(Prosper Loan Data)

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Preliminary Wrangling

> A dataset that contains information about loans, its composed of information about the loan amoint, the borrower categeory, the loan period and so on.

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
```

> Load in your dataset and describe its properties through the questions below. Try and motivate your exploration goals through this section.

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

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

Out[3]:

	ListingKey	ListingNumber	ListingCreationDate	CreditGrade	Term	LoanStatus	ClosedDate	BorrowerAPR	BorrowerRa
0	1021339766868145413AB3B	193129	2007-08-26 19:09:29.263000000	C	36	Completed	2009-08-14 00:00:00	0.16516	0.15
1	10273602499503308B223C1	1209647	2014-02-27 08:28:07.900000000	NaN	36	Current	NaN	0.12016	0.09
2	0EE9337825851032864889A	81716	2007-01-05 15:00:47.090000000	HR	36	Completed	2009-12-17 00:00:00	0.28269	0.27
3	0EF5356002482715299901A	658116	2012-10-22 11:02:35.010000000	NaN	36	Current	NaN	0.12528	0.09
4	0F023589499656230C5E3E2	909464	2013-09-14 18:38:39.097000000	NaN	36	Current	NaN	0.24614	0.20

5 rows × 81 columns

In [4]:
```
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 [5]:
```
LoanOriginalAmount', 'BorrowerAPR', 'StatedMonthlyIncome', 'Term', 'ProsperRating (Alpha)',
entStatus', 'MonthlyLoanPayment','Investors', 'Occupation', 'CreditGrade','EmploymentStatusDuration','LoanStatus
d_col]
```

In [6]:
```
dfa.head()
```

Out[6]:

	LoanOriginalAmount	BorrowerAPR	StatedMonthlyIncome	Term	ProsperRating (Alpha)	EmploymentStatus	MonthlyLoanPayment	Investors	Oc
0	9425	0.16516	3083.333333	36	NaN	Self-employed	330.43	258	
1	10000	0.12016	6125.000000	36	A	Employed	318.93	1	Pr
2	3001	0.28269	2083.333333	36	NaN	Not available	123.32	41	
3	10000	0.12528	2875.000000	36	A	Employed	321.45	158	
4	15000	0.24614	9583.333333	36	D	Employed	563.97	20	

In [7]:
```
dfa.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 113937 entries, 0 to 113936
Data columns (total 13 columns):
 #   Column                     Non-Null Count   Dtype  
---  ------                     --------------   -----  
 0   LoanOriginalAmount         113937 non-null  int64  
 1   BorrowerAPR                113912 non-null  float64
 2   StatedMonthlyIncome        113937 non-null  float64
 3   Term                       113937 non-null  int64  
 4   ProsperRating (Alpha)      84853 non-null   object 
 5   EmploymentStatus           111682 non-null  object 
 6   MonthlyLoanPayment         113937 non-null  float64
 7   Investors                  113937 non-null  int64  
 8   Occupation                 110349 non-null  object 
 9   CreditGrade                28953 non-null   object 
 10  EmploymentStatusDuration   106312 non-null  float64
 11  LoanStatus                 113937 non-null  object 
 12  BorrowerRate               113937 non-null  float64
dtypes: float64(5), int64(3), object(5)
memory usage: 11.3+ MB
```

What is the structure of your dataset?

> dataset is composed of 81 columns with 11397 notices in the rows(not all columns with the same number of notices, but i ll investigate only 10 features (columns) witch are the most important

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

> the main features are the amount of money borrowed, the period and categeorising the borrower

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

> stated monthly income, loan original amount,

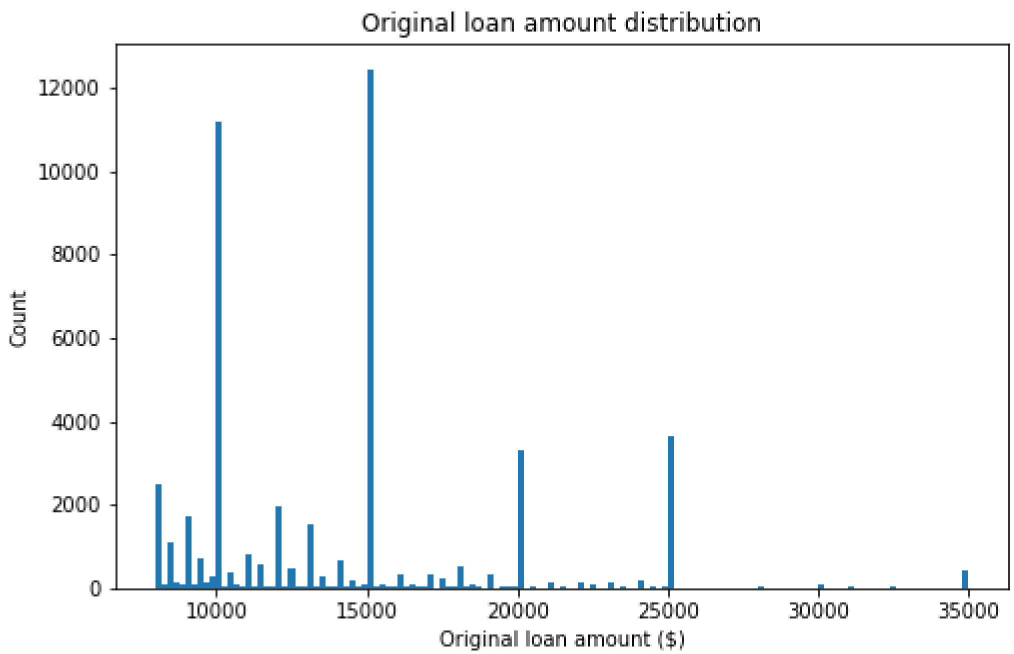
Univariate Exploration

> In this section, investigate distributions of individual variables. If you see unusual points or outliers, take a deeper look to clean things up and prepare yourself to look at relationships between variables.

we will start with investigating some variables like loan original amount, monthly income, employment status

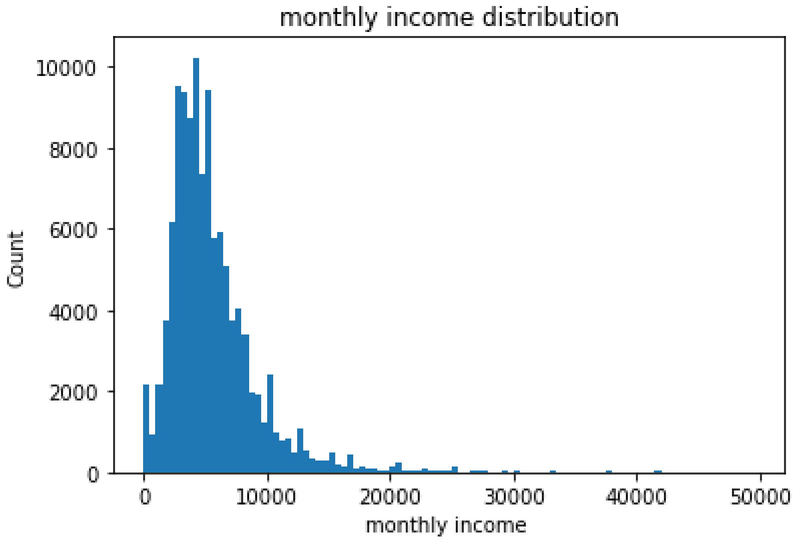
In [8]:
```
#global color coding
default_color = sb.color_palette()[0]
```

In [9]:
```
bins = np.arange(8000, dfa.LoanOriginalAmount.max()+200, 200)
plt.figure(figsize=[8, 5])
plt.hist(data = dfa, x = 'LoanOriginalAmount', bins = bins);
plt.title('Original loan amount distribution')
plt.ylabel('Count')
plt.xlabel('Original loan amount ($)');
```



we can notice that the largest spikes are at 10, 15, 20, 25 ks, while the smaller spikes noticed at 7, 9, 13 ks

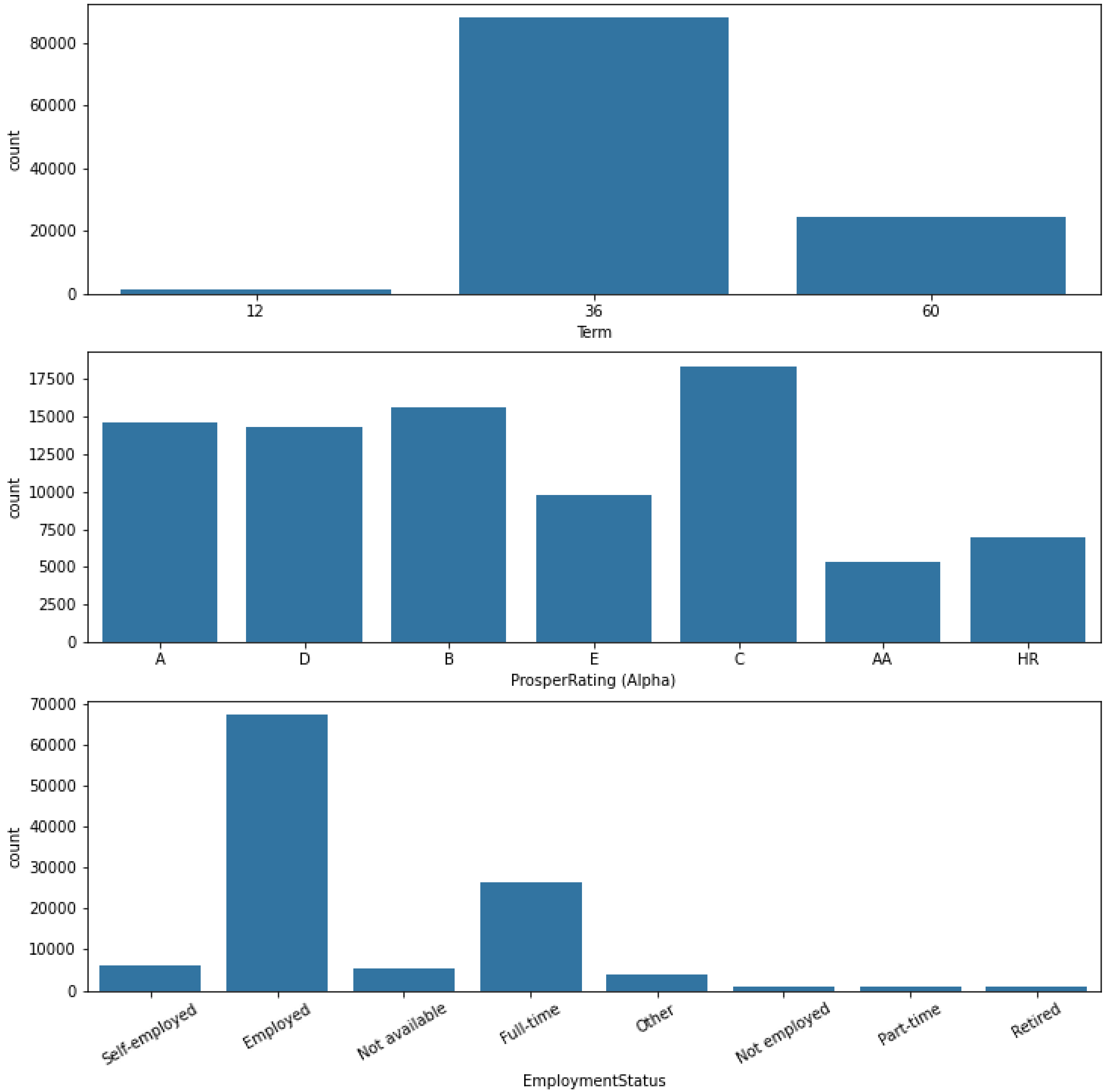
In [10]:
```
bins_smi = np.arange(0, 50000, 500)
plt.hist(data = dfa, x = 'StatedMonthlyIncome', bins=bins_smi);
plt.title('monthly income distribution')
plt.ylabel('Count')
plt.xlabel('monthly income ');
```



we can notice that monthly income distribution is right skewed

In [11]:

```
fig, ax = plt.subplots(nrows=3, figsize = [12,12])
sb.countplot(data = dfa, x = 'Term', color = default_color, ax = ax[0])
sb.countplot(data = dfa, x = 'ProsperRating (Alpha)', color = default_color, ax = ax[1])
sb.countplot(data = dfa, x = 'EmploymentStatus', color = default_color, ax = ax[2]);
plt.xticks(rotation=30);
```

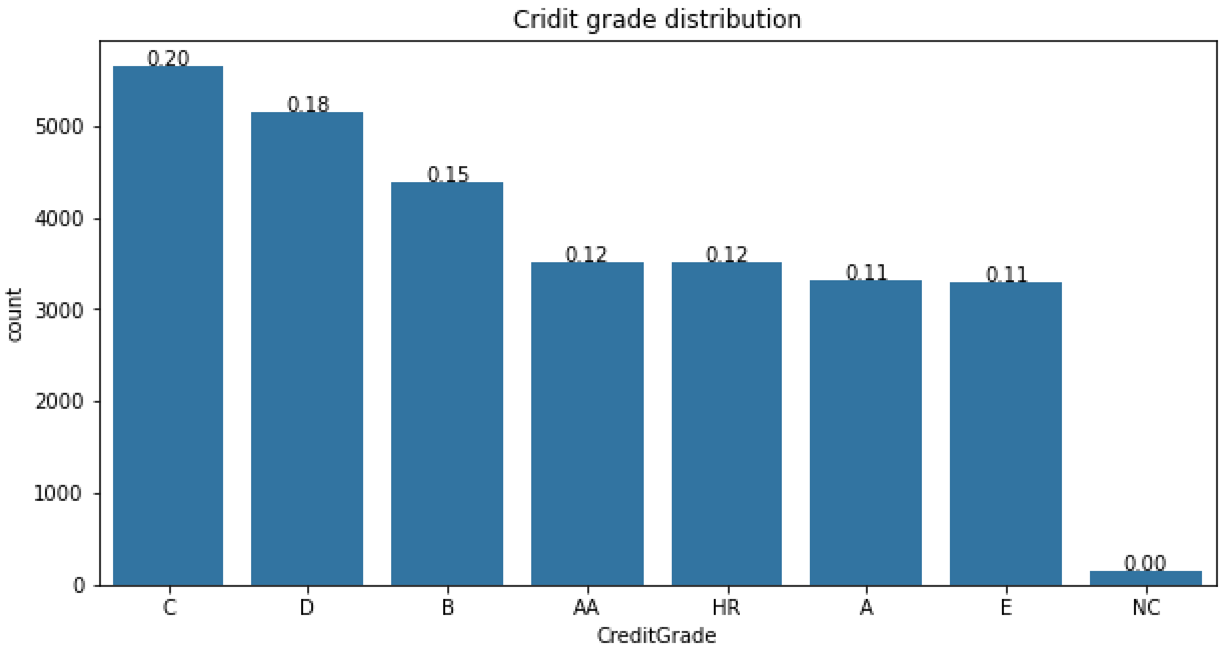


count
80000
60000
40000
20000
0
12
36
60
Term
count
17500
15000
12500
10000
7500
5000
2500
0
A
D
B
E
C
AA
HR
ProsperRating (Alpha)
count
70000
60000
50000
40000
30000
20000
10000
0
Self-employed
Employed
Not available
Full-time
Other
Not employed
Part-time
Retired
EmploymentStatus

we can notice that most of the loans are for a 36 months period, taken by fulltime jobs holder, with a ratind (a,b,c,d)

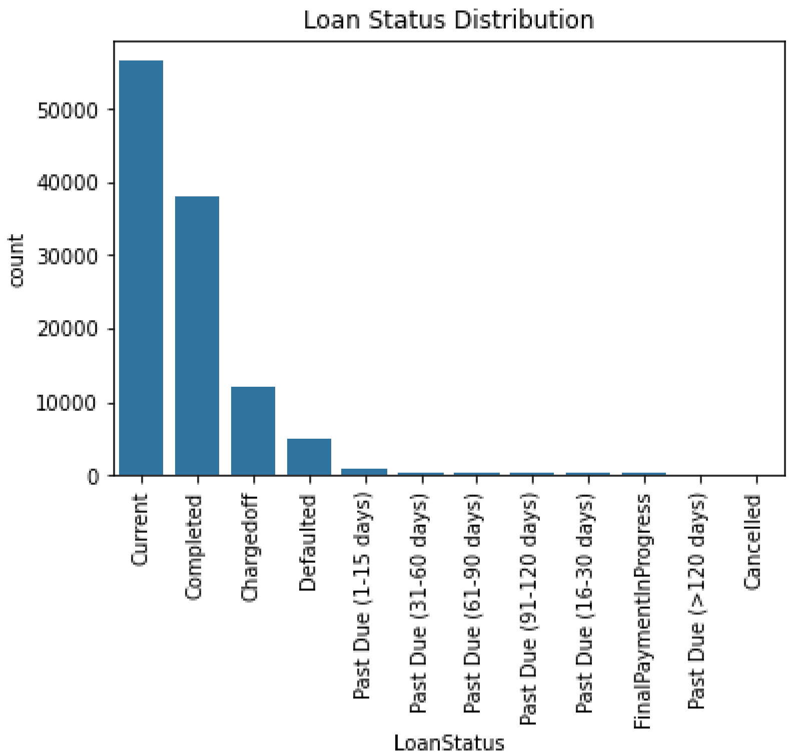
In [12]:

```
total_credit = dfa.CreditGrade.notnull().sum()
order_credit = dfa.CreditGrade.value_counts().index.tolist()
fig = plt.figure(figsize = (10,5))
ax_credit = sb.countplot(data = dfa, x = 'CreditGrade', color = default_color, order = order_credit)

for cg in ax_credit.patches:
    height = cg.get_height()
    ax_credit.text(cg.get_x()+cg.get_width()/2.,
            height + 3,
            '{:1.2f}'.format(height/total_credit),
            ha="center")
plt.title('Cridit grade distribution')
plt.show();
```



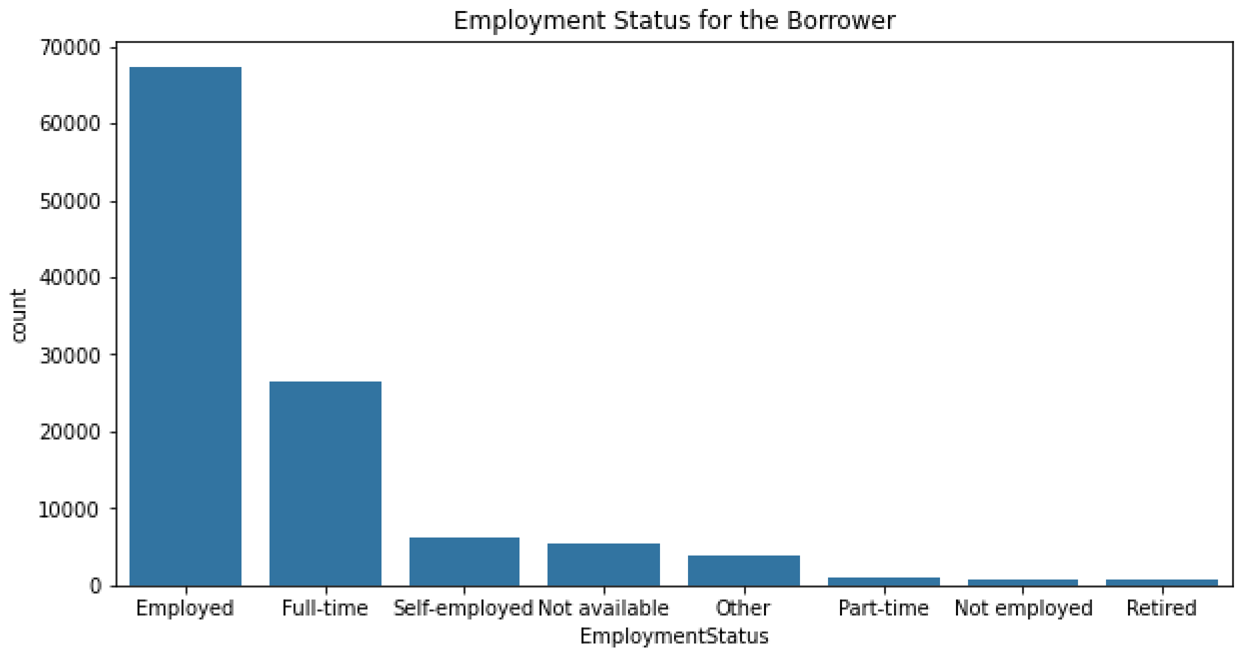
In [13]:

```
# Loan status distribution
order_status = dfa.LoanStatus.value_counts().index.tolist()
ax = sb.countplot(data = dfa, x = 'LoanStatus', color = default_color, order = order_status)
plt.xticks(rotation=90)
plt.title('Loan Status Distribution')

plt.show();
```



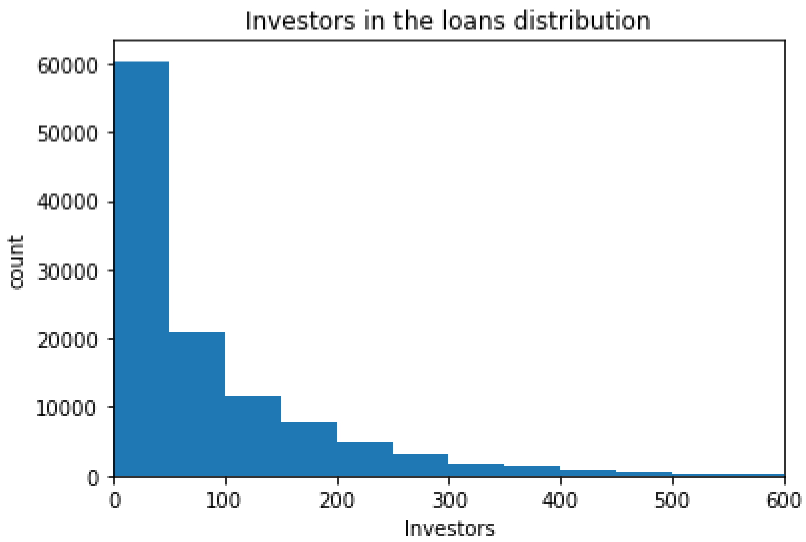
we can notice that the most amount of lians are current, which cal=n lead us to further invedstigations

In [14]:
```
order_employment = dfa.EmploymentStatus.value_counts().index.tolist()
fig = plt.figure(figsize = (10,5))
plt.title('Employment Status for the Borrower')
sb.countplot(data = dfa, x = 'EmploymentStatus',  color = default_color,order = order_employment);
```



In [15]:
```
bins =  np.arange(0, df['Investors'].max()+50, 50)
plt.title('Investors in the loans distribution')
plt.hist(data =df, x='Investors', bins=bins)
plt.xlim((0,600));
plt.xlabel('Investors')
plt.ylabel('count')
```

Out[15]:
```
Text(0, 0.5, 'count')
```



> Make sure that, after every plot or related series of plots, that you include a Markdown cell with comments about what you observed, and what you plan on investigating next.

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

> there is no unusual, its logic that loan increases as the investors increased and as the customer is employed!

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?

> no there is no need for more operations !

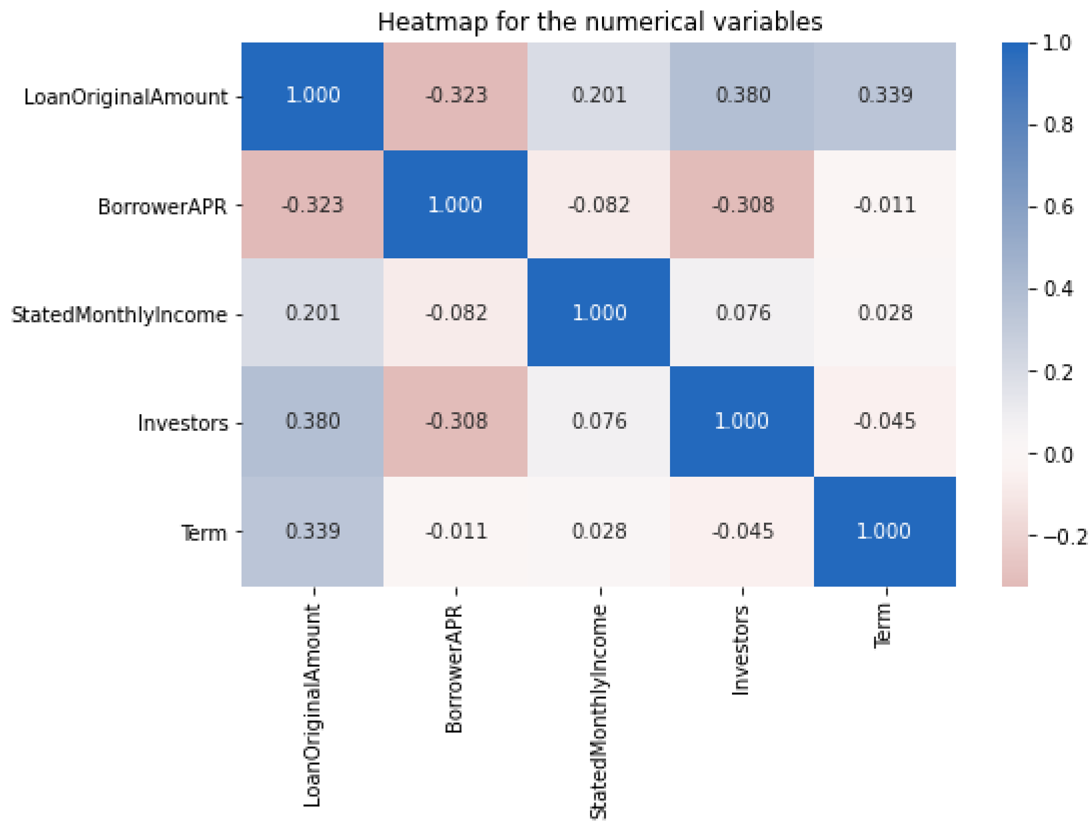
Bivariate Exploration

> In this section, investigate relationships between pairs of variables in your data. Make sure the variables that you cover here have been introduced in some fashion in the previous section (univariate exploration).

In [16]:

```
num_vars = ['LoanOriginalAmount', 'BorrowerAPR', 'StatedMonthlyIncome','Investors', 'Term']
cat_vars = ['Term', 'ProsperRating (Alpha)', 'EmploymentStatus', 'CreditGrade']
```

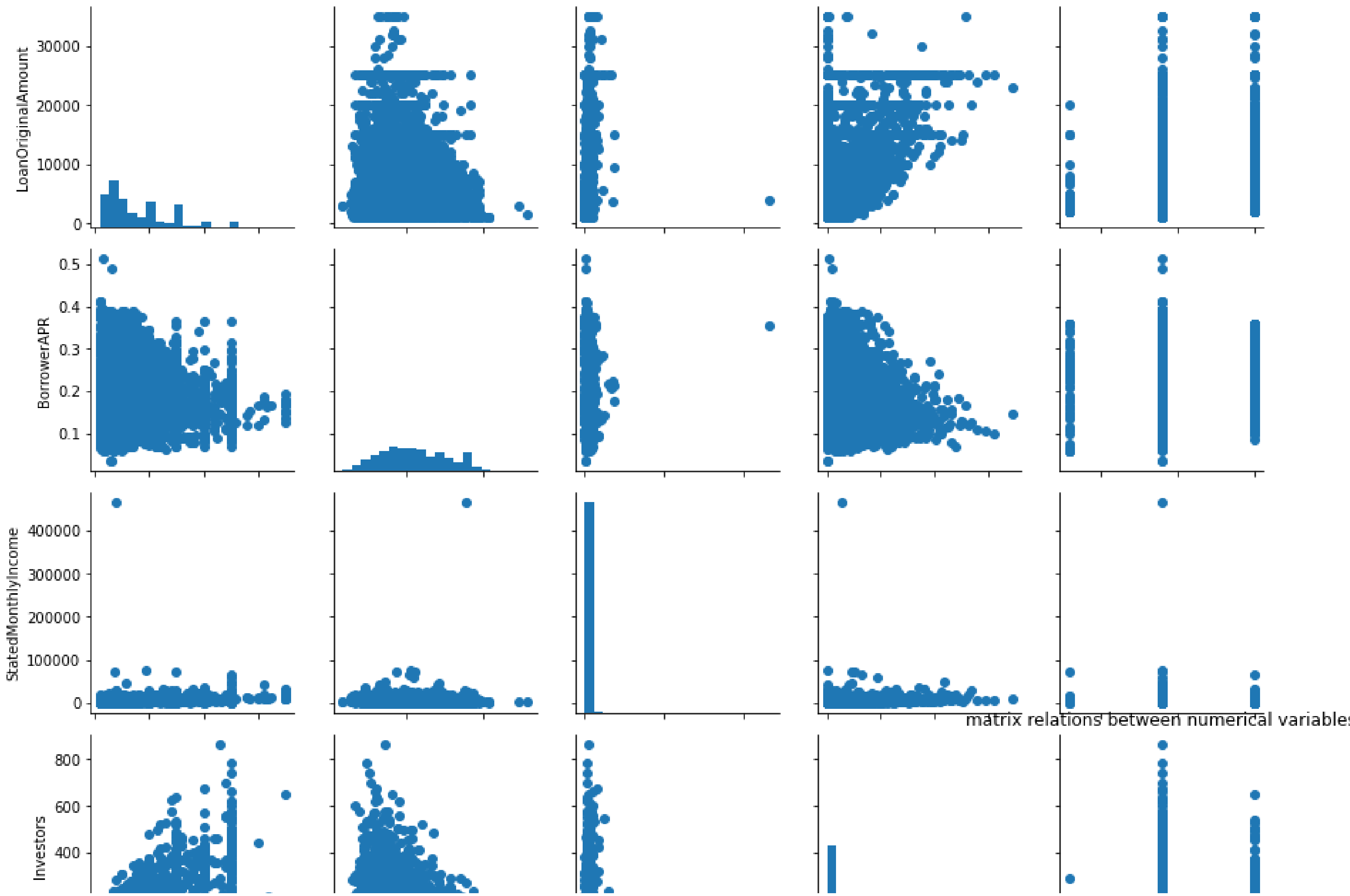
In [17]:
```
plt.figure(figsize = [8, 5])
sb.heatmap(dfa[num_vars].corr(), annot = True, fmt = '.3f',
           cmap = 'vlag_r', center = 0)
plt.title('Heatmap for the numerical variables');
```

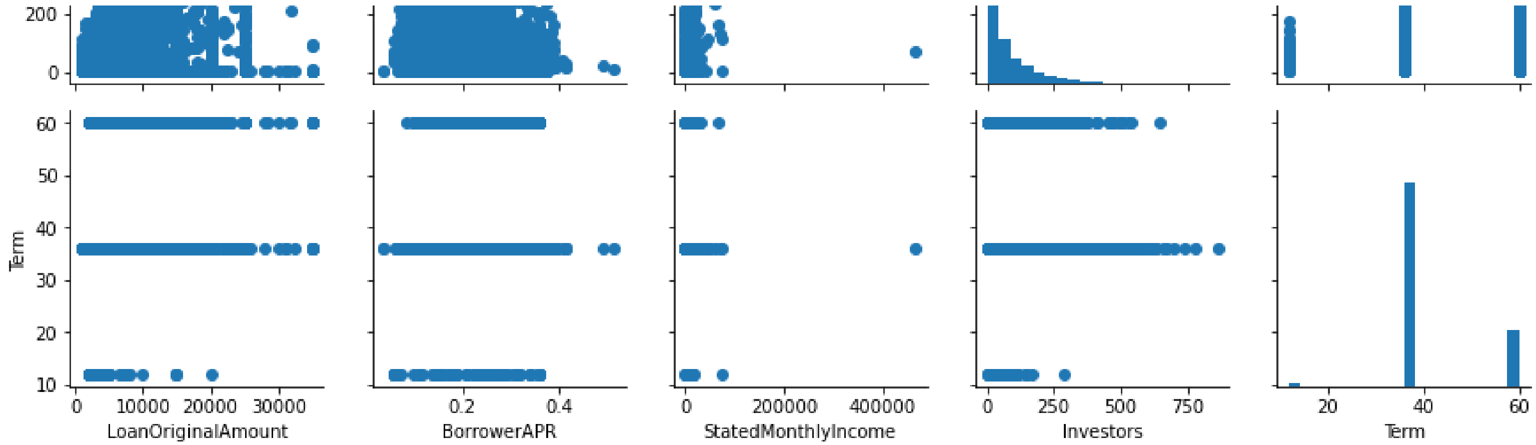


we can notice some strong corelations between investors & loan amount, term& loan amount. this may need further invistigation

In [18]:
```python
samples = np.random.choice(dfa.shape[0], 5000, replace = False)
loan_samp = dfa.loc[samples,:]

g = sb.PairGrid(data = loan_samp, vars = num_vars)
g = g.map_diag(plt.hist, bins = 20);
g.map_offdiag(plt.scatter)
plt.title('matrix relations between numerical variables')
```

Out[18]: `Text(0.5, 1.0, 'matrix relations between numerical variables')`

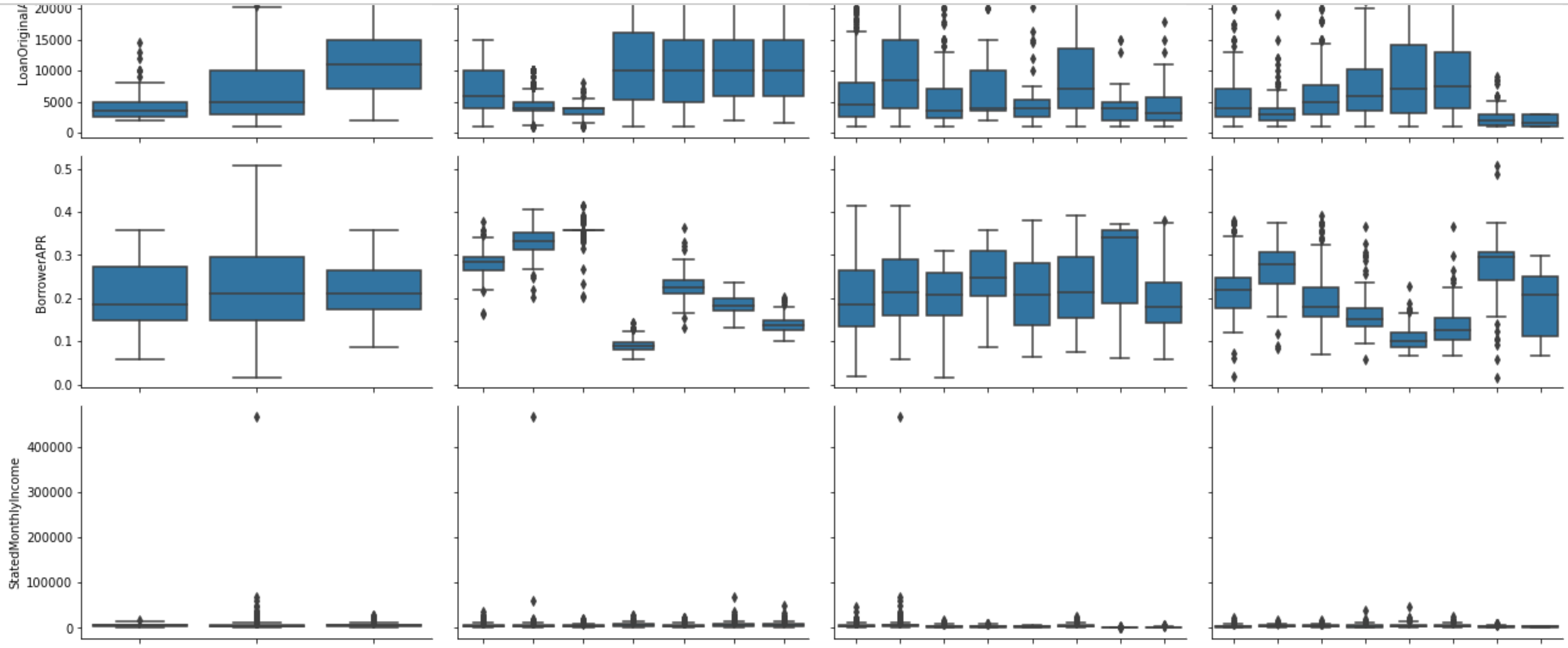




we can record some notices here, a -ve relationship between investors and borrower apr & monthly income

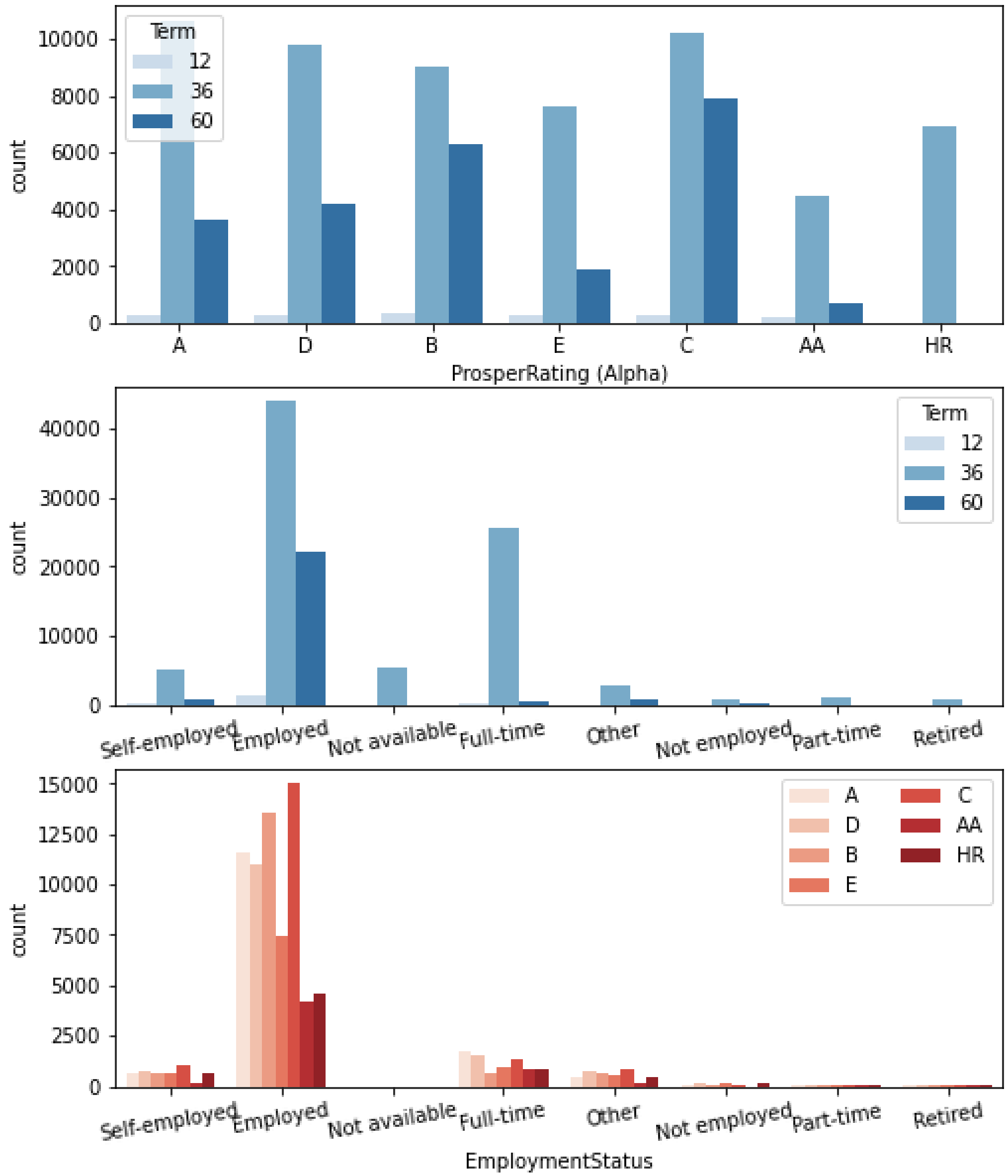
In [19]:

```
# we will highlight the relation between numerical and categorial
samples = np.random.choice(dfa.shape[0], 5000, replace = False)
loans_samp = dfa.loc[samples,:]

def boxgrid(x, y, **kwargs):
    sb.boxplot(x, y, color = default_color)

plt.figure(figsize = [10, 10])
g = sb.PairGrid(data = loans_samp, y_vars = num_vars, x_vars = cat_vars,
                size = 3, aspect = 1.5,)
g.map(boxgrid)
plt.title('relation between numerical and categorial variables')
plt.xticks(rotation=90)
plt.show();
```



In [20]:

```
plt.figure(figsize = [8, 10])
# subplot 1: Prosper rating relates to term
plt.subplot(3, 1, 1)
sb.countplot(data = dfa, x = 'ProsperRating (Alpha)', hue = 'Term', palette = 'Blues')

# subplot 2: employment status relates to. term
ax = plt.subplot(3, 1, 2)
sb.countplot(data = dfa, x = 'EmploymentStatus', hue = 'Term', palette = 'Blues')
plt.xticks(rotation=10)

# subplot 3: Prosper rating vs. employment status, use different color palette
ax = plt.subplot(3, 1, 3)
sb.countplot(data = dfa, x = 'EmploymentStatus', hue = 'ProsperRating (Alpha)', palette = 'Reds')
ax.legend(loc = 1, ncol = 2); # re-arrange legend to remove overlapping

plt.xticks(rotation=10);
```



the peak of the long term loans is in the rating c in case of emplyed person

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

> the employed people as they have the most loans, the less term of loan they have!

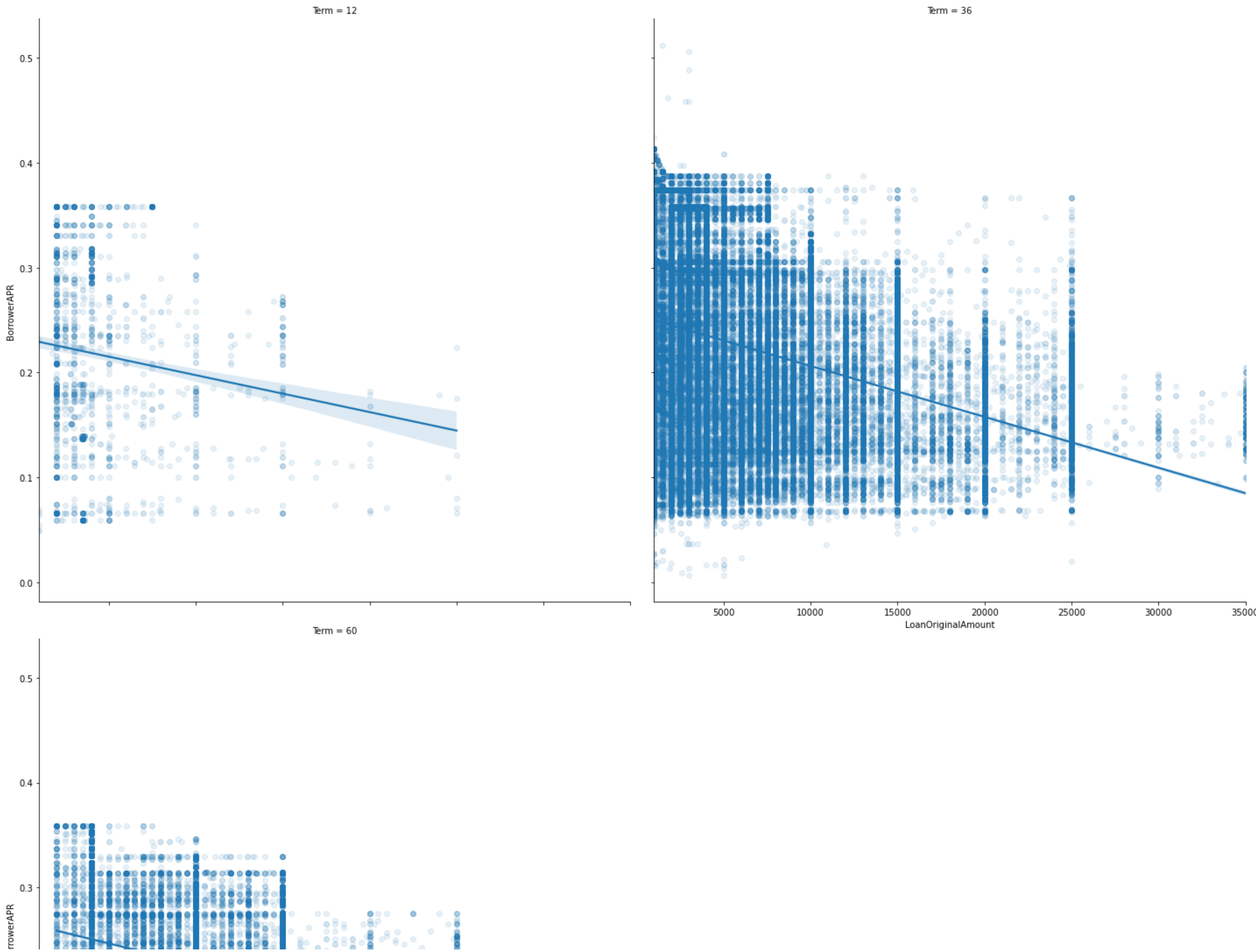
Did you observe any interesting relationships between the other features (not the main feature(s) of interest)?

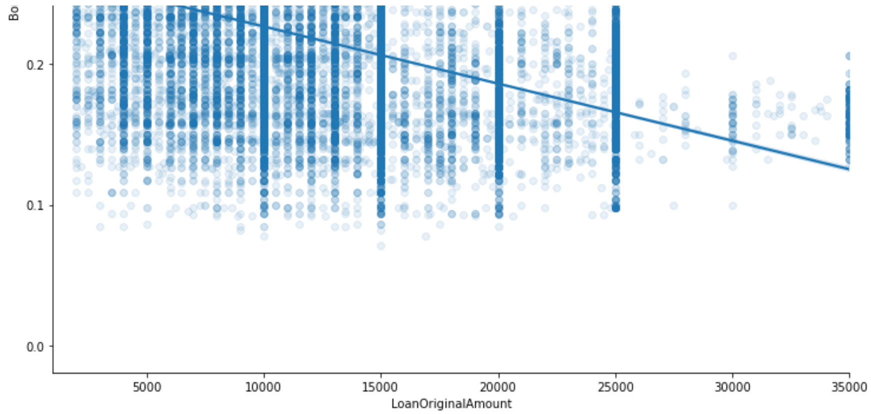
> I am astonished about the result that self employed people have less loan as the employed!

Multivariate Exploration

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

In [21]:
```
#  APR and loan amount in the highlight of Term investigating
g=sb.FacetGrid(data=dfa, aspect=1, height=10, col='Term', col_wrap=2)
g.map(sb.regplot, 'LoanOriginalAmount', 'BorrowerAPR', x_jitter=0.04, scatter_kws={'alpha':0.1});
g.add_legend();
```

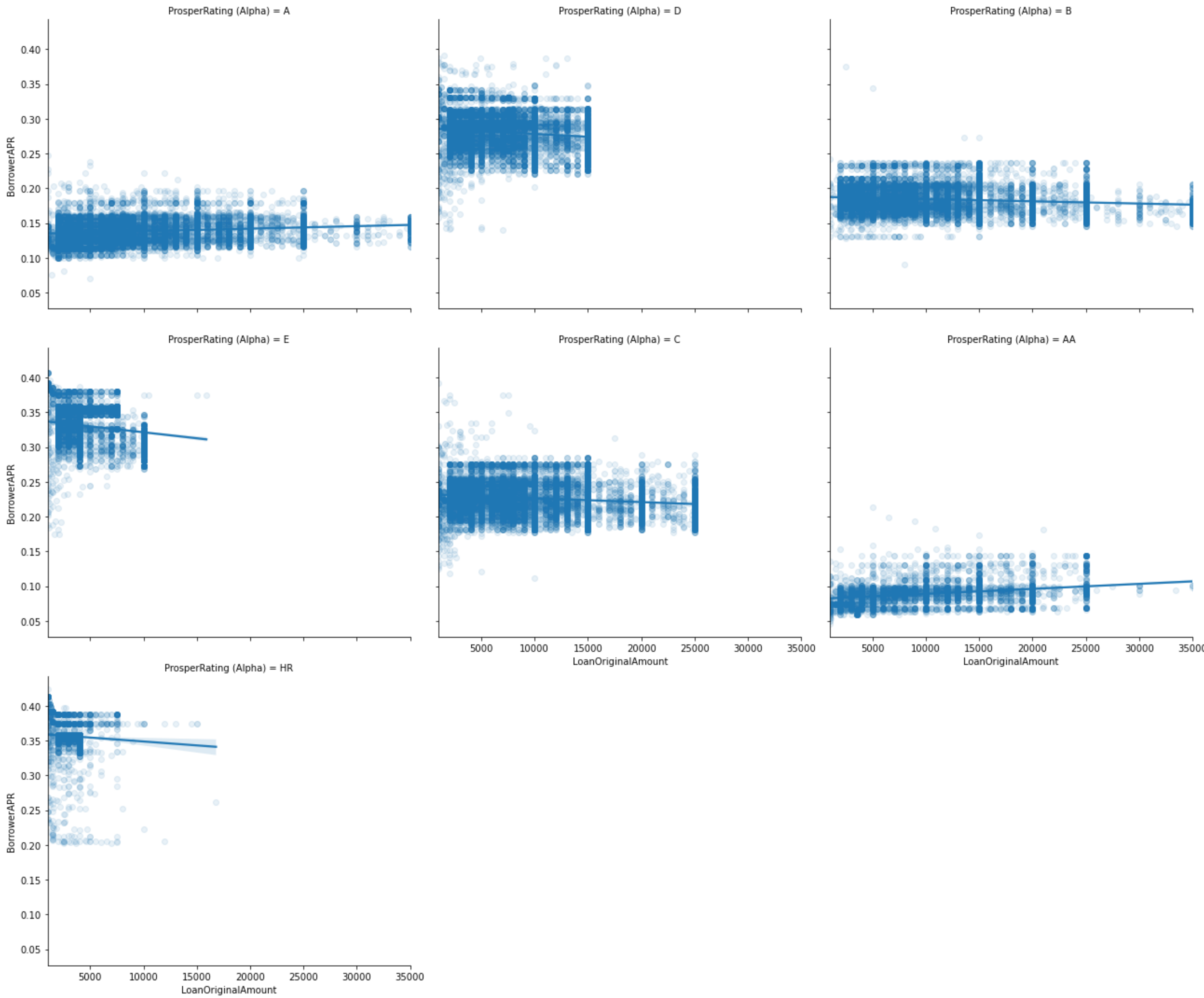




we can notice more the -ve relation that we stated above

In [22]:

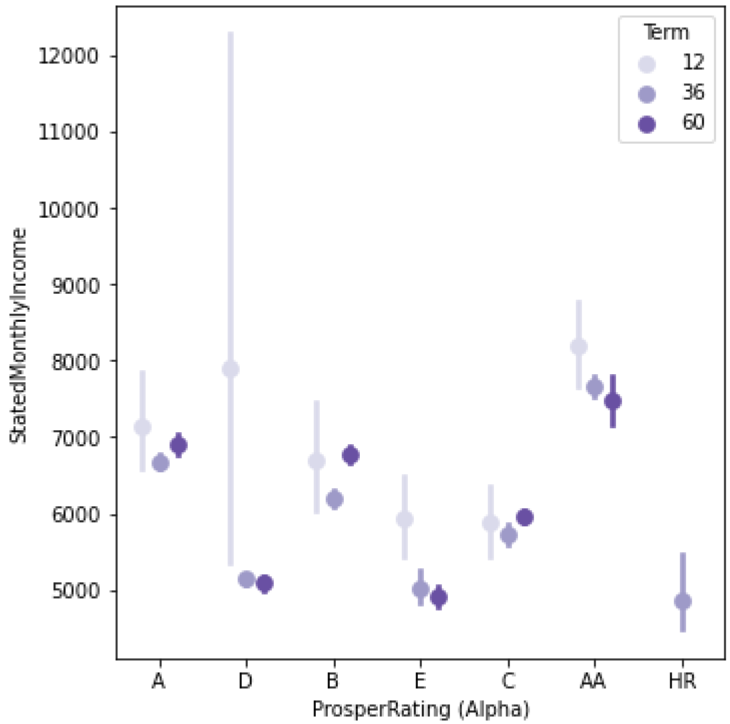
```
#  how APR and loan amount relates?
g=sb.FacetGrid(data=dfa, aspect=1.2, height=5, col='ProsperRating (Alpha)', col_wrap=3)
g.map(sb.regplot, 'LoanOriginalAmount', 'BorrowerAPR', x_jitter=0.04, scatter_kws={'alpha':0.1});
g.add_legend();
```

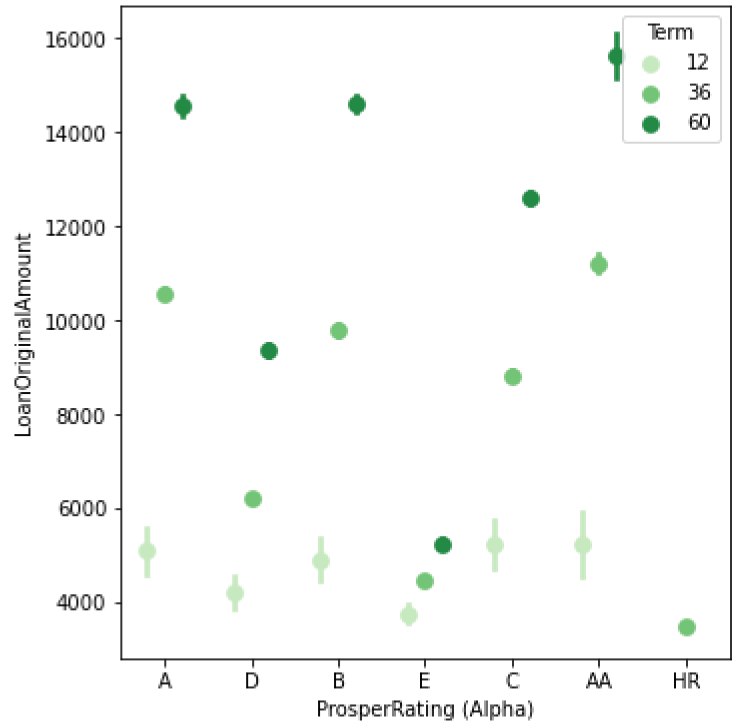


the -ve relationship is more clearly appearing

In [23]:

```
fig, ax = plt.subplots(ncols=2, figsize=[12,6])
sb.pointplot(data = dfa, x = 'ProsperRating (Alpha)', y = 'StatedMonthlyIncome', hue = 'Term',
            palette = 'Purples', linestyles = '', dodge = 0.4, ax=ax[0])
sb.pointplot(data = dfa, x = 'ProsperRating (Alpha)', y = 'LoanOriginalAmount', hue = 'Term',
            palette = 'Greens', linestyles = '', dodge = 0.4, ax=ax[1]);
```





the loan goes in a logterm as the income aand loan amount increase

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?

> we find that the relation ship between loan amount and oan term increases as the APR increases, which mean as the trust in the customer increase you can lend him more money for more time to pay!

Were there any interesting or surprising interactions between features?

> data analytics is always interesting as you can read facts through numbers, !

> At the end of your report, make sure that you export the notebook as an html file from the `File > Download as... > HTML` menu. Make sure you keep track of where the exported file goes, so you can put it in the same folder as this notebook for project submission. Also, make sure you remove all of the quote-formatted guide notes like this one before you finish your report!

In [24]:
```
!jupyter nbconvert exploration_template - Copy.ipynb --to slides --no-input
```

```
[NbConvertApp] WARNING | pattern '-' matched no files
[NbConvertApp] WARNING | pattern 'Copy.ipynb' matched no files
[NbConvertApp] Converting notebook exploration_template.ipynb to slides
[NbConvertApp] Writing 588895 bytes to exploration_template.slides.html
```