(Loan Data from Prosper)

by (Ahmed Tarek)

Investigation Overview

In this presentation I will attempt to answer some questions:

- What attributes affect the borrower's annual percentage rate?

  > This question is helpful for borrowers to decide on taking loans.

- What attributes affect a loan’s outcome status?

  > This is very critical for banks to minimize the risk and to set the right interest rate.

- insight on increasing Prosper profits from loans.

Dataset Overview

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
```

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

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_loans.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_loans.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

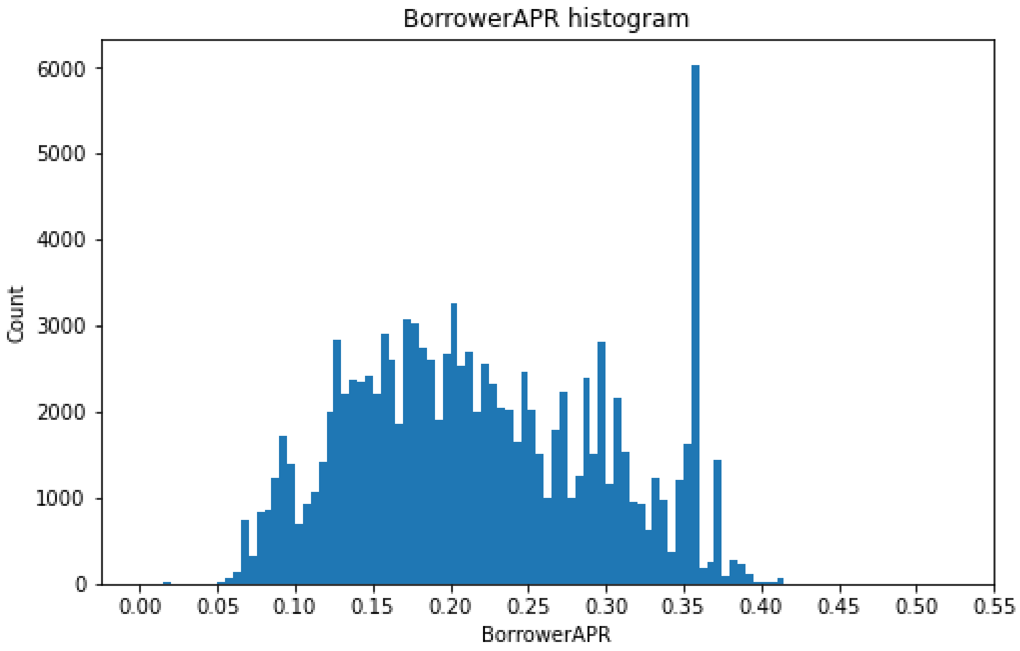
8 rows × 61 columns

Univariate Exploration

Lets take a look at the BorrowerAPR

It appears that this distribution is multimodal with several peaks. A peak at 0.08, 0.2, 0.3, and an exceptionally high peak at 0.36.

In [5]:
```
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.xlabel('BorrowerAPR')
plt.ylabel('Count')
plt.title('BorrowerAPR histogram');
```

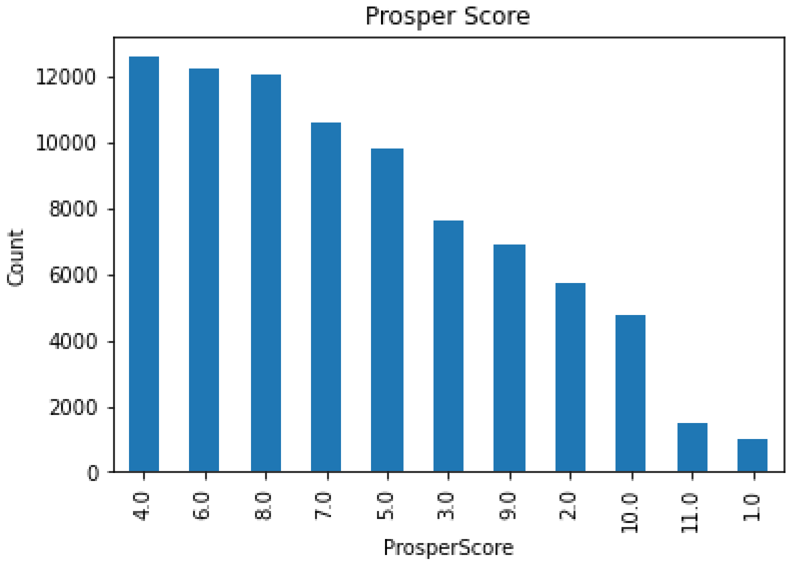


Let's look at Prosper Score which is a custom risk score built using historical Prosper data.

Most of the borrower got low Prosper Score of 4 that means they are risky 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.

In [6]:

```
df_loans.ProsperScore.value_counts().plot(kind='bar')
plt.xlabel('ProsperScore')
plt.ylabel('Count')
plt.title('Prosper Score');
```

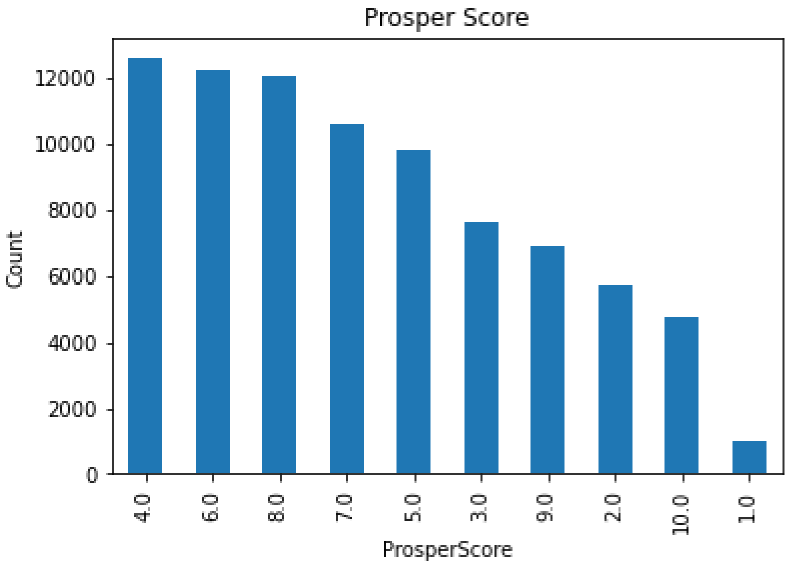


This shows that there are scores above 10 which is not possible since the score is from 1-10. This data must be removed.

In [7]:

```
df_loans = df_loans[df_loans.ProsperScore != 11]
```

In [8]:
```
df_loans.ProsperScore.value_counts().plot(kind='bar')
plt.xlabel('ProsperScore')
plt.ylabel('Count')
plt.title('Prosper Score');
```



Now lets look at ProsperRating (Alpha) and Occupation

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

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

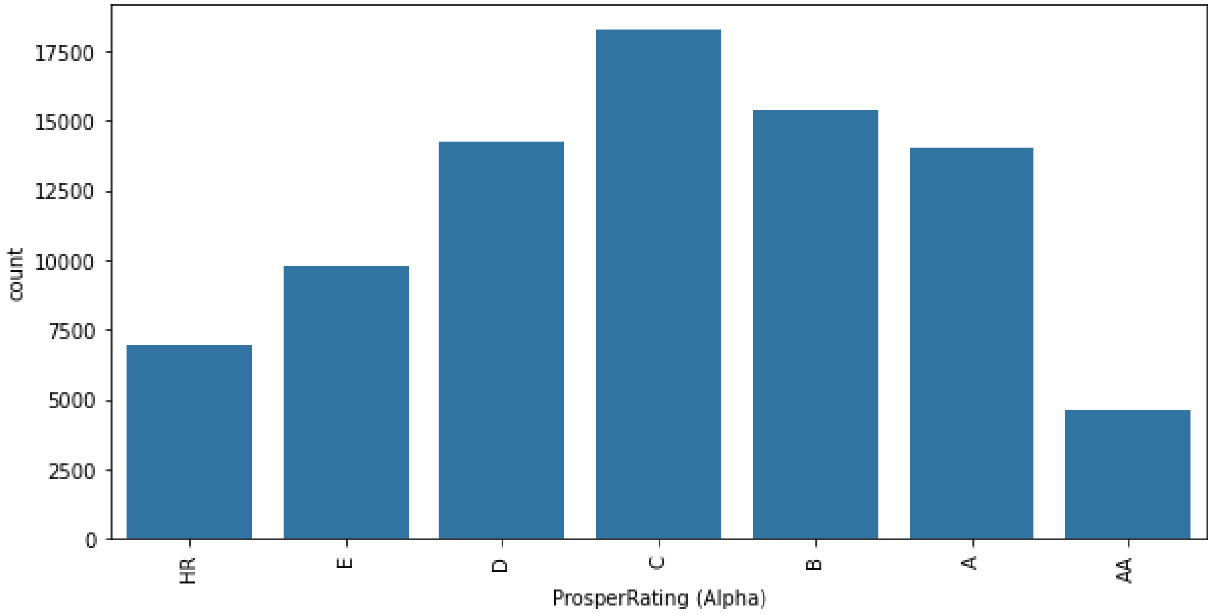
In [9]:

```
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
```

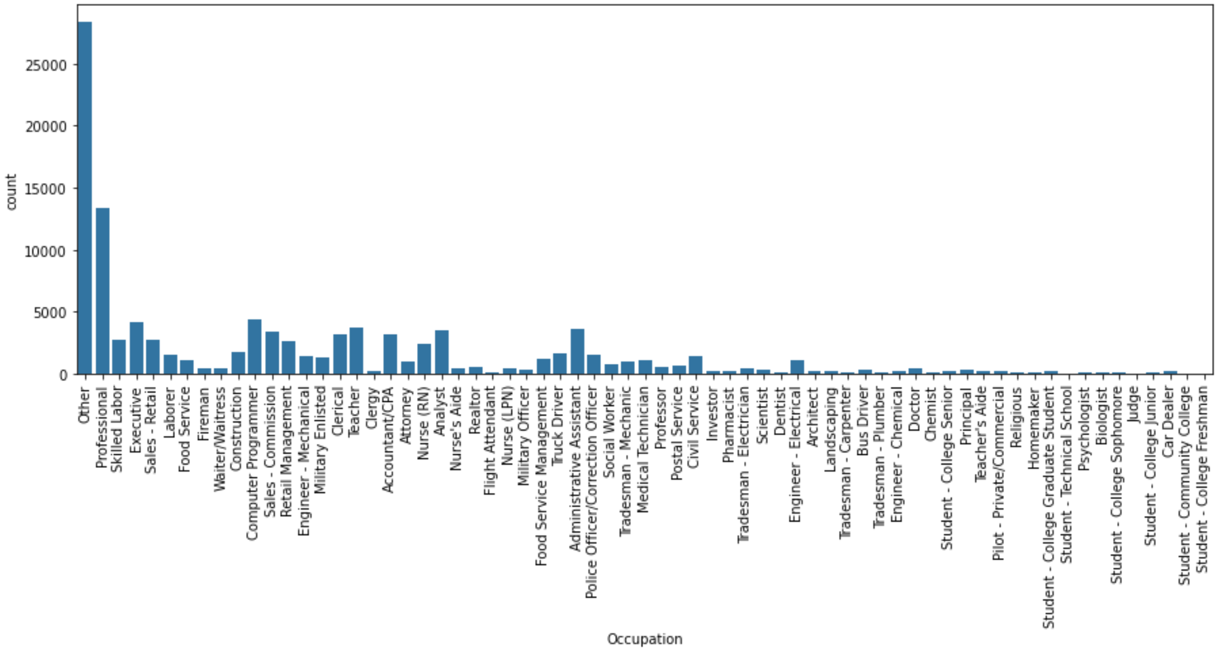
```
<ipython-input-9-983a76435ecb>:3: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/sta
ble/user_guide/indexing.html#returning-a-view-versus-a-copy (https://pandas.pyd
ata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-c
opy)
  df_loans['ProsperRating (Alpha)'] = df_loans['ProsperRating (Alpha)'].astype
(ordered_var)
```

In [10]:

```
fig = plt.subplots(figsize = [10, 5])

default_color = sb.color_palette()[0]
sb.countplot(data = df_loans, x = 'ProsperRating (Alpha)', color = default_color)
plt.xticks(rotation=90);
```



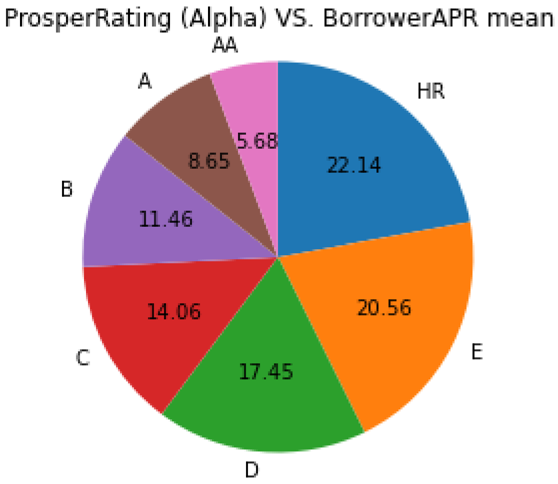
In [11]:
```
fig = plt.subplots(figsize = [15, 5])

default_color = sb.color_palette()[0]
sb.countplot(data = df_loans, x = 'Occupation', color = default_color)
plt.xticks(rotation=90);
```



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

Notice that the highest rating of AA received the lowest BorrowerAPR (5.61), while the lowerest rating of HR received the highest BorrowerAPR (22.17). This shows that borrowers with higher ratings received lower BorrowerAPR.

In [12]:
```
ProsperRatingAlpha_mean = df_loans.groupby('ProsperRating (Alpha)').BorrowerAPR.m

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



I am interested in knowing more about the LoanOriginalAmount

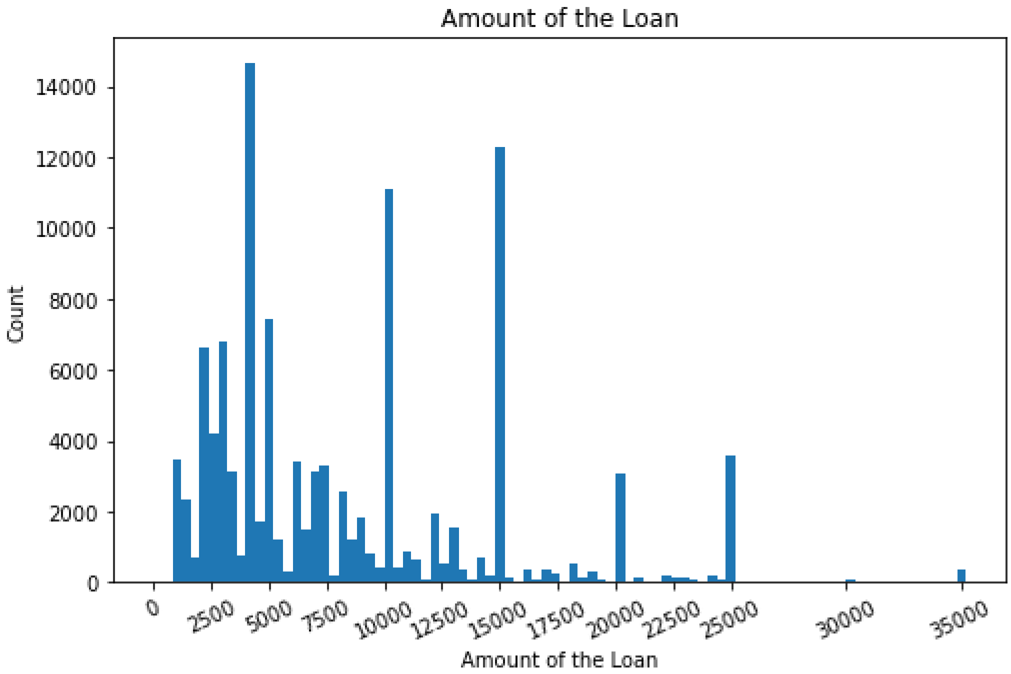
The histogram has serval peaks at around 4,000, 10,000, and 15,000. But most of the values are in the lower end between 2500 and 10,000. The most loaned amounts are 4,000 and 15,000. The mean loan amount is between 8200.

In [13]:
```
df_loans.LoanOriginalAmount.mean()
```

Out[13]:
```
8252.601132635735
```

In [14]:

```
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.xlabel('Amount of the Loan')
plt.ylabel('Count')
plt.title('Amount of the Loan')
plt.xticks([0,2500,5000,7500,10000,12500,15000,17500,20000,22500,25000,30000,3500
```

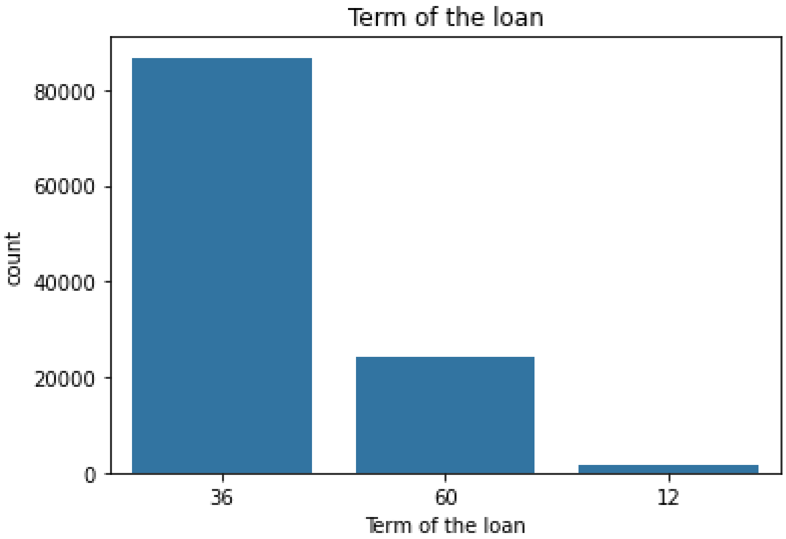


Now lets see if there is a relation between the LoanOriginalAmount and Term

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.

In [15]:

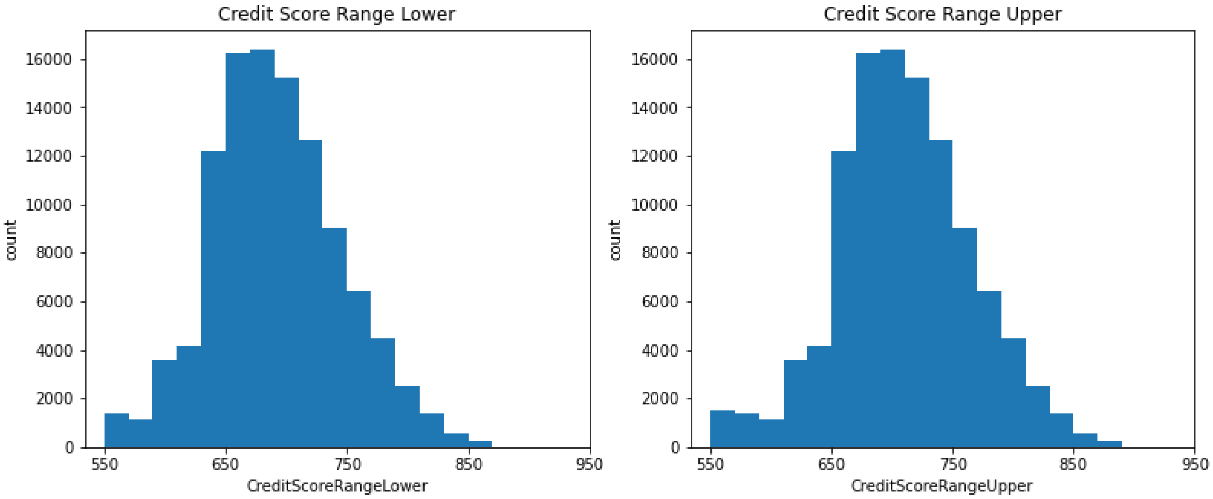
```
base_color = sb.color_palette()[0]
sb.countplot(data = df_loans, x='Term', color = base_color, order = df_loans.Term
plt.xlabel('Term of the loan')
plt.title('Term of the loan');
```



Lets look at the CreditScoreRangeLower and CreditScoreRangeUpper

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

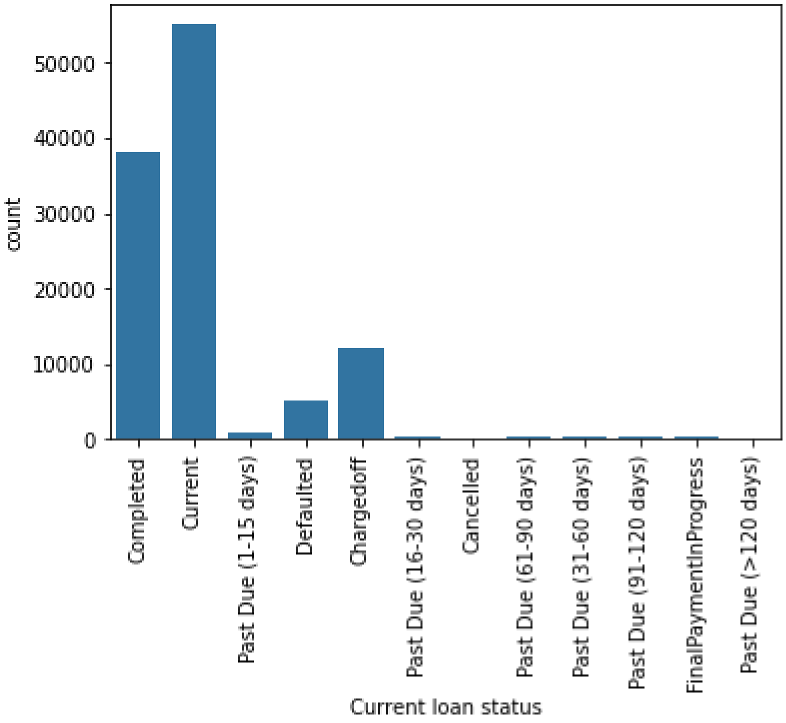
In [16]:
```
plt.figure(figsize = [13, 5])


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.xlabel('CreditScoreRangeLower')
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.xlabel('CreditScoreRangeUpper')
plt.ylabel('count');
```



Now lets take a look at the loan status

Most of the loans are current or completed.

In [17]:
```
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);
```



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

In [18]:

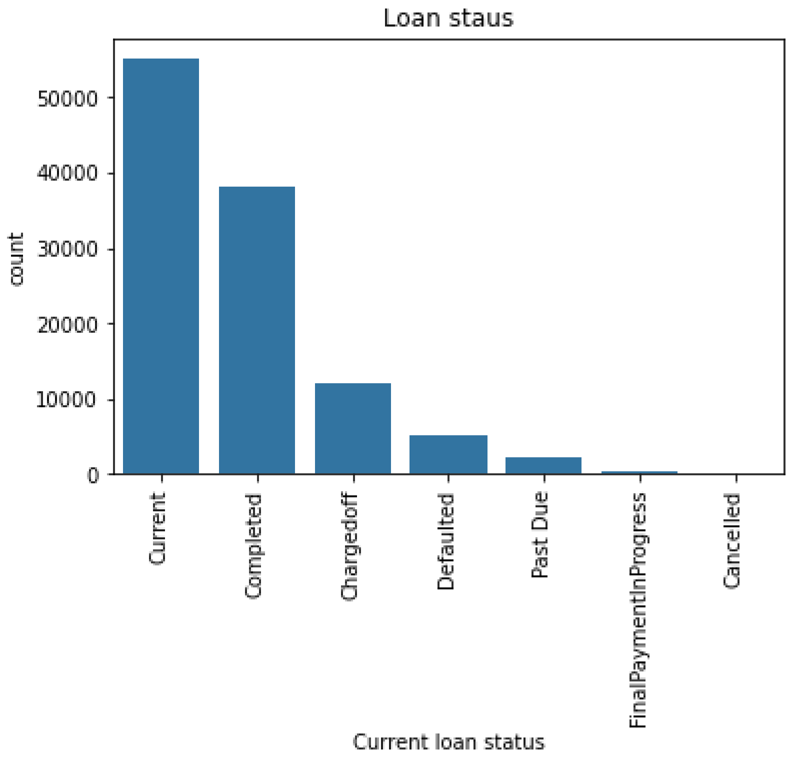
```
df_loans.LoanStatus = df_loans.LoanStatus.replace(['Past Due (1-15 days)', 'Past 
                                                   'Past Due (91-120 days)','Past
                                                   'Past Due (>120 days)'],'Past 

df_loans.LoanStatus.value_counts()
```

```
C:\Users\Ahmed\anaconda3\lib\site-packages\pandas\core\generic.py:5168: Setting
WithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/sta
ble/user_guide/indexing.html#returning-a-view-versus-a-copy (https://pandas.pyd
ata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-c
opy)
  self[name] = value
```

Out[18]:

```
Current                   55157
Completed                 38043
Chargedoff                11992
Defaulted                  5017
Past Due                   2065
FinalPaymentInProgress      202
Cancelled                     5
Name: LoanStatus, dtype: int64
```

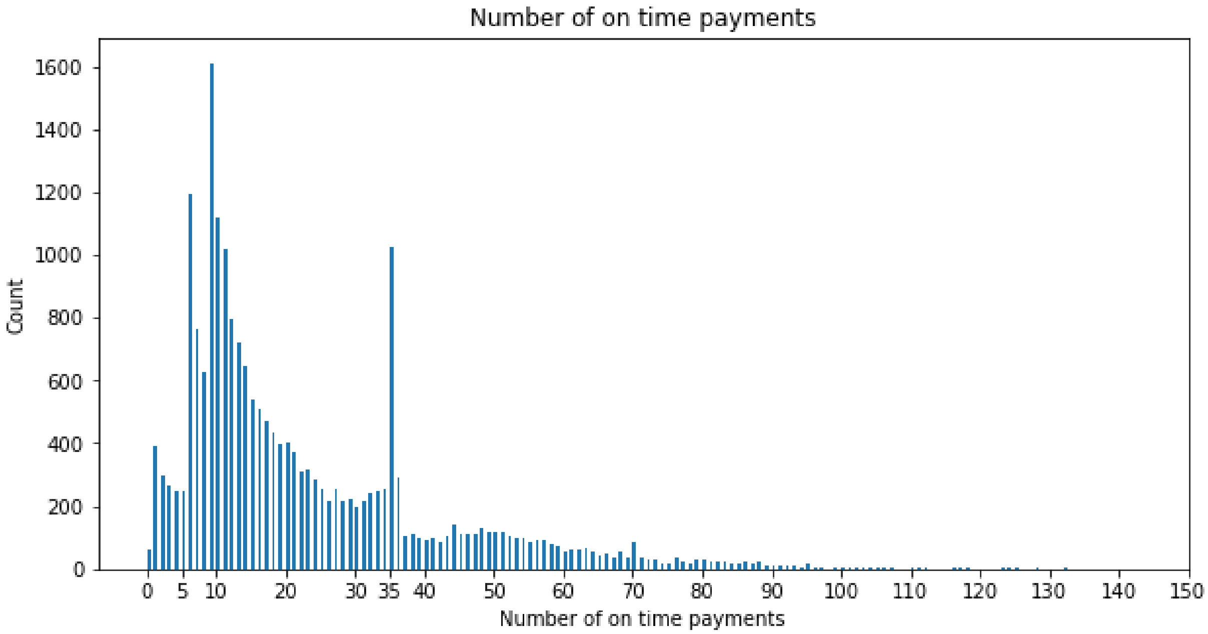
In [19]:
```
base_color = sb.color_palette()[0]
sb.countplot(data = df_loans, x = 'LoanStatus', color = base_color, order = df_lo
plt.xlabel('Current loan status')
plt.xticks(rotation = 90)
plt.title('Loan staus');
```



Now lets look at the TotalProsperPaymentsBilled (Number of on time payments)

The distribution of the number of on-time payments has two peaks 9 and 35. Notice that the distribution is right-skewed with most of the values on the lower end and fewer values on the higher end. This would make the distribution multimodal. It seems like that most of the borrowers had missed paying some of the monthly payments on time.

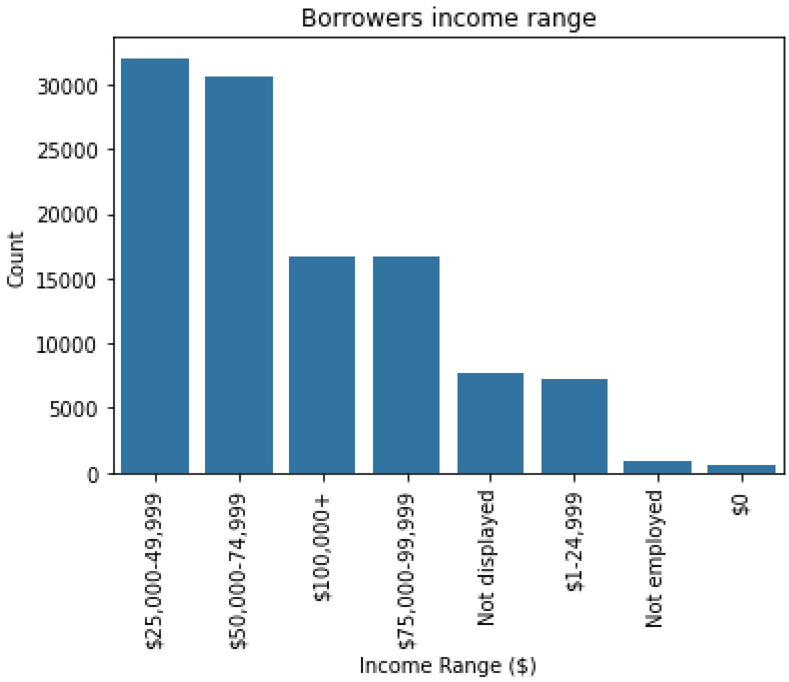
In [20]:
```
binsize = 0.5
bins = np.arange(df_loans.TotalProsperPaymentsBilled.min(), df_loans.TotalProsper

plt.figure(figsize=[10, 5])
plt.hist(data = df_loans, x = 'TotalProsperPaymentsBilled', bins = bins)
plt.xlabel('Number of on time payments')
plt.ylabel('Count')
plt.title('Number of on time payments')
plt.xticks([0,5,10,20,30,35,40,50,60,70,80,90,100,110,120,130,140,150])
plt.show()
```



Now the IncomeRange

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.

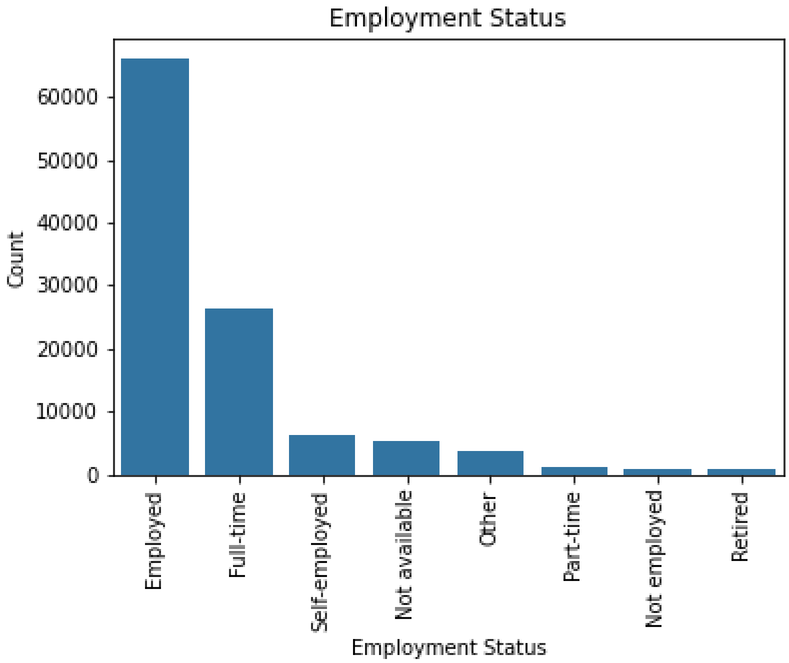
In [21]:
```
sb.countplot(data= df_loans, x= 'IncomeRange', color= base_color, order = df_loan
plt.xticks(rotation=90)
plt.xlabel('Income Range ($)')
plt.ylabel('Count')
plt.title('Borrowers income range');
```



Lets check the EmploymentStatus to find out

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

In [22]:
```
sb.countplot(data= df_loans, x= 'EmploymentStatus', color= base_color, order = d
plt.xticks(rotation=90)
plt.xlabel('Employment Status')
plt.ylabel('Count')
plt.title('Employment Status');
```

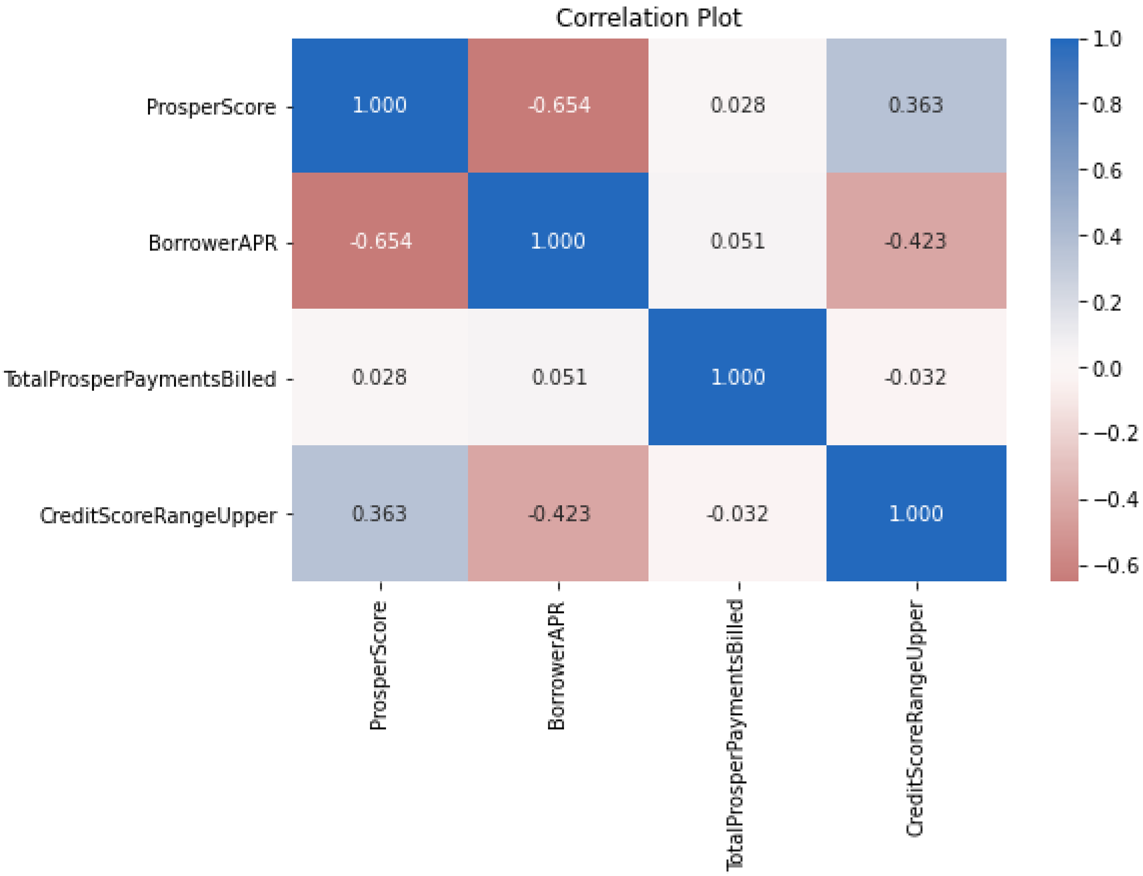


Bivariate Exploration

Lets look at the numeric variables

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.

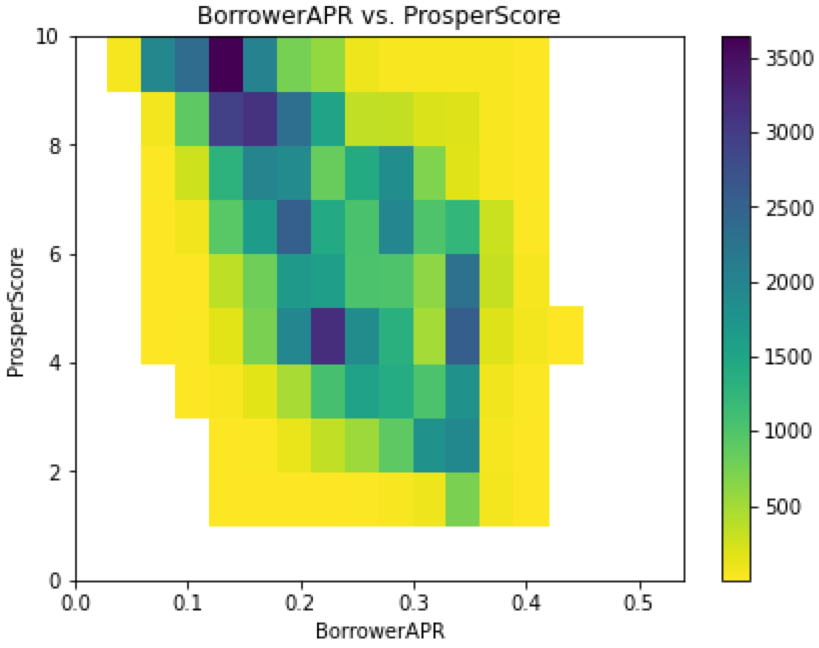
In [23]:
```
num_var = ['ProsperScore', 'BorrowerAPR', 'TotalProsperPaymentsBilled', 'CreditSc

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



Lets look more closely at ProsperScore vs BorrowerAPR

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

In [24]:
```
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');
```

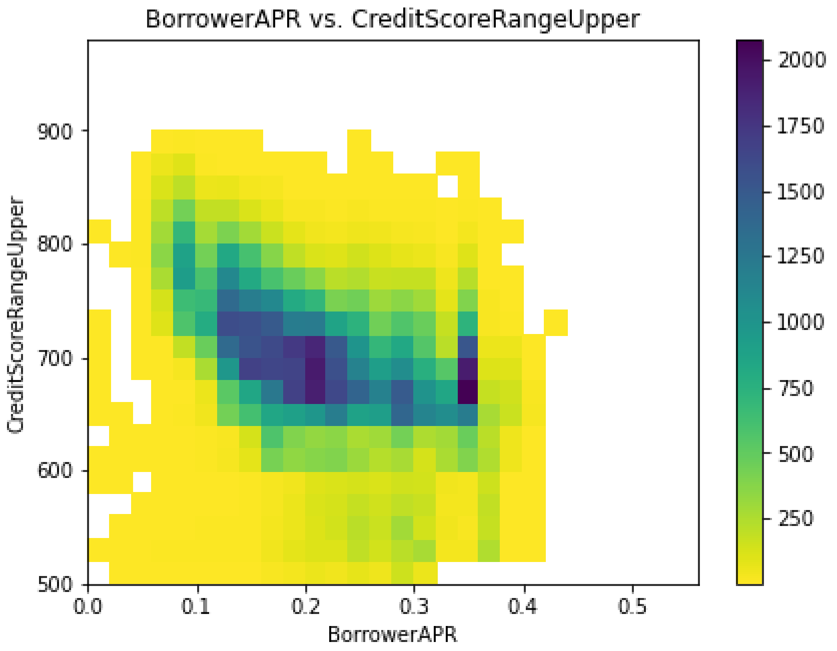


Now BorrowerAPR vs. CreditScoreRangeUpper

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

In [25]:

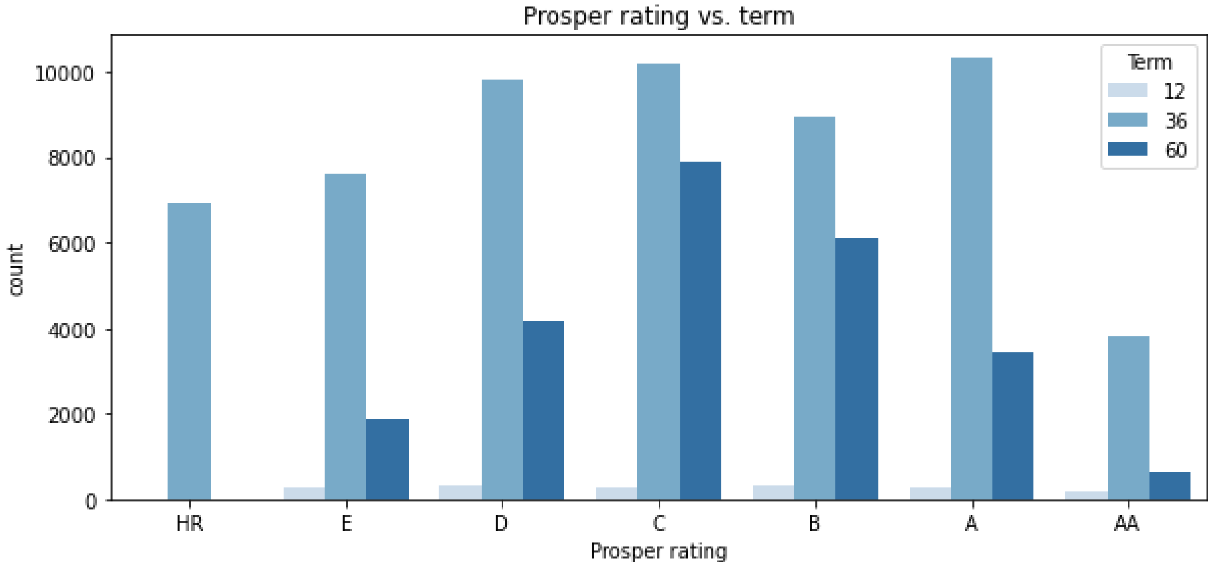
```
plt.figure(figsize = [15, 5])

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');
```



let's look at relationships between the categorical features.

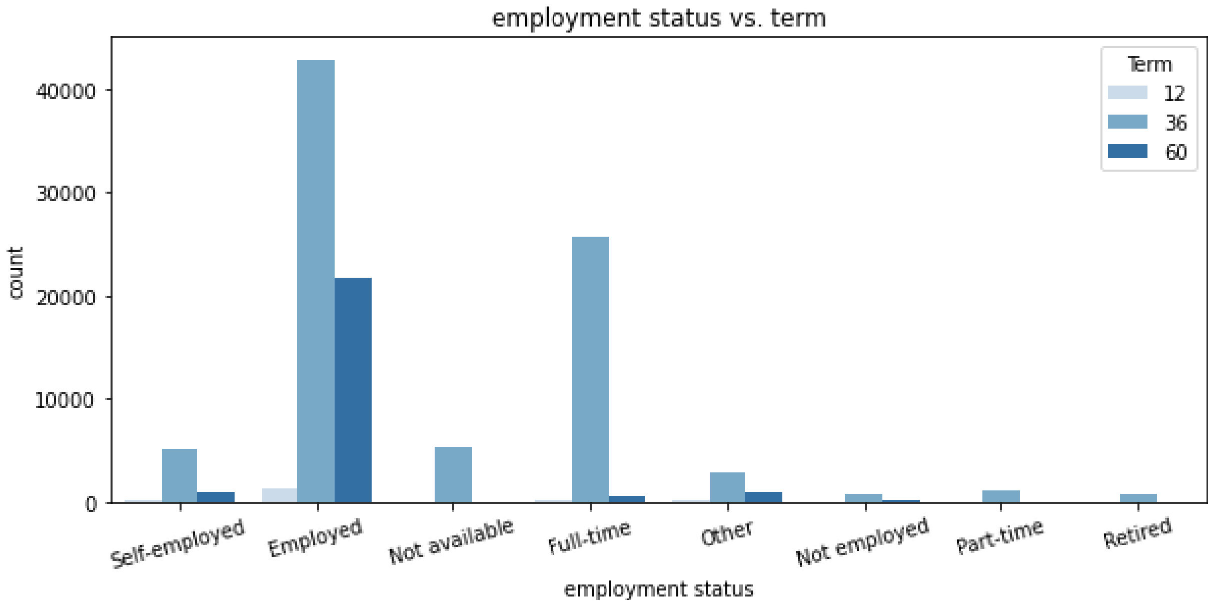
We can see that there is an interaction between term and Prosper rating. The most popular term was 36 and most of the employed especially with full-time jobs took that kind of loan. And of course, the higher proper ratings were given to the employed personnel.

```
In [26]: plt.figure(figsize = [10, 20])

         # 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');
```



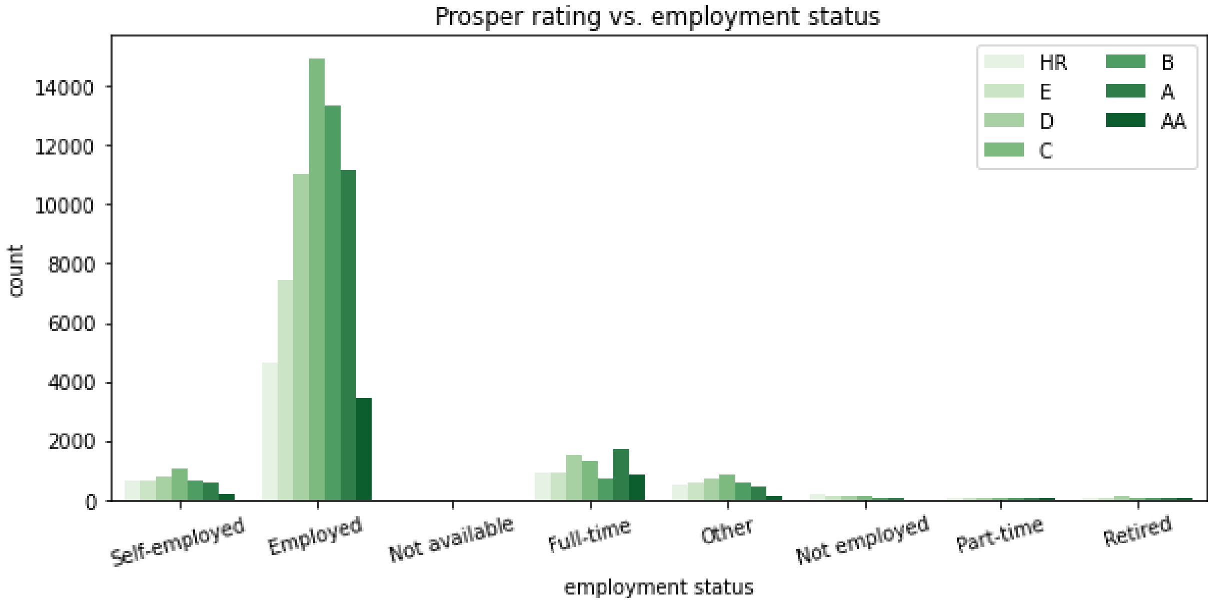
In [27]:

```
# employment status vs. term
plt.figure(figsize = [10, 20])

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');
```



In [28]:

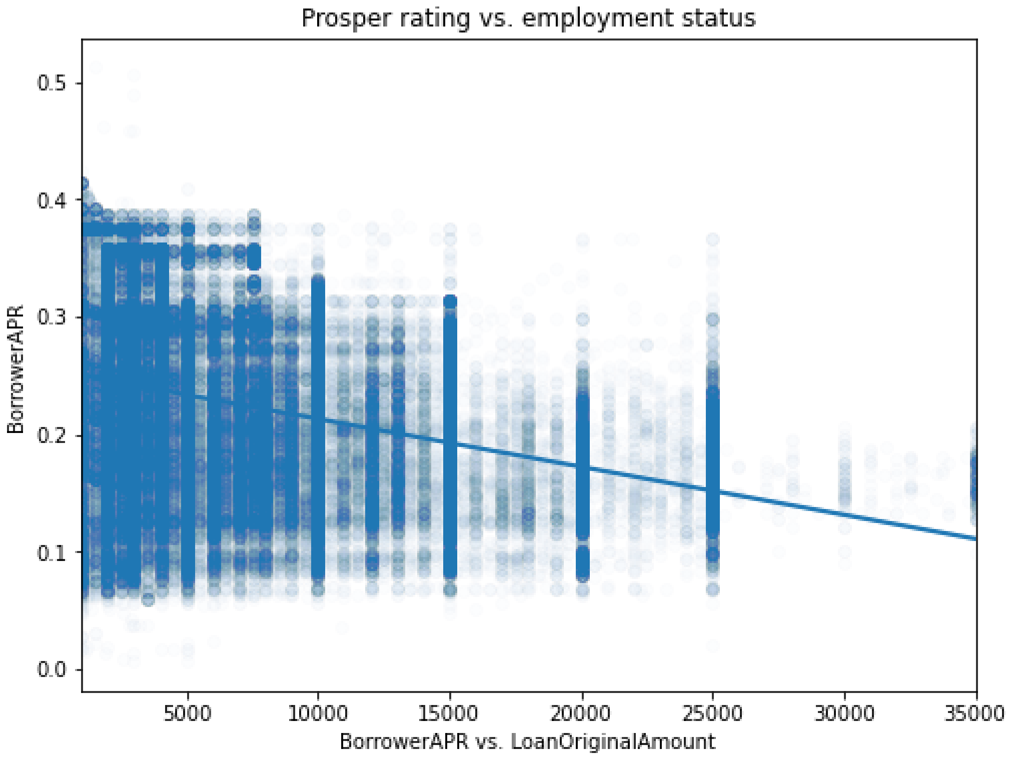
```
# Prosper rating vs. employment status
plt.figure(figsize = [10, 20])
ax = plt.subplot(4, 1, 3)
sb.countplot(data = df_loans, x = 'EmploymentStatus', hue = 'ProsperRating (Alpha
ax.legend(loc = 1, ncol = 2)
plt.xticks(rotation = 15)
plt.xlabel('employment status')
plt.title('Prosper rating vs. employment status');
```



Lets see how borrower APR and loan original amount are related

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.

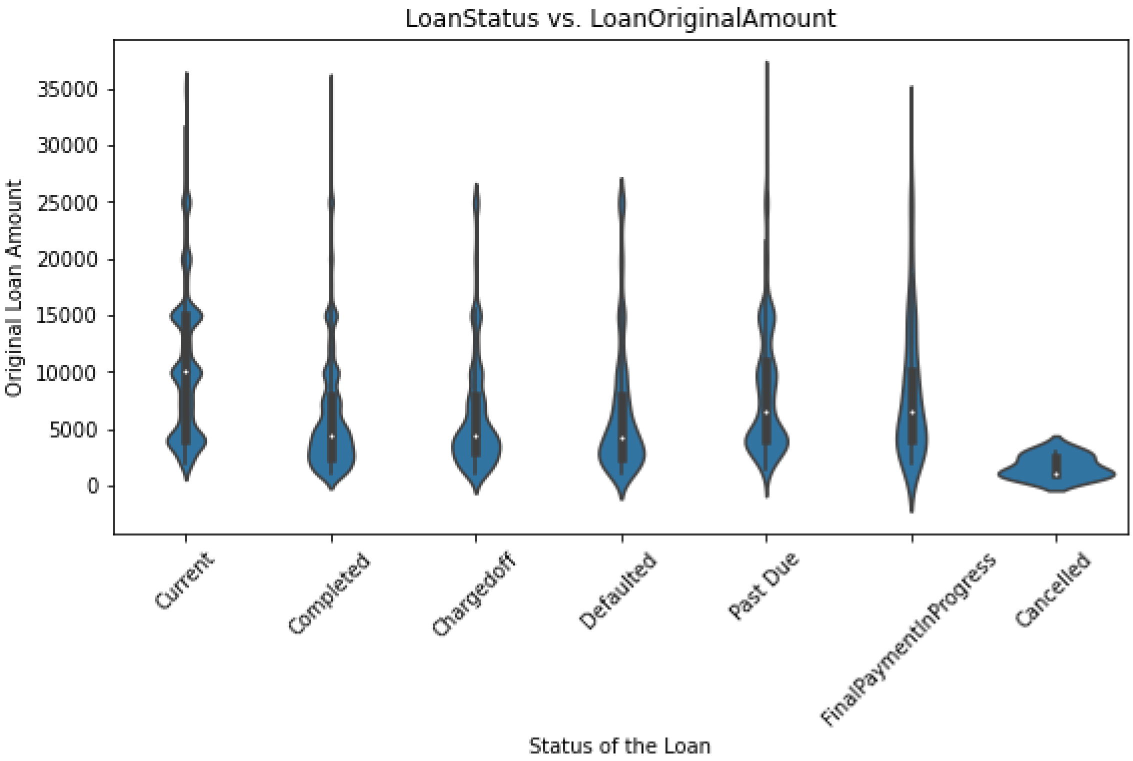
In [29]:
```
plt.figure(figsize = [8, 6])
sb.regplot(data = df_loans, x = 'LoanOriginalAmount', y = 'BorrowerAPR', scatter_
plt.xlabel('BorrowerAPR vs. LoanOriginalAmount')
plt.title('Prosper rating vs. employment status');
```



Now the relation between LoanStatus and LoanOriginalAmount

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

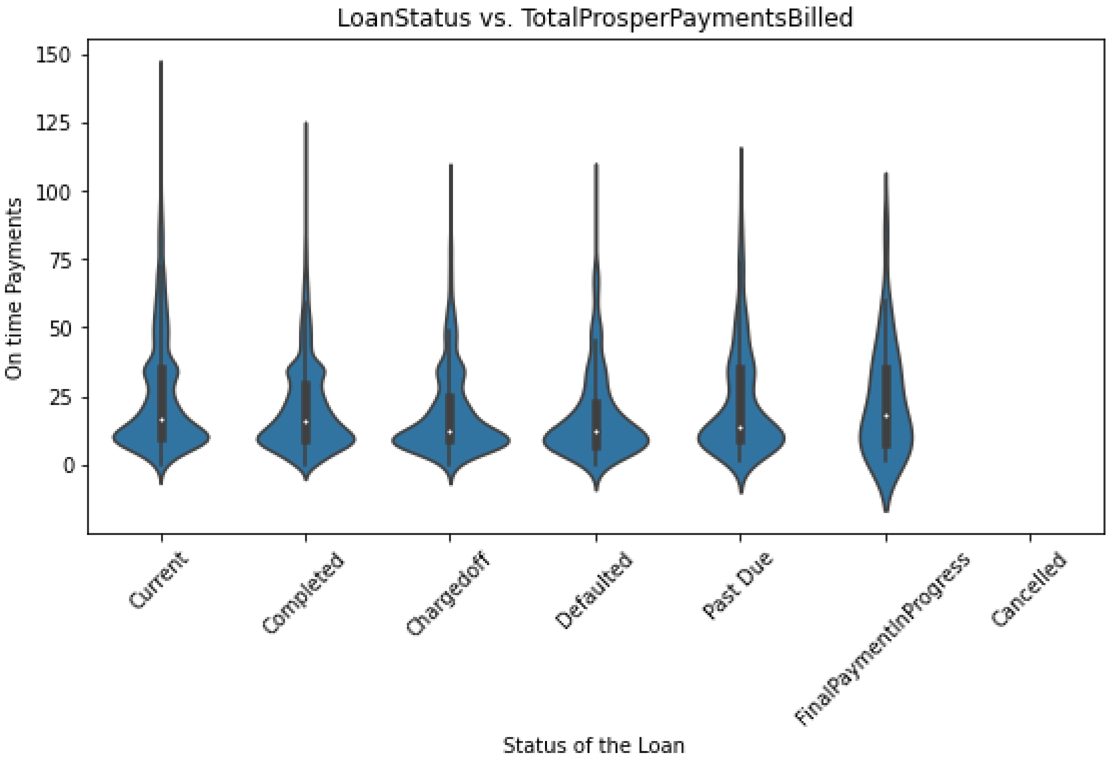
In [30]:
```
plt.figure(figsize = [20, 10])

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');
```



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

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

In [31]:
```python
plt.figure(figsize = [20, 10])

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');
```

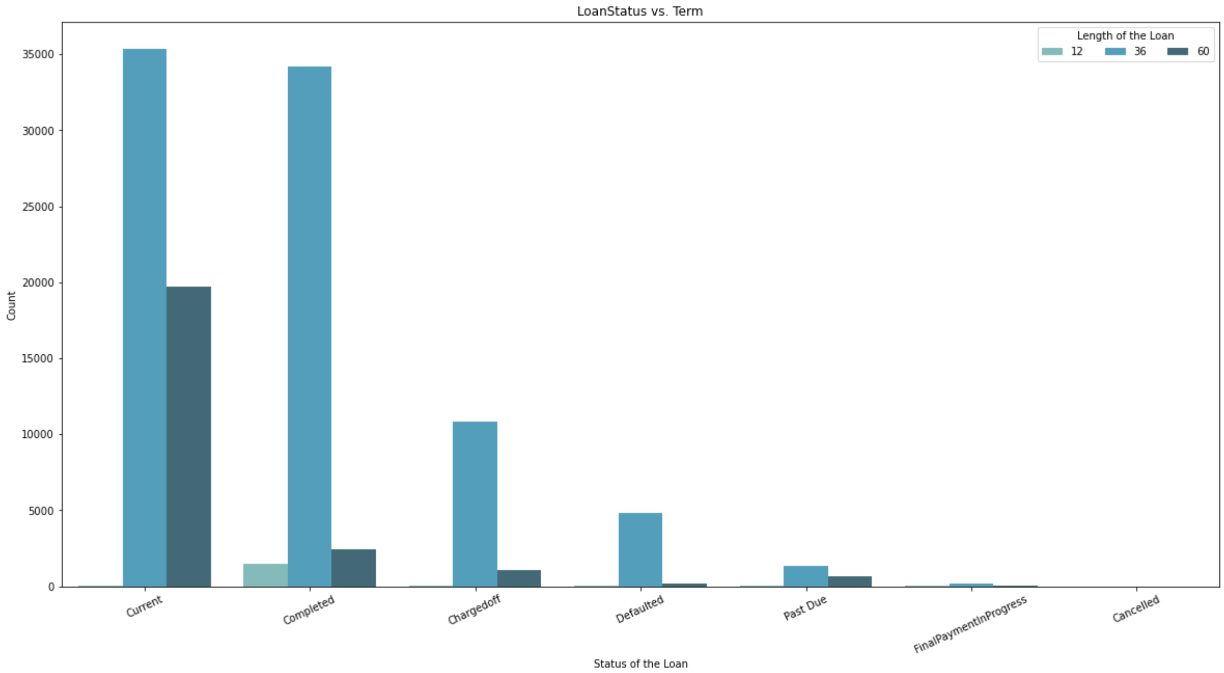


Relation between loan status and term

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

In [32]:

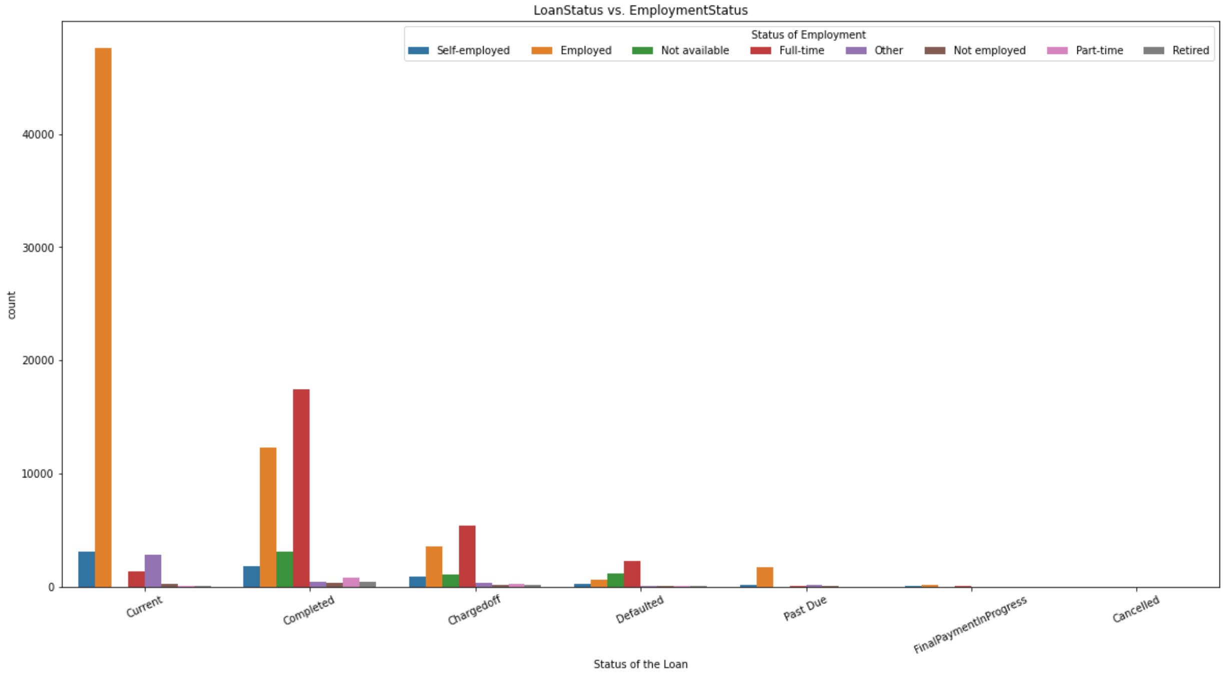
```
plt.figure(figsize = [20,10])

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');
```



Relation between loan status and employment status

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.

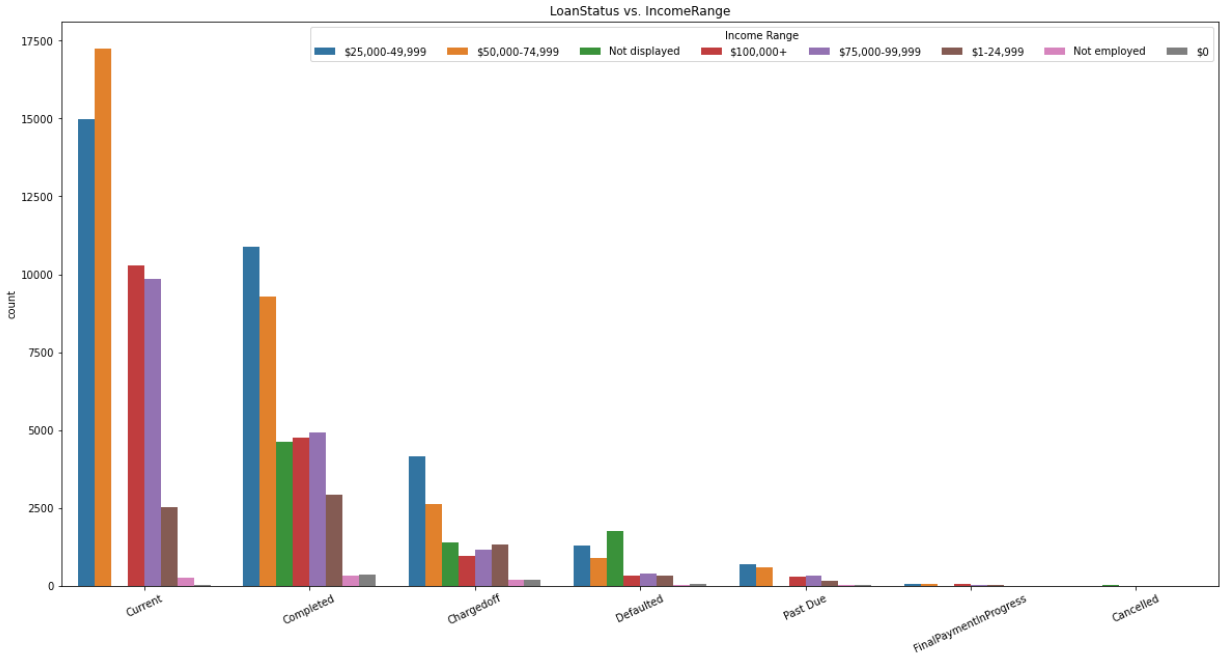
In [33]:
```
plt.figure(figsize = [20,10])

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');
```



Relation between loan status and income range

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

```
In [34]: plt.figure(figsize = [20,10])

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



Relation between prosper score and loan status

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 4.

In [35]:

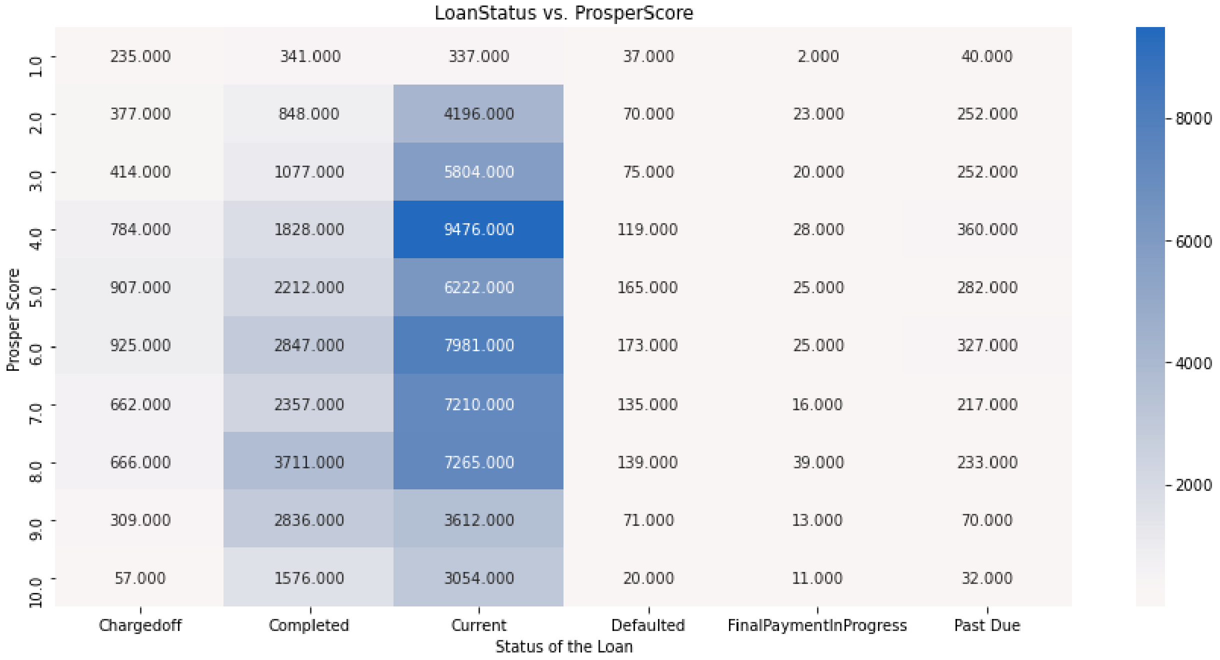
```
# first I need to reshape the data
reshape = df_loans.groupby(['LoanStatus', 'ProsperScore']).size()
reshape = reshape.reset_index(name = 'count')
reshape = reshape.pivot(index = 'ProsperScore', columns = 'LoanStatus', values =
reshape
```

Out[35]:

LoanStatus	Chargedoff	Completed	Current	Defaulted	FinalPaymentInProgress	Past Due
ProsperScore						
1.0	235	341	337	37	2	40
2.0	377	848	4196	70	23	252
3.0	414	1077	5804	75	20	252
4.0	784	1828	9476	119	28	360
5.0	907	2212	6222	165	25	282
6.0	925	2847	7981	173	25	327
7.0	662	2357	7210	135	16	217
8.0	666	3711	7265	139	39	233
9.0	309	2836	3612	71	13	70
10.0	57	1576	3054	20	11	32

In [36]:

```
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');
```



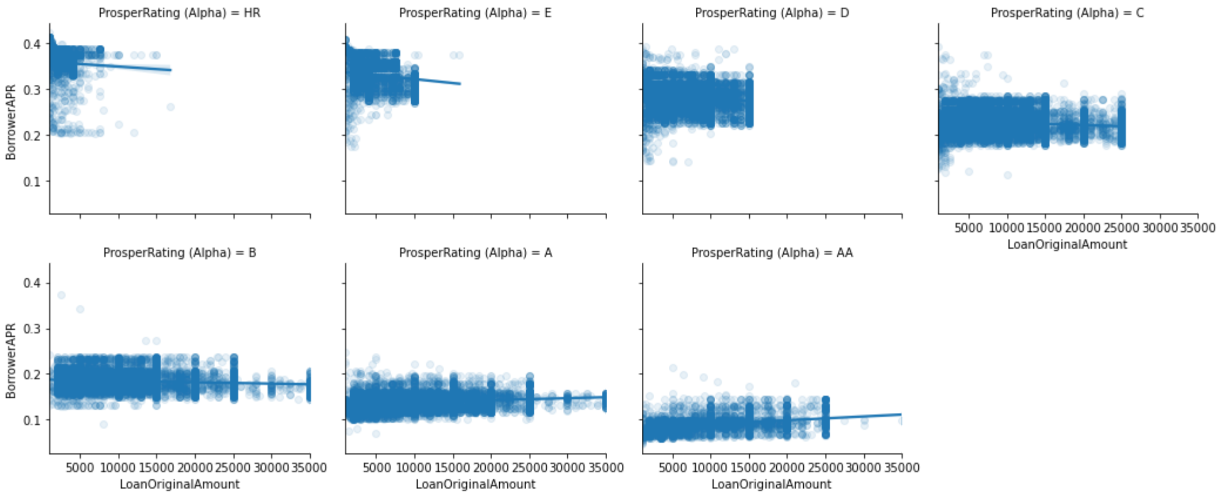
Multivariate Exploration

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

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.

```
In [37]: g=sb.FacetGrid(data = df_loans, aspect = 1.2, height = 5, col = 'ProsperRating (A
         g.map(sb.regplot, 'LoanOriginalAmount', 'BorrowerAPR', x_jitter=0.04, scatter_kws
         g.add_legend();
```

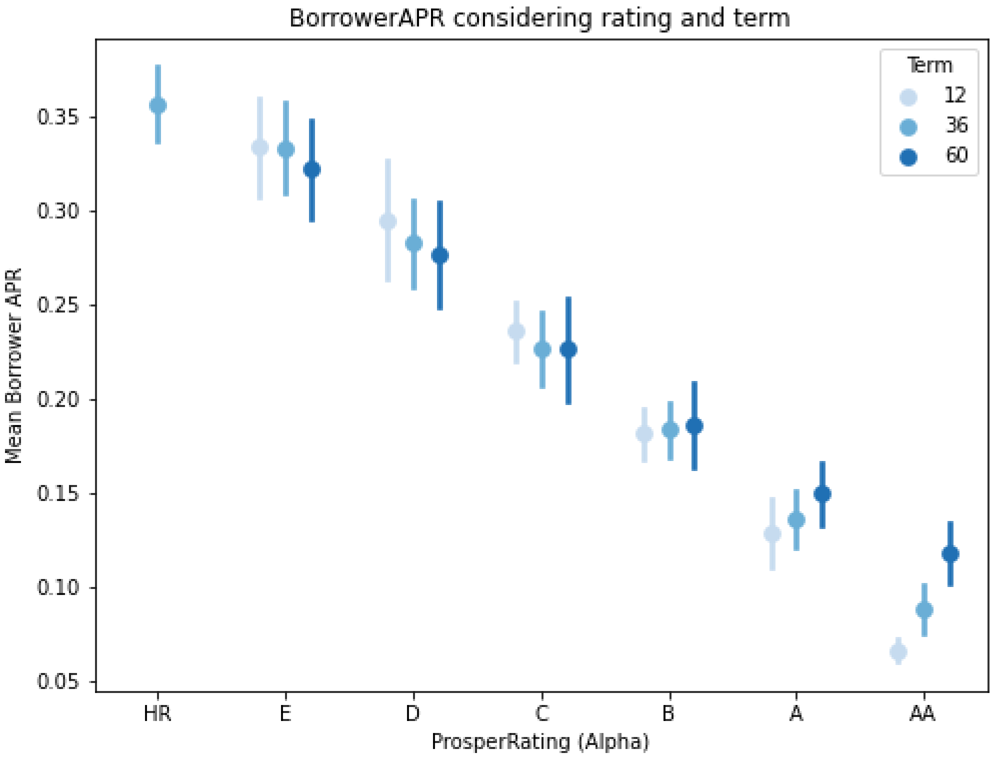
```
C:\Users\Ahmed\anaconda3\lib\site-packages\seaborn\axisgrid.py:316: UserWarnin
g: The `size` parameter has been renamed to `height`; please update your code.
  warnings.warn(msg, UserWarning)
```



BorrowerAPR considering rating and term

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.

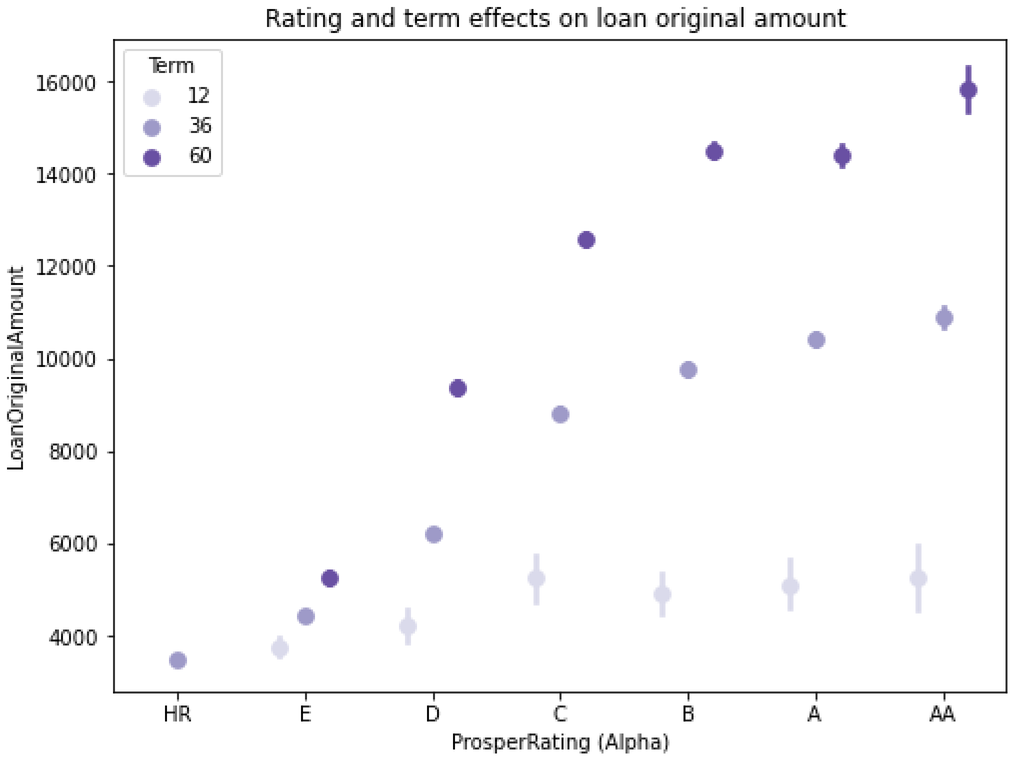
In [38]:
```
fig = plt.figure(figsize = [8,6])

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);
```



The rating and term effects on loan original amount

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

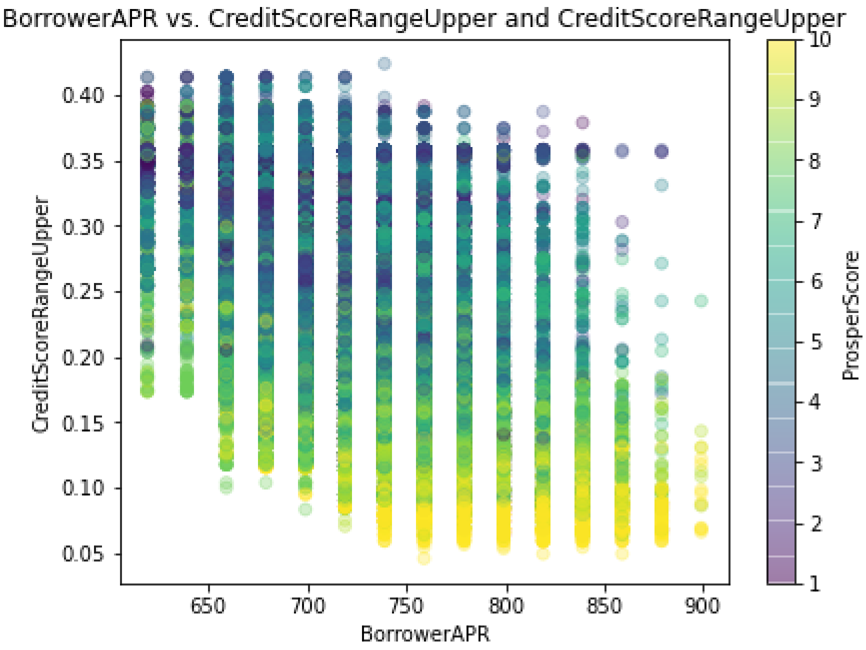
In [39]:
```
fig, ax = plt.subplots(figsize=[8,6])

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



BorrowerAPR considering CreditScoreRangeUpper and ProsperScore

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

In [40]:
```
plt.figure(figsize = [15, 5])

plt.subplot(1, 2, 2)
plt.scatter(data = df_loans, x = 'CreditScoreRangeUpper', y = 'BorrowerAPR', c ='
plt.colorbar(label = 'ProsperScore')
plt.title('BorrowerAPR vs. CreditScoreRangeUpper and CreditScoreRangeUpper')
plt.xlabel('BorrowerAPR')
plt.ylabel('CreditScoreRangeUpper');
```



Conclusion

After the demonstration, we answer the previously answered questions as follows:

- Prosper seem to give loans to all level of borrowers, but more is given to borrowers with a score of (C to A).
- We can see that the higher the borrowers rating the lower the annual rate of interest is charged (APR).

- APR is affected directly with the following attributes:

  > - Loan amount: when the amount increases the APR decrease.
  > - Term: as the most popular term is 36, it is also the most completed term which means it gets a higher score rating so as well the APR of the borrower decreases.
  > - Income: borrowers with an income range of (25000 - 74999) get more loans and also complete their loans on time, therefore gets a prosper rating of 8, so as well the APR is low for them.

- The APR also is low for borrowers who get large loans, but also make more than 100000+ as well as complete their loans on time.
- The most popular loans amount are between 2500 - 10000 as well as the term of 36 months, which is reasonable because small amounts are paid in a short time and preferable between borrowers.
- Borrowers who are employed tend to get more loans and pay on time and complete their loans therefore get higher scores.

Few insights on how Prosper could increase their profits from loans:

- Notice that most borrowers' income is between (25000 - 74000), so I think that prosper should focus their marketing plan on the middle-class segment.
- The most popular term of loans is the short ones, as the average loan amount is between 8200 dollars. I think that a marketing promotion plan should include activities the borrowers do like shopping for example to encourage more clients of that sort of loan.

In [45]:
```
!jupyter nbconvert slide_deck_Loan_Data_from_Prosper.ipynb --to slides --post ser
```

```
[NbConvertApp] WARNING | Config option `kernel_spec_manager_class` not recogniz
ed by `NbConvertApp`.
[NbConvertApp] Converting notebook slide_deck_Loan_Data_from_Prosper.ipynb to s
lides
Traceback (most recent call last):
  File "C:\Users\Ahmed\anaconda3\Scripts\jupyter-nbconvert-script.py", line 10,
in <module>
    sys.exit(main())
  File "C:\Users\Ahmed\anaconda3\lib\site-packages\jupyter_core\application.p
y", line 270, in launch_instance
    return super(JupyterApp, cls).launch_instance(argv=argv, **kwargs)
  File "C:\Users\Ahmed\anaconda3\lib\site-packages\traitlets\config\applicatio
n.py", line 845, in launch_instance
    app.start()
  File "C:\Users\Ahmed\anaconda3\lib\site-packages\nbconvert\nbconvertapp.py",
line 350, in start
    self.convert_notebooks()
  File "C:\Users\Ahmed\anaconda3\lib\site-packages\nbconvert\nbconvertapp.py",
line 524, in convert_notebooks
    self.convert_single_notebook(notebook_filename)
  File "C:\Users\Ahmed\anaconda3\lib\site-packages\nbconvert\nbconvertapp.py",
line 489, in convert_single_notebook
    output, resources = self.export_single_notebook(notebook_filename, resource
s, input_buffer=input_buffer)
  File "C:\Users\Ahmed\anaconda3\lib\site-packages\nbconvert\nbconvertapp.py",
line 418, in export_single_notebook
    output, resources = self.exporter.from_filename(notebook_filename, resource
s=resources)
  File "C:\Users\Ahmed\anaconda3\lib\site-packages\nbconvert\exporters\exporte
r.py", line 181, in from_filename
    return self.from_file(f, resources=resources, **kw)
  File "C:\Users\Ahmed\anaconda3\lib\site-packages\nbconvert\exporters\exporte
r.py", line 199, in from_file
    return self.from_notebook_node(nbformat.read(file_stream, as_version=4), re
sources=resources, **kw)
  File "C:\Users\Ahmed\anaconda3\lib\site-packages\nbconvert\exporters\html.p
y", line 119, in from_notebook_node
    return super().from_notebook_node(nb, resources, **kw)
  File "C:\Users\Ahmed\anaconda3\lib\site-packages\nbconvert\exporters\template
exporter.py", line 384, in from_notebook_node
    output = self.template.render(nb=nb_copy, resources=resources)
  File "C:\Users\Ahmed\anaconda3\lib\site-packages\jinja2\environment.py", line
1090, in render
    self.environment.handle_exception()
  File "C:\Users\Ahmed\anaconda3\lib\site-packages\jinja2\environment.py", line
832, in handle_exception
    reraise(*rewrite_traceback_stack(source=source))
  File "C:\Users\Ahmed\anaconda3\lib\site-packages\jinja2\_compat.py", line 28,
in reraise
    raise value.with_traceback(tb)
  File "C:\Users\Ahmed\Udacity visualization project\output_toggle.tpl", line
5, in top-level template code
    {%- extends 'slides_reveal.tpl' -%}
jinja2.exceptions.TemplateNotFound: slides_reveal.tpl
```

```
In [ ]:
```