prosperLoanData

October 2, 2022

1 Loan Data (from Prosper) Exploration

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Multivariate Exploration Summary

Conclusions

Feedback

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

I don't know now but I expect to find out what features can explain loans interest.

What factors affect a loan's outcome status?

What affects the borrower's APR or interest rate?

Are there differences between loans depending on how large the original loan amount was?

Preliminary Wrangling

This data set contains 113,937 loans with 81 variables on each loan, including loan amount, borrower rate (or interest rate), current loan status, borrower income, and many others.

- This data dictionary explains the variables in the data set.
- You are not expected to explore all of the variables in the dataset! Focus your exploration on about 10-15 of them.

[1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
```

unicodedecodeerror-utf-8-codec-while-reading-a-csv-file

[2]:
```
prosperLoanData = pd.read_csv('prosperLoanData.csv', encoding='utf-8',␣
 ↪engine='python')
```

We need to expand the number of displayable columns so it fits the number of columns of the DataFrame which is 81.

how-do-i-expand-the-output-display-to-see-more-columns-of-a-pandas-dataframe

[3]:
```
pd.set_option('display.max_rows', 50)
pd.set_option('display.max_columns', 81)
#pd.set_option('display.width', 1000)
```

[4]:
```
prosperLoanData.head(10)
```

[4]:
```
                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  EstimatedEffectiveYield  EstimatedLoss  \
0        0.1580       0.1380                      NaN            NaN
1        0.0920       0.0820                  0.07960         0.0249
2        0.2750       0.2400                      NaN            NaN
3        0.0974       0.0874                  0.08490         0.0249
4        0.2085       0.1985                  0.18316         0.0925
5        0.1314       0.1214                  0.11567         0.0449
6        0.2712       0.2612                  0.23820         0.1275
7        0.2019       0.1919                  0.17830         0.0799
8        0.0629       0.0529                  0.05221         0.0099
9        0.0629       0.0529                  0.05221         0.0099

   EstimatedReturn  ProsperRating (numeric) ProsperRating (Alpha)  \
0              NaN                      NaN                   NaN
1          0.05470                      6.0                     A
2              NaN                      NaN                   NaN
3          0.06000                      6.0                     A
4          0.09066                      3.0                     D
5          0.07077                      5.0                     B
6          0.11070                      2.0                     E
7          0.09840                      4.0                     C
8          0.04231                      7.0                    AA
9          0.04231                      7.0                    AA
```

```
   ProsperScore  ListingCategory (numeric) BorrowerState      Occupation  \
0           NaN                          0            CO           Other   
1           7.0                          2            CO    Professional   
2           NaN                          0            GA           Other   
3           9.0                         16            GA   Skilled Labor   
4           4.0                          2            MN       Executive   
5          10.0                          1            NM    Professional   
6           2.0                          1            KS  Sales - Retail   
7           4.0                          2            CA         Laborer   
8           9.0                          7            IL    Food Service   
9          11.0                          7            IL    Food Service   

  EmploymentStatus  EmploymentStatusDuration  IsBorrowerHomeowner  \
0    Self-employed                       2.0                 True   
1         Employed                      44.0                False   
2    Not available                       NaN                False   
3         Employed                     113.0                 True   
4         Employed                      44.0                 True   
5         Employed                      82.0                 True   
6         Employed                     172.0                False   
7         Employed                     103.0                False   
8         Employed                     269.0                 True   
9         Employed                     269.0                 True   

   CurrentlyInGroup                GroupKey            DateCreditPulled  \
0              True                     NaN  2007-08-26 18:41:46.780000000   
1             False                     NaN            2014-02-27 08:28:14   
2              True  783C3371218786870A73D20  2007-01-02 14:09:10.060000000   
3             False                     NaN            2012-10-22 11:02:32   
4             False                     NaN            2013-09-14 18:38:44   
5             False                     NaN            2013-12-14 08:26:40   
6             False                     NaN            2013-04-12 09:52:53   
7             False                     NaN            2013-05-05 06:49:25   
8             False                     NaN            2013-12-02 10:43:39   
9             False                     NaN            2013-12-02 10:43:39   

   CreditScoreRangeLower  CreditScoreRangeUpper FirstRecordedCreditLine  \
0                  640.0                  659.0     2001-10-11 00:00:00   
1                  680.0                  699.0     1996-03-18 00:00:00   
2                  480.0                  499.0     2002-07-27 00:00:00   
3                  800.0                  819.0     1983-02-28 00:00:00   
4                  680.0                  699.0     2004-02-20 00:00:00   
5                  740.0                  759.0     1973-03-01 00:00:00   
6                  680.0                  699.0     2000-09-29 00:00:00   
7                  700.0                  719.0     1999-02-25 00:00:00   
8                  820.0                  839.0     1993-04-01 00:00:00   
```

```
9                 820.0                 839.0     1993-04-01 00:00:00

   CurrentCreditLines  OpenCreditLines  TotalCreditLinespast7years  \
0                 5.0              4.0                        12.0
1                14.0             14.0                        29.0
2                 NaN              NaN                         3.0
3                 5.0              5.0                        29.0
4                19.0             19.0                        49.0
5                21.0             17.0                        49.0
6                10.0              7.0                        20.0
7                 6.0              6.0                        10.0
8                17.0             16.0                        32.0
9                17.0             16.0                        32.0

   OpenRevolvingAccounts  OpenRevolvingMonthlyPayment  InquiriesLast6Months  \
0                      1                         24.0                   3.0
1                     13                        389.0                   3.0
2                      0                          0.0                   0.0
3                      7                        115.0                   0.0
4                      6                        220.0                   1.0
5                     13                       1410.0                   0.0
6                      6                        214.0                   0.0
7                      5                        101.0                   3.0
8                     12                        219.0                   1.0
9                     12                        219.0                   1.0

   TotalInquiries  CurrentDelinquencies  AmountDelinquent  \
0             3.0                   2.0             472.0
1             5.0                   0.0               0.0
2             1.0                   1.0               NaN
3             1.0                   4.0           10056.0
4             9.0                   0.0               0.0
5             2.0                   0.0               0.0
6             0.0                   0.0               0.0
7            16.0                   0.0               0.0
8             6.0                   0.0               0.0
9             6.0                   0.0               0.0

   DelinquenciesLast7Years  PublicRecordsLast10Years  \
0                      4.0                       0.0
1                      0.0                       1.0
2                      0.0                       0.0
3                     14.0                       0.0
4                      0.0                       0.0
5                      0.0                       0.0
6                      0.0                       0.0
7                      0.0                       1.0
```

8	0.0	0.0
9	0.0	0.0

	PublicRecordsLast12Months	RevolvingCreditBalance	BankcardUtilization \
0	0.0	0.0	0.00
1	0.0	3989.0	0.21
2	NaN	NaN	NaN
3	0.0	1444.0	0.04
4	0.0	6193.0	0.81
5	0.0	62999.0	0.39
6	0.0	5812.0	0.72
7	0.0	1260.0	0.13
8	0.0	9906.0	0.11
9	0.0	9906.0	0.11

	AvailableBankcardCredit	TotalTrades	TradesNeverDelinquent (percentage) \
0	1500.0	11.0	0.81
1	10266.0	29.0	1.00
2	NaN	NaN	NaN
3	30754.0	26.0	0.76
4	695.0	39.0	0.95
5	86509.0	47.0	1.00
6	1929.0	16.0	0.68
7	2181.0	10.0	0.80
8	77696.0	29.0	1.00
9	77696.0	29.0	1.00

	TradesOpenedLast6Months	DebtToIncomeRatio	IncomeRange \
0	0.0	0.17	$25,000-49,999
1	2.0	0.18	$50,000-74,999
2	NaN	0.06	Not displayed
3	0.0	0.15	$25,000-49,999
4	2.0	0.26	$100,000+
5	0.0	0.36	$100,000+
6	0.0	0.27	$25,000-49,999
7	0.0	0.24	$25,000-49,999
8	1.0	0.25	$25,000-49,999
9	1.0	0.25	$25,000-49,999

	IncomeVerifiable	StatedMonthlyIncome	LoanKey \
0	True	3083.333333	E33A3400205839220442E84
1	True	6125.000000	9E3B37071505919926B1D82
2	True	2083.333333	6954337960046817851BCB2
3	True	2875.000000	A0393664465886295619C51
4	True	9583.333333	A180369302188889200689E
5	True	8333.333333	C3D63702273952547E79520
6	True	2083.333333	CE963680102927767790520

```
7              True          3355.750000  0C87368108902149313D53B
8              True          3333.333333  02163700809231365A56A1C
9              True          3333.333333  02163700809231365A56A1C

   TotalProsperLoans  TotalProsperPaymentsBilled  OnTimeProsperPayments  \
0                NaN                         NaN                    NaN
1                NaN                         NaN                    NaN
2                NaN                         NaN                    NaN
3                NaN                         NaN                    NaN
4                1.0                        11.0                   11.0
5                NaN                         NaN                    NaN
6                NaN                         NaN                    NaN
7                NaN                         NaN                    NaN
8                NaN                         NaN                    NaN
9                NaN                         NaN                    NaN

   ProsperPaymentsLessThanOneMonthLate  ProsperPaymentsOneMonthPlusLate  \
0                                  NaN                              NaN
1                                  NaN                              NaN
2                                  NaN                              NaN
3                                  NaN                              NaN
4                                  0.0                              0.0
5                                  NaN                              NaN
6                                  NaN                              NaN
7                                  NaN                              NaN
8                                  NaN                              NaN
9                                  NaN                              NaN

   ProsperPrincipalBorrowed  ProsperPrincipalOutstanding  \
0                       NaN                          NaN
1                       NaN                          NaN
2                       NaN                          NaN
3                       NaN                          NaN
4                   11000.0                       9947.9
5                       NaN                          NaN
6                       NaN                          NaN
7                       NaN                          NaN
8                       NaN                          NaN
9                       NaN                          NaN

   ScorexChangeAtTimeOfListing  LoanCurrentDaysDelinquent  \
0                          NaN                          0
1                          NaN                          0
2                          NaN                          0
3                          NaN                          0
4                          NaN                          0
5                          NaN                          0
```

```
6                          NaN                          0
7                          NaN                          0
8                          NaN                          0
9                          NaN                          0

   LoanFirstDefaultedCycleNumber  LoanMonthsSinceOrigination  LoanNumber  \
0                            NaN                          78       19141
1                            NaN                           0      134815
2                            NaN                          86        6466
3                            NaN                          16       77296
4                            NaN                           6      102670
5                            NaN                           3      123257
6                            NaN                          11       88353
7                            NaN                          10       90051
8                            NaN                           3      121268
9                            NaN                           3      121268

   LoanOriginalAmount  LoanOriginationDate LoanOriginationQuarter  \
0                9425  2007-09-12 00:00:00                Q3 2007
1               10000  2014-03-03 00:00:00                Q1 2014
2                3001  2007-01-17 00:00:00                Q1 2007
3               10000  2012-11-01 00:00:00                Q4 2012
4               15000  2013-09-20 00:00:00                Q3 2013
5               15000  2013-12-24 00:00:00                Q4 2013
6                3000  2013-04-18 00:00:00                Q2 2013
7               10000  2013-05-13 00:00:00                Q2 2013
8               10000  2013-12-12 00:00:00                Q4 2013
9               10000  2013-12-12 00:00:00                Q4 2013

                 MemberKey  MonthlyLoanPayment  LP_CustomerPayments  \
0  1F3E3376408759268057EDA              330.43             11396.14
1  1D13370546739025387B2F4              318.93                 0.00
2  5F7033715035555618FA612              123.32              4186.63
3  9ADE3560698354750680C6D2             321.45              5143.20
4  36CE356043264555721F06C              563.97              2819.85
5  874A3701157341738DE458F              342.37               679.34
6  AA4535764146102879D5959              122.67              1226.70
7  737F3470895450356810C074             372.60              3353.40
8  49A53699682291323D04D66              305.54               611.08
9  49A53699682291323D04D66              305.54               611.08

   LP_CustomerPrincipalPayments  LP_InterestandFees  LP_ServiceFees  \
0                       9425.00             1971.14         -133.18
1                          0.00                0.00            0.00
2                       3001.00             1185.63          -24.20
3                       4091.09             1052.11         -108.01
4                       1563.22             1256.63          -60.27
```

```
5                   351.89              327.45         -25.33
6                   604.25              622.45         -22.95
7                  1955.89             1397.51         -69.21
8                   505.58              105.50         -16.77
9                   505.58              105.50         -16.77

   LP_CollectionFees  LP_GrossPrincipalLoss  LP_NetPrincipalLoss  \
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

   LP_NonPrincipalRecoverypayments  PercentFunded  Recommendations  \
0                              0.0            1.0                0
1                              0.0            1.0                0
2                              0.0            1.0                0
3                              0.0            1.0                0
4                              0.0            1.0                0
5                              0.0            1.0                0
6                              0.0            1.0                0
7                              0.0            1.0                0
8                              0.0            1.0                0
9                              0.0            1.0                0

   InvestmentFromFriendsCount  InvestmentFromFriendsAmount  Investors
0                           0                          0.0        258
1                           0                          0.0          1
2                           0                          0.0         41
3                           0                          0.0        158
4                           0                          0.0         20
5                           0                          0.0          1
6                           0                          0.0          1
7                           0                          0.0          1
8                           0                          0.0          1
9                           0                          0.0          1
```

[5]:
```
# Getting basic informations about the dataset
prosperLoanData.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
```

Univariate Exploration of Data

Question 1: What is the trend of the `LoanStatus` variable ?

We'll start looking at the trend of the `LoanStatus` variable.

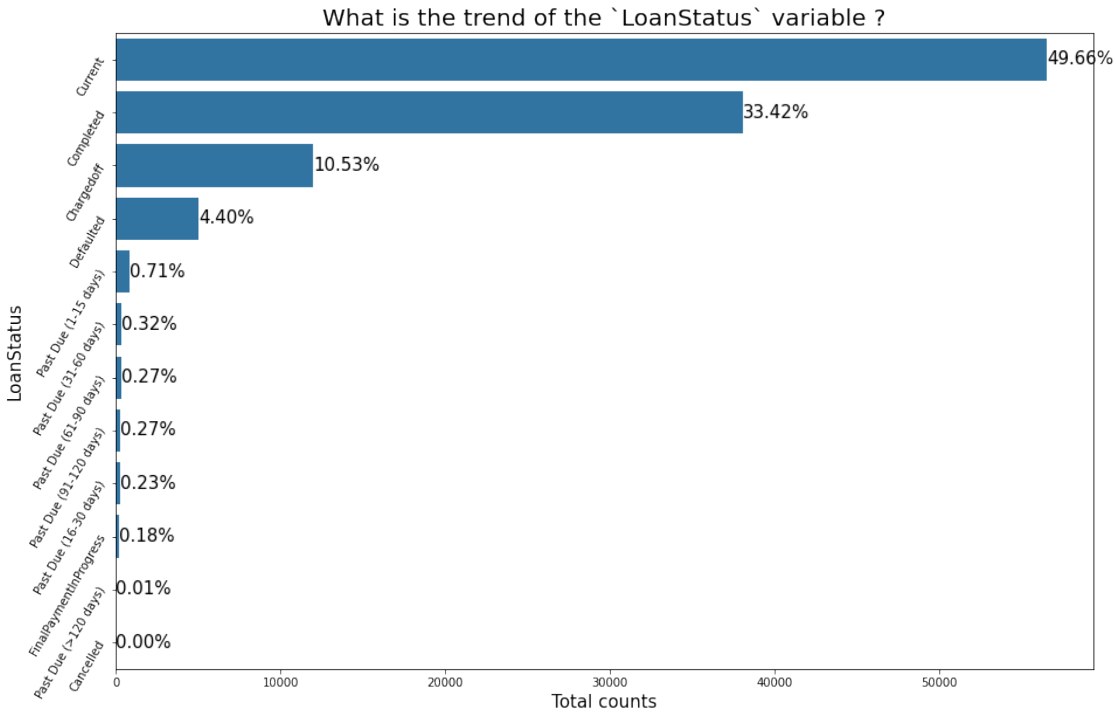
`LoanStatus` : The current status of the loan: Cancelled, Chargedoff, Completed, Current, Defaulted, FinalPaymentInProgress, PastDue. The PastDue status will be accompanied by a delinquency bucket.

[6]:
```
def special_barplot(data, colname):
    # Getting order from the greatest to the lowest
    prosperLoanData = data
    col_name = colname

    type_counts = prosperLoanData[col_name].value_counts()
    order = type_counts.index
    n_total = type_counts.sum()
    color = sns.color_palette()[0]
    plt.figure(figsize = (15, 10))
    f = sns.countplot(data=prosperLoanData, y=col_name, order=order,␣
↪color=color);
    try:
        for index in range(type_counts.shape[0]):
            count = type_counts[index]
            percent_str = f'{100 * count / n_total:0.2f}%'
            plt.text(x=count+3, y=index, s=percent_str, va='center',␣
↪fontdict={'fontsize': 15});

        xticks = list(type_counts.values)[::-1]
        #print(xticks)
        xlabels = [f'{elt:0.1f}' for elt in xticks]
        yticks = list(type_counts.index)
        #print(yticks)
        ylabels = [f'{elt}' for elt in yticks]
        #plt.xticks(ticks=xticks, labels=xlabels, rotation=30)
        plt.yticks(ticks=np.arange(len(yticks)), labels=ylabels, rotation=60)
    except Exception as e :
        #print(e)
        pass
```

[7]:
```
special_barplot(data=prosperLoanData, colname='LoanStatus')
#f.set_xticklabels(labels = list(type_counts.values), minor=True, rotation=360)
plt.title('What is the trend of the `LoanStatus` variable ?',␣
↪fontdict={'fontsize': 20});
plt.xlabel(xlabel='Total counts', fontdict={'fontsize': 15});
plt.ylabel(ylabel='LoanStatus', fontdict={'fontsize': 15});
```

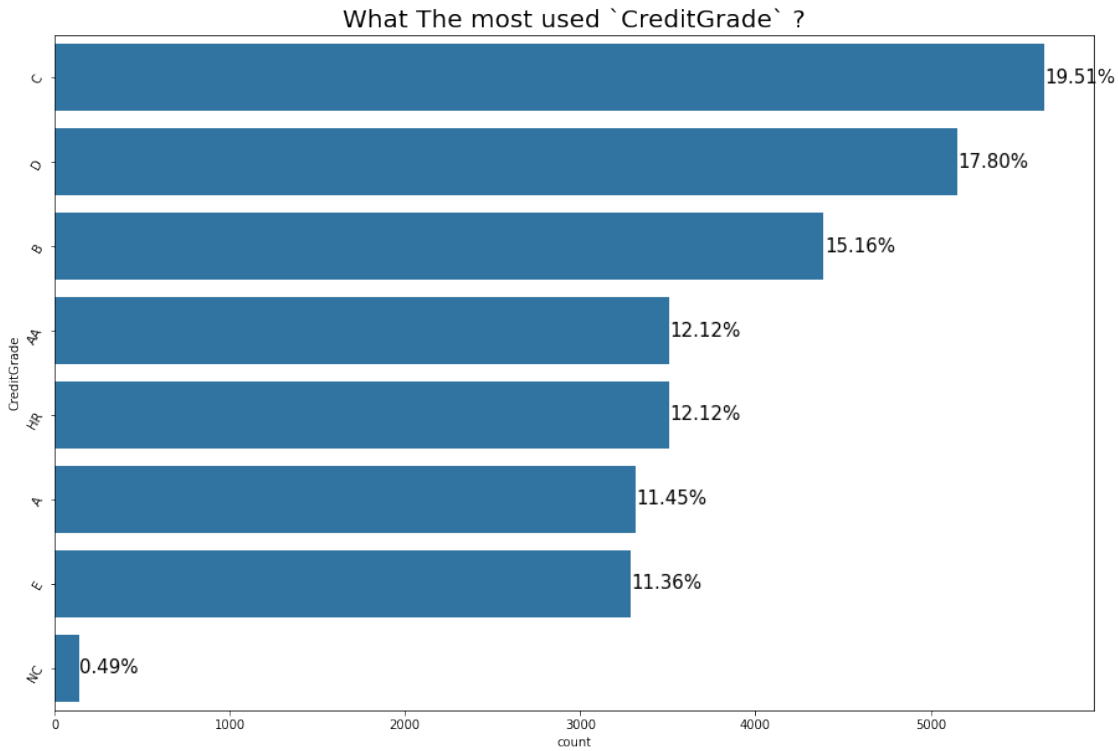


- As we can see, most of the loans are ongoing `49.66%`, some are already completed `33.42%` and the less are chargedoff `10.53%`. All the other statuses are not so relevant because they have little percentages.

Question 2: What The most used `CreditGrade` ?

`CreditGrade` : The Credit rating that was assigned at the time the listing went live. Applicable for listings pre-2009 period and will only be populated for those listings.

[8]:
```
special_barplot(data=prosperLoanData, colname='CreditGrade');
plt.title('What The most used `CreditGrade` ?', fontdict={'fontsize': 20});
```

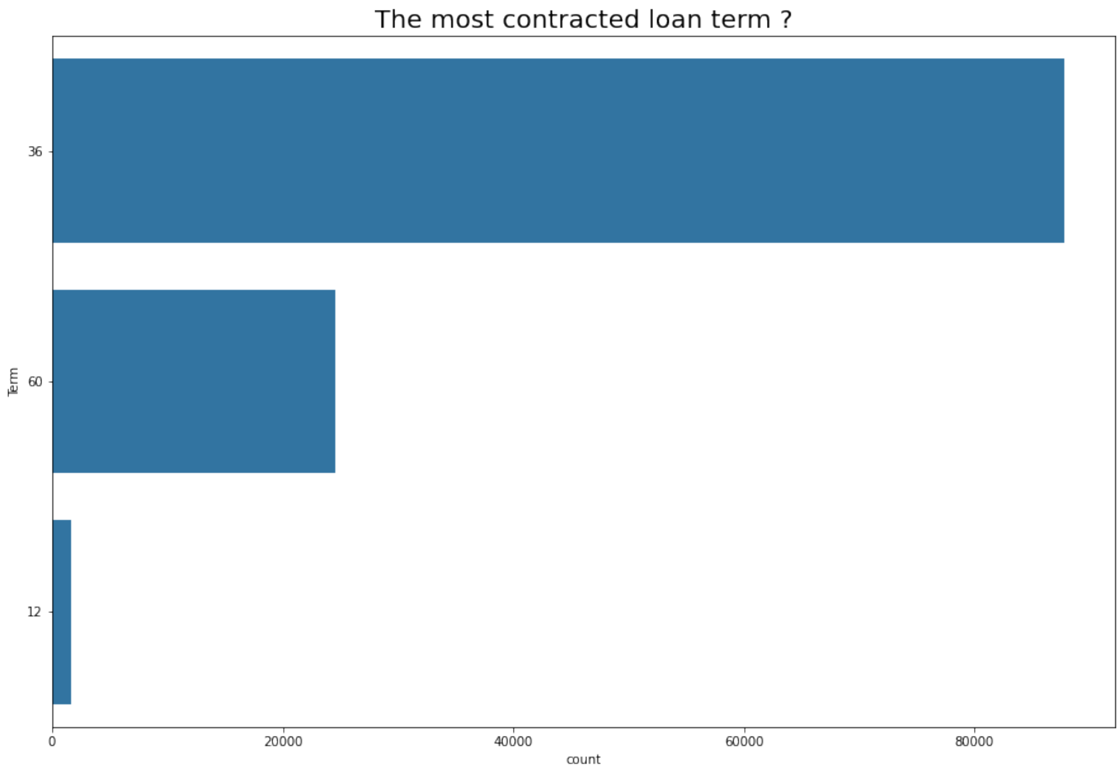


- The grade `C` is the most represented with `19.51%`
- The grade `D` is the second most represented with `17.80%`
- The grade `B` is the third most represented with `15.16%`

Question 3: The most contracted loan `Term` ?

`Term` : The length of the loan expressed in months.

[9]:
```
special_barplot(data=prosperLoanData, colname='Term');
plt.title('The most contracted loan term ?', fontdict={'fontsize': 20});
```



The most contracted loan term is the length of `36 months` with more than 80000 contracts.

Question 4: `BorrowerAPR` distribution

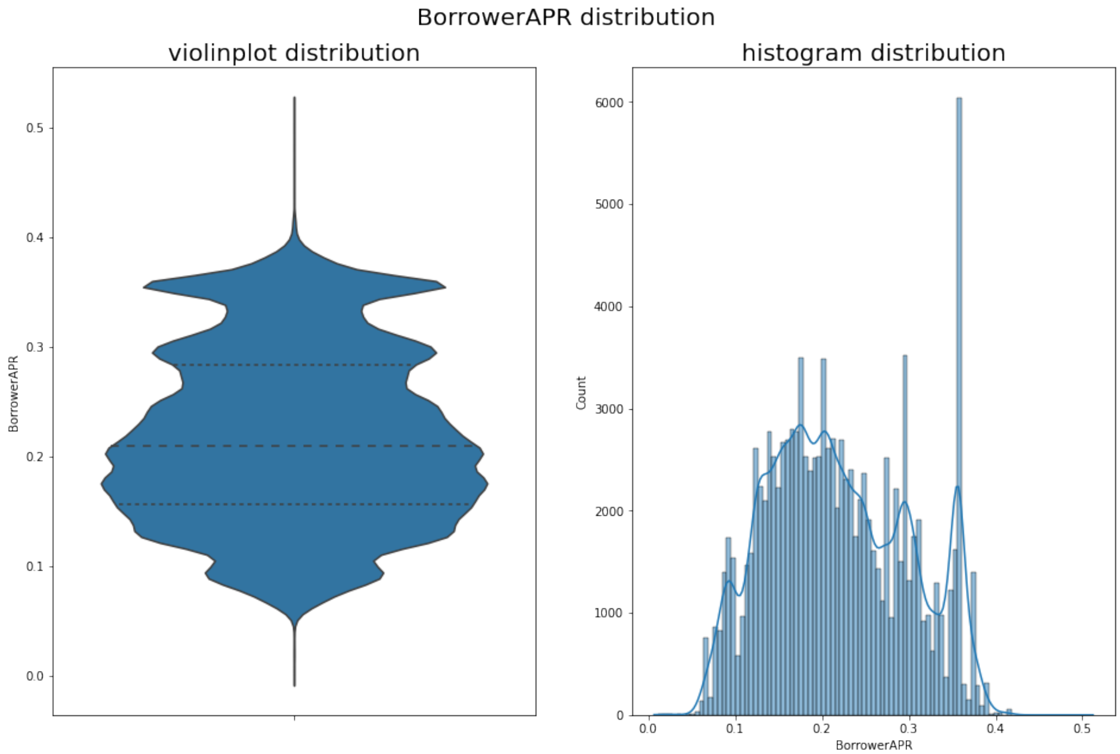
`BorrowerAPR` : The Borrower's Annual Percentage Rate (APR) for the loan.

[10]:
```
prosperLoanData['BorrowerAPR'].describe()
```

[10]:
```
count    113912.000000
mean          0.218828
std           0.080364
min           0.006530
25%           0.156290
50%           0.209760
75%           0.283810
max           0.512290
Name: BorrowerAPR, dtype: float64
```

[11]:
```
plt.figure(figsize = (16, 10));
plt.suptitle('BorrowerAPR distribution', x=0.5, y=0.95, fontproperties={'size':␣
 ↪20});
plt.subplot(1, 2, 1)
sns.violinplot(data=prosperLoanData, y='BorrowerAPR', inner='quartile');
plt.title('violinplot distribution', fontdict={'fontsize': 20});
```

```
plt.subplot(1, 2, 2)
sns.histplot(data=prosperLoanData, x='BorrowerAPR', kde=True);
plt.title('histogram distribution', fontdict={'fontsize': 20});
```

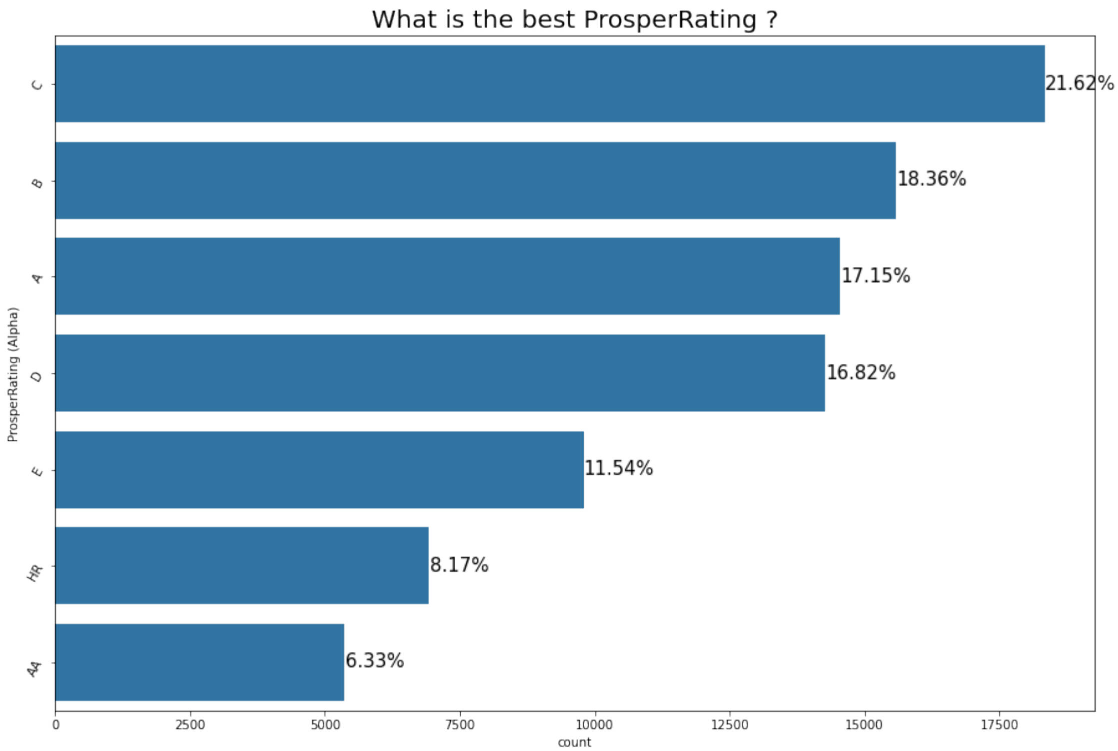


- The distribution is slightly normal
- With a standard deviation of `0.080364` the median value of the BorrowerAPR is `0.209760` and it is closest to the mean `0.218828`. It means that the BorrowerAPR is really good for loans.

Question 5: What is the best `ProsperRating` ?

`ProsperRating (Alpha)` : The Prosper Rating assigned at the time the listing was created between AA - HR. Applicable for loans originated after July 2009.

[12]:
```
special_barplot(data=prosperLoanData, colname='ProsperRating (Alpha)');
plt.title('What is the best ProsperRating ?', fontdict={'fontsize': 20});
```



The best ProsperRating is * The grade `C` is the most represented with `21.62%` and followed by * The grade `B` is the second most represented with `18.36%` and followed by * The grade `A` is the third most represented with `17.15%`

Question 6: `ProsperScore` distribution

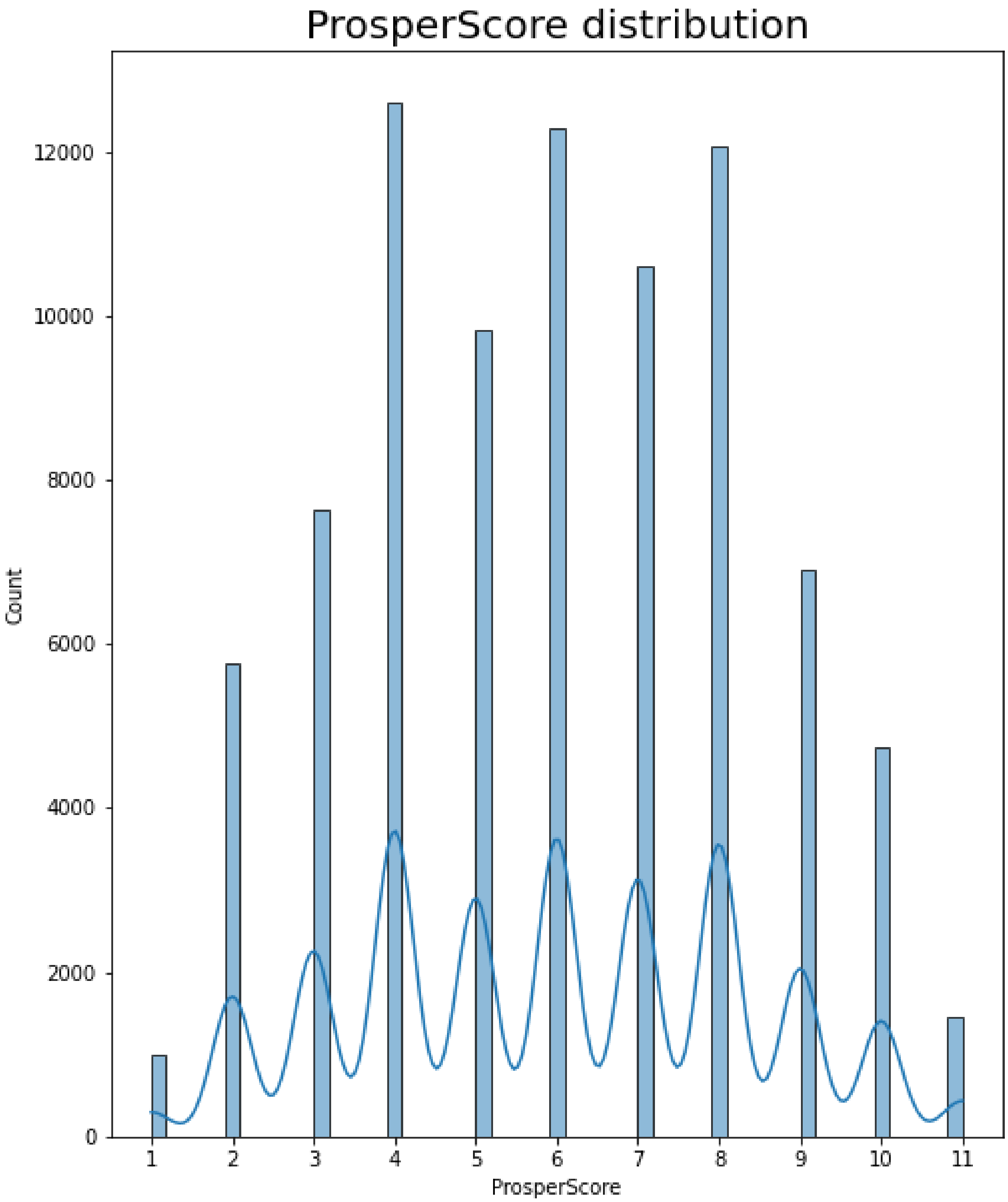
`ProsperScore` : A custom risk score built using historical Prosper data. The score ranges from 1-10, with 10 being the best, or lowest risk score. Applicable for loans originated after July 2009.

[13]:
```
prosperLoanData['ProsperScore'].describe()
```

[13]:
```
count    84853.000000
mean         5.950067
std          2.376501
min          1.000000
25%          4.000000
50%          6.000000
75%          8.000000
max         11.000000
Name: ProsperScore, dtype: float64
```

[14]:
```
plt.figure(figsize = (8, 10));
sns.histplot(data=prosperLoanData, x='ProsperScore', kde=True);
plt.xticks(ticks=range(1, 11 + 1), labels=[f'{i}' for i in range(1, 11 + 1)])
```

```python
plt.title('ProsperScore distribution', fontdict={'fontsize': 20});
```



- The most highest `ProsperScore` are `4` then `6` then `8`. More than 12000 loans are relataed to houses with such ProsperScore.

Question 7: `ListingCategory` distribution

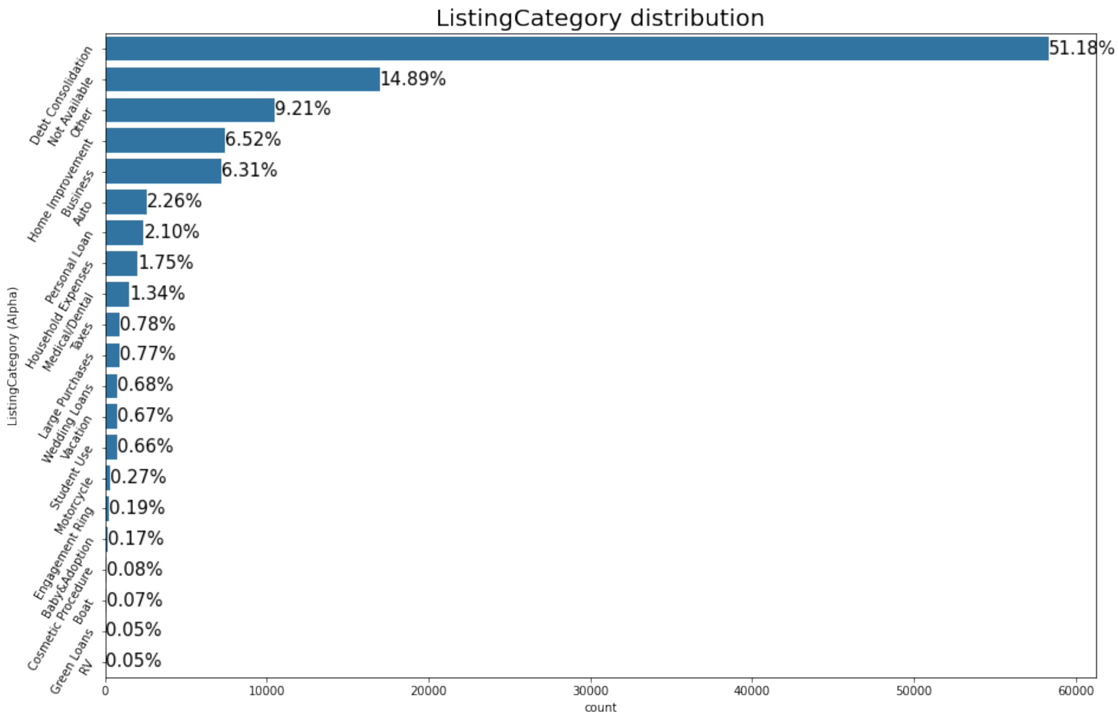
`ListingCategory` : The category of the listing that the borrower selected when posting their listing: 0 - Not Available, 1 - Debt Consolidation, 2 - Home Improvement, 3 - Business, 4 - Personal Loan, 5 - Student Use, 6 - Auto, 7- Other, 8 - Baby&Adoption, 9 - Boat, 10 - Cosmetic Procedure, 11 - Engagement Ring, 12 - Green Loans, 13 - Household Expenses, 14 - Large Purchases, 15 - Medical/Dental, 16 - Motorcycle, 17 - RV, 18 - Taxes, 19 - Vacation, 20 - Wedding Loans

[15]:
```
prosperLoanData['ListingCategory (numeric)'].describe()
```

[15]:
```
count    113937.000000
mean          2.774209
std           3.996797
min           0.000000
25%           1.000000
50%           1.000000
75%           3.000000
max          20.000000
Name: ListingCategory (numeric), dtype: float64
```

[16]:
```
# Creating a dict for ListingCategory
ListingCategoryDict ={0 : 'Not Available', 1 : 'Debt Consolidation', 2 : 'Home␣
↪Improvement', 3 : 'Business', 4 : 'Personal Loan', 5 : 'Student Use', 6 :␣
↪'Auto', 7 : 'Other', 8 : 'Baby&Adoption', 9 : 'Boat', 10 : 'Cosmetic␣
↪Procedure', 11 : 'Engagement Ring', 12 : 'Green Loans', 13 : 'Household␣
↪Expenses', 14 : 'Large Purchases', 15 : 'Medical/Dental', 16 : 'Motorcycle',␣
↪17 : 'RV', 18 : 'Taxes', 19 : 'Vacation', 20 : 'Wedding Loans'}
```

[17]:
```
#plt.figure(figsize = (8, 10));
# Creating a variable for coresponding listing category numbers to their␣
↪meaning.
prosperLoanData['ListingCategory (Alpha)'] = prosperLoanData['ListingCategory␣
↪(numeric)'].apply(lambda val: ListingCategoryDict[val]);
special_barplot(data=prosperLoanData, colname='ListingCategory (Alpha)');
plt.title('ListingCategory distribution', fontdict={'fontsize': 20});
```



Most of the loans are for `Debt Consolidation`. Really inspiring.

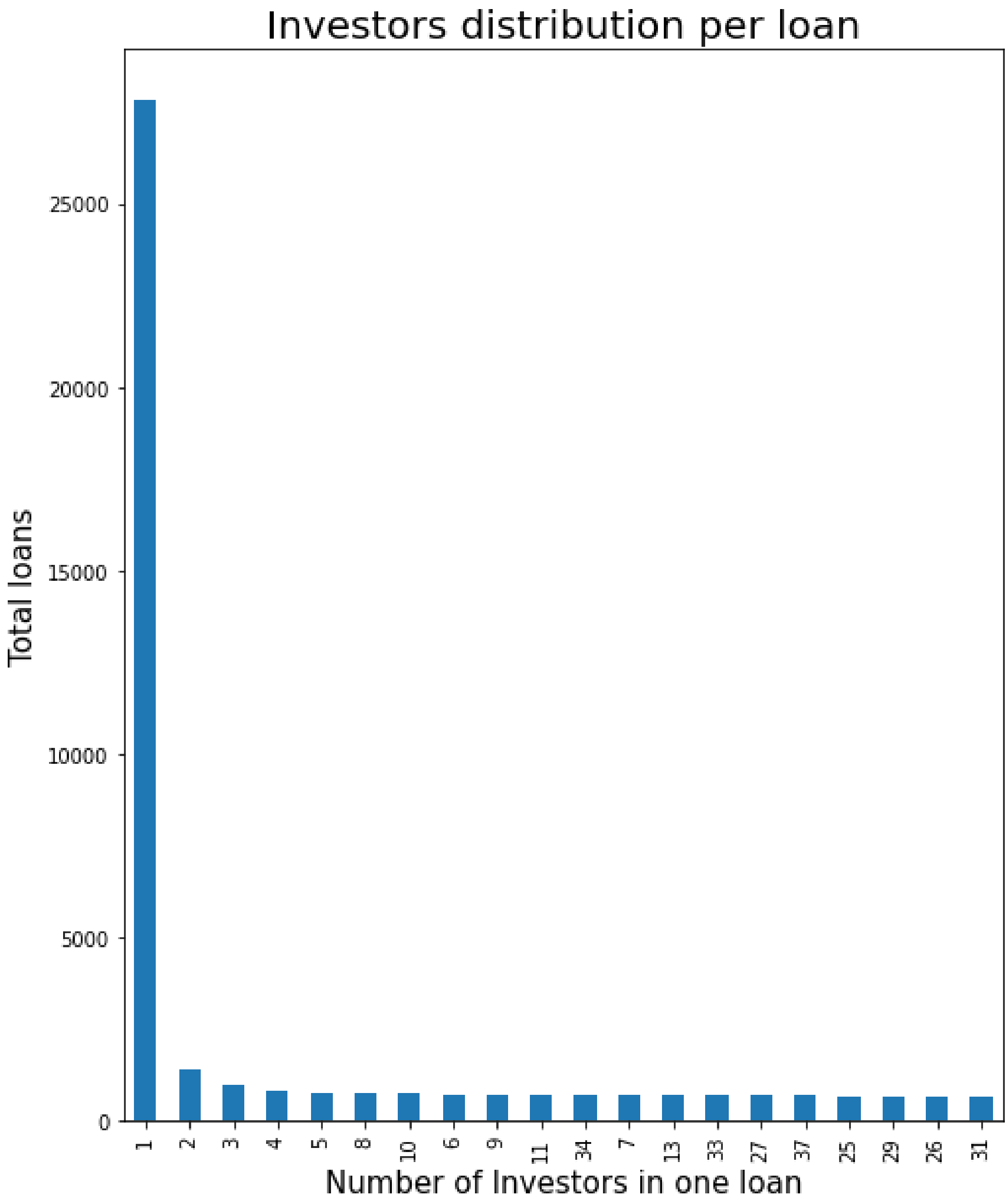
Question 8: `Investors` distribution

`Investors` : The number of investors that funded the loan.

[18]:
```
prosperLoanData['Investors'].value_counts().nlargest(5)
```

[18]:
```
1    27814
2     1386
3      991
4      827
5      753
Name: Investors, dtype: int64
```

[19]:
```
plt.figure(figsize = (8, 10));
prosperLoanData['Investors'].value_counts().nlargest(20).plot(kind='bar');
plt.title('Investors distribution per loan', fontdict={'fontsize': 20});
plt.xlabel(xlabel='Number of Investors in one loan', fontdict={'fontsize': 15});
plt.ylabel(ylabel='Total loans', fontdict={'fontsize': 15});
```



Almost all loans are funded by one investor. (More than 25000 loans.)

Question 9: `EmploymentStatus`, `Occupation`, `EmploymentStatusDuration` and `IsBorrowerHomeowner` distribution

`EmploymentStatus` : The employment status of the borrower at the time they posted the listing.

`Occupation` : The Occupation selected by the Borrower at the time they created the listing.

`EmploymentStatusDuration` : The length in months of the employment status at the time the listing was created.

`IsBorrowerHomeowner` : A Borrower will be classified as a homowner if they have a mortgage on their credit profile or provide documentation confirming they are a homeowner.

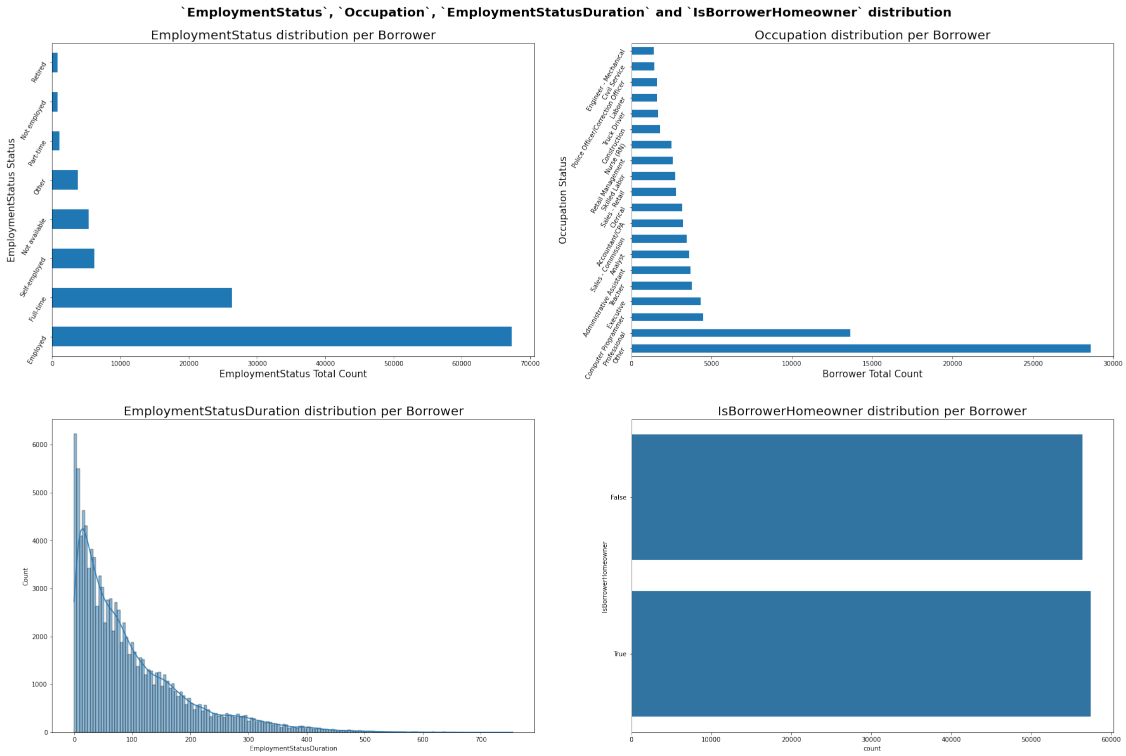
[20]:
```
plt.figure(figsize = (30, 20));
plt.suptitle('`EmploymentStatus`, `Occupation`, `EmploymentStatusDuration` and␣
↪`IsBorrowerHomeowner` distribution', fontsize=20, fontweight='bold', x=0.5,␣
↪y=0.92)

plt.subplot(2, 2, 1)
prosperLoanData['EmploymentStatus'].value_counts().nlargest(20).
↪plot(kind='barh');
plt.title('EmploymentStatus distribution per Borrower', fontdict={'fontsize':␣
↪20});
plt.xlabel(xlabel='EmploymentStatus Total Count', fontdict={'fontsize': 15});
plt.ylabel(ylabel='EmploymentStatus Status', fontdict={'fontsize': 15});
plt.yticks(rotation=60);

plt.subplot(2, 2, 2)
prosperLoanData['Occupation'].value_counts().nlargest(20).plot(kind='barh');
plt.title('Occupation distribution per Borrower', fontdict={'fontsize': 20});
plt.xlabel(xlabel='Borrower Total Count', fontdict={'fontsize': 15});
plt.ylabel(ylabel='Occupation Status', fontdict={'fontsize': 15});
plt.yticks(rotation=60);

plt.subplot(2, 2, 3)
sns.histplot(data=prosperLoanData, x='EmploymentStatusDuration', kde=True);
plt.title('EmploymentStatusDuration distribution per Borrower',␣
↪fontdict={'fontsize': 20});

plt.subplot(2, 2, 4);
sns.countplot(data=prosperLoanData, y='IsBorrowerHomeowner', color=sns.
↪color_palette()[0]);
plt.title('IsBorrowerHomeowner distribution per Borrower', fontdict={'fontsize':
↪ 20});
```

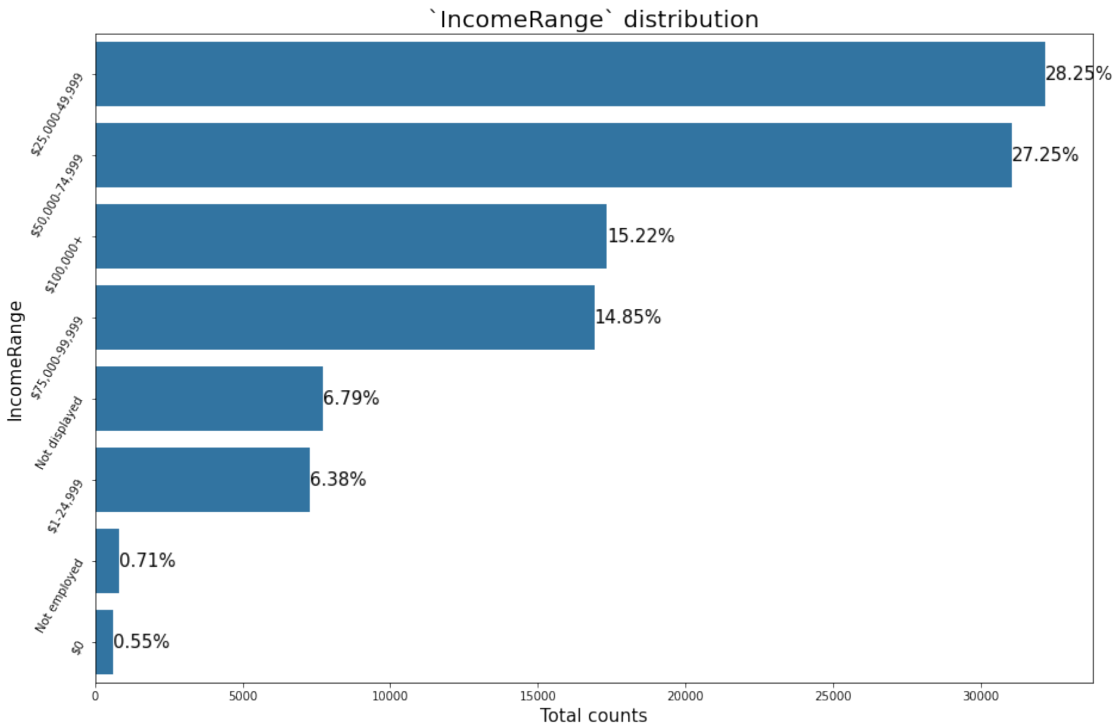


- Most of the Borrowers are employed(Employed, Full-time or Self-employed)
- Most of the Borrowers don't specify their Occupations.
  - More than `10000` Borrowers are `Professionals`
  - Around `5000` Borrowers are `Computer Programmer` and `Executive`
  - Around `4000` Borrowers are `Teacher`, `Administrative Assistant` and `Analyst`
- Around `50%` of Borrowers are either Homeowners or not Homeowners.
- Looks like there needs to be an employee for some time (about 100 months) in order to the a borrower, assuming your employement come with high revenues. (to be able to be Homeowner.)

Question 10: `IncomeRange` distribution

`IncomeRange` : The income range of the borrower at the time the listing was created.

[21]:
```
special_barplot(data=prosperLoanData, colname='IncomeRange')
#f.set_xticklabels(labels = list(type_counts.values), minor=True, rotation=360)
plt.title('`IncomeRange` distribution', fontdict={'fontsize': 20});
plt.xlabel(xlabel='Total counts', fontdict={'fontsize': 15});
plt.ylabel(ylabel='IncomeRange', fontdict={'fontsize': 15});
```



- Clearly you must have a minimum `IncomeRange` of `$25,000` to be sure to have a loan.

Univariate Exploration Summary

Question 1: What is the trend of the `LoanStatus` variable ?

- As we can see, most of the loans are ongoing `49.66%`, some are already completed `33.42%` and the less are chargedoff `10.53%`. All the other statuses are not so relevant because they have little percentages.

Question 2: What The most used `CreditGrade` ?

- The grade `C` is the most represented with `19.51%`
- The grade `D` is the second most represented with `17.80%`
- The grade `B` is the third most represented with `15.16%`

Question 3: The most contracted loan `Term` ?

- The most contracted loan term is the length of `36 months` with more than 80000 contracts.

Question 4: BorrowerAPR distribution

- The distribution is slightly normal
- With a standard deviation of `0.080364` the median value of the BorrowerAPR is `0.209760` and it is closest to the mean `0.218828`. It means that the BorrowerAPR is really good for loans.

Question 5: What is the best ProsperRating ? The best ProsperRating is * The grade `C` is the most represented with `21.62%` and followed by * The grade `B` is the second most represented with `18.36%` and followed by * The grade `A` is the third most represented with `17.15%`

Question 6: `ProsperScore` distribution

- The most highest `ProsperScore` are `4` then `6` then `8`. More than 12000 loans are relataed to houses with such ProsperScore.

Question 7: `ListingCategory` distribution

- Most of the loans are for `Debt Consolidation`. Really inspiring.

Question 8: `Investors` distribution

- Almost all loans are funded by one investor. (More than 25000 loans.)

Question 9: `EmploymentStatus`, `Occupation`, `EmploymentStatusDuration` and `IsBorrowerHomeowner` distribution

- Most of the Borrowers are employed(Employed, Full-time or Self-employed)
- Most of the Borrowers don't specify their Occupations.
  - More than `10000` Borrowers are `Professionals`
  - Around `5000` Borrowers are `Computer Programmer` and `Executive`
  - Around `4000` Borrowers are `Teacher`, `Administrative Assistant` and `Analyst`
- Around `50%` of Borrowers are either Homeowners or not Homeowners.
- Looks like there needs to be an employee for some time (about 100 months) in order to the a borrower, assuming your employement come with high revenues. (to be able to be Homeowner.)

Question 10: `IncomeRange` distribution

- Clearly you must have a minimum `IncomeRange` of `$25,000` to be sure to have a loan.

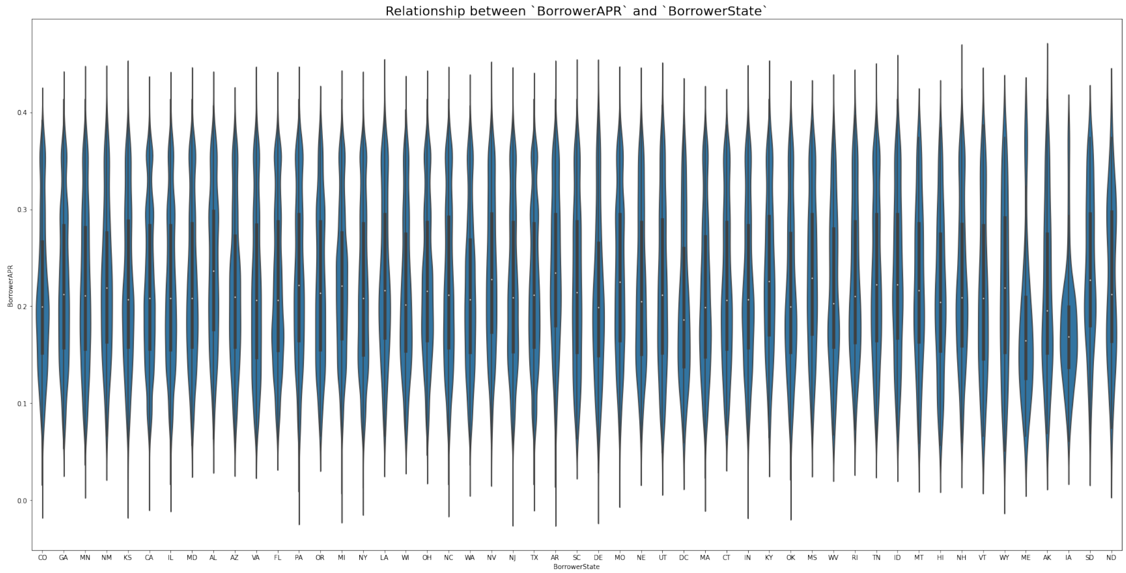
Bivariate Exploration of Data

Question 1: Relationship between `BorrowerAPR` and `BorrowerState`

`BorrowerAPR` : The Borrower's Annual Percentage Rate (APR) for the loan.

`BorrowerState` : The two letter abbreviation of the state of the address of the borrower at the time the Listing was created.

[22]:
```python
color = sns.color_palette()[0]
plt.figure(figsize = (30, 15));
sns.violinplot(data=prosperLoanData, x='BorrowerState', y='BorrowerAPR',␣
 ↪inner='box', color=color);
plt.title('Relationship between `BorrowerAPR` and `BorrowerState`',␣
 ↪fontdict={'fontsize': 20});
```



Per each`BorrowerState`, the `BorrowerAPR` are slightly the same. There is not much difference of `BorrowerAPR` according to differents `BorrowerState`.

Question 2: Relationship between `ProsperRating (Alpha)` and `ProsperScore`

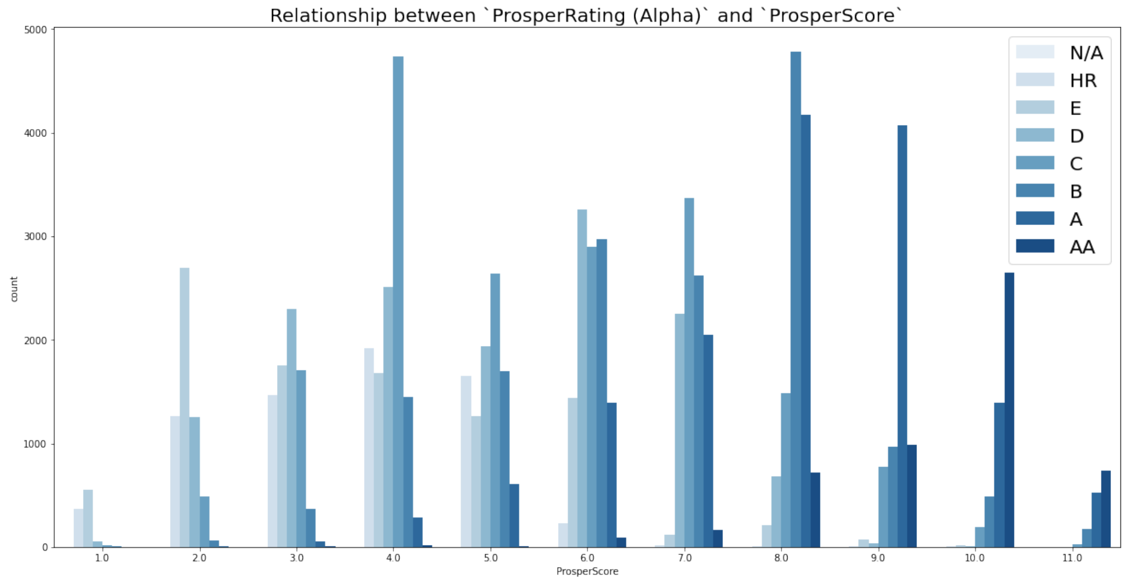
`ProsperRating (Alpha)` : The Prosper Rating assigned at the time the listing was created between AA - HR. Applicable for loans originated after July 2009.

`ProsperScore` : A custom risk score built using historical Prosper data. The score ranges from 1-10, with 10 being the best, or lowest risk score. Applicable for loans originated after July 2009.

[23]:
```python
# Let's convert ProsperRating (Alpha) to a CategoricalDtype
classes = ['N/A', 'HR', 'E', 'D', 'C', 'B', 'A', 'AA']
# Creating Category
cat_classes = pd.api.types.CategoricalDtype(categories=classes, ordered=True)
# Converting to CategoricalDtype
prosperLoanData['ProsperRating (Alpha)'] = prosperLoanData['ProsperRating (Alpha)'].astype(cat_classes)
# Testing
prosperLoanData['ProsperRating (Alpha)'].info()
```

```
<class 'pandas.core.series.Series'>
RangeIndex: 113937 entries, 0 to 113936
Series name: ProsperRating (Alpha)
Non-Null Count  Dtype
--------------  -----
84853 non-null  category
dtypes: category(1)
memory usage: 111.7 KB
```

[24]:
```
color = sns.color_palette()[0]
plt.figure(figsize = (20, 10));
sns.countplot(data=prosperLoanData, x='ProsperScore', hue='ProsperRating␣
↪(Alpha)', palette='Blues');
plt.legend(fontsize=20, loc='upper right');
plt.title('Relationship between `ProsperRating (Alpha)` and `ProsperScore`',␣
↪fontdict={'fontsize': 20});
```



- Loans with high ProsperScore(like 8, 9 or 10) are associated with high ProsperRating(like B, A or AA)
- Loans with median ProsperScore(like 5, 6 or 7) are associated with low or median ProsperRating(like E, D or C)
- Loans with low ProsperScore(like 1, 2 or 4) are associated with low ProsperRating(like HR, E or D)

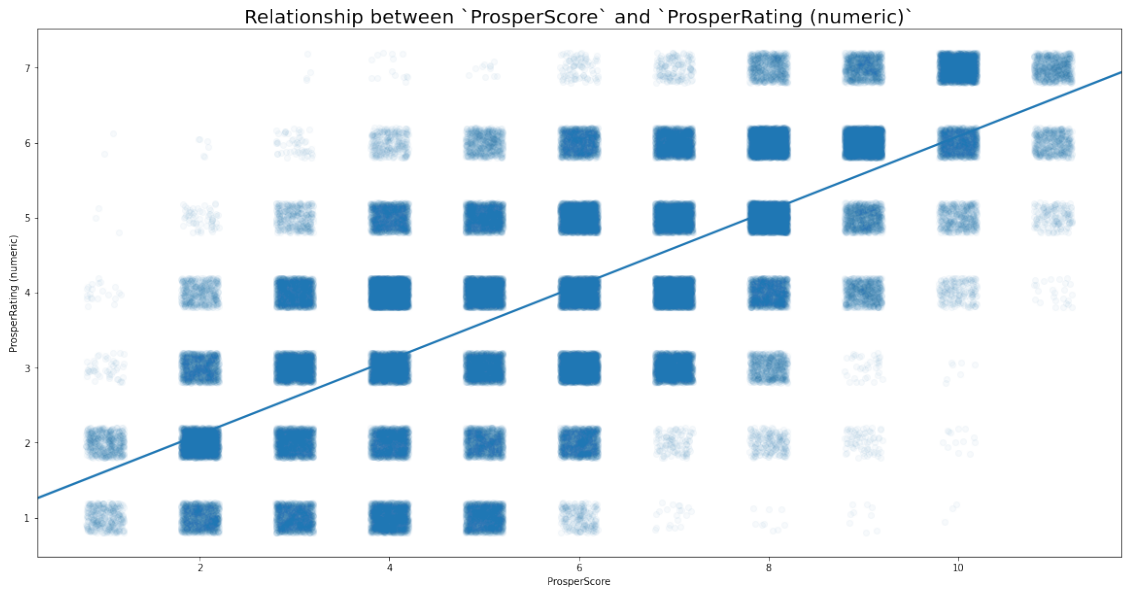
Question 3: Relationship between `ProsperScore` and `ProsperRating (numeric)`

`ProsperRating (numeric)` : The Prosper Rating assigned at the time the listing was created: 0 - N/A, 1 - HR, 2 - E, 3 - D, 4 - C, 5 - B, 6 - A, 7 - AA. Applicable for loans originated after July 2009.

`ProsperScore` : A custom risk score built using historical Prosper data. The score ranges from 1-10, with 10 being the best, or lowest risk score. Applicable for loans originated after July 2009.

[25]:
```
color = sns.color_palette()[0]
plt.figure(figsize = (20, 10));
sns.regplot(data=prosperLoanData, x='ProsperScore', y='ProsperRating␣
↪(numeric)', x_jitter=0.2, y_jitter=0.2, truncate=False, scatter_kws={'alpha':
↪ 1/30});
```

```
plt.title('Relationship between `ProsperScore` and `ProsperRating (numeric)`',
  fontdict={'fontsize': 20});
```



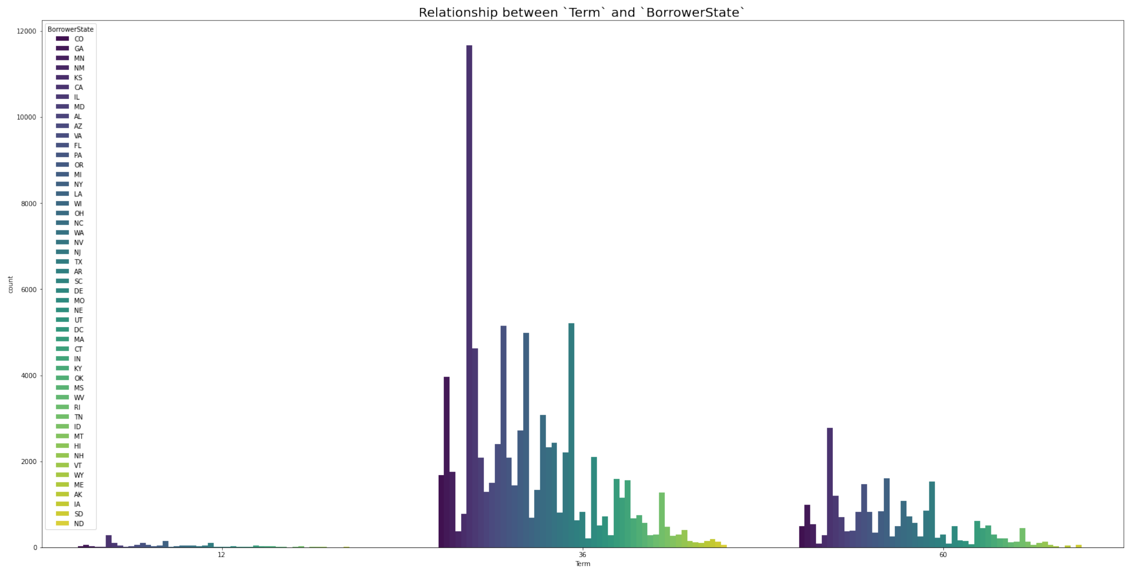
- The higher the `ProsperScore`, the higher the `ProsperRating (numeric)`
- There is a positive correlation between `ProsperScore` and `ProsperRating (numeric)`

Question 4: Relationship between `Term` and `BorrowerState`

`Term` : The length of the loan expressed in months.

`BorrowerState` : The two letter abbreviation of the state of the address of the borrower at the time the Listing was created.

[26]:
```
plt.figure(figsize = (30, 15));
sns.countplot(data=prosperLoanData, x='Term', hue='BorrowerState',
  palette='viridis');
plt.title('Relationship between `Term` and `BorrowerState`',
  fontdict={'fontsize': 20});
```



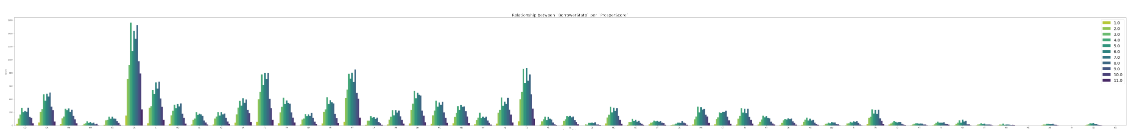
- Most of the loans are for the lenght of `36 months` and the first five(06) BorrowerState's codes with high loans are `CA` `CO`, `GA`, `MN`, `NM` and `KS`

Question 5: Relationship between `BorrowerState` per `ProsperScore`

`BorrowerState` : The two letter abbreviation of the state of the address of the borrower at the time the Listing was created.

`ProsperScore` : A custom risk score built using historical Prosper data. The score ranges from 1-10, with 10 being the best, or lowest risk score. Applicable for loans originated after July 2009.

[27]:
```python
color = sns.color_palette()[0]
plt.figure(figsize = (100, 10));
sns.countplot(data=prosperLoanData, x='BorrowerState', hue='ProsperScore', palette='viridis_r');
plt.legend(fontsize=20, loc='upper right');
plt.title('Relationship between `BorrowerState` per `ProsperScore`', fontdict={'fontsize': 20});
```



- There are five BorrowerState with Highest ProsperScore: `CA`, `FL`, `NY`, `TX` and `IL`

Bivariate Exploration Summary

Question 1: Relationship between `BorrowerAPR` and `BorrowerState`

- Per each`BorrowerState`, the `BorrowerAPR` are slightly the same. There is not much difference of `BorrowerAPR` according to differents `BorrowerState`.

Question 2: Relationship between `ProsperRating (Alpha)` and `ProsperScore`

- Loans with high ProsperScore(like 8, 9 or 10) are associated with high ProsperRating(like B, A or AA)
- Loans with median ProsperScore(like 5, 6 or 7) are associated with low or median ProsperRating(like E, D or C)
- Loans with low ProsperScore(like 1, 2 or 4) are associated with low ProsperRating(like HR, E or D)

Question 3: Relationship between `ProsperScore` and `ProsperRating (numeric)`

- The most contracted loan term is the length of `36 months` with more than 80000 contracts.

Question 4: Relationship between `Term` and `BorrowerState`

- Most of the loans are for the lenght of `36 months` and the first five(05) BorrowerState's codes with high loans are `CO`, `GA`, `MN`, `NM` and `KS`

Question 5: Relationship between `BorrowerState` per `ProsperScore`

- There are five BorrowerState with Highest ProsperScore: `CA`, `FL`, `NY`, `TX` and `IL`

Multivariate Exploration of Data

Question 1: Relationship between `ProsperScore` and `BorrowerAPR` per `ProsperRating (Alpha)`

`ProsperScore` : A custom risk score built using historical Prosper data. The score ranges from 1-10, with 10 being the best, or lowest risk score. Applicable for loans originated after July 2009.

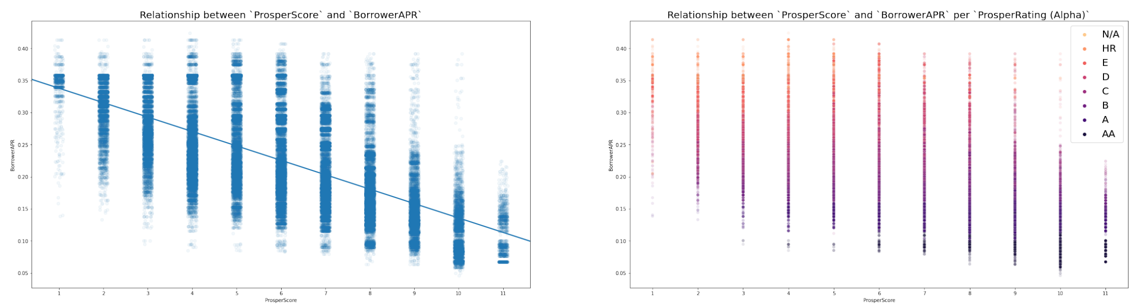
`BorrowerAPR` : The Borrower's Annual Percentage Rate (APR) for the loan.

`ProsperRating (Alpha)` : The Prosper Rating assigned at the time the listing was created between AA - HR. Applicable for loans originated after July 2009.

[28]:
```
color = sns.color_palette()[0]
#plt.figure(figsize = (30, 20));
#plt.suptitle('`EmploymentStatus`, `Occupation`, `EmploymentStatusDuration` and␣
↪`IsBorrowerHomeowner` distribution', fontsize=20, fontweight='bold', x=0.5,␣
↪y=0.92)
plt.figure(figsize = (40, 10));

plt.subplot(1, 2, 1)
sns.regplot(data=prosperLoanData, x='ProsperScore', y='BorrowerAPR',␣
↪truncate=False, x_jitter=0.1, scatter_kws={'alpha': 1/20});
plt.xticks(ticks=range(1, 11 + 1), labels=[f'{i}' for i in range(1, 11 + 1)])
plt.title('Relationship between `ProsperScore` and `BorrowerAPR`',␣
↪fontdict={'fontsize': 20});
```

```python
plt.subplot(1, 2, 2)
sns.scatterplot(data=prosperLoanData, x='ProsperScore', y='BorrowerAPR', hue='ProsperRating (Alpha)', x_jitter=0.3, palette='magma_r', alpha=1/10);
plt.xticks(ticks=range(1, 11 + 1), labels=[f'{i}' for i in range(1, 11 + 1)])
plt.legend(fontsize=20, loc='upper right');
plt.title('Relationship between `ProsperScore` and `BorrowerAPR` per `ProsperRating (Alpha)`', fontdict={'fontsize': 20});
```



- The higher the ProsperScore the lower the BorrowerAPR. There is a neagtive correlation between these variables.
- The lower the ProsperRating is (HR or E or D) the higher the BorrowerAPR is, among every ProsperScore values
- The better the ProsperRating is (A or AA), the lower the BorrowerAPR is.
- The better the ProsperRating is (A or AA) and much more the higher the ProsperScore is (with 10 being the best, or lowest risk score), the most lower the BorrowerAPR is

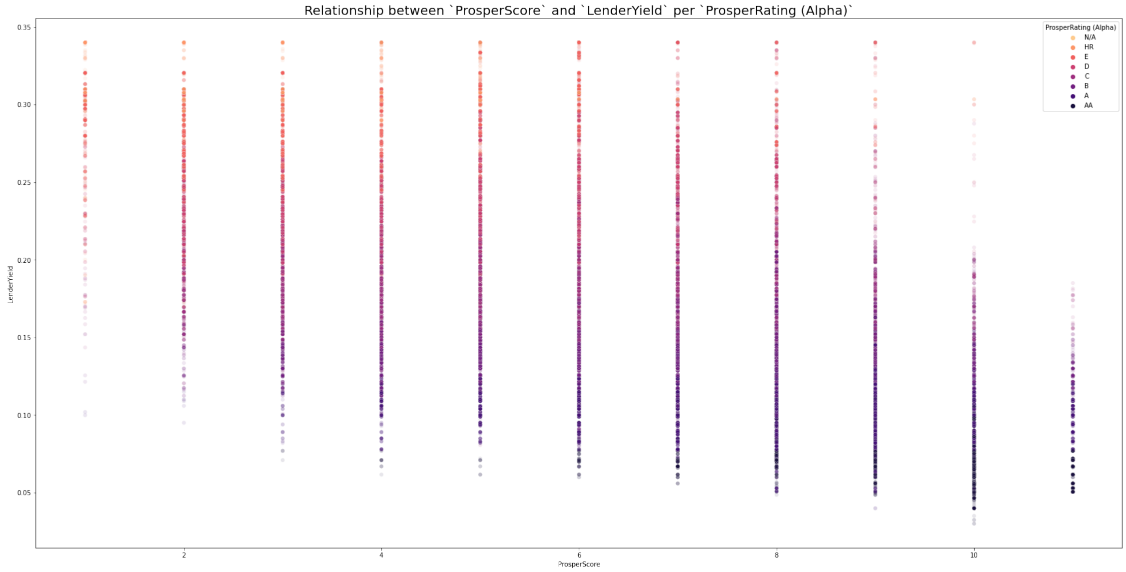
Question 2: Relationship between `ProsperScore` and `LenderYield` per `ProsperRating (Alpha)`

`ProsperScore` : A custom risk score built using historical Prosper data. The score ranges from 1-10, with 10 being the best, or lowest risk score. Applicable for loans originated after July 2009.

`LenderYield` : The Lender yield on the loan. Lender yield is equal to the interest rate on the loan less the servicing fee.

`ProsperRating (Alpha)` : The Prosper Rating assigned at the time the listing was created between AA - HR. Applicable for loans originated after July 2009.

[29]:
```python
plt.figure(figsize = (30, 15));
sns.scatterplot(data=prosperLoanData, x='ProsperScore', y='LenderYield', hue='ProsperRating (Alpha)', x_jitter=0.3, palette='magma_r', alpha=1/10);
plt.title('Relationship between `ProsperScore` and `LenderYield` per `ProsperRating (Alpha)`', fontdict={'fontsize': 20});
```



- The higher the `ProsperScore`, the higher the `ProsperRating (Alpha)` the lower the `LenderYield`

Question 3: Relationship between `LoanOriginalAmount` and `BorrowerAPR` per `ProsperRating (Alpha)` per `IncomeRange`

[30]:
```python
prosperLoanData['IncomeRange'].unique()
```

[30]:
```
array(['$25,000-49,999', '$50,000-74,999', 'Not displayed', '$100,000+',
       '$75,000-99,999', '$1-24,999', 'Not employed', '$0'], dtype=object)
```

[31]:
```python
# Let's convert IncomeRange to a CategoricalDtype
classes = ['Not displayed', 'Not employed', '$0', '$1-24,999', '$25,000-49,999', '$50,000-74,999', '$75,000-99,999', '$100,000+']
# Creating Category
cat_classes = pd.api.types.CategoricalDtype(categories=classes, ordered=True)
# Converting to CategoricalDtype
prosperLoanData['IncomeRange'] = prosperLoanData['IncomeRange'].astype(cat_classes)
# Testing
prosperLoanData['IncomeRange'].info()
```

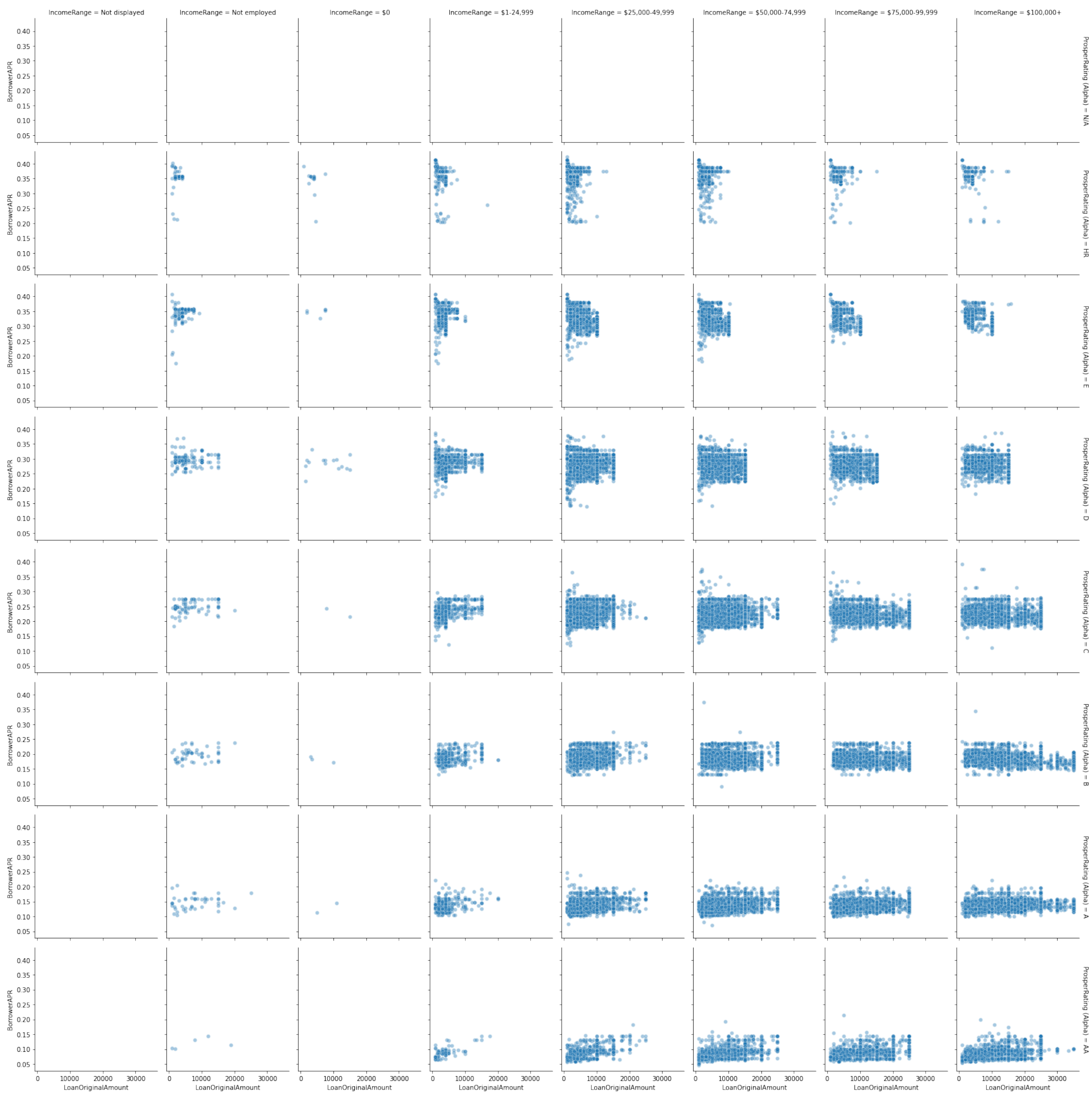
```
<class 'pandas.core.series.Series'>
RangeIndex: 113937 entries, 0 to 113936
Series name: IncomeRange
Non-Null Count   Dtype
--------------   -----
113937 non-null  category
dtypes: category(1)
```

```
memory usage: 111.7 KB
```

[32]:

```python
plt.figure(figsize = (20, 10));
g = sns.FacetGrid(data=prosperLoanData, col='IncomeRange', row='ProsperRating (Alpha)', margin_titles=True);
g.map_dataframe(sns.scatterplot, x='LoanOriginalAmount', y='BorrowerAPR', alpha=0.4);
```

```
<Figure size 1440x720 with 0 Axes>
```



- For `IncomeRange ='Not employed'` it is really difficult to have loan with even a little amount`LoanOriginalAmount` , with even a lower `ProsperRating (Alpha)` score
- For `'IncomeRange =$0'` it is merely impossible to have a loan no matter the `ProsperRating (Alpha)` score

- The `BorrowerAPR` range tend to be lower when the `IncomeRange` tend to be higher and the `ProsperRating (Alpha)` score higher
- The `LoanOriginalAmount` range tend to be higher when the `IncomeRange` tend to be higher and the `ProsperRating (Alpha)` score higher

Multivariate Exploration Summary

Question 1: Relationship between `ProsperScore` and `BorrowerAPR` per `ProsperRating (Alpha)`

- The higher the ProsperScore the lower the BorrowerAPR. There is a neagtive correlation between these variables.
- The lower the ProsperRating is (HR or E or D) the higher the BorrowerAPR is, among every ProsperScore values
- The better the ProsperRating is (A or AA), the lower the BorrowerAPR is.
- The better the ProsperRating is (A or AA) and much more the higher the ProsperScore is (with 10 being the best, or lowest risk score), the most lower the BorrowerAPR is

Question 2: Relationship between `ProsperScore` and `LenderYield` per `ProsperRating (Alpha)`

- The higher the `ProsperScore`, the higher the `ProsperRating (Alpha)` the lower the `LenderYield`

Question 3: Relationship between `LoanOriginalAmount` and `BorrowerAPR` per `ProsperRating (Alpha)` per `IncomeRange`

- For `IncomeRange ='Not employed'` it is really difficult to have loan with even a little amount`LoanOriginalAmount` , with even a lower `ProsperRating (Alpha)` score
- For `'IncomeRange =$0'` it is merely impossible to have a loan no matter the `ProsperRating (Alpha)` score
- The `BorrowerAPR` range tend to be lower when the `IncomeRange` tend to be higher and the `ProsperRating (Alpha)` score higher
- The `LoanOriginalAmount` range tend to be higher when the `IncomeRange` tend to be higher and the `ProsperRating (Alpha)` score higher

Conclusions

1.1.1 Univariate Exploration Summary

Question 1: What is the trend of the `LoanStatus` variable ?

- As we can see, most of the loans are ongoing `49.66%`, some are already completed `33.42%` and the less are chargedoff `10.53%`. All the other statuses are not so relevant because they have little percentages.

Question 2: What The most used `CreditGrade` ?

- The grade `C` is the most represented with `19.51%`
- The grade `D` is the second most represented with `17.80%`
- The grade `B` is the third most represented with `15.16%`

Question 3: The most contracted loan `Term` ?

- The most contracted loan term is the length of `36 months` with more than 80000 contracts.

Question 4: BorrowerAPR distribution

- The distribution is slightly normal
- With a standard deviation of `0.080364` the median value of the BorrowerAPR is `0.209760` and it is closest to the mean `0.218828`. It means that the BorrowerAPR is really good for loans.

Question 5: What is the best ProsperRating ? The best ProsperRating is * The grade `C` is the most represented with `21.62%` and followed by * The grade `B` is the second most represented with `18.36%` and followed by * The grade `A` is the third most represented with `17.15%`

Question 6: `ProsperScore` distribution

- The most highest `ProsperScore` are `4` then `6` then `8`. More than 12000 loans are relataed to houses with such ProsperScore.

Question 7: `ListingCategory` distribution

- Most of the loans are for `Debt Consolidation`. Really inspiring.

Question 8: `Investors` distribution

- Almost all loans are funded by one investor. (More than 25000 loans.)

Question 9: `EmploymentStatus`, `Occupation`, `EmploymentStatusDuration` and `IsBorrowerHomeowner` distribution

- Most of the Borrowers are employed(Employed, Full-time or Self-employed)
- Most of the Borrowers don't specify their Occupations.
  - More than `10000` Borrowers are `Professionals`
  - Around `5000` Borrowers are `Computer Programmer` and `Executive`
  - Around `4000` Borrowers are `Teacher`, `Administrative Assistant` and `Analyst`
- Around `50%` of Borrowers are either Homeowners or not Homeowners.
- Looks like there needs to be an employee for some time (about 100 months) in order to the a borrower, assuming your employement come with high revenues. (to be able to be Homeowner.)

Question 10: `IncomeRange` distribution

- Clearly you must have a minimum `IncomeRange` of `$25,000` to be sure to have a loan.

1.1.2 Bivariate Exploration Summary

Question 1: Relationship between `BorrowerAPR` and `BorrowerState`

- Per each`BorrowerState`, the `BorrowerAPR` are slightly the same. There is not much difference of `BorrowerAPR` according to differents `BorrowerState`.

Question 2: Relationship between `ProsperRating (Alpha)` and `ProsperScore`

- Loans with high ProsperScore(like 8, 9 or 10) are associated with high ProsperRating(like B, A or AA)
- Loans with median ProsperScore(like 5, 6 or 7) are associated with low or median ProsperRating(like E, D or C)
- Loans with low ProsperScore(like 1, 2 or 4) are associated with low ProsperRating(like HR, E or D)

Question 3: Relationship between `ProsperScore` and `ProsperRating (numeric)`

- The most contracted loan term is the length of `36 months` with more than 80000 contracts.

Question 4: Relationship between `Term` and `BorrowerState`

- Most of the loans are for the lenght of `36 months` and the first five(05) BorrowerState's codes with high loans are `CO`, `GA`, `MN`, `NM` and `KS`

Question 5: Relationship between `BorrowerState` per `ProsperScore`

- There are five BorrowerState with Highest ProsperScore: `CA`, `FL`, `NY`, `TX` and `IL`

1.1.3 Multivariate Exploration Summary

Question 1: Relationship between `ProsperScore` and `BorrowerAPR` per `ProsperRating (Alpha)`

- The higher the ProsperScore the lower the BorrowerAPR. There is a neagtive correlation between these variables.
- The lower the ProsperRating is (HR or E or D) the higher the BorrowerAPR is, among every ProsperScore values
- The better the ProsperRating is (A or AA), the lower the BorrowerAPR is.
- The better the ProsperRating is (A or AA) and much more the higher the ProsperScore is (with 10 being the best, or lowest risk score), the most lower the BorrowerAPR is

Question 2: Relationship between `ProsperScore` and `LenderYield` per `ProsperRating (Alpha)`

- The higher the `ProsperScore`, the higher the `ProsperRating (Alpha)` the lower the `LenderYield`

Question 3: Relationship between `LoanOriginalAmount` and `BorrowerAPR` per `ProsperRating (Alpha)` per `IncomeRange`

- For `IncomeRange ='Not employed'` it is really difficult to have loan with even a little amount`LoanOriginalAmount` , with even a lower `ProsperRating (Alpha)` score
- For `'IncomeRange =$0'` it is merely impossible to have a loan no matter the `ProsperRating (Alpha)` score
- The `BorrowerAPR` range tend to be lower when the `IncomeRange` tend to be higher and the `ProsperRating (Alpha)` score higher
- The `LoanOriginalAmount` range tend to be higher when the `IncomeRange` tend to be higher and the `ProsperRating (Alpha)` score higher

Feedback

Thank you for paying attention to my work. Please I need your review to improve myself.

- What do you notice about each visualization?
- What questions do you have about the data?
- What relationships do you notice?
- What do you think is the main takeaway from the report / presentation?
- Is there anything that you don't understand from the plots?

Kindly reach me:

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- GitHub : jozias-tema
- Gmail : jozias-tema

[33]:
```
#!pip install keyboard
import keyboard
keyboard.press_and_release('ctrl+s+Enter')
```

Let's export to html and pdf

[96]:
```
from subprocess import call
call(['python', '-m', 'nbconvert', 'prosperLoanData.ipynb', '--to', 'pdf'])
```

[96]: 0

[97]:
```
from subprocess import call
call(['python', '-m', 'nbconvert', 'prosperLoanData.ipynb', '--to', 'html'])
```

[97]: 0

[95]:
```
keyboard.press_and_release('ctrl+s+Enter')
```