 - 74999) seem to be the ones who get more loans and pay them on time.

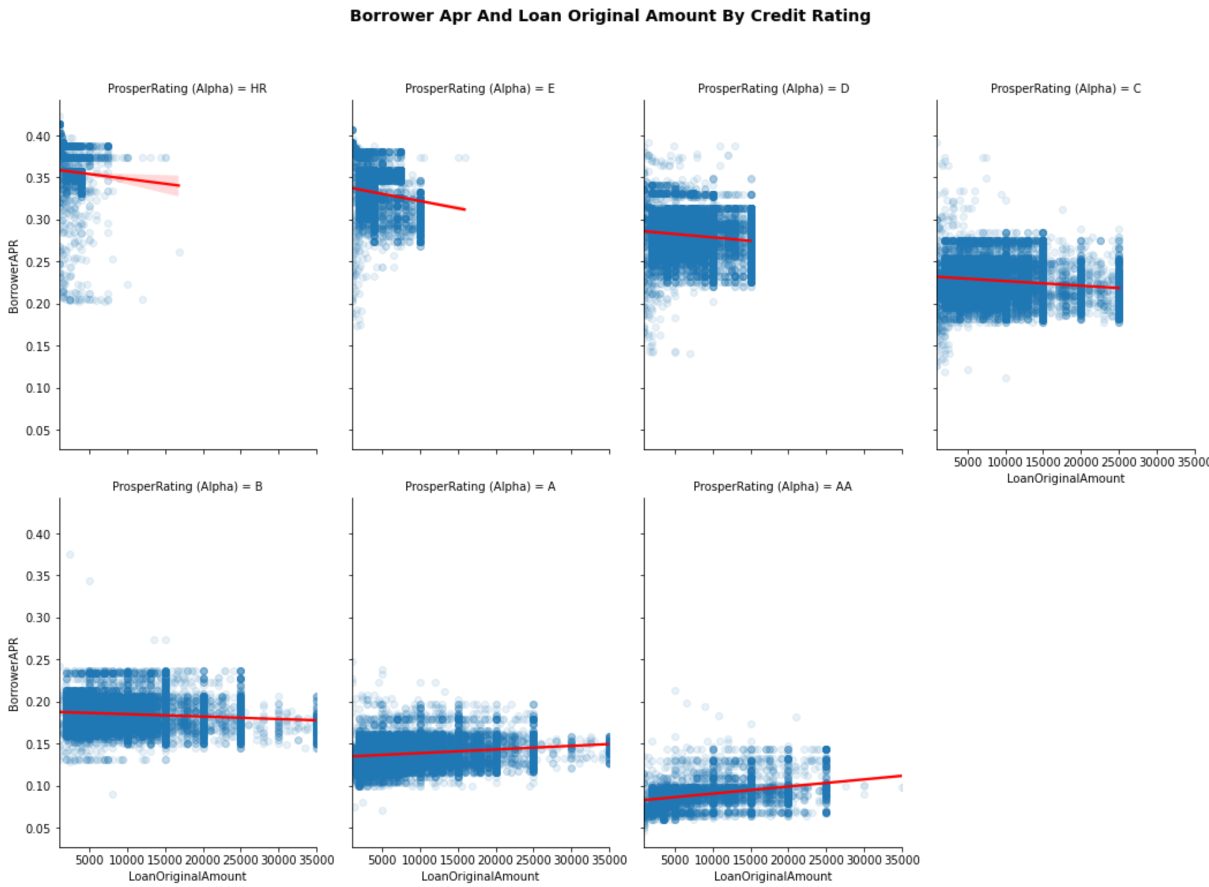
Did you observe any interesting relationships between the other features (not the main feature(s) of interest)?

- There is an interaction between prospering rating and term. There are more 60-month loans on B and C ratings, while there are only 36 months loans for HR rating.

Multivariate Exploration

Prosper rating effect on relationship between borrower APR and loan original amount

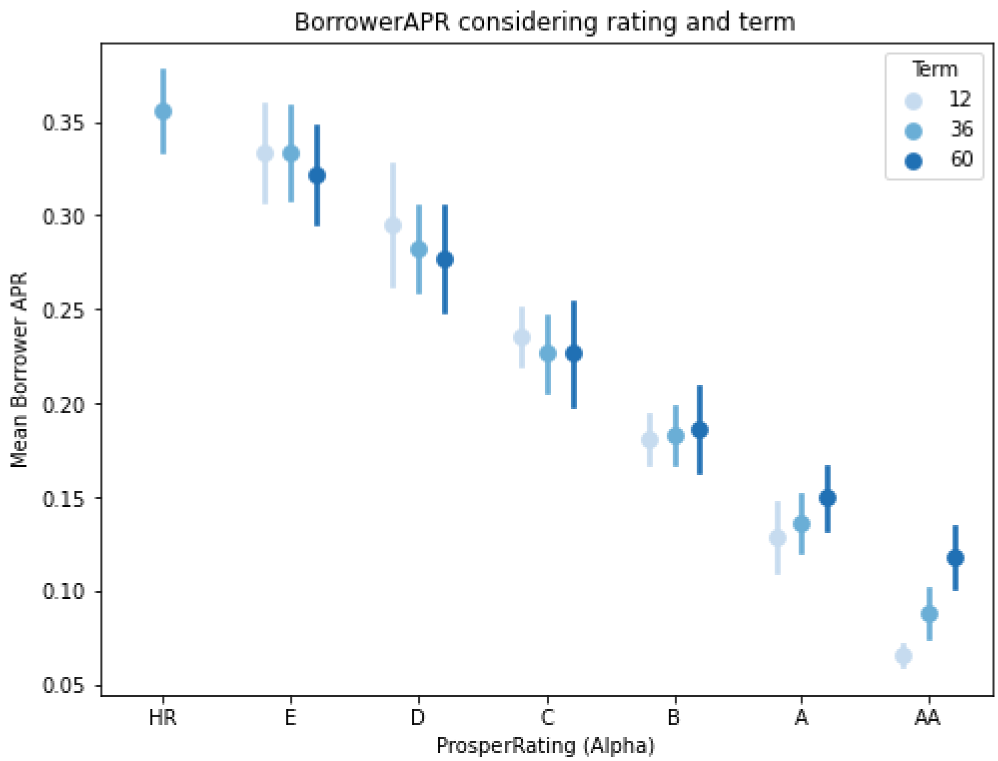
In [45]:
```
# Prosper rating effect on relationship of APR and loan amount
g=sb.FacetGrid(data = df_loans, aspect = (14.70/4)/(10.27/2), height = 10.27/2, c
g.map(sb.regplot, 'LoanOriginalAmount', 'BorrowerAPR', x_jitter=0.04, scatter_kws
g.add_legend();
plt.suptitle('Borrower APR and loan original amount by credit rating'.title(), y=
plt.tight_layout();
```



The loan amount increases with a better rating, the borrower's APR decreases with a better rating. The relationship between borrower APR and loan amount raises from negative to slightly positive when the prosper ratings are increased from HR to A or better. Maybe because people with A or AA ratings tend to borrow more money, and pay on time.

BorrowerAPR considering rating and term

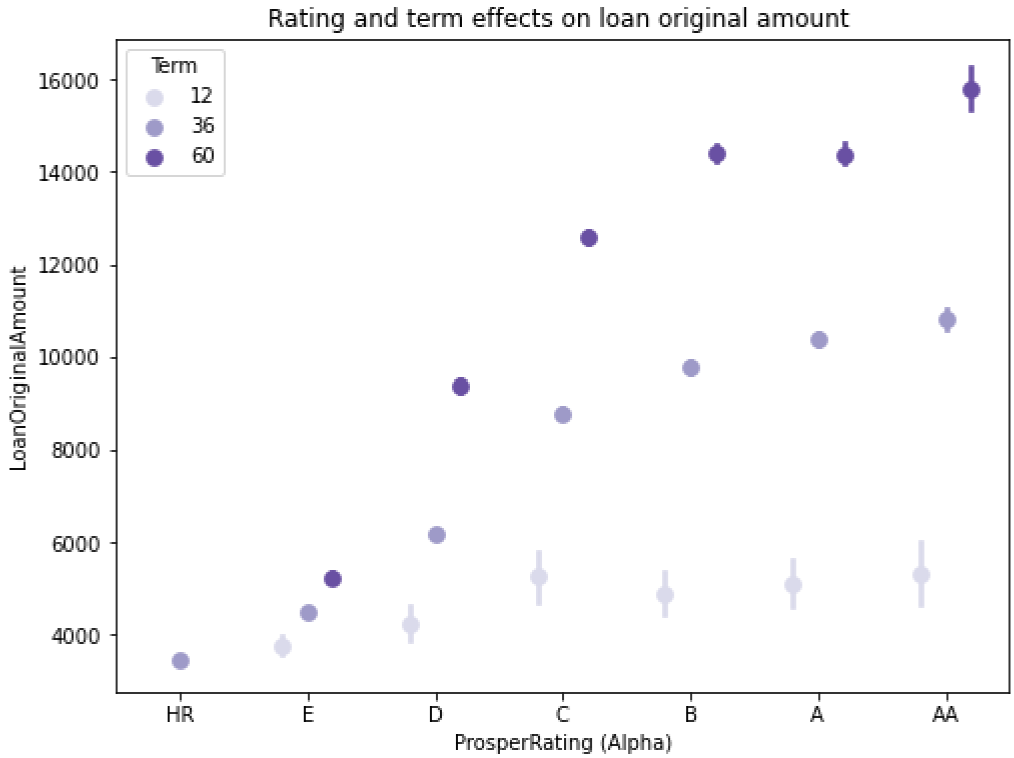
In [46]:
```
# BorrowerAPR considering rating and term
fig = plt.figure(figsize = [8,6])

ax = sb.pointplot(data = df_loans, x = 'ProsperRating (Alpha)', y = 'BorrowerAPR'
plt.title('BorrowerAPR considering rating and term')
plt.ylabel('Mean Borrower APR')
ax.set_yticklabels([],minor = True);
```



Notice that for prosper rating from HR to D the borrower APR increases with the decrease of borrow term, then it starts to shift from C to AA rating.

The rating and term effects on loan original amount

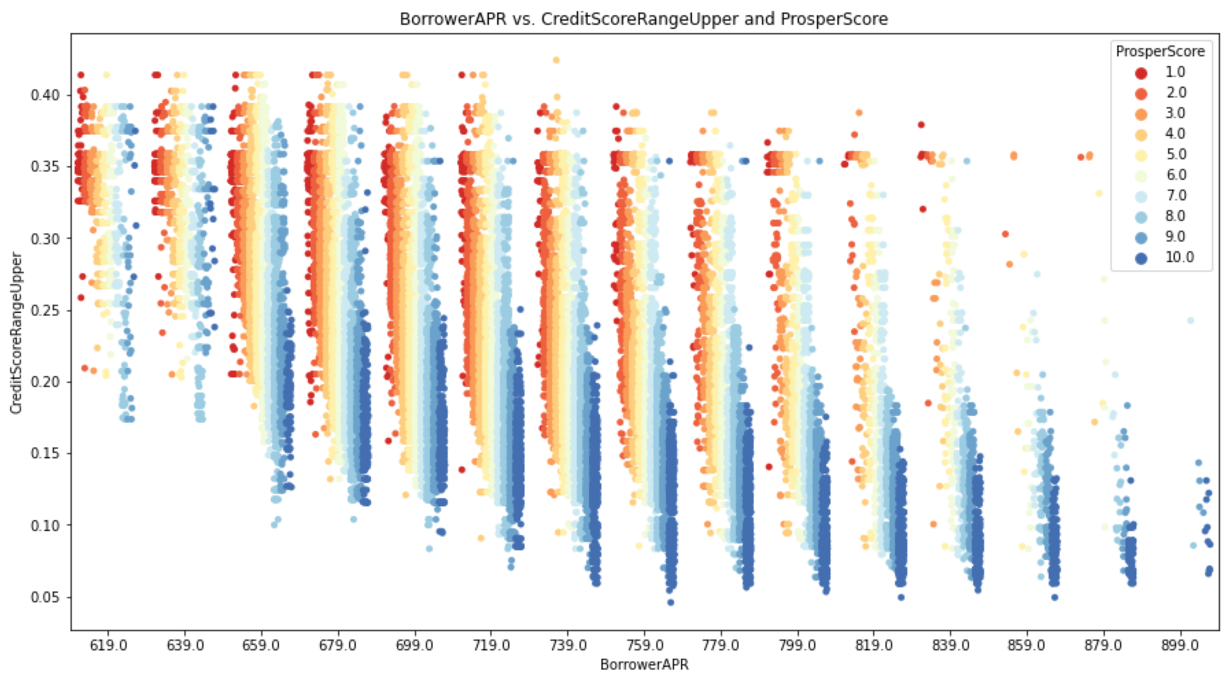
In [47]:
```
# Rating and term effects on loan original amount
fig, ax = plt.subplots(figsize=[8,6])

sb.pointplot(data = df_loans, x = 'ProsperRating (Alpha)', y = 'LoanOriginalAmour
             linestyles = '', dodge = 0.4)
plt.title('Rating and term effects on loan original amount ');
```



Notice that with a better prosper rating, the loan amount of all three terms increases.

BorrowerAPR considering CreditScoreRangeUpper and ProsperScore

In [48]:
```
# BorrowerAPR vs. CreditScoreRangeUpper and ProsperScore
plt.figure(figsize = [15, 8])

sb.stripplot(data = df_loans, x = 'CreditScoreRangeUpper', y = 'BorrowerAPR', hue
             dodge = True, palette = 'RdYlBu')
plt.title('BorrowerAPR vs. CreditScoreRangeUpper and ProsperScore')
plt.xlabel('BorrowerAPR')
plt.ylabel('CreditScoreRangeUpper');
```



Notice that CreditScoreRangeUpper increase as BorrowerAPR decrease in the plots, this proves that CreditScoreRangeUpper and ProsperScore negatively correlated to BorrowerAPR.

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 loan amount increases with a better rating, the borrower APR decreases with a better rating. The relationship between borrower APR and loan amount raises from negative to slightly positive when the prosper ratings are increased from HR to A or better and pay on time.
> - Notice that for prosper rating from HR to D the borrower APR increases with the decrease of borrow term, then it starts to shift from C to AA rating.
> - Notice that with a better prosper rating, the loan amount of all terms increases.
> - Notice that CreditScoreRangeUpper increase as BorrowerAPR decrease in the plots, This proves that CreditScoreRangeUpper and ProsperScore negatively correlated to BorrowerAPR.

Were there any interesting or surprising interactions between features?

> - The borrower APR increases with the decrease of borrow term for people with HR to D ratings. Then it starts to shift for people with C to AA ratings, the APR decreases with the increase of borrow term.

In [ ]: