Loan Data

Introduction

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. The aim of the data analysis is to provide a graphical summary of important features of the data set and predicting the Loan outcome in the dataset.

Columns Description

[Click here (https://docs.google.com/spreadsheets/d/1gDyi_L4UvIrLTEC6Wri5nbaMmkGmLQBk-Yx3z0XDEtl/edit#gid=0)](https://docs.google.com/spreadsheets/d/1gDyi_L4UvIrLTEC6Wri5nbaMmkGmLQBk-Yx3z0XDEtl/edit#gid=0)

In [1]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
```

In [2]:

```
df=pd.read_csv("prosperLoanData.csv")
```

In [3]:

```
df.head(5)
```

Out[3]:

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

5 rows × 81 columns

In [4]:

```
df.info()
```

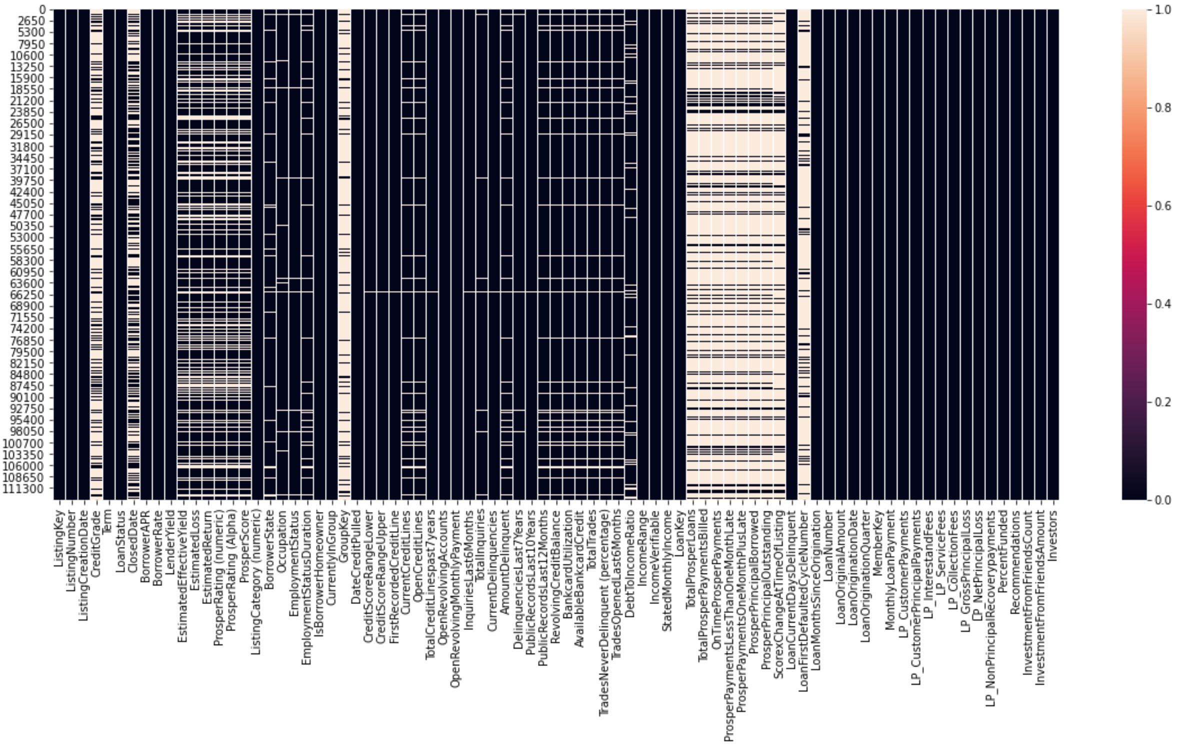
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 113937 entries, 0 to 113936
Data columns (total 81 columns):
 #   Column                               Non-Null Count   Dtype  
---  ------                               --------------   -----  
 0   ListingKey                           113937 non-null  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: 60.7+ MB
```

Checking for Null Values

In [5]:

```
fig, ax = plt.subplots(figsize = (20,8))
ax = sns.heatmap(df.isnull(), vmin=0, vmax = 1)
```



Checking for Duplicate Values

In [6]:

```
df[df.duplicated()]
```

Out[6]:

ListingKey	ListingNumber	ListingCreationDate	CreditGrade	Term	LoanStatus	ClosedDate

0 rows × 81 columns

The above result shows no duplicate value is present

Renaming columns

In [7]:

```
df.rename(columns={'ListingCategory (numeric)' : 'ListingCategory_Numeric','ProsperRating (
```

In [8]:

```
# Selecting useful columns for my analysis
column = ['ListingNumber' ,'LoanStatus','EstimatedEffectiveYield' ,  'BorrowerAPR' , 'Borro
         'ProsperRating_Alpha','ProsperScore', 'EmploymentStatus','Occupation','Employment
         'IncomeVerifiable', 'StatedMonthlyIncome', 'MonthlyLoanPayment','Recommendations'
         'LoanOriginalAmount' ,'PercentFunded','IncomeRange', 'Investors','BorrowerState']
```

In [9]:

```
df_raw=df[column]
df_raw.head(3)
```

Out[9]:

	ListingNumber	LoanStatus	EstimatedEffectiveYield	BorrowerAPR	BorrowerRate	ProsperRati
0	193129	Completed	NaN	0.16516	0.158	
1	1209647	Current	0.0796	0.12016	0.092	
2	81716	Completed	NaN	0.28269	0.275	

3 rows × 22 columns

Removing data having null Values

In [10]:

```
loan=df_raw.dropna()
```

Testing:

In [11]:

```
loan.head()
```

Out[11]:

	ListingNumber	LoanStatus	EstimatedEffectiveYield	BorrowerAPR	BorrowerRate	ProsperRati
1	1209647	Current	0.07960	0.12016	0.0920	
3	658116	Current	0.08490	0.12528	0.0974	
4	909464	Current	0.18316	0.24614	0.2085	
5	1074836	Current	0.11567	0.15425	0.1314	
6	750899	Current	0.23820	0.31032	0.2712	

5 rows × 22 columns

In [12]:

```
loan.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 76216 entries, 1 to 113936
Data columns (total 22 columns):
 #   Column                     Non-Null Count  Dtype  
---  ------                     --------------  -----  
 0   ListingNumber              76216 non-null  int64  
 1   LoanStatus                 76216 non-null  object 
 2   EstimatedEffectiveYield    76216 non-null  float64
 3   BorrowerAPR                76216 non-null  float64
 4   BorrowerRate               76216 non-null  float64
 5   ProsperRating_Numeric      76216 non-null  float64
 6   ProsperRating_Alpha        76216 non-null  object 
 7   ProsperScore               76216 non-null  float64
 8   EmploymentStatus           76216 non-null  object 
 9   Occupation                 76216 non-null  object 
 10  EmploymentStatusDuration   76216 non-null  float64
 11  IsBorrowerHomeowner        76216 non-null  bool   
 12  IncomeVerifiable           76216 non-null  bool   
 13  StatedMonthlyIncome        76216 non-null  float64
 14  MonthlyLoanPayment         76216 non-null  float64
 15  Recommendations            76216 non-null  int64  
 16  DebtToIncomeRatio          76216 non-null  float64
 17  LoanOriginalAmount         76216 non-null  int64  
 18  PercentFunded              76216 non-null  float64
 19  IncomeRange                76216 non-null  object 
 20  Investors                  76216 non-null  int64  
 21  BorrowerState              76216 non-null  object 
dtypes: bool(2), float64(10), int64(4), object(6)
memory usage: 10.6+ MB
```

In [13]:

```
loan.describe()
```

Out[13]:

	ListingNumber	EstimatedEffectiveYield	BorrowerAPR	BorrowerRate	ProsperRating_Num
count	7.621600e+04	76216.000000	76216.000000	76216.000000	76216.000
mean	7.737463e+05	0.166738	0.223901	0.193621	4.132
std	2.344166e+05	0.067595	0.079372	0.074088	1.661
min	4.162750e+05	-0.181600	0.045830	0.040000	1.000
25%	5.603650e+05	0.114800	0.161570	0.134900	3.000
50%	7.425500e+05	0.157670	0.215660	0.184500	4.000
75%	9.747142e+05	0.219000	0.287800	0.254900	5.000
max	1.255149e+06	0.319900	0.423950	0.360000	7.000

Univariate Exploration

Loan Status

In [14]:

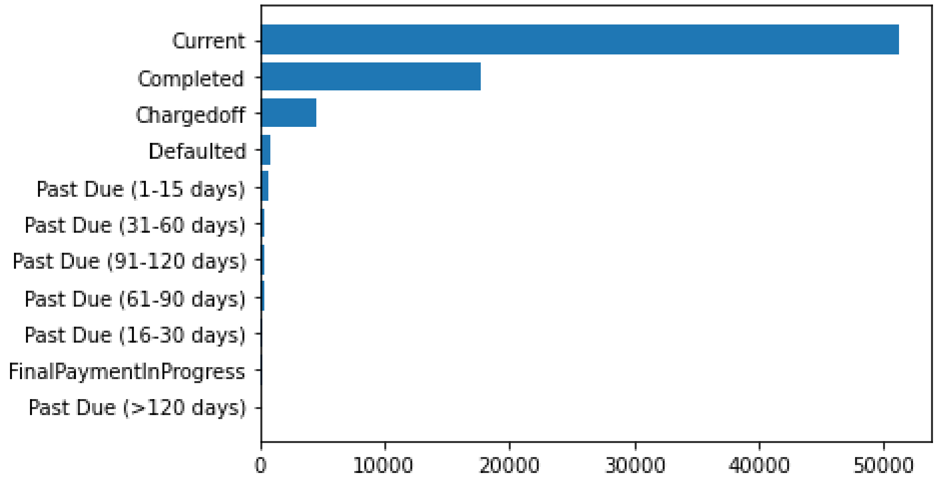
```
loan.LoanStatus.value_counts()
```

Out[14]:

```
Current                   51170
Completed                 17687
Chargedoff                 4444
Defaulted                   885
Past Due (1-15 days)        714
Past Due (31-60 days)       322
Past Due (91-120 days)      277
Past Due (61-90 days)       275
Past Due (16-30 days)       241
FinalPaymentInProgress      187
Past Due (>120 days)         14
Name: LoanStatus, dtype: int64
```

In [15]:

```
counts = loan["LoanStatus"].value_counts().sort_values()
plt.barh(counts.index, counts.values);
```

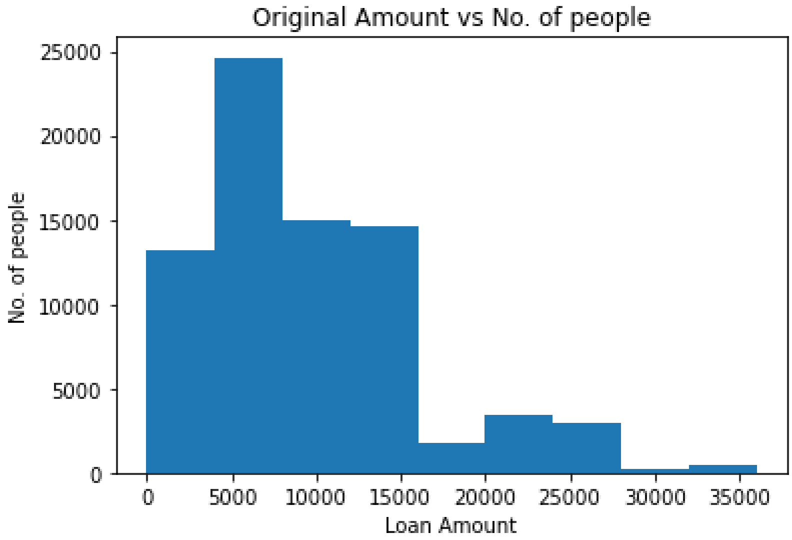


The above graph shows loan status of maximum people is "current".

Loan Amount

In [16]:

```
plt.hist(loan.LoanOriginalAmount,bins=np.arange(0,40000,4000))
plt.title("Original Amount vs No. of people")
plt.ylabel("No. of people")
plt.xlabel("Loan Amount");
```

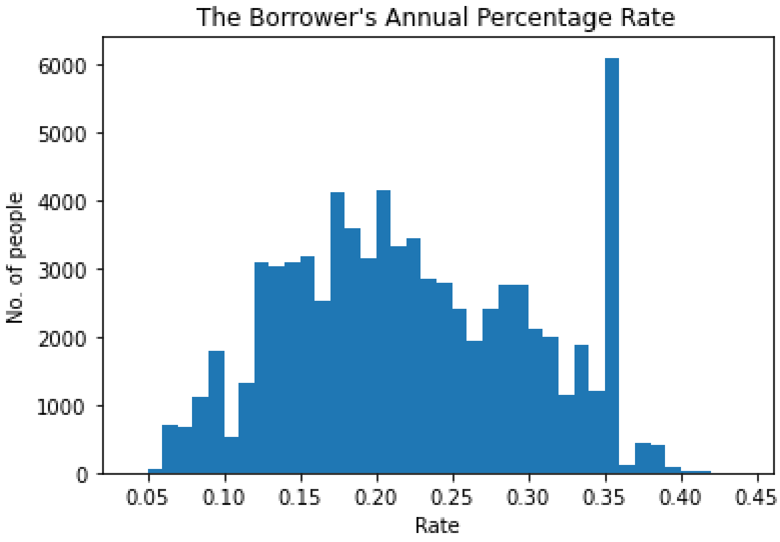


The above graph shows Loan amount is usually between 0-15000. Maximum no. of people have loan amount in the range (approx) 4000-7500.

The Borrower's Annual Percentage Rate

In [17]:

```
plt.hist(loan.BorrowerAPR,bins=np.arange(0.04,0.45,0.01))
plt.title("The Borrower's Annual Percentage Rate");
plt.ylabel("No. of people")
plt.xlabel("Rate");
```

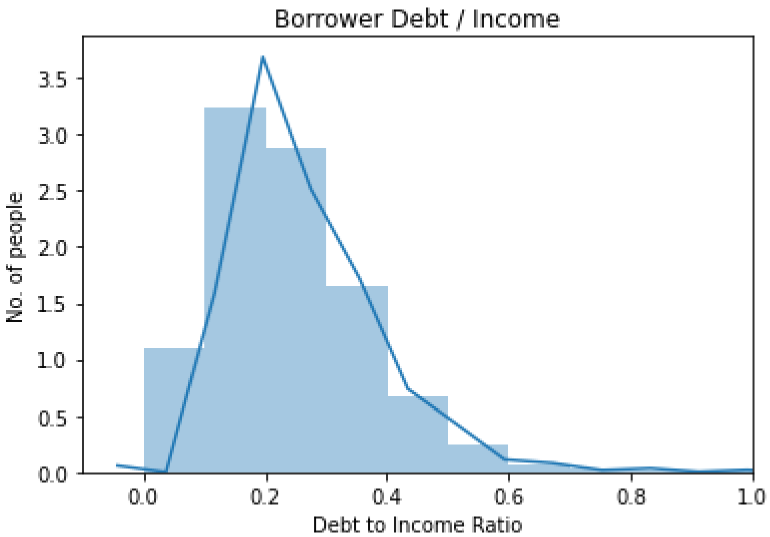


The borrower percentage rate varies most commonly between 0.12 -036. The most common rate being 0.35-0.36.

Borrower Debt / Income

In [18]:

```
base_color = sns.color_palette()[1]
sns.distplot(loan.DebtToIncomeRatio, bins = 100)
plt.xlim(-0.1, 1)
plt.xlabel('Debt to Income Ratio')
plt.ylabel('No. of people')
plt.title('Borrower Debt / Income');
```

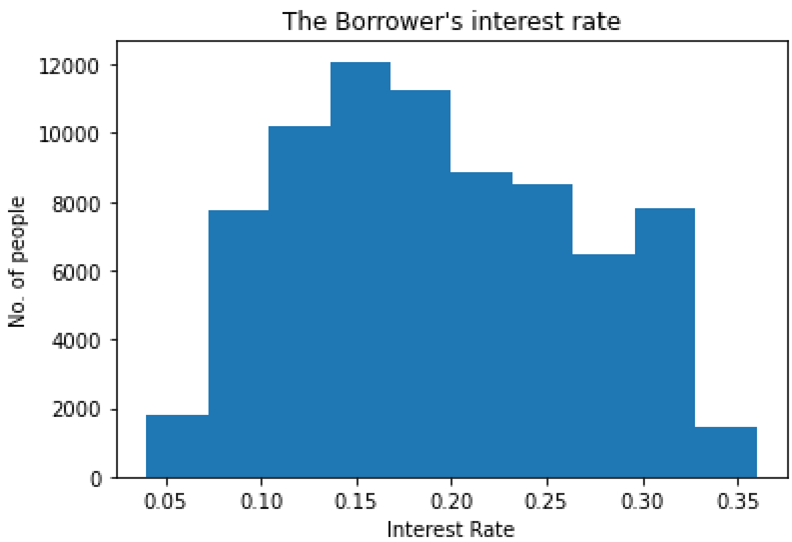


Frequent value Borrower Debt to Income Ratio lies in 0.1-0.3

The Borrower's interest rate

In [19]:

```
plt.hist(data = loan, x = 'BorrowerRate')
plt.xlabel('Interest Rate')
plt.ylabel('No. of people')
plt.title("The Borrower's interest rate");
```



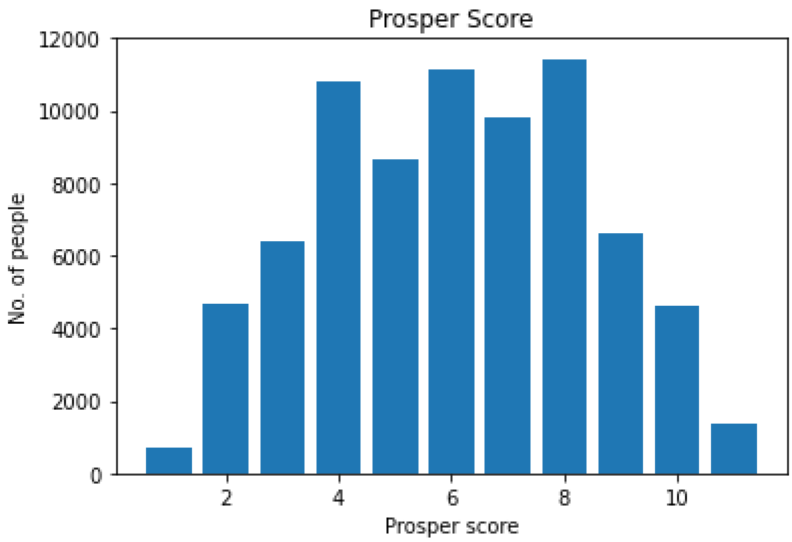
The borrowers interest rate varies mostly between 0.7-0.32

Prosper Score

The score ranges from 1-10, with 10 being the best, or lowest risk score.

In [20]:

```
ax = plt.subplots()
counts = loan["ProsperScore"].value_counts().sort_values()
plt.bar(counts.index, counts.values)
plt.xlabel('Prosper score')
plt.ylabel('No. of people')
plt.title('Prosper Score');
```



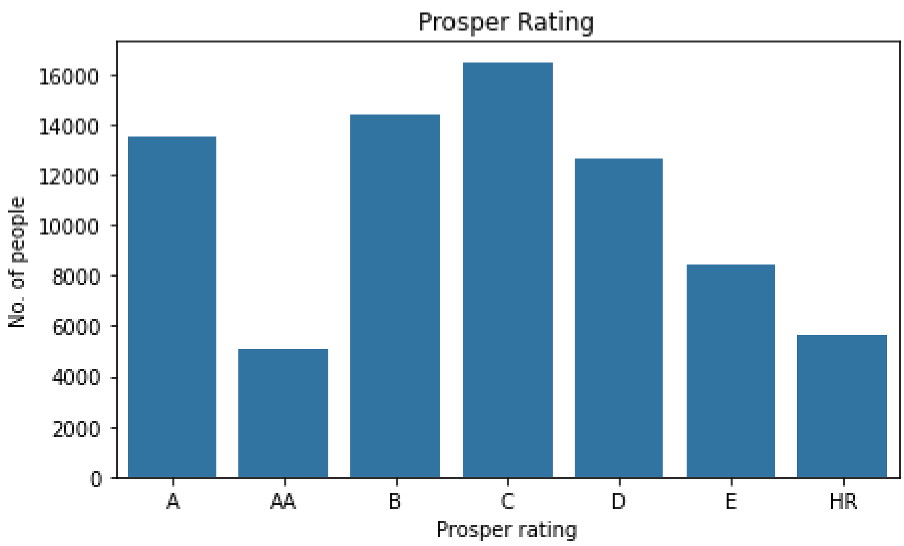
The graph shows the borrowers are almost equally distributed, having both high as well as low risk borrowers.

Prosper Rating Alpha

(0 - N/A, 1 - HR, 2 - E, 3 - D, 4 - C, 5 - B, 6 - A, 7 - AA.)

In [21]:

```
base_color = sns.color_palette()[0]
plt.figure(figsize=(7, 4))
sns.countplot(data=loan,x="ProsperRating_Alpha",order=["A","AA","B","C","D","E","HR"],color
plt.xlabel('Prosper rating')
plt.ylabel('No. of people')
plt.title('Prosper Rating');
```



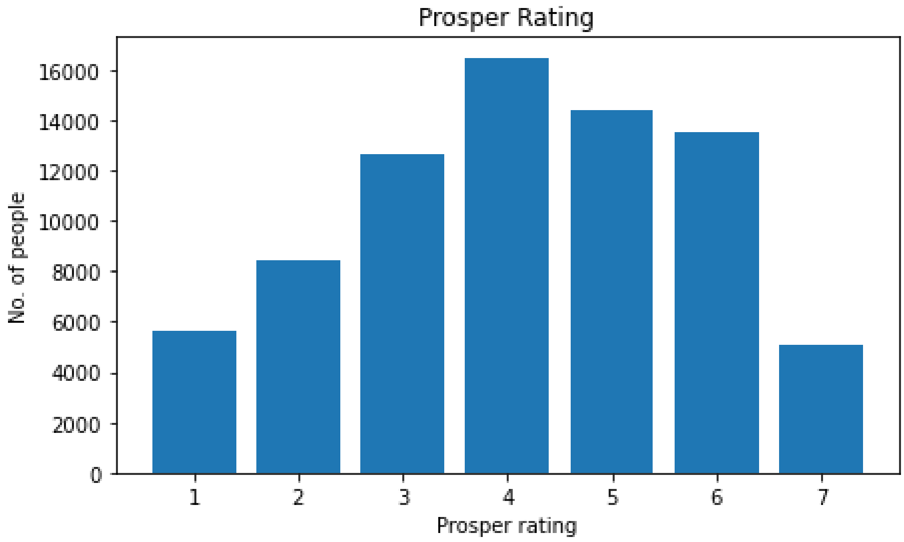
The common prosper ratings are C,B and A respectively which is quite good. But HR also has reasonable number which cannot be ignored

Prosper Rating (Numeric)

(0 - N/A, 1 - HR, 2 - E, 3 - D, 4 - C, 5 - B, 6 - A, 7 - AA.)

In [22]:

```
plt.figure(figsize=(7, 4))
counts = loan["ProsperRating_Numeric"].value_counts().sort_values()
plt.bar(counts.index, counts.values)
plt.xlabel('Prosper rating')
plt.ylabel('No. of people')
plt.title('Prosper Rating');
```



The most common prosper rating is 4. But even borrowers with rating 1 are present.

Employment Status Of Borrower

In [23]:

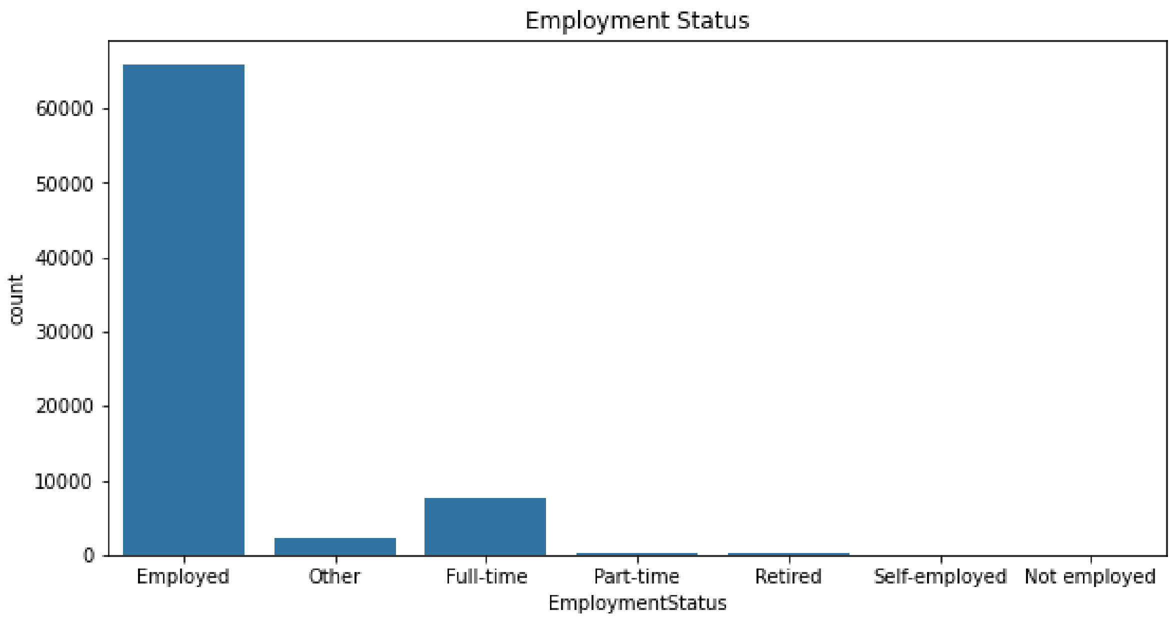
```
loan.EmploymentStatus.value_counts()
```

Out[23]:

```
Employed         65883
Full-time         7577
Other             2194
Retired            320
Part-time          199
Self-employed       42
Not employed         1
Name: EmploymentStatus, dtype: int64
```

In [24]:

```
base_color = sns.color_palette()[0]
bars= ['Employed', 'Other', 'Full-time', 'Part-time', 'Retired',
       'Self-employed', 'Not employed']
x1, x2 = plt.subplots(figsize=(10,5))
sns.countplot(data = loan, x = "EmploymentStatus",order = bars,color=base_color)
x2.set_title("Employment Status");
```

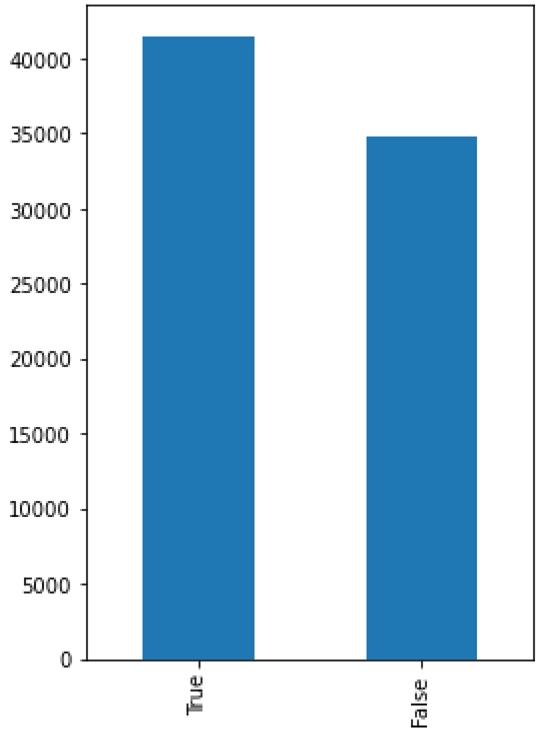


Most of the people who took loans are employed.

Homeowner?

In [25]:

```
loan['IsBorrowerHomeowner'].value_counts().plot(kind='bar', figsize=[4,6],);
```



More people are houseowners.

Income of borrower

In [26]:

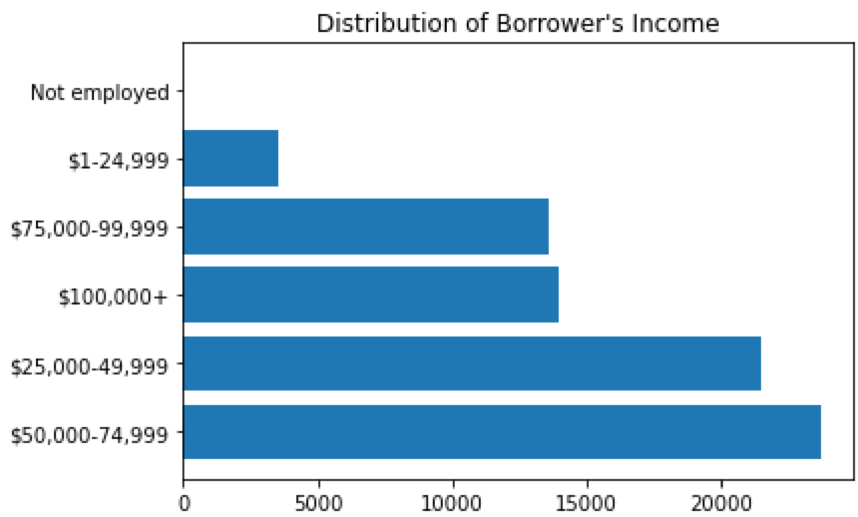
```
loan.IncomeRange.value_counts()
```

Out[26]:

```
$50,000-74,999    23692
$25,000-49,999    21421
$100,000+         13977
$75,000-99,999    13547
$1-24,999          3578
Not employed          1
Name: IncomeRange, dtype: int64
```

In [27]:

```
counts = loan["IncomeRange"].value_counts()
plt.barh(counts.index, counts.values)
plt.title("Distribution of Borrower's Income");
```

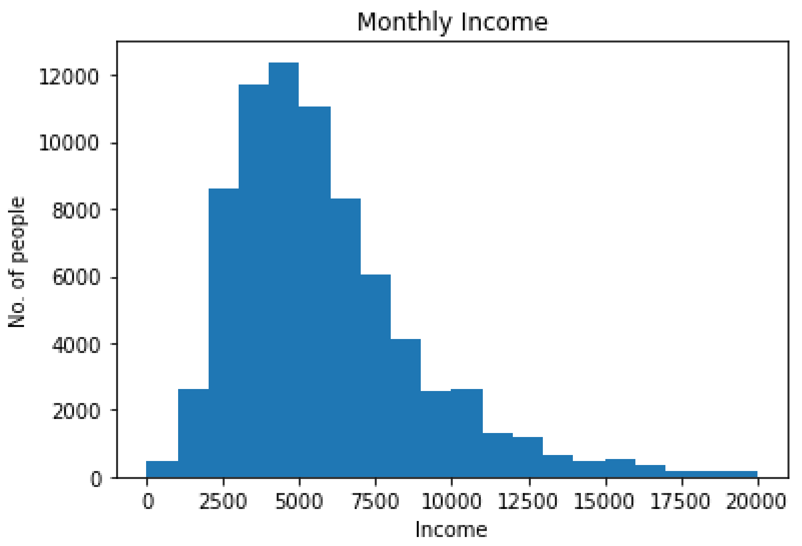


Most of the borrowers have income in the range 50,000-74,999 and 25,000-49,999 respectively

Monthly Income

In [28]:

```
loan_sub = loan[loan['StatedMonthlyIncome'] <= 20000]
bin_edges = np.arange(0, loan_sub['StatedMonthlyIncome'].max()+1000, 1000)
plt.hist(data =loan_sub, x = 'StatedMonthlyIncome', bins = bin_edges)
plt.xlabel('Income')
plt.ylabel('No. of people')
plt.title('Monthly Income');
```

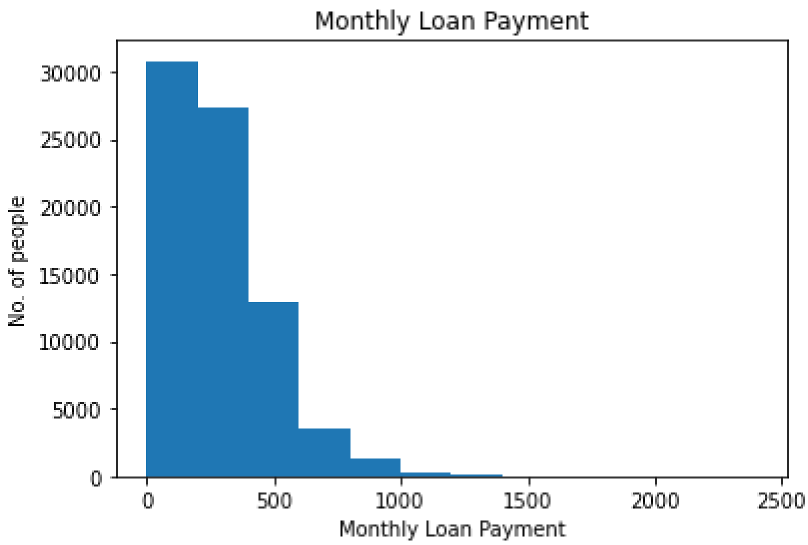


Monthly Income is right skewed. The common range is 1000-7000 approximately.

Monthly Loan Payment

In [29]:

```
bin_edges = np.arange(0, loan['MonthlyLoanPayment'].max()+200, 200)
plt.hist(data =loan,x = 'MonthlyLoanPayment',bins = bin_edges)
plt.xlabel('Monthly Loan Payment')
plt.ylabel('No. of people');
plt.title("Monthly Loan Payment");
```



Monthly loan payment is right skewed,common range lies in 0-400.

Summary:

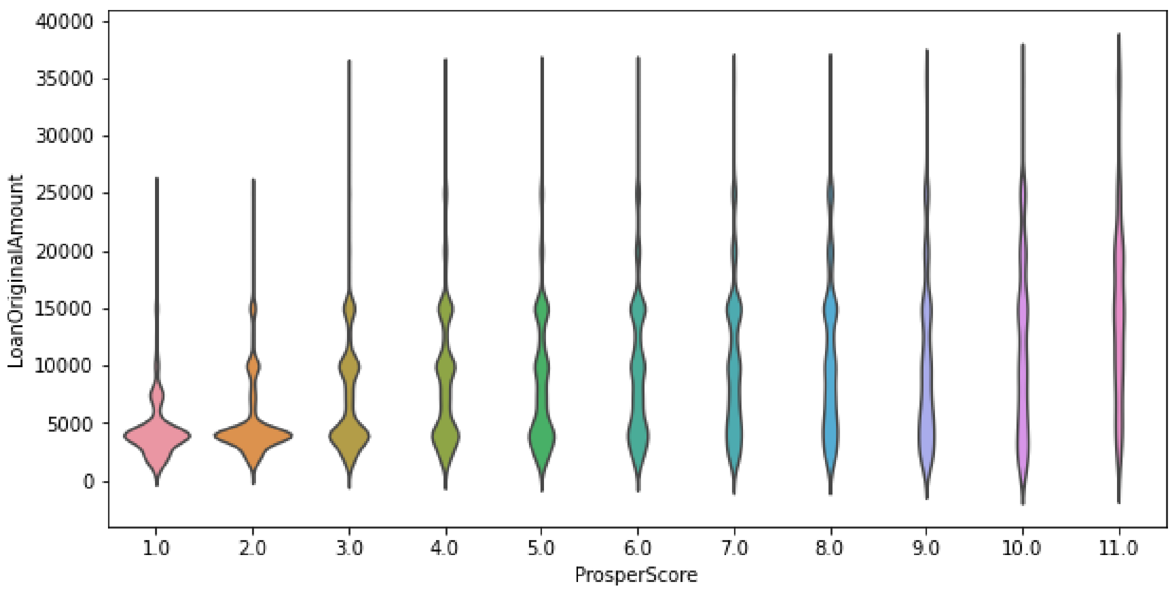
- Loan status of maximum people is "current".
- Loan amount is usually between 0-15000. Maximum no. of people have loan amount in the range (approx) 4000-7500.
- The borrower percentage rate varies most commonly between 0.12 -036. The most common rate being 0.35-0.36.
- Frequent value Borrower Debt to Income Ratio lies in 0.1-0.3.
- The borrowers interest rate varies mostly between 0.7-0.32
- The borrowers are almost equally distributed, having both high as well as low risk borrowers.
- The common prosper ratings are C,B and A respectively which is quite good. But HR also has reasonable number which cannot be ignored
- The most common prosper rating is 4. But even borrowers with rating 1 are present.
- Most of the people who took loans are employed.
- More people are houseowners.
- Most of the borrowers have income in the range 50,000-74,999 and 25,000-49,999 respectively
- Monthly Income is right skewed. The common range is 1000-7000 approximately.
- Monthly loan payment is right skewed,common range lies in 0-400.

Bivariate Exploration

Prosper Score and Loan Amount

In [30]:

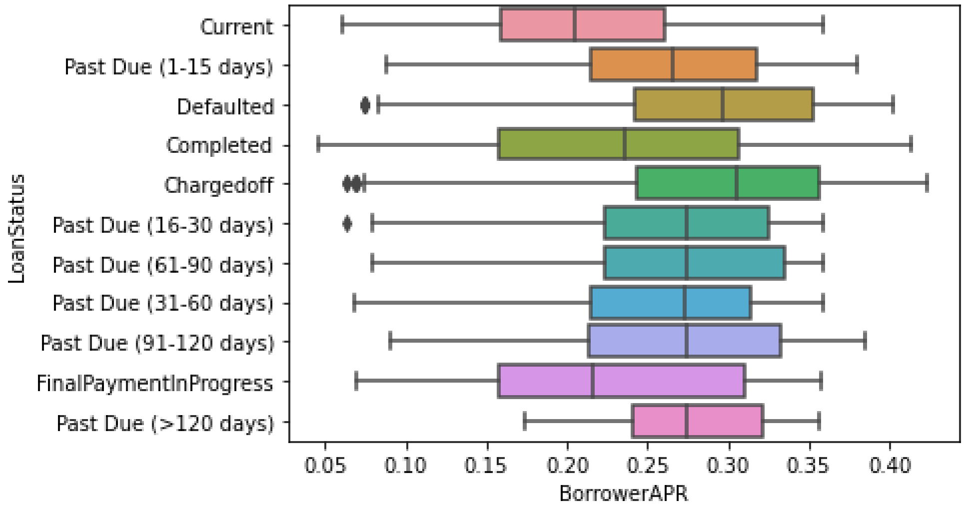
```
plt.figure(figsize=[10,5])
sns.violinplot(data=loan, x='ProsperScore', y='LoanOriginalAmount',inner= None);
```



Loan status and borrower APR

In [31]:

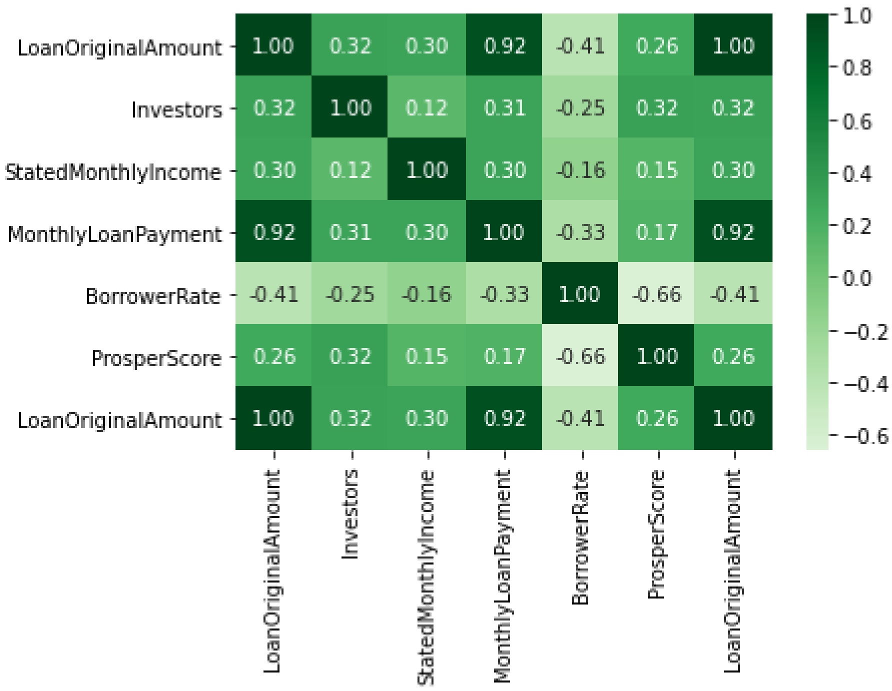
```
sns.boxplot(data = loan, y='LoanStatus',x = 'BorrowerAPR');
```



Correlation between important numeric variables

In [32]:

```
x=['LoanOriginalAmount', 'Investors','StatedMonthlyIncome', 'MonthlyLoanPayment', 'Borrower
sns.heatmap(loan[x].corr(), annot = True, fmt = '.2f',cmap = "Greens", center = 0);
```



	LoanOriginalAmount	Investors	StatedMonthlyIncome	MonthlyLoanPayment	BorrowerRate	ProsperScore	LoanOriginalAmount
LoanOriginalAmount	1.00	0.32	0.30	0.92	-0.41	0.26	1.00
Investors	0.32	1.00	0.12	0.31	-0.25	0.32	0.32
StatedMonthlyIncome	0.30	0.12	1.00	0.30	-0.16	0.15	0.30
MonthlyLoanPayment	0.92	0.31	0.30	1.00	-0.33	0.17	0.92
BorrowerRate	-0.41	-0.25	-0.16	-0.33	1.00	-0.66	-0.41
ProsperScore	0.26	0.32	0.15	0.17	-0.66	1.00	0.26
LoanOriginalAmount	1.00	0.32	0.30	0.92	-0.41	0.26	1.00

The figure shows correlation between different important factors.Postitive correlation is between Loanoriginalamount and monthlyloanpayment.Negative correaltion is between borrowerrate and loanoriginalamount, borrowerrate and prosper score

Borrower Interest Rate vs Prosper score

In [33]:

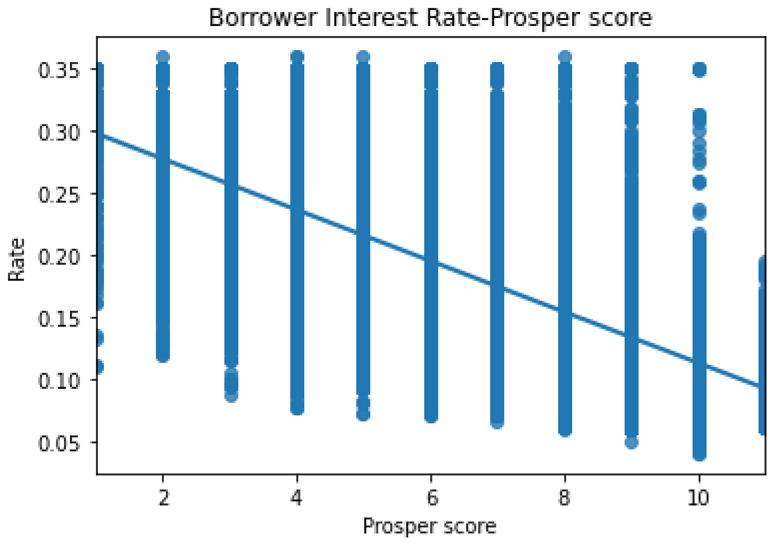
```
loan[["ProsperScore","BorrowerRate"]].corr()
```

Out[33]:

	ProsperScore	BorrowerRate
ProsperScore	1.00000	-0.65832
BorrowerRate	-0.65832	1.00000

In [34]:

```
sns.regplot(data = loan, x = 'ProsperScore', y ='BorrowerRate')
plt.xlabel('Prosper score')
plt.ylabel('Rate')
plt.title('Borrower Interest Rate-Prosper score');
```



The figure clearly shows that Borrower Interest Rate and Prosper score are inversely related to each other

Loan Amount vs Borrower Interest Rate

In [35]:

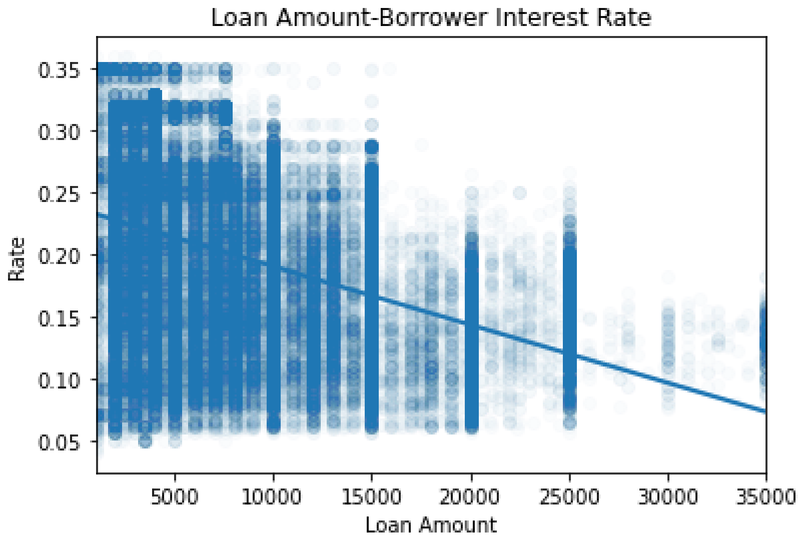
```
loan[["LoanOriginalAmount","BorrowerRate"]].corr()
```

Out[35]:

	LoanOriginalAmount	BorrowerRate
LoanOriginalAmount	1.00000	-0.40686
BorrowerRate	-0.40686	1.00000

In [36]:

```
sns.regplot(data = loan, x = 'LoanOriginalAmount', y ="BorrowerRate",scatter_kws = {'alpha'
plt.xlabel('Loan Amount')
plt.ylabel('Rate')
plt.title('Loan Amount-Borrower Interest Rate');
```



The figure clearly shows Loan Amount and Borrower Interest Rate are negatively correlated.

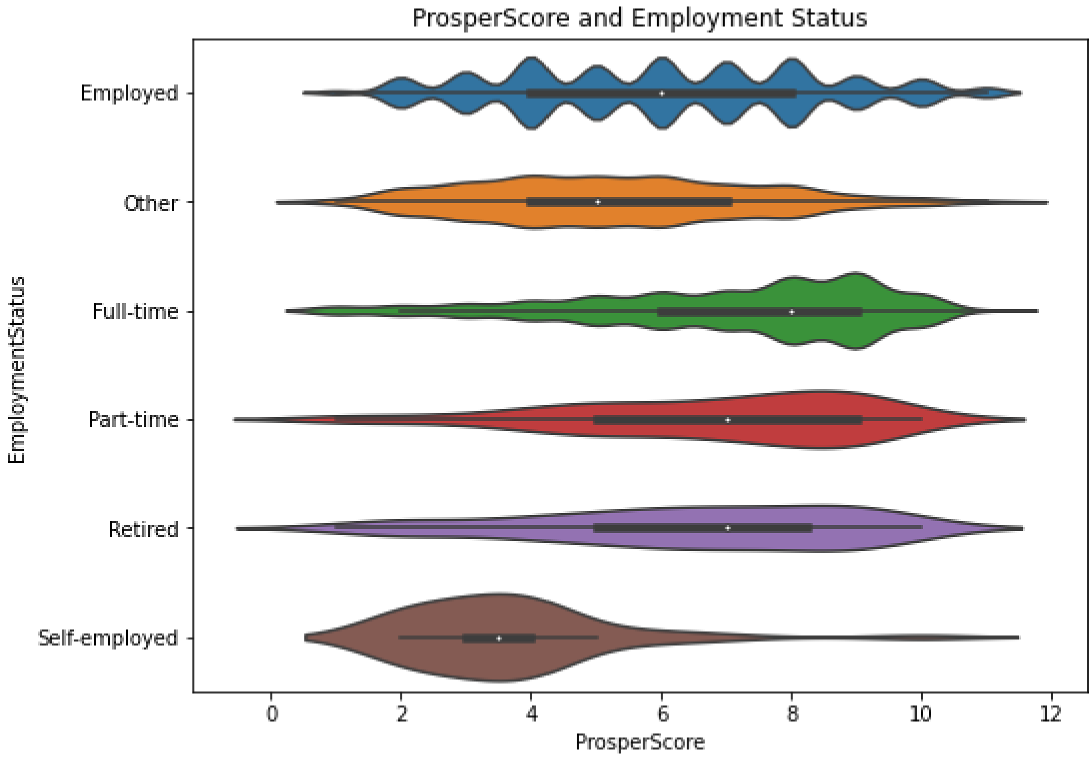
ProsperScore and Employment Status

In [37]:

```
loan_df= loan[loan['IncomeRange'] != 'Not employed']
plt.figure(figsize = [8, 6])
sns.boxplot(data = loan_df, x = 'EmploymentStatus', y = 'ProsperScore');
plt.title('ProsperScore and Employment Status');
```

In [68]:

```
plt.figure(figsize = [8, 6])
sns.violinplot(data = loan_df, y = 'EmploymentStatus', x = 'ProsperScore')
plt.title('ProsperScore and Employment Status');
```

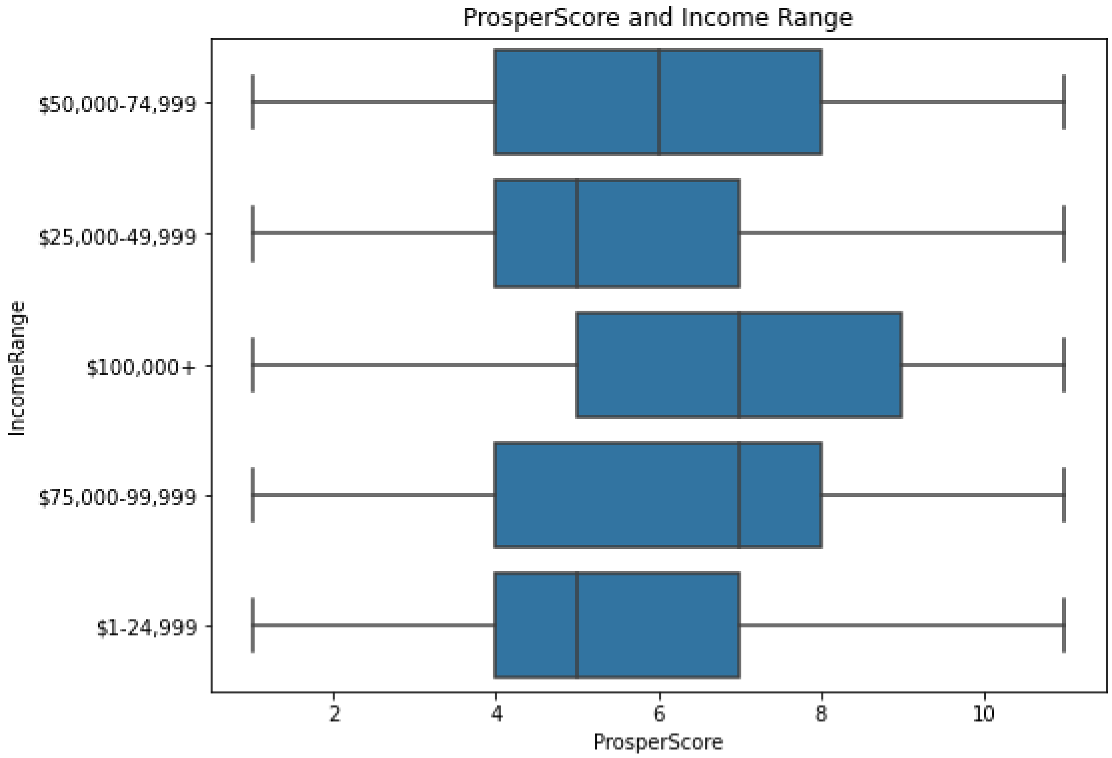


Self employed have least prosper rating with some outliners present. Full time, part time and retired have high prosper rating.

Prosper Score and Income

In [69]:

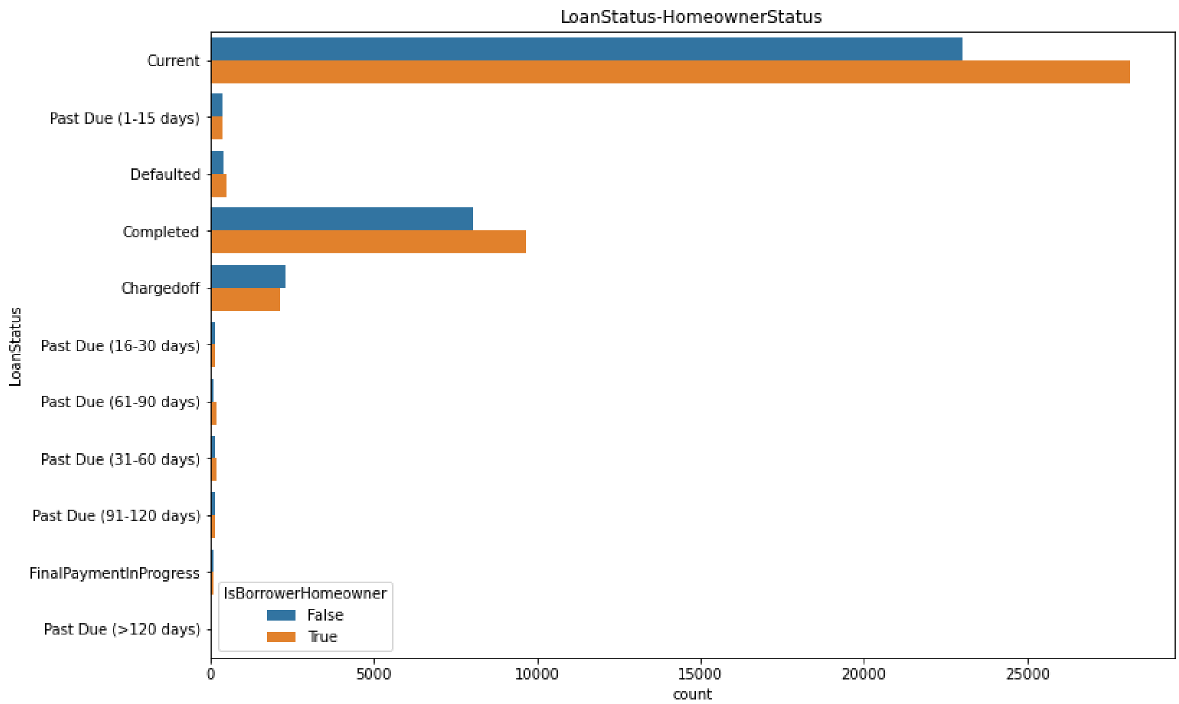
```
plt.figure(figsize = [8, 6])
base_color = sns.color_palette()[0]
sns.boxplot(data = loan_df, x = 'ProsperScore', y = 'IncomeRange', color = base_color);
plt.title('ProsperScore and Income Range');
```



People with income range 75,000-99,999 and 100,000+ have high prosper score. 75,000-99,999 : q2:7 and q3:8 100,000 : q2:7 and q3:9

In [40]:

```
plt.figure(figsize = [12, 8])
sns.countplot(data = loan, y = 'LoanStatus', hue = 'IsBorrowerHomeowner')
plt.title('LoanStatus-HomeownerStatus');
```



Summary:

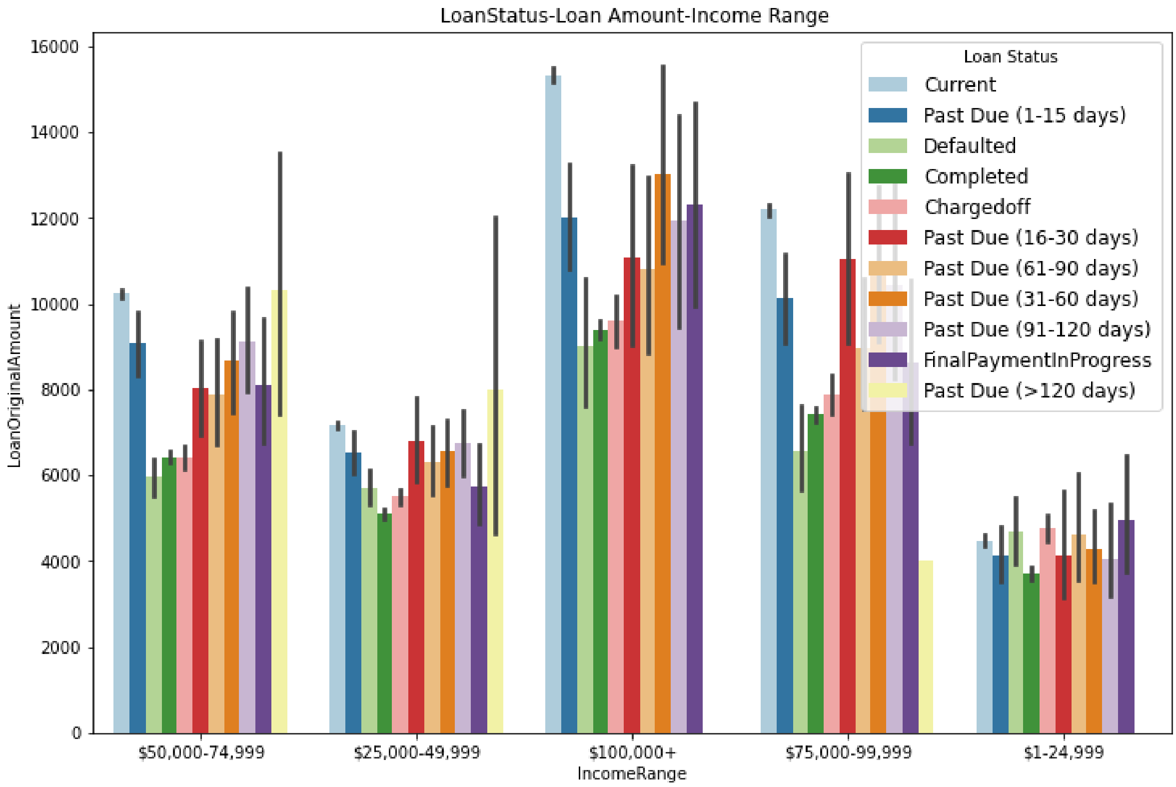
- Postitive correlation is between Loanoriginalamount and monthlyloanpayment.Negative correaltion is between borrowerrate and loanoriginalamount, borrowerrate and prosper score.
- Borrower Interest Rate and Prosper score are inversely related to each other.Borrowers with high prosper score get loan at lower annual percentage rate
- Loan Amount and Borrower Interest Rate are negatively correlated.Also loans of lesser amount is given at low annual percentage rate.
- Self employed have least prosper rating with some outliners present. Full time, part time and retired have high prosper rating. So full time employees get loan at a lesser rate as compared to others.Self-employed have to pay a high annual rate.Also full time employees gets loan easily whereas self-employed do not get loan easily.
- Prosper score affects the loan original amount.People with less prosper score have lesser loan amount than people with higher prosper score. Therefore it's easier to get high amount loan with higher prosper score
- People with income range 75,000-99,999 and 100,000+ have high prosper score. People with income > 75,000 get loan easily.
- Therefore people with higher income have higher prosper score and thereby they get high amount loans at a lower borrowerAPR.

Multivariable Exploration

Relation between LoanStatus-Loan Amount-Income Range

In [60]:

```
plt.figure(figsize = [12, 8])
x = sns.barplot(data = loan_df, x = 'IncomeRange', y = 'LoanOriginalAmount', hue = 'LoanSta
x.legend(loc=0, fontsize = 12, title = 'Loan Status')
plt.title(' LoanStatus-Loan Amount-Income Range');
```

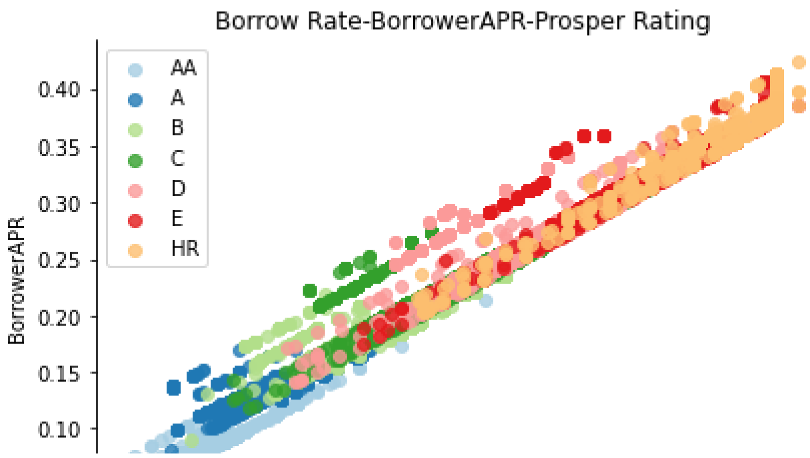


Relation between Borrow Rate,BorrowerAPR and Prosper Rating

In [42]:

```
x = sns.FacetGrid(data = loan, hue = 'ProsperRating_Alpha', hue_order = ['AA','A','B','C','
x.map(sns.regplot,"BorrowerRate","BorrowerAPR", fit_reg = False);
plt.legend(fontsize = 10)
plt.title("Borrow Rate-BorrowerAPR-Prosper Rating");
```

```
c:\users\mridu\appdata\local\programs\python\python38-32\lib\site-package
s\seaborn\axisgrid.py:243: UserWarning: The `size` parameter has been ren
amed to `height`; please update your code.
  warnings.warn(msg, UserWarning)
```



In [43]:

```
loan_df.info()
```

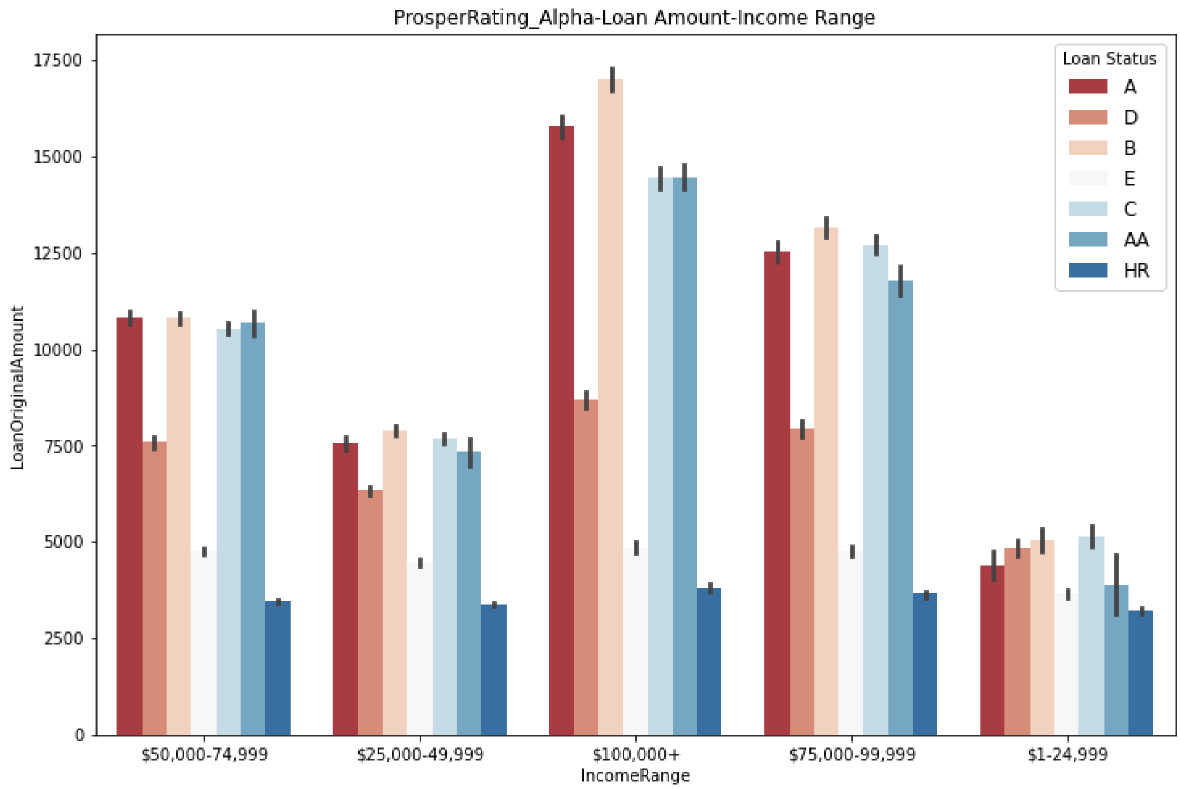
```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 76215 entries, 1 to 113936
Data columns (total 22 columns):
 #   Column                     Non-Null Count  Dtype  
---  ------                     --------------  -----  
 0   ListingNumber              76215 non-null  int64  
 1   LoanStatus                 76215 non-null  object 
 2   EstimatedEffectiveYield    76215 non-null  float64
 3   BorrowerAPR                76215 non-null  float64
 4   BorrowerRate               76215 non-null  float64
 5   ProsperRating_Numeric      76215 non-null  float64
 6   ProsperRating_Alpha        76215 non-null  object 
 7   ProsperScore               76215 non-null  float64
 8   EmploymentStatus           76215 non-null  object 
 9   Occupation                 76215 non-null  object 
 10  EmploymentStatusDuration   76215 non-null  float64
 11  IsBorrowerHomeowner        76215 non-null  bool   
 12  IncomeVerifiable           76215 non-null  bool   
 13  StatedMonthlyIncome        76215 non-null  float64
 14  MonthlyLoanPayment         76215 non-null  float64
 15  Recommendations            76215 non-null  int64  
 16  DebtToIncomeRatio          76215 non-null  float64
 17  LoanOriginalAmount         76215 non-null  int64  
 18  PercentFunded              76215 non-null  float64
 19  IncomeRange                76215 non-null  object 
 20  Investors                  76215 non-null  int64  
 21  BorrowerState              76215 non-null  object 
dtypes: bool(2), float64(10), int64(4), object(6)
memory usage: 12.6+ MB
```

High prosper rating has lesser Borrower rate and lesser borrower APR

Relation between ProsperRating_Alpha,Loan Amount and Income Range

In [59]:

```
plt.figure(figsize = [12, 8])
x = sns.barplot(data = loan_df, x = 'IncomeRange', y = 'LoanOriginalAmount', hue = 'Prosper
x.legend(loc=0, fontsize = 12, title = 'Loan Status')
plt.title('ProsperRating_Alpha-Loan Amount-Income Range');
```

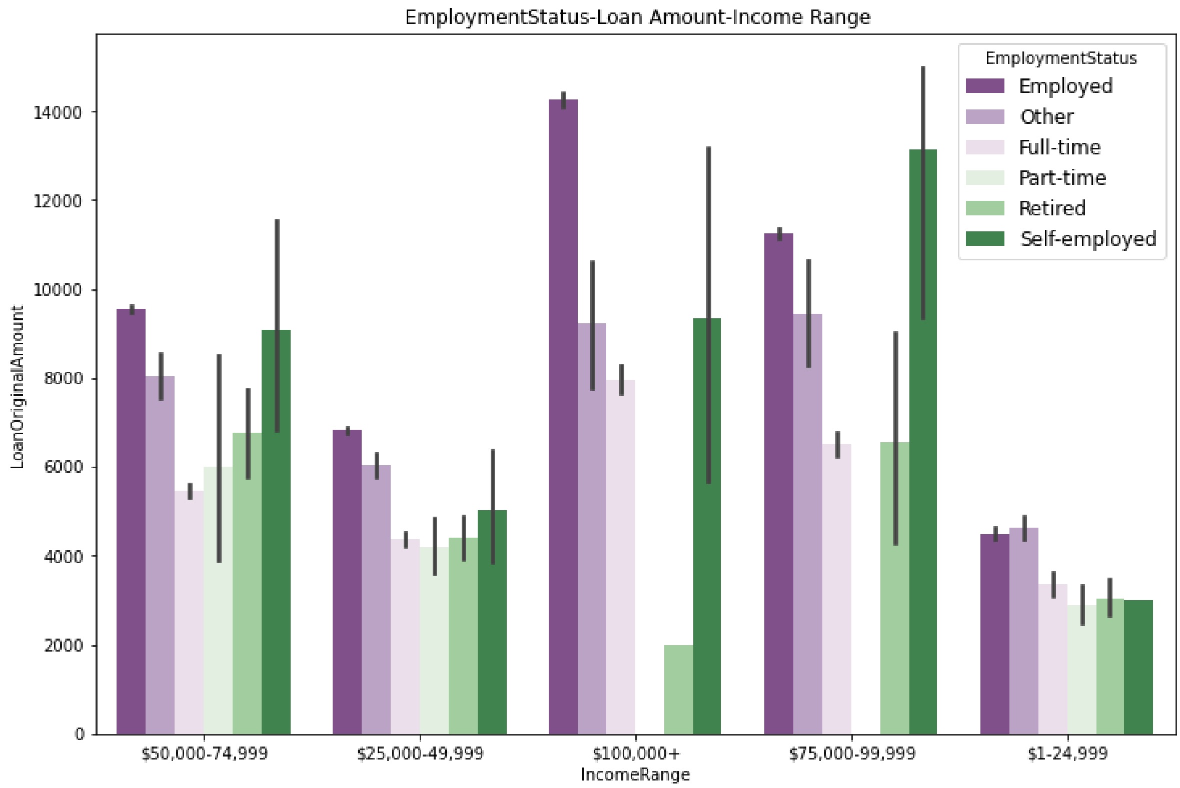


Income range 1-24,999 has large number of prosper rating as HR compared to the total borrowers in that range.

Relation between EmploymentStatus_Alpha,Loan Amount and Income Range

In [64]:

```
plt.figure(figsize = [12 ,8])
x = sns.barplot(data = loan_df, x = 'IncomeRange', y = 'LoanOriginalAmount', hue = 'Employm
x.legend(loc=0, fontsize = 12, title = 'EmploymentStatus')
plt.title(' EmploymentStatus-Loan Amount-Income Range');
```



Employees with status 'Employed' and 'self-employed' take loans of larger amount. Employess with less income take loans of lesser total amount(Around 3000-5000)

Summary:

- High prosper rating has lesser Borrower rate and lesser borrower APR.So borrowers with high prosper rating get loans at a lesser rate and borrowerAPR
- Income range 100,000 + take loans with high original amount and have most common loan status as current.
- Income range 1-24,9999 takes low amount loans.Income Range 50,000-74,999 have most number of past due(>120 days) as status.Income range 1-24,999 has large number of prosper rating as HR compared to the total borrowers in that range.So employees having income in this range have lesser chance of getting loans of high amount.
- Employees with status 'Employed' and 'self-employed' take loans of larger amount. Employess with less income take loans of lesser total amount(Around 3000-5000)