Prosper Loan Data Exploration

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Introduction

> Prosper was founded in 2005 as the first peer-to-peer lending marketplace in the United States. Since then, Prosper has facilitated more than USD 12 billion in loans to more than 770,000 people.

This dataset contains 113,937 loans with 81 columns for each loan. These columns includes borrower income, borrower rate, current loan status, loan amount, and so on.
This investigation will be analyzing factors that influence borrow's APR and how each loan were taken by what type of borrowers. Gotten from: https://www.prosper.com/about

Preliminary Wrangling

In [1]:
```
# import all packages and set plots to be embedded inline
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sb
%matplotlib inline

# Configuring Pandas; expand maximum number of columns and row displayed
pd.set_option('display.max_columns', None)
pd.set_option('display.max_rows', None)

import warnings
warnings.filterwarnings("ignore")
print('complete')
```

```
complete
```

In [2]:
```
# Load the dataset
```

```
df_complete = pd.read_csv('prosperLoanData.csv')
df_complete.head()
```

Out[2]:

	ListingKey	ListingNumber	ListingCreationDate	CreditGrade	Term	LoanStatus	Clo
0	10213397668681454 13AB3B	193129	2007-08-26 19:09:29.263000000	C	36	Completed	20
1	10273602499503308B223C1	1209647	2014-02-27 08:28:07.900000000	NaN	36	Current	
2	0EE9337825851032864889A	81716	2007-01-05 15:00:47.090000000	HR	36	Completed	20
3	0EF53560024827152 99901A	658116	2012-10-22 11:02:35.010000000	NaN	36	Current	
4	0F023589499656230C5E3E2	909464	2013-09-14 18:38:39.097000000	NaN	36	Current	

In [3]:

```
# DataFrame summary showing datatypes and full info
df_complete.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
```

Cleaning

> There are a lot of variables in this dataset. I will take a subset of the variables for my analysis

In [4]:
```
# Select interested variables
variables = ['ListingCreationDate', 'LoanOriginalAmount', 'LoanOriginationDate', 'List
             'ProsperRating (Alpha)','ProsperScore', 'Occupation', 'IncomeVerifiable',
             'LoanStatus','CreditScoreRangeLower', 'CurrentCreditLines', 'IncomeRange'
             'OpenRevolvingAccounts', 'DebtToIncomeRatio', 'CreditScoreRangeUpper','Bo
```

In [5]:
```
# View the created dataframe
df_complete[variables].head()
```

Out[5]:

	ListingCreationDate	LoanOriginalAmount	LoanOriginationDate	ListingCategory (numeric)	ProsperRating (Alpha)	Pr
0	2007-08-26 19:09:29.263000000	9425	2007-09-12 00:00:00	0	NaN	
1	2014-02-27 08:28:07.900000000	10000	2014-03-03 00:00:00	2	A	
2	2007-01-05 15:00:47.090000000	3001	2007-01-17 00:00:00	0	NaN	
3	2012-10-22 11:02:35.010000000	10000	2012-11-01 00:00:00	16	A	
4	2013-09-14 18:38:39.097000000	15000	2013-09-20 00:00:00	2	D	

In [6]:
```
# view the statistics
df_complete[variables].describe()
```

Out[6]:

	LoanOriginalAmount	ListingCategory (numeric)	ProsperScore	CreditScoreRangeLower	CurrentCreditLine
count	113937.00000	113937.000000	84853.000000	113346.000000	106333.00000
mean	8337.01385	2.774209	5.950067	685.567731	10.31719
std	6245.80058	3.996797	2.376501	66.458275	5.45786
min	1000.00000	0.000000	1.000000	0.000000	0.00000
25%	4000.00000	1.000000	4.000000	660.000000	7.00000
50%	6500.00000	1.000000	6.000000	680.000000	10.00000
75%	12000.00000	3.000000	8.000000	720.000000	13.00000
max	35000.00000	20.000000	11.000000	880.000000	59.00000

In [7]:
```
# Are there duplicates
sum(df_complete[variables].duplicated())
```

Out[7]: 0

In [8]:
```
# Total number of columns containing null values
df_complete[variables].isnull().sum()
```

Out[8]:
```
ListingCreationDate              0
LoanOriginalAmount               0
LoanOriginationDate              0
ListingCategory (numeric)        0
ProsperRating (Alpha)        29084
ProsperScore                 29084
Occupation                    3588
IncomeVerifiable                 0
EmploymentStatus              2255
IsBorrowerHomeowner              0
LoanStatus                       0
CreditScoreRangeLower          591
CurrentCreditLines            7604
IncomeRange                      0
BorrowerRate                     0
StatedMonthlyIncome              0
OpenRevolvingAccounts            0
DebtToIncomeRatio             8554
CreditScoreRangeUpper          591
BorrowerState                 5515
Term                             0
BorrowerAPR                     25
dtype: int64
```

In [9]:
```
df = df_complete[variables]
```

In [10]:
```
# Rename columns
df.rename(columns={'ListingCategory (numeric)': 'ListingCategory', 'ProsperRating (Alp
```

In [11]:
```
# Convert date columns from strings to dates
df.LoanOriginationDate = pd.to_datetime(df.LoanOriginationDate)
df.ListingCreationDate = pd.to_datetime(df.ListingCreationDate)
```

In [12]:
```
# Removing all numeric values from the ListingCategory column
list_cat = {0 : 'Not Available', 1 : 'Debt Consolidation', 2 : 'Home Improvement', 3:
            4 : 'Personal Loan', 5 : 'Student Use', 6 : 'Auto', 7 : 'Other', 8 : 'Baby
            9 : 'Boat', 10 : 'Cosmetic Procedure', 11 : 'Engagement Ring', 12 : 'Green
           13 : 'Household Expenses', 14 : 'Large Purchases', 15 : 'Medical or Dental'
           17 : 'RV', 18 : 'Taxes', 19 : 'Vacation', 20 : 'Wedding Loans'}

df['ListingCategory'] = df['ListingCategory'].map(list_cat)
```

In [13]:
```
# Convert ProsperRating from strings to categorical datatype
prosper_rating = ['AA', 'A', 'B', 'C', 'D', 'E','HR']
correct_rating = pd.api.types.CategoricalDtype(ordered = True, categories = prosper_ra
df['ProsperRating'] = df['ProsperRating'].astype(correct_rating)
```

In [14]:
```
# Occupation Unique Values
df['Occupation'].unique()
```

Out[14]:
```
array(['Other', 'Professional', 'Skilled Labor', 'Executive',
       'Sales - Retail', 'Laborer', 'Food Service', 'Fireman',
       'Waiter/Waitress', 'Construction', 'Computer Programmer',
       'Sales - Commission', 'Retail Management', 'Engineer - Mechanical',
       'Military Enlisted', 'Clerical', nan, 'Teacher', 'Clergy',
       'Accountant/CPA', 'Attorney', 'Nurse (RN)', 'Analyst',
       "Nurse's Aide", 'Investor', 'Realtor', 'Flight Attendant',
       'Nurse (LPN)', 'Military Officer', 'Food Service Management',
       'Truck Driver', 'Administrative Assistant',
       'Police Officer/Correction Officer', 'Social Worker',
       'Tradesman - Mechanic', 'Medical Technician', 'Professor',
       'Postal Service', 'Civil Service', 'Pharmacist',
       'Tradesman - Electrician', 'Scientist', 'Dentist',
       'Engineer - Electrical', 'Architect', 'Landscaping',
       'Tradesman - Carpenter', 'Bus Driver', 'Tradesman - Plumber',
       'Engineer - Chemical', 'Doctor', 'Chemist',
       'Student - College Senior', 'Principal', "Teacher's Aide",
       'Pilot - Private/Commercial', 'Religious', 'Homemaker',
       'Student - College Graduate Student', 'Student - Technical School',
       'Psychologist', 'Biologist', 'Student - College Sophomore',
       'Judge', 'Student - College Junior', 'Car Dealer',
       'Student - Community College', 'Student - College Freshman'],
      dtype=object)
```

In [15]:
```
#Search for null values
null_values = df.Occupation.isnull().sum()
print('There are {} duplicate records in the dataset'.format(null_values))
```

```
There are 3588 duplicate records in the dataset
```

In [16]:
```
# Filling null values with Not Specified
df['Occupation'] = df['Occupation'].fillna('Not Specified')
```

In [17]:
```
#ProsperRating and BorrowerAPR are 2 important variables for this analysis. I will sel
empty_values = ['BorrowerAPR', 'ProsperRating']

for values in empty_values:
    df = df[df[values].notnull()]
```

In [18]:
```
df.shape
```

Out[18]:
```
(84853, 22)
```

What is the structure of your dataset?

> My dataset was initially a loan database of 113937(rows) with 81 columns(variables). In each row(loan listing), there is a lot of insight that can be gotten on the situations surrounding each loan in the dataset. However, to be able to carry out a good analysis, I selected a subset of these variables.

The present data frame contains 84853 rows (84853 loans) with 22 features. Most variables are numeric in nature.

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

> The dataset currently contains loads of information. However, I am interested in finding out:
>
> - The factors that may cause people to take loans.
> - The different factors that can influence the amount a borrower can get. ProsperRating, Occupation, EmploymentStatus etc.
> - The loans size borrowers take out from Prosper?

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

> There are so many features to explore. However I think the following features will help in my analysis; `ProsperScore` , `LoanStatus` , `BorrowerState` , `isBorrowerHomeowner` , `IncomeRange` , `BorrowerAPR` , `ProsperRating` , `EmploymentStatus` , `IncomeVerifiable` ....

My interested features are however not limited to this. Additional features might be required.

The Question-Visualization-Observations frame work will be used throughout the exploration process. For this exploration phase, I will be exploring the different variables in the dataset to see how they're distributed and to generally understand their importance in the dataset.

Creating Functions To Be Used

In [19]:
```
# Function to call the figsize
def fig_size(a,b):
    # calling figsize parameters
    return plt.figure(figsize=(a,b))
```

In [20]:
```
#This function gives chart title, x and y axis. It is created to avoid repetition
def pltlabels(a,b,c):
    return plt.title(a),plt.xlabel(b),plt.ylabel(c)
```

In [21]:
```
color=sb.color_palette()[0]
```

Univariate Exploration

> In this section, i will look at how some of my interested variables are distributed using charts.

Prosper Score

Question:

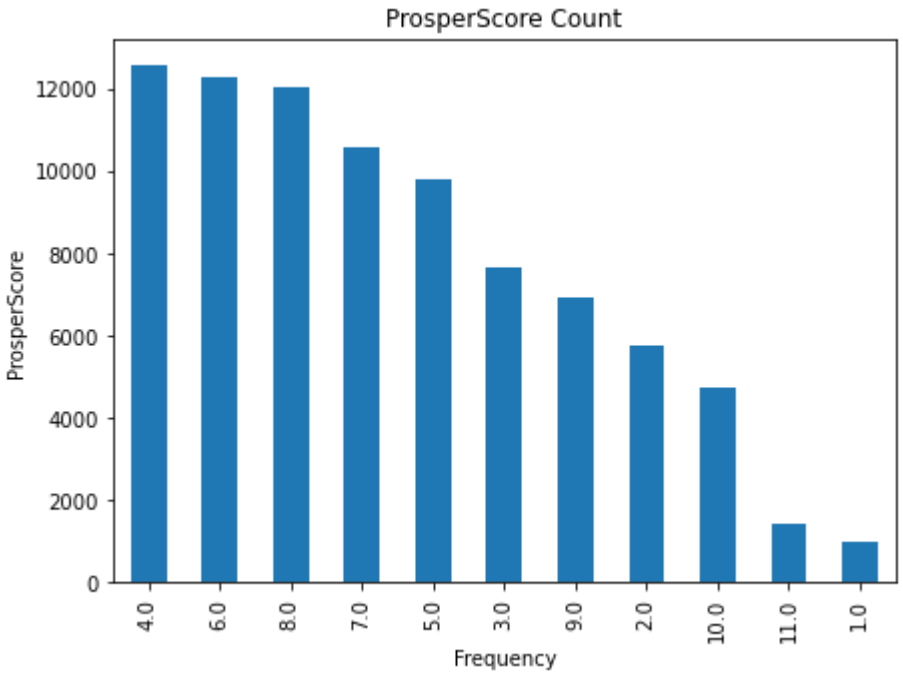
The ProsperScore column calculates the risk score built using historical Prosper data. Which ProsperScore has the highest number of borrowers?

Visualization:

In [22]:
```
# Make a count to know the Sore with the highest number
df.ProsperScore.value_counts()
```

Out[22]:
```
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 [23]:
```
# Plot a barchart for visualization
fig_size(7, 5)
df_complete.ProsperScore.value_counts().plot(kind='bar')
pltlabels('ProsperScore Count', 'Frequency', 'ProsperScore');
```



Observation:

The ProsperScore ranges from 1 to 11, with 11 being the lowest risk, to 1 being the highest risk. The high points are 4, 6, and 8. The lowest being 1. This shows that borrowers with the highest risk score are the least population in the dataset. Most borrowers fall within 4-8 risk score.

Loan Status

Question:

What is the distrubution of loan status across listings in the dataset. Are borrowers settling their loans?

Visualization:

In [24]:
```
loan_stats = df['LoanStatus'].unique()
print(loan_stats)
```

```
['Current' 'Past Due (1-15 days)' 'Defaulted' 'Completed' 'Chargedoff'
 'Past Due (16-30 days)' 'Past Due (61-90 days)' 'Past Due (31-60 days)'
 'Past Due (91-120 days)' 'FinalPaymentInProgress' 'Past Due (>120 days)']
```

There are a lot of Past Due dates. So I will merge all of them into one unique value called **Past Due**

In [25]:
```
# Merging all Past Due dates
df['LoanStatus'] = df['LoanStatus'].apply(lambda x: x if 'Past Due' not in x else 'Pas

# Convert LoanStatus to a categorical variable. This is gotten from the data dictionar
dict_LoanStatus = ['Defaulted','Chargedoff', 'Past Due', 'Current', 'FinalPaymentInPrc

status_order = pd.api.types.CategoricalDtype(ordered = True, categories = dict_LoanSta

df['LoanStatus'] = df['LoanStatus'].astype(status_order)
```

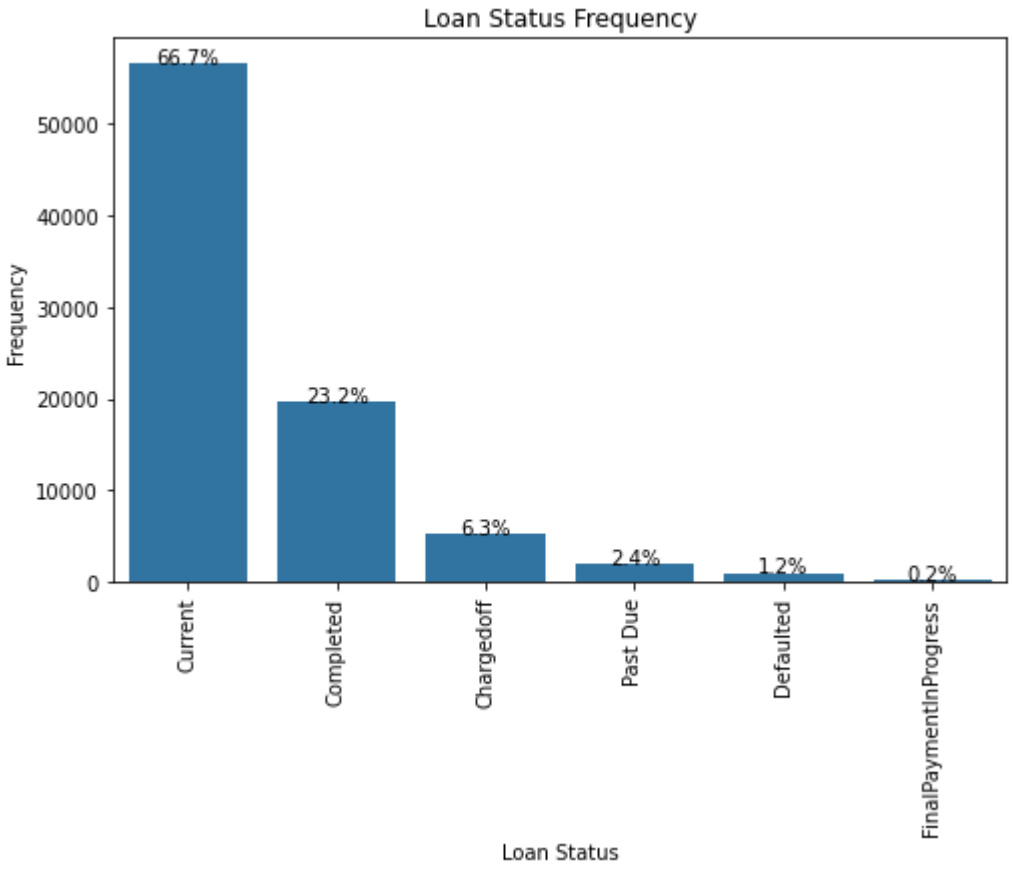
In [26]:
```
# Plot barchart for visualization
count_status = df['LoanStatus'].value_counts()
order_status = count_status.index
loans = df['LoanStatus'].value_counts().sum()

fig_size(8, 5)
sb.countplot(data=df, x='LoanStatus', color=color, order = order_status)
pltlabels('Loan Status Frequency', 'Loan Status', 'Frequency');

# get the current tick locations and labels
locs, labels = plt.xticks(rotation=90)

# loop through each pair of locations and labels
for loc, label in zip(locs, labels):
    # get the text property for the label to get the correct count
    count = count_status[label.get_text()]
    pct_string = '{:0.1f}%'.format(100*count/loans)

    # print the annotation just below the top of the bar
    plt.text(loc, count+2, pct_string, ha = 'center', color = 'black')
```



Observation:

From the visualization above, the dataset is majorly populated with current loans which takes 66.7% of the total loans (over 50,000 current loans) and they are serviced by Prosper's borrowers. Completed loans take 23% (about 20,000 loans) of the total loans have been completed. Charged off loans are about 5,000 and they take 6% of the loans. 1.2% have defaulted. The remaining 2.4% of loans has the status Past Due and was grouped under a single status: Past Due.

Borrowers APR

Question:

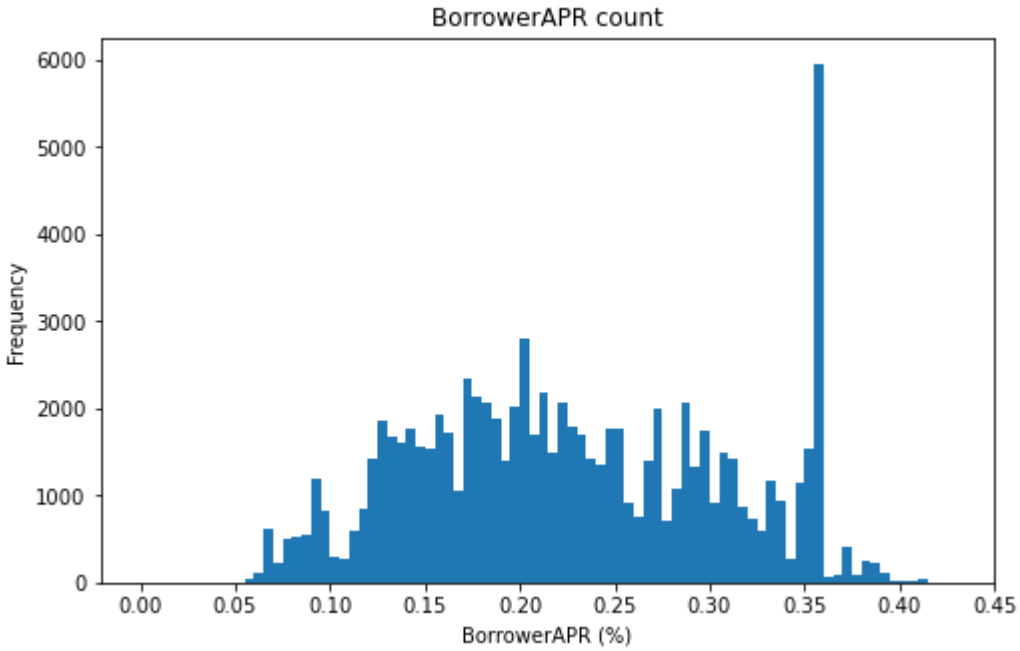
What is the distrbution of Borrower APR values in the dataset?

Visualization:

In [27]:
```
# check where APR has the most counts
df.BorrowerAPR.value_counts().head()
```

Out[27]:
```
0.35797    3672
0.35643    1644
0.30532     902
0.29510     747
0.35356     721
Name: BorrowerAPR, dtype: int64
```

In [28]:
```
# see the counts for all BorrowerAPR values
fig_size(8, 5)
bins = np.arange(0, df['BorrowerAPR'].max(), 0.005)
plt.hist(data = df, x = 'BorrowerAPR', bins = bins)
pltlabels('BorrowerAPR count', 'BorrowerAPR (%)', 'Frequency');
plt.xticks(np.arange(0, df['BorrowerAPR'].max()+0.05, 0.05));
```



Observation:

The highest BorrowerAPR is 0.35797% with 3672 counts. The lowest rate is 0.35356% with just 721 count. The Borrower APR plot has a multimodal distribution, with different peaks.

Employment Status

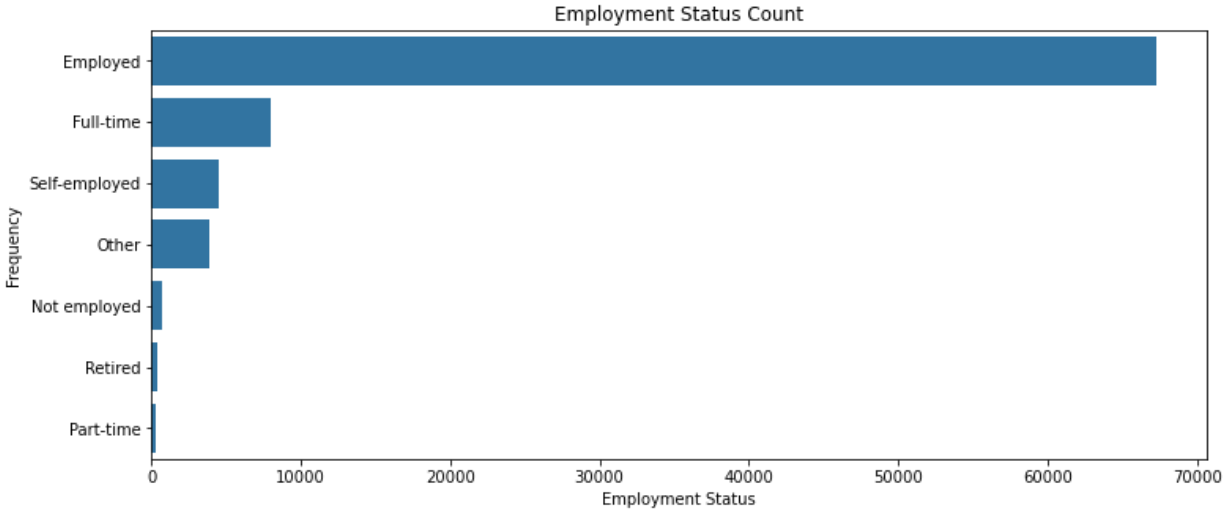
Question:

What is the distribution of Employment Status accross the borrowers. What is the status of people with the most loans?

Visualization:

In [29]:
```
# Plot EmploymentStatus chat
fig_size(12, 5)
employment_stat = df['EmploymentStatus'].value_counts().index
```

```
sb.countplot(data = df, y='EmploymentStatus', order = employment_stat, color=color)
pltlabels('Employment Status Count', 'Employment Status', 'Frequency');
```



Observation:

Employed individuals take the highest count of borrowers. This makes sense because one would need a source of income to pay off borrowed loans. It would be difficult to get a loan without a job. It is however surprising that people that did not specify their employment status (Other) have more count than borrowers with part-time jobs.

Occupation

Question:

What is the Occupation of borrowers with the most loans?

Visualization:

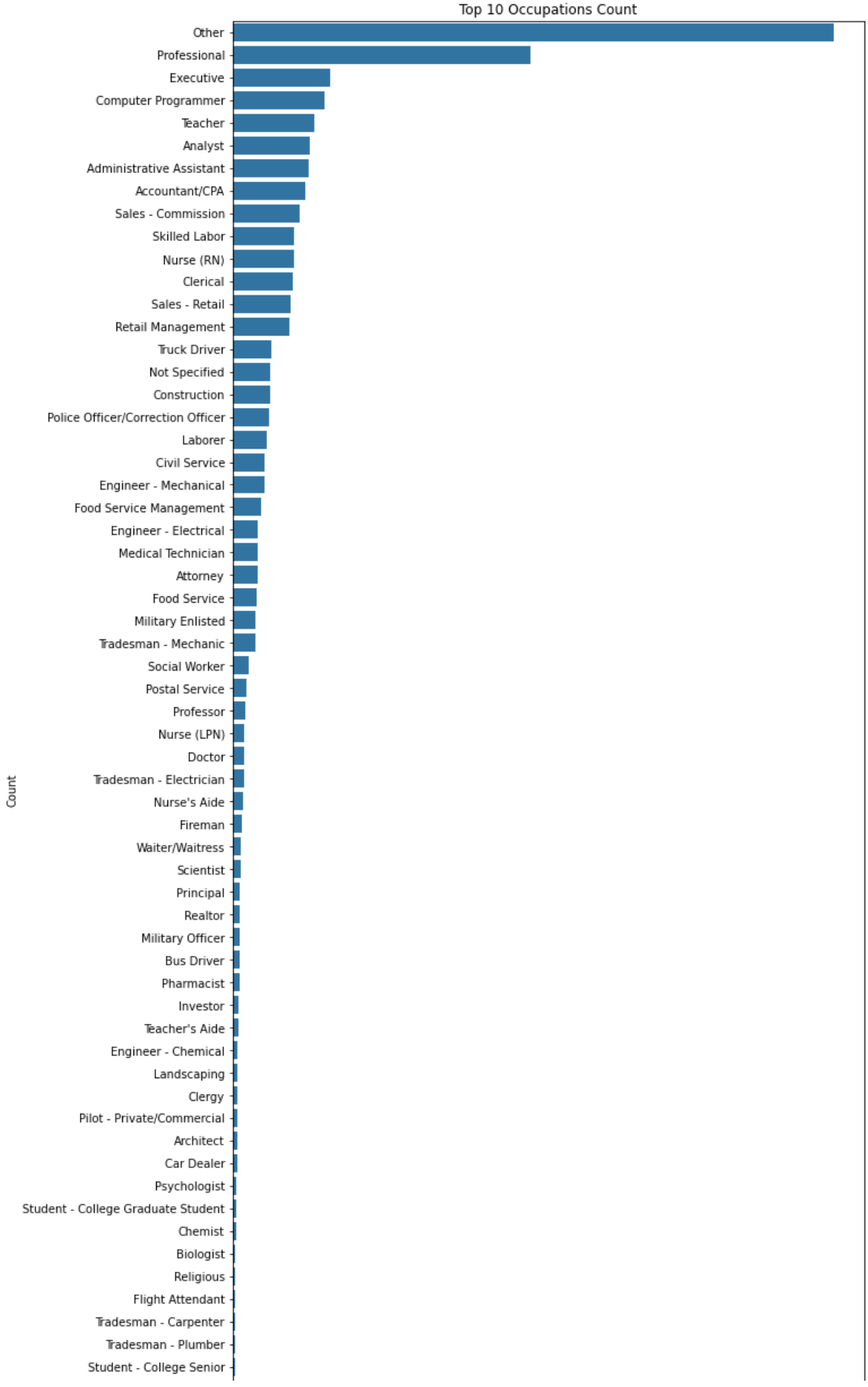
In [30]:
```
occupation_count = df.Occupation.value_counts()
print(occupation_count)
```

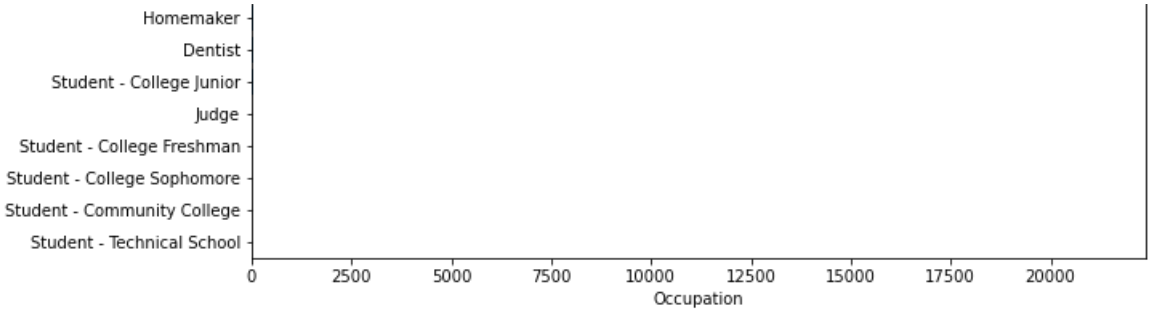
Other	21317
Professional	10542
Executive	3468
Computer Programmer	3236
Teacher	2888
Analyst	2735
Administrative Assistant	2708
Accountant/CPA	2574
Sales - Commission	2350
Skilled Labor	2180
Nurse (RN)	2159
Clerical	2116
Sales - Retail	2029
Retail Management	2001
Truck Driver	1366
Not Specified	1333
Construction	1326
Police Officer/Correction Officer	1277
Laborer	1217
Civil Service	1139
Engineer - Mechanical	1135
Food Service Management	1005
Engineer - Electrical	900
Medical Technician	891
Attorney	866
Food Service	837
Military Enlisted	824
Tradesman - Mechanic	797
Social Worker	575
Postal Service	487
Professor	452
Nurse (LPN)	416
Doctor	393
Tradesman - Electrician	385
Nurse's Aide	382
Fireman	319
Waiter/Waitress	294
Scientist	292
Principal	262
Realtor	252
Military Officer	252
Bus Driver	250
Pharmacist	225
Investor	201
Teacher's Aide	200
Engineer - Chemical	176
Landscaping	172
Clergy	157
Pilot - Private/Commercial	153
Architect	149
Car Dealer	143
Psychologist	118
Student - College Graduate Student	112
Chemist	109
Biologist	95
Religious	93
Flight Attendant	87

```
Tradesman - Carpenter                    85
Tradesman - Plumber                      74
Student - College Senior                 70
Homemaker                                57
Dentist                                  56
Student - College Junior                 27
Judge                                    22
Student - College Freshman               17
Student - College Sophomore              16
Student - Community College              10
Student - Technical School                2
Name: Occupation, dtype: int64
```

In [31]:

```
fig_size(10,25)
order = occupation_count.index
sb.countplot(data=df, y='Occupation', color=color, order=order)
pltlabels('Top 10 Occupations Count', 'Occupation', 'Count');
```


Top 10 Occupations Count
Count
Other
Professional
Executive
Computer Programmer
Teacher
Analyst
Administrative Assistant
Accountant/CPA
Sales - Commission
Skilled Labor
Nurse (RN)
Clerical
Sales - Retail
Retail Management
Truck Driver
Not Specified
Construction
Police Officer/Correction Officer
Laborer
Civil Service
Engineer - Mechanical
Food Service Management
Engineer - Electrical
Medical Technician
Attorney
Food Service
Military Enlisted
Tradesman - Mechanic
Social Worker
Postal Service
Professor
Nurse (LPN)
Doctor
Tradesman - Electrician
Nurse's Aide
Fireman
Waiter/Waitress
Scientist
Principal
Realtor
Military Officer
Bus Driver
Pharmacist
Investor
Teacher's Aide
Engineer - Chemical
Landscaping
Clergy
Pilot - Private/Commercial
Architect
Car Dealer
Psychologist
Student - College Graduate Student
Chemist
Biologist
Religious
Flight Attendant
Tradesman - Carpenter
Tradesman - Plumber
Student - College Senior



Observation

Surprisingly, 21317 loans were given out to borrowers that did not disclose their oppcupation (**Others**). Earlier, I filled rows with empty Occupation values with **Unknown**, and it is also surprising to see that these individuals had access to loans (Not Specified - 1333).
Most borrowers on Prosper indicate to be Professionals, Computer Programmer, Administrative Assistant, Executive, Teacher, Analyst. There are also loan packages for Students

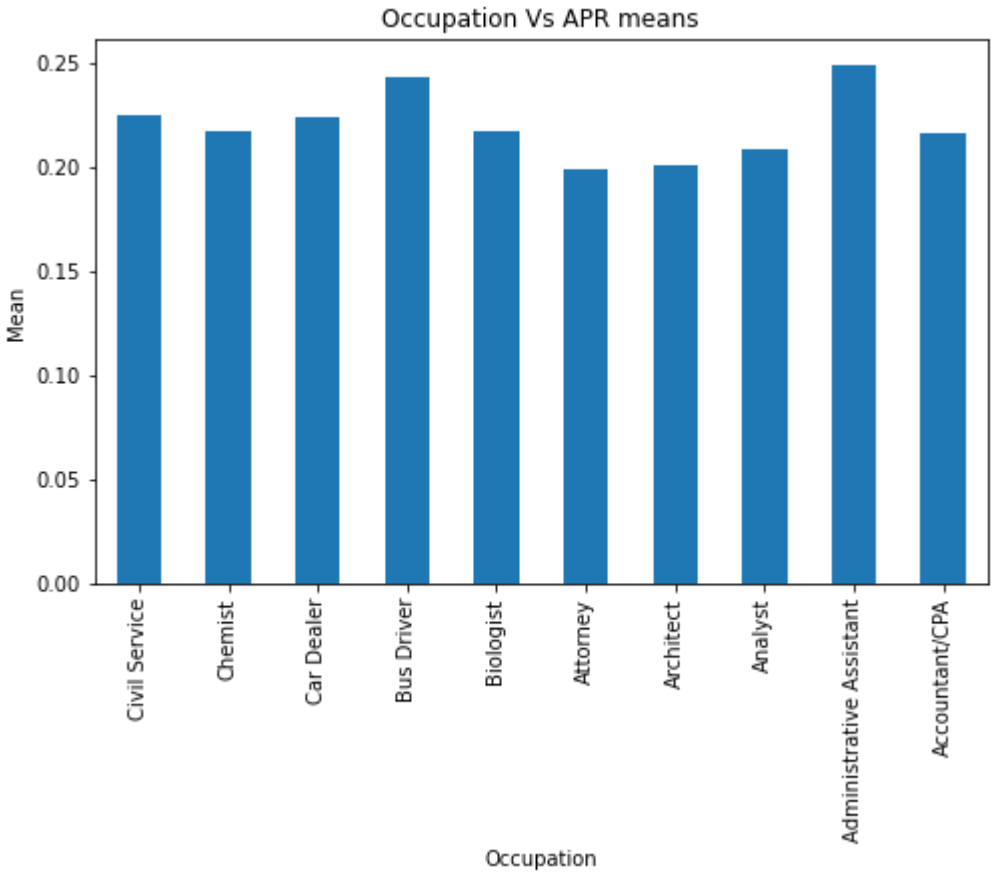
Occupation vs BorrowerAPR

Question:

Which occupation has the highest BorrowerAPR? I'll select the top 10 occupations with high APR means

Visualization:

In [32]:
```
# bar plot for APR means for each top 10 occupations.
Top_Occupation = df.groupby('Occupation').BorrowerAPR.mean()[9::-1]
fig_size(8, 5)
Top_Occupation.plot(kind = 'bar')
pltlabels('Occupation Vs APR means', 'Occupation', 'Mean');
```



Observation

All these occupations have about same BorrowerAPR values. Therefore occupation is not the best factor to analyze the BorrowerAPR, because it is unclear and many other reasons should also be considers to be analyzed.

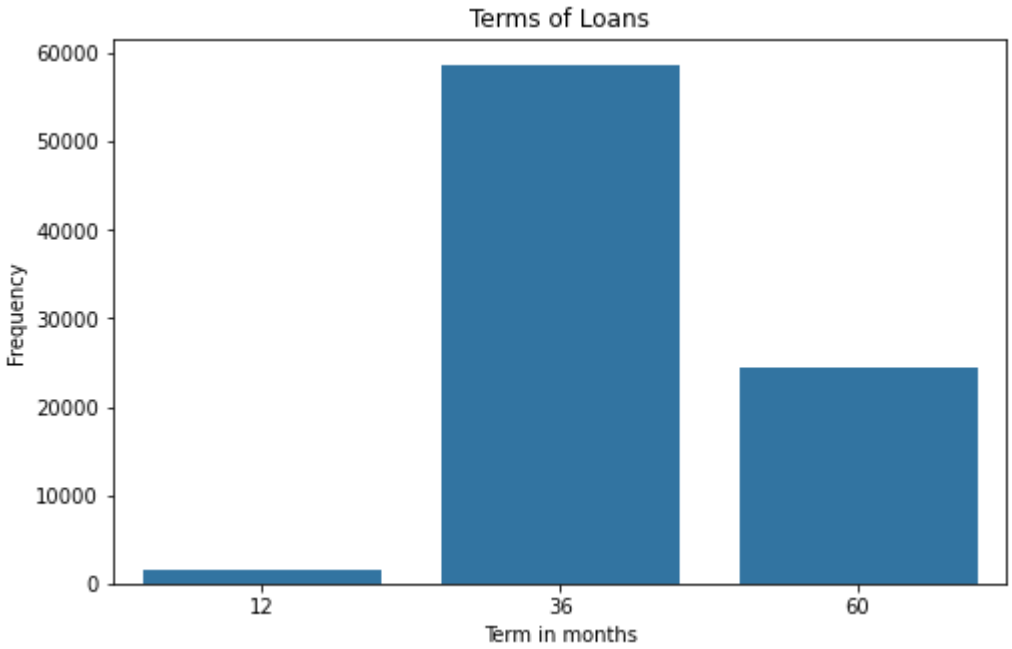
Loan Terms

Question:

What is the most commonly requested loan term?

Visualization:

In [33]:
```
# Plot term of loans
fig_size(8, 5)
sb.countplot(data = df, x='Term', color=color)
pltlabels('Terms of Loans', 'Term in months', 'Frequency');
```



Observation

There are 3 types of loans: 1 year, Medium term loans (3 years) and Long term loans (5 years). Most of the loans taken were for 3 years(36 months), while 12 months loan had the least frequency. With some loans being for 5 years(60 months).

Wages Group

Question:

I will group the wage group column into 3 groups (Low, Medium and High). This is to investigate which wage group has the highest number of requested loans?

Visualization:

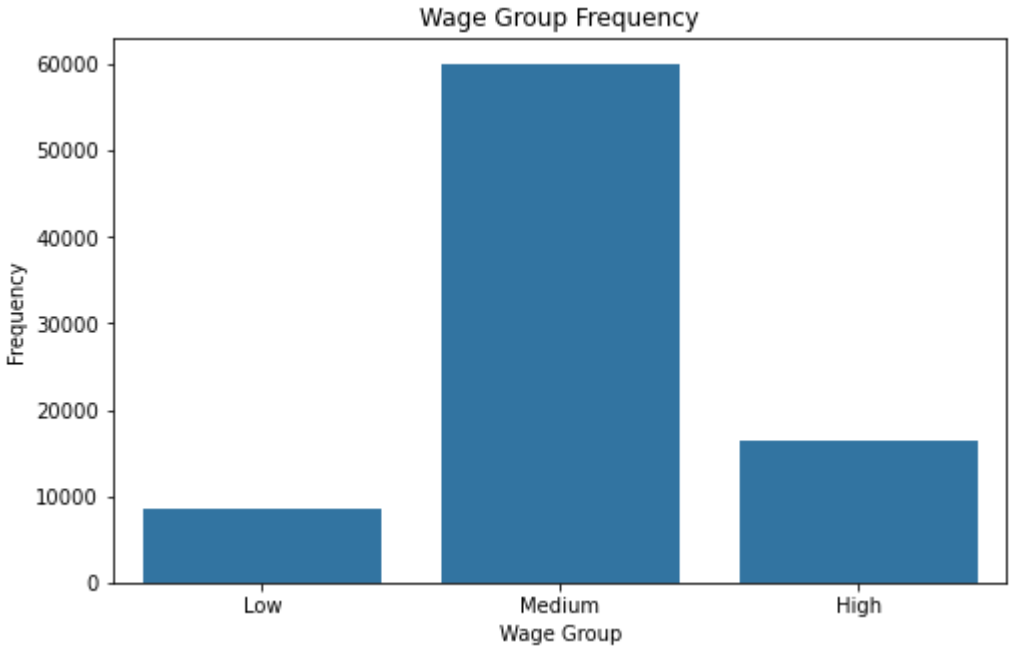
In [34]:
```
# create a group function
def group(row):
    if row["StatedMonthlyIncome"]<2500:
        return 'Low'
    if row["StatedMonthlyIncome"]<8000:
        return 'Medium'
    else:
        return 'High'

df['WageGroup'] = df.apply(group, axis=1)
wagegroup_count = df.WageGroup.value_counts()
print(wagegroup_count)

# convert string to ordinal category type
ordinal_class = ['Low', 'Medium', 'High']
ordered_variable = pd.api.types.CategoricalDtype(ordered = True, categories = ordinal_
df['WageGroup'] = df['WageGroup'].astype(ordered_variable)
```

```
# Plot the new variable
fig_size(8, 5)
sb.countplot(data = df, x = 'WageGroup', color = color)
pltlabels('Wage Group Frequency', 'Wage Group', 'Frequency');
```

```
Medium    60037
High      16344
Low        8472
Name: WageGroup, dtype: int64
```



Observation:

The middle class (people with an average monthly salary between 2500 and 8000 dollars) have taken the highest count of loans which is about 60,037 loans. I expected the low earners to have the highest count of loans but surprisingly, they have the lowest count at 8472 loans. This may be due to inability to pay back loans.

Income Verifiable

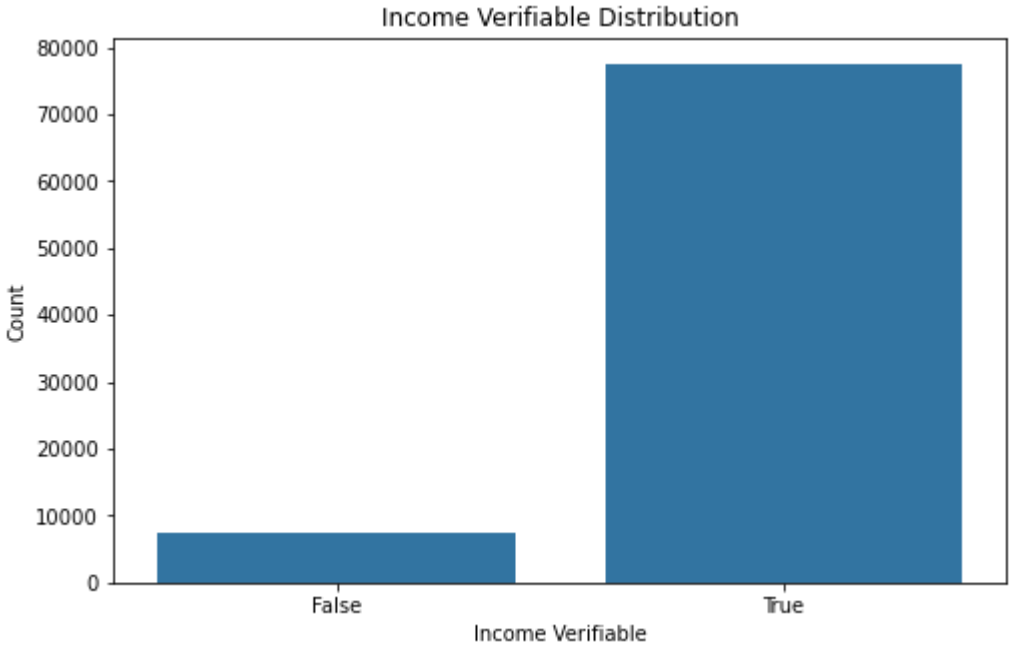
Question:

How is the income verifiable variable distributed? Does a verifiable income influence a loan request?

Visualization:

In [35]:
```
fig_size(8, 5)
income_verifiable = df.IncomeVerifiable.value_counts()
print(income_verifiable)
sb.countplot(data=df, x='IncomeVerifiable', color = color)
pltlabels('Income Verifiable Distribution', 'Income Verifiable', 'Count');
```

```
True     77520
False     7333
Name: IncomeVerifiable, dtype: int64
```



Observation:

As expected, majority of the borrowers (77520 borrowers) have a verifiable means of income, this is needed to ascertain if the borrower will be able to service the loan. But surprisingly, some individuals without any verifiable means of income (7333) were granted loans.

Loan Original Amount

Question:

What is the most requested loan amount?

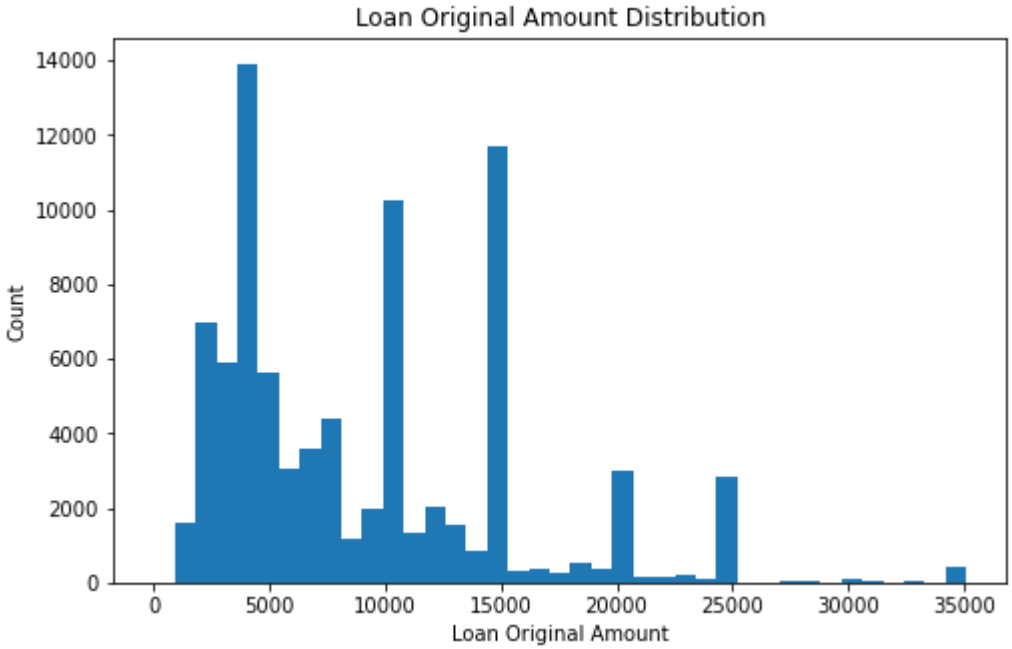
Visualization:

In [36]:
```
df.LoanOriginalAmount.value_counts().nlargest(8)
```

Out[36]:
```
4000     13233
15000    11460
10000     9816
2000      4591
5000      4224
3000      3451
20000     2928
25000     2788
Name: LoanOriginalAmount, dtype: int64
```

In [37]:
```
fig_size(8, 5)
bins = np.arange(0, df['LoanOriginalAmount'].max()+900, 900)
```

```
plt.hist(data = df, x = 'LoanOriginalAmount', bins = bins)
pltlabels('Loan Original Amount Distribution', 'Loan Original Amount', 'Count');
```



Observation:

The most frequently loaned amount is 4000 dollars with a count of 13233, 15000 dollars with a count of 11460 is the second most frequent loan amount. The loan amount with the least count is 25000 dollars (2788 count)

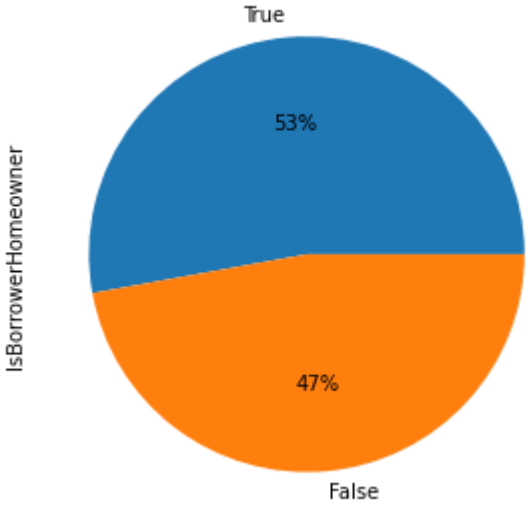
IsBorrowerHomeowner

Question:

How many percent of borrowers are homeowners?

Visualization:

In [38]:
```
fig_size(8,5)
df.IsBorrowerHomeowner.value_counts().plot(kind='pie', autopct='%1.0f%%');
```



Observation:

53% of loans belongs to a borrower who is a home owner while 43% belongs to non-homeowners. Homeowners requests for more loans on Prosper than their counterparts.

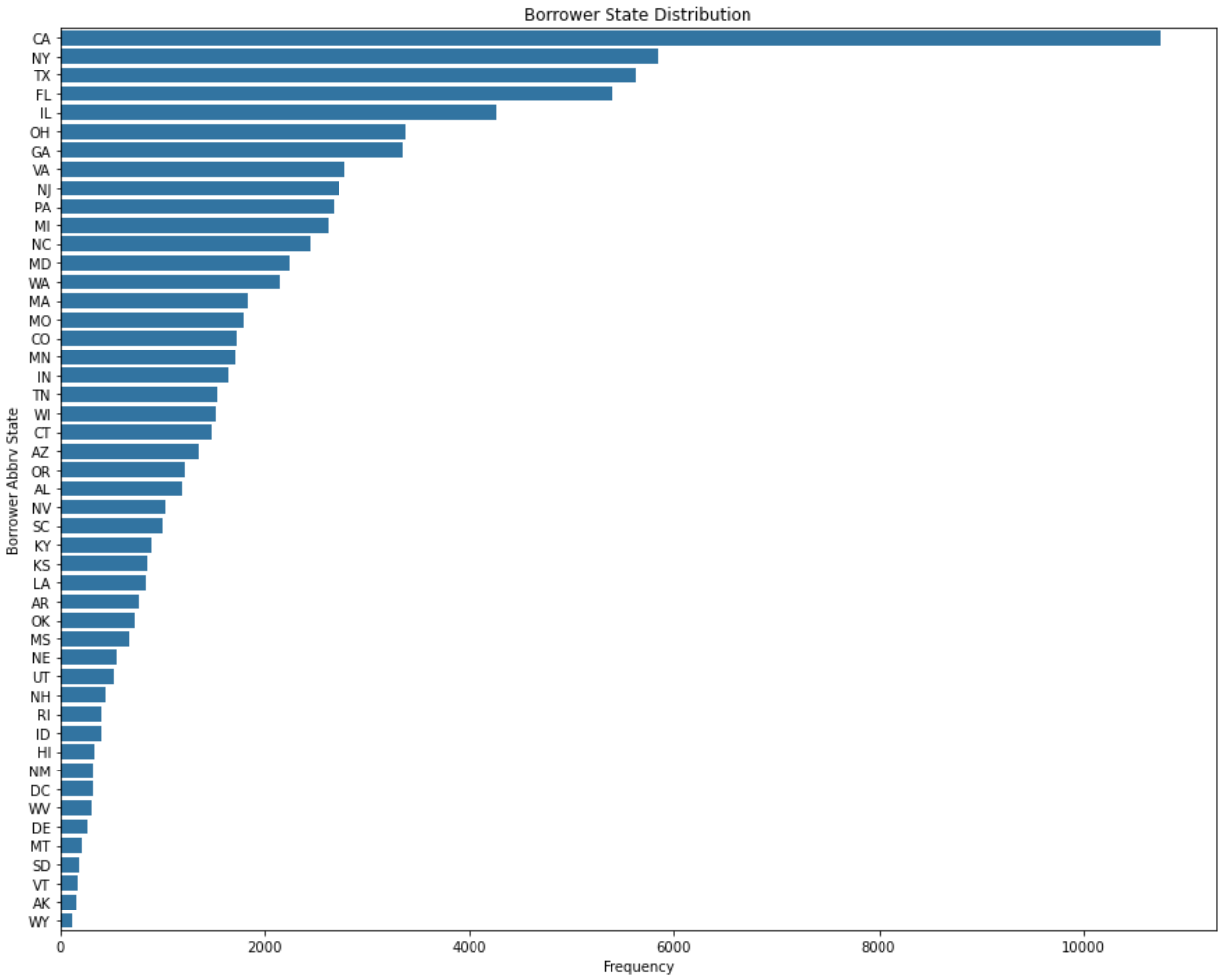
Borrowers Location

Question:

What is the distrubtion of borrower's state? Which state has the highest amount of borrowers?

Visualization:

In [39]:
```
fig_size(15,12)
order = df.BorrowerState.value_counts().index
sb.countplot(data=df, y='BorrowerState', color=color, order=order)
pltlabels('Borrower State Distribution', 'Frequency', 'Borrower Abbrv State');
```



Observation:

Most borrowers are from California. It has the highest number of borrowers by a wide margin. Wyoming has the lowest count of borrowers.

Listing Category

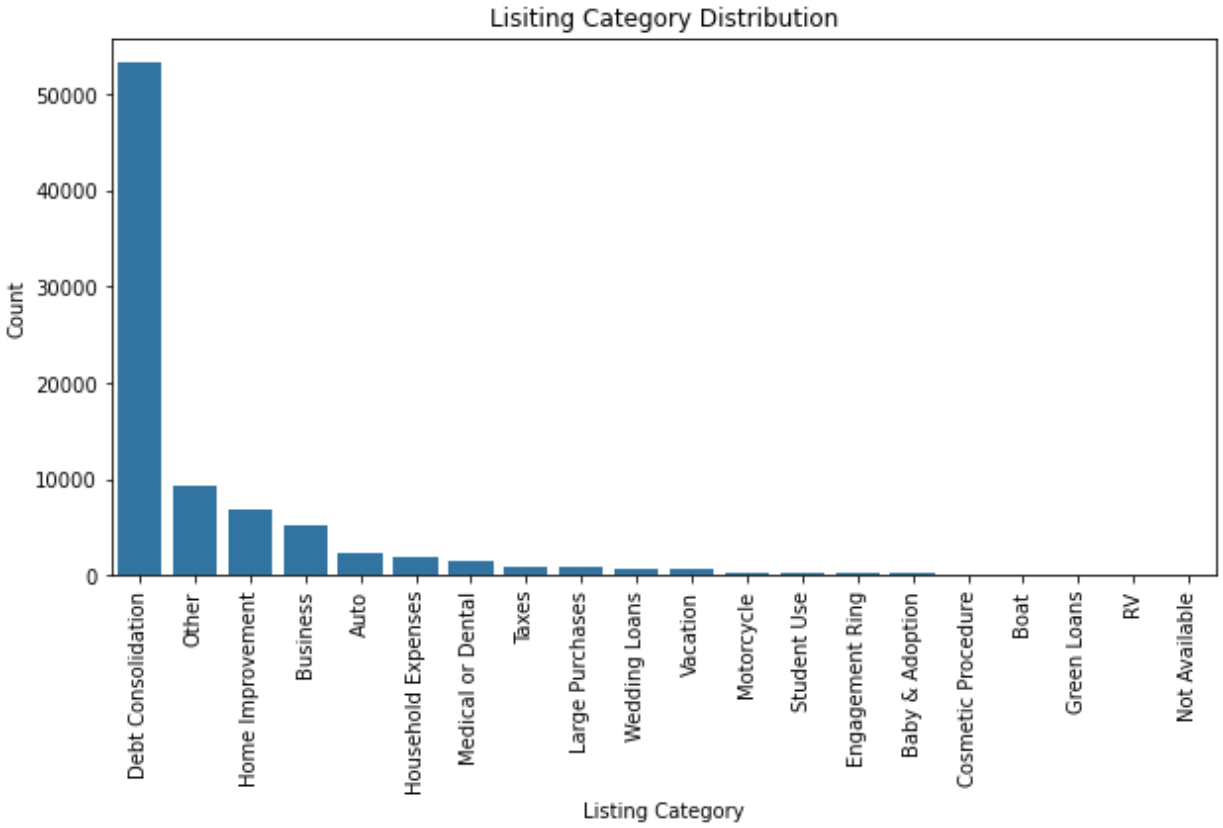
Question:

How is the ListingCategory Variable distributed?

Visualization:

In [40]:
```
List_cat = df.ListingCategory.value_counts()
print(List_cat)
fig_size(10, 5)
order = List_cat.index
sb.countplot(data=df, x='ListingCategory', color = color, order=order)
plt.xticks(rotation=90)
pltlabels('Lisiting Category Distribution', 'Listing Category', 'Count');
```

```
Debt Consolidation    53180
Other                  9218
Home Improvement       6801
Business               5298
Auto                   2237
Household Expenses     1996
Medical or Dental      1522
Taxes                   885
Large Purchases         876
Wedding Loans           771
Vacation                768
Motorcycle              304
Student Use             274
Engagement Ring         217
Baby & Adoption         199
Cosmetic Procedure       91
Boat                     85
Green Loans              59
RV                       52
Not Available            20
Name: ListingCategory, dtype: int64
```



Observation:

From the visualization and count above, it can be seen that the highest reason people requested loans is Debt Consolidation with 53180 loans. People took more loans to pay off outstanding loans. Shocking right?. People also took out loans for other reasons like Medical appointments and Baby Adoption.

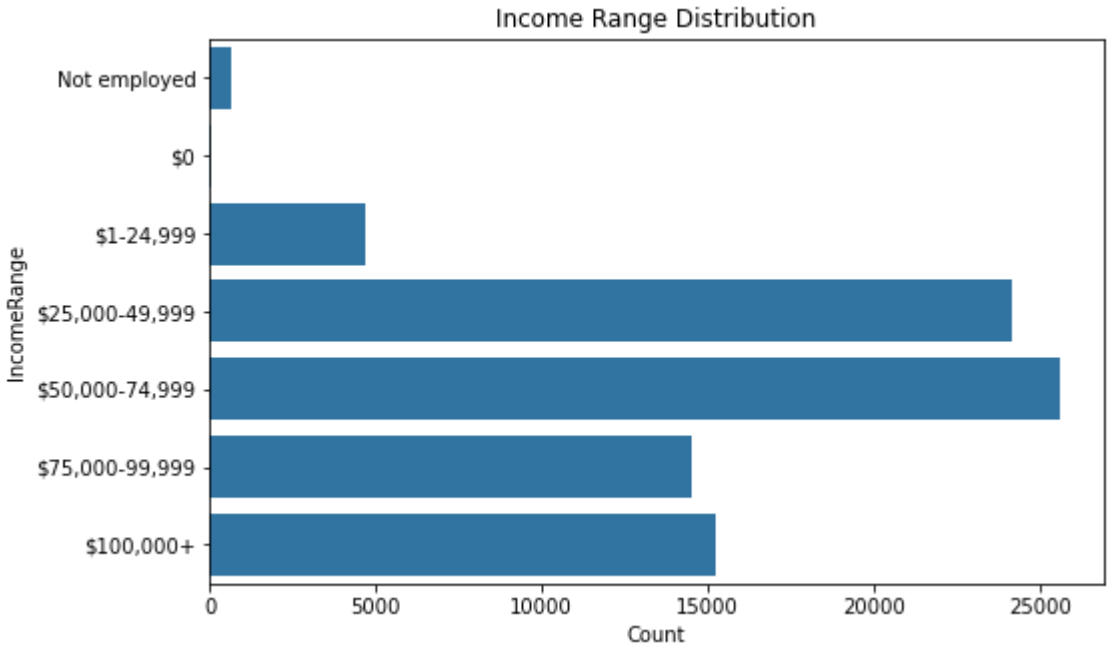
Income Range

Question:

What is the distribution of Income Range among the borrowers?

Visualization:

In [41]:
```
fig_size(8, 5)
order =  ['Not employed','$0','$1-24,999','$25,000-49,999','$50,000-74,999','$75,000-9
sb.countplot(data = df, y = 'IncomeRange', color = color, order=order)
plt.xticks(rotation = 0)
pltlabels('Income Range Distribution', 'Count', 'IncomeRange');
```



Observation:

Borrowers fell among differrent income ranges. Although the highest count of borrowers fell within the 50,000 - 74,999 range, Income Range doesn't seem to be a major factor as people earning over 100,000 still borrowed from Prosper.

DebtToIncomeRatio

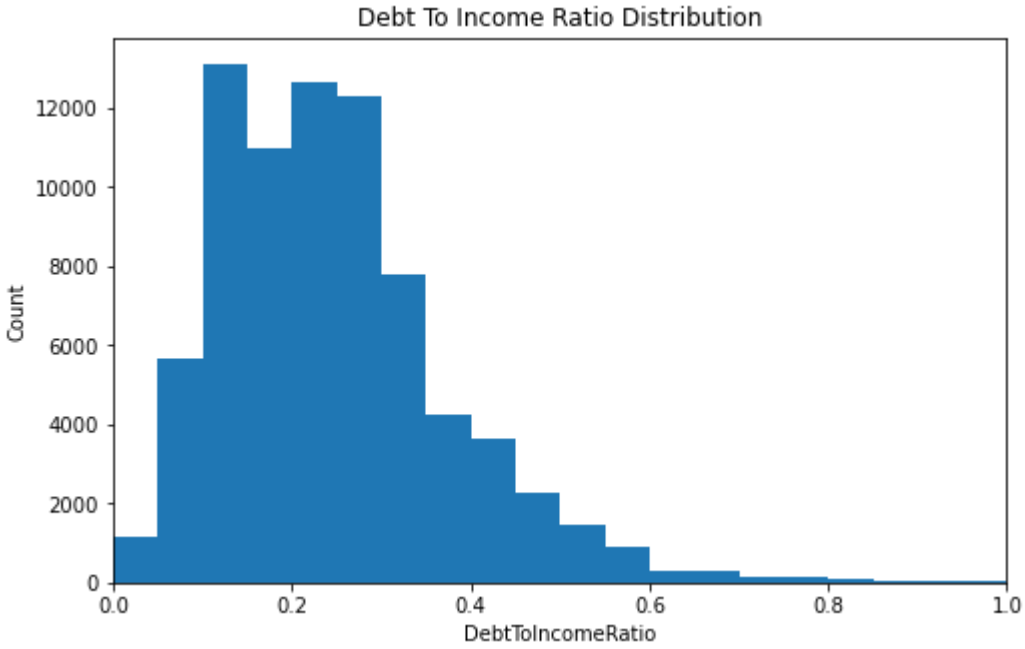
Question:

What is the distribution of the values of DebtToIncomeRatio between the borrowers?

Visualization:

In [42]:
```
fig_size(8, 5)
binsize = 0.05
bins = np.arange(0, df['DebtToIncomeRatio'].max()+binsize, binsize)
plt.hist(data = df, x = 'DebtToIncomeRatio', bins = bins)
```

```
pltlabels('Debt To Income Ratio Distribution', 'DebtToIncomeRatio', 'Count')
plt.xlim(0,1);
```



Observation:

The distribution is skewed to the right. The chart above suggests that borrowers have a good balance between debt and income.

ProsperRating

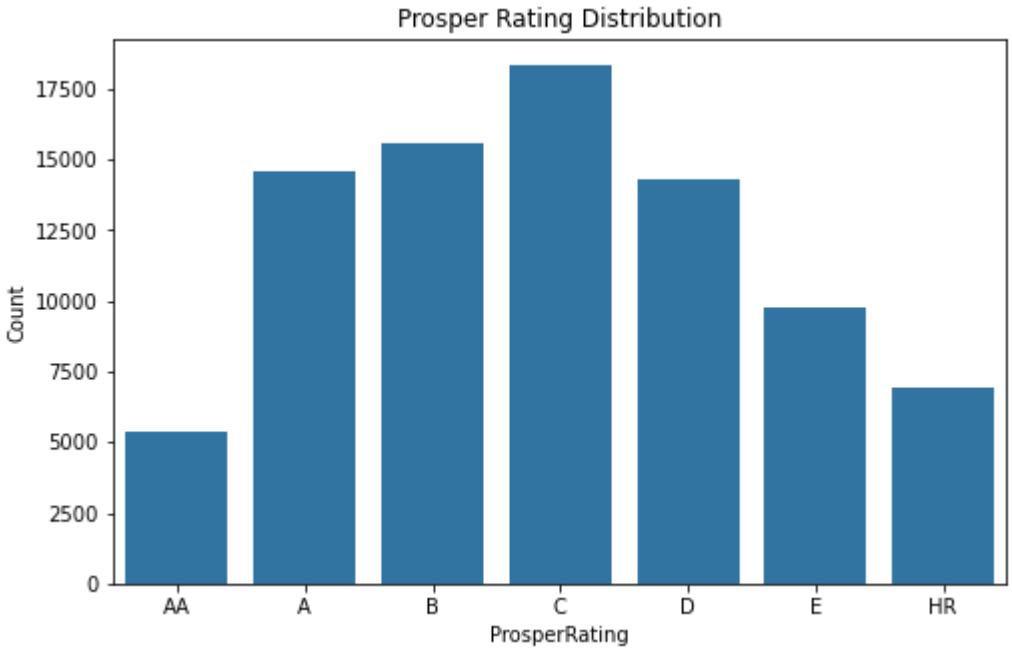
Question:

What is the distribution of rating of borrowers on Prosper?

Visualization:

In [43]:
```
rating = df.ProsperRating.value_counts()
print(rating)
fig_size(8, 5)
sb.countplot(data = df, x = 'ProsperRating', color = color)
pltlabels('Prosper Rating Distribution', 'ProsperRating', 'Count');
```

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



Observations:

Borrowers Rating are displayed in order from highest rating to lowest rating (AA, A, B, C, D, E, HR). The highest rating of AA has the lowest count 5372, Rating C received the highest count of 18345.

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

> Surprisingly, 21317 loans were given out to borrowers that did not disclose their oppcupation they instead selected **Others** as their occupation. I filled rows with empty Occupation values with **Not Specified**, and it is also surprising to see that these individuals had access to loans (Not Specified - 1333). I however did not see any need to do transformations.

Also, a lot of people didn't specify why they requested for loans and some other people specified **Other** as their reason. This wasn't a major issue as they didn't make up majority of the population.

Bivariate Exploration

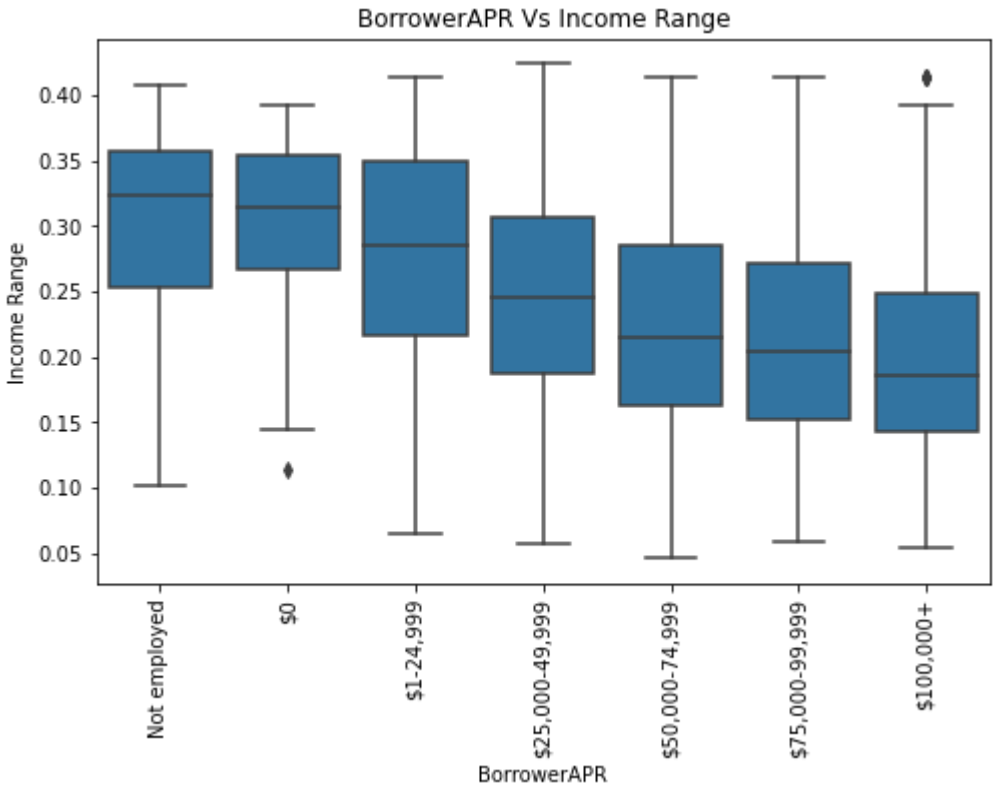
I'll continue my analysis by trying to find interesting relationships that show how one variable affects another variable. I am more interested in finding out how the IncomeRange and BorrrowerAPR features relate to selected variables

Question:

What is relationship between BorrowerAPR and IncomeRange?

Visualization:

In [44]:
```
order = ['Not employed','$0','$1-24,999','$25,000-49,999','$50,000-74,999','$75,000-99
fig_size(8,5)
sb.boxplot(data=df, x='IncomeRange', y='BorrowerAPR', color=color, order=order)
plt.xticks(rotation=90)
pltlabels('BorrowerAPR Vs Income Range','BorrowerAPR', 'Income Range');
```



Observation:

The plot shows that Borrower APR reduces as the Income Range of borrowers increase. This means that borrrowers that have high income enjoy lower interest rates on the platform. This make sense becasue people with higher income tend to be more reliable and therefore given lower BorrowerAPR.

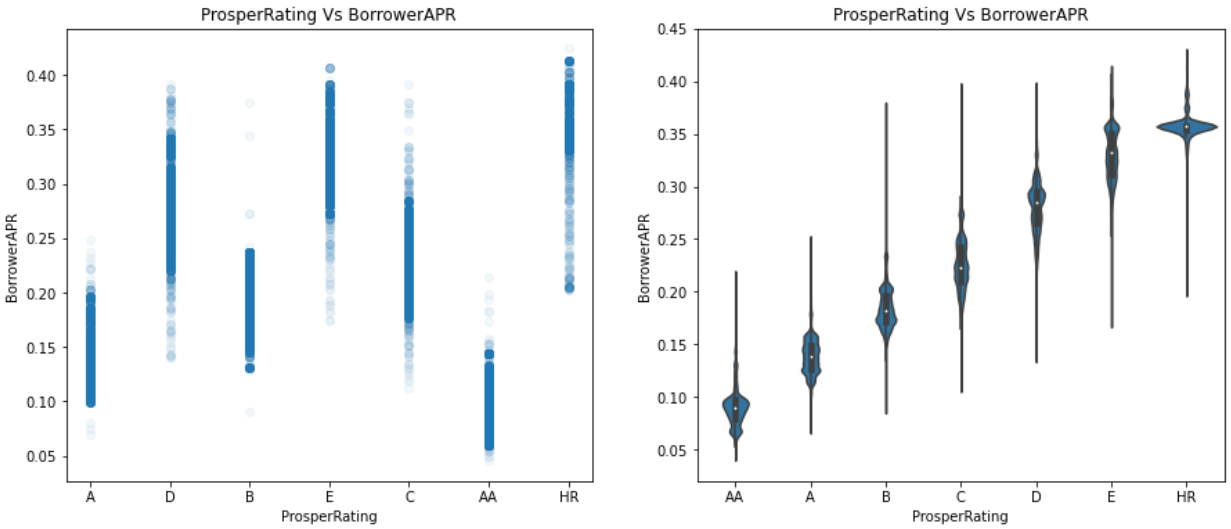
Question:

What is relationship between BorrowerAPR and ProsperRating?

Visualization:

In [45]:
```
fig_size (15, 6)
plt.subplot(1, 2, 1)
plt.scatter(data = df, x = 'ProsperRating', y = 'BorrowerAPR', alpha =  0.05)
pltlabels('ProsperRating Vs BorrowerAPR','ProsperRating', 'BorrowerAPR');
```

```
plt.subplot(1, 2, 2)
sb.violinplot(data=df, x='ProsperRating', y='BorrowerAPR', color=color)
pltlabels('ProsperRating Vs BorrowerAPR','ProsperRating', 'BorrowerAPR');
```



Observation:

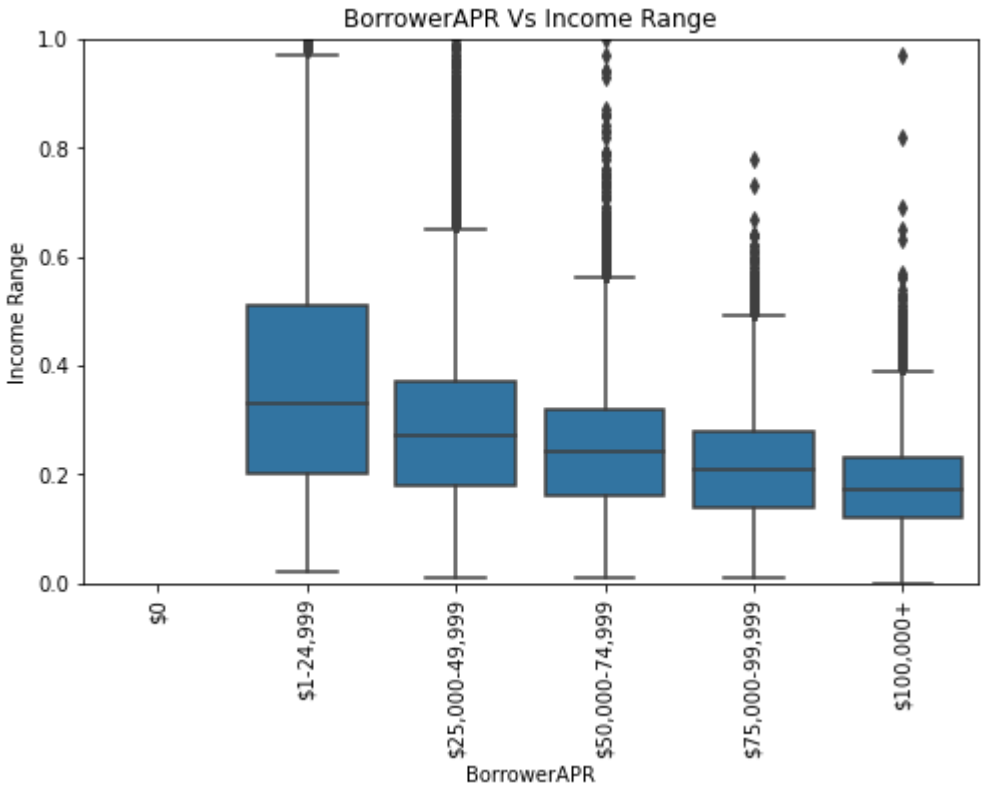
It can be observed that BorrowerAPR is inverse proportional to the Prosper rating.

Question:

What is the relationship between IncomeRange and DebtToIncomeRatio?

Visualization:

In [46]:
```
fig_size(8,5)
order = ['$0','$1-24,999','$25,000-49,999','$50,000-74,999','$75,000-99,999','$100,000
fig = sb.boxplot(data=df, x='IncomeRange', y='DebtToIncomeRatio', color=color, order=c
fig.axes.set_ylim(0, 1) #Zooming in to see the boxplot clearly
plt.xticks(rotation=90)
pltlabels('BorrowerAPR Vs Income Range','BorrowerAPR', 'Income Range');
```



Observation:

From the visualization above, borrowers with a high income have a lower debt to income ratio as they earn enough to settle off their loans quickly and easily. People within the highest range (100,000+) have the lowest ratio.

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?

> The plots above were helpful to preview some possible variables relationship to BorrowerAPR and Income Range. From the plots, I saw that
>
> - As the Income Range of borrowers increase, BorrowerAPR reduces.
> - BorrowerAPR is inverse proportional to the Prosper rating.
> - The higher the income of a borrower, the lower debt to income ratio.

Multivariate Exploration

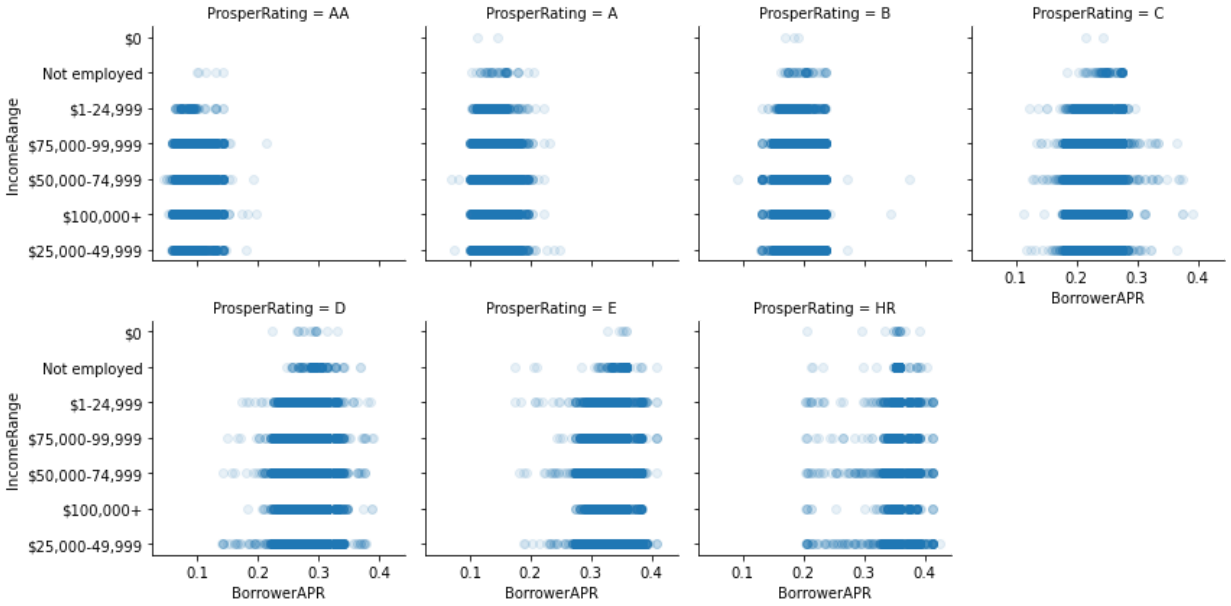
BorrowerAPR Vs IncomeRange and ProsperRating

Visualization:

In [47]:
```
g = sb.FacetGrid(data = df, col = 'ProsperRating', col_wrap = 4, size = 3)
```

```
g.map(plt.scatter, 'BorrowerAPR', 'IncomeRange', alpha = 0.1)
g.set_xlabels('BorrowerAPR')
g.set_ylabels('IncomeRange')

plt.show()
```

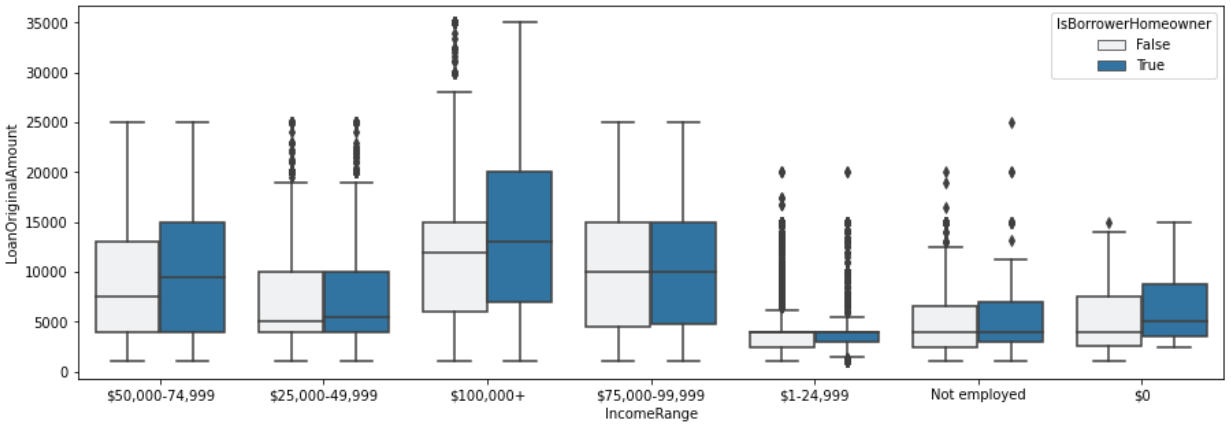


Observation:

This visualization helps to analyze BorrowerAPR vs IncomeRange on different Prosper ratings. The patterns shows the Higest rating AA of borrowers have the lowest APR. For low rating HR, the borrowers have the highest APR. This visualization classifies groups of borrowers in terms of APR received based on their rating and Income.

Loan amount Vs IncomeRange and Home Owner

In [48]:
```
#plot boxplot
fig_size(15, 5)
sb.boxplot(data = df, x = 'IncomeRange', y = 'LoanOriginalAmount',hue = 'IsBorrowerHom
```



Observation:

From the plot above, it can be observed that irrespective of the borrowers income range, being a home owner is an important element to getting a higher loan amount as it gives advantage on collateral

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?

> Having a collateral and a high income helps borrowers in getting higher loan amount. It is clearly visible that being a home owner is a very important element to get a higher loan amount.

Also patterns from the plot above shows that the Higest rating AA of borrowers have the lowest APR. For low rating HR, the borrowers have the highest APR. This confirms what was earlier stated that the Higher the ProsperRating, the Lower the BorrowerAPR and vice versa.

Conclusions:

> I was surprised that people with unverified occupation(other) were granted loans. Employed individuals make the highest count of borrowers. This makes sense because one would need a source of income to pay off borrowed loans. It would be difficult to get a loan without a job.
> .

Trying to understand the different motivations for people to request loans, I found surprising results. Rather than take loans to start businesses or purchase assets, the largest population of people collected loans to consolidate debt. Debt consolidation also accounts for the highest loan amounts collected from the platform on average. Asides business purposes, borrowers seem to depend on huge loans to finance weddings, child adoptions, boat acquisitions, and the purchase of engagement rings.

References:

To finish this project, I got some help from the following links:

- Guide to Bivariate Analysis in Python AnalyticsVidhya
- Effective Visualization TowardsDataScience
- Working with Missing Data Geeksforgeeks
- Video tutorials from YouTube
- Pandas documentation
- Matplotlib documentation