# Alx-t project 3

August 31, 2022

Project3(Alx-t): Data visualization (Loan Data From Prosper)

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[1]:
```
#Importing all needed libraries.......
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
from warnings import filterwarnings
filterwarnings("ignore")# to ingore some filter warnings especially from the␣
↪seaborn library
%matplotlib inline
```

## 0.1 DATA WRANGLING

### DATA GATHERING

[2]:
```
#loading the dataset........
loan_dt = pd.read_csv('prosperLoanData.csv')
loan_dt.head(10)
```

[2]:
```
                ListingKey  ListingNumber            ListingCreationDate  \
0  1021339766868145413AB3B         193129  2007-08-26 19:09:29.263000000
1  10273602499503308B223C1        1209647  2014-02-27 08:28:07.900000000
2  0EE9337825851032864889A          81716  2007-01-05 15:00:47.090000000
3  0EF5356002482715299901A         658116  2012-10-22 11:02:35.010000000
4  0F023589499656230C5E3E2         909464  2013-09-14 18:38:39.097000000
5  0F05359734824199381F61D        1074836  2013-12-14 08:26:37.093000000
6  0F0A3576754255009D63151         750899  2013-04-12 09:52:56.147000000
7  0F1035772717087366F9EA7         768193  2013-05-05 06:49:27.493000000
8  0F043596202561788EA13D5        1023355  2013-12-02 10:43:39.117000000
9  0F043596202561788EA13D5        1023355  2013-12-02 10:43:39.117000000

  CreditGrade  Term LoanStatus           ClosedDate  BorrowerAPR  \
0           C    36  Completed  2009-08-14 00:00:00      0.16516
1         NaN    36    Current                  NaN      0.12016
2          HR    36  Completed  2009-12-17 00:00:00      0.28269
```

```
3         NaN    36    Current                  NaN      0.12528
4         NaN    36    Current                  NaN      0.24614
5         NaN    60    Current                  NaN      0.15425
6         NaN    36    Current                  NaN      0.31032
7         NaN    36    Current                  NaN      0.23939
8         NaN    36    Current                  NaN      0.07620
9         NaN    36    Current                  NaN      0.07620

   BorrowerRate  LenderYield  …  LP_ServiceFees  LP_CollectionFees  \
0        0.1580       0.1380  …         -133.18                0.0
1        0.0920       0.0820  …            0.00                0.0
2        0.2750       0.2400  …          -24.20                0.0
3        0.0974       0.0874  …         -108.01                0.0
4        0.2085       0.1985  …          -60.27                0.0
5        0.1314       0.1214  …          -25.33                0.0
6        0.2712       0.2612  …          -22.95                0.0
7        0.2019       0.1919  …          -69.21                0.0
8        0.0629       0.0529  …          -16.77                0.0
9        0.0629       0.0529  …          -16.77                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
3                    0.0                  0.0                              0.0
4                    0.0                  0.0                              0.0
5                    0.0                  0.0                              0.0
6                    0.0                  0.0                              0.0
7                    0.0                  0.0                              0.0
8                    0.0                  0.0                              0.0
9                    0.0                  0.0                              0.0

   PercentFunded  Recommendations InvestmentFromFriendsCount  \
0            1.0                0                          0
1            1.0                0                          0
2            1.0                0                          0
3            1.0                0                          0
4            1.0                0                          0
5            1.0                0                          0
6            1.0                0                          0
7            1.0                0                          0
8            1.0                0                          0
9            1.0                0                          0

  InvestmentFromFriendsAmount Investors
0                         0.0       258
1                         0.0         1
```

```
2                         0.0        41
3                         0.0       158
4                         0.0        20
5                         0.0         1
6                         0.0         1
7                         0.0         1
8                         0.0         1
9                         0.0         1

[10 rows x 81 columns]
```

**DATA ACESSMENT**

[3]:
```python
#getting the dataset info()
loan_dt.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
```

[4]:
```
#getting a list of all columns
loan_dt.columns
```

[4]:
```
Index(['ListingKey', 'ListingNumber', 'ListingCreationDate', 'CreditGrade',
       'Term', 'LoanStatus', 'ClosedDate', 'BorrowerAPR', 'BorrowerRate',
       'LenderYield', 'EstimatedEffectiveYield', 'EstimatedLoss',
       'EstimatedReturn', 'ProsperRating (numeric)', 'ProsperRating (Alpha)',
       'ProsperScore', 'ListingCategory (numeric)', 'BorrowerState',
       'Occupation', 'EmploymentStatus', 'EmploymentStatusDuration',
       'IsBorrowerHomeowner', 'CurrentlyInGroup', 'GroupKey',
       'DateCreditPulled', 'CreditScoreRangeLower', 'CreditScoreRangeUpper',
       'FirstRecordedCreditLine', 'CurrentCreditLines', 'OpenCreditLines',
       'TotalCreditLinespast7years', 'OpenRevolvingAccounts',
       'OpenRevolvingMonthlyPayment', 'InquiriesLast6Months', 'TotalInquiries',
       'CurrentDelinquencies', 'AmountDelinquent', 'DelinquenciesLast7Years',
       'PublicRecordsLast10Years', 'PublicRecordsLast12Months',
       'RevolvingCreditBalance', 'BankcardUtilization',
       'AvailableBankcardCredit', 'TotalTrades',
       'TradesNeverDelinquent (percentage)', 'TradesOpenedLast6Months',
       'DebtToIncomeRatio', 'IncomeRange', 'IncomeVerifiable',
       'StatedMonthlyIncome', 'LoanKey', 'TotalProsperLoans',
       'TotalProsperPaymentsBilled', 'OnTimeProsperPayments',
       'ProsperPaymentsLessThanOneMonthLate',
       'ProsperPaymentsOneMonthPlusLate', 'ProsperPrincipalBorrowed',
       'ProsperPrincipalOutstanding', 'ScorexChangeAtTimeOfListing',
       'LoanCurrentDaysDelinquent', 'LoanFirstDefaultedCycleNumber',
       'LoanMonthsSinceOrigination', 'LoanNumber', 'LoanOriginalAmount',
       'LoanOriginationDate', 'LoanOriginationQuarter', 'MemberKey',
       'MonthlyLoanPayment', 'LP_CustomerPayments',
       'LP_CustomerPrincipalPayments', 'LP_InterestandFees', 'LP_ServiceFees',
       'LP_CollectionFees', 'LP_GrossPrincipalLoss', 'LP_NetPrincipalLoss',
       'LP_NonPrincipalRecoverypayments', 'PercentFunded', 'Recommendations',
       'InvestmentFromFriendsCount', 'InvestmentFromFriendsAmount',
       'Investors'],
      dtype='object')
```

[5]:
```
#getting the total number of row and columns for the dataset
loan_dt.shape
```

[5]: (113937, 81)

[6]:
```
#getting sum of all null values present across all columns.
loan_dt.isnull().sum()
```

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

[7]:
```
#getting  sum of duplicated rows for ListingKey
loan_dt['ListingKey'].duplicated().value_counts()
```

[7]:
```
False    113066
True        871
Name: ListingKey, dtype: int64
```

[8]:
```
#getting sum of duplcated rows ListingNumber
loan_dt['ListingNumber'].duplicated().sum()
```

[8]: 871

[9]:
```
#getting value count for ListingNumber
loan_dt['ProsperRating (numeric)'].value_counts()
```

[9]:
```
4.0    18345
5.0    15581
6.0    14551
3.0    14274
2.0     9795
1.0     6935
7.0     5372
Name: ProsperRating (numeric), dtype: int64
```

[10]:
```
#getting value count for ProsperRating (Alpha)
loan_dt['ProsperRating (Alpha)'].value_counts()
```

[10]:
```
C     18345
B     15581
```

```
A     14551
D     14274
E      9795
HR     6935
AA     5372
Name: ProsperRating (Alpha), dtype: int64
```

[11]:
```
#getting sum of duplicated rows for ListingCreationDate
loan_dt['ListingCreationDate'].duplicated().value_counts()
```

[11]:
```
False    113064
True        873
Name: ListingCreationDate, dtype: int64
```

[12]:
```
#getting value count for LoanStatus
loan_dt['LoanStatus'].value_counts()
```

[12]:
```
Current                   56576
Completed                 38074
Chargedoff                11992
Defaulted                  5018
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
Cancelled                     5
Name: LoanStatus, dtype: int64
```

[13]:
```
#getting value count for BorrowerState
loan_dt['BorrowerState'].value_counts()
```

[13]:
```
CA    14717
TX     6842
NY     6729
FL     6720
IL     5921
GA     5008
OH     4197
MI     3593
VA     3278
NJ     3097
NC     3084
WA     3048
PA     2972
```

```
MD      2821
MO      2615
MN      2318
MA      2242
CO      2210
IN      2078
AZ      1901
WI      1842
OR      1817
TN      1737
AL      1679
CT      1627
SC      1122
NV      1090
KS      1062
KY       983
OK       971
LA       954
UT       877
AR       855
MS       787
NE       674
ID       599
NH       551
NM       472
RI       435
HI       409
WV       391
DC       382
MT       330
DE       300
VT       207
AK       200
SD       189
IA       186
WY       150
ME       101
ND        52
Name: BorrowerState, dtype: int64
```

[14]:
```
#getting value count for Occupation
loan_dt['Occupation'].value_counts()
```

[14]:
```
Other                          28617
Professional                   13628
Computer Programmer             4478
Executive                       4311
```

```
Teacher                             3759
                                  …
Dentist                               68
Student - College Freshman            41
Student - Community College           28
Judge                                 22
Student - Technical School            16
Name: Occupation, Length: 67, dtype: int64
```

[15]:
```
#getting value count for EmploymentStatus
loan_dt['EmploymentStatus'].value_counts()
```

[15]:
```
Employed         67322
Full-time        26355
Self-employed     6134
Not available     5347
Other             3806
Part-time         1088
Not employed       835
Retired            795
Name: EmploymentStatus, dtype: int64
```

[16]:
```
#getting value count for GroupKey
loan_dt['GroupKey'].value_counts()
```

[16]:
```
783C3371218786870A73D20    1140
3D4D3366260257624AB272D     916
6A3B336601725506917317E     698
FEF83377364176536637E50     611
C9643379247860156A00EC0     342
                           …
3AC33365576889313A6722F       1
199A33716841673327BF690       1
398233659571461105A2C60       1
49753420463763105C8092D       1
D1413413671123312FAD936       1
Name: GroupKey, Length: 706, dtype: int64
```

[17]:
```
#getting value count for FirstRecordedCreditLine
loan_dt['FirstRecordedCreditLine'].value_counts()
```

[17]:
```
1993-12-01 00:00:00    185
1994-11-01 00:00:00    178
1995-11-01 00:00:00    168
1990-04-01 00:00:00    161
1995-03-01 00:00:00    159
                     …
```

```
1979-01-05 00:00:00      1
1978-09-11 00:00:00      1
1980-03-10 00:00:00      1
1981-07-18 00:00:00      1
2006-09-10 00:00:00      1
Name: FirstRecordedCreditLine, Length: 11585, dtype: int64
```

[18]:
```
#getting value count for IncomeRange
loan_dt['IncomeRange'].value_counts()
```

[18]:
```
$25,000-49,999    32192
$50,000-74,999    31050
$100,000+         17337
$75,000-99,999    16916
Not displayed      7741
$1-24,999          7274
Not employed        806
$0                  621
Name: IncomeRange, dtype: int64
```

[19]:
```
#getting value count for LoanOriginationQuarter
loan_dt['LoanOriginationQuarter'].value_counts()
```

[19]:
```
Q4 2013    14450
Q1 2014    12172
Q3 2013     9180
Q2 2013     7099
Q3 2012     5632
Q2 2012     5061
Q1 2012     4435
Q4 2012     4425
Q2 2008     4344
Q4 2011     3913
Q1 2013     3616
Q3 2008     3602
Q2 2007     3118
Q3 2011     3093
Q1 2007     3079
Q1 2008     3074
Q3 2007     2671
Q4 2007     2592
Q2 2011     2478
Q4 2006     2403
Q3 2006     1934
Q1 2011     1744
Q4 2010     1600
Q2 2010     1539
```

```
Q4 2009     1449
Q3 2010     1270
Q2 2006     1254
Q1 2010     1243
Q3 2009      585
Q4 2008      532
Q1 2006      315
Q4 2005       22
Q2 2009       13
Name: LoanOriginationQuarter, dtype: int64
```

[20]:
```
#getting value count for FirstRecordedCreditLine
loan_dt['FirstRecordedCreditLine'].value_counts()
```

[20]:
```
1993-12-01 00:00:00    185
1994-11-01 00:00:00    178
1995-11-01 00:00:00    168
1990-04-01 00:00:00    161
1995-03-01 00:00:00    159
                      …
1979-01-05 00:00:00      1
1978-09-11 00:00:00      1
1980-03-10 00:00:00      1
1981-07-18 00:00:00      1
2006-09-10 00:00:00      1
Name: FirstRecordedCreditLine, Length: 11585, dtype: int64
```

[21]:
```
#Describing a dataset to get basic statistical information.
loan_dt.describe()
```

[21]:
```
       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]
```

[22]:
```
#Getting info() about the dataset.
loan_dt.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
```

### Quality

#### `prosperLoanData` table

- Duplicate data i.e there are 871 duplicated data in the ListingKey column which is a unique key.
- Some categorical ordinal data have missing data

- Some columns have missing data.

#### Tidiness

#### prosperLoanData table

- Many columns are not needed for this particular analysis. i.e the needed columns are 'ListingKey', 'Term', 'LoanStatus', 'BorrowerState', 'Occupation', 'EmploymentStatus', 'ProsperRating'

### DATA CLEANING

[23]:
```
#Creating a data copy
loan_dt_clean = loan_dt.copy()
```

#### Define

#### (Duplicate data i.e there are 871 duplicated data in the ListingKey column which is a unique key.)

- Use the pd.drop_duplicated() to remove duplicate keys.

#### Code

[24]:
```
#Dropping duplicate values.
loan_dt_clean = loan_dt_clean.drop_duplicates(subset=['ListingKey'])
```

#### Test

[25]:
```
#Testing to see if duplicate values have been dropped
loan_dt_clean ['ListingKey'].duplicated().value_counts()
```

[25]:
```
False    113066
Name: ListingKey, dtype: int64
```

#### Define

#### (Some categorical ordinal data have missing data.)

#### Code

[26]:
```
#Using fillna() to replace all null values in ProsperRating (numeric) with 0.0
loan_dt_clean ['ProsperRating (numeric)'] = loan_dt_clean ['ProsperRating␣
↪(numeric)'].fillna(0.0)

#using the loc[] to replace every 0.0 in ProsperRating (numeric) with No Rating␣
↪in ProsperRating (Alpha).
loan_dt_clean.loc[(loan_dt_clean['ProsperRating (numeric)'] == 0.0),␣
↪'ProsperRating (Alpha)'] = 'No rating'
```

**Test**

[27]:
```
#Testing to see if there are still null values
loan_dt_clean['ProsperRating (Alpha)'].value_counts()
```

[27]:
```
No rating    29084
C            18096
B            15368
A            14390
D            14170
E             9716
HR            6917
AA            5325
Name: ProsperRating (Alpha), dtype: int64
```

**Define**

**(Many columns are not needed for this particular analysis. i.e the needed columns are 'ListingKey', 'Term', 'LoanStatus', 'BorrowerState', 'Occupation', 'EmploymentStatus', 'ProsperRating (Alpha)', 'LoanOriginalAmount', 'BorrowerAPR', 'StatedMonthlyIncome', 'IsBorrowerHomeowner', 'BorrowerRate', 'IncomeRange'.)**

- Drop all columns execpt from the mentioned columns

**Code**

[28]:
```
#Adding only columns needed to the loan_dt_clean dataset
loan_dt_clean = loan_dt_clean[['ListingKey', 'Term', 'LoanStatus',␣
↪'BorrowerState', 'EmploymentStatus', 'ProsperRating (Alpha)',␣
↪'LoanOriginalAmount', 'BorrowerAPR', 'StatedMonthlyIncome',␣
↪'LoanOriginationDate', 'IsBorrowerHomeowner', 'BorrowerRate', ␣
↪'IncomeRange']]
```

**Test**

[29]:
```
#Checking the info() of the dataset
loan_dt_clean.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 113066 entries, 0 to 113936
Data columns (total 13 columns):
 #   Column                 Non-Null Count   Dtype
---  ------                 --------------   -----
 0   ListingKey             113066 non-null  object
 1   Term                   113066 non-null  int64
 2   LoanStatus             113066 non-null  object
 3   BorrowerState          107551 non-null  object
 4   EmploymentStatus       110811 non-null  object
 5   ProsperRating (Alpha)  113066 non-null  object
 6   LoanOriginalAmount     113066 non-null  int64
```

```
 7   BorrowerAPR            113041 non-null  float64
 8   StatedMonthlyIncome    113066 non-null  float64
 9   LoanOriginationDate    113066 non-null  object
 10  IsBorrowerHomeowner    113066 non-null  bool
 11  BorrowerRate           113066 non-null  float64
 12  IncomeRange            113066 non-null  object
dtypes: bool(1), float64(3), int64(2), object(7)
memory usage: 11.3+ MB
```

[30]:
```
#Dropping null values in 'BorrowerState' and 'EmploymentStatus'
loan_dt_clean= loan_dt_clean.dropna(subset=['BorrowerState'])
loan_dt_clean= loan_dt_clean.dropna(subset=['EmploymentStatus'])
```

[31]:
```
#Checking for null values
loan_dt_clean['BorrowerState'].isnull().sum()
#getting info() about loan_dt_clean
loan_dt_clean.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 106683 entries, 0 to 113936
Data columns (total 13 columns):
 #   Column                 Non-Null Count   Dtype
---  ------                 --------------   -----
 0   ListingKey             106683 non-null  object
 1   Term                   106683 non-null  int64
 2   LoanStatus             106683 non-null  object
 3   BorrowerState          106683 non-null  object
 4   EmploymentStatus       106683 non-null  object
 5   ProsperRating (Alpha)  106683 non-null  object
 6   LoanOriginalAmount     106683 non-null  int64
 7   BorrowerAPR            106683 non-null  float64
 8   StatedMonthlyIncome    106683 non-null  float64
 9   LoanOriginationDate    106683 non-null  object
 10  IsBorrowerHomeowner    106683 non-null  bool
 11  BorrowerRate           106683 non-null  float64
 12  IncomeRange            106683 non-null  object
dtypes: bool(1), float64(3), int64(2), object(7)
memory usage: 10.7+ MB
```

[32]:
```
#Converting to data type for LoanOriginationDate to datetime
loan_dt_clean['LoanOriginationDate'] = pd.
 ↪to_datetime(loan_dt_clean['LoanOriginationDate'])
#Extracting year from the datetime series
loan_dt_clean['year'] = loan_dt_clean['LoanOriginationDate'].dt.year
# creating month column with an Index of formatted strings specified by the␣
 ↪date_format using the dt.strftime('%b ') function
loan_dt_clean['month']= loan_dt_clean['LoanOriginationDate'].dt.strftime('%b')
```

```
loan_dt_clean.to_csv("loan_dt_cleaned", index = False)
```

[33]:
```
#checking to see the new columns created.
loan_dt_clean.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 106683 entries, 0 to 113936
Data columns (total 15 columns):
 #   Column                Non-Null Count   Dtype
---  ------                --------------   -----
 0   ListingKey            106683 non-null  object
 1   Term                  106683 non-null  int64
 2   LoanStatus            106683 non-null  object
 3   BorrowerState         106683 non-null  object
 4   EmploymentStatus      106683 non-null  object
 5   ProsperRating (Alpha)  106683 non-null  object
 6   LoanOriginalAmount    106683 non-null  int64
 7   BorrowerAPR           106683 non-null  float64
 8   StatedMonthlyIncome   106683 non-null  float64
 9   LoanOriginationDate   106683 non-null  datetime64[ns]
 10  IsBorrowerHomeowner   106683 non-null  bool
 11  BorrowerRate          106683 non-null  float64
 12  IncomeRange           106683 non-null  object
 13  year                  106683 non-null  int64
 14  month                 106683 non-null  object
dtypes: bool(1), datetime64[ns](1), float64(3), int64(3), object(7)
memory usage: 12.3+ MB
```

## 0.2 Exploratory Data Analysis

### 0.2.1 Defining some functions to allow for re-use

[34]:
```
def Prosper_countplot (x,y,df,x_data,index,angle,x_label,y_label,val):
    '''This function helps to create a countplot and require the following␣
↪variables, 'x,y,df,x_data,index,angle,x_label,y_label,val' '''
    plt.figure(figsize = (x,y))
    base_color = sns.color_palette()[index]
    ax = sns.countplot(data = df, x = x_data, color = base_color)
    plt.bar_label(ax.containers[0],size=val)
    plt.xticks(rotation= angle)
    plt.xlabel(x_label)
    plt.ylabel(y_label);

def Prosper_pie (column):
    '''This function helps to create a pie chart and it requires the variable␣
↪'column' '''
    sorted_counts = loan_dt_clean[column].value_counts()
```

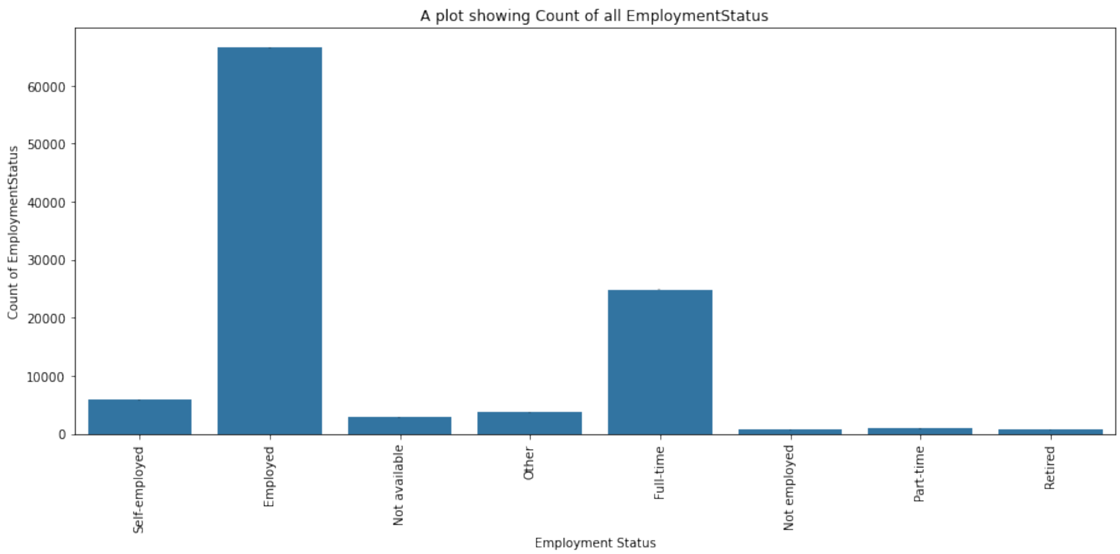
```
    plt.pie(sorted_counts, labels = sorted_counts.index, autopct='%2.2f%%',␣
↪startangle = 90, counterclock = False, wedgeprops = {'width' : 0.4} );
     # We have the used option `Square`.
     # Though, you can use either one specified here - https://matplotlib.org/
↪api/_as_gen/matplotlib.pyplot.axis.html?
↪highlight=pyplot%20axis#matplotlib-pyplot-axis
    plt.axis('square');

def Prosper_distplot (x, y, column, index, angle, no_of_bins, Bool, x_label,␣
↪y_label ):
    '''This function helps to create a histogram and it requires the variables ␣
↪'x, y, column, index, angle, no_of_bins, Bool, x_label, y_label' '''
    plt.figure(figsize=(x,y))
    base_color = sns.color_palette()[index]
    ax = sns.distplot(loan_dt_clean[column], color = base_color, bins =␣
↪no_of_bins, kde = Bool)
    plt.xticks(rotation=angle)
    plt.xlabel(x_label)
    plt.ylabel(y_label);
```

### 0.2.2 Univariate Plot

**What is the employment status of most of Prospers clients**

- A larger percentage of them are employed, a good number of them are full time eployees while the rest of them are either nopartime retired or not employed.

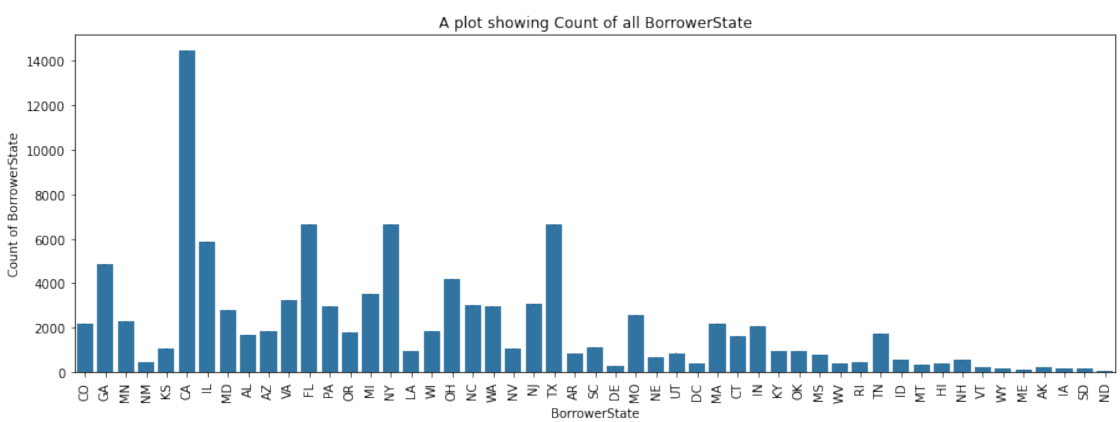
[50]:
```
# calling the Countplot() function to show a count of the employmentstatus all␣
↪through the dataset.
Employment_Status = Prosper_countplot(15,6,loan_dt_clean, 'EmploymentStatus',␣
↪0,90, 'Employment Status','Count of EmploymentStatus',0 )
plt.title('A plot showing Count of all EmploymentStatus');
```




**which of the state have the highest number of borrowers.**

- Califonia CA seems to be leading the pack with more than 14000 borrowers.

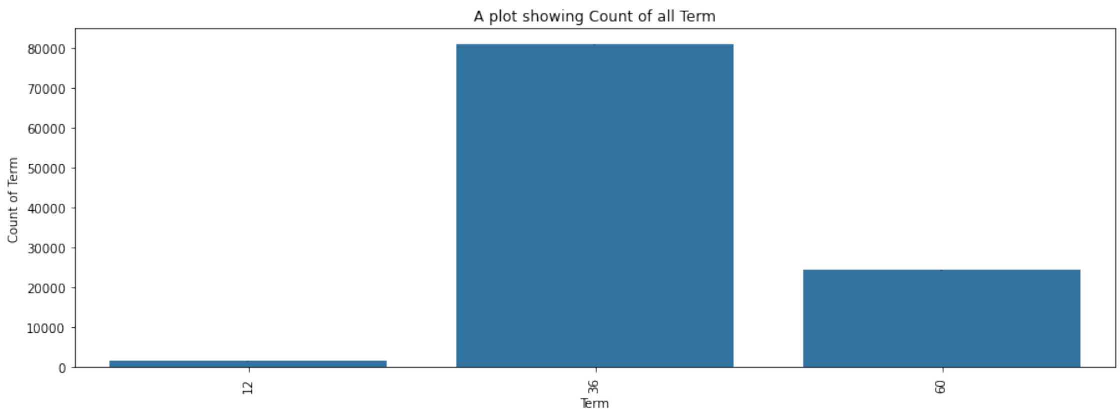
```
[36]: # Using a Countplot function to show a count of distinct BorrowerState all
      ↪through the dataset.
      Employment_Status = Prosper_countplot(15,5,loan_dt_clean, 'BorrowerState',
      ↪0,90, 'BorrowerState','Count of BorrowerState',0)
      plt.title('A plot showing Count of all BorrowerState');
```




**Which of the Terms has the highest Ocurrence**

- 36 Terms is clearly the most occuring followed by 60 and the least is 30 Term.

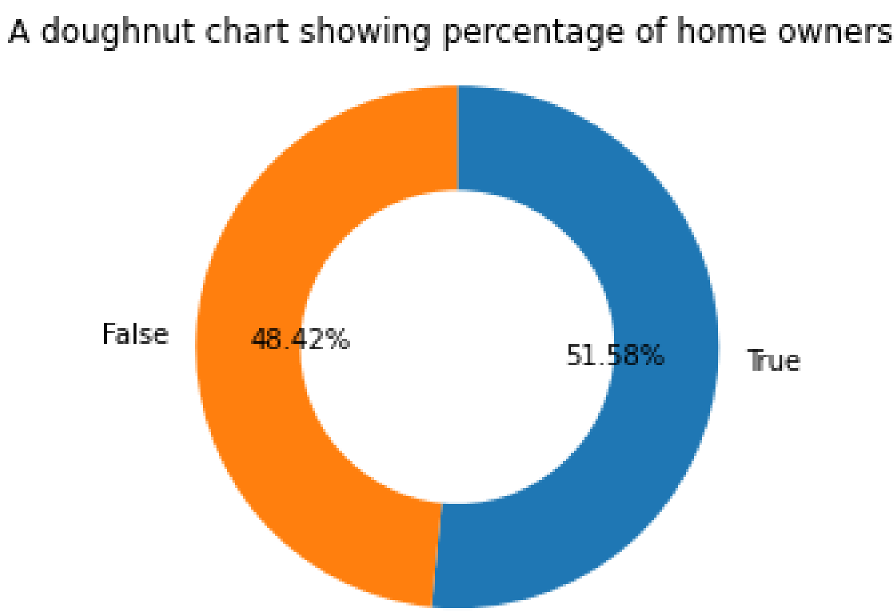
[37]:
```
#Ploting a barchart using the countplot() to show the number of distinct 'Term'␣
↪across the dataset.
Employment_Status = Prosper_countplot(15,5,loan_dt_clean, 'Term', 0,90,␣
↪'Term','Count of Term',0)
plt.title('A plot showing Count of all Term');
```




**what percentage of the borrowers are home owners.**

- Only 51.58% of the Borrowers are Home owners.

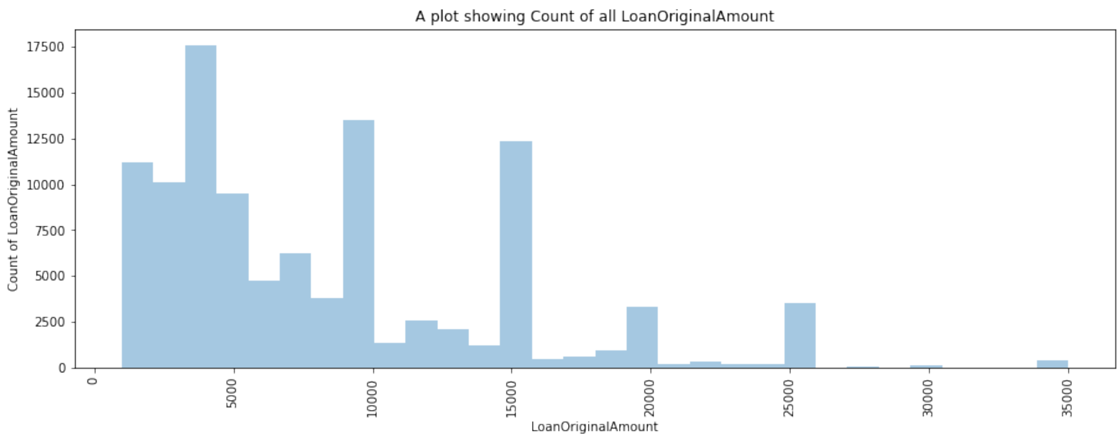
[38]:
```
#Calling the proper_pie function to get the percentage of borrowers that are␣
↪homeowners.
Home_owner = Prosper_pie('IsBorrowerHomeowner')
plt.title('A doughnut chart showing percentage of home owners ');
```



**what kind of distribution is LoanOriginalAmount.**

- LoanOriginalAmount is a multimodal distribution and starts from 1000, with its highest peak at about 17,500.
- This shows that the amount the borrowers collected is widely distributed, between 1000 and slight close to 3500 dollars

[39]:
```
#Using the distplot function to plot a histogram showing the the distribution␣
↪of LoanOriginalAmount across the dataset.
Loan_original_amount = Prosper_distplot (15, 5, 'LoanOriginalAmount', 0, 90,␣
↪30, False, 'LoanOriginalAmount', 'Count of LoanOriginalAmount')
plt.title('A plot showing Count of all LoanOriginalAmount');
```

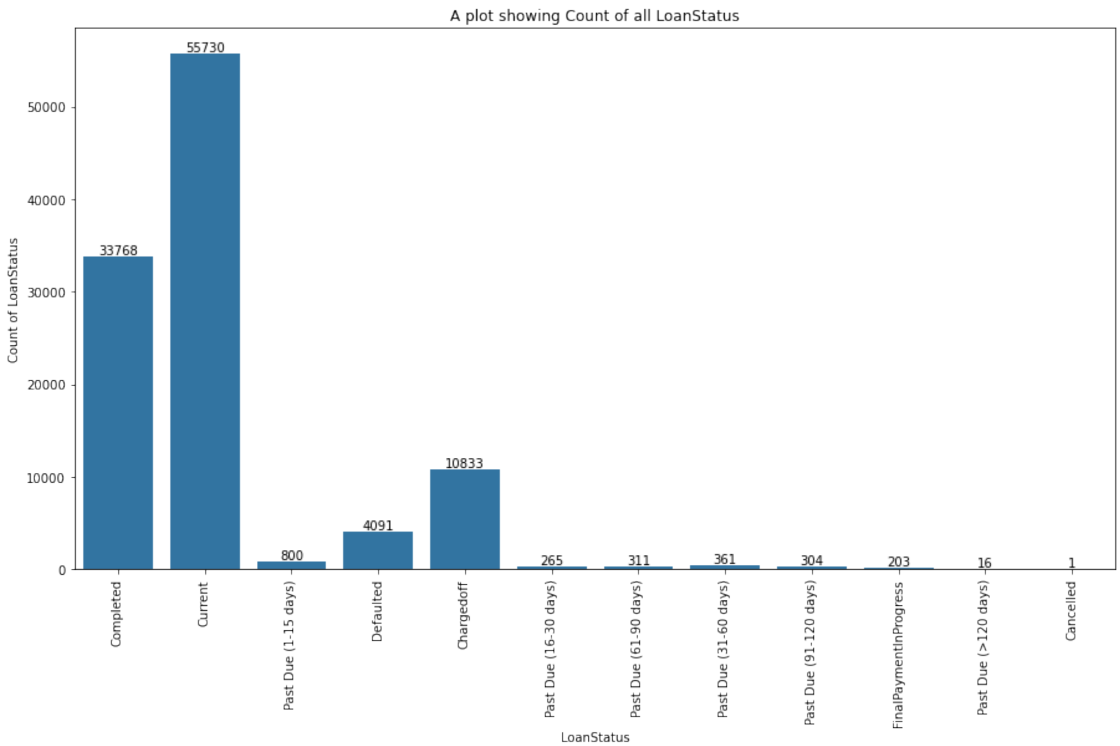



**Which of the loan status is most Dominant.**

- Current and Completed are the most dominant.

- 10.2% of the entire loan has been charged off as bad debt.

[40]:
```
# Creating a bar chart using the countplot to show count on loanstatus
#Increasing the plot size.
Employment_Status = Prosper_countplot(15,8,loan_dt_clean, 'LoanStatus', 0,90,␣
↪'LoanStatus','Count of LoanStatus',10)
plt.title('A plot showing Count of all LoanStatus');

# Percentage charged off as bad debt.
# status = loan_dt_clean['LoanStatus'].count()
# gain = 10833/status * 100
# gain = 10.154382610162818
```

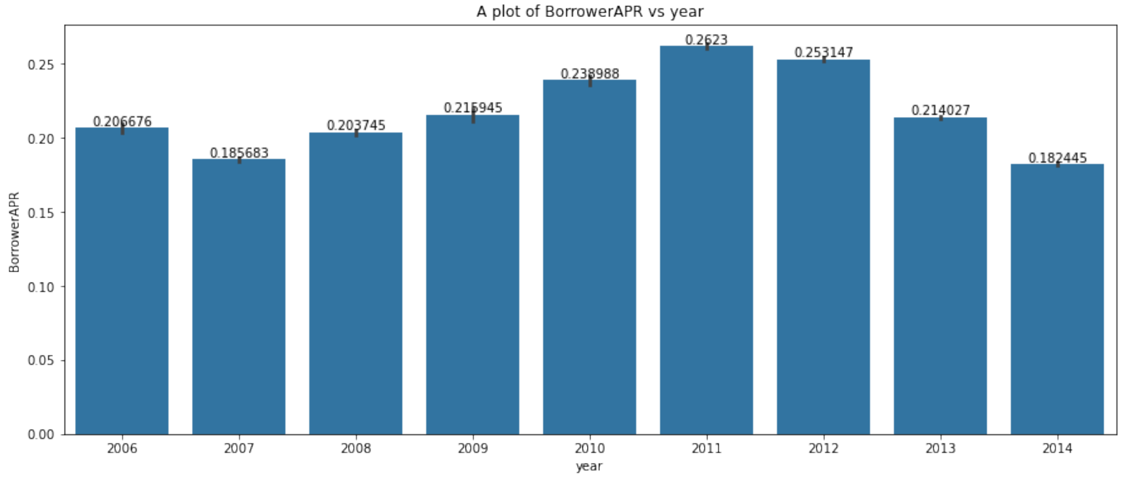



### 0.2.3 Bivariate Analysis

**What is the relationship between year and BorrowerAPR**

- The distribution shows that 2006 had 0.2% with a slight fall to 2007 and a gradual increase till 2011 which was the highest APR % rate about 0.25%. A steady fall occurred from 2012 to 2014.

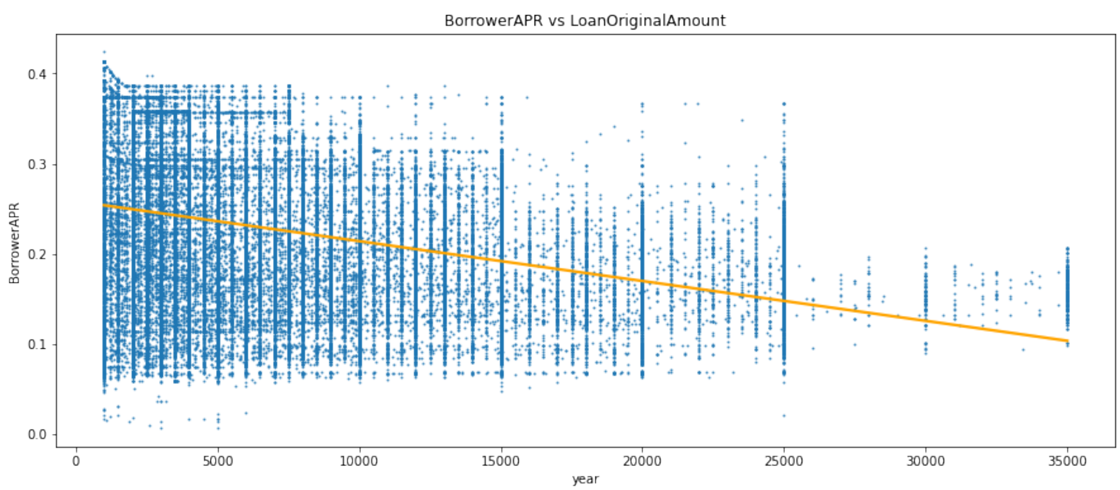
[41]:
```
# creating a barplot to show distribution of BorrowerAPR across the years.
base_color = sns.color_palette()[0]
plt.figure(figsize= (15,6))
ax = sns.barplot(data = loan_dt_clean, x = 'year', y = 'BorrowerAPR', color =␣
 ↪base_color )
#to label bars with their respective values.
for i in ax.containers:
    ax.bar_label(i,)

plt.title('A plot of BorrowerAPR vs year')
plt.xlabel('year')
plt.ylabel('BorrowerAPR');
```




**What is the correlation between LoanOriginalAmount and BorrowerAPR**

- This plot shows a negative correlation between the borrowerAPR and LoanOriginalAmount the the range of borrowerAPR decrease with the increase of LoanOriginalAmount.

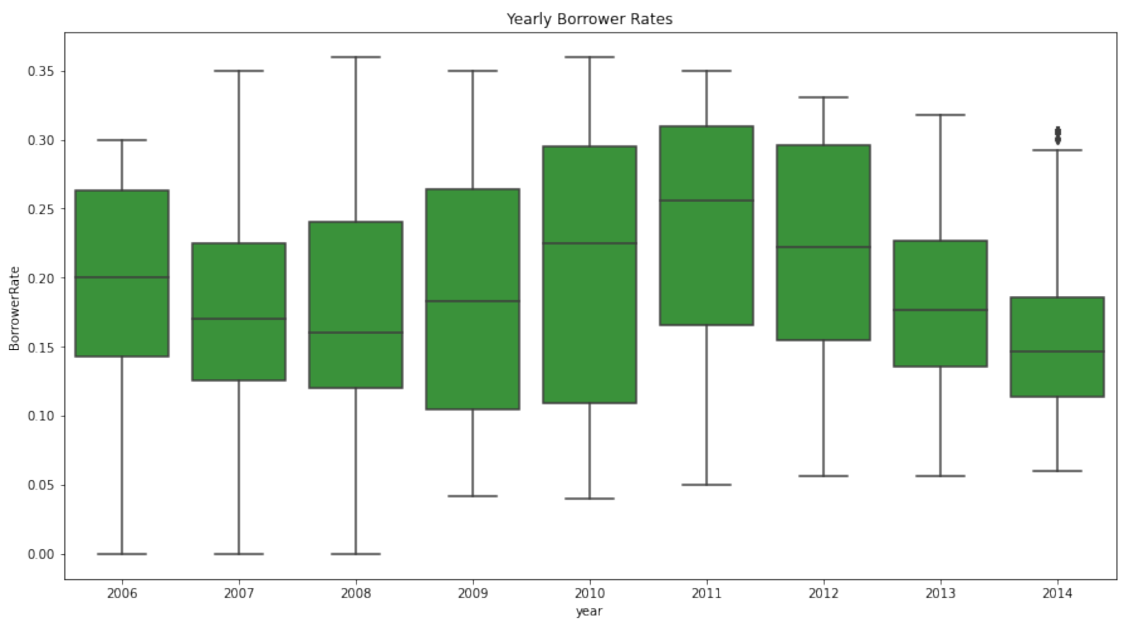
[42]:
```
#Using the regplot function to create a scatter plot showing correlation␣
 ↪between LoanOriginalAmount and BorrowerAPR
plt.figure(figsize = [15, 6])
sns.regplot(data = loan_dt_clean, x = 'LoanOriginalAmount', y = 'BorrowerAPR',␣
 ↪scatter_kws={'s':1}, line_kws={'color':'Orange'})
plt.title('BorrowerAPR vs LoanOriginalAmount')
plt.xlabel('year')
plt.ylabel('BorrowerAPR');
```



### What is the yearly trend of borrowerRates?

- It is interesting to see that the median of the distribution(borrowerRates) goes high up after 2008 until 2011. And since then, there has been a decline in the median value for borrowerRates until 2014.

[43]:
```
# Creating a boxplot to show the relationship between BorrowerRate across the␣
↪years.
plt.figure(figsize=[15, 8]);
base_color = sns.color_palette()[2];
sns.boxplot(data =loan_dt_clean, x = 'year', y = 'BorrowerRate', color =␣
↪base_color);
plt.title('Yearly Borrower Rates');
```

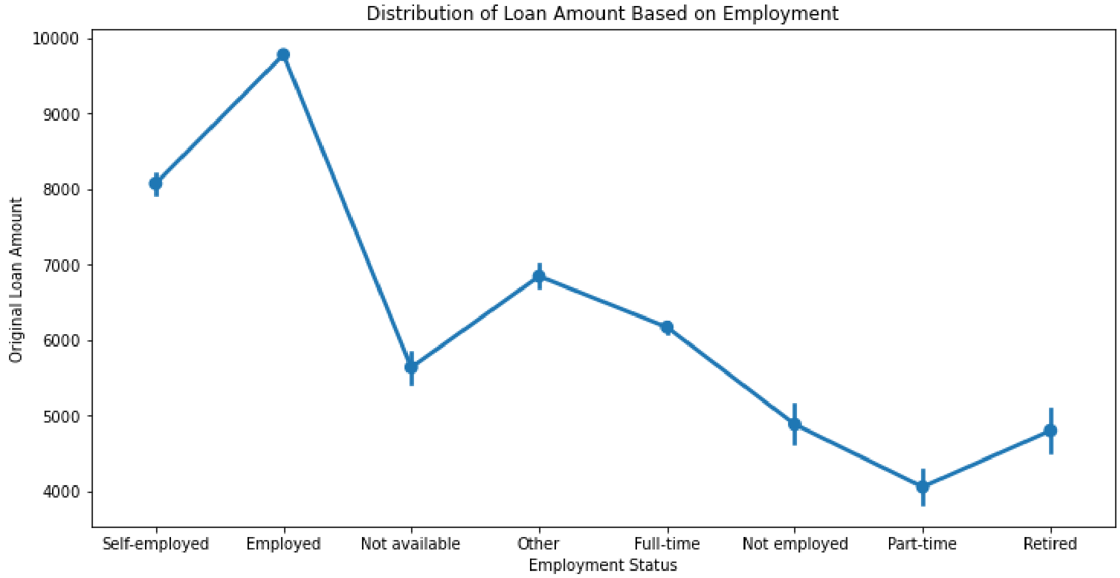



### Does the Employment Status affect the Amount of Loan Taken ?

- It can be seen from the pointplot that the borrowers who are Employed, haves Loans of Higher Amounts when compared to borrowers with other categories of employment.
- Also borrowers who are Retired & Not Employed, have taken loans of Lower Amounts when compared with other Employment categories.

[44]:
```
#Using the pointplot() to show how Does the Employment Status affect the Amount␣
↪of Loan Taken.
fig = plt.figure(figsize=(12,6))
sns.pointplot(y='LoanOriginalAmount', x='EmploymentStatus', data=loan_dt_clean)
plt.title('Distribution of Loan Amount Based on Employment')
plt.xlabel('Employment Status')
plt.ylabel('Original Loan Amount')
```

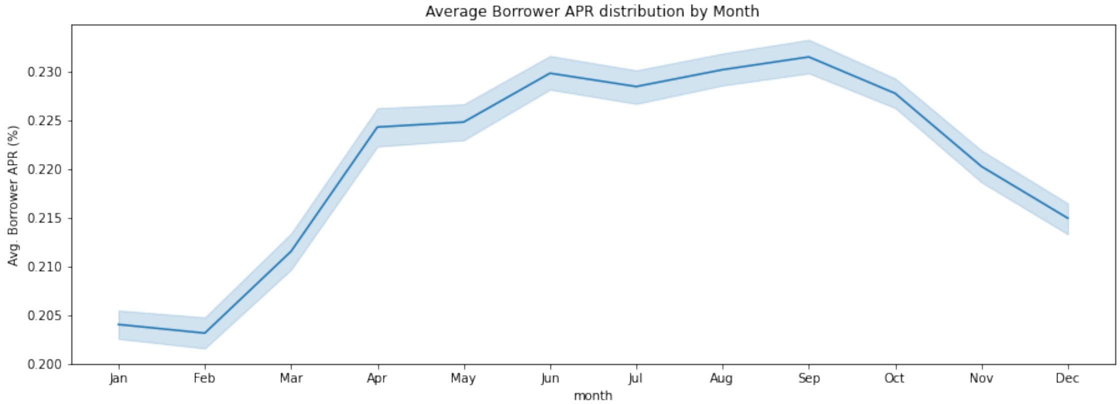
```
plt.show()
```




### What is the average borrower APR distribution by Month

- There is only a slightly noticeable change from jan to feb and a steady increase until April which maintains a constant rate till may, there are noticeable increment from may till september after which we experience a rapid declination in the BorrowerAPR value.

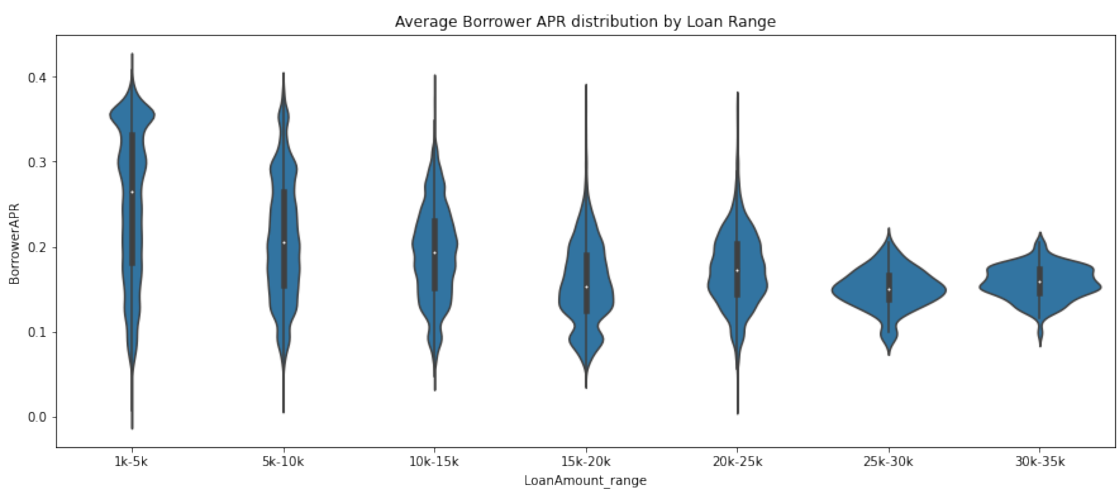
[45]:
```
# setting order categories by month
month=['Jan','Feb','Mar','Apr','May','Jun','Jul','Aug','Sep','Oct','Nov','Dec']
# ordering it into a categorical type data
set_m = pd.api.types.CategoricalDtype(ordered=True, categories=month)
# setting it into the prosper rating
loan_dt_clean['month'] = loan_dt_clean['month'].astype(set_m)
plt.figure(figsize = [15, 5])
# creating a line plot to show the distribution
sns.lineplot(data=loan_dt_clean,x='month',y='BorrowerAPR');
plt.ylabel('Avg. Borrower APR (%)');
plt.title('Average Borrower APR distribution by Month');
```




### How does LoanAmount_range affect BorrowerAPR

- There is a steady declination in the maen rate from 1k-15k then produces an irregular trend from 15k-25k, then goes to show that the highest LoanAmount_range experience a significant drop in there mean rate.

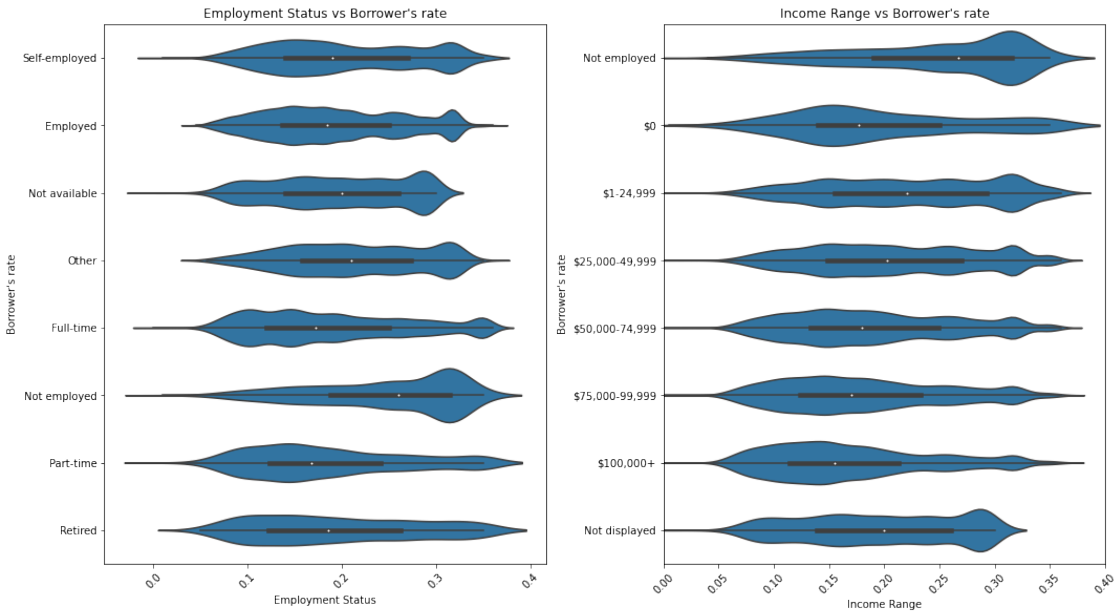
[46]:
```
# using the .cut function to create a new column for loan amount range
loan_dt_clean['LoanAmount_range']=pd.cut(loan_dt_clean.
↪LoanOriginalAmount,bins=[1000,5000,10000,15000,20000,25000,30000,35000],labels=['1k-5k','5k
plt.figure(figsize = [15, 6])
base_color = sns.color_palette()[0]
# plotting the violinplot
sns.violinplot(data=loan_dt_clean, x='LoanAmount_range', y='BorrowerAPR',␣
↪color=base_color);
plt.title('Average Borrower APR distribution by Loan Range');
```



**BorrowerRate vs. Employmentstatus and BorrowerRate vs. IncomeRange**

- individuals who are employed don't necessarily have lower BorrowerRate. But unemployment does have a higher median BorrowerRate and higher concentrate of frequency are above the median. Looking at the income range plot, there is a slight trend that the higher the income range is,the lower median BorrowerRate.

[47]:
```
# creating a boxplot clearly showing the median distribution between␣
↪BorrowerRate vs. Employmentstatus and BorrowerRate vs. IncomeRange

plt.figure(figsize=[15, 8.27]);
colorChoice = sns.color_palette()[0]

plt.subplot(1,2,1)
sns.violinplot(data = loan_dt_clean, y = 'EmploymentStatus', x =␣
↪'BorrowerRate', color=colorChoice);
plt.title('Employment Status vs Borrower\'s rate');
plt.ylabel('Borrower\'s rate');
plt.xlabel('Employment Status');
plt.xticks(rotation=45);

plt.subplot(1,2,2)
income_order = ['Not employed', '$0', '$1-24,999',␣
↪'$25,000-49,999','$50,000-74,999', '$75,000-99,999', '$100,000+', 'Not␣
↪displayed']
sns.violinplot(data = loan_dt_clean, y = 'IncomeRange', x = 'BorrowerRate',␣
↪color=colorChoice, order = income_order);
plt.title('Income Range vs Borrower\'s rate');
plt.ylabel('Borrower\'s rate');
plt.xlabel('Income Range');
plt.xticks(rotation=45);
plt.xlim(0,0.4);

plt.tight_layout()
```

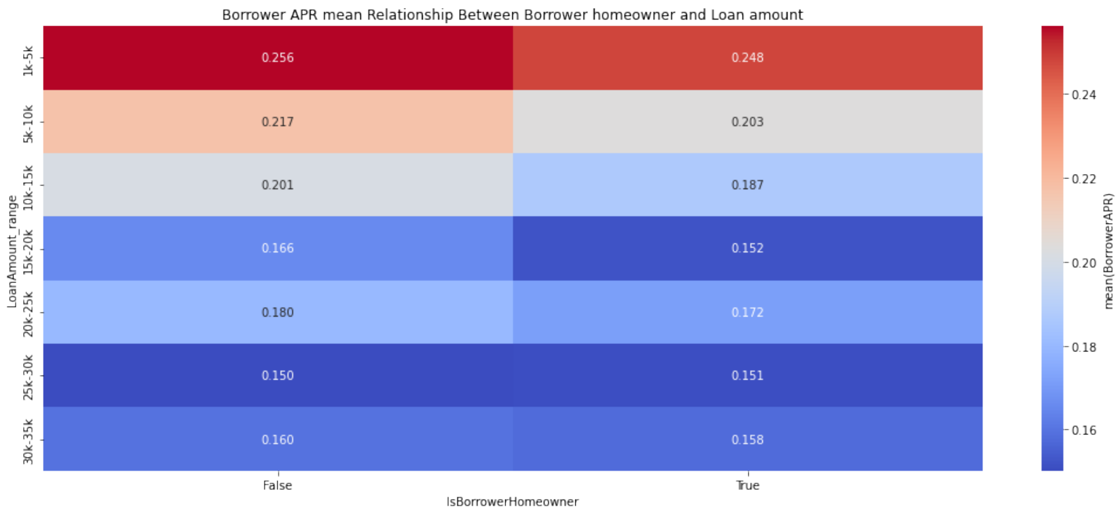



### 0.2.4 Multivariate Analysis

**How does the Borrower APR affect LoanAmount_range and Homeownership**

- LoanAmount_range has a negative corellation with Borrower APR while is no major effect Borrower APR on Homeownership

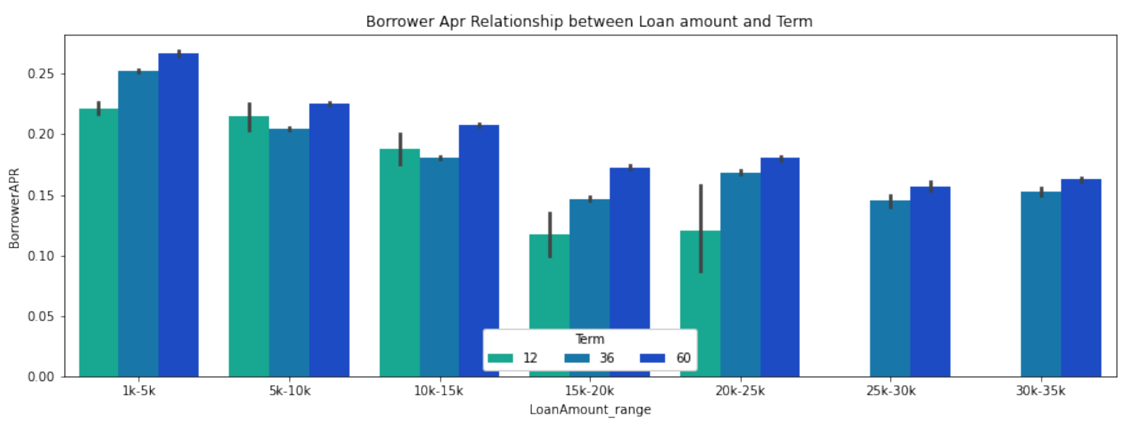
[48]:
```
#Using the heatmap() to show the Relationship amongs the Borrower APR affect␣
↪LoanAmount_range and Homeownership
group=loan_dt_clean.groupby(['LoanAmount_range','IsBorrowerHomeowner']).
↪mean()['BorrowerAPR']
group=group.reset_index(name='BorrowerAPR_mean')
group=group.pivot(index = 'LoanAmount_range', columns = 'IsBorrowerHomeowner',␣
↪values = 'BorrowerAPR_mean')
plt.figure(figsize = [18,7 ]);
sns.heatmap(group,annot = True, fmt = '.3f',cbar_kws = {'label' :␣
↪'mean(BorrowerAPR)'}, cmap="coolwarm");
plt.title('Borrower APR mean Relationship Between Borrower homeowner and Loan␣
↪amount');
```




**Does the term have a significance effect on the LoanAmount_range and BorrowerAPR**

- The barplots shows that the longer term(60 months) had higher borrowerAPR. which means the longer the term the individual collect the loan the more likely the BorrowerAPR increases.

[49]:
```
# creating a bar plot for the distribution
plt.figure(figsize = [15, 5])
Axi = sns.barplot(data=loan_dt_clean, x='LoanAmount_range', y='BorrowerAPR',␣
 ↪hue='Term', palette="winter_r")
Axi.legend(loc = 8, ncol = 3, framealpha = 1, title = 'Term')
plt.title("Borrower Apr Relationship between Loan amount and Term");
```



## 0.3 Conclusion

From this analysis, individuals who are employed don't necessarily have lower BorrowerRate. But unemployment does have a higher median BorrowerRate and higher concentrate of frequency are above the median. Looking at the income range plot, there is a slight trend that the higher the income range is,the lower median BorrowerRate. Also individuals who are employed don't necessarily have lower BorrowerRate. But unemployment does have a higher median BorrowerRate and higher concentrate of frequency are above the median. Looking at the income range plot, there is a slight trend that the higher the income range is,the lower median BorrowerRate.