Part_I_ProsperLoan_Exploratory_Analysis

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1 Data Analysis on Propser Loan Dataset

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1.2 Introduction

The objective of the project is to use Python visualization libraries to explore a dataset thoroughly. The analysis begins with exploring univariate variables followed by bivariate and multivariate analysis. This analysis is followed by a short presentation to convey and highlight important findings using explanatory data analysis. A slide deck is prepared with explanatory visuals that follows the major path of exploration and a story is conveyed for better understanding.

1.3 Preliminary Wrangling

```
In [44]: #import all packages to be used in project
         import numpy as np
         import pandas as pd
         import matplotlib.pyplot as plt
         import requests
         import matplotlib.patches as mpatches
         import seaborn as sb
         import numpy as np
         from scipy.stats import norm

         import warnings
         warnings.filterwarnings('ignore')

         %matplotlib inline
```

Gathering Data: Source of data from link provided by Udacity

Loading the ProsperLoan dataset into a dataframe

```
In [45]: #Load downloaded dataset from Udacity provided link.
         #Read CSV file via pandas into a dataframe df_ploan.

         df_ploan = pd.read_csv('prosperLoanData.csv')
```

Assess Data: Assessing data visually and programatically

Visual Assessment

In [46]:
```
#Get visual overview of dataset
df_ploan.head()
```

Out[46]:
```
                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

  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

   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

   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

   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

  InvestmentFromFriendsAmount Investors
0                         0.0       258
1                         0.0         1
2                         0.0        41
3                         0.0       158
4                         0.0        20
```

```
[5 rows x 81 columns]
```

- Data loaded successfully with 81 columns or variables.

```
In [47]: #Get structure of dataset
         df_ploan.shape
```

```
Out[47]: (113937, 81)
```

- The dataset, has 113937 rows or entries and 81 columns.

Programatic Assessment

```
In [48]: #Explore descriptive statistics
         df_ploan.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 113937 entries, 0 to 113936
Data columns (total 81 columns):
ListingKey                             113937 non-null object
ListingNumber                          113937 non-null int64
ListingCreationDate                    113937 non-null object
CreditGrade                            28953 non-null object
Term                                   113937 non-null int64
LoanStatus                             113937 non-null object
ClosedDate                             55089 non-null object
BorrowerAPR                            113912 non-null float64
BorrowerRate                           113937 non-null float64
LenderYield                            113937 non-null float64
EstimatedEffectiveYield                84853 non-null float64
EstimatedLoss                          84853 non-null float64
EstimatedReturn                        84853 non-null float64
ProsperRating (numeric)                84853 non-null float64
ProsperRating (Alpha)                  84853 non-null object
ProsperScore                           84853 non-null float64
ListingCategory (numeric)              113937 non-null int64
BorrowerState                          108422 non-null object
Occupation                             110349 non-null object
EmploymentStatus                       111682 non-null object
EmploymentStatusDuration               106312 non-null float64
IsBorrowerHomeowner                    113937 non-null bool
CurrentlyInGroup                       113937 non-null bool
GroupKey                               13341 non-null object
DateCreditPulled                       113937 non-null object
CreditScoreRangeLower                  113346 non-null float64
CreditScoreRangeUpper                  113346 non-null float64
FirstRecordedCreditLine                113240 non-null object
CurrentCreditLines                     106333 non-null float64
```

```
OpenCreditLines                       106333 non-null float64
TotalCreditLinespast7years            113240 non-null float64
OpenRevolvingAccounts                 113937 non-null int64
OpenRevolvingMonthlyPayment           113937 non-null float64
InquiriesLast6Months                  113240 non-null float64
TotalInquiries                        112778 non-null float64
CurrentDelinquencies                  113240 non-null float64
AmountDelinquent                      106315 non-null float64
DelinquenciesLast7Years               112947 non-null float64
PublicRecordsLast10Years              113240 non-null float64
PublicRecordsLast12Months             106333 non-null float64
RevolvingCreditBalance                106333 non-null float64
BankcardUtilization                   106333 non-null float64
AvailableBankcardCredit               106393 non-null float64
TotalTrades                           106393 non-null float64
TradesNeverDelinquent (percentage)    106393 non-null float64
TradesOpenedLast6Months               106393 non-null float64
DebtToIncomeRatio                     105383 non-null float64
IncomeRange                           113937 non-null object
IncomeVerifiable                      113937 non-null bool
StatedMonthlyIncome                   113937 non-null float64
LoanKey                               113937 non-null object
TotalProsperLoans                     22085 non-null float64
TotalProsperPaymentsBilled            22085 non-null float64
OnTimeProsperPayments                 22085 non-null float64
ProsperPaymentsLessThanOneMonthLate   22085 non-null float64
ProsperPaymentsOneMonthPlusLate       22085 non-null float64
ProsperPrincipalBorrowed              22085 non-null float64
ProsperPrincipalOutstanding           22085 non-null float64
ScorexChangeAtTimeOfListing           18928 non-null float64
LoanCurrentDaysDelinquent             113937 non-null int64
LoanFirstDefaultedCycleNumber         16952 non-null float64
LoanMonthsSinceOrigination            113937 non-null int64
LoanNumber                            113937 non-null int64
LoanOriginalAmount                    113937 non-null int64
LoanOriginationDate                   113937 non-null object
LoanOriginationQuarter                113937 non-null object
MemberKey                             113937 non-null object
MonthlyLoanPayment                    113937 non-null float64
LP_CustomerPayments                   113937 non-null float64
LP_CustomerPrincipalPayments          113937 non-null float64
LP_InterestandFees                    113937 non-null float64
LP_ServiceFees                        113937 non-null float64
LP_CollectionFees                     113937 non-null float64
LP_GrossPrincipalLoss                 113937 non-null float64
LP_NetPrincipalLoss                   113937 non-null float64
LP_NonPrincipalRecoverypayments       113937 non-null float64
PercentFunded                         113937 non-null float64
```

```
Recommendations                        113937 non-null int64
InvestmentFromFriendsCount             113937 non-null int64
InvestmentFromFriendsAmount            113937 non-null float64
Investors                              113937 non-null int64
dtypes: bool(3), float64(50), int64(11), object(17)
memory usage: 68.1+ MB
```

In [49]:
```
#Explore descriptive statistics
df_ploan.describe()
```

Out[49]:
```
       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]
```

- 61 columns are of numerical data type. As such statistics such as mean, standard deviation, and inter quartile ranges were performed in the summary statistics.

In [50]:
```
#Find missing values
df_ploan.isnull()
```

Out[50]:
```
       ListingKey  ListingNumber  ListingCreationDate  CreditGrade   Term  \
0           False          False                False        False  False
1           False          False                False         True  False
2           False          False                False        False  False
3           False          False                False         True  False
4           False          False                False         True  False
5           False          False                False         True  False
6           False          False                False         True  False
7           False          False                False         True  False
8           False          False                False         True  False
9           False          False                False         True  False
10          False          False                False         True  False
11          False          False                False        False  False
12          False          False                False         True  False
13          False          False                False         True  False
14          False          False                False         True  False
15          False          False                False         True  False
```

16	False	False	False	True	False
17	False	False	False	False	False
18	False	False	False	True	False
19	False	False	False	True	False
20	False	False	False	True	False
21	False	False	False	False	False
22	False	False	False	True	False
23	False	False	False	True	False
24	False	False	False	True	False
25	False	False	False	True	False
26	False	False	False	True	False
27	False	False	False	True	False
28	False	False	False	True	False
29	False	False	False	True	False
...	...	...	...	...	...
113907	False	False	False	True	False
113908	False	False	False	True	False
113909	False	False	False	True	False
113910	False	False	False	True	False
113911	False	False	False	True	False
113912	False	False	False	True	False
113913	False	False	False	True	False
113914	False	False	False	False	False
113915	False	False	False	False	False
113916	False	False	False	True	False
113917	False	False	False	True	False
113918	False	False	False	False	False
113919	False	False	False	True	False
113920	False	False	False	True	False
113921	False	False	False	False	False
113922	False	False	False	False	False
113923	False	False	False	False	False
113924	False	False	False	True	False
113925	False	False	False	True	False
113926	False	False	False	False	False
113927	False	False	False	False	False
113928	False	False	False	True	False
113929	False	False	False	True	False
113930	False	False	False	True	False
113931	False	False	False	True	False
113932	False	False	False	True	False
113933	False	False	False	True	False
113934	False	False	False	True	False
113935	False	False	False	True	False
113936	False	False	False	True	False

	LoanStatus	ClosedDate	BorrowerAPR	BorrowerRate	LenderYield \
0	False	False	False	False	False

1	False	True	False	False	False
2	False	False	False	False	False
3	False	True	False	False	False
4	False	True	False	False	False
5	False	True	False	False	False
6	False	True	False	False	False
7	False	True	False	False	False
8	False	True	False	False	False
9	False	True	False	False	False
10	False	True	False	False	False
11	False	False	False	False	False
12	False	True	False	False	False
13	False	True	False	False	False
14	False	True	False	False	False
15	False	False	False	False	False
16	False	True	False	False	False
17	False	False	False	False	False
18	False	True	False	False	False
19	False	True	False	False	False
20	False	True	False	False	False
21	False	False	False	False	False
22	False	True	False	False	False
23	False	False	False	False	False
24	False	True	False	False	False
25	False	True	False	False	False
26	False	False	False	False	False
27	False	False	False	False	False
28	False	True	False	False	False
29	False	True	False	False	False
...	...	...	...	...	...
113907	False	True	False	False	False
113908	False	False	False	False	False
113909	False	True	False	False	False
113910	False	True	False	False	False
113911	False	True	False	False	False
113912	False	True	False	False	False
113913	False	False	False	False	False
113914	False	False	False	False	False
113915	False	False	False	False	False
113916	False	True	False	False	False
113917	False	True	False	False	False
113918	False	False	False	False	False
113919	False	True	False	False	False
113920	False	True	False	False	False
113921	False	False	True	False	False
113922	False	False	False	False	False
113923	False	False	False	False	False
113924	False	True	False	False	False

```
113925       False         True        False          False         False
113926       False        False        False          False         False
113927       False        False        False          False         False
113928       False        False        False          False         False
113929       False        False        False          False         False
113930       False         True        False          False         False
113931       False         True        False          False         False
113932       False         True        False          False         False
113933       False         True        False          False         False
113934       False         True        False          False         False
113935       False        False        False          False         False
113936       False         True        False          False         False

         ...     LP_ServiceFees  LP_CollectionFees  LP_GrossPrincipalLoss  \
0        ...              False              False                  False
1        ...              False              False                  False
2        ...              False              False                  False
3        ...              False              False                  False
4        ...              False              False                  False
5        ...              False              False                  False
6        ...              False              False                  False
7        ...              False              False                  False
8        ...              False              False                  False
9        ...              False              False                  False
10       ...              False              False                  False
11       ...              False              False                  False
12       ...              False              False                  False
13       ...              False              False                  False
14       ...              False              False                  False
15       ...              False              False                  False
16       ...              False              False                  False
17       ...              False              False                  False
18       ...              False              False                  False
19       ...              False              False                  False
20       ...              False              False                  False
21       ...              False              False                  False
22       ...              False              False                  False
23       ...              False              False                  False
24       ...              False              False                  False
25       ...              False              False                  False
26       ...              False              False                  False
27       ...              False              False                  False
28       ...              False              False                  False
29       ...              False              False                  False
...      ...                ...                ...                    ...
113907   ...              False              False                  False
113908   ...              False              False                  False
113909   ...              False              False                  False
```

```
113910    ...             False            False                  False
113911    ...             False            False                  False
113912    ...             False            False                  False
113913    ...             False            False                  False
113914    ...             False            False                  False
113915    ...             False            False                  False
113916    ...             False            False                  False
113917    ...             False            False                  False
113918    ...             False            False                  False
113919    ...             False            False                  False
113920    ...             False            False                  False
113921    ...             False            False                  False
113922    ...             False            False                  False
113923    ...             False            False                  False
113924    ...             False            False                  False
113925    ...             False            False                  False
113926    ...             False            False                  False
113927    ...             False            False                  False
113928    ...             False            False                  False
113929    ...             False            False                  False
113930    ...             False            False                  False
113931    ...             False            False                  False
113932    ...             False            False                  False
113933    ...             False            False                  False
113934    ...             False            False                  False
113935    ...             False            False                  False
113936    ...             False            False                  False

        LP_NetPrincipalLoss  LP_NonPrincipalRecoverypayments  PercentFunded  \
0                     False                            False          False
1                     False                            False          False
2                     False                            False          False
3                     False                            False          False
4                     False                            False          False
5                     False                            False          False
6                     False                            False          False
7                     False                            False          False
8                     False                            False          False
9                     False                            False          False
10                    False                            False          False
11                    False                            False          False
12                    False                            False          False
13                    False                            False          False
14                    False                            False          False
15                    False                            False          False
16                    False                            False          False
17                    False                            False          False
18                    False                            False          False
```

```
19                      False                               False           False
20                      False                               False           False
21                      False                               False           False
22                      False                               False           False
23                      False                               False           False
24                      False                               False           False
25                      False                               False           False
26                      False                               False           False
27                      False                               False           False
28                      False                               False           False
29                      False                               False           False
...                       ...                                 ...             ...
113907                  False                               False           False
113908                  False                               False           False
113909                  False                               False           False
113910                  False                               False           False
113911                  False                               False           False
113912                  False                               False           False
113913                  False                               False           False
113914                  False                               False           False
113915                  False                               False           False
113916                  False                               False           False
113917                  False                               False           False
113918                  False                               False           False
113919                  False                               False           False
113920                  False                               False           False
113921                  False                               False           False
113922                  False                               False           False
113923                  False                               False           False
113924                  False                               False           False
113925                  False                               False           False
113926                  False                               False           False
113927                  False                               False           False
113928                  False                               False           False
113929                  False                               False           False
113930                  False                               False           False
113931                  False                               False           False
113932                  False                               False           False
113933                  False                               False           False
113934                  False                               False           False
113935                  False                               False           False
113936                  False                               False           False

        Recommendations  InvestmentFromFriendsCount  \
0                 False                       False
1                 False                       False
2                 False                       False
3                 False                       False
```

4	False	False
5	False	False
6	False	False
7	False	False
8	False	False
9	False	False
10	False	False
11	False	False
12	False	False
13	False	False
14	False	False
15	False	False
16	False	False
17	False	False
18	False	False
19	False	False
20	False	False
21	False	False
22	False	False
23	False	False
24	False	False
25	False	False
26	False	False
27	False	False
28	False	False
29	False	False
...	...	...
113907	False	False
113908	False	False
113909	False	False
113910	False	False
113911	False	False
113912	False	False
113913	False	False
113914	False	False
113915	False	False
113916	False	False
113917	False	False
113918	False	False
113919	False	False
113920	False	False
113921	False	False
113922	False	False
113923	False	False
113924	False	False
113925	False	False
113926	False	False
113927	False	False

```
113928             False                         False
113929             False                         False
113930             False                         False
113931             False                         False
113932             False                         False
113933             False                         False
113934             False                         False
113935             False                         False
113936             False                         False

        InvestmentFromFriendsAmount  Investors
0                             False      False
1                             False      False
2                             False      False
3                             False      False
4                             False      False
5                             False      False
6                             False      False
7                             False      False
8                             False      False
9                             False      False
10                            False      False
11                            False      False
12                            False      False
13                            False      False
14                            False      False
15                            False      False
16                            False      False
17                            False      False
18                            False      False
19                            False      False
20                            False      False
21                            False      False
22                            False      False
23                            False      False
24                            False      False
25                            False      False
26                            False      False
27                            False      False
28                            False      False
29                            False      False
...                             ...        ...
113907                        False      False
113908                        False      False
113909                        False      False
113910                        False      False
113911                        False      False
113912                        False      False
```

```
113913                            False      False
113914                            False      False
113915                            False      False
113916                            False      False
113917                            False      False
113918                            False      False
113919                            False      False
113920                            False      False
113921                            False      False
113922                            False      False
113923                            False      False
113924                            False      False
113925                            False      False
113926                            False      False
113927                            False      False
113928                            False      False
113929                            False      False
113930                            False      False
113931                            False      False
113932                            False      False
113933                            False      False
113934                            False      False
113935                            False      False
113936                            False      False

[113937 rows x 81 columns]
```

- There are a lot missing entries, as part of the dataset columns certain missing entries for example, OnTimeProsperPayments is the number of on time payments the borrower had made on Prosper loans at the time they created this listing. This value will be null if the borrower has no prior loans.

1.3.1 What is the structure of your dataset?

The dataset has are 113,937 loans entries with 81 variables. The variables are numeric and categorical in nature where 61 variables are of numeric type and the remaing of string or object type.

For this project two main categories will be considered from the variables:

1. The demorgraphic information (The basic borrower information)
2. The loan performance indicators (Loan performance variables)

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

As a prospective partner I will like to know: 1. What are the base type of borrowers? 2. What is the cuurent state of loans, are there more default loans? 3. What is the relationship between the Borrower Rate on loans and employment status? 4. What is the relationship between EmploymentStatus vs BorrowerRate in each LoanStatus?

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

The dataset has a lot of features to explore. But for the purposes of this project we will focus on an few features to handle our problem statment.

The demorgrphic information will consider:

1. **IncomeRange** - The income range of the borrower at the time the listing was created.
2. **EmploymentStatus** - The employment status of the borrower at the time they posted the listing.
3. **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
4. **IsBorrowerHomeowner** - A Borrower will be classified as a homeowner if they have a mortgage on their credit profile or provide documentation confirming they are a homeowner.

The general performance of loans can be determined by the following indicators:

1. **LoanStatus** - The current status of the loan: Cancelled, Chargedoff, Completed, Current, Defaulted, FinalPaymentInProgress, PastDue. The PastDue status will be accompanied by a delinquency bucket.
2. **EstimatedReturn** - The estimated return assigned to the listing at the time it was created. Estimated return is the difference between the Estimated Effective Yield and the Estimated Loss Rate. Applicable for loans originated after July 2009. This is on an annual percentage rate (APR).
3. **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.
4. **Term** - The length of the loan expressed in months.
5. **BorrowerRate** - The Borrower's interest rate for this loan.

```
In [51]: df_new = df_ploan.loc[:, ['LoanOriginationDate','IncomeRange','EmploymentStatus','Listi
```

```
In [52]: df_new.head()
```

```
Out[52]:    LoanOriginationDate     IncomeRange EmploymentStatus  \
        0  2007-09-12 00:00:00  $25,000-49,999    Self-employed
        1  2014-03-03 00:00:00  $50,000-74,999         Employed
        2  2007-01-17 00:00:00   Not displayed    Not available
        3  2012-11-01 00:00:00  $25,000-49,999         Employed
        4  2013-09-20 00:00:00        $100,000+         Employed

           ListingCategory (numeric)  IsBorrowerHomeowner LoanStatus  EstimatedReturn  \
        0                          0                 True  Completed              NaN
        1                          2                False    Current          0.05470
        2                          0                False  Completed              NaN
```

```
3                          16                True    Current           0.06000
4                           2                True    Current           0.09066

   ProsperScore  Term  BorrowerRate
0           NaN    36        0.1580
1           7.0    36        0.0920
2           NaN    36        0.2750
3           9.0    36        0.0974
4           4.0    36        0.2085
```

1.4 Univariate Exploration

This section explores data using univariate methods for our two categories to get a better idea of the variable distribution.

```
In [53]: #function created to avoid code repetition
         def lchart_labels(x_label,y_label,title):
             plt.title(title)
             plt.xlabel(x_label)
             plt.ylabel(y_label)
```

1.4.1 Plot I to V below gives answers to What are the base type of borrowers?

1.4.2 PLOT I

1.4.3 Income Range

For our variables of interest we start be looking at our demographic features commencing with income range of borrowers.

```
In [54]: df_new.IncomeRange.value_counts()

Out[54]: $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
```

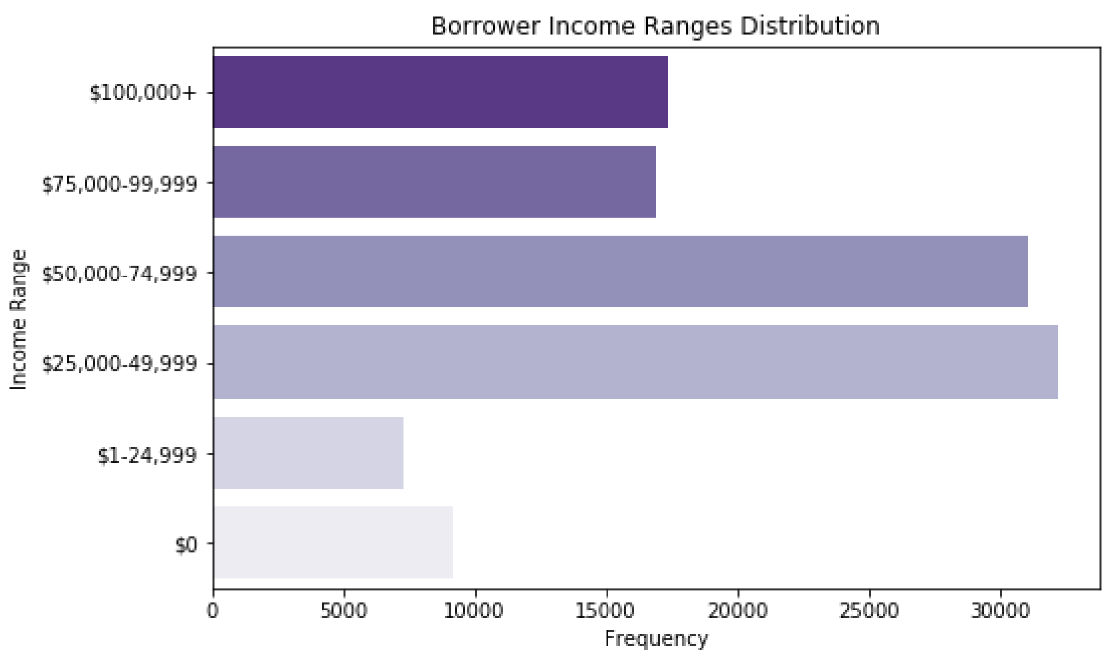
- From the result we have to rename some of the entries as they are similar in meaning to get a better picture of the data.

```
In [55]: df_new['IncomeRange'].replace(['Not employed', 'Not displayed'], '$0', inplace = True)

In [56]: #Check to confirm changes made are effected
         df_new['IncomeRange'].value_counts()
```

```
Out[56]: $25,000-49,999    32192
         $50,000-74,999    31050
         $100,000+         17337
         $75,000-99,999    16916
         $0                 9168
         $1-24,999          7274
         Name: IncomeRange, dtype: int64
```

```
In [57]: # put the income range in an ordinal category
         ord_income = ['$100,000+', '$75,000-99,999', '$50,000-74,999', '$25,000-49,999', '$1-24
         ordered_income_var = pd.api.types.CategoricalDtype(ordered = True, categories = ord_inc
         df_new['IncomeRange'] = df_new['IncomeRange'].astype(ordered_income_var)
```

```
In [58]: # A bar chart to display distribution
         plt.figure(figsize = [8, 5])
         income_plot = sb.countplot(data = df_new, y = 'IncomeRange', palette = "Purples_r")
         lchart_labels('Frequency','Income Range','Borrower Income Ranges Distribution');
```



- From the bar chart above, majority of borrowers have an income range of \$25k-49k followed by an income range of \$50k-74k. The minimum number of borrowers fall within \$1-24k income range.

1.4.4 PLOT II

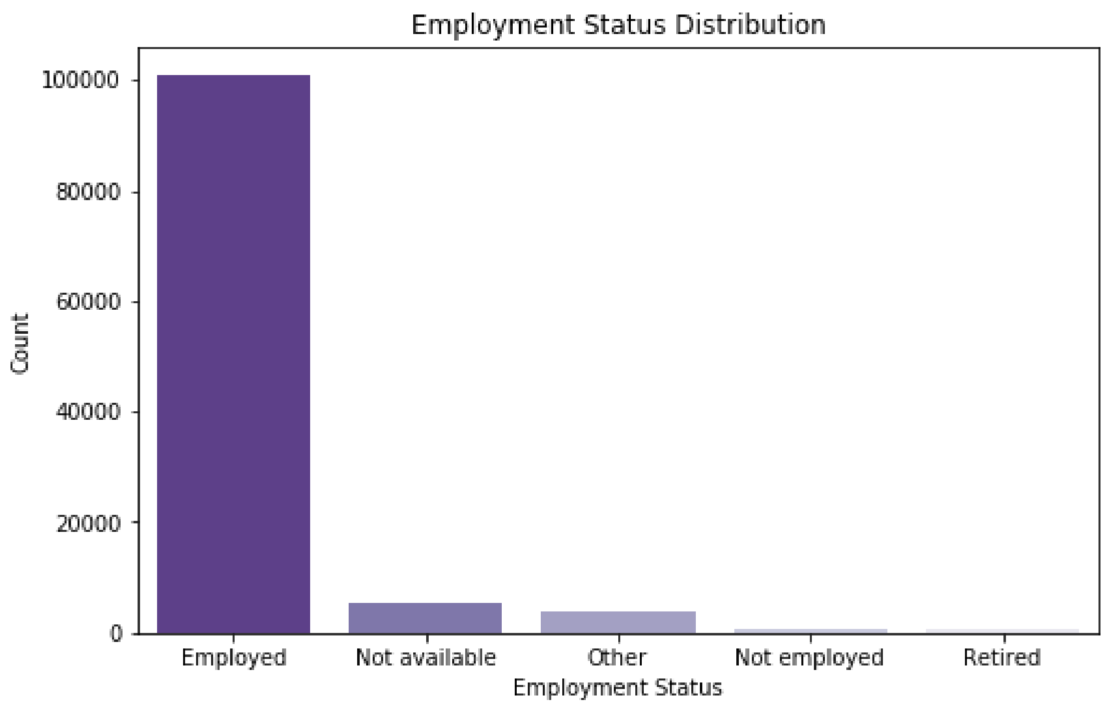
1.4.5 Employment Status

```
In [59]: df_new.EmploymentStatus.value_counts()
```

```
Out[59]: 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
```

```
In [60]: #Replace entries with similar categorizations
         emply_stat = df_new['EmploymentStatus'].replace(['Full-time', 'Self-employed','Part-tim
```

```
In [61]: # A bar chart to display employment status distribution
         plt.figure(figsize = [8, 5])
         emp_plot = sb.countplot(data = df_new, x = 'EmploymentStatus', palette = "Purples_r")
         lchart_labels('Employment Status','Count','Employment Status Distribution');
```



- From the bar chart above over 100,000 borrowers are employed. These are made up of fully employed, self-employed and partially employed borrowers. 795 borrowers are retired representing the shortest bar.

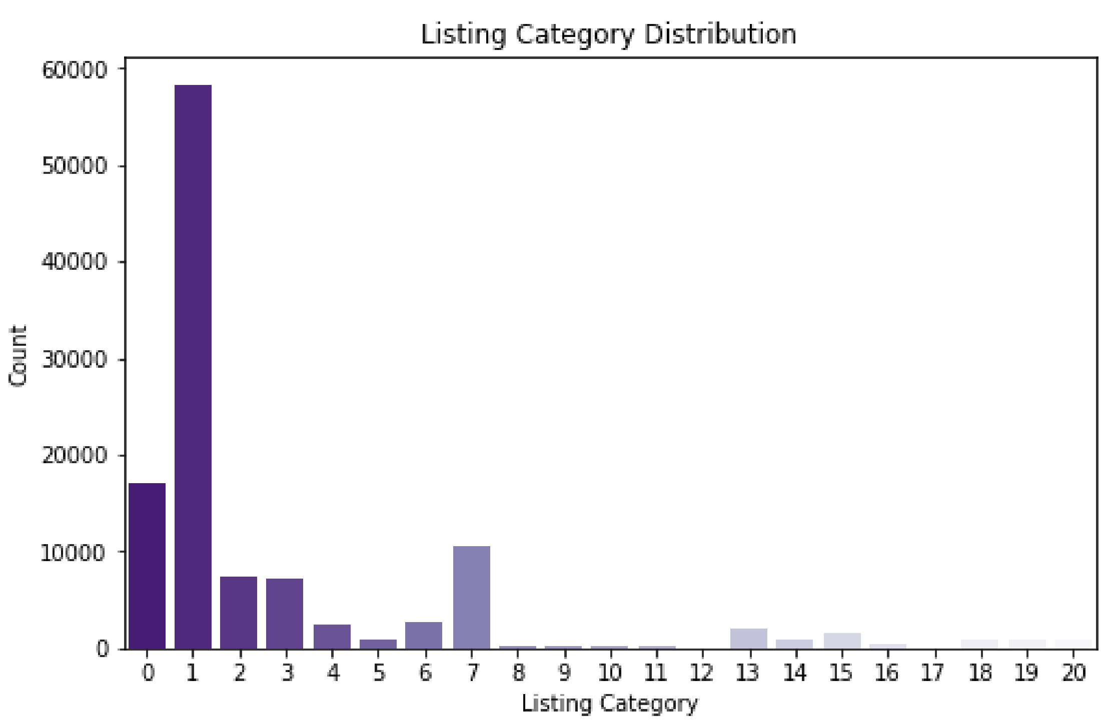
1.4.6 PLOT III

1.4.7 Listing Category

```
In [62]: df_new['ListingCategory (numeric)'].value_counts()
```

```
Out[62]: 1     58308
         0     16965
         7     10494
         2      7433
         3      7189
         6      2572
         4      2395
         13     1996
         15     1522
         18      885
         14      876
         20      771
         19      768
         5       756
         16      304
         11      217
         8       199
         10       91
         9        85
         12       59
         17       52
         Name: ListingCategory (numeric), dtype: int64
```

```
In [63]: # A bar chart to display listing categories distribution
         plt.figure(figsize = [8, 5])
         emp_plot = sb.countplot(data = df_new, x = 'ListingCategory (numeric)', palette = "Purp
         lchart_labels('Listing Category','Count','Listing Category Distribution');
```



- From the bar chart above, 58308 being the highest of loans are taken for the purposes of Debt Consolidation indicated by 1.

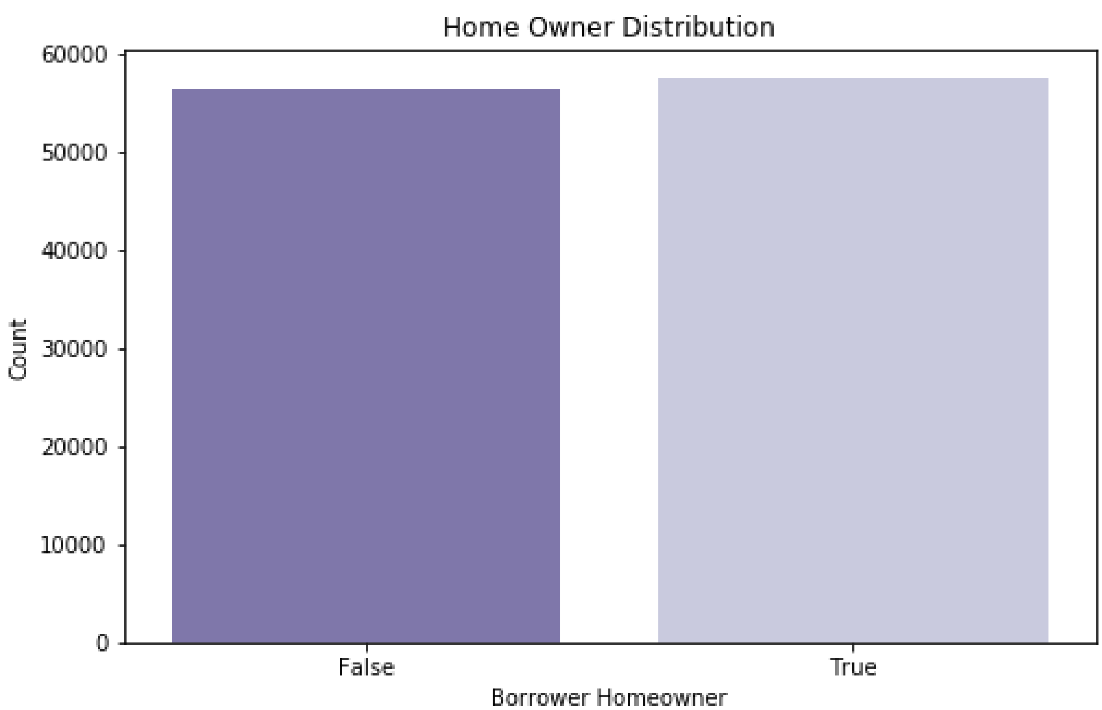
1.4.8 PLOT IV

1.4.9 Home Owners

In [64]:
```
df_new['IsBorrowerHomeowner'].value_counts()
```

Out[64]:
```
True     57478
False    56459
Name: IsBorrowerHomeowner, dtype: int64
```

In [65]:
```
# A bar chart to display borrowers who are home owners distribution
plt.figure(figsize = [8, 5])
emp_plot = sb.countplot(data = df_new, x = 'IsBorrowerHomeowner', palette = "Purples_r"
lchart_labels('Borrower Homeowner','Count','Home Owner Distribution');
```



- The bar chart above indicates the borrowers who are home owners are 1,019, more than those who are not home owners.

1.4.10 Plot V attends to the question What is the cuurent state of loans, are there more default loans?

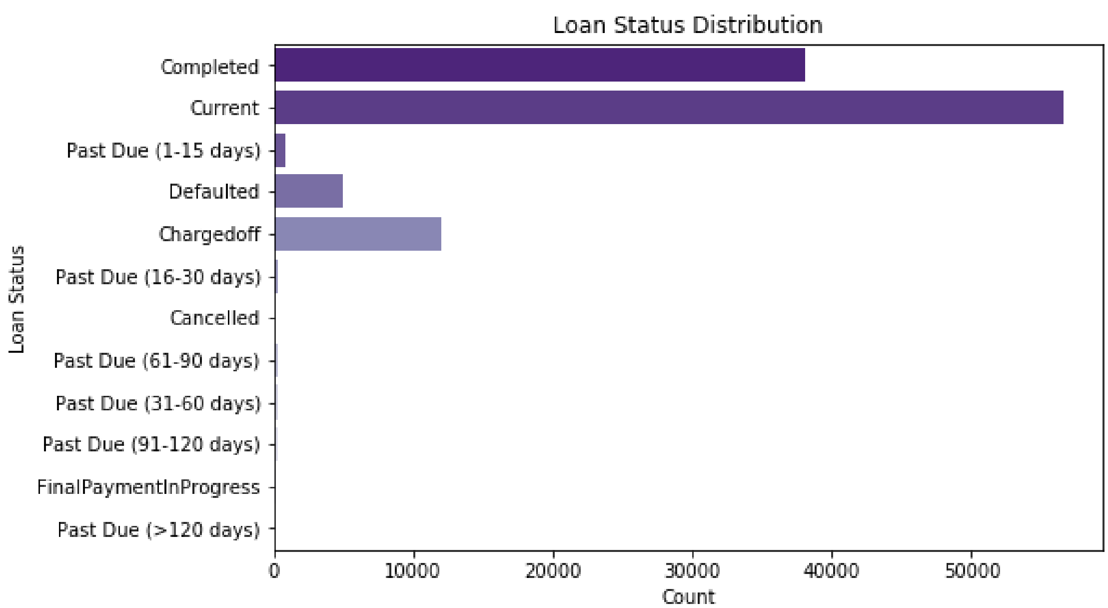
1.4.11 PLOT V

1.4.12 Loan Status

In [66]:
```
df_new['LoanStatus'].value_counts()
```

Out[66]:
```
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
```

In [67]:
```
# A bar chart to display borrowers loan status
plt.figure(figsize = [8, 5])
emp_plot = sb.countplot(data = df_new, y = 'LoanStatus', palette = "Purples_r")
lchart_labels('Count','Loan Status','Loan Status Distribution');
```



- From the above chart 56,576 being the highest represents current loans, whereas, 38,074 of the loans have been completed. There is a record of 5,018 defaulted loans.

1.4.13 PLOT VI

1.4.14 Estimated Return

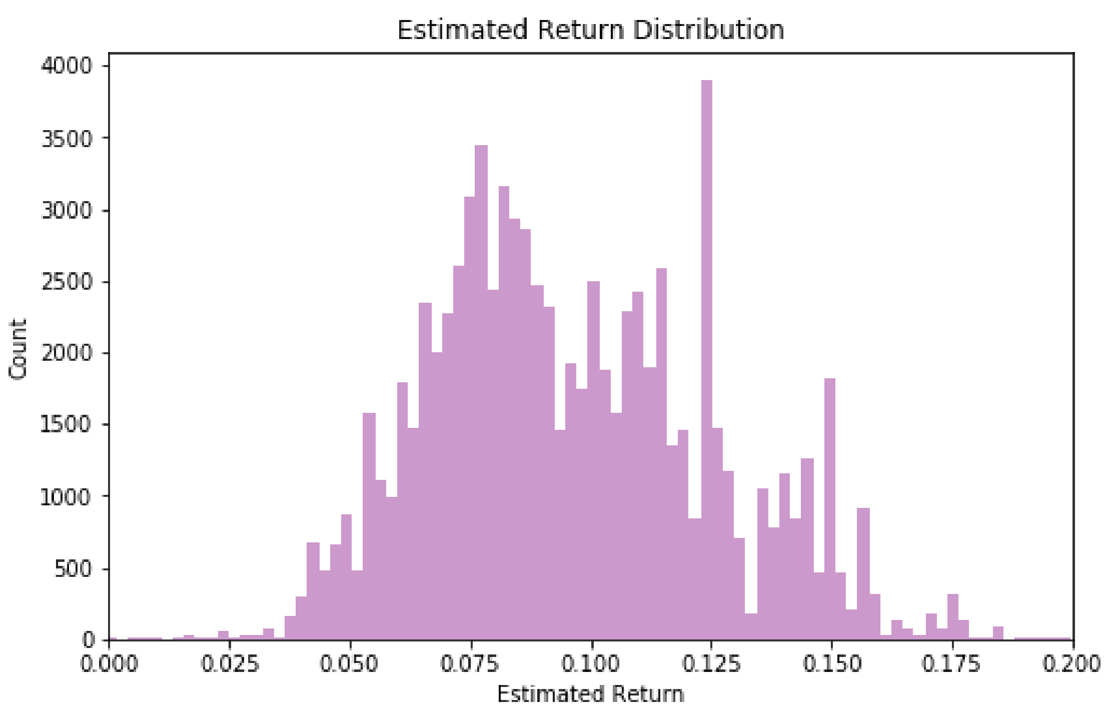
In [68]:
```
df_new['EstimatedReturn'].describe()
```

Out[68]:
```
count    84853.000000
mean         0.096068
std          0.030403
min         -0.182700
25%          0.074080
50%          0.091700
75%          0.116600
max          0.283700
Name: EstimatedReturn, dtype: float64
```

- The output of the description could be distorted because of the null values. To avert this we have to remove missing value entries.

In [69]:
```
# drop missing entries in estimated return
df_new.EstimatedReturn.dropna(axis = 0, inplace = True)
```

In [70]:
```
# histogram plot
plt.figure(figsize = [8,5])
sb.distplot(df_new.EstimatedReturn, kde = False, bins = 200, color = "Purple")
plt.xlim(0, .2)
lchart_labels('Estimated Return','Count','Estimated Return Distribution');
plt.show()
```



- The estimated return is the difference between the Estimated Effective Yield and the Estimated Loss Rate. From the histogram, it looks left skewed with a mean of 0.09 and a standard deviation of 0.03.

1.4.15 PLOT VII

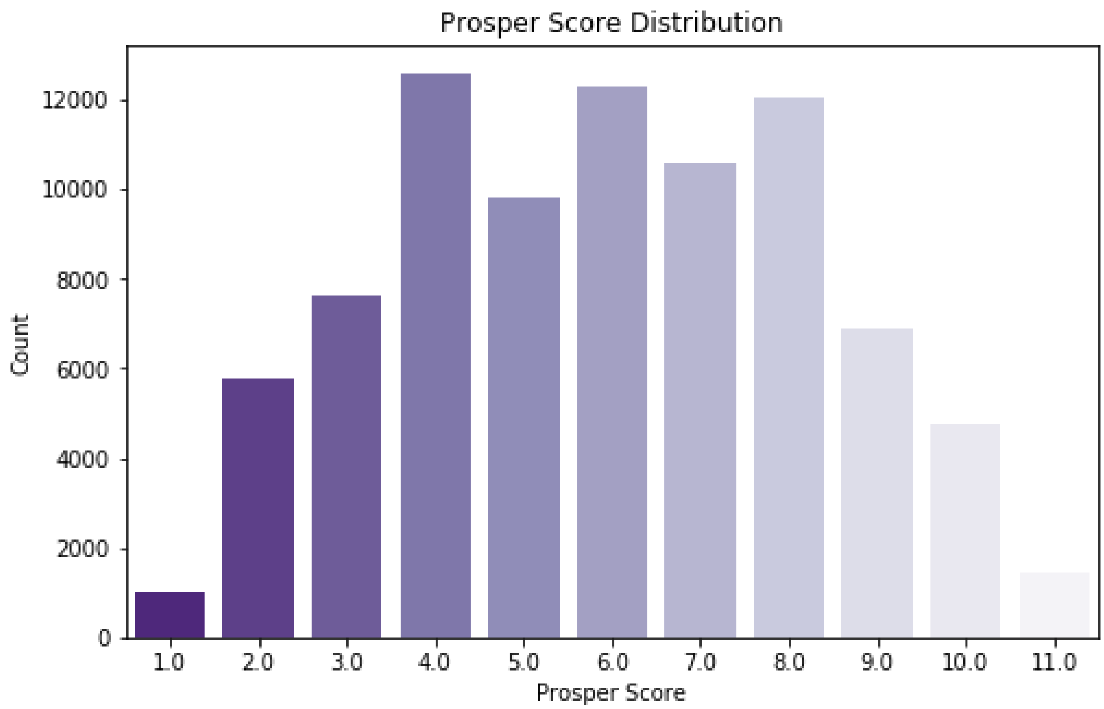
1.4.16 Prosper Score

Prosper Score: A custom risk score built using historic Prosper data. The score ranges from 1-11, with 11 being the best, or lowest risk score. Prosper website::

In [71]:
```
df_new['ProsperScore'].value_counts()
```

Out[71]:
```
4.0     12595
6.0     12278
8.0     12053
7.0     10597
5.0      9813
3.0      7642
9.0      6911
2.0      5766
10.0     4750
11.0     1456
1.0       992
Name: ProsperScore, dtype: int64
```

In [72]:
```
# A bar chart to display Prosper Score
plt.figure(figsize = [8, 5])
emp_plot = sb.countplot(data = df_new, x = 'ProsperScore', palette = "Purples_r")
lchart_labels('Prosper Score','Count','Prosper Score Distribution');
```

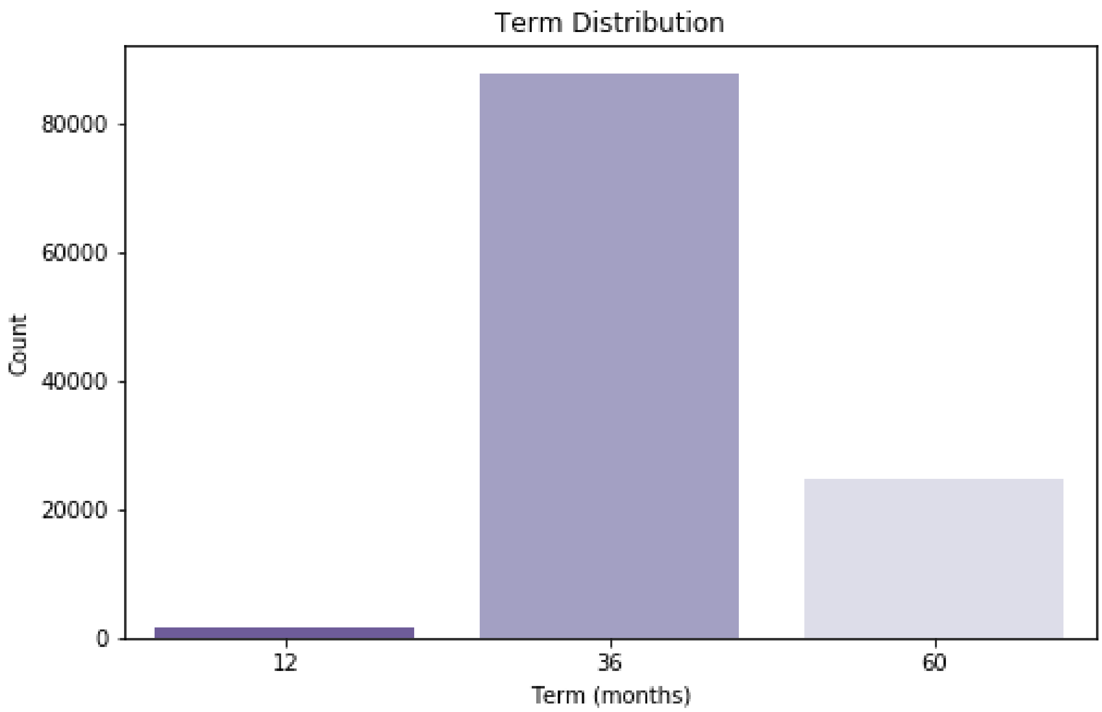


- The highest-rated loan score is 4 with 12595, which has a high risk according to the prosper scare rating. The best rating of 11 has a frequency of 1456, which is the second least on the bar chart. The appearance of the chart almost seems bell shaped which is similar to a normal distribution.

1.4.17 PLOT VIII

1.4.18 Loan Term

```
In [73]: df_new['Term'].value_counts()

Out[73]: 36    87778
         60    24545
         12     1614
         Name: Term, dtype: int64

In [74]: # A bar chart to display Term of various loans
         plt.figure(figsize = [8, 5])
         sb.countplot(data = df_new, x = 'Term', palette = "Purples_r")
         lchart_labels('Term (months)','Count','Term Distribution');
```



- The highest Term is 36 months with 87,778 loans associated, followed by 60 months with 24,545 loans.

1.4.19 PLOT IX

1.4.20 Loan Borrower Rate

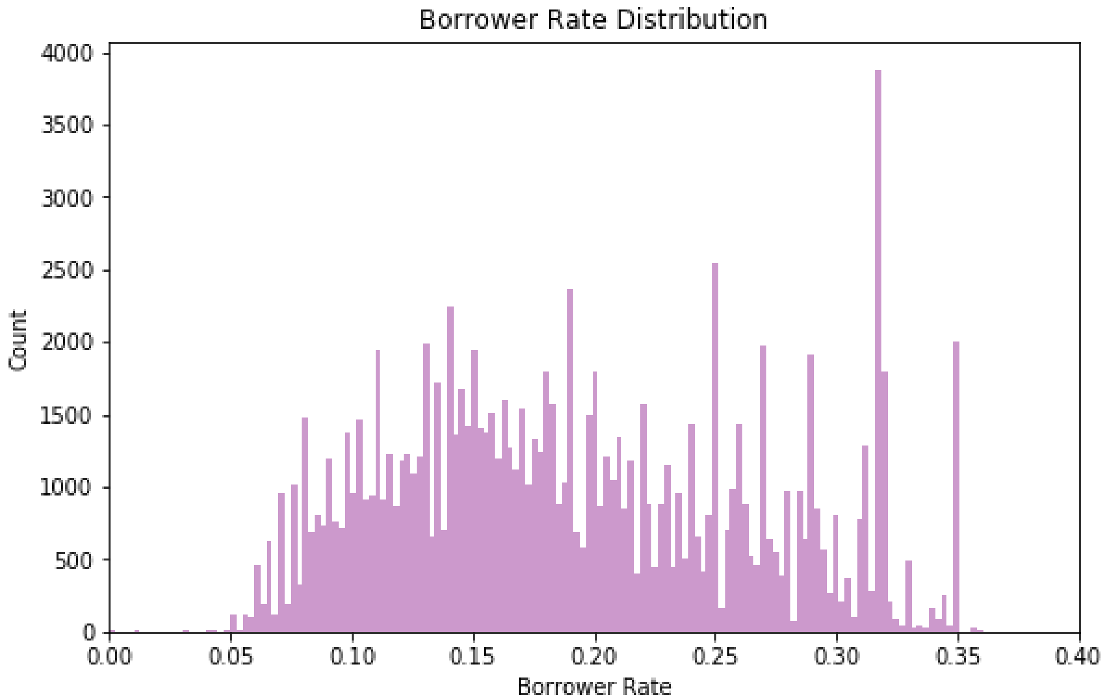
```
In [75]: df_new['BorrowerRate'].value_counts()
```

```
Out[75]: 0.3177    3672
         0.3500    1905
         0.3199    1651
         0.2900    1508
         0.2699    1319
         0.1500    1182
         0.1400    1035
         0.1099     949
         0.2000     907
         0.1585     806
         0.1800     800
         0.1299     782
         0.2099     776
         0.2599     761
         0.2199     739
         0.1620     733
```

```
0.3134    726
0.1899    713
0.1550    713
0.1840    669
0.1449    629
0.1700    621
0.2085    613
0.2049    610
0.0990    610
0.1249    596
0.2500    578
0.2400    575
0.0974    566
0.1189    565
         ...
0.0658      1
0.3153      1
0.1666      1
0.3433      1
0.1873      1
0.3360      1
0.0742      1
0.0868      1
0.0846      1
0.2777      1
0.3106      1
0.0832      1
0.0797      1
0.1432      1
0.2216      1
0.2252      1
0.2431      1
0.1822      1
0.3071      1
0.0614      1
0.3478      1
0.0638      1
0.0827      1
0.1367      1
0.2881      1
0.2717      1
0.1732      1
0.1704      1
0.1786      1
0.1721      1
Name: BorrowerRate, Length: 2294, dtype: int64
```

In [76]:
```
#Borrower Rate Distribution
```

```
plt.figure(figsize = [8,5])
sb.distplot(df_new.BorrowerRate, kde = False, bins = 200, color = "Purple")
plt.xlim(0, .4)
lchart_labels('Borrower Rate','Count','Borrower Rate Distribution');
plt.show()
```



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

For our variables of interest we started by looking at our demographic features commencing with income range of borrowers we had to rename some of the entries as they are similar in meaning to get a better picture of the data. Majority of borrowers have an income range of \$25k-49k followed by an income range of \$50k-74k. The minimum number of borrowers fall within \$1-24k income range. For employment status over 100,000 borrowers are employed. These are made up of fully employed, self-employed and partially employed borrowers. 795 borrowers are retired representing the shortest bar. About 58,308 being the highest of loans are taken for the purposes of Debt Consolidation indicated by 1. There are 1,019 more borrowers who are home owners, than those who are not home owners. This means majority have a mortgage on their credit profile or provide documentation confirming they are a homeowner.

For the current loan distribution as of the time dataset was downlaoeded 56,576 was the highest representing current loans, whereas, 38,074 of the loans have been completed. There is a record of 5,018 defaulted loans. The estimated return description result indicated missing values could distort our exploration. To avert this we removed missing value entries.

The estimated return is the difference between the Estimated Effective Yield and the Estimated Loss Rate. From the histogram, it looks left skewed with a mean of 0.09 and a standard deviation of 0.03. The highest-rated loan score is 4 with 12595, which has a high risk according to the prosper scare rating. The best rating of 11 has a frequency of 1456, which is the second least on the bar chart.

1.4.22 Of the features you investigated, were there any unusual distributions? Did you perform any operations on the data to tidy, adjust, or change the form of the data? If so, why did you do this?

The data in mostly had missing data which where justified for certain variables. For variables such as the esitmated return missing values had to be dropped as it distorted the statistics operated on the variable.

1.5 Bivariate Exploration

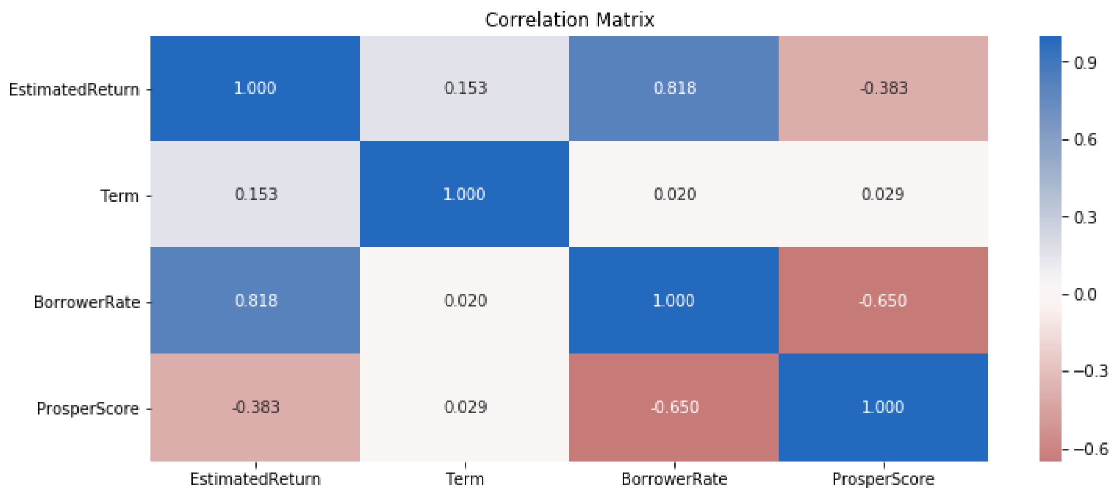
In this section, we investigate relationships between pairs of variables in the data. As varibles are of quantitative and qualitative types we will use a couple of methods that are best suited.

```
In [77]: # numeric and categorical variables
         num_variables = ['EstimatedReturn', 'Term', 'BorrowerRate', 'ProsperScore']
         cat_variables = ['IncomeRange', 'LoanStatus', 'IsBorrowerHomeowner', 'ListingCategory (
```

1.5.1 PLOT I

1.5.2 Correlation matrix for all numeric variables

```
In [78]: # Correlation matrix for all numeric variables
         plt.figure(figsize = [12, 5])
         sb.heatmap(df_new[num_variables].corr(), annot = True, fmt = '.3f',
                    cmap = 'vlag_r', center = 0)
         plt.title('Correlation Matrix')
         plt.show()
```

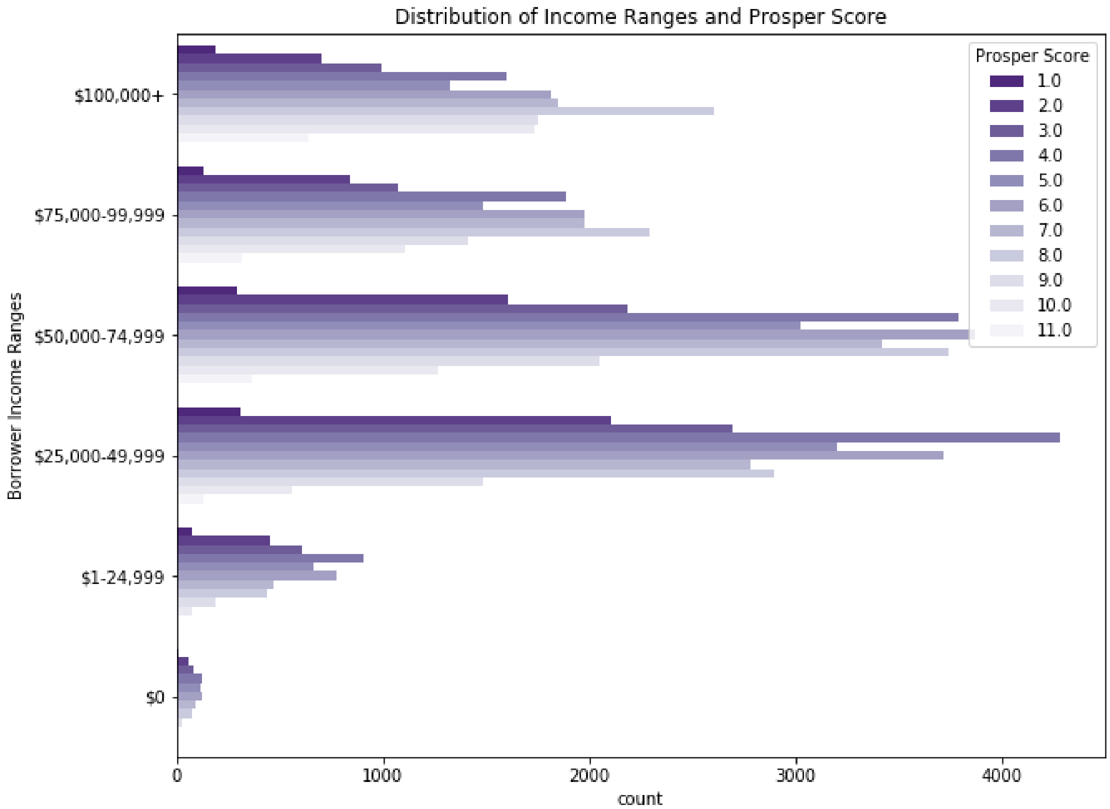


- ProsperScore is negatively related to EstimatedReturn and BorrowerRate but positively related to loan Term.
- BorrowerRate is positively related to EstimatedReturn and loan Term but negatively related to ProsperScore.

1.5.3 PLOT II

1.5.4 Clustered bar chart to find distribution between Income Range and Prosper Score

In [79]:
```
# clustered bar chart
plt.figure(figsize = [10,8])

ax = sb.countplot(data = df_new, y = 'IncomeRange', hue = 'ProsperScore',
                  palette = 'Purples_r')

ax.legend(title = 'Prosper Score')
plt.title('Distribution of Income Ranges and Prosper Score')
plt.ylabel('Borrower Income Ranges');
```



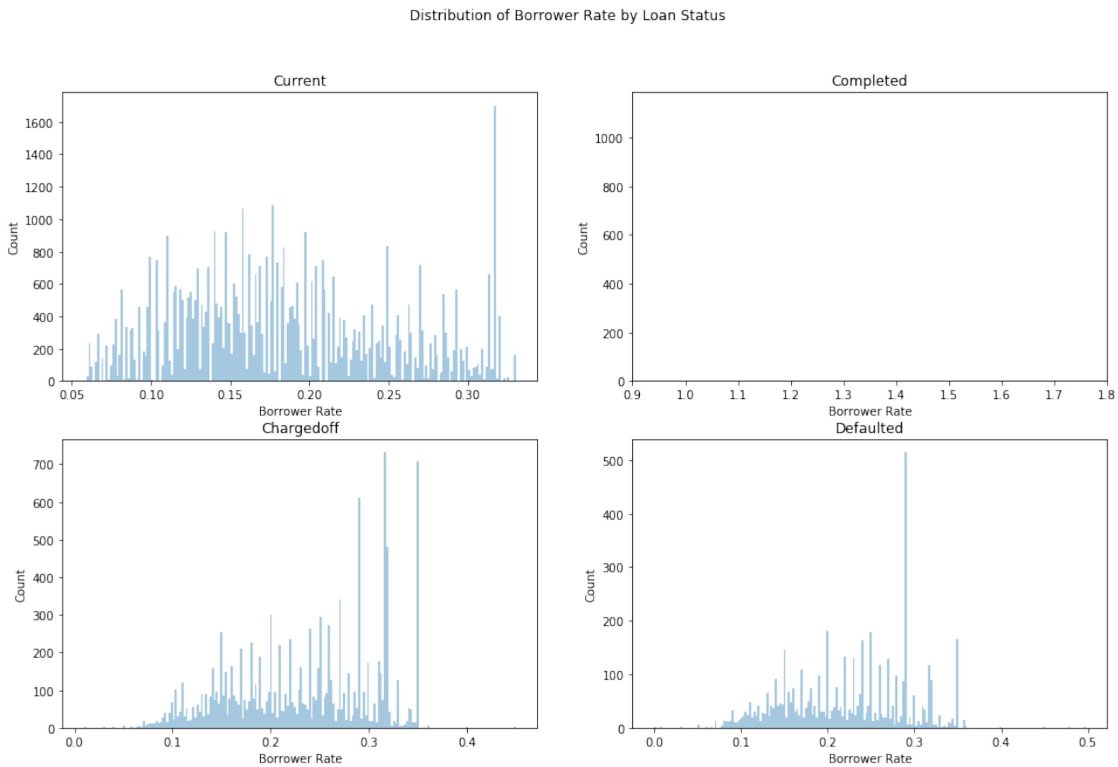
- The ProsperScore of 4 is the highest score which falls within the salary range of \$25k-49k of borrowers.
- For the salary range of \$50k-74k we realize the highest ProsperScore is 6 which has a better risk level than 4.

1.5.5 PLOT III

1.5.6 Multiplot for Loan Status variables against Borrower Rate

```
In [80]: # multiplot for loan status

         variables = ['Current', 'Completed', 'Chargedoff', 'Defaulted']

         plt.figure(figsize = [16, 10])

         # loop through variables list
         for i in range(len(variables)):
             plt.subplot(2, 2, i+1)

             sb.distplot(df_new.query('LoanStatus == "{}"'.format(variables[i])).BorrowerRate,
                         kde = False, bins = 200)
```

```
        plt.xlabel('Borrower Rate')
        plt.ylabel('Count')
        plt.title(variables[i])

    plt.subplot(2, 2, 2)
    plt.xlim(.9, 1.8)

    plt.suptitle('Distribution of Borrower Rate by Loan Status');
```



- Current loans have interest rates ranging from 10% to 35%
- Similar can be said of chargedoff loans
- The highest interest rate on borrowing for default loans fell between 20% to 30%

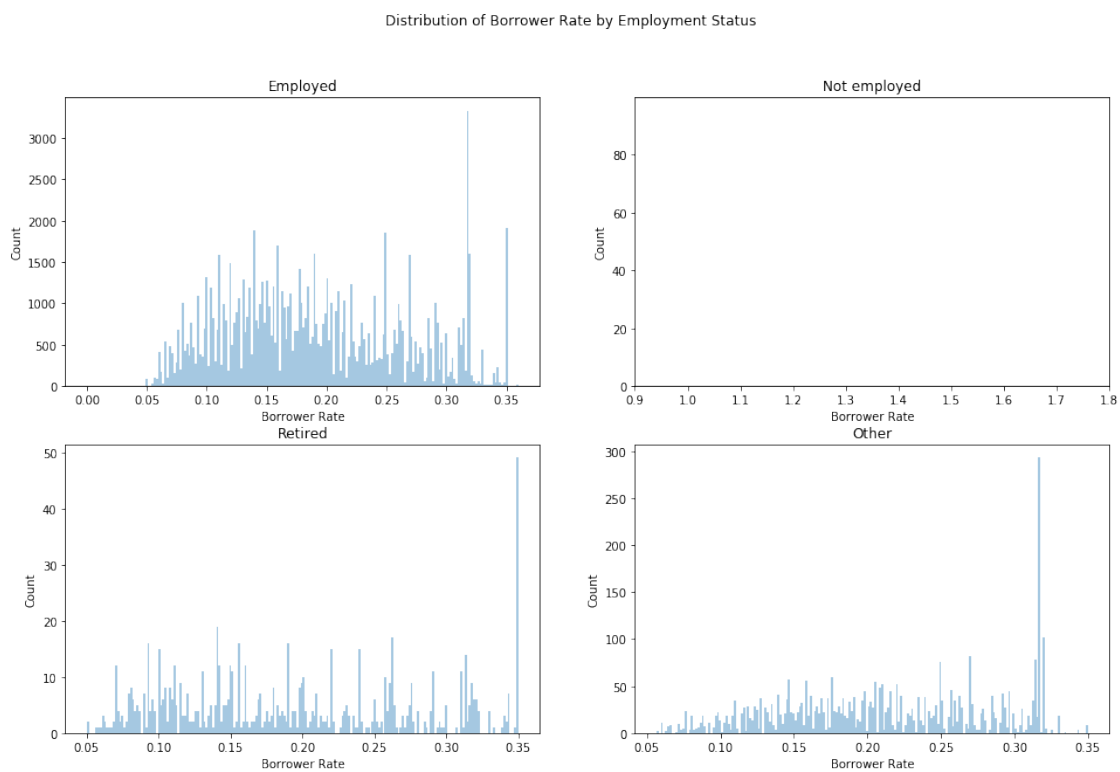
1.5.7 Findings for What is the relationship between the Borrower Rate on loans and employment status?

1.5.8 PLOT IV

1.5.9 Multiplot for employment Status variables against Borrower Rate

```
In [81]: # multiplot for loan status

         variables = ['Employed', 'Not employed', 'Retired', 'Other']
```

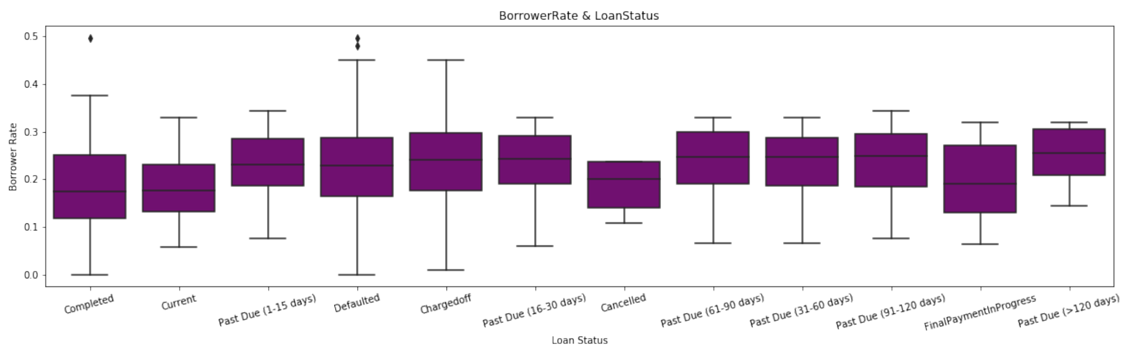
```python
plt.figure(figsize = [16, 10])

# loop through variables list
for i in range(len(variables)):
    plt.subplot(2, 2, i+1)

    sb.distplot(df_new.query('EmploymentStatus == "{}"'.format(variables[i])).BorrowerR
                 kde = False, bins = 200)

    plt.xlabel('Borrower Rate')
    plt.ylabel('Count')
    plt.title(variables[i])

plt.subplot(2, 2, 2)
plt.xlim(.9, 1.8)

plt.suptitle('Distribution of Borrower Rate by Employment Status');
```



- Employed borrowers have a highest rate range between 30-35%
- Retired borrowers have a highest borrower rate of 35%

1.5.10 PLOT V

```
In [82]: # Borrower APR vs Status of Loan
         plt.figure(figsize = [20, 5])
         sb.boxplot(data=df_new,y='BorrowerRate',x='LoanStatus',color='purple');
         plt.title('BorrowerRate & LoanStatus');
         plt.ylabel('Borrower Rate');
         plt.xlabel('Loan Status');
         plt.xticks(rotation=15);
```



- From the chart, completed and current loan statuses have the lowest borrower rates.
- It is observed, loans that are past due have higher borrower rates.

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

ProsperScore is moderately negatively related to EstimatedReturn and BorrowerRate but positively related to loan Term. BorrowerRate is strongly positively related to EstimatedReturn and loan Term but negatively related to ProsperScore. The ProsperScore of 4 is the highest score which falls within the salary range of \$25k-49k of borrowers. For the salary range of \$50k-74k we realize the highest ProsperScore is 6 which has a better risk level than 4. Current loans have interest rates ranging from 10% to 35% as well as chargeoff. The highest interest rate on borrowing for default loans fell between 20% to 30%.

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

Employed borrowers have a highest rate range between 30-35% and retired borrowers have a highest borrower rate of 35%.

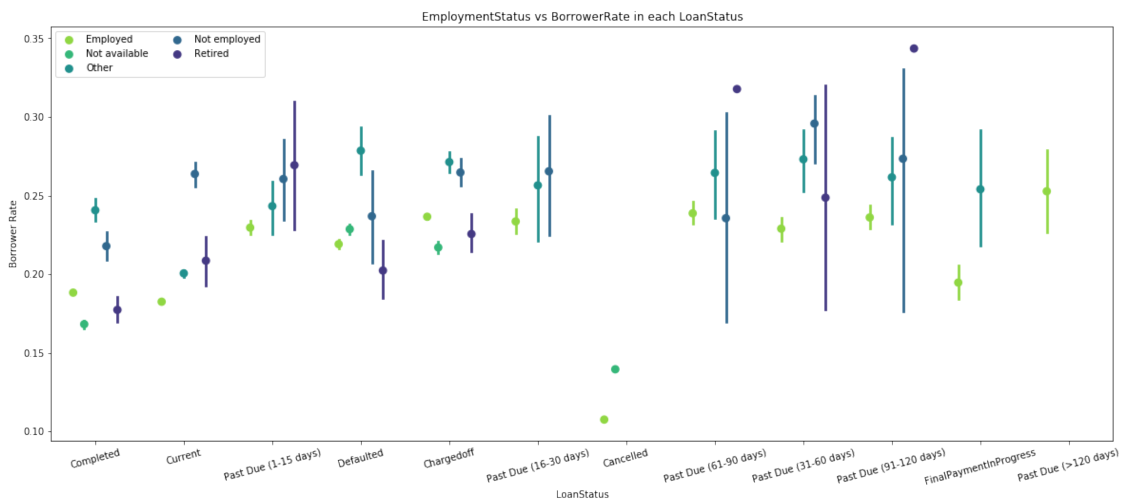
1.6 Multivariate Exploration

In this sectiion we create plots of three or more variables to investigate our data even further. Here we derive insights from previous explorations of selected variables.

1.6.1 PLOT I

EmploymentStatus vs BorrowerRate in each LoanStatus

In [83]:
```
# EmploymentStatus vs BorrowerRate in each LoanStatus
fig = plt.figure(figsize = [20,8])
ax = sb.pointplot(data = df_new, x = 'LoanStatus', y = 'BorrowerRate', hue = 'Employmen
                  dodge = 0.5, palette = 'viridis_r')
plt.title('EmploymentStatus vs BorrowerRate in each LoanStatus')
plt.ylabel('Borrower Rate')
plt.xticks(rotation=15)
plt.legend(ncol=2)
plt.show();
```

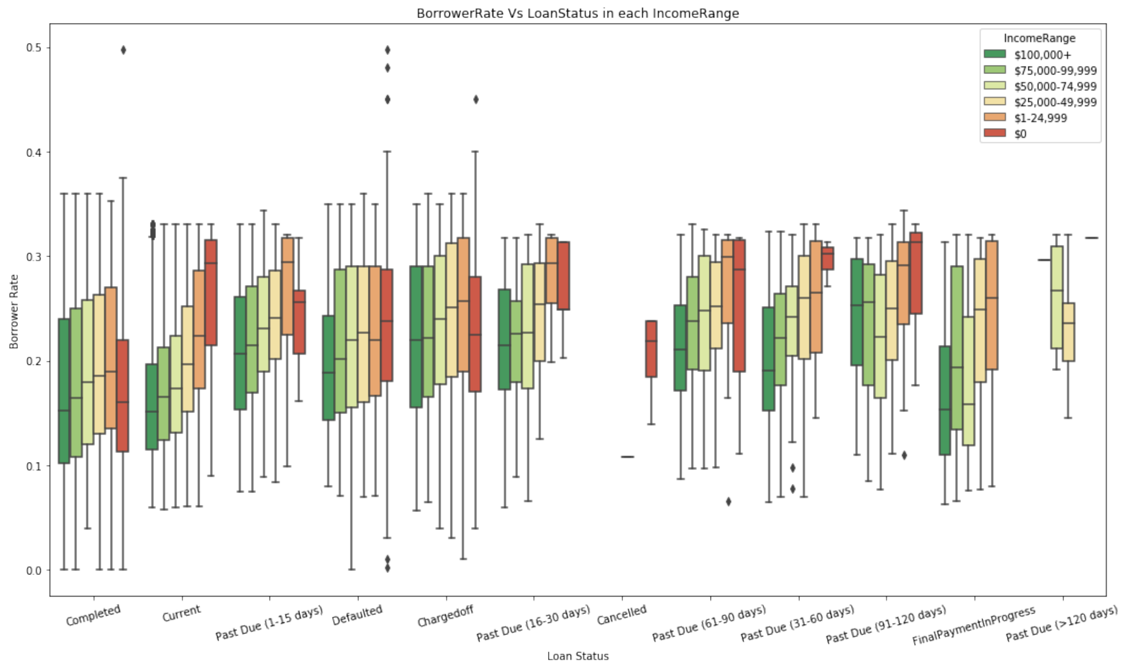


- Retired and not employed have the highest borrower rate especially with past due loans.

1.6.2 PLOT II

1.6.3 LoanStatus Vs BorrowerRate in each IncomeRange

In [84]:
```
# LoanStatus Vs BorrowerRate in each EmploymentStatus
plt.figure(figsize=[18,10])
sb.boxplot(x="LoanStatus", y="BorrowerRate", hue="IncomeRange", data=df_new, palette="R
plt.title('BorrowerRate Vs LoanStatus in each IncomeRange');
plt.xlabel('Loan Status');
plt.ylabel('Borrower Rate');
plt.xticks(rotation = 15);
```



- Past due loan statuses have higher borrower rates for borrower's with no income or \$0 and \$1-25k income range.

1.6.4 Talk about some of the relationships you observed in this part of the investigation. Were there features that strengthened each other in terms of looking at your feature(s) of interest?

Retired and not employed employment statuses have the highest borrower rate especially with past due loans. Past due loan statuses have higher borrower rates for borrower's with no income or \$0 and \$1-25k income range. We can induce, borrowers who are retired and not employed with with \$0-25k income range may not perform well on loans taken.

1.6.5 Were there any interesting or surprising interactions between features?

There are a few outliers in chargeoff, defaulted loan, and pastDue(31-60 days) status.

1.7 Conclusions

From our exploration ProsperScore is moderately negatively related to EstimatedReturn and BorrowerRate but positively related to loan Term. This means as ProsperScore increases EstimatedReturn and BorrowerRate decreases and vice versa. Further, it was realized BorrowerRate is strongly positively related to EstimatedReturn and loan Term but negatively related to ProsperScore. This means a unit increase in BorrowerRate will lead to an increase in EstimatedReturn and loan Term. We can therefore say, longer loan terms have higher BorrowerRates.

Our exploration also brought to the fore, the fact that most loans taken from Prosper Loan are for the purposes of Debt Consolidation. Also, default loans were mainly by borrowers whose employment status was not employed and retired with incomerange or \$0 and \$1-25k. The highest-rated loan score is 4 with 12595, which has a high risk according to the prosper scare rating. The best rating of 11 has a frequency of 1456, which is the second least on the bar chart.

```
In [ ]:
```