Part_I_exploration

June 29, 2022

1 Part I - Communicate data findings from loan data at Prosper

1.1 by Gabriel Ntwari

1.2 Introduction

The project will explore the features that are considered while giving loans at Prosper Marketplace Inc. a company that provides loans to borrowers.The dataset used 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.Based on the mentioned variables a loan can be granted or not.

1.3 Preliminary Wrangling

[1]:
```
# import all packages and modules
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings("ignore")
%matplotlib inline
```

[2]:
```
# loading the dataset
loan_data = pd.read_csv('prosperLoanData.csv')
```

[3]:
```
# printing data shape and othe information
print(loan_data.shape)
print("--------------------------------------------------------------------------------")
print(loan_data.info())
```

```
(113937, 81)
--------------------------------------------------------------------------------
<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
None
```

[4]:
```
#data description
loan_data.head(3)
```

[4]:

	ListingKey	ListingNumber	ListingCreationDate	CreditGrade	Term	LoanStatus	ClosedDate	BorrowerAPR
0	1021339766868145413AB3B	193129	2007-08-26 19:09:29.263000000	C	36	Completed	2009-08-14 00:00:00	0.16516
1	1027360249950330B223C1	1209647	2014-02-27 08:28:07.900000000	NaN	36	Current	NaN	0.12016
2	0EE9337825851032864889A	81716	2007-01-05 15:00:47.090000000	HR	36	Completed	2009-12-17 00:00:00	0.28269

```
   BorrowerRate  LenderYield  …  LP_ServiceFees  LP_CollectionFees  \
0         0.158        0.138  …         -133.18                0.0
1         0.092        0.082  …            0.00                0.0
2         0.275        0.240  …          -24.20                0.0

   LP_GrossPrincipalLoss  LP_NetPrincipalLoss LP_NonPrincipalRecoverypayments  \
0                    0.0                  0.0                             0.0
1                    0.0                  0.0                             0.0
2                    0.0                  0.0                             0.0

   PercentFunded  Recommendations InvestmentFromFriendsCount  \
0            1.0                0                          0
1            1.0                0                          0
2            1.0                0                          0

  InvestmentFromFriendsAmount Investors
0                         0.0       258
1                         0.0         1
2                         0.0        41

[3 rows x 81 columns]
```

[5]:
```
loan_data.describe()
```

[5]:
```
       ListingNumber           Term    BorrowerAPR   BorrowerRate  \
count   1.139370e+05  113937.000000  113912.000000  113937.000000
mean    6.278857e+05      40.830248       0.218828       0.192764
std     3.280762e+05      10.436212       0.080364       0.074818
min     4.000000e+00      12.000000       0.006530       0.000000
25%     4.009190e+05      36.000000       0.156290       0.134000
50%     6.005540e+05      36.000000       0.209760       0.184000
75%     8.926340e+05      36.000000       0.283810       0.250000
max     1.255725e+06      60.000000       0.512290       0.497500

         LenderYield  EstimatedEffectiveYield  EstimatedLoss  EstimatedReturn  \
count  113937.000000             84853.000000   84853.000000     84853.000000
mean        0.182701                 0.168661       0.080306         0.096068
std         0.074516                 0.068467       0.046764         0.030403
min        -0.010000                -0.182700       0.004900        -0.182700
25%         0.124200                 0.115670       0.042400         0.074080
50%         0.173000                 0.161500       0.072400         0.091700
75%         0.240000                 0.224300       0.112000         0.116600
max         0.492500                 0.319900       0.366000         0.283700

       ProsperRating (numeric)  ProsperScore  …  LP_ServiceFees  \
count             84853.000000  84853.000000  …   113937.000000
```

```
mean                   4.072243      5.950067  …      -54.725641
std                    1.673227      2.376501  …       60.675425
min                    1.000000      1.000000  …     -664.870000
25%                    3.000000      4.000000  …      -73.180000
50%                    4.000000      6.000000  …      -34.440000
75%                    5.000000      8.000000  …      -13.920000
max                    7.000000     11.000000  …       32.060000

       LP_CollectionFees  LP_GrossPrincipalLoss  LP_NetPrincipalLoss  \
count      113937.000000          113937.000000        113937.000000
mean          -14.242698             700.446342           681.420499
std           109.232758            2388.513831          2357.167068
min         -9274.750000             -94.200000          -954.550000
25%             0.000000               0.000000             0.000000
50%             0.000000               0.000000             0.000000
75%             0.000000               0.000000             0.000000
max             0.000000           25000.000000         25000.000000

       LP_NonPrincipalRecoverypayments  PercentFunded  Recommendations  \
count                     113937.000000  113937.000000    113937.000000
mean                         25.142686       0.998584         0.048027
std                         275.657937       0.017919         0.332353
min                           0.000000       0.700000         0.000000
25%                           0.000000       1.000000         0.000000
50%                           0.000000       1.000000         0.000000
75%                           0.000000       1.000000         0.000000
max                       21117.900000       1.012500        39.000000

       InvestmentFromFriendsCount  InvestmentFromFriendsAmount      Investors
count                113937.000000                113937.000000  113937.000000
mean                      0.023460                    16.550751      80.475228
std                       0.232412                   294.545422     103.239020
min                       0.000000                     0.000000       1.000000
25%                       0.000000                     0.000000       2.000000
50%                       0.000000                     0.000000      44.000000
75%                       0.000000                     0.000000     115.000000
max                      33.000000                 25000.000000    1189.000000

[8 rows x 61 columns]
```

[6]:
```
# checking duplicated data entries
sum(loan_data.duplicated())
```

[6]: 0

[7]:
```
# checking  null values on each columns
loan_data.isnull().sum()
```

[7]:
```
ListingKey                          0
ListingNumber                       0
ListingCreationDate                 0
CreditGrade                     84984
Term                                0
                                  ...
PercentFunded                       0
Recommendations                     0
InvestmentFromFriendsCount          0
InvestmentFromFriendsAmount         0
Investors                           0
Length: 81, dtype: int64
```

1.3.1 Cleanning the dataset

[8]:
```
#Dropping columns with 75 % or more of Missing Values in their content
perctange =75
min_count =  int(((100-perctange)/100)*loan_data.shape[0] + 1)
loan_data = loan_data.dropna( axis=1, thresh=min_count)
loan_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 113937 entries, 0 to 113936
Data columns (total 71 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  DateCreditPulled                    113937 non-null  object
24  CreditScoreRangeLower               113346 non-null  float64
25  CreditScoreRangeUpper               113346 non-null  float64
26  FirstRecordedCreditLine             113240 non-null  object
27  CurrentCreditLines                  106333 non-null  float64
28  OpenCreditLines                     106333 non-null  float64
29  TotalCreditLinespast7years          113240 non-null  float64
30  OpenRevolvingAccounts               113937 non-null  int64
31  OpenRevolvingMonthlyPayment         113937 non-null  float64
32  InquiriesLast6Months                113240 non-null  float64
33  TotalInquiries                      112778 non-null  float64
34  CurrentDelinquencies                113240 non-null  float64
35  AmountDelinquent                    106315 non-null  float64
36  DelinquenciesLast7Years             112947 non-null  float64
37  PublicRecordsLast10Years            113240 non-null  float64
38  PublicRecordsLast12Months           106333 non-null  float64
39  RevolvingCreditBalance              106333 non-null  float64
40  BankcardUtilization                 106333 non-null  float64
41  AvailableBankcardCredit             106393 non-null  float64
42  TotalTrades                         106393 non-null  float64
43  TradesNeverDelinquent (percentage)  106393 non-null  float64
44  TradesOpenedLast6Months             106393 non-null  float64
45  DebtToIncomeRatio                   105383 non-null  float64
46  IncomeRange                         113937 non-null  object
47  IncomeVerifiable                    113937 non-null  bool
48  StatedMonthlyIncome                 113937 non-null  float64
49  LoanKey                             113937 non-null  object
50  LoanCurrentDaysDelinquent           113937 non-null  int64
51  LoanMonthsSinceOrigination          113937 non-null  int64
52  LoanNumber                          113937 non-null  int64
53  LoanOriginalAmount                  113937 non-null  int64
54  LoanOriginationDate                 113937 non-null  object
55  LoanOriginationQuarter              113937 non-null  object
56  MemberKey                           113937 non-null  object
57  MonthlyLoanPayment                  113937 non-null  float64
58  LP_CustomerPayments                 113937 non-null  float64
59  LP_CustomerPrincipalPayments        113937 non-null  float64
60  LP_InterestandFees                  113937 non-null  float64
61  LP_ServiceFees                      113937 non-null  float64
62  LP_CollectionFees                   113937 non-null  float64
63  LP_GrossPrincipalLoss               113937 non-null  float64
64  LP_NetPrincipalLoss                 113937 non-null  float64
65  LP_NonPrincipalRecoverypayments     113937 non-null  float64
66  PercentFunded                       113937 non-null  float64
67  Recommendations                     113937 non-null  int64
68  InvestmentFromFriendsCount          113937 non-null  int64
69  InvestmentFromFriendsAmount         113937 non-null  float64
```

```
 70  Investors                            113937 non-null  int64
dtypes: bool(3), float64(41), int64(11), object(16)
memory usage: 59.4+ MB
```

[9]:
```
# remove columns and columns withat are not useful in the Dateset
loan_data.drop(['ListingKey', 'ListingNumber', 'CreditGrade',
                'ClosedDate', 'CurrentlyInGroup', 'DateCreditPulled',
                'FirstRecordedCreditLine', 'EmploymentStatusDuration',
                'DebtToIncomeRatio','LoanKey'], axis=1, inplace = True)
loan_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 113937 entries, 0 to 113936
Data columns (total 61 columns):
 #   Column                               Non-Null Count   Dtype
---  ------                               --------------   -----
 0   ListingCreationDate                  113937 non-null  object
 1   Term                                 113937 non-null  int64
 2   LoanStatus                           113937 non-null  object
 3   BorrowerAPR                          113912 non-null  float64
 4   BorrowerRate                         113937 non-null  float64
 5   LenderYield                          113937 non-null  float64
 6   EstimatedEffectiveYield              84853 non-null   float64
 7   EstimatedLoss                        84853 non-null   float64
 8   EstimatedReturn                      84853 non-null   float64
 9   ProsperRating (numeric)              84853 non-null   float64
 10  ProsperRating (Alpha)                84853 non-null   object
 11  ProsperScore                         84853 non-null   float64
 12  ListingCategory (numeric)            113937 non-null  int64
 13  BorrowerState                        108422 non-null  object
 14  Occupation                           110349 non-null  object
 15  EmploymentStatus                     111682 non-null  object
 16  IsBorrowerHomeowner                  113937 non-null  bool
 17  CreditScoreRangeLower                113346 non-null  float64
 18  CreditScoreRangeUpper                113346 non-null  float64
 19  CurrentCreditLines                   106333 non-null  float64
 20  OpenCreditLines                      106333 non-null  float64
 21  TotalCreditLinespast7years           113240 non-null  float64
 22  OpenRevolvingAccounts                113937 non-null  int64
 23  OpenRevolvingMonthlyPayment          113937 non-null  float64
 24  InquiriesLast6Months                 113240 non-null  float64
 25  TotalInquiries                       112778 non-null  float64
 26  CurrentDelinquencies                 113240 non-null  float64
 27  AmountDelinquent                     106315 non-null  float64
 28  DelinquenciesLast7Years              112947 non-null  float64
 29  PublicRecordsLast10Years             113240 non-null  float64
 30  PublicRecordsLast12Months            106333 non-null  float64
 31  RevolvingCreditBalance               106333 non-null  float64
```

```
 32  BankcardUtilization                  106333 non-null  float64
 33  AvailableBankcardCredit              106393 non-null  float64
 34  TotalTrades                          106393 non-null  float64
 35  TradesNeverDelinquent (percentage)   106393 non-null  float64
 36  TradesOpenedLast6Months              106393 non-null  float64
 37  IncomeRange                          113937 non-null  object
 38  IncomeVerifiable                     113937 non-null  bool
 39  StatedMonthlyIncome                  113937 non-null  float64
 40  LoanCurrentDaysDelinquent            113937 non-null  int64
 41  LoanMonthsSinceOrigination           113937 non-null  int64
 42  LoanNumber                           113937 non-null  int64
 43  LoanOriginalAmount                   113937 non-null  int64
 44  LoanOriginationDate                  113937 non-null  object
 45  LoanOriginationQuarter               113937 non-null  object
 46  MemberKey                            113937 non-null  object
 47  MonthlyLoanPayment                   113937 non-null  float64
 48  LP_CustomerPayments                  113937 non-null  float64
 49  LP_CustomerPrincipalPayments         113937 non-null  float64
 50  LP_InterestandFees                   113937 non-null  float64
 51  LP_ServiceFees                       113937 non-null  float64
 52  LP_CollectionFees                    113937 non-null  float64
 53  LP_GrossPrincipalLoss                113937 non-null  float64
 54  LP_NetPrincipalLoss                  113937 non-null  float64
 55  LP_NonPrincipalRecoverypayments      113937 non-null  float64
 56  PercentFunded                        113937 non-null  float64
 57  Recommendations                      113937 non-null  int64
 58  InvestmentFromFriendsCount           113937 non-null  int64
 59  InvestmentFromFriendsAmount          113937 non-null  float64
 60  Investors                            113937 non-null  int64
dtypes: bool(2), float64(39), int64(10), object(10)
memory usage: 51.5+ MB
```

[10]:
```
# filter out loans without ProsperScores
loan_data_cleanned= loan_data[loan_data['ProsperScore'].isnull()==False]

loan_data_cleanned['Occupation']=loan_data_cleanned['Occupation'].fillna('Not␣
↪Mentioned')
```

[11]:
```
loan_data_cleanned.isnull().sum()
```

[11]:
```
ListingCreationDate           0
Term                          0
LoanStatus                    0
BorrowerAPR                   0
BorrowerRate                  0
                             ..
PercentFunded                 0
```

```
Recommendations                0
InvestmentFromFriendsCount     0
InvestmentFromFriendsAmount    0
Investors                      0
Length: 61, dtype: int64
```

[12]:
```
#converting date into datetime
loan_data_cleanned['ListingCreationDate']=pd.
 ↪to_datetime(loan_data_cleanned['ListingCreationDate'])
```

[13]:
```
loan_data_cleanned.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 84853 entries, 1 to 113936
Data columns (total 61 columns):
 #   Column                              Non-Null Count  Dtype
---  ------                              --------------  -----
 0   ListingCreationDate                 84853 non-null  datetime64[ns]
 1   Term                                84853 non-null  int64
 2   LoanStatus                          84853 non-null  object
 3   BorrowerAPR                         84853 non-null  float64
 4   BorrowerRate                        84853 non-null  float64
 5   LenderYield                         84853 non-null  float64
 6   EstimatedEffectiveYield             84853 non-null  float64
 7   EstimatedLoss                       84853 non-null  float64
 8   EstimatedReturn                     84853 non-null  float64
 9   ProsperRating (numeric)             84853 non-null  float64
 10  ProsperRating (Alpha)               84853 non-null  object
 11  ProsperScore                        84853 non-null  float64
 12  ListingCategory (numeric)           84853 non-null  int64
 13  BorrowerState                       84853 non-null  object
 14  Occupation                          84853 non-null  object
 15  EmploymentStatus                    84853 non-null  object
 16  IsBorrowerHomeowner                 84853 non-null  bool
 17  CreditScoreRangeLower               84853 non-null  float64
 18  CreditScoreRangeUpper               84853 non-null  float64
 19  CurrentCreditLines                  84853 non-null  float64
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 25  TotalInquiries                      84853 non-null  float64
 26  CurrentDelinquencies                84853 non-null  float64
 27  AmountDelinquent                    84853 non-null  float64
 28  DelinquenciesLast7Years             84853 non-null  float64
 29  PublicRecordsLast10Years            84853 non-null  float64
 30  PublicRecordsLast12Months           84853 non-null  float64
```

```
 31  RevolvingCreditBalance              84853 non-null  float64
 32  BankcardUtilization                 84853 non-null  float64
 33  AvailableBankcardCredit             84853 non-null  float64
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 35  TradesNeverDelinquent (percentage)  84853 non-null  float64
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 41  LoanMonthsSinceOrigination          84853 non-null  int64
 42  LoanNumber                          84853 non-null  int64
 43  LoanOriginalAmount                  84853 non-null  int64
 44  LoanOriginationDate                 84853 non-null  object
 45  LoanOriginationQuarter              84853 non-null  object
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 51  LP_ServiceFees                      84853 non-null  float64
 52  LP_CollectionFees                   84853 non-null  float64
 53  LP_GrossPrincipalLoss               84853 non-null  float64
 54  LP_NetPrincipalLoss                 84853 non-null  float64
 55  LP_NonPrincipalRecoverypayments     84853 non-null  float64
 56  PercentFunded                       84853 non-null  float64
 57  Recommendations                     84853 non-null  int64
 58  InvestmentFromFriendsCount          84853 non-null  int64
 59  InvestmentFromFriendsAmount         84853 non-null  float64
 60  Investors                           84853 non-null  int64
dtypes: bool(2), datetime64[ns](1), float64(39), int64(10), object(9)
memory usage: 39.0+ MB
```

[ ]:

1.3.2 What is the structure of your dataset?

There was total of 113937 loans data saved in the dataset and 81 features. After cleanning the dataset, there are 84853 observations and 61 features remaining where the features contain information regarding the loans given.

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

The Borrower's Annual Percentage Rate (APR) for the loan, Listing Category, occupation,Employment Status,Prosper Score and Rating,and income Range.

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

The Prosper Rating and score can affect Borrower's APR because the higher rating the lower the risk. With low risks there are posibility of getting bigger loans. Creditscore and income Range could also have similar effect on Borrower's APR as Prosper Rating.

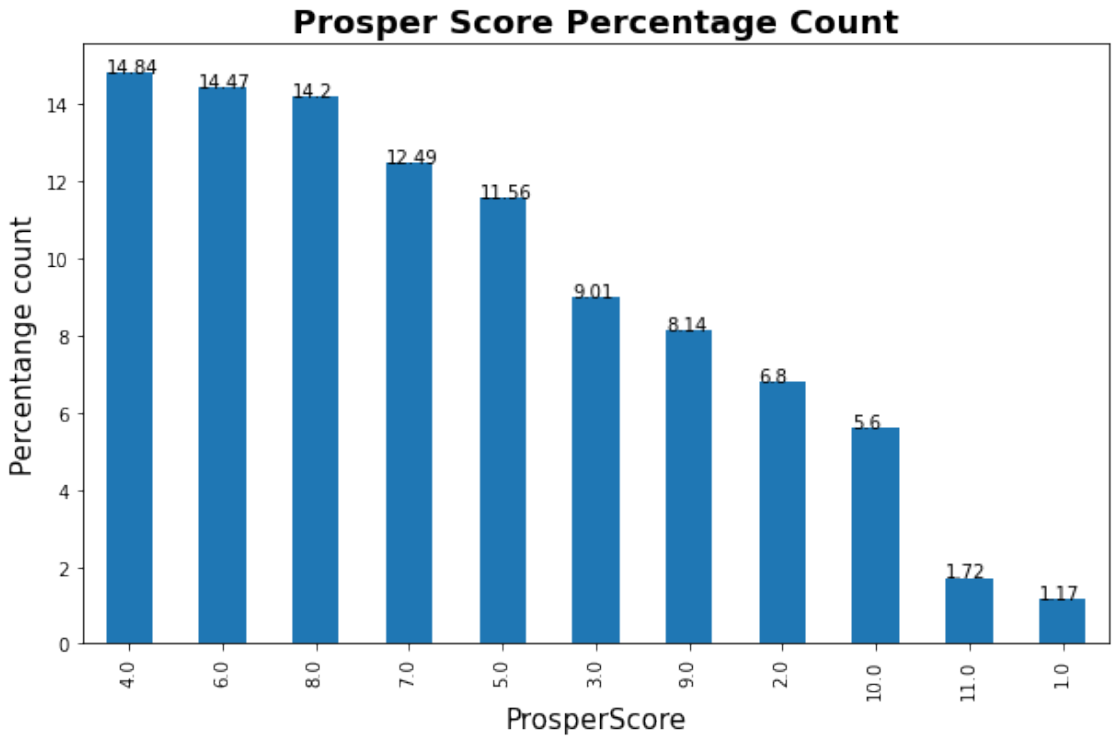
1.4 Univariate Exploration

1. How is Prosper Score is distributed in the data?

[14]:
```
# get score counts
ProsperScore_distribution=loan_data_cleanned['ProsperScore'].value_counts()
print('Prosper Score Count')
print(ProsperScore_distribution)
print(40*('**'))

#Setting figure size
plt.figure(figsize=[10, 6])

#plotting percentage count
ax=(ProsperScore_distribution/len(loan_data_cleanned)*100).plot(kind='bar')

"""
The following loop will annote for each graph
"""
for p in ax.patches:
    ax.annotate(str(round(p.get_height(),2)), (p.get_x(), p.get_height()))

'''
The following codes will label the plot
'''
plt.title('Prosper Score Percentage Count',fontsize=18,fontweight="bold")
plt.ylabel('Percentange count',fontsize=15)
plt.xlabel('ProsperScore',fontsize=15)
plt.show()
```

```
Prosper Score Count
4.0     12595
6.0     12278
8.0     12053
7.0     10597
5.0      9813
3.0      7642
9.0      6911
2.0      5766
10.0     4750
11.0     1456
1.0       992
Name: ProsperScore, dtype: int64
```

****



From the plot, Most people has score given is 4.0 with around 14.8% of all the people score, it is followed by 6.0 with 14.47% of all given scores and then 8.0 with around 14.2 of frequency. the last 3 given scores are 10.0,11.0 and 1.0 with 5.6%,1.72% and 1.17% of frquencies respectively.

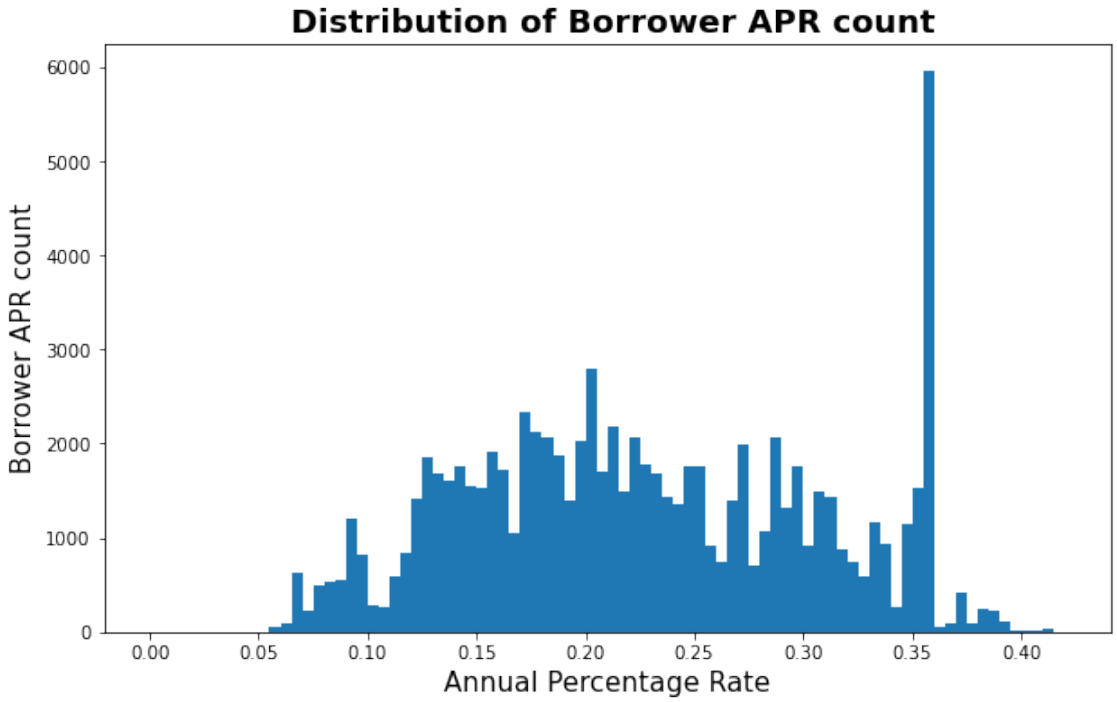
The score ranges from 1-11, with 11 being the best, or lowest risk score.

2. What is the distribution of Annual Percentage rate from the data?

[15]:
```
# checking where APR counts(top 20)
print('Top 20 Borrower APR Count')
print(loan_data_cleanned.BorrowerAPR.value_counts().head(20))
print(40*('**'))


"""
plotting APR distribution
"""

plt.figure(figsize=[10, 6]) # figure size
binz= np.arange(0, loan_data_cleanned['BorrowerAPR'].max(), 0.005) # definning␣
↪bins
ticks=np.arange(0, loan_data_cleanned['BorrowerAPR'].max(), 0.05) # defining␣
↪xtics
```

```
plt.hist(data = loan_data_cleanned, x = 'BorrowerAPR', bins = binz) # plotting␣
 ↪histogram

#labes
plt.title(' Distribution of Borrower APR count',fontsize=18,fontweight="bold")
plt.xlabel('Annual Percentage Rate',fontsize=15)
plt.ylabel('Borrower APR count',fontsize=15)
plt.xticks(ticks)
plt.show()
```

```
Top 20 Borrower APR Count
0.35797    3672
0.35643    1644
0.30532     902
0.29510     747
0.35356     721
0.15833     651
0.24246     605
0.24758     601
0.12528     559
0.17359     547
0.15324     547
0.27462     534
0.27285     506
0.13799     489
0.12691     456
0.25781     444
0.26528     430
0.19501     425
0.20462     420
0.23318     416
Name: BorrowerAPR, dtype: int64
**********************************************************************************
```



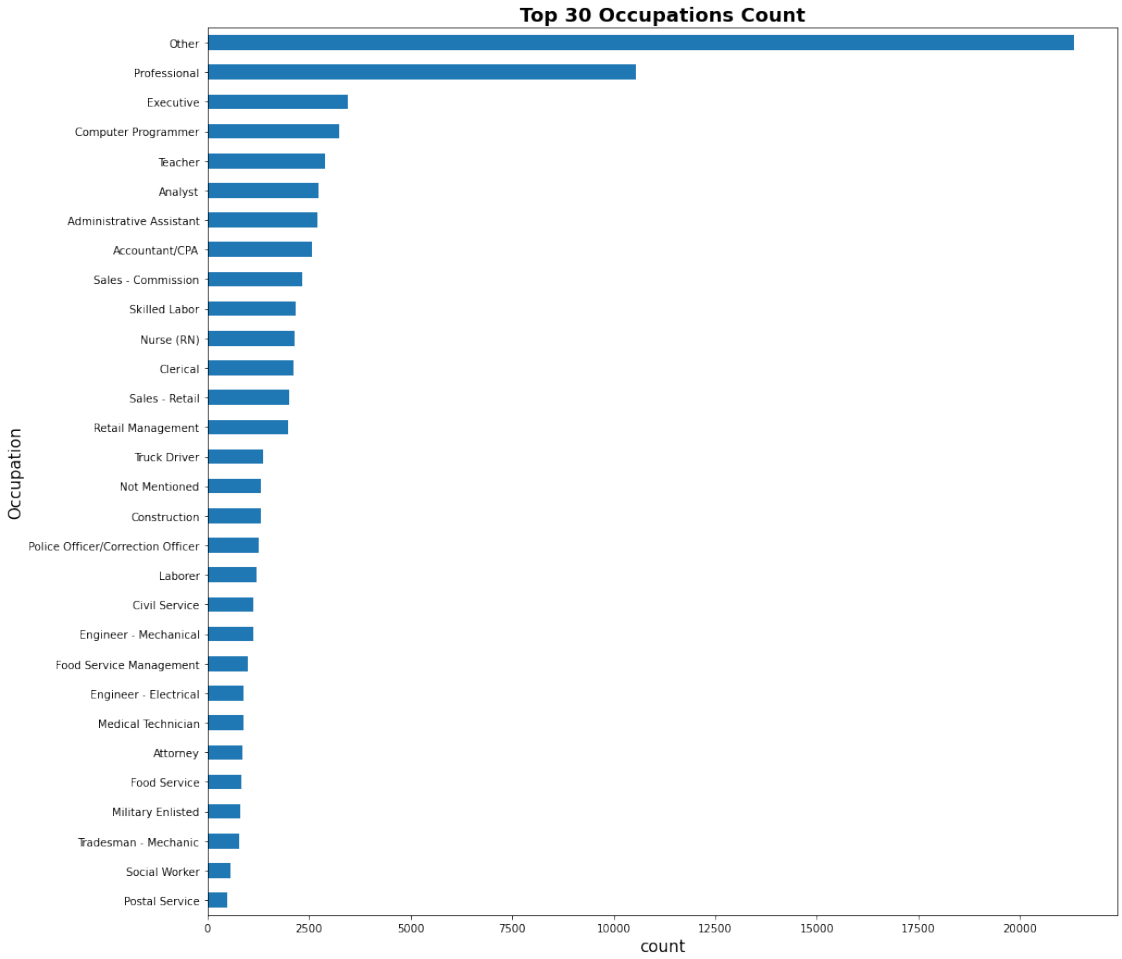
From the following histogram,There is roughly normal distribution in the annual percentage rates with two outliers with abnormal counts at 0.35797% and at 0.35643%. the APR frequencies tend to increase as the APR rise from around 0.05% up to 0.20% and then the frequencies decline as APR increases toward 0.40%.

3. Which are the top occupations subjected to taking loans

[16]:
```
print('Top 30 occupations subjected to taking loans')
print(loan_data_cleanned['Occupation'].value_counts().head(30).
 ↪sort_values(ascending=False))
print(40*('**'))

# top 30 occupations of borrowers plotting
plt.figure(figsize=[15, 15])
ax=loan_data_cleanned['Occupation'].value_counts().head(30).sort_values().
 ↪plot(kind='barh')
plt.title('Top 30 Occupations Count',fontsize=18,fontweight="bold")
plt.xlabel('count',fontsize=15)
plt.ylabel('Occupation',fontsize=15)
plt.show()
```

```
Top 30 occupations subjected to taking loans
Other                                21317
Professional                         10542
Executive                             3468
Computer Programmer                   3236
```

```
Teacher                              2888
Analyst                              2735
Administrative Assistant             2708
Accountant/CPA                       2574
Sales - Commission                   2350
Skilled Labor                        2180
Nurse (RN)                           2159
Clerical                             2116
Sales - Retail                       2029
Retail Management                    2001
Truck Driver                         1366
Not Mentioned                        1333
Construction                         1326
Police Officer/Correction Officer    1277
Laborer                              1217
Civil Service                        1139
Engineer - Mechanical                1135
Food Service Management              1005
Engineer - Electrical                 900
Medical Technician                    891
Attorney                              866
Food Service                          837
Military Enlisted                     824
Tradesman - Mechanic                  797
Social Worker                         575
Postal Service                        487
Name: Occupation, dtype: int64
********************************************************************************
```



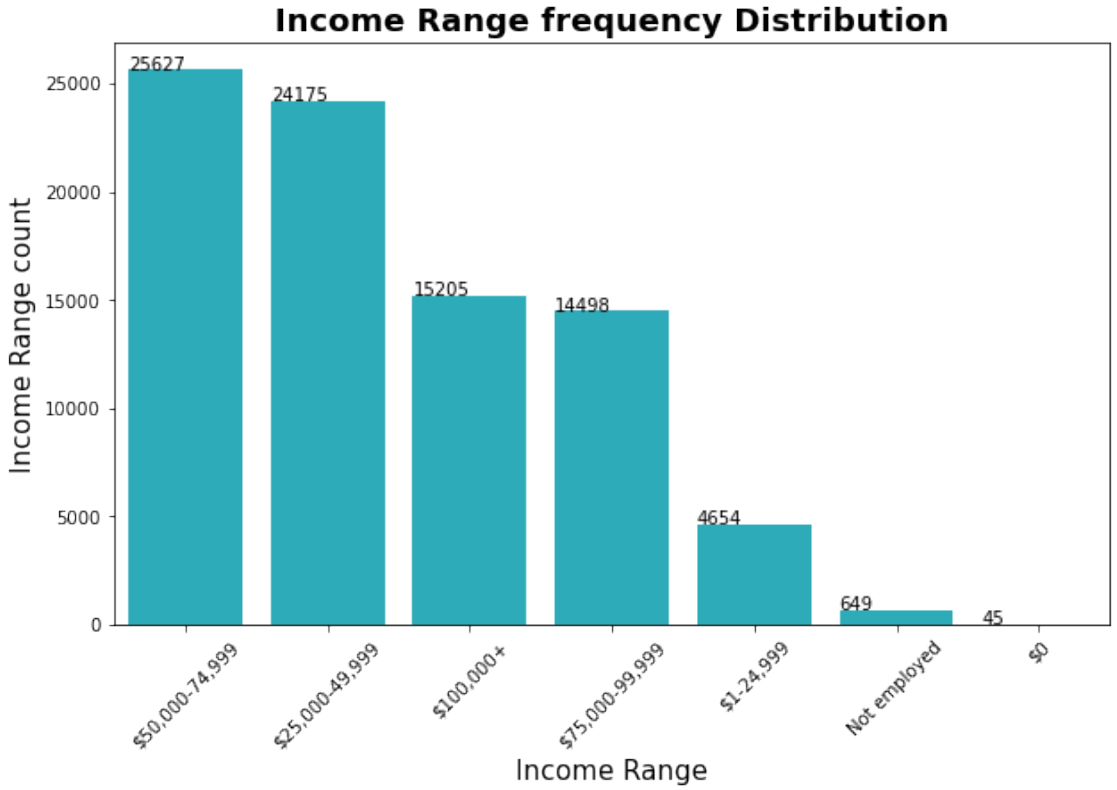
The graph shows that many borrowers mentioned **other** and **Professional** as their jobs. with known jobs, **Exectives** are the most people who seek for loans, followed by **Programmers** and then **Teachers** followed by **Analysts** and the then **Administrative assistants**. other occupations such as **Accountants,Skilled Labors,Nurses** are also present in top 10. **Drivers**,**engineers** and **Attorney** are also present in top 30.

4. Does the income considered in loan guaranteeing?

[17]:
```
print("Income Range distribution")
print(loan_data_cleanned['IncomeRange'].value_counts())
print(40*('**'))
plt.figure(figsize=[10, 6])
ax=sns.countplot(data = loan_data_cleanned, x = 'IncomeRange', color = sns.
 ↪color_palette()[9])
for p in ax.patches:
    ax.annotate(str(round(p.get_height(),2)), (p.get_x(), p.get_height()))

plt.title('Income Range frequency Distribution',fontsize=18,fontweight="bold")
```

```
plt.ylabel('Income Range count',fontsize=15)
plt.xlabel('Income Range',fontsize=15)
plt.xticks(rotation=45)
plt.show()
```

```
Income Range distribution
$50,000-74,999    25627
$25,000-49,999    24175
$100,000+         15205
$75,000-99,999    14498
$1-24,999          4654
Not employed        649
$0                   45
Name: IncomeRange, dtype: int64
**********************************************************************************
```

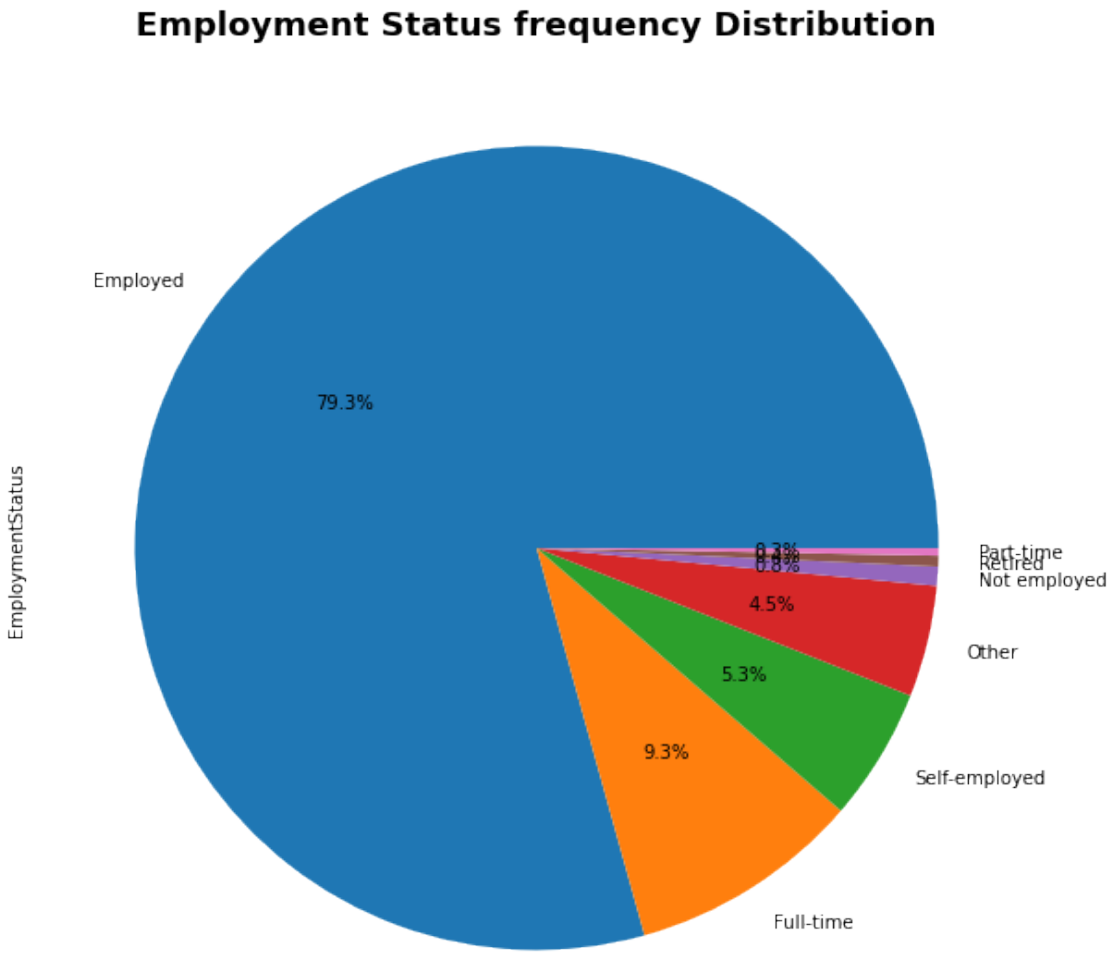


The plot shows that most individual who has a loan has an income range from 40k to 75k are present in dataset, they are followed with ones of 25k to 50k. The unemployed ones and the ones with income of 0k are very few. From the graph it is not clear whether the individuals with more income are likely to get the loans and more investagatiions are required for a better conclusion.

5. How is Employment Status is distributed in data

[18]:
```
print("Employment Status distribution")
print(loan_data_cleanned['EmploymentStatus'].value_counts())
print(40*('**'))

# plotting
plt.figure(figsize=(10,10))
loan_data_cleanned['EmploymentStatus'].value_counts().
 ↪plot(kind='pie',autopct='%1.1f%%');

# labels
plt.title('Employment Status frequency␣
 ↪Distribution',fontsize=18,fontweight="bold");
```

```
Employment Status distribution
Employed         67310
Full-time         7927
Self-employed     4538
Other             3806
Not employed       649
Retired            367
Part-time          256
Name: EmploymentStatus, dtype: int64
********************************************************************************
```



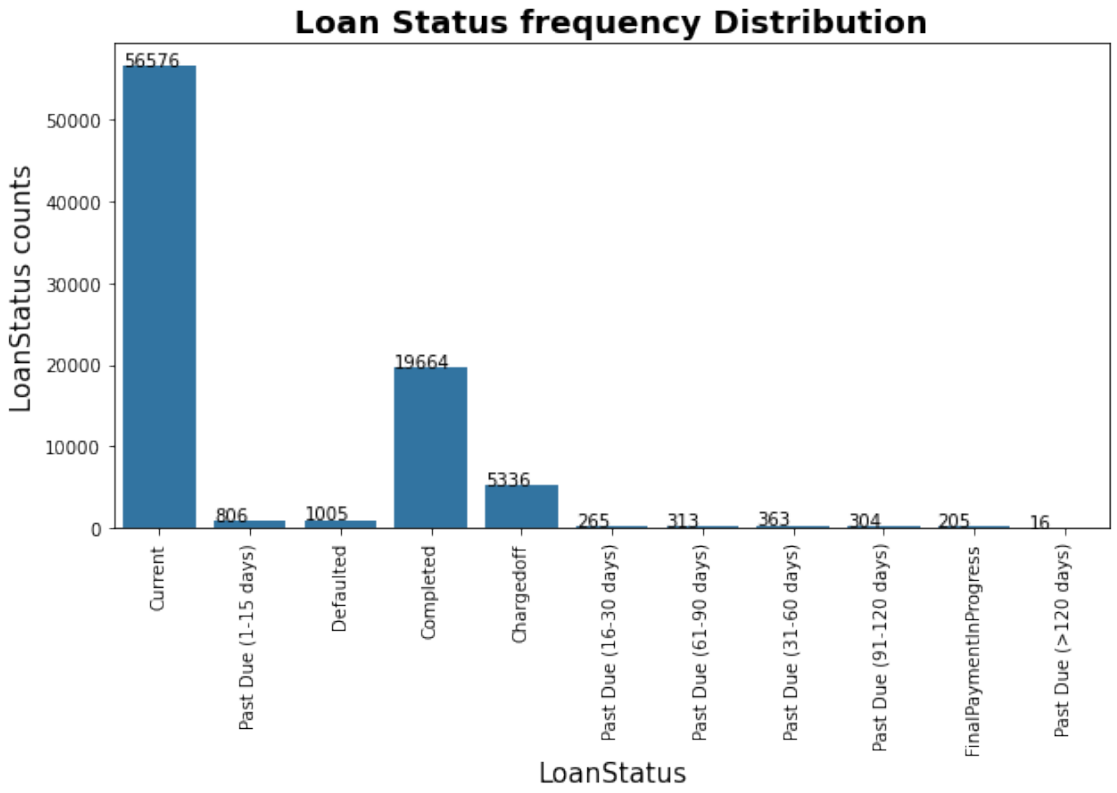
The plot shows that it is rare that unemployed and retired individual seek for loans from Prosper. Around 79.3% of loan seekers are employed people,9.3% are full_time, while self-employed people are 5.3%.

6. What is the loan status of people who has a loan from Prosper?

[19]:
```
print("loan status distribution")
print(loan_data_cleanned['LoanStatus'].value_counts())
print(40*('**'))

plt.figure(figsize=[10, 5])

ax=sns.countplot(data = loan_data_cleanned, x = 'LoanStatus', color = sns.
 ↪color_palette()[0])
for p in ax.patches:
```

```
    ax.annotate(str(round(p.get_height(),2)), (p.get_x(), p.get_height()))

plt.title('Loan Status frequency Distribution',fontsize=18,fontweight="bold");
plt.ylabel('LoanStatus counts',fontsize=15)
plt.xlabel('LoanStatus',fontsize=15)
plt.xticks(rotation=90)
plt.show()
```

```
loan status distribution
Current                    56576
Completed                  19664
Chargedoff                  5336
Defaulted                   1005
Past Due (1-15 days)         806
Past Due (31-60 days)        363
Past Due (61-90 days)        313
Past Due (91-120 days)       304
Past Due (16-30 days)        265
FinalPaymentInProgress       205
Past Due (>120 days)          16
Name: LoanStatus, dtype: int64
**********************************************************************************
```



The current status of the loan: Cancelled, Chargedoff, Completed, Current, Defaulted, FinalPaymentInProgress, PastDue. The PastDue status will be accompanied by a delinquency bucket.

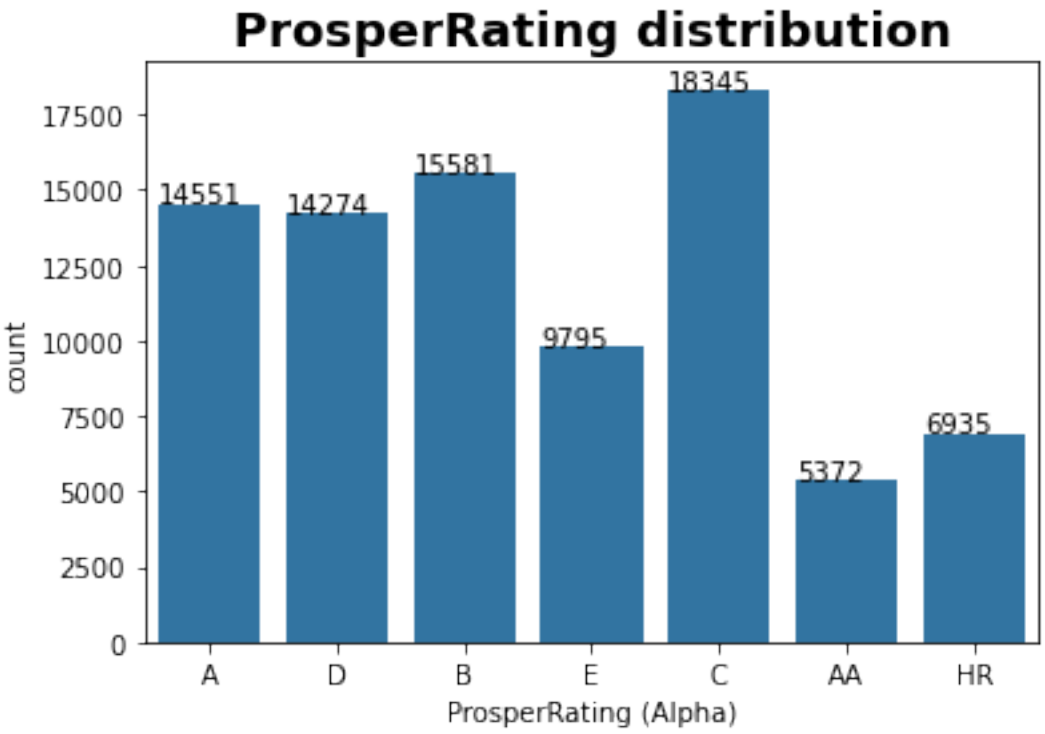
The plot shows that more than 50,000 individuals has a loan with Prosper, while around 20,000 have completed thier loans. Around 5,000 people are in chargedoff status.

[ ]:

7. How is Prosper ratings of individuals is distributed in the data?

[20]:
```
print("ProsperRating (Alpha) distribution")
print(loan_data_cleanned['ProsperRating (Alpha)'].value_counts())
print(40*('**'))

ax=sns.countplot(data = loan_data_cleanned, x = 'ProsperRating (Alpha)', color␣
↪= sns.color_palette()[0])
for p in ax.patches:
    ax.annotate(str(round(p.get_height(),2)), (p.get_x(), p.get_height()))
plt.title('ProsperRating distribution',fontsize=18,fontweight="bold")
plt.show()
```

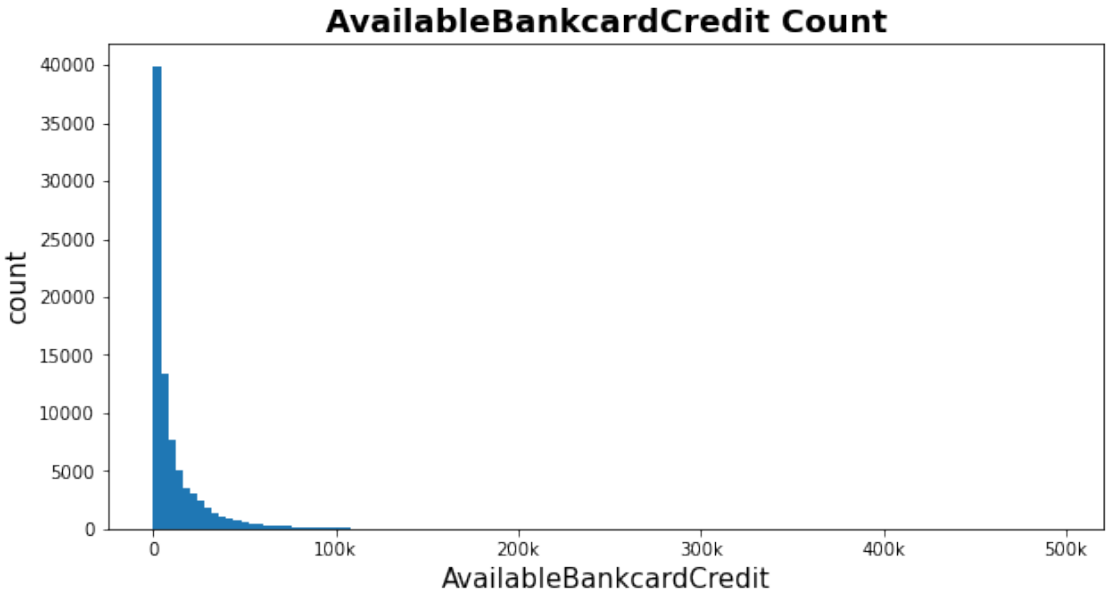
```
ProsperRating (Alpha) distribution
C     18345
B     15581
A     14551
D     14274
E      9795
HR     6935
AA     5372
Name: ProsperRating (Alpha), dtype: int64
********************************************************************************
```



The Prosper Rating assigned at the time the listing was created between AA - HR. Applicable for loans originated after July 2009. From the plot, Majority of people are in group C, followed by group B and then group A. Group AA has the least people in data.

8. What is AvailableBankcardCredit distribution

[21]:
```
#Check for counts for AvailableBankcardCredit

plt.figure(figsize=[10, 5])
bins = np.arange(0, 498374, 4000)
plt.hist(data = loan_data_cleanned, x = 'AvailableBankcardCredit', bins = bins)
plt.xticks([0, 1e5, 2e5, 3e5, 4e5, 5e5], [0, '100k', '200k', '300k', '400k',␣
↪'500k'])
plt.title('AvailableBankcardCredit Count',fontsize=18,fontweight="bold")
plt.xlabel('AvailableBankcardCredit',fontsize=15)
plt.ylabel('count',fontsize=15);
```



Most AvailableBankcardCredit counts fall in values from 0 to 100k and the majority are at 0. Clearly there are few percent of people who have higher bank total credits than 100k

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

From Prosper score,most people has score given is 4.0 with around 14.8% of all the people, it is followed by 6.0 with 14.47% of all given scores and then 8.0 with around 14.2 of frequency. the last 3 given scores are 10.0,11.0 and 1.0 with 5.6%,1.72% and 1.17% of frquencies respectively. There is roughly normal distribution in the annual percentage rates with two outliers with abnormal counts at 0.35797% and at 0.35643%. Many borrowers mentioned other and Professional as their jobs. with known jobs, Exectives are the most people who seek for loans, followed by Programmers and then Teachers followed by Analysts and the then Administrative assistants.Most individual who has a loan has an income range from 40k to 75k are present in dataset, they are followed with ones of 25k to 50k. The unemployed ones and the ones with income of 0k are very few. There are more than 50,000 individuals has a loan with Prosper, while around 20,000 have completed thier loans. Around 5,000 people are in chargedoff status. Around 79.3% ofloan seekers are employed people,9.3% are full_time, while self-employed people are 5.3%. Most AvailableBankcardCredit counts fall in values from 0 to 100k and the majority are at 0.

1.4.2 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?

There is no unusual distributions in my datasets apart from suprising findings, some operation have been made like replacing NaN values and selecting only dataset with

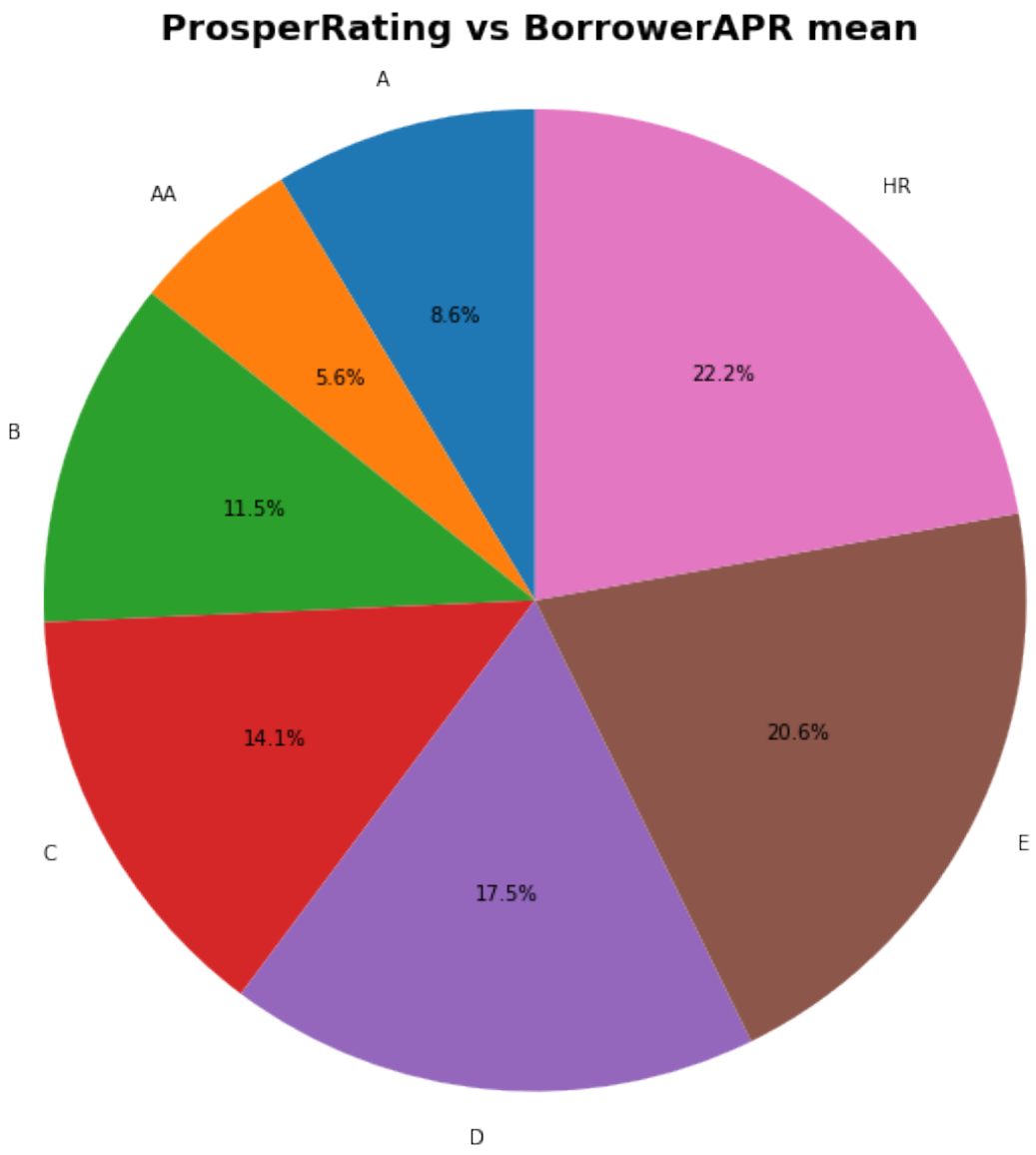
known Prosper Score.

1.5 Bivariate Exploration

9. What is the relationship between ProsperRating (Alpha) and BorrowerAPR

[22]:
```
ProsperRating_mean = loan_data_cleanned.groupby('ProsperRating␣
 ↪(Alpha)')['BorrowerAPR'].mean()
print(ProsperRating_mean)
print(40*('**'))

plt.figure(figsize=(10,10))
plt.pie(ProsperRating_mean, labels = ProsperRating_mean.index, startangle = 90,
     autopct='%1.1f%%')
plt.axis('square')
plt.title('ProsperRating vs BorrowerAPR mean',fontsize=18,fontweight="bold");
```

```
ProsperRating (Alpha)
A     0.138909
AA    0.090041
B     0.184030
C     0.226124
D     0.280581
E     0.330551
HR    0.356061
Name: BorrowerAPR, dtype: float64
********************************************************************************
```

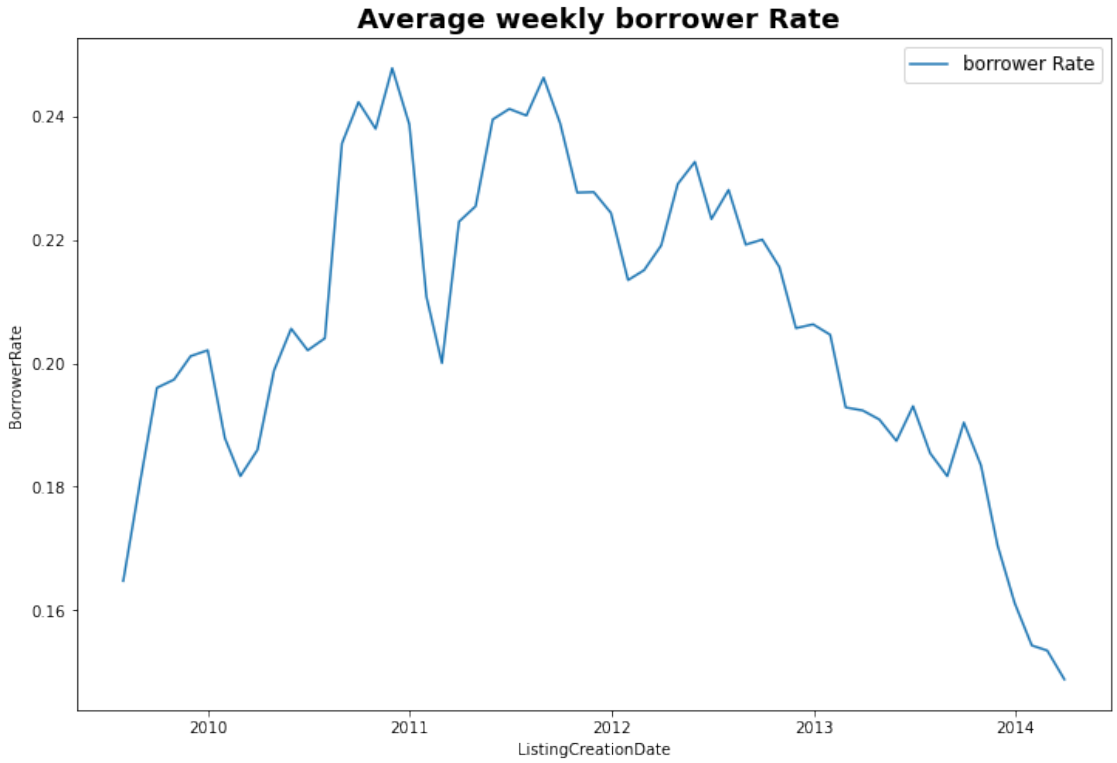


Borrowers Rating are displayed in order from highest rating to lowest rating (A, AA, B, C, D, E, HR) in counter_clockwise direction and their mean values are displayed as percentage of the sum of the means. We can see a pattern that the highest rating of AA received lowest APR (5.6%), whereas the lowerest rating received the highest APR (22.2%). This proves the point that borrowers with higher rating received lower APR..

10 What is the trend of borrower rates over years?

[23]:
```
# resampling data at monthly basis
df=loan_data_cleanned.set_index('ListingCreationDate').resample('M').mean()
#ploting
plt.figure(figsize=(12,8))
sns.lineplot(df.index,df['BorrowerRate'])# ploting monthly resampled data
```

```
plt.title(' Average weekly borrower Rate',fontsize=18,fontweight="bold") #tilte␣
 ↪of plot
plt.legend(labels=["borrower Rate"],fontsize = 'large') # legend of plot
plt.show()# displaying
```



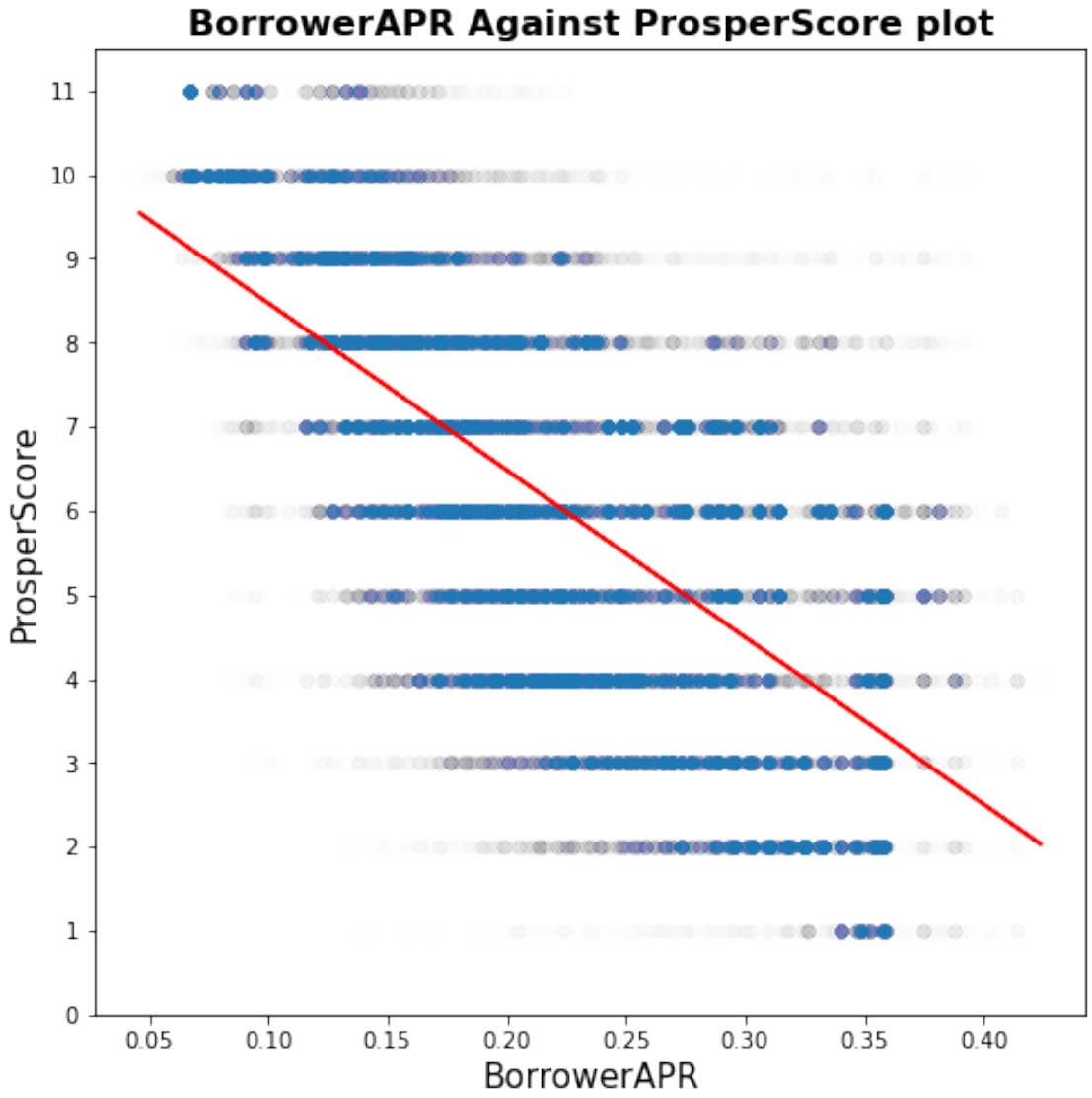
The average monthly Borrower Rates generally increased from 2009 at 0.162 to 2011 at 0.25,in Mid 2011, there was a sharp fall to 0.20 which recovered at the of the year. from 2012 to 2014, there was a gradual fall in borrower rates from 0.24 to 0.15

The peak years were 2011 and 2012

11. What is the relationship between ProsperScore and BorrowerAPR

[24]:
```
# scatter and heat plot for comparing ProsperScore and BorrowerAPR.
plt.figure(figsize = [8, 8])
plt.scatter(data = loan_data_cleanned, x = 'BorrowerAPR', y = 'ProsperScore',␣
 ↪alpha =  0.005)
a, b = np.polyfit(loan_data_cleanned['BorrowerAPR'],␣
 ↪loan_data_cleanned['ProsperScore'], 1)
plt.plot(loan_data_cleanned['BorrowerAPR'],␣
 ↪a*loan_data_cleanned['BorrowerAPR']+b,color='r')
plt.yticks(np.arange(0, 12, 1))
plt.title('BorrowerAPR Against ProsperScore plot',fontsize=16,fontweight="bold")
plt.xlabel('BorrowerAPR',fontsize=15)
```

```
plt.ylabel('ProsperScore',fontsize=15)
plt.show()
```

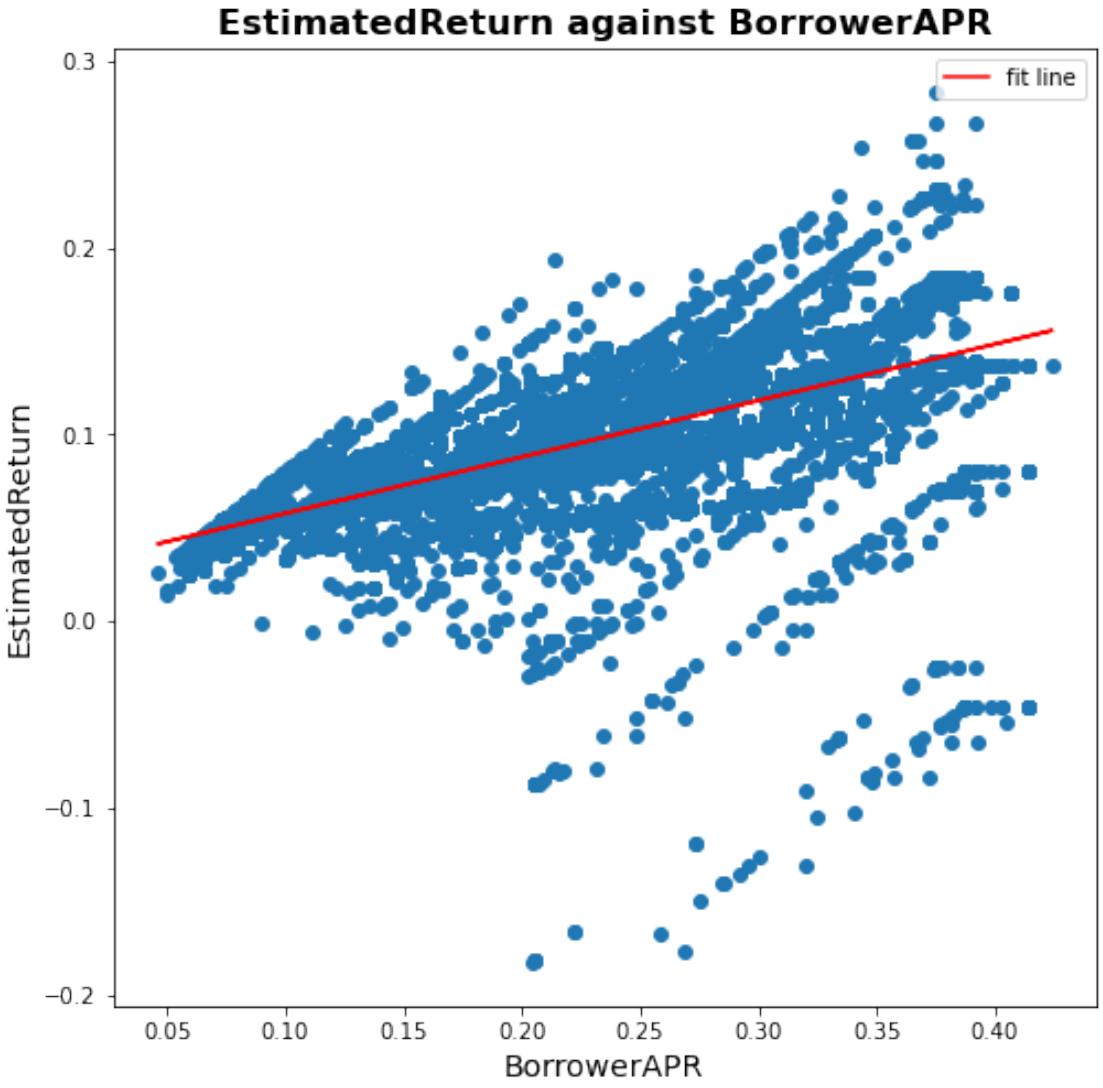


The plot shows that as the BorrowAPR increases, the ProsperScore reduces,There is a negative correlation between these variables. This make sense becasue people with higher rating tend to be more reliable and therefore given lower BorrowerAPR

12. What is the relationship between EstimatedReturn and BorrowerAPR

[25]:
```
plt.figure(figsize = [8, 8])
a, b = np.polyfit(loan_data_cleanned['BorrowerAPR'],␣
 ↪loan_data_cleanned["EstimatedReturn"], 1)
```

```
plt.
 ↪scatter(loan_data_cleanned["BorrowerAPR"],loan_data_cleanned["EstimatedReturn"])
plt.plot(loan_data_cleanned['BorrowerAPR'],␣
 ↪a*loan_data_cleanned['BorrowerAPR']+b,color='r',label='fit line')
plt.legend()
plt.title('EstimatedReturn against BorrowerAPR',fontsize=16,fontweight="bold")
plt.xlabel('BorrowerAPR',fontsize=14,)
plt.ylabel('EstimatedReturn',fontsize=14,)
plt.show()
```



The graph shows that a positive correlation between BorrowerAPR and EstimatedReturn, generally as the value of BorrowerAPR increases, the EstimatedReturn value is expected to increase as well.

1.5.1 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?

We have seen that the highest rating of AA received lowest APR (5.6), whereas the lowerest rating received the highest APR (22.2). As the BorrowAPR increases, the ProsperScore reduces,There is a negative correlation between these variables. This make sense becasue people with higher rating tend to be more reliable and therefore given lower BorrowerAPR There is a positive correlation between BorrowerAPR and EstimatedReturn, generally as the value of BorrowerAPR increases, the EstimatedReturn value is expected to increase as well.

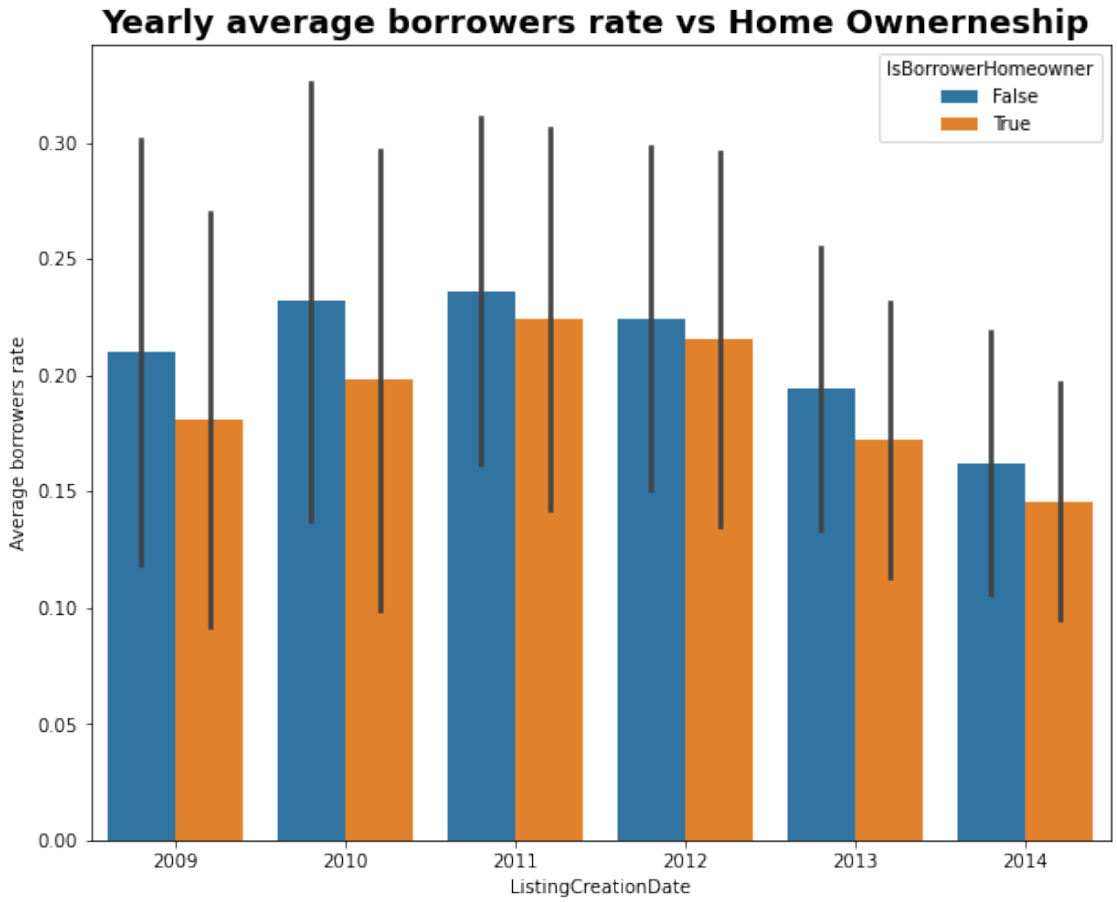
1.5.2 Did you observe any interesting relationships between the other features (not the main feature(s) of interest)?

The average monthly Borrower Rates generally increased from 2009 at 0.162 to 2011 at 0.25,in Mid 2011, from 2012 to 2014, there was a gradual fall in borrower rates from 0.24 to 0.15 and the peak years were 2011 and 2012

1.6 Multivariate Exploration

13. Does being a homeowner affect borrower rate?

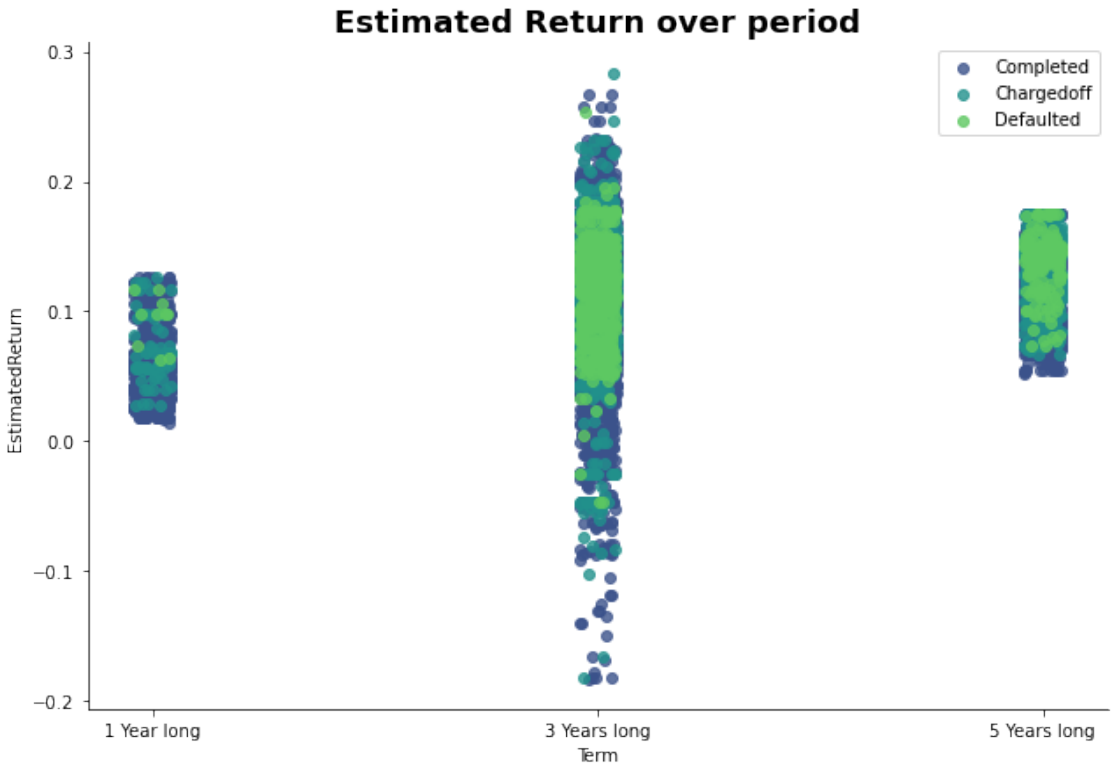
[26]:
```
plt.figure(figsize=[10, 8]);
sns.barplot(data = loan_data_cleanned, x =␣
 ↪loan_data_cleanned['ListingCreationDate'].apply(lambda x: x.year),
            y = 'BorrowerRate', hue = 'IsBorrowerHomeowner', ci = 'sd');
plt.ylabel('Average borrowers rate');
plt.title('Yearly average borrowers rate vs Home Ownerneship␣
 ↪',fontsize=18,fontweight="bold");
plt.show()
```



According to the plot, and based on yearly averages, from 2009 to 2014, people with homes are given low rates compared with people without houses. It does seem like homeowners have a slightly lower rate that non-homeowners.

14.How does the length of time affect Returns?

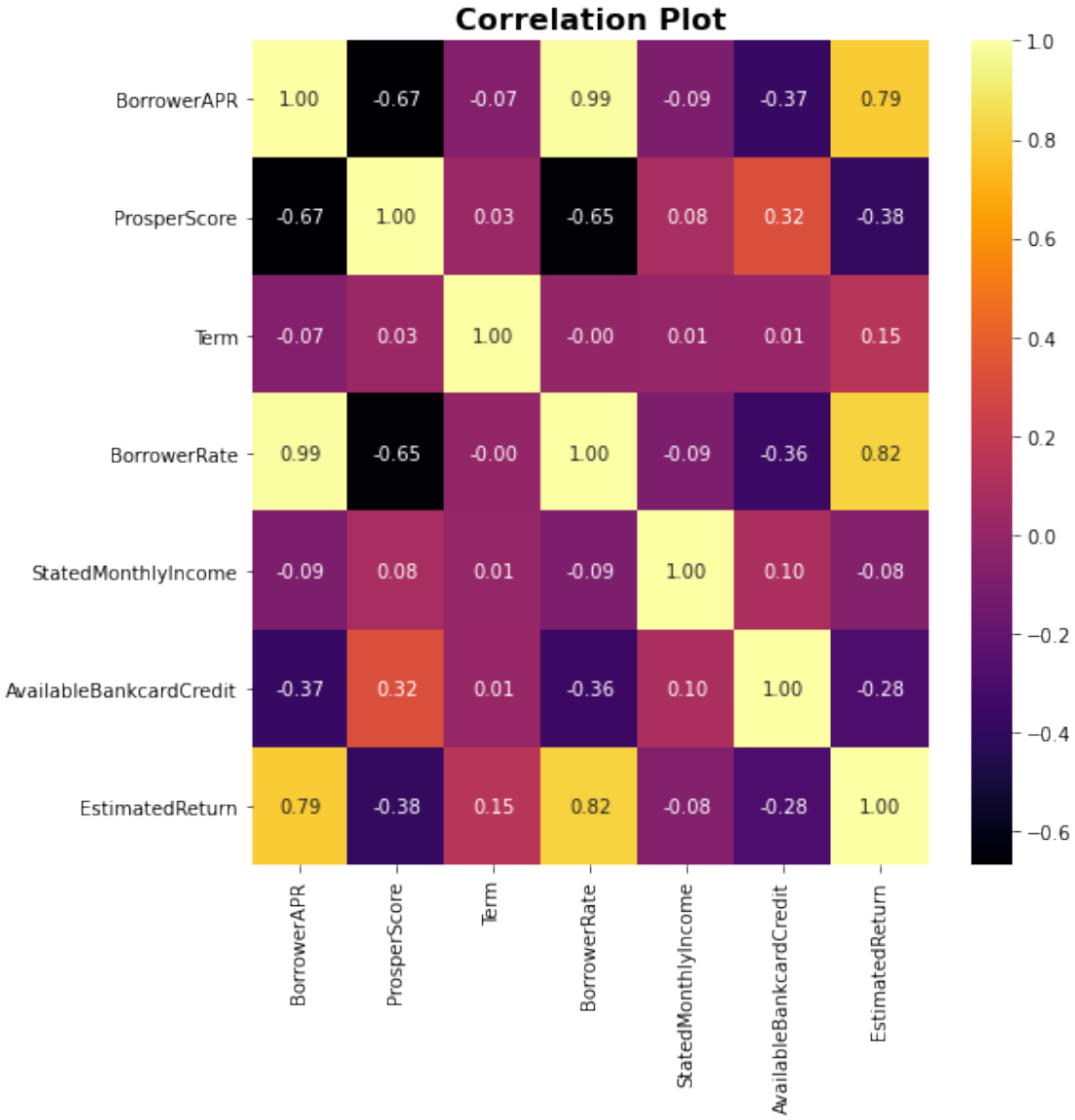
[27]:
```
plot = sns.FacetGrid(data = loan_data_cleanned, hue = 'LoanStatus',
                     hue_order = ['Completed','Chargedoff','Defaulted'],
                     size = 6, aspect = 1.5, palette="viridis")
plot.map(sns.regplot,"Term", "EstimatedReturn", fit_reg = False, x_jitter=True)
plot.set(xticks=np.arange(12,84,24),xticklabels=["1 Year long", "3 Years long",␣
 ↪"5 Years long" ])
plt.legend(loc=1)
plt.title('Estimated Return over period', fontsize=18,fontweight="bold")
plt.show()
```



For 1 year loans have the lowest history of defaulting with its highest peak is at 0.12 of Estimated Return. For 3 years loans have the widest range of expected returns, with more extreme rates seeming to have lower defaults historically and with the peak around 0.28 of Estimated return. For 5 year loans have higher returns on average than 1 year but at a much higher risk of default historically with peak around 0.19 of Estimated return.

15. what are the correlations among variables?

[28]:
```
# correlation plot

columns = ['BorrowerAPR', 'ProsperScore','Term','BorrowerRate',
           'StatedMonthlyIncome', 'AvailableBankcardCredit','EstimatedReturn']

plt.figure(figsize = [8, 8])
sns.heatmap(loan_data_cleanned[columns].corr(), annot = True, fmt = '.2f',
            cmap = 'inferno')
plt.title('Correlation Plot',fontsize=16,fontweight="bold")
plt.show()
```



There are two strong positive relationships between BorrowerRate and BorrowerAPR, and between BorrowerAPR and EstimatedReturn, this means the rates and returns are dependent to borrower APR. BorrowerAPR and ProsperScore are negative because borrowers with lower score are more likely to pay higher APR. Similarly, higher CreditScore means the borrowers are more trustworthy, therefore it recevied lower APR.

[ ]:

1.6.1 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?

Based on yearly averages, from 2009 to 2014, people with homes are given low rates compared with people without houses. It does seem like homeowners have a slightly lower rate that non-homeowners. For 1 year loans have the lowest history of defaulting with its highest peak is at 0.12 of Estimated Return. For 3 years loans have the widest range of expected returns, with more extreme rates seeming to have lower defaults historically and with the peak around 0.28 of Estimated return. For 5 year loans have higher returns on average than 1 year but at a much higher risk of default historically with peak around 0.19 of Estimated return. here are two strong positive relationships between BorrowerRate and BorrowerAPR, and between BorrowerAPR and EstimatedReturn, this means the rates and returns are dependent to borrower APR. BorrowerAPR and ProsperScore are negative because borrowers with lower score are more likely to pay higher APR. Similarly, higher CreditScore means the borrowers are more trustworthy, therefore it recevied lower APR.

1.6.2 Were there any interesting or surprising interactions between features?

The surprising fact is that the 1 year loans are more likely to be tradedoff than other loans

1.7 Conclusions

```
The project was designed to discover insight from a dataset of loans from on Prosper. At fi
Individual variables have been analysed using diferent data visualizations such as pie char
For Bivariate analysis, in 2011 and 2012 was the years where rates was very high compared t
In multivariate exploration, it's observed that within each income range group, the rate in
```

Limitations Almost data from 2016 to 2019 was not analysed since they have not ProsperScores this a huge data that could affect decision making. Some columns contains lots of Null values which I dropped to get a clean dataset. Machine Learning models such as PCA are needed to reduce number of features.