partI_explore

August 19, 2022

1 Table of Contents

Introduction

- The data set contains 113,937 loans with 81 variables on each loan, including loan amount, borrower rate (or interest rate), current loan status, borrower income, and many others.
- The data dictionary (df_desc) explains the variables in the data set.

Preliminary Wrangling

The Wrangling process will be carried out in the fashion - Gather - Assess - Visual - Programmatic - Clean - Define - Code - Test

Import modules

[130]:
```
import matplotlib.pyplot as plt
import seaborn as sb
import pandas as pd
import numpy as np
import sys
import os
import warnings; warnings.simplefilter('ignore')

%matplotlib inline
```

1.0.6 Gather

[131]:
```
df = pd.read_csv('prosperLoanData.csv')
df_desc = pd.read_csv('Prosper Loan Data - Variable Definitions - Sheet1.csv')
```

1.0.7 Assess

[132]:
```
df.tail(5)
```

[132]:

```
                     ListingKey  ListingNumber           ListingCreationDate  \
113932  E6D93576557248271696O6C         753087  2013-04-14 05:55:02.663000000
113933  E6DB353036033497292EE43         537216  2011-11-03 20:42:55.333000000
113934  E6E135961700520296928B1        1069178  2013-12-13 05:49:12.703000000
113935  E6EB3531504622671970D9E         539056  2011-11-14 13:18:26.597000000
113936  E6ED3600409833199F711B7        1140093  2014-01-15 09:27:37.657000000

       CreditGrade  Term             LoanStatus           ClosedDate  \
113932         NaN    36                Current                  NaN
113933         NaN    36  FinalPaymentInProgress                  NaN
113934         NaN    60                Current                  NaN
113935         NaN    60              Completed  2013-08-13 00:00:00
113936         NaN    36                Current                  NaN

        BorrowerAPR  BorrowerRate  LenderYield  …  LP_ServiceFees  \
113932      0.22354        0.1864       0.1764  …          -75.58
113933      0.13220        0.1110       0.1010  …          -30.05
113934      0.23984        0.2150       0.2050  …          -16.91
113935      0.28408        0.2605       0.2505  …         -235.05
113936      0.13189        0.1039       0.0939  …           -1.70

        LP_CollectionFees  LP_GrossPrincipalLoss  LP_NetPrincipalLoss  \
113932                0.0                    0.0                  0.0
113933                0.0                    0.0                  0.0
113934                0.0                    0.0                  0.0
113935                0.0                    0.0                  0.0
113936                0.0                    0.0                  0.0

       LP_NonPrincipalRecoverypayments  PercentFunded  Recommendations  \
113932                             0.0            1.0                0
113933                             0.0            1.0                0
113934                             0.0            1.0                0
113935                             0.0            1.0                0
113936                             0.0            1.0                0

       InvestmentFromFriendsCount InvestmentFromFriendsAmount Investors
113932                          0                        0.0         1
113933                          0                        0.0        22
113934                          0                        0.0       119
113935                          0                        0.0       274
113936                          0                        0.0         1

[5 rows x 81 columns]
```

[133]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 113937 entries, 0 to 113936
Data columns (total 81 columns):
 #   Column                                Non-Null Count   Dtype
---  ------                                --------------   -----
 0   ListingKey                            113937 non-null  object
 1   ListingNumber                         113937 non-null  int64
 2   ListingCreationDate                   113937 non-null  object
 3   CreditGrade                           28953 non-null   object
 4   Term                                  113937 non-null  int64
 5   LoanStatus                            113937 non-null  object
 6   ClosedDate                            55089 non-null   object
 7   BorrowerAPR                           113912 non-null  float64
 8   BorrowerRate                          113937 non-null  float64
 9   LenderYield                           113937 non-null  float64
 10  EstimatedEffectiveYield               84853 non-null   float64
 11  EstimatedLoss                         84853 non-null   float64
 12  EstimatedReturn                       84853 non-null   float64
 13  ProsperRating (numeric)               84853 non-null   float64
 14  ProsperRating (Alpha)                 84853 non-null   object
 15  ProsperScore                          84853 non-null   float64
 16  ListingCategory (numeric)             113937 non-null  int64
 17  BorrowerState                         108422 non-null  object
 18  Occupation                            110349 non-null  object
 19  EmploymentStatus                      111682 non-null  object
 20  EmploymentStatusDuration              106312 non-null  float64
 21  IsBorrowerHomeowner                   113937 non-null  bool
 22  CurrentlyInGroup                      113937 non-null  bool
 23  GroupKey                              13341 non-null   object
 24  DateCreditPulled                      113937 non-null  object
 25  CreditScoreRangeLower                 113346 non-null  float64
 26  CreditScoreRangeUpper                 113346 non-null  float64
 27  FirstRecordedCreditLine               113240 non-null  object
 28  CurrentCreditLines                    106333 non-null  float64
 29  OpenCreditLines                       106333 non-null  float64
 30  TotalCreditLinespast7years            113240 non-null  float64
 31  OpenRevolvingAccounts                 113937 non-null  int64
 32  OpenRevolvingMonthlyPayment           113937 non-null  float64
 33  InquiriesLast6Months                  113240 non-null  float64
 34  TotalInquiries                        112778 non-null  float64
 35  CurrentDelinquencies                  113240 non-null  float64
 36  AmountDelinquent                      106315 non-null  float64
 37  DelinquenciesLast7Years               112947 non-null  float64
 38  PublicRecordsLast10Years              113240 non-null  float64
 39  PublicRecordsLast12Months             106333 non-null  float64
```

```
 40  RevolvingCreditBalance                106333 non-null  float64
 41  BankcardUtilization                   106333 non-null  float64
 42  AvailableBankcardCredit               106393 non-null  float64
 43  TotalTrades                           106393 non-null  float64
 44  TradesNeverDelinquent (percentage)    106393 non-null  float64
 45  TradesOpenedLast6Months               106393 non-null  float64
 46  DebtToIncomeRatio                     105383 non-null  float64
 47  IncomeRange                           113937 non-null  object
 48  IncomeVerifiable                      113937 non-null  bool
 49  StatedMonthlyIncome                   113937 non-null  float64
 50  LoanKey                               113937 non-null  object
 51  TotalProsperLoans                     22085 non-null   float64
 52  TotalProsperPaymentsBilled            22085 non-null   float64
 53  OnTimeProsperPayments                 22085 non-null   float64
 54  ProsperPaymentsLessThanOneMonthLate   22085 non-null   float64
 55  ProsperPaymentsOneMonthPlusLate       22085 non-null   float64
 56  ProsperPrincipalBorrowed              22085 non-null   float64
 57  ProsperPrincipalOutstanding           22085 non-null   float64
 58  ScorexChangeAtTimeOfListing           18928 non-null   float64
 59  LoanCurrentDaysDelinquent             113937 non-null  int64
 60  LoanFirstDefaultedCycleNumber         16952 non-null   float64
 61  LoanMonthsSinceOrigination            113937 non-null  int64
 62  LoanNumber                            113937 non-null  int64
 63  LoanOriginalAmount                    113937 non-null  int64
 64  LoanOriginationDate                   113937 non-null  object
 65  LoanOriginationQuarter                113937 non-null  object
 66  MemberKey                             113937 non-null  object
 67  MonthlyLoanPayment                    113937 non-null  float64
 68  LP_CustomerPayments                   113937 non-null  float64
 69  LP_CustomerPrincipalPayments          113937 non-null  float64
 70  LP_InterestandFees                    113937 non-null  float64
 71  LP_ServiceFees                        113937 non-null  float64
 72  LP_CollectionFees                     113937 non-null  float64
 73  LP_GrossPrincipalLoss                 113937 non-null  float64
 74  LP_NetPrincipalLoss                   113937 non-null  float64
 75  LP_NonPrincipalRecoverypayments       113937 non-null  float64
 76  PercentFunded                         113937 non-null  float64
 77  Recommendations                       113937 non-null  int64
 78  InvestmentFromFriendsCount            113937 non-null  int64
 79  InvestmentFromFriendsAmount           113937 non-null  float64
 80  Investors                             113937 non-null  int64
dtypes: bool(3), float64(50), int64(11), object(17)
memory usage: 68.1+ MB
```

[134]:
```
df.describe()
```

[134]:

	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]
```

1.0.8 Clean

Issues to be fixed

Tidy Issues

1. Create a new dataframe from columns of Interest
2. Create a new feature `CreditScoreRange` from `CreditScoreRangeUpper` and `CreditScoreRangeLower`

Quality Issues

1.0.9 Issue 1

Define

- Create a new data frame `df_new` from the columns of Interest
- columns of interest
  - CreditGrade
  - Term
  - LoanStatus
  - ClosedDate
  - BorrowerAPR
  - LenderYield
  - ListingCategory (numeric)
  - BorrowerState
  - Occupation
  - EmploymentStatus
  - EmployementStatusDuration
  - IsBorrowerHomeowner
  - CreditScoreRange = `f"${CreditScoreRangeLower} - ${CreditScoreRangeUpper}"`
  - CurrentDelinquencies

- AmountDelinquent
- DelinquuenciesLast7Years
- RevolvingCreditBalance
- BankcardUtilization
- AvalibleBankcardCredit
- DebtToIncomeRatio
- IncomeRange
- IncomeVerifiable
- StatedMonthlyIncome
- LoanOriginalAmount
- LoanOriginationDate
- LoanOriginationQuarter
- MonthlyLoanPayment
- LP_ServiceFees

Code

[135]:
```
columnsOfInterest = ['CreditGrade', 'Term', 'LoanStatus', 'ClosedDate',␣
 ↪'BorrowerAPR', 'BorrowerRate', 'LenderYield', 'ListingCategory (numeric)',␣
 ↪'BorrowerState', 'Occupation', 'EmploymentStatus',␣
 ↪'EmploymentStatusDuration', 'IsBorrowerHomeowner', 'CreditScoreRangeLower',␣
 ↪'CreditScoreRangeUpper', 'CurrentDelinquencies', 'AmountDelinquent',␣
 ↪'DelinquenciesLast7Years', 'RevolvingCreditBalance', 'BankcardUtilization',␣
 ↪'AvailableBankcardCredit', 'DebtToIncomeRatio', 'IncomeRange',␣
 ↪'IncomeVerifiable', 'StatedMonthlyIncome', 'LoanOriginalAmount',␣
 ↪'LoanOriginationDate', 'LoanOriginationQuarter', 'MonthlyLoanPayment',␣
 ↪'LP_ServiceFees']
df_new = df[columnsOfInterest].copy()
```

Test

[136]:
```
df_new.head()
```

[136]:

	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	ListingCategory (numeric)	BorrowerState	\
0	0.1580	0.1380	0	CO	
1	0.0920	0.0820	2	CO	
2	0.2750	0.2400	0	GA	
3	0.0974	0.0874	16	GA	
4	0.2085	0.1985	2	MN	

	Occupation	…	AvailableBankcardCredit	DebtToIncomeRatio	\

```
0          Other  …                 1500.0              0.17
1   Professional  …                10266.0              0.18
2          Other  …                    NaN              0.06
3  Skilled Labor  …                30754.0              0.15
4      Executive  …                  695.0              0.26

      IncomeRange  IncomeVerifiable  StatedMonthlyIncome  LoanOriginalAmount  \
0  $25,000-49,999              True          3083.333333                9425
1  $50,000-74,999              True          6125.000000               10000
2   Not displayed              True          2083.333333                3001
3  $25,000-49,999              True          2875.000000               10000
4       $100,000+              True          9583.333333               15000

   LoanOriginationDate  LoanOriginationQuarter  MonthlyLoanPayment  \
0  2007-09-12 00:00:00                Q3 2007              330.43
1  2014-03-03 00:00:00                Q1 2014              318.93
2  2007-01-17 00:00:00                Q1 2007              123.32
3  2012-11-01 00:00:00                Q4 2012              321.45
4  2013-09-20 00:00:00                Q3 2013              563.97

   LP_ServiceFees
0         -133.18
1            0.00
2          -24.20
3         -108.01
4          -60.27

[5 rows x 30 columns]
```

[137]:
```
df_new.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 113937 entries, 0 to 113936
Data columns (total 30 columns):
 #   Column                     Non-Null Count   Dtype
---  ------                     --------------   -----
 0   CreditGrade                28953 non-null   object
 1   Term                       113937 non-null  int64
 2   LoanStatus                 113937 non-null  object
 3   ClosedDate                 55089 non-null   object
 4   BorrowerAPR                113912 non-null  float64
 5   BorrowerRate               113937 non-null  float64
 6   LenderYield                113937 non-null  float64
 7   ListingCategory (numeric)  113937 non-null  int64
 8   BorrowerState              108422 non-null  object
 9   Occupation                 110349 non-null  object
 10  EmploymentStatus           111682 non-null  object
```

```
 11  EmploymentStatusDuration   106312 non-null  float64
 12  IsBorrowerHomeowner        113937 non-null  bool
 13  CreditScoreRangeLower      113346 non-null  float64
 14  CreditScoreRangeUpper      113346 non-null  float64
 15  CurrentDelinquencies       113240 non-null  float64
 16  AmountDelinquent           106315 non-null  float64
 17  DelinquenciesLast7Years    112947 non-null  float64
 18  RevolvingCreditBalance     106333 non-null  float64
 19  BankcardUtilization        106333 non-null  float64
 20  AvailableBankcardCredit    106393 non-null  float64
 21  DebtToIncomeRatio          105383 non-null  float64
 22  IncomeRange                113937 non-null  object
 23  IncomeVerifiable           113937 non-null  bool
 24  StatedMonthlyIncome        113937 non-null  float64
 25  LoanOriginalAmount         113937 non-null  int64
 26  LoanOriginationDate        113937 non-null  object
 27  LoanOriginationQuarter     113937 non-null  object
 28  MonthlyLoanPayment         113937 non-null  float64
 29  LP_ServiceFees             113937 non-null  float64
dtypes: bool(2), float64(16), int64(3), object(9)
memory usage: 24.6+ MB
```

1.0.10 Issue 2

Define - Create a new feature `CreditScoreRange` from `CreditScoreRangeUpper` and `CreditScoreRangeLower`

Code

[138]:
```
rangeVal = [f"${i} - {j}" for i,j in zip(df_new['CreditScoreRangeLower'],␣
 ↪df_new['CreditScoreRangeUpper'])]
df_new['CreditScoreRange'] = rangeVal
```

Test

[139]:
```
df_new['CreditScoreRange'].unique()
```

[139]:
```
array(['$640.0 - 659.0', '$680.0 - 699.0', '$480.0 - 499.0',
       '$800.0 - 819.0', '$740.0 - 759.0', '$700.0 - 719.0',
       '$820.0 - 839.0', '$760.0 - 779.0', '$660.0 - 679.0',
       '$620.0 - 639.0', '$720.0 - 739.0', '$520.0 - 539.0',
       '$780.0 - 799.0', '$600.0 - 619.0', '$580.0 - 599.0',
       '$540.0 - 559.0', '$560.0 - 579.0', '$500.0 - 519.0',
       '$840.0 - 859.0', '$860.0 - 879.0', '$nan - nan', '$460.0 - 479.0',
       '$0.0 - 19.0', '$880.0 - 899.0', '$440.0 - 459.0',
       '$420.0 - 439.0', '$360.0 - 379.0'], dtype=object)
```

Next we explore quality Issues

[140]:
```
df_new.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 113937 entries, 0 to 113936
Data columns (total 31 columns):
 #   Column                      Non-Null Count   Dtype
---  ------                      --------------   -----
 0   CreditGrade                 28953 non-null   object
 1   Term                        113937 non-null  int64
 2   LoanStatus                  113937 non-null  object
 3   ClosedDate                  55089 non-null   object
 4   BorrowerAPR                 113912 non-null  float64
 5   BorrowerRate                113937 non-null  float64
 6   LenderYield                 113937 non-null  float64
 7   ListingCategory (numeric)   113937 non-null  int64
 8   BorrowerState               108422 non-null  object
 9   Occupation                  110349 non-null  object
 10  EmploymentStatus            111682 non-null  object
 11  EmploymentStatusDuration    106312 non-null  float64
 12  IsBorrowerHomeowner         113937 non-null  bool
 13  CreditScoreRangeLower       113346 non-null  float64
 14  CreditScoreRangeUpper       113346 non-null  float64
 15  CurrentDelinquencies        113240 non-null  float64
 16  AmountDelinquent            106315 non-null  float64
 17  DelinquenciesLast7Years     112947 non-null  float64
 18  RevolvingCreditBalance      106333 non-null  float64
 19  BankcardUtilization         106333 non-null  float64
 20  AvailableBankcardCredit     106393 non-null  float64
 21  DebtToIncomeRatio           105383 non-null  float64
 22  IncomeRange                 113937 non-null  object
 23  IncomeVerifiable            113937 non-null  bool
 24  StatedMonthlyIncome         113937 non-null  float64
 25  LoanOriginalAmount          113937 non-null  int64
 26  LoanOriginationDate         113937 non-null  object
 27  LoanOriginationQuarter      113937 non-null  object
 28  MonthlyLoanPayment          113937 non-null  float64
 29  LP_ServiceFees              113937 non-null  float64
 30  CreditScoreRange            113937 non-null  object
dtypes: bool(2), float64(16), int64(3), object(10)
memory usage: 25.4+ MB
```

[141]:
```
df_new.duplicated().sum()
```

[141]: 871

- All 871 duplicate entries need to be dropped

1.0.11 Quality Issues

3. Drop columns `CreditScoreRangeUpperand` `CreditScoreRangeLower`.
4. Change `CLosedDate`, `LoanOriginationDate` dtype to `datetime`.
5. Drop Duplicate Entries.
6. Remove years from `LoanOriginationQuarter` and leave only quarters `Q{1..4}`.
7. Change `ListingCategory (numeric)` Dtype to `str`.
8. Create `LoanOriginationyear` column from `LoanOriginationDate`

1.0.12 Issue 3

Define

- Drop `CreditScoreRangeUpper`, `CreditScoreRangeLower`

Code

[142]:
```
df_new.drop(['CreditScoreRangeUpper', 'CreditScoreRangeLower'], axis=1,␣
↪inplace=True)
```

Test

[143]:
```
df_new.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 113937 entries, 0 to 113936
Data columns (total 29 columns):
 #   Column                      Non-Null Count   Dtype
---  ------                      --------------   -----
 0   CreditGrade                 28953 non-null   object
 1   Term                        113937 non-null  int64
 2   LoanStatus                  113937 non-null  object
 3   ClosedDate                  55089 non-null   object
 4   BorrowerAPR                 113912 non-null  float64
 5   BorrowerRate                113937 non-null  float64
 6   LenderYield                 113937 non-null  float64
 7   ListingCategory (numeric)   113937 non-null  int64
 8   BorrowerState               108422 non-null  object
 9   Occupation                  110349 non-null  object
 10  EmploymentStatus            111682 non-null  object
 11  EmploymentStatusDuration    106312 non-null  float64
 12  IsBorrowerHomeowner         113937 non-null  bool
 13  CurrentDelinquencies        113240 non-null  float64
 14  AmountDelinquent            106315 non-null  float64
 15  DelinquenciesLast7Years     112947 non-null  float64
 16  RevolvingCreditBalance      106333 non-null  float64
 17  BankcardUtilization         106333 non-null  float64
 18  AvailableBankcardCredit     106393 non-null  float64
 19  DebtToIncomeRatio           105383 non-null  float64
 20  IncomeRange                 113937 non-null  object
```

```
 21  IncomeVerifiable           113937 non-null  bool
 22  StatedMonthlyIncome        113937 non-null  float64
 23  LoanOriginalAmount         113937 non-null  int64
 24  LoanOriginationDate        113937 non-null  object
 25  LoanOriginationQuarter     113937 non-null  object
 26  MonthlyLoanPayment         113937 non-null  float64
 27  LP_ServiceFees             113937 non-null  float64
 28  CreditScoreRange           113937 non-null  object
dtypes: bool(2), float64(14), int64(3), object(10)
memory usage: 23.7+ MB
```

1.0.13 Issue 4

Define

- Change `CLosedDate`, `LoanOriginationDate` dtype to datetime

Code

[144]:
```
df_new['ClosedDate'] = pd.to_datetime(df['ClosedDate'])
df_new['LoanOriginationDate'] = pd.to_datetime(df['LoanOriginationDate'])
```

Test

[145]:
```
df_new['ClosedDate'], df_new['LoanOriginationDate']
```

[145]:
```
(0        2009-08-14
 1               NaT
 2        2009-12-17
 3               NaT
 4               NaT
             ...
 113932          NaT
 113933          NaT
 113934          NaT
 113935   2013-08-13
 113936          NaT
 Name: ClosedDate, Length: 113937, dtype: datetime64[ns],
 0        2007-09-12
 1        2014-03-03
 2        2007-01-17
 3        2012-11-01
 4        2013-09-20
             ...
 113932   2013-04-22
 113933   2011-11-07
 113934   2013-12-23
 113935   2011-11-21
 113936   2014-01-21
```

```
Name: LoanOriginationDate, Length: 113937, dtype: datetime64[ns])
```

- DataTypes Changed

1.0.14 Issue 5

Define

- Drop duplicate entries

Code

[146]:
```
df_new.drop_duplicates(inplace=True)
```

Test

[147]:
```
df_new.duplicated().sum()
```

[147]:
```
0
```

[148]:
```
df_new.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 113066 entries, 0 to 113936
Data columns (total 29 columns):
 #   Column                      Non-Null Count   Dtype
---  ------                      --------------   -----
 0   CreditGrade                 28953 non-null   object
 1   Term                        113066 non-null  int64
 2   LoanStatus                  113066 non-null  object
 3   ClosedDate                  55076 non-null   datetime64[ns]
 4   BorrowerAPR                 113041 non-null  float64
 5   BorrowerRate                113066 non-null  float64
 6   LenderYield                 113066 non-null  float64
 7   ListingCategory (numeric)   113066 non-null  int64
 8   BorrowerState               107551 non-null  object
 9   Occupation                  109537 non-null  object
 10  EmploymentStatus            110811 non-null  object
 11  EmploymentStatusDuration    105441 non-null  float64
 12  IsBorrowerHomeowner         113066 non-null  bool
 13  CurrentDelinquencies        112369 non-null  float64
 14  AmountDelinquent            105444 non-null  float64
 15  DelinquenciesLast7Years     112076 non-null  float64
 16  RevolvingCreditBalance      105462 non-null  float64
 17  BankcardUtilization         105462 non-null  float64
 18  AvailableBankcardCredit     105522 non-null  float64
 19  DebtToIncomeRatio           104594 non-null  float64
 20  IncomeRange                 113066 non-null  object
 21  IncomeVerifiable            113066 non-null  bool
 22  StatedMonthlyIncome         113066 non-null  float64
```

```
 23  LoanOriginalAmount          113066 non-null  int64
 24  LoanOriginationDate         113066 non-null  datetime64[ns]
 25  LoanOriginationQuarter      113066 non-null  object
 26  MonthlyLoanPayment          113066 non-null  float64
 27  LP_ServiceFees              113066 non-null  float64
 28  CreditScoreRange            113066 non-null  object
dtypes: bool(2), datetime64[ns](2), float64(14), int64(3), object(8)
memory usage: 24.4+ MB
```

1.0.15 Issue 6

Define

- Remove years from `LoanOriginationQuarter` from index 0 to 5 `[:-5]`

Code

[149]:
```
df_new['LoanOriginationQuarter'] = df_new['LoanOriginationQuarter'].str[0:-5]
```

Test

[150]:
```
df_new['LoanOriginationQuarter'].unique()
```

[150]:
```
array(['Q3', 'Q1', 'Q4', 'Q2'], dtype=object)
```

1.0.16 Issue 7

Define

- Change `ListingCategory (numeric)` Dtype to `str`

Code

[151]:
```
df_new['ListingCategory (numeric)'] = df_new['ListingCategory (numeric)'].
↪astype('string')
```

1.0.17 Test

[152]:
```
df_new['ListingCategory (numeric)'].dtype
```

[152]:
```
string[python]
```

1.0.18 Issue 8

Define Create `LoanOriginationyear` column from `LoanOriginationDate`.

Code

[153]:
```
df_new['LoanOriginationYear'] = pd.DatetimeIndex(df_new['LoanOriginationDate']).
↪year
```

Test

[154]:
```
df_new['LoanOriginationYear'].dtype
```

[154]:
```
dtype('int64')
```

Univariate, Bivariate, and Multivariate Data Exploration

- Question
- Visualisation
- Observation

Questions of Interest form our features

- What factors affect the loans outcome?
- What affects the BorrowerAPR or Interest rate?
- Are there differences between loans depending on how large the original loan amount was?

Categorical variables

- CreditGrade -> ordinal
- LoanStatus -> nominal
- ClosedDate -> Ordinal
- Occupation -> nominal
- EmploymentStatus -> nominal
- CreditScoreRange -> ordinal
-

1.1 ##### Quantitative variables

variables to be explored for each question of interest. (Q.O.I)

1. What factors affect loan's outcome status?
   - Univariate exploration
     - LoanStatus
     - BorrowerState
     - EmploymentStatus
     - EmploymentStatusDuration
     - IsBorrowerHomeOwner
     - LoanOriginationQuarter
     - IncomeRange
     - Occupation
     - DebtToIncomeRatio
     - CreditGrade
2. What affects the BorrowerAPR or Interest rate?
   - Univariate exploration
     - BorrowerApr
     - LoanOriginationAmount

1.1.1 Univariate Exploration

countplot prototype function

[155]:
```
def count_plot1(col_name, hu=None, pal=0):
    # LoanStatus value counts
    col_counts = df_new[f'{col_name}'].value_counts()

    # base color palette
    base_color = sb.color_palette()[pal]

    # sum of all non-null entries
    nonNull_count = df_new[f'{col_name}'].value_counts().sum()

    # figure plot
    plt.figure(figsize=(15,8))
    sb.countplot(data=df_new, y=f'{col_name}', hue=hu, color=base_color)

    # percentage texts
    for i in range(col_counts.shape[0]):
        count = col_counts[i]
        pct = '{:0.1f}%'.format(count/nonNull_count*100)
        plt.text(count+1, i, pct, va='center')

    plt.title(f'{col_name} frequency Distribution');
    plt.ylabel(f'{col_name}');
    plt.xlabel('Frequency');



'''
This function can be used for Univariate and Bivariate plots
'''
def count_plot2(col_name, y=True, hu=None, cord=(15,5), pal=0):
    # LoanStatus value counts
    col_counts = df_new[f'{col_name}'].value_counts()

    # base color palette
    base_color = sb.color_palette()[pal]

    # sum of all non-null entries
    nonNull_count = df_new[f'{col_name}'].value_counts().sum()

    # figure plot
    plt.figure(figsize=cord)
    if y==True:
        sb.countplot(data=df_new, y=f'{col_name}', hue=hu, color=base_color)
        plt.ylabel(f'{col_name}');
        plt.xlabel('Frequency');
        plt.yticks(rotation=45)
```

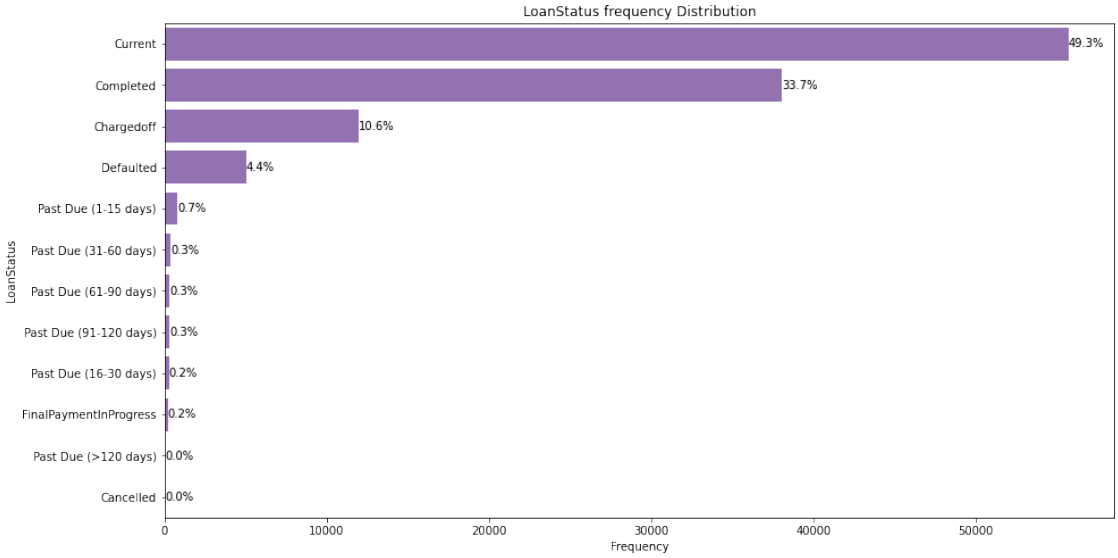
```
    else:
        sb.countplot(data=df_new, x=f'{col_name}', hue=hu, color=base_color)
        plt.title(f'{col_name} frequency Distribution');
        plt.ylabel('frequency');
        plt.xlabel(f'{col_name}');
        plt.xticks(rotation = 45)
```

[156]:
```
# Convert EmploymentStatus, IncomeRange, LoanStatus, CreditScoreRange.. to␣
↪ordered categorical data type
var_dict = {'EmploymentStatus': ['Employed','Full-time','Self-employed','Not␣
↪available','Other','Part-time','Not employed','Retired'],
            'IncomeRange':␣
↪['$25,000-49,999','$50,000-74,999','$100,000+','$75,000-99,999','Not␣
↪displayed','$1-24,999','Not employed','$0'],
            'LoanStatus': ['Current','Completed','Chargedoff','Defaulted','Past␣
↪Due (1-15 days)','Past Due (31-60 days)','Past Due (61-90 days)','Past Due␣
↪(91-120 days)','Past Due (16-30 days)','FinalPaymentInProgress','Past Due␣
↪(>120 days)','Cancelled'],
            'LoanOriginationQuarter': ['Q1','Q2','Q3','Q4'].reverse(),
            'CreditGrade': ['AA','A','B','C','D','E','NC','HR'].reverse(),
            'ListingCategory (numeric)':␣
↪['0','1','2','3','4','5','6','7','8','9','10','11','12','13','14','15','16','17','18','20']
           }

for var in var_dict:
    ordered_var = pd.api.types.CategoricalDtype(ordered = True, categories =␣
↪var_dict[var])
    df_new[var] = df_new[var].astype(ordered_var)
```

LoanStatus exploration

- This is a nominal Categorical datatype
- QOI: barplot
- Nominal data should be ordered in visualisation

[157]:
```
count_plot1('LoanStatus', pal=4)
```

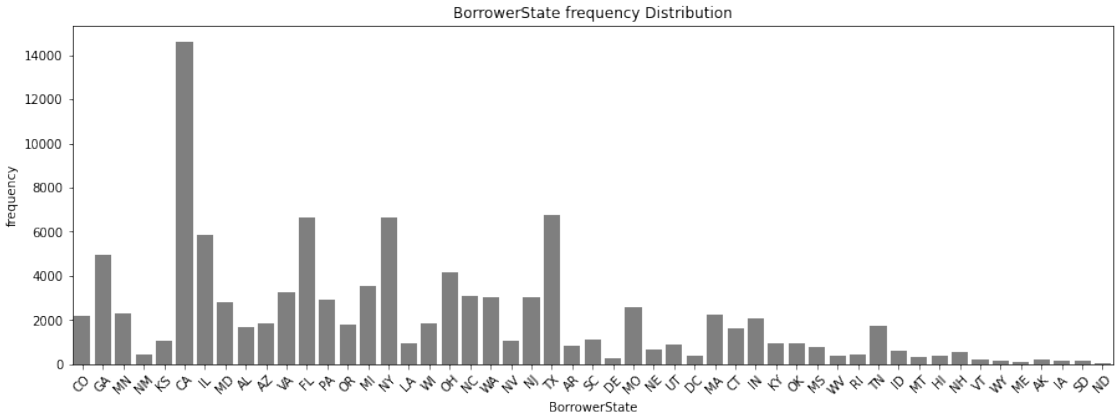


Observation

- Current loans account for 49.3% of the investment
- Completed Loan terms account for 33.7% of the investment
- Charged loans account for (see Gloasry section for used words and their meanings)
- No loan exceeds 4 months (this can be possibly a policy terming loans exceeding 4 months as `Chargedoff`)

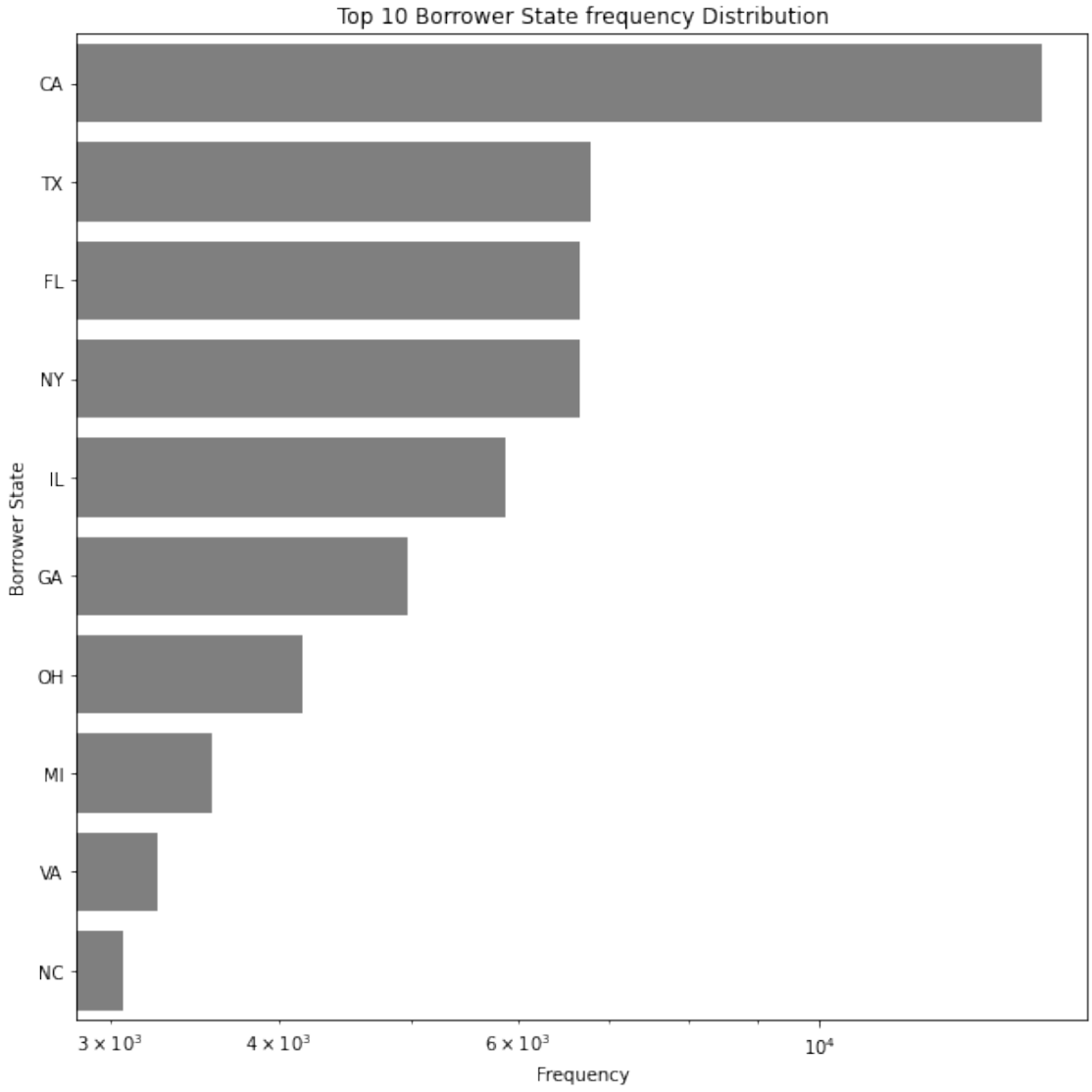
BorrowerState

[158]:
```
count_plot2('BorrowerState',y=False, pal=7)
```



- we extract the topten borrower States and explore them closely.

[159]:
```
base_color = sb.color_palette()[7]
plt.figure(figsize=[10, 10]);
top_ten_states = ['CA','TX','NY','FL','IL','GA','OH','MI','VA','NC']
state_sub = df_new.loc[df['BorrowerState'].isin(top_ten_states)]

sb.countplot(data = state_sub, y = 'BorrowerState', color = base_color, order =␣
 ↪state_sub['BorrowerState'].value_counts().index);
plt.title('Top 10 Borrower State frequency Distribution');
plt.ylabel('Borrower State');
plt.xlabel('Frequency');
plt.xscale('log');
```

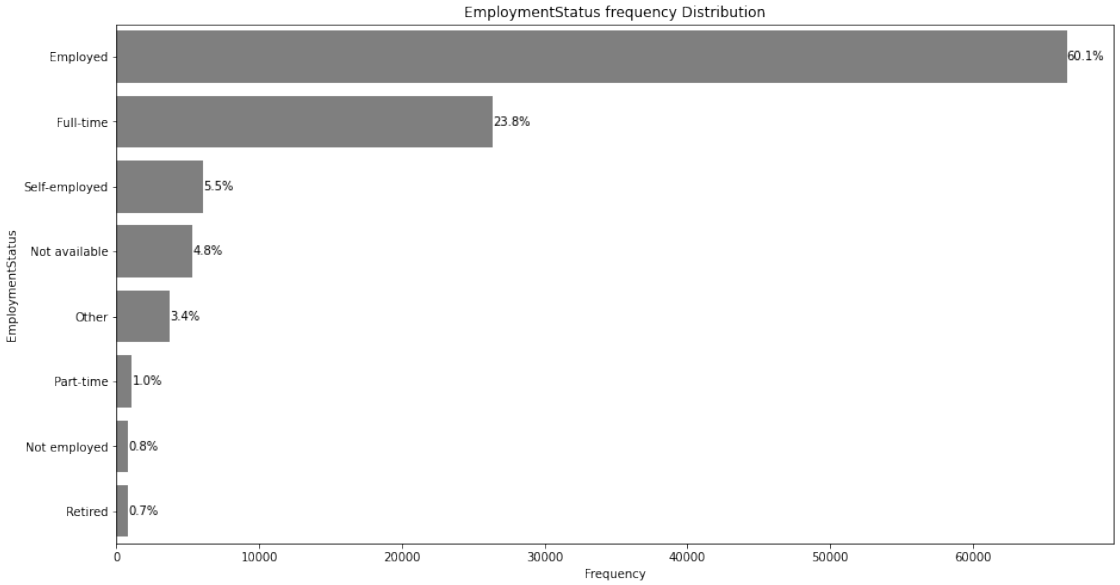


Observations

- California has the highest number of loan applicants followed by Texas et'al.

Employment status

[160]:
```
count_plot1('EmploymentStatus', pal=7)
```

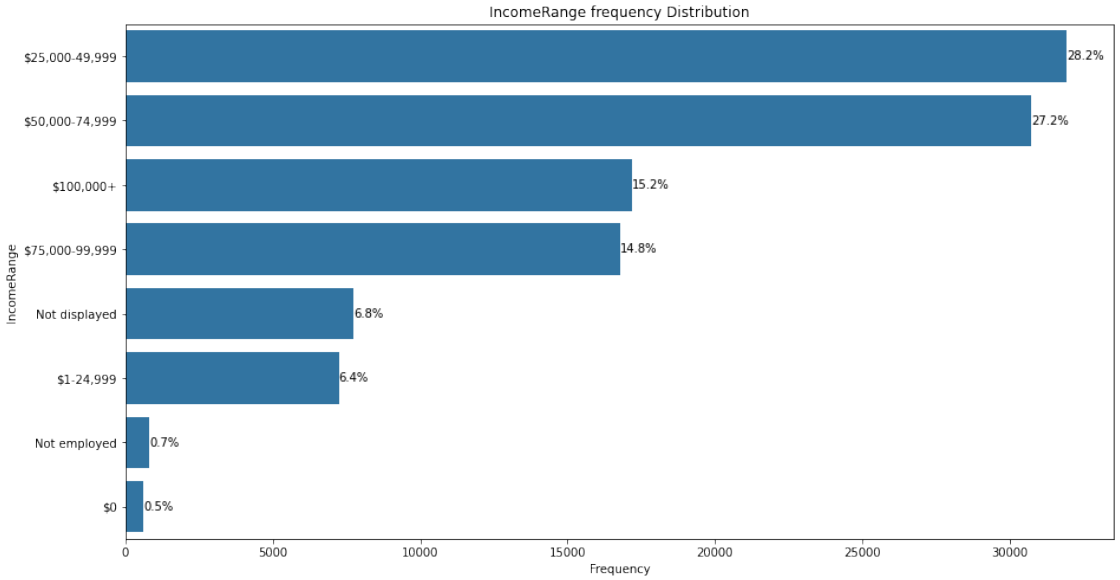


Observation

- Most Borrowers are `employed` and `full time`

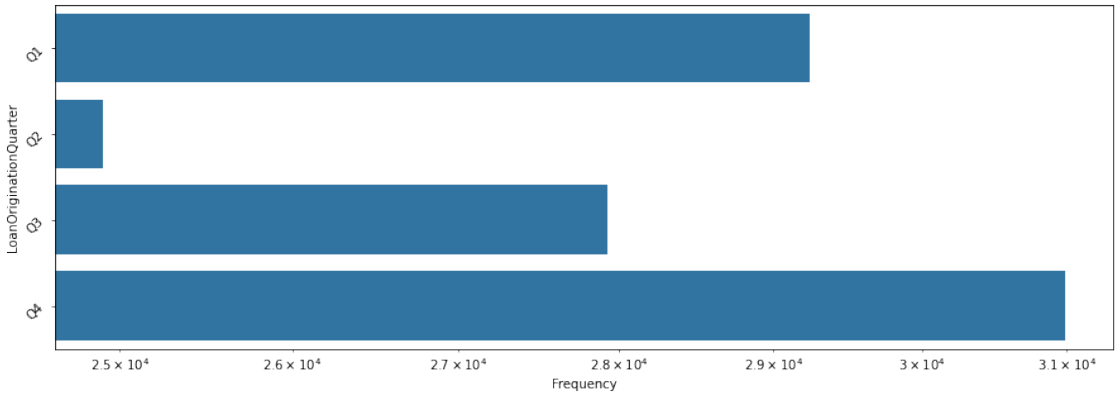
IncomeRange

[161]:
```
count_plot1('IncomeRange')
```



LoanOriginationQuarter

[162]:
```
count_plot2('LoanOriginationQuarter')
plt.xscale('log')
```

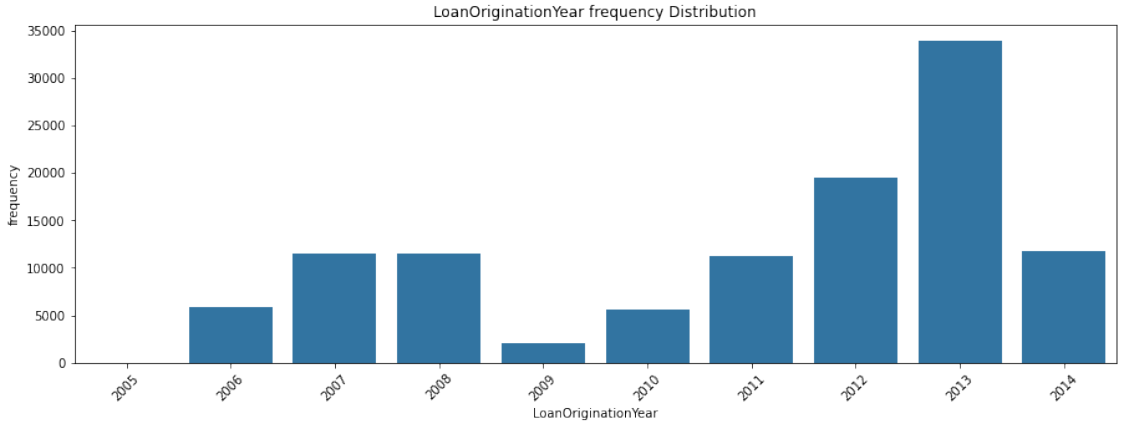


Observations

- Most loans are taken in the last quarter
- This pattern could be attributed to the need to celebrate the `yuletide` in Style, and also the need to meet up with the financial demands in the first quarter.

LoanOriginationYear

[163]:
```
count_plot2('LoanOriginationYear', y=False)
```



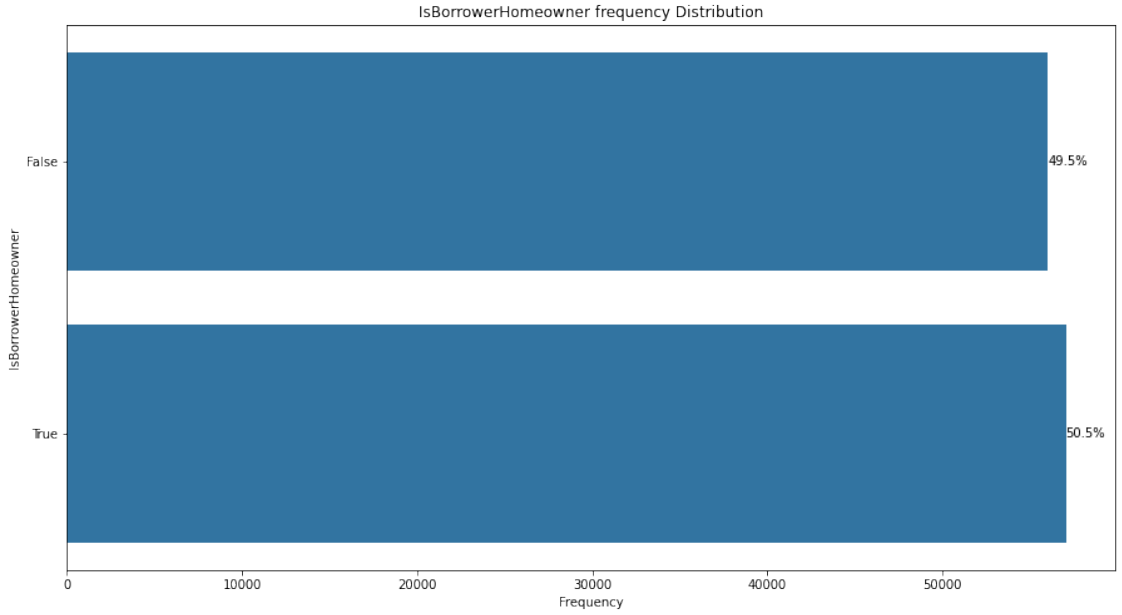
Observations

- The number of loan applications increase over time.

[ ]:

IsBorrowerHomeowner

[164]:
```
count_plot1('IsBorrowerHomeowner')
```

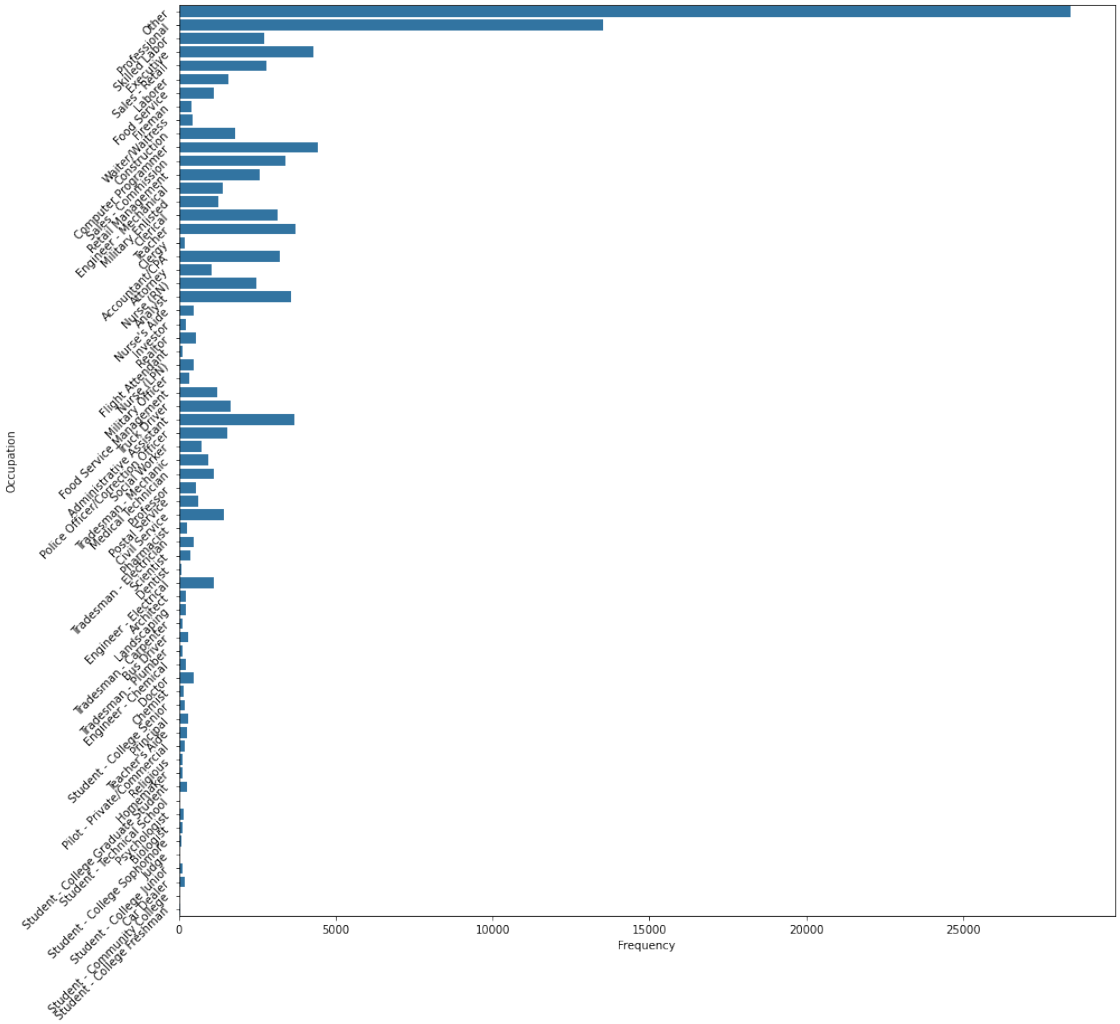


Observations

- The values are evenly split between Home Owners and those who are not, hence no evidence of any relationship `for now`.

Occupation (top ten Occupations on the Loan client listing)

[165]:
```
count_plot2('Occupation', cord=(15,15))
```

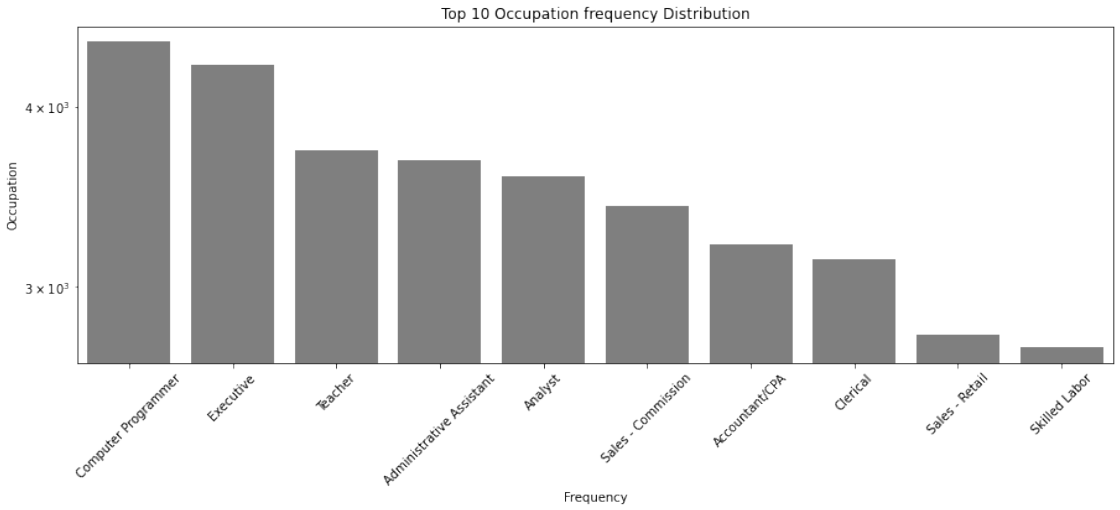


- we take the top ten Occupations and explore them closer

[166]:
```
base_color = sb.color_palette()[7]
plt.figure(figsize=[15, 5]);
top_ten_occupation = ['Computer␣
 ↪Programmer','Executive','Teacher','Administrative␣
 ↪Assistant','Analyst','Sales - Commission','Accountant/CPA','Clerical','Sales␣
 ↪- Retail','Skilled Labor']
occupation_sub = df_new.loc[df['Occupation'].isin(top_ten_occupation)]
```

```
sb.countplot(data = occupation_sub, x = 'Occupation', color = base_color, order␣
 ↪= occupation_sub['Occupation'].value_counts().index);
plt.title('Top 10 Occupation frequency Distribution');
plt.ylabel('Occupation');
plt.xlabel('Frequency');
plt.yscale('log');
plt.xticks(rotation=45)
```

[166]:
```
(array([0, 1, 2, 3, 4, 5, 6, 7, 8, 9]),
 [Text(0, 0, 'Computer Programmer'),
  Text(1, 0, 'Executive'),
  Text(2, 0, 'Teacher'),
  Text(3, 0, 'Administrative Assistant'),
  Text(4, 0, 'Analyst'),
  Text(5, 0, 'Sales - Commission'),
  Text(6, 0, 'Accountant/CPA'),
  Text(7, 0, 'Clerical'),
  Text(8, 0, 'Sales - Retail'),
  Text(9, 0, 'Skilled Labor')])
```

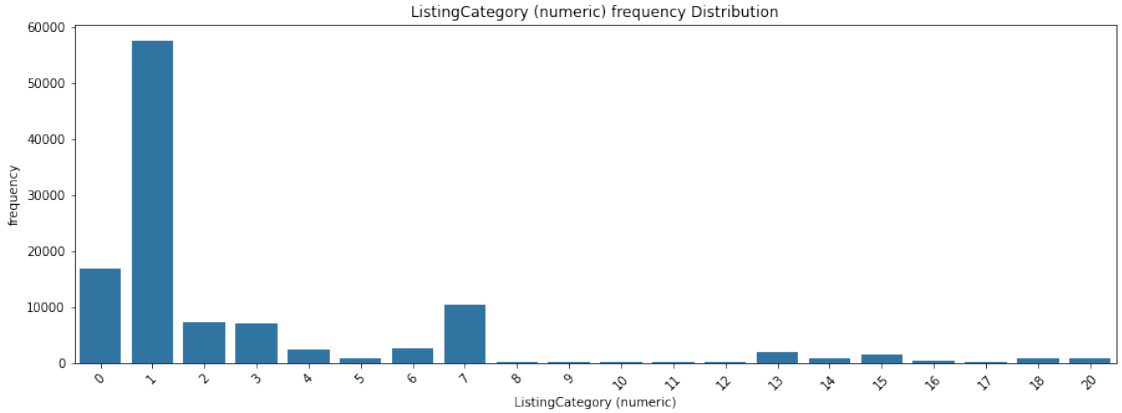


Observations

- We can see Programmers topping this chart with executives following suit.
- This are also some of the highest paid workers on a global scale.
- This could be also associated to the need to multiply wealth by some of the highest earners.

ListingCategory (numeric)

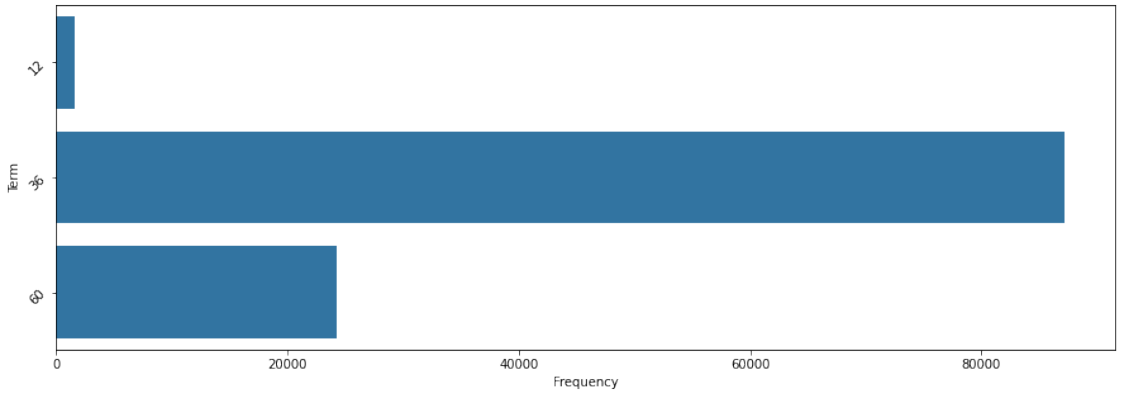
[167]:
```
count_plot2('ListingCategory (numeric)', y=False)
```



Observations

- Category 1 (Debt Consolidation) accounts for most listings followed by 2&& 3
- This could imply favourable loan conditions from `Prosper`.

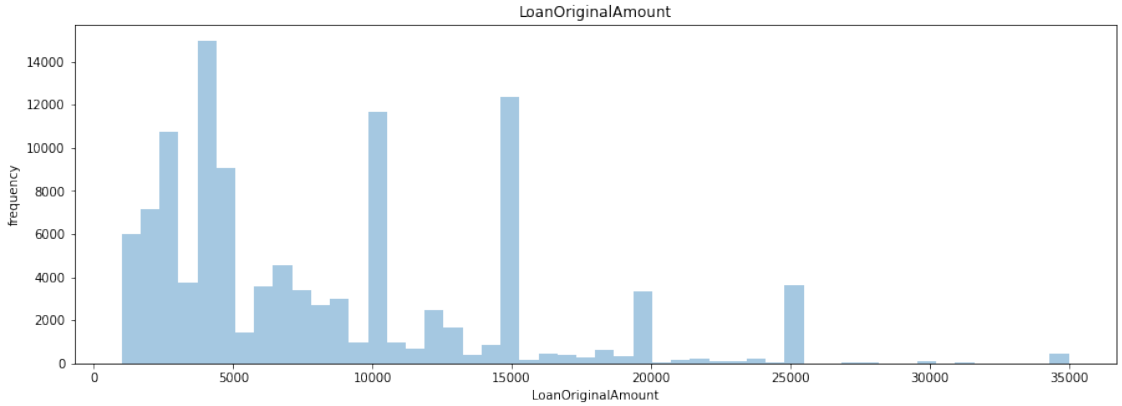
[168]:
```
count_plot2('Term')
```



[169]:
```
def dist_plot(col_name):
    plt.figure(figsize=(15,5))
    sb.distplot(df_new[f'{col_name}'], kde=False)
    plt.title(f'{col_name}')
    plt.xlabel(f'{col_name}')
    plt.ylabel('frequency')
```

LoanOriginalAMount

[170]:
```
dist_plot('LoanOriginalAmount')
```

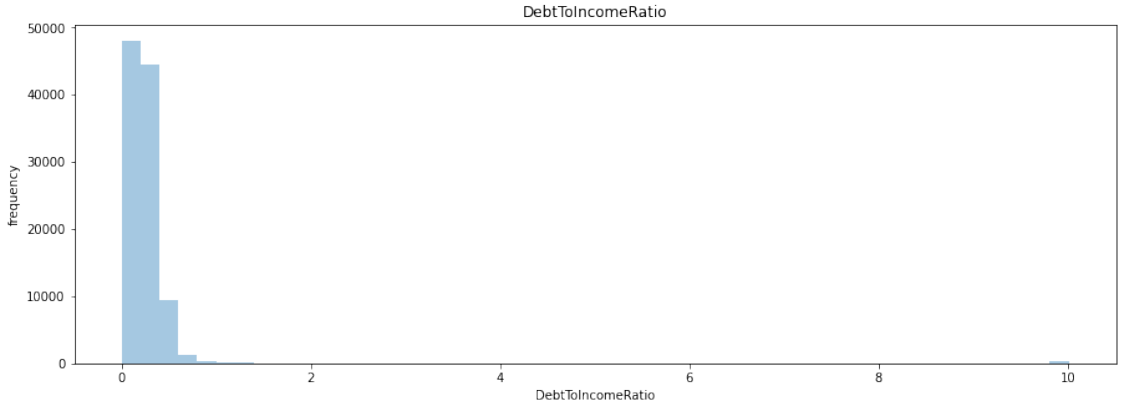


Observations

- The Loans are in majorly in multiples of $5000
- This pattern could be psycological as most of the loans exceeding $5000 are majorly in multiples of $5000

DebtToIncomeRatio

[171]:
```
dist_plot('DebtToIncomeRatio')
```



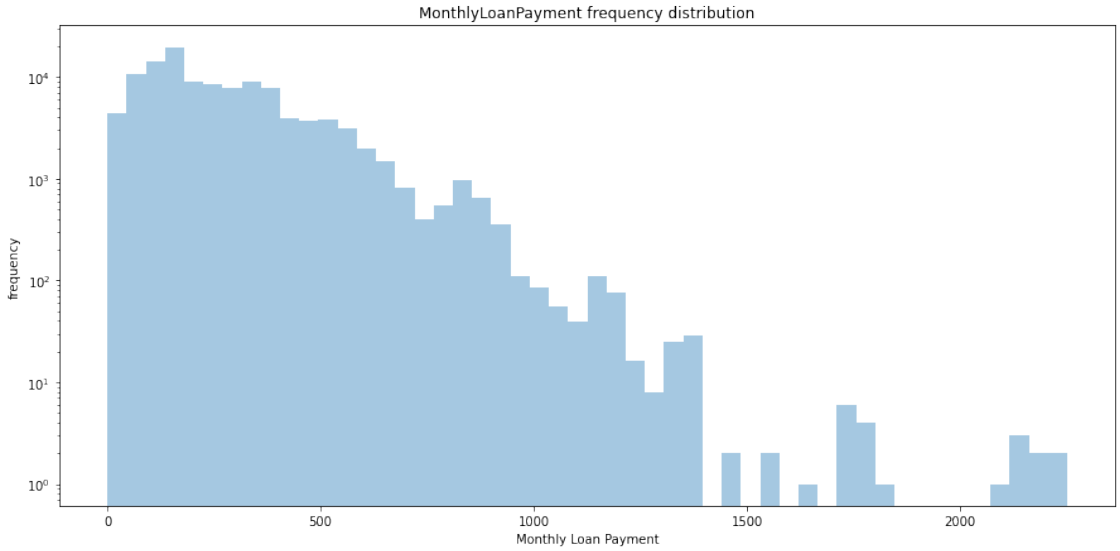
Observations

- This distribution is rightly skewed which indicates most loans not exceeding 100% of their Income.

MonthlyLoanPayment

[172]:
```
plt.figure(figsize=(15,7))
sb.distplot(df_new['MonthlyLoanPayment'], kde=False)
```

```
plt.title('MonthlyLoanPayment frequency distribution')
plt.xlabel('Monthly Loan Payment')
plt.ylabel('frequency')
plt.yscale('log')
```

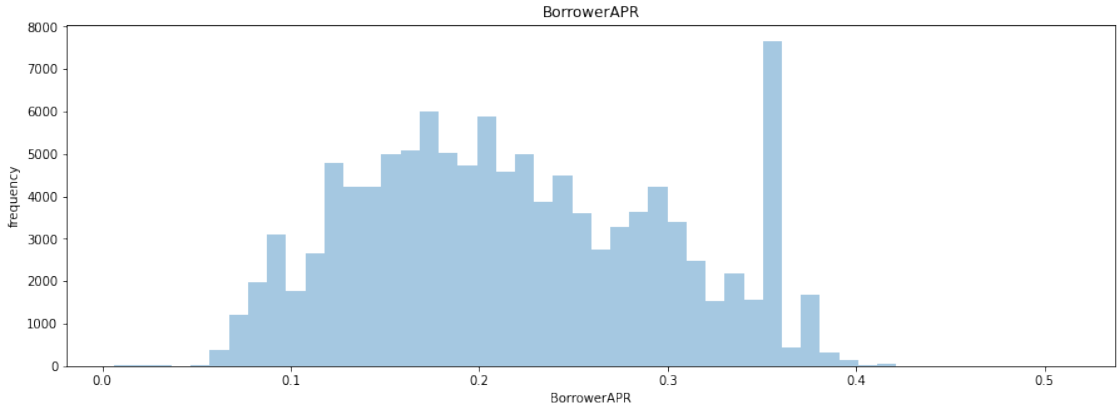


Observations

- Monthly Loan Payments fall between $0 to $500, with about 200000+ clients paying less than $250 monthly.

BorrowerApr

[173]:
```
dist_plot('BorrowerAPR')
```



Univariate Exploration Observations

- This distribution is of the similitude of a normally distributed data, with most `BorrowerAPR` values between `0.15` and `0.3`

1.1.2 Bivariate Exploration

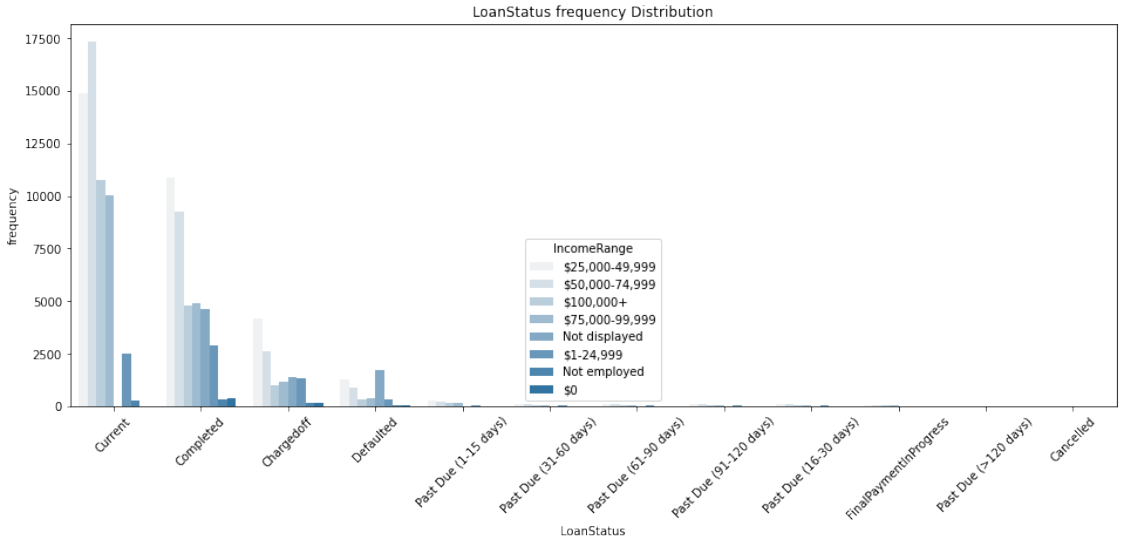
- violin plots: categorical vs quantitative plots.
- Scatterplots: for quantitative variables vs quantitative variables.

plots:

- EmploymentStatus vs LoanOriginationAmount
- LoanOriginationAmount vs LoanStatus
- Occupation vs LoanAmount

QOI: what the relationship between `IncomeRange` and `LoanOriginationQuarter`

[174]:
```
count_plot2('LoanStatus', hu='IncomeRange', cord=(16,6), y=False)
```

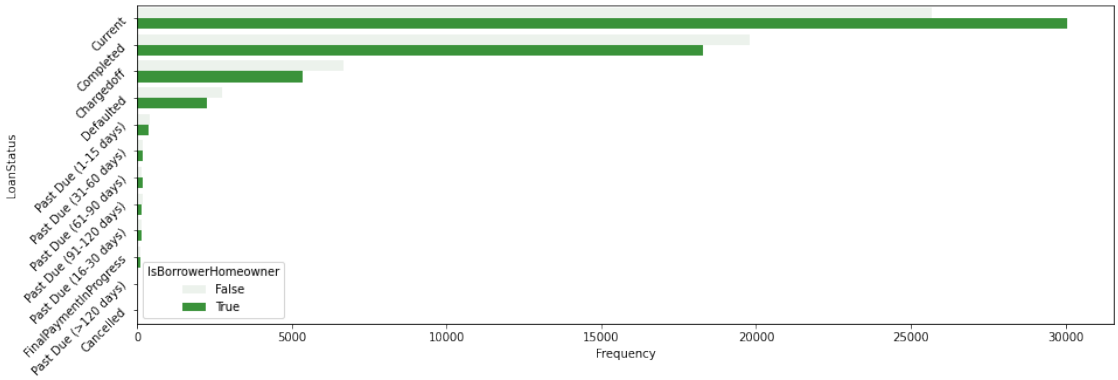


Observations

- High earners are usually associated with good performing loans.
- Summarily;
  - `IncomeRange` affects loan performance (`LoanStatus`).

QOI: What is the relationship between `Loan Status` and `Home Ownership`

[175]:
```
count_plot2('LoanStatus', hu='IsBorrowerHomeowner', pal=2)
```

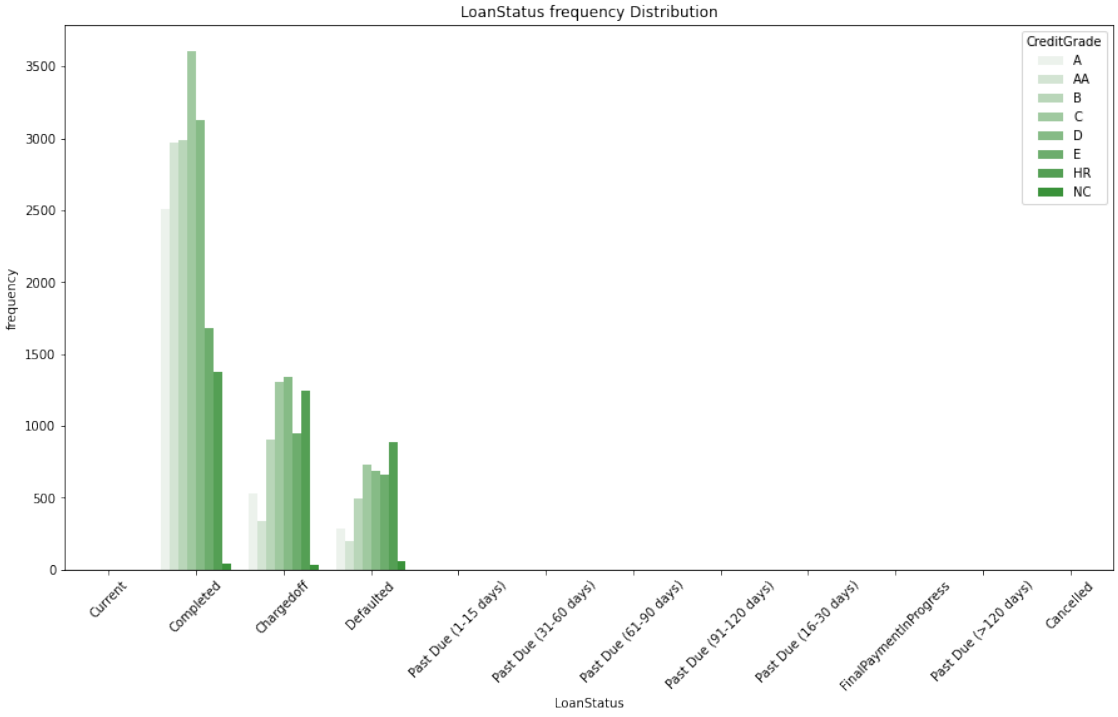


Observations

- There is no clear evidence that Home ownership affects `Loan Status`.

QOI: What is the Relationship between `Loan Status`, and `CreditGrade`.

[176]:
```
count_plot2('LoanStatus', hu='CreditGrade', pal=2, cord=(15,8), y=False)
```

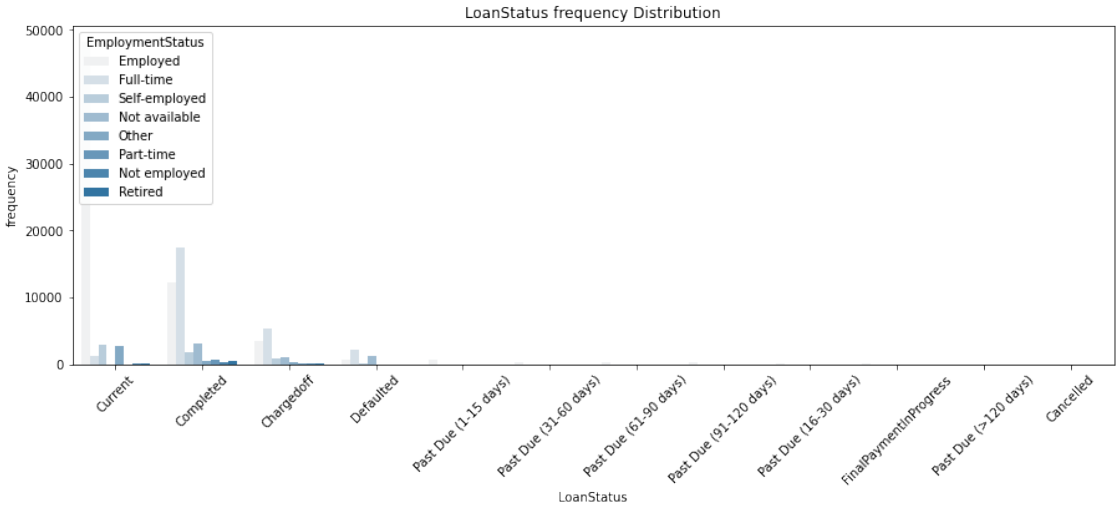


Observations

- `Completed` Loans range majorly between `AA` and `D` Grade, with with a mode Grade of `C`.

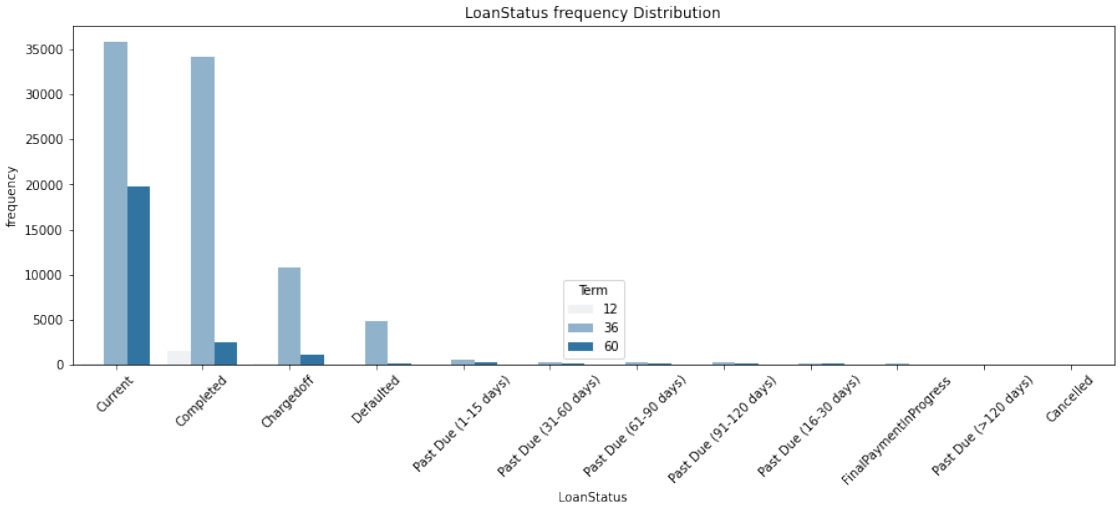
- `Charged off` and `Defaulted` Loans have a similar distribution with mode Grades of `D` and `C` respectively.
- Summarily, `CreditGrade` affects loan performance and is an indicator of loan performance over the years.

[177]:
```
count_plot2('LoanStatus', hu='EmploymentStatus', y=False)
```



QOI: Whats is the relationship between `LoanStatus` and `Term`.

[178]:
```
count_plot2('LoanStatus', hu='Term', y=False)
```



Observations

- Despite a significant portio of the loans being longterm, there is no clear evidence of loan `Term` affecting `Loan Status`.

Observations (qualitative vs Qualitative analysis)

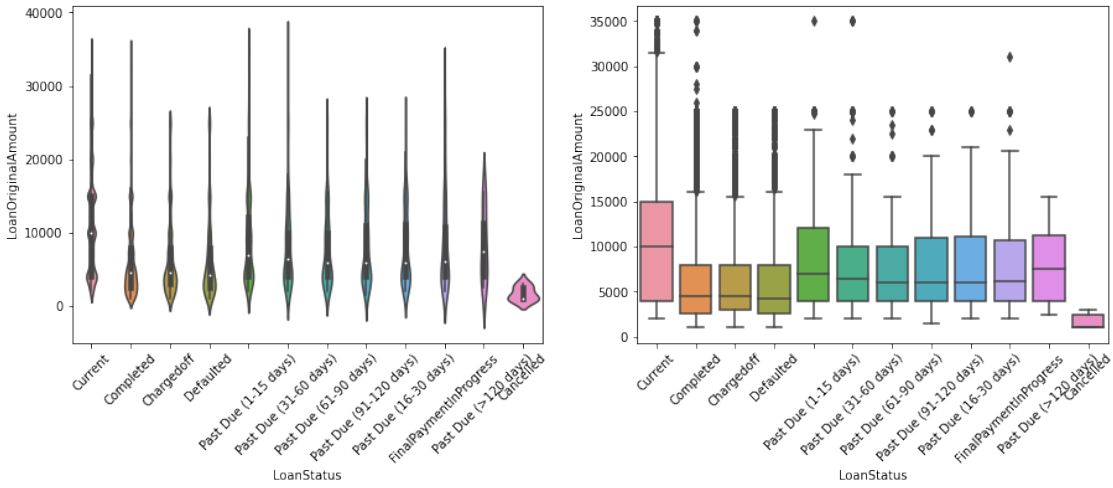
- `IncomeRange`, `CreditGrade`, `EmploymentStatus` affect loan performance.
- However, home ownership (`IsBorrowerHomeOwner`) and `Term` have no pronounced effect on Loan performance (`LoanStatus`).

Quantitative Vs Qualitative exploration

[179]:
```
'''
violin plot
    args
        df: data
        X: variable for X axis
        Y: variable for Y axis
        cord: cordinates for dimension of plot
        hu
'''
def violin(df, X, Y, cord, hu=None):
    plt.figure(figsize=cord)
    sb.violinplot(data=df, x=X, y=Yn, hue=hu)
    plt.xticks(rotation=45)

def box(df, X, Y, cord, hu=None):
    plt.figure(figsize=cord)
    sb.boxplot(data=df, x=X, y=Y, hue=hu)
    plt.xticks(rotation=45)

# subplot for violin plot and box plot
def boxviolin(df, X,Y,cord, hu=None):
    plt.figure(figsize=cord)
    plt.subplot(1,2,2)

    #subplot row=1, column=1
    plt.subplot(1,2,1)
    sb.violinplot(data=df, x=X, y=Y, hue=hu)
    plt.xticks(rotation=45)

    #subplot row=1, column=2
    plt.subplot(1,2,2)
    sb.boxplot(data=df, x=X, y=Y, hue=hu)
    plt.xticks(rotation=45)
```

What is the relationship between `LoanOriginalAmount` and `LoanStatus`

[180]:
```
boxviolin(df_new, X='LoanStatus', Y='LoanOriginalAmount', cord=(15,5))
```

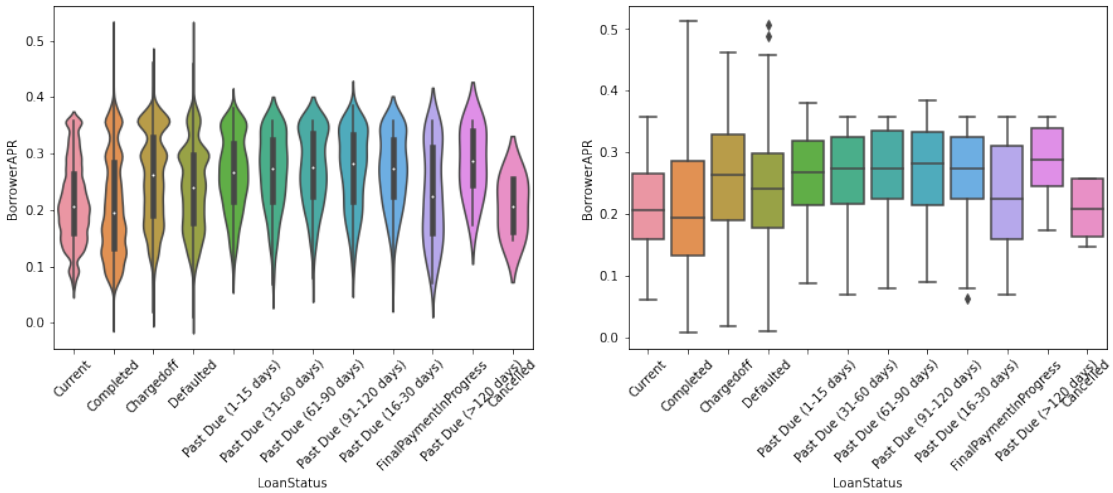


Observations

- Current Loans with a median value of `$10000` and a high of `$31000` have higher chances of becoming `Past Due`.
- `Completed`, `Chargedoff`, `Defaulted` loans with a median value of `$5000`, and a high of less than `$10000` have lesser summary statistics than the `Current` loans.
- Summarily, `Current` loans with quartile above the `Completed`, `Chargedoff`, `Defaulted` have higher chances of becoming `Past Due`.
- Summarily;
  - Aside the tendencies of most current loans to becoming past due, there is no clear evidence that `LoanOriginalAmount` affects loan Performance.

What is the relationship between `BorrowerAPR` and `LoanStatus`.

[181]:
```
boxviolin(df_new, X='LoanStatus', Y='BorrowerAPR', cord=(15,5))
```



Observation

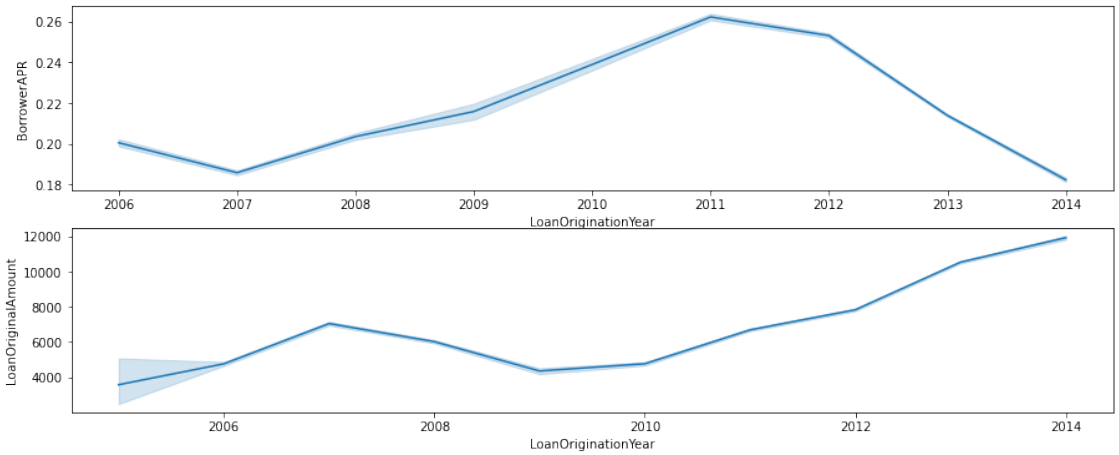
- `Current` and `Completed` loans are characterised by lower `BorrowerAPR` values, with `Completed` loans having the lowest.
- `FinalPaymentsInProgress` has lower `BorrowerAPR` values.
- It makes sense to see why `Chargedoff`, `Defaulted` and `PastDue({1..30} days)` are characterised by higher values.
- Summarily
  - Loans with lower `BorrowerAPR` are either completed, current OR with a fraction in Final payment.
  - `Low APR => fast payment`, and `high APR => extended payment time`.
  - `BorrowerAPR` has pronounced effect on `LoanStatus`.

Numeric Bivariate Exploration (quantitative vs quantitative)

What is the relationship between `LoanOriginalAmount` and `BorrowerAPR`

[182]:
```
plt.figure(figsize=(15,6))
plt.subplot(2,1,1)

plt.subplot(2,1,1)
sb.lineplot(data=df_new, x="LoanOriginationYear", y="BorrowerAPR")

plt.subplot(2,1,2)
sb.lineplot(data=df_new, x="LoanOriginationYear", y="LoanOriginalAmount")
```

[182]:
```
<AxesSubplot:xlabel='LoanOriginationYear', ylabel='LoanOriginalAmount'>
```



Observations

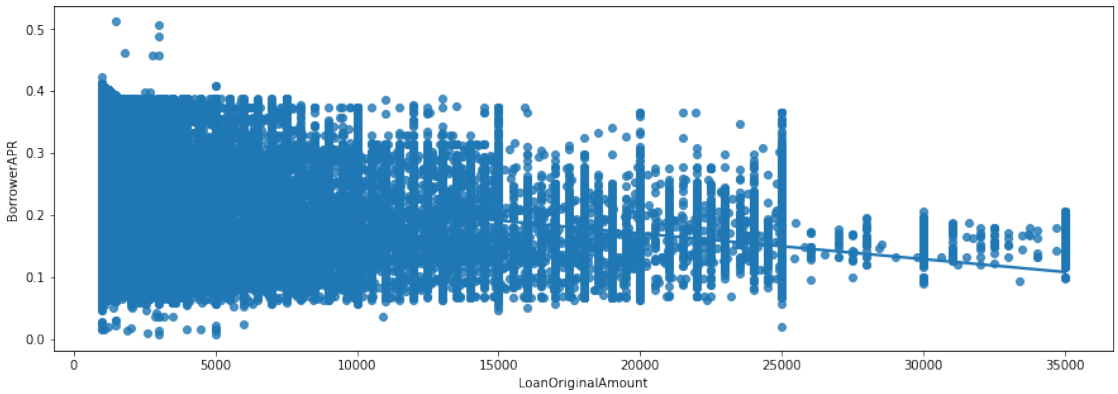
- `BorrowerAPR` decreases with an increase in `LoanOriginalAmount`.

- More insights on this pattern will be explored in the multivariate exploration section.

What is the relationship between BorrowerAPR and LoanOriginalAmount

[183]:
```
plt.figure(figsize=(15,5))
sb.regplot(data=df_new, x='LoanOriginalAmount', y='BorrowerAPR')
```

[183]: <AxesSubplot:xlabel='LoanOriginalAmount', ylabel='BorrowerAPR'>

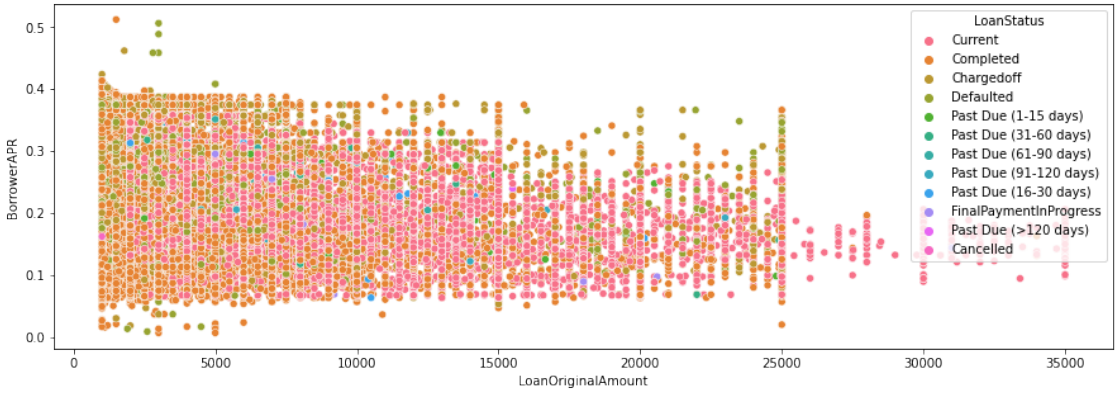


Observations

- LoanOriginalAmount increases BorrowerAPR decreases.

[184]:
```
plt.figure(figsize=(15,5))
sb.scatterplot(data=df_new, x='LoanOriginalAmount', y='BorrowerAPR',␣
↪hue='LoanStatus')
```

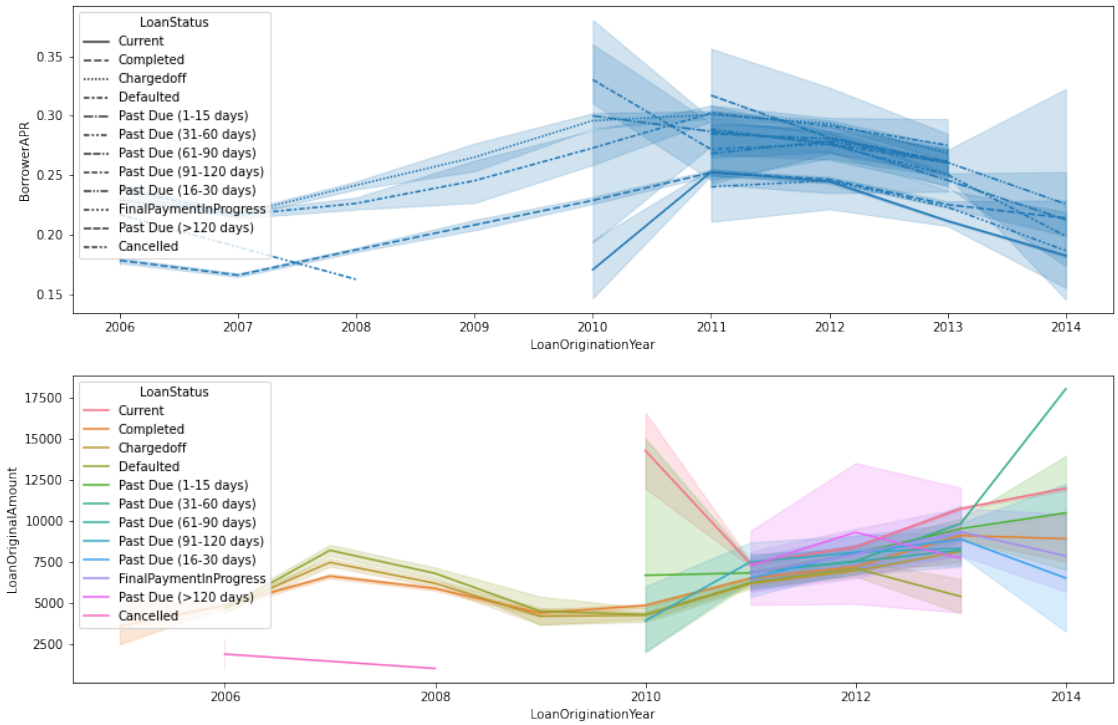
[184]: <AxesSubplot:xlabel='LoanOriginalAmount', ylabel='BorrowerAPR'>



Multivariate Eploration

[185]:
```
plt.figure(figsize=(15,10))
plt.subplot(2,1,1)

plt.subplot(2,1,1)
sb.lineplot(data=df_new, x="LoanOriginationYear", y="BorrowerAPR",␣
 ↪style='LoanStatus')

plt.subplot(2,1,2)
sb.lineplot(data=df_new, x="LoanOriginationYear", y="LoanOriginalAmount",␣
 ↪hue='LoanStatus')
```

[185]:
```
<AxesSubplot:xlabel='LoanOriginationYear', ylabel='LoanOriginalAmount'>
```



Observations

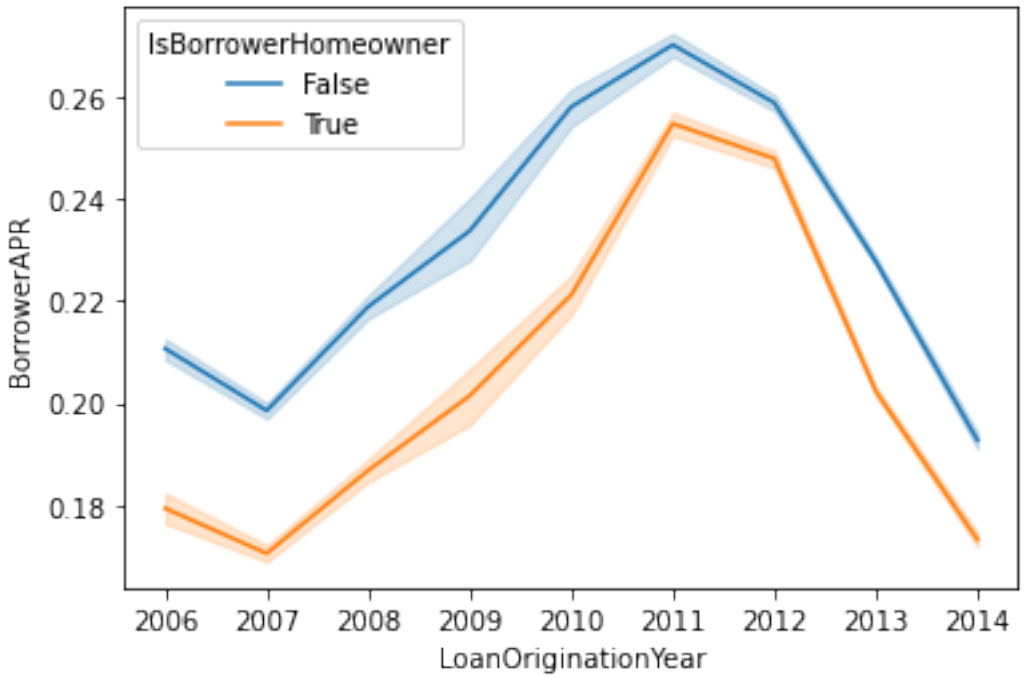
- Here, we see completed loans having lower `BorrowerAPR` along the years
- Charged of loans also have higher `BorrowerAPR`, and
- Current loans characterised by lower `BorrowerAPR`.
- Summarily;
  - productive loans are characterised by lower `BorrowerAPR` while with loans with worst performance have higher `BorrowerAPR`.
  - Lowering the `BorrowerAPR` would improve the loan performace.

– The declining BorrowerAPR along the years can be attributed to customer feedback and results of loan performance access

What is the relationship between `IsBorrowerHomeowner` and `LoanOriginationYear`

[186]:
```
sb.lineplot(data=df_new, x="LoanOriginationYear", y="BorrowerAPR",␣
↪hue='IsBorrowerHomeowner')
```

[186]: <AxesSubplot:xlabel='LoanOriginationYear', ylabel='BorrowerAPR'>



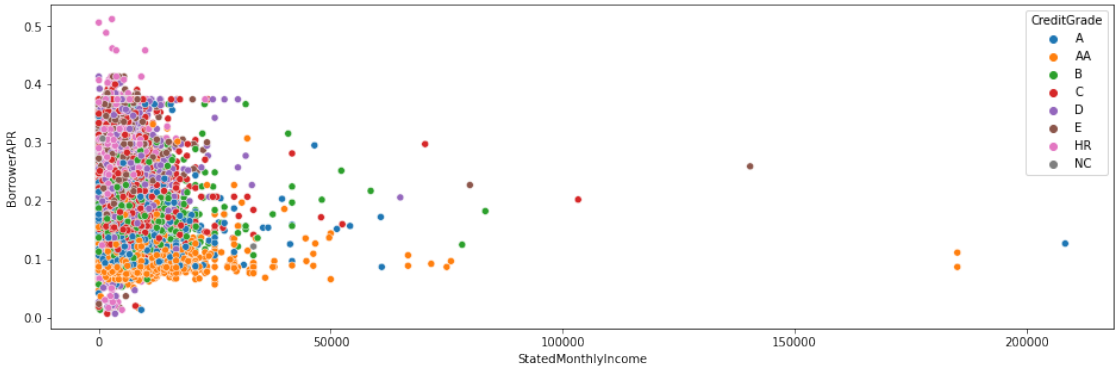
Observations

- `BorrowerAPR` peaks in the year `2011` and declines steadily.
- Home owners have lower `BorrowerAPR`.

What is the relationship between `BorrowerAPR` and `StatedMonthlyIncome`.

[187]:
```
plt.figure(figsize=(16,5))
sb.scatterplot(data=df_new, y='BorrowerAPR', x='StatedMonthlyIncome',␣
↪hue='CreditGrade')
```

[187]: <AxesSubplot:xlabel='StatedMonthlyIncome', ylabel='BorrowerAPR'>

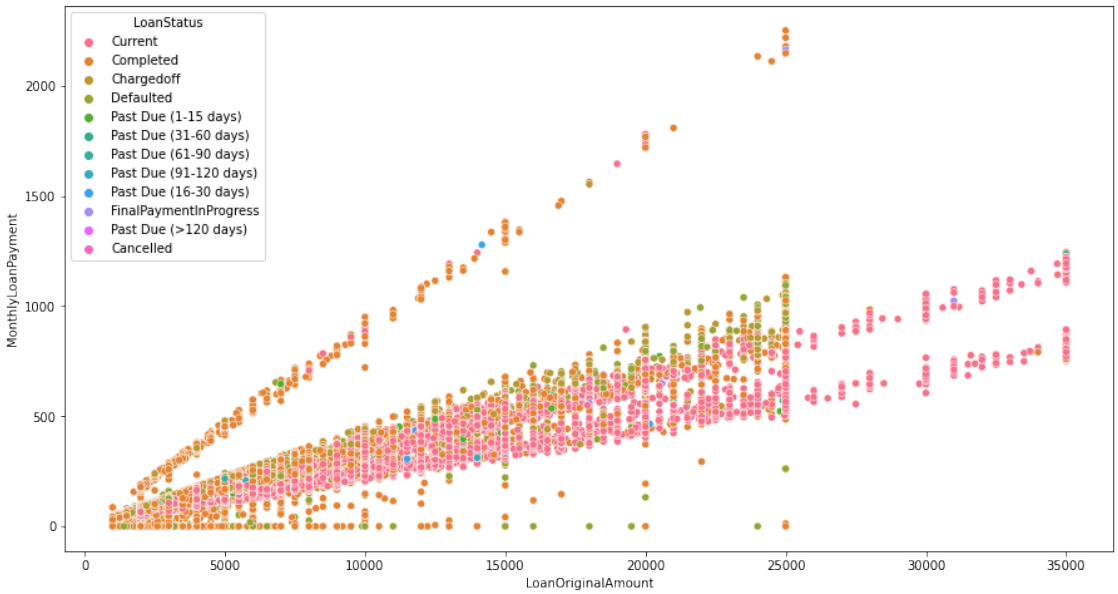


Observations

- High `StatedMonthlyIncome` is associated with low `BorrowerAPR` and low `StatedMothlyIncome` associated with high `APR`.
- Good Credit Rating is associated with low `BorrowerAPR`.

[188]:
```
plt.figure(figsize=(15,8))
sb.scatterplot(data=df_new, y='MonthlyLoanPayment', x='LoanOriginalAmount',␣
↪hue='LoanStatus')
```

[188]: `<AxesSubplot:xlabel='LoanOriginalAmount', ylabel='MonthlyLoanPayment'>`



1.1.3 Overall Summary

Univariate exploration

1.
   - `Default` loans account for `10.6%` of the loans.
   - `Completed` loans account for `33.7%` of the loans.
   - `Current` loan saccount for 49.3% of the loans.
2.
   - California has the highest number of loan applicants with `Texas`, `Florida`, `NewYork`, etc. following suit.
3.
   - Employed clients account for 60.1% of the total loan applicants, wit 23.8% working full-time.
4.
   - Applicants earning `$(25k - 74999k)` account for `55.4%` while clients earning `$(75k - 100k+)` account for 30% of the total.
5.
   - Most loan are in the fourth and first quarter respectively.
6.
   - Most loans were recorded in 2013 with a high of 34000 loans.
7.
   - `Home Ownership (IsBorrowerHomeowner)` has no effect on `loan performance (LoanStatus)`.
8.
   - `Computer Programmer`, `Executives`, `Teachers`, etc.. are some the major loan applicants
9.
   - `Debtconsolidation` accounts for most loan categories.
10.
    - The loans are najorly longterm with a significant portion having a span of three years.
11.
    - Loan Amounts are mostly in multiples of `$5000`.
12.
    - A significant portion of the loan payments fall below `$1000`.
13.
    - The BorrowerAPR for most loans falls between `0.15` to `0.3`.

Bivariate Exploration

category vs category

1.
   - `IncomeRange` affects `LoanStatus`.
2.
   - `Homeownership` has no effect on `LoanStatus`.
3.
   - `CreditGrade` is a reflection of previous loan performance `(LoanStatus)`.
4.
   - `EmploymentStatus` has mild effect on `LoanStatus`.
5.
   - Loan `Term` has no effect on `LoanStatus`. #### Numeric vs Category
6.
   - Despite the tendencies of current loans being `pastdue`, there is no clear statistics showing that `LoanOriginalAmount` has any pronounced effect on `LoanStatus`.
7.
   - `BorrowerAPR` has significant effect on `LoanStatus`. #### numeric vs numeric
8.
   - `BorrowerAPR` decreases with an increase in `LoanOriginalAmount`.
   - `BorrowerAPR` and `LoanOriginalAmount` are negatively correlated.

- Along the years, `Completed` loans have lower `BorrowerApr` amidst increasing `LoanOriginalAmount`.
- `Canceled` loans are also characterised by high increasing `LoanOriginalAmounts` and deacreasing `BorrowerAPR`. #### Multivariate exploration

9. - `MonthlyLoanPayment` and `LoanOriginalAmount` are positively correlated with completed loans hiving a higher correlation coeficient.
10. - Home owners have lower `BorrowerAPR` than those who do not own homes.
11. - Lower `BorrowerAPR` values are associated with better `CreditGrades`.

Conclusions

- From our summary, we have that

1. `LoanStatus` is majorly affected by
   - `IncomeRange`
   - `EmploymentStatus`
   - `CreditGrade`
2. `BorrowerAPR` is majorly inlfuenced by;
   - `LoanOriginalAmount`
   - Home ownership `IsBorrowerHomeowner`

Glosary

Charge-off loan

- This means a lender or creditor has written the account off as a loss, and the account is closed to future charges.

Default Loan

- This occurs when a borrower fails to pay back a debt according to the initial arrangement.

NR

- `Not Reported`, this indicates that an update has not been provided between the lender and Credit Reference Agency for that month. In the eyes of a prospective lender it means that they cannot tell whether a payment was made or missed, so this is a neutral marker.

Save data for explanatory data visualization

[189]:
```
df_new.to_csv('prosper_clean.csv')
```