Part_I_exploration

August 10, 2022

1 Part I - Loan Data from Prosper

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1.2 Introduction

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

1.3 Preliminary Wrangling

```
In [42]: # 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
```

Gather and Assess the loan data

```
In [43]: # Load the Loan Data from the URL
         loan_df = pd.read_csv('https://s3.amazonaws.com/udacity-hosted-downloads/ud651/prosperL

         #Examine the first 5 rows
         loan_df.head()
```

```
Out[43]:                  ListingKey  ListingNumber            ListingCreationDate  \
         0  1021339766868145413AB3B         193129  2007-08-26 19:09:29.263000000
         1  10273602499503308B223C1        1209647  2014-02-27 08:28:07.900000000
         2  0EE9337825851032864889A          81716  2007-01-05 15:00:47.090000000
         3  0EF5356002482715299901A         658116  2012-10-22 11:02:35.010000000
         4  0F023589499656230C5E3E2         909464  2013-09-14 18:38:39.097000000

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

```
2          HR    36  Completed  2009-12-17 00:00:00      0.28269
3         NaN    36    Current                  NaN      0.12528
4         NaN    36    Current                  NaN      0.24614

   BorrowerRate  LenderYield    ...     LP_ServiceFees  LP_CollectionFees  \
0        0.1580       0.1380    ...            -133.18                0.0
1        0.0920       0.0820    ...               0.00                0.0
2        0.2750       0.2400    ...             -24.20                0.0
3        0.0974       0.0874    ...            -108.01                0.0
4        0.2085       0.1985    ...             -60.27                0.0

   LP_GrossPrincipalLoss  LP_NetPrincipalLoss LP_NonPrincipalRecoverypayments  \
0                    0.0                  0.0                             0.0
1                    0.0                  0.0                             0.0
2                    0.0                  0.0                             0.0
3                    0.0                  0.0                             0.0
4                    0.0                  0.0                             0.0

   PercentFunded  Recommendations InvestmentFromFriendsCount  \
0            1.0                0                          0
1            1.0                0                          0
2            1.0                0                          0
3            1.0                0                          0
4            1.0                0                          0

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

[5 rows x 81 columns]
```

In [44]:
```
# Check for dataset information
loan_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 113937 entries, 0 to 113936
Data columns (total 81 columns):
ListingKey                             113937 non-null object
ListingNumber                          113937 non-null int64
ListingCreationDate                    113937 non-null object
CreditGrade                            28953 non-null object
Term                                   113937 non-null int64
LoanStatus                             113937 non-null object
ClosedDate                             55089 non-null object
BorrowerAPR                            113912 non-null float64
```

```
BorrowerRate                          113937 non-null float64
LenderYield                           113937 non-null float64
EstimatedEffectiveYield               84853 non-null float64
EstimatedLoss                         84853 non-null float64
EstimatedReturn                       84853 non-null float64
ProsperRating (numeric)               84853 non-null float64
ProsperRating (Alpha)                 84853 non-null object
ProsperScore                          84853 non-null float64
ListingCategory (numeric)             113937 non-null int64
BorrowerState                         108422 non-null object
Occupation                            110349 non-null object
EmploymentStatus                      111682 non-null object
EmploymentStatusDuration              106312 non-null float64
IsBorrowerHomeowner                   113937 non-null bool
CurrentlyInGroup                      113937 non-null bool
GroupKey                              13341 non-null object
DateCreditPulled                      113937 non-null object
CreditScoreRangeLower                 113346 non-null float64
CreditScoreRangeUpper                 113346 non-null float64
FirstRecordedCreditLine               113240 non-null object
CurrentCreditLines                    106333 non-null float64
OpenCreditLines                       106333 non-null float64
TotalCreditLinespast7years            113240 non-null float64
OpenRevolvingAccounts                 113937 non-null int64
OpenRevolvingMonthlyPayment           113937 non-null float64
InquiriesLast6Months                  113240 non-null float64
TotalInquiries                        112778 non-null float64
CurrentDelinquencies                  113240 non-null float64
AmountDelinquent                      106315 non-null float64
DelinquenciesLast7Years               112947 non-null float64
PublicRecordsLast10Years              113240 non-null float64
PublicRecordsLast12Months             106333 non-null float64
RevolvingCreditBalance                106333 non-null float64
BankcardUtilization                   106333 non-null float64
AvailableBankcardCredit               106393 non-null float64
TotalTrades                           106393 non-null float64
TradesNeverDelinquent (percentage)    106393 non-null float64
TradesOpenedLast6Months               106393 non-null float64
DebtToIncomeRatio                     105383 non-null float64
IncomeRange                           113937 non-null object
IncomeVerifiable                      113937 non-null bool
StatedMonthlyIncome                   113937 non-null float64
LoanKey                               113937 non-null object
TotalProsperLoans                     22085 non-null float64
TotalProsperPaymentsBilled            22085 non-null float64
OnTimeProsperPayments                 22085 non-null float64
ProsperPaymentsLessThanOneMonthLate   22085 non-null float64
ProsperPaymentsOneMonthPlusLate       22085 non-null float64
```

```
ProsperPrincipalBorrowed                22085 non-null float64
ProsperPrincipalOutstanding             22085 non-null float64
ScorexChangeAtTimeOfListing             18928 non-null float64
LoanCurrentDaysDelinquent               113937 non-null int64
LoanFirstDefaultedCycleNumber           16952 non-null float64
LoanMonthsSinceOrigination              113937 non-null int64
LoanNumber                              113937 non-null int64
LoanOriginalAmount                      113937 non-null int64
LoanOriginationDate                     113937 non-null object
LoanOriginationQuarter                  113937 non-null object
MemberKey                               113937 non-null object
MonthlyLoanPayment                      113937 non-null float64
LP_CustomerPayments                     113937 non-null float64
LP_CustomerPrincipalPayments            113937 non-null float64
LP_InterestandFees                      113937 non-null float64
LP_ServiceFees                          113937 non-null float64
LP_CollectionFees                       113937 non-null float64
LP_GrossPrincipalLoss                   113937 non-null float64
LP_NetPrincipalLoss                     113937 non-null float64
LP_NonPrincipalRecoverypayments         113937 non-null float64
PercentFunded                           113937 non-null float64
Recommendations                         113937 non-null int64
InvestmentFromFriendsCount              113937 non-null int64
InvestmentFromFriendsAmount             113937 non-null float64
Investors                               113937 non-null int64
dtypes: bool(3), float64(50), int64(11), object(17)
memory usage: 68.1+ MB
```

In [45]:
```python
# Check the shape of the data
loan_df.shape
```

Out[45]: (113937, 81)

For the purpose of simplicity, I have selected the below columns from the list of features in the dataset

In [46]:
```python
selected_col =  [
    'Term', 'LoanStatus', 'BorrowerRate', 'ProsperRating (Alpha)', 'ListingCategory (nu
    'StatedMonthlyIncome', 'LoanOriginalAmount', 'LoanOriginationDate', 'BorrowerAPR',
    'BorrowerState','Occupation'
]
```

In [47]:
```python
# Use the above list to filter the loan data
loan_df_copy = loan_df.copy()

#drop columns that are not needed
for col in loan_df_copy.columns:
    if col not in selected_col:
```

```
        del loan_df_copy[col]

loan_df_copy.head()
```

Out[47]:
```
   Term LoanStatus  BorrowerAPR  BorrowerRate ProsperRating (Alpha)  \
0    36  Completed      0.16516        0.1580                   NaN
1    36    Current      0.12016        0.0920                     A
2    36  Completed      0.28269        0.2750                   NaN
3    36    Current      0.12528        0.0974                     A
4    36    Current      0.24614        0.2085                     D

   ListingCategory (numeric) BorrowerState    Occupation EmploymentStatus  \
0                          0            CO         Other    Self-employed
1                          2            CO  Professional         Employed
2                          0            GA         Other    Not available
3                         16            GA  Skilled Labor        Employed
4                          2            MN     Executive         Employed

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

   LoanOriginationDate
0  2007-09-12 00:00:00
1  2014-03-03 00:00:00
2  2007-01-17 00:00:00
3  2012-11-01 00:00:00
4  2013-09-20 00:00:00
```

In [48]:
```
# Extracting Year in which Loan Originated
loan_df_copy['LoanOriginationYear'] = pd.DatetimeIndex(loan_df_copy['LoanOriginationDat
```

In [49]:
```
loan_df_copy.isna().sum()
```

Out[49]:
```
Term                             0
LoanStatus                       0
BorrowerAPR                     25
BorrowerRate                     0
ProsperRating (Alpha)        29084
ListingCategory (numeric)        0
BorrowerState                 5515
Occupation                    3588
EmploymentStatus              2255
IncomeRange                      0
StatedMonthlyIncome              0
LoanOriginalAmount               0
```

```
LoanOriginationDate             0
LoanOriginationYear             0
dtype: int64
```

In [50]: loan_df_copy.info()

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 113937 entries, 0 to 113936
Data columns (total 14 columns):
Term                         113937 non-null int64
LoanStatus                   113937 non-null object
BorrowerAPR                  113912 non-null float64
BorrowerRate                 113937 non-null float64
ProsperRating (Alpha)        84853 non-null object
ListingCategory (numeric)    113937 non-null int64
BorrowerState                108422 non-null object
Occupation                   110349 non-null object
EmploymentStatus             111682 non-null object
IncomeRange                  113937 non-null object
StatedMonthlyIncome          113937 non-null float64
LoanOriginalAmount           113937 non-null int64
LoanOriginationDate          113937 non-null object
LoanOriginationYear          113937 non-null int64
dtypes: float64(3), int64(4), object(7)
memory usage: 12.2+ MB
```

In [51]: loan_df_copy.describe()

Out[51]:

	Term	BorrowerAPR	BorrowerRate	ListingCategory (numeric) \
count	113937.000000	113912.000000	113937.000000	113937.000000
mean	40.830248	0.218828	0.192764	2.774209
std	10.436212	0.080364	0.074818	3.996797
min	12.000000	0.006530	0.000000	0.000000
25%	36.000000	0.156290	0.134000	1.000000
50%	36.000000	0.209760	0.184000	1.000000
75%	36.000000	0.283810	0.250000	3.000000
max	60.000000	0.512290	0.497500	20.000000

	StatedMonthlyIncome	LoanOriginalAmount	LoanOriginationYear
count	1.139370e+05	113937.00000	113937.000000
mean	5.608026e+03	8337.01385	2011.042611
std	7.478497e+03	6245.80058	2.506634
min	0.000000e+00	1000.00000	2005.000000
25%	3.200333e+03	4000.00000	2008.000000
50%	4.666667e+03	6500.00000	2012.000000
75%	6.825000e+03	12000.00000	2013.000000
max	1.750003e+06	35000.00000	2014.000000

Clean the Data The following were discovered in the analysis 1. Some columns have missing values 2. LoanOriginationDate has datatype Object 3. Some columns like ProsperRating (Alpha) and listingCategory (numeric) need renaming 4. The listing category need to be encoded based on information in the data dictionary 5. Regularize the loan status column to have only completed and defaulted as status

```
In [52]: # Drop column with missing Prosper rating data
         loan_df_copy.dropna(subset=['ProsperRating (Alpha)'], inplace=True)
```

```
In [53]: # Change the datatype for LoanOriginationDate
         loan_df_copy['LoanOriginationDate'] = pd.to_datetime(loan_df['LoanOriginationDate'])
```

```
In [54]: # Rename columns
         loan_df_copy.rename(columns = {'ProsperRating (Alpha)':'ProsperRating'}, inplace = True
```

```
In [55]: # Encode the listing category
         list_dict = {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/Dental',
                      17 : 'RV', 18 : 'Taxes', 19 : 'Vacation', 20 : 'Wedding Loans'}

         loan_df_copy['ListingCategory'] = loan_df_copy['ListingCategory (numeric)'].map(list_di
         loan_df_copy.drop(['ListingCategory (numeric)'], axis=1, inplace=True)
```

```
In [56]: # Let us regularize the Loan Status Column to only have Completed and Defaulted
         condition = (loan_df_copy['LoanStatus'] == 'Completed') | (loan_df_copy['LoanStatus'] =
                         (loan_df_copy['LoanStatus'] == 'Chargedoff')
         loan_df_copy = loan_df_copy[condition]

         def regularize_loan_status(row):
             if row['LoanStatus'] == 'Chargedoff':
                 return 'Defaulted'
             else:
                 return row['LoanStatus']

         loan_df_copy['LoanStatus'] = loan_df_copy.apply(regularize_loan_status, axis=1)
```

```
In [57]: #check the datatypes and ensure no missing value
         loan_df_copy.info()
         loan_df_copy.shape
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 26005 entries, 15 to 113935
Data columns (total 14 columns):
Term                   26005 non-null int64
LoanStatus             26005 non-null object
BorrowerAPR            26005 non-null float64
BorrowerRate           26005 non-null float64
```

```
ProsperRating          26005 non-null object
BorrowerState          26005 non-null object
Occupation             25992 non-null object
EmploymentStatus       26005 non-null object
IncomeRange            26005 non-null object
StatedMonthlyIncome    26005 non-null float64
LoanOriginalAmount     26005 non-null int64
LoanOriginationDate    26005 non-null datetime64[ns]
LoanOriginationYear    26005 non-null int64
ListingCategory        26005 non-null object
dtypes: datetime64[ns](1), float64(3), int64(3), object(7)
memory usage: 3.0+ MB
```

Out[57]: (26005, 14)

In [58]:
```
# Check the Loan Status for regularization
loan_df_copy['LoanStatus'].value_counts()
```

Out[58]:
```
Completed    19664
Defaulted     6341
Name: LoanStatus, dtype: int64
```

1.3.1 What is the structure of your dataset?

The original dataset contains 113,937 loans with 81 features (including LoanOriginalAmount, BorrowerAPR, StatedMonthlyIncome, Term, ProsperRating, EmploymentStatus and many others) but it has been cleaned and the new structure contains 84,853 loans and 14 features

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

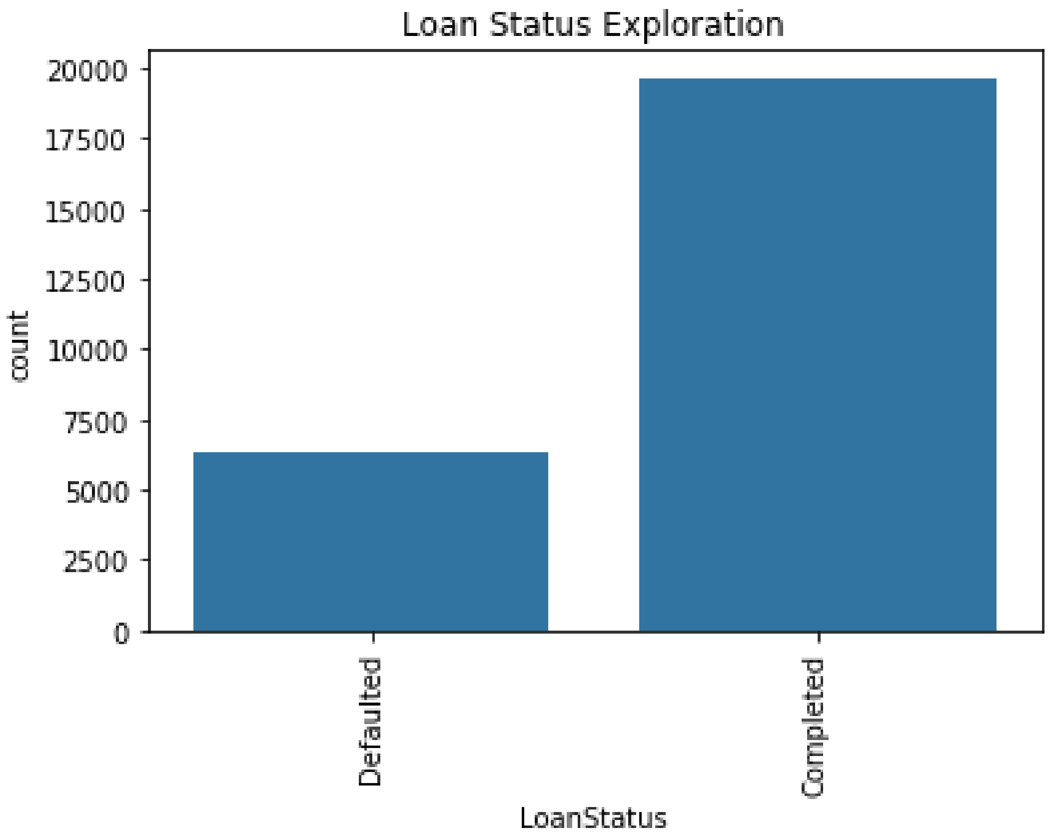
I am particularly interested in features that affect the loan status especially defaults

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

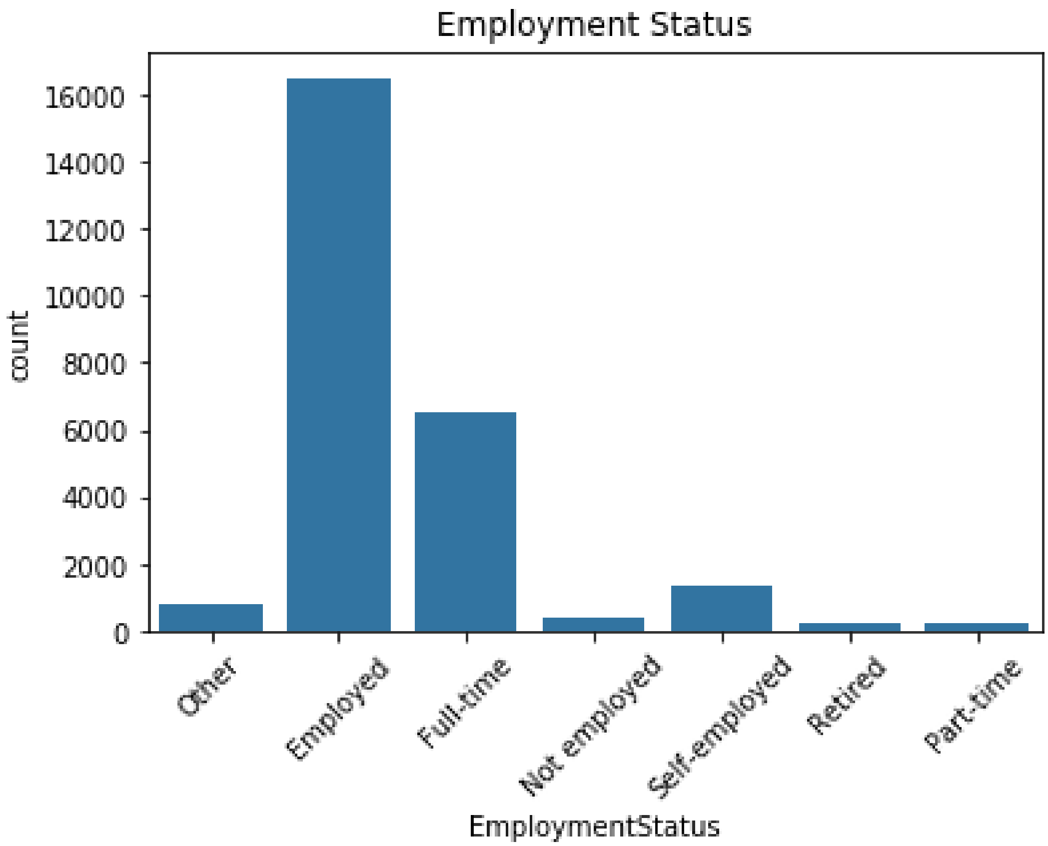
The features that will support my investigation are LoanOriginalAmount, Term, BorrowerRate, ProsperRating, occupation, ListingCategory , StatedMonthlyIncome and EmploymentStatus

1.4 Univariate Exploration

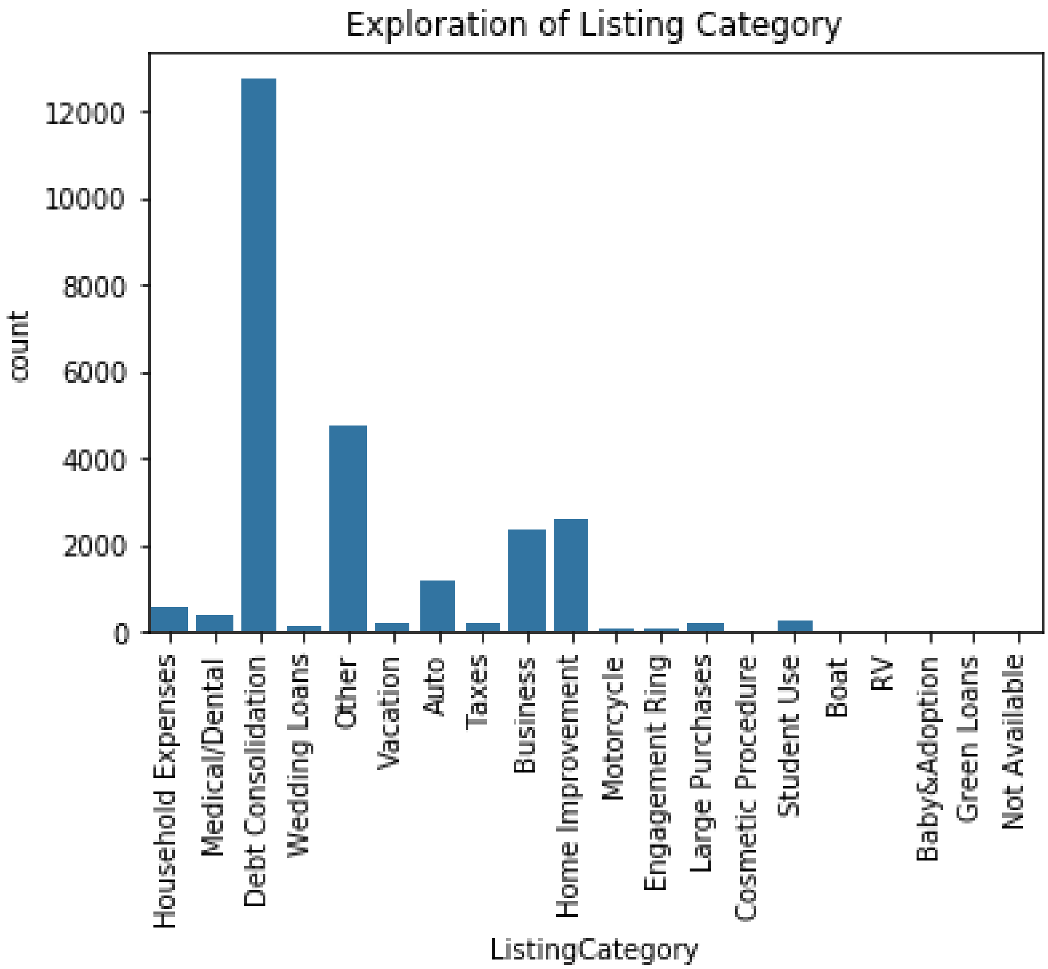
In [59]:
```
# Loan Status
base_color = sb.color_palette()[0]
plt.xticks(rotation=90)
plt.title('Loan Status Exploration')
sb.countplot(data = loan_df_copy, x = 'LoanStatus', color = base_color);
```



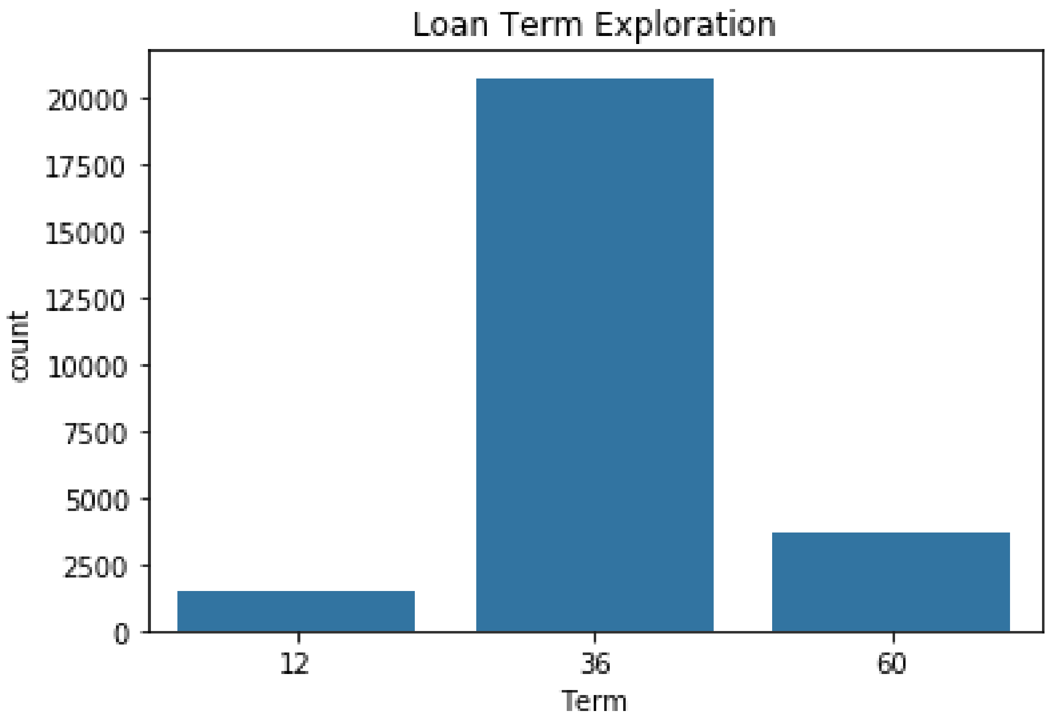

```
In [60]: # Employment Status
         base_color = sb.color_palette()[0]
         plt.xticks(rotation=45)
         plt.title('Employment Status')
         sb.countplot(data = loan_df_copy, x = 'EmploymentStatus', color = base_color);
```



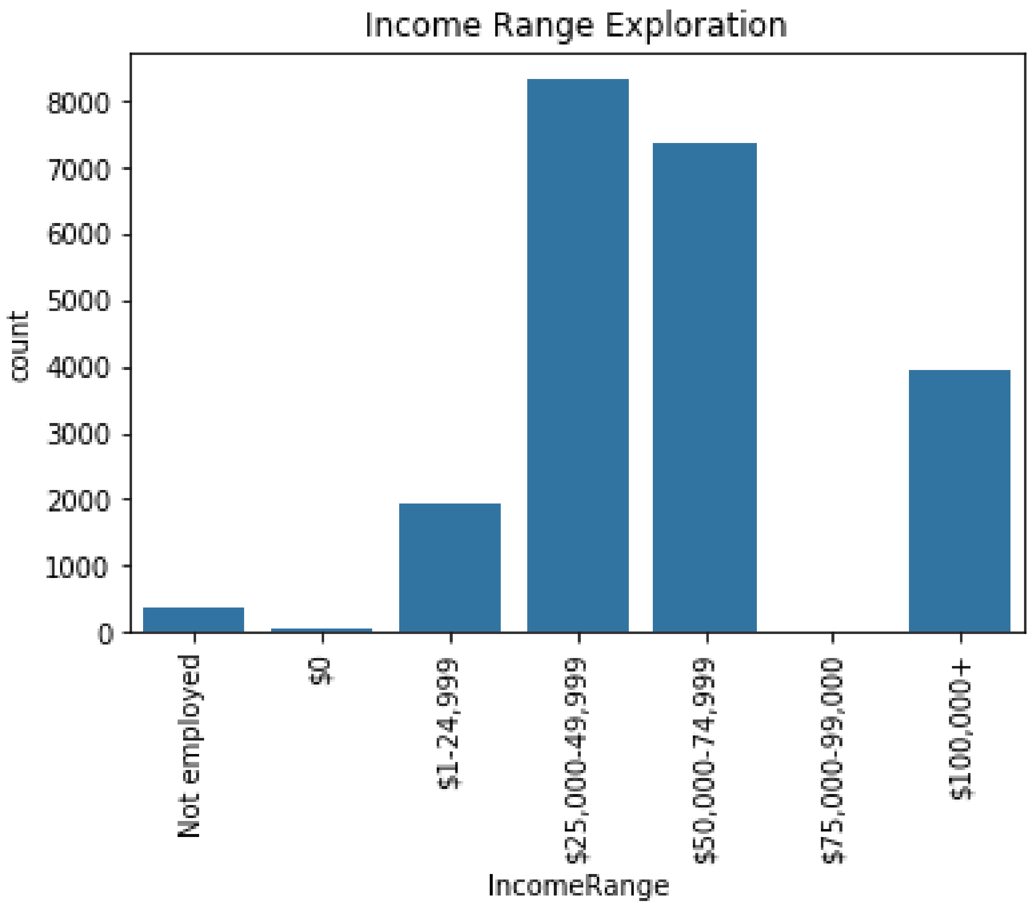

```
In [61]: # Listing Category
         base_color = sb.color_palette()[0]
         plt.xticks(rotation=90)
         plt.title('Exploration of Listing Category')
         sb.countplot(data = loan_df_copy, x = 'ListingCategory', color = base_color);
```



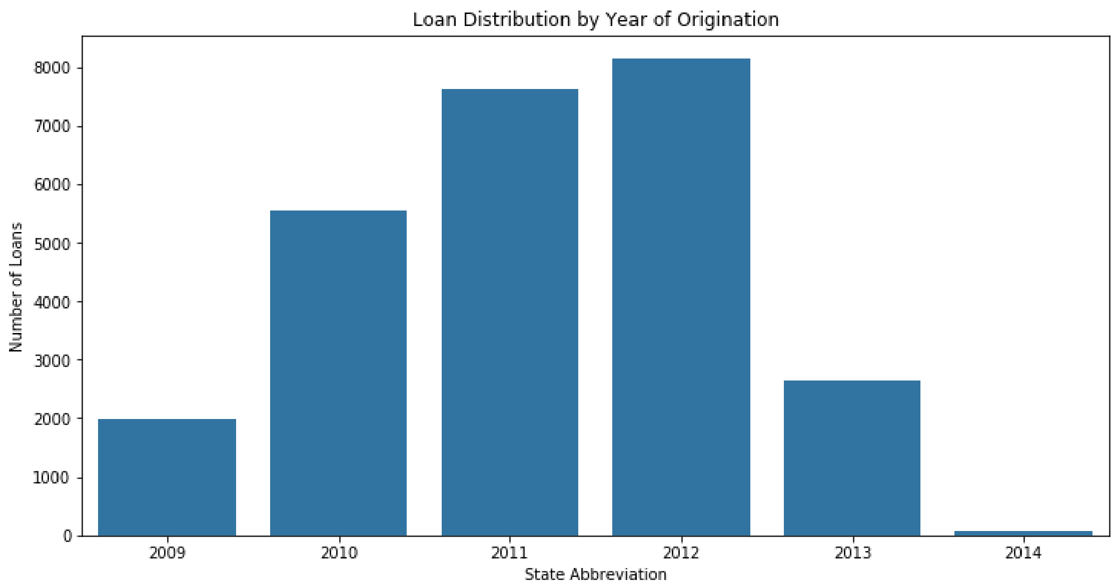
In [62]:
```
# Term
base_color = sb.color_palette()[0]

plt.title('Loan Term Exploration')
sb.countplot(data = loan_df_copy, x = 'Term', color = base_color);
```



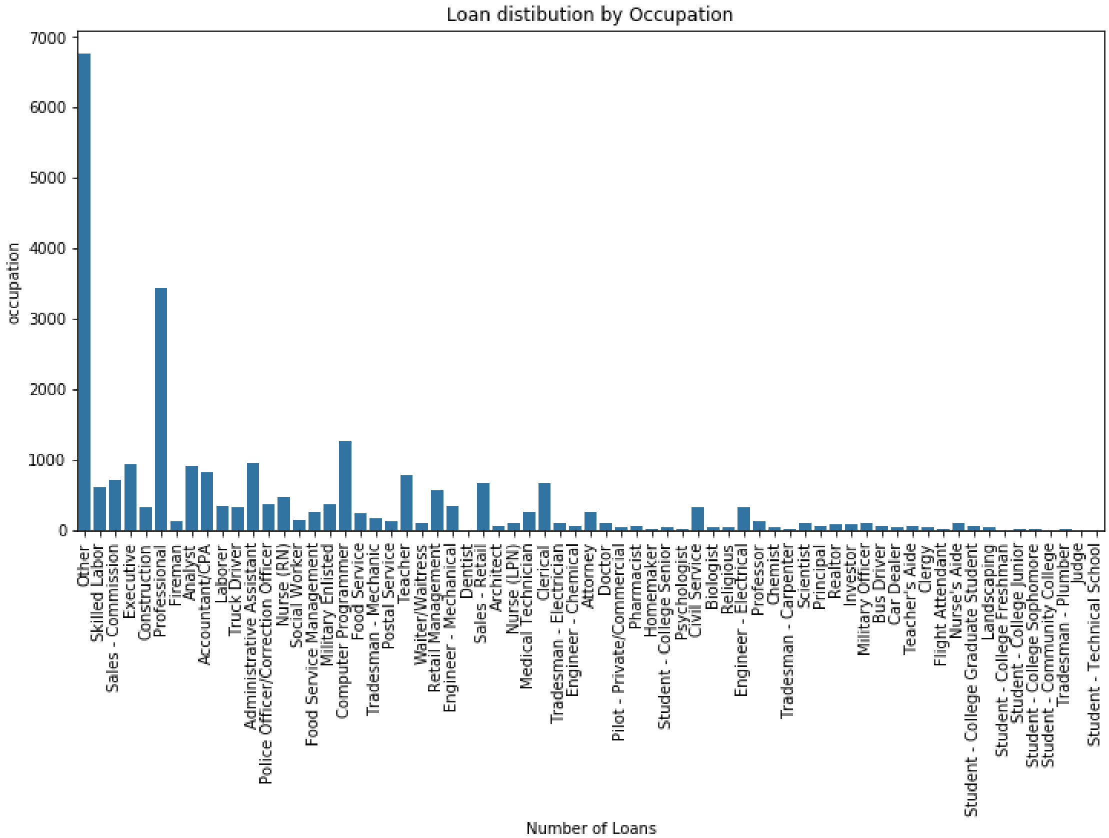

```
In [63]: # Income Range Exploration
         plt.title('Income Range Exploration')
         plt.xticks(rotation=90)
         order = ['Not employed','$0','$1-24,999','$25,000-49,999','$50,000-74,999','$75,000-99,
         sb.countplot(data = loan_df_copy, x = 'IncomeRange', color = base_color, order=order);
```



In [64]:
```
fig = plt.figure(figsize=(12,6))
sb.countplot(x='LoanOriginationYear', data=loan_df_copy, color = base_color)
plt.title('Loan Distribution by Year of Origination')
plt.xlabel('State Abbreviation')
plt.ylabel('Number of Loans')
plt.show()
```




```
In [65]: fig = plt.figure(figsize=(12,6))
         sb.countplot(x='Occupation', data=loan_df_copy, color = base_color)
         plt.title('Loan distibution by Occupation')
         plt.xticks(rotation=90)
         plt.xlabel('Number of Loans')
         plt.ylabel('occupation')
         plt.show()
```



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

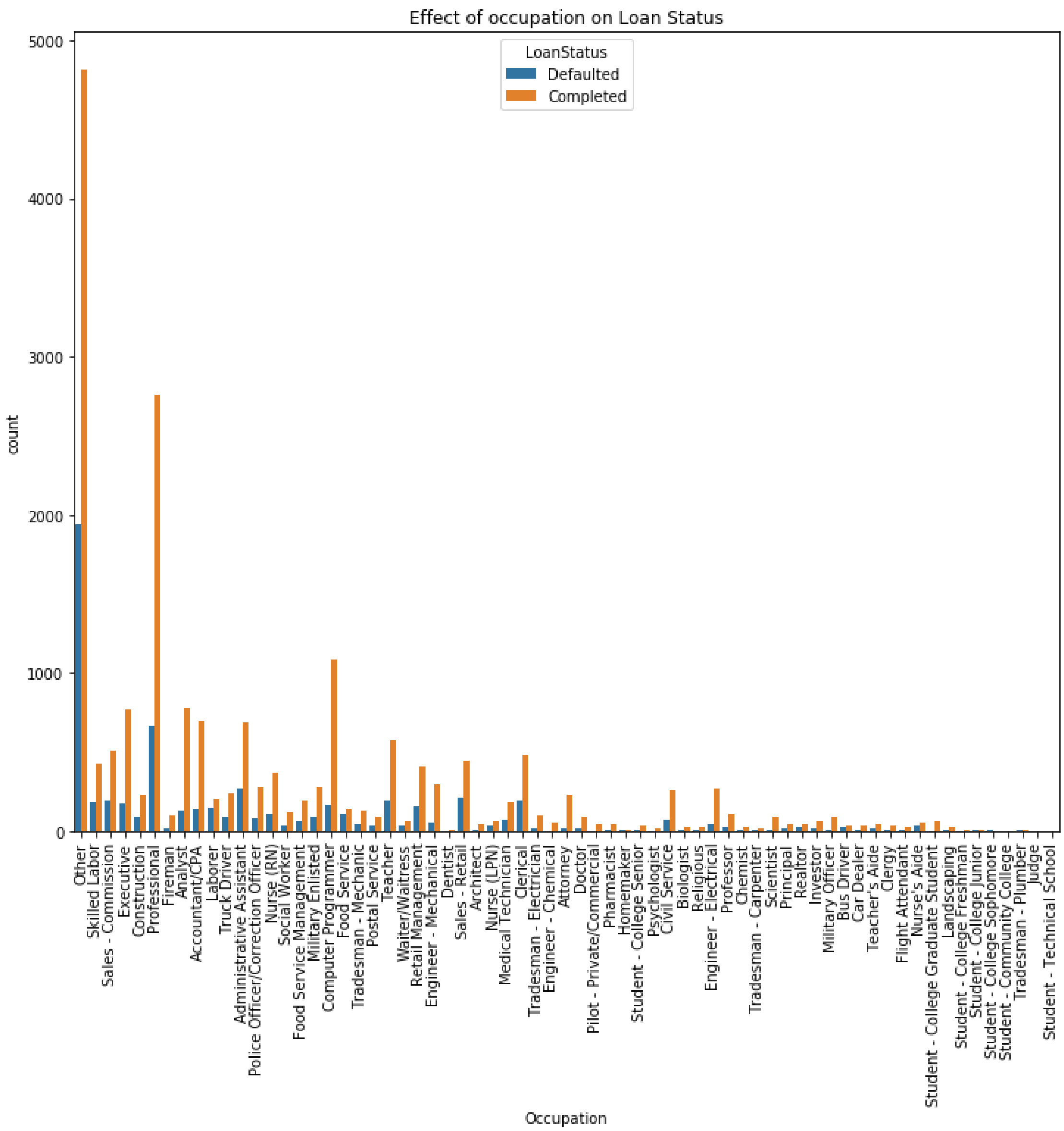
I investigated the features LoanStatus, EmploymentStatus, StatedMonthlyIncome, Term and IncomeRange. Majority of the Loan have term of 36 months and are taken by people who are employed, more loans were given to people who have earnings between income range [25,000 - 74,999], surprisingly, people earning higher than this range seem to take lesser loan. Also I observed that majority of the loan originated in year 2013 and they have a loan status of current with few defaults

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

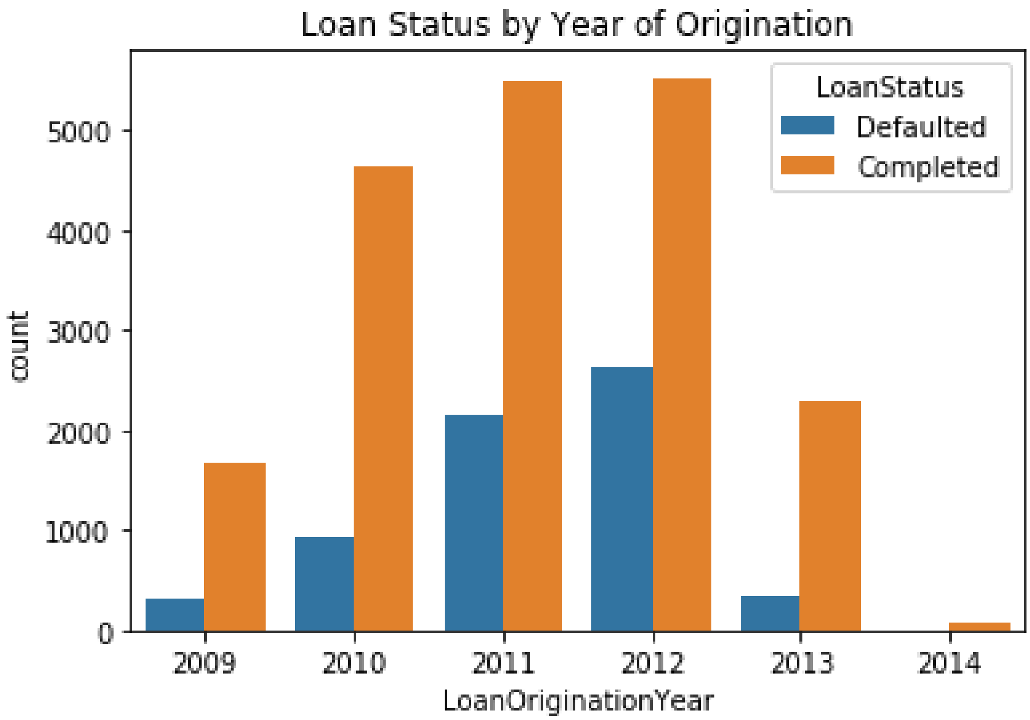
In the monthly stated Income, I had to do some transformations using the mean and standard deviation to get the boundary and adjusting the limit of the x axis of the plot so that I can get the actual distribution. Also, I extracted the year column from Loan origination date to do year on Year analysis and also did an encoding for the loan listing category to ensure proper visualization

1.5 Bivariate Exploration

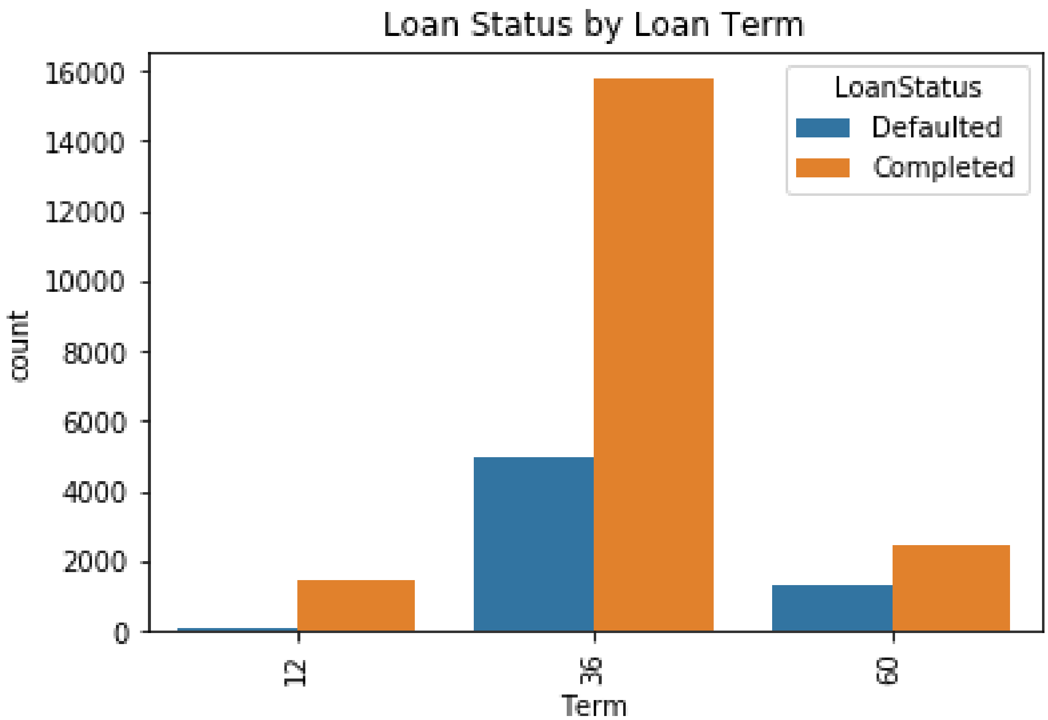
```
In [66]: # Let us check how occupation relates to Loan Status
         plt.figure(figsize = [12, 10])
         plt.title('Effect of occupation on Loan Status')
         plt.xticks(rotation=90)
         sb.countplot(data = loan_df_copy, x = 'Occupation', hue = 'LoanStatus');
```



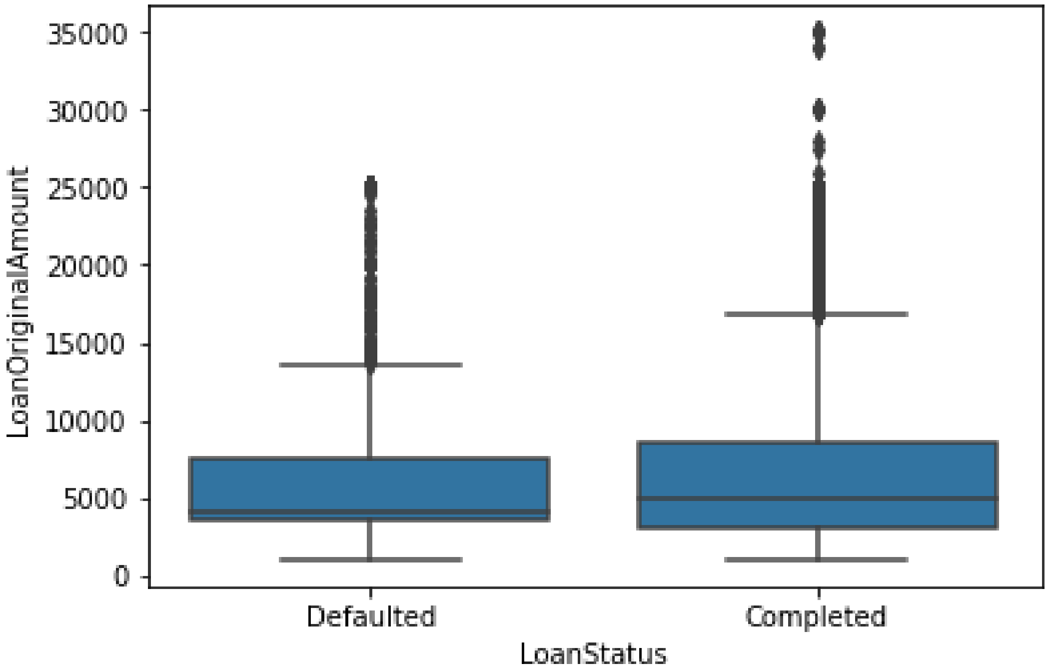

```
In [67]: #Loan Status by Year of Origination
         plt.title('Loan Status by Year of Origination')
         sb.countplot(data = loan_df_copy, x = 'LoanOriginationYear', hue = 'LoanStatus');
```



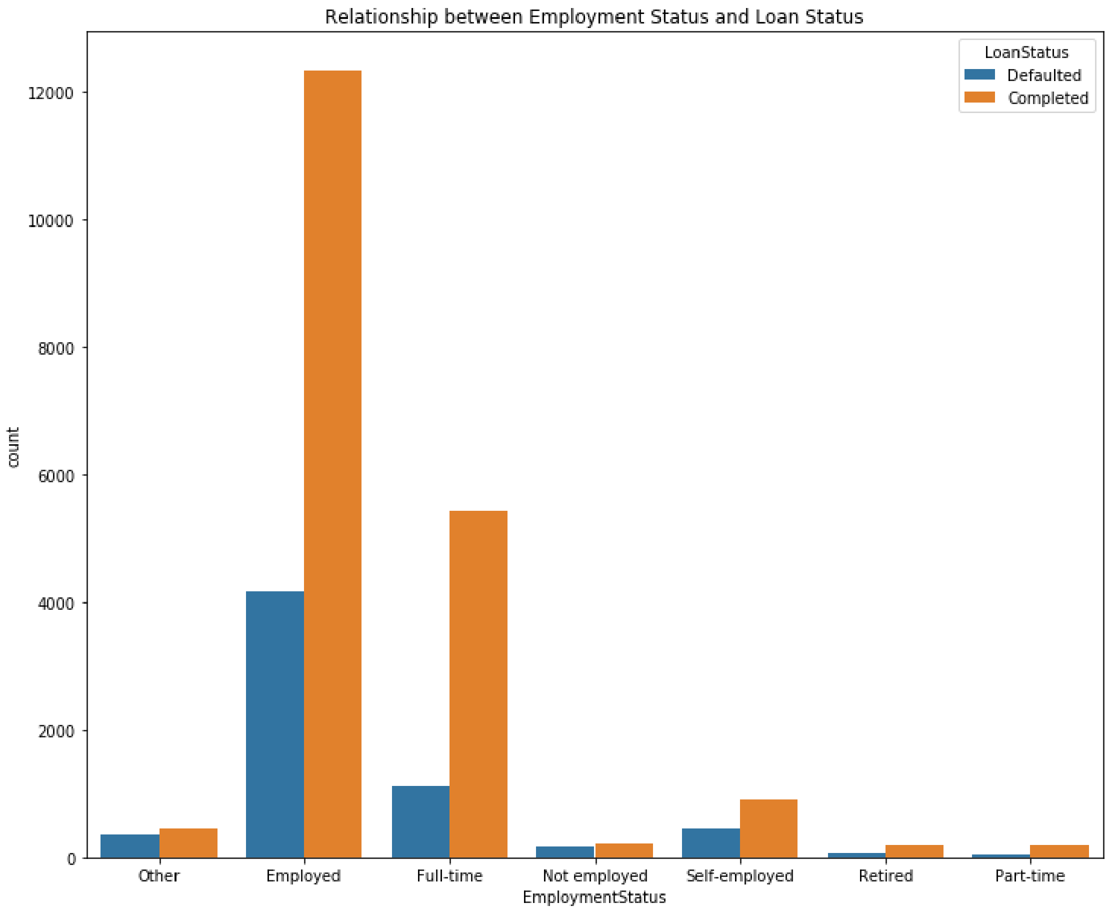

```
In [68]: #Loan Status by Loan Term
         plt.title('Loan Status by Loan Term')
         plt.xticks(rotation=90)
         sb.countplot(data = loan_df_copy, x = 'Term', hue = 'LoanStatus');
```



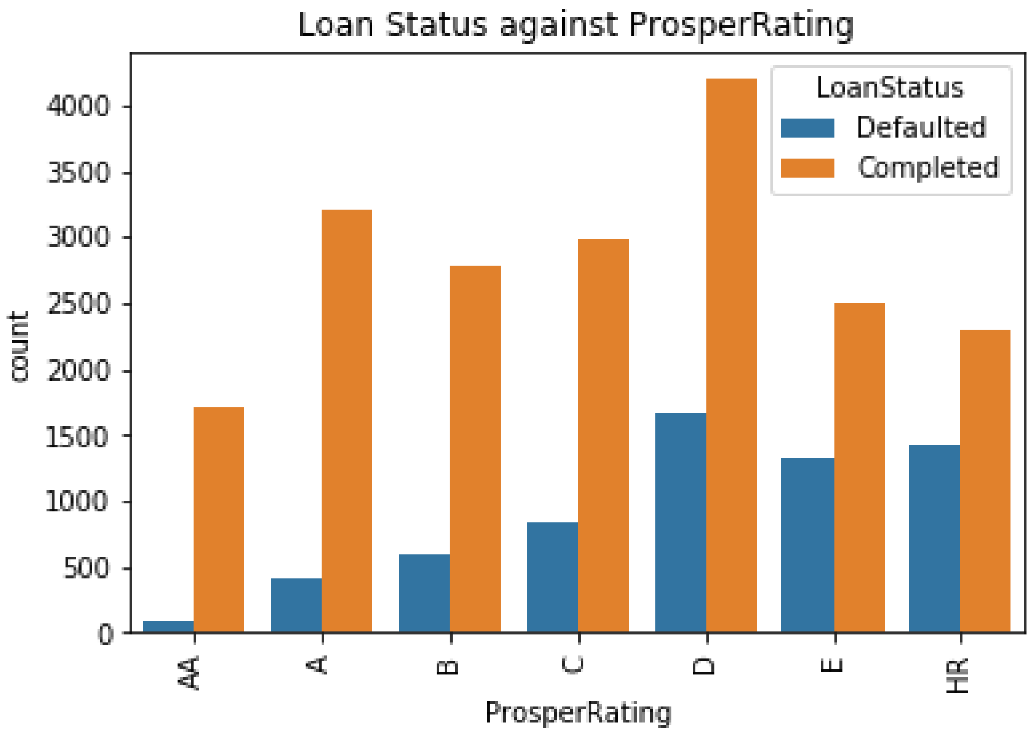
In [69]: # Let us check the relationship between Loan status and Loan Amount
```
sb.boxplot(data = loan_df_copy, x = 'LoanStatus', y = 'LoanOriginalAmount', color = bas
```



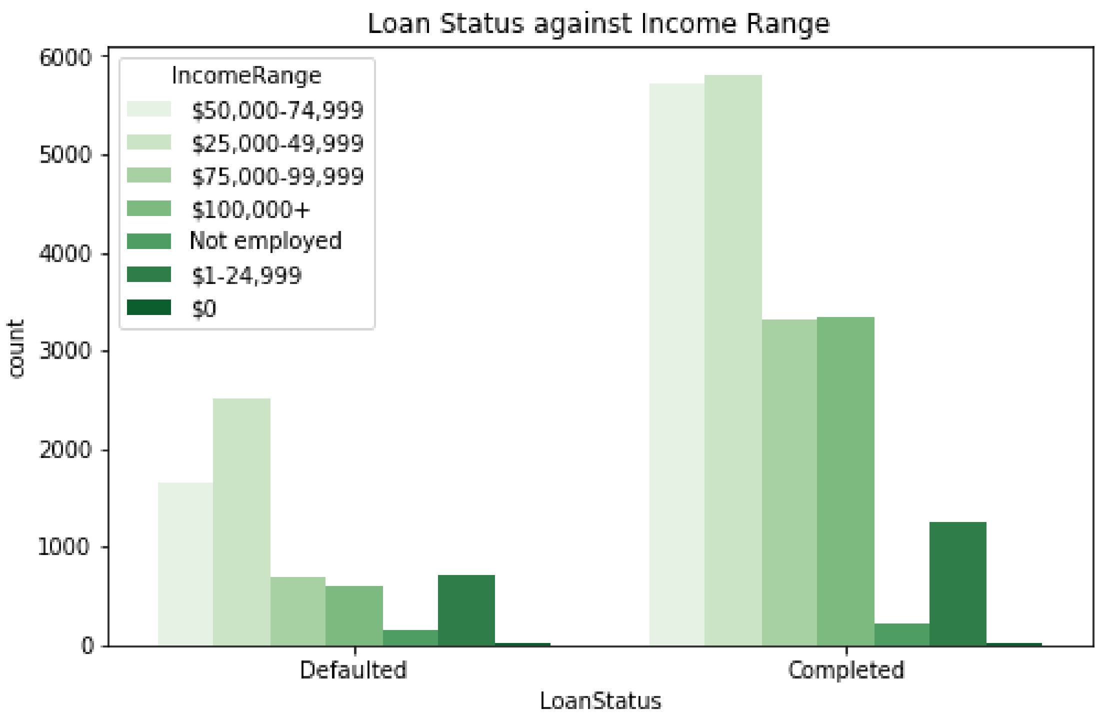
```
In [70]: # Let us check the relationship between prosper rating and Employemnt status
         plt.figure(figsize = [12, 10])
         plt.title('Relationship between Employment Status and Loan Status')
         sb.countplot(data = loan_df_copy, x = 'EmploymentStatus', hue = 'LoanStatus');
```



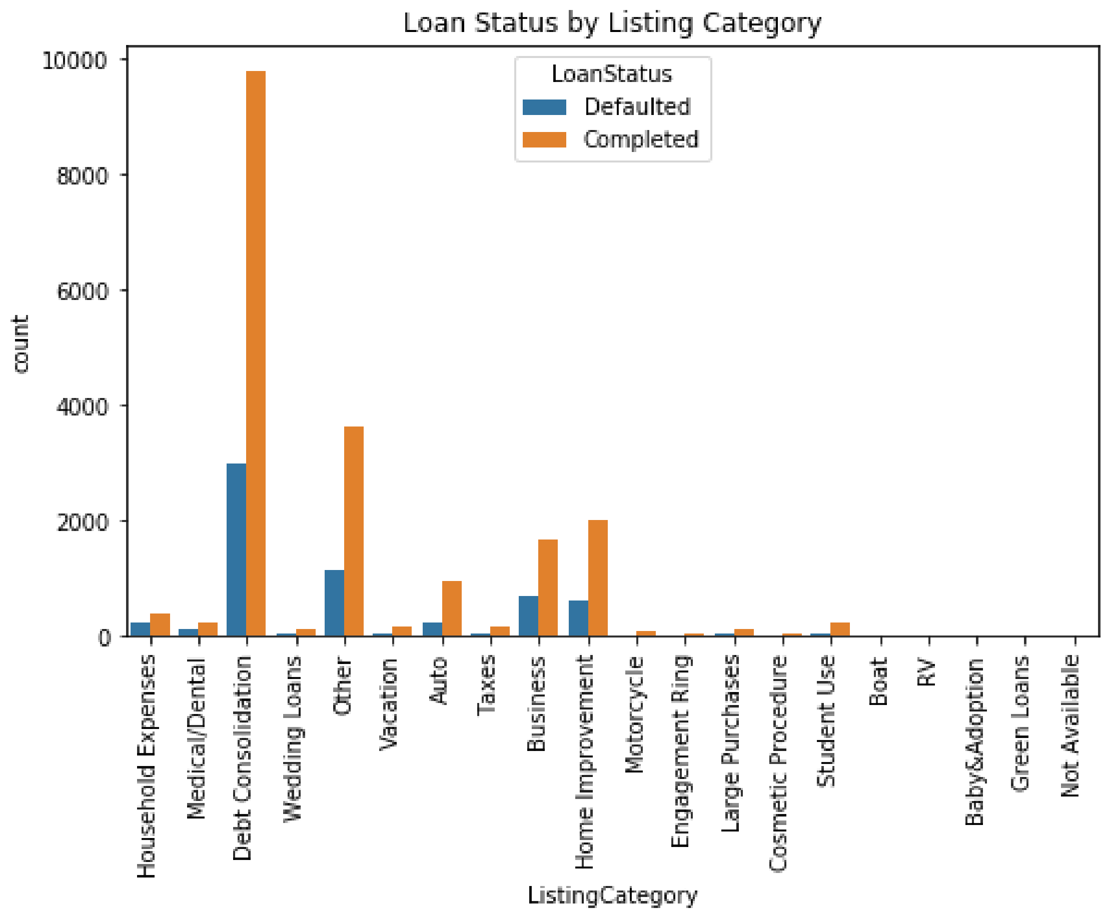

```
In [71]: # Plot of Listing Category and Loan Status
         plt.title('Loan Status against ProsperRating')
         plt.xticks(rotation=90)
         xorder = ['AA', 'A', 'B', 'C', 'D', 'E', 'HR']
         sb.countplot(data = loan_df_copy, x = 'ProsperRating', hue = 'LoanStatus', order=xorder
```



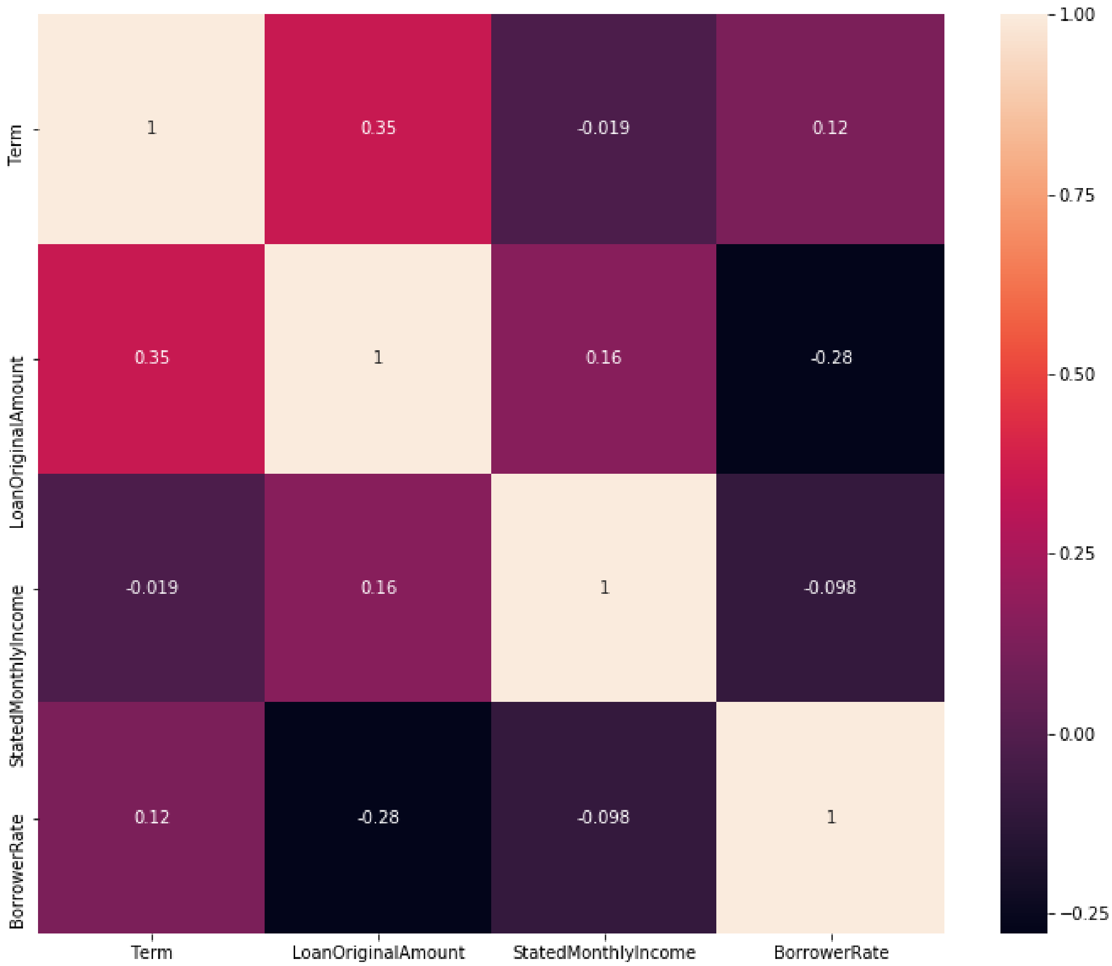

```
In [72]: # Income Range and Loan Status
         plt.figure(figsize = [8, 5])
         plt.title('Loan Status against Income Range')
         sb.countplot(data = loan_df_copy.query("LoanStatus in ('Defaulted','Completed')"), x =
```




```
In [73]: # Loan Listing by Listing Category
         plt.figure(figsize = [8, 5])
         plt.title('Loan Status by Listing Category')
         plt.xticks(rotation=90)
         sb.countplot(data = loan_df_copy, x = 'ListingCategory', hue = 'LoanStatus');
```



In [74]:
```
# Let us plot a heatmap of the data set to see the correlation
plt.figure(figsize = [12, 10])
sb.heatmap(loan_df_copy[['Term','LoanOriginalAmount','StatedMonthlyIncome','BorrowerRat
```



1.5.1 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?

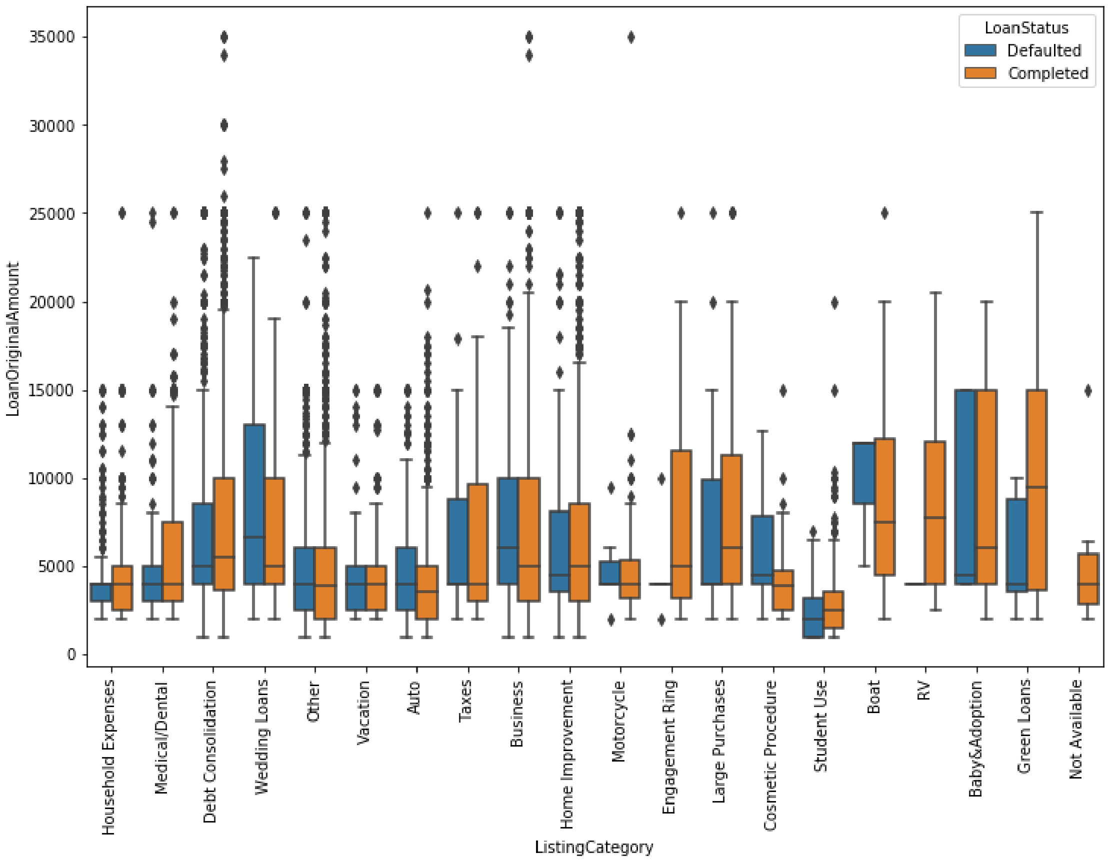
The majority of people who defaulted in paying their loan are employed in a full-time job and Most of the defaulters are within the income range [25,000 - 49,999]. My investigation further shows that people with debt consolidation as reason tends to default more on loan and the majority of loans fall under the prosper rating D category. Majority of the Loan default have Loan amount between 4000 and 8000

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

There is a positive correlation between Loan Original Amount and Monthly stated Income and also between Loan Original Amount and Loan Term. However, there is a slightly negative correlation between StatedMonthlyIncomea and Term

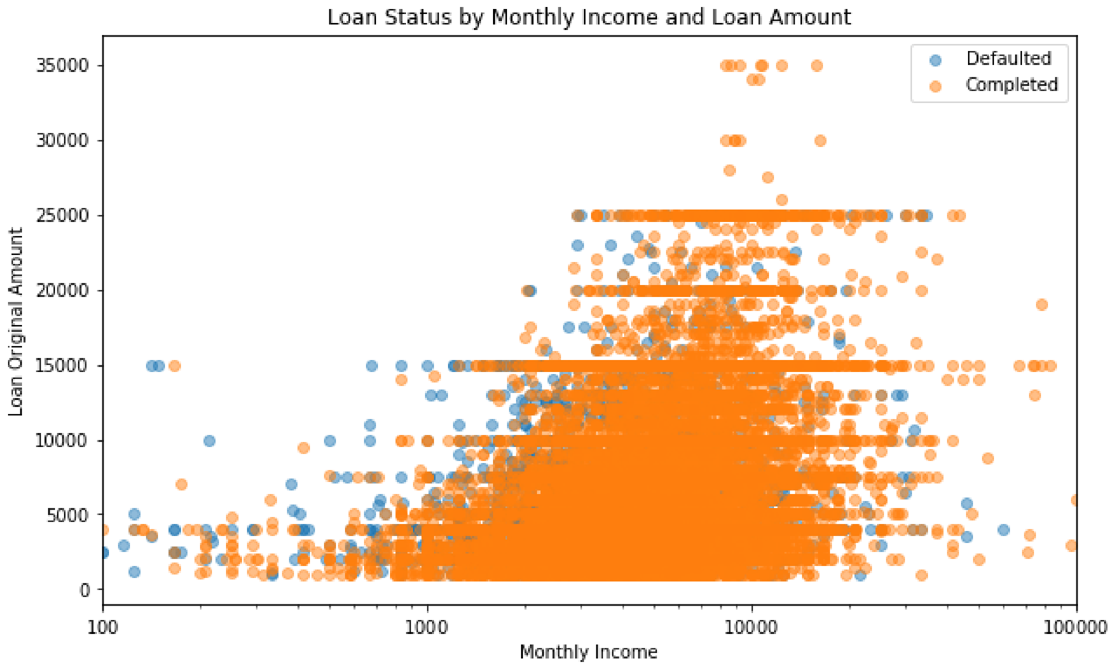
1.6 Multivariate Exploration

In [75]:
```
# Exploring Original Loan Amount, Listing Category and Loan Status
plt.figure(figsize = [12, 8])
plt.xticks(rotation=90)
sb.boxplot(data=loan_df_copy, x='ListingCategory', y='LoanOriginalAmount', hue='LoanSta
```

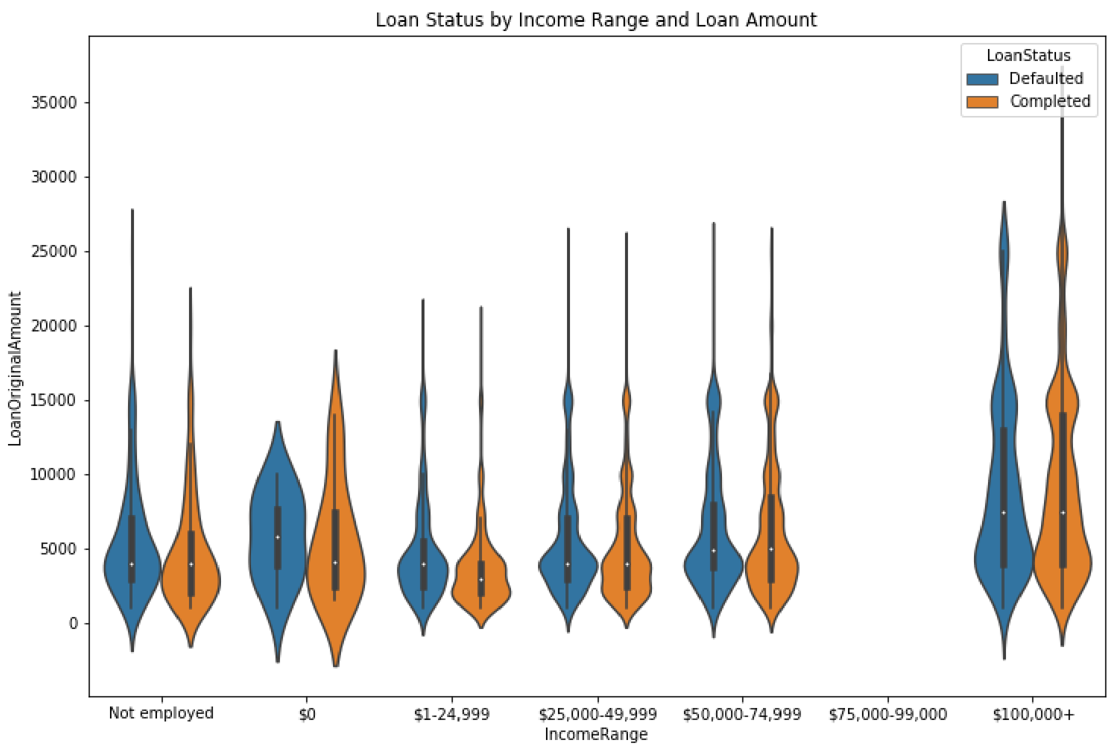


In [82]:
```
# Exploring Original Loan Amount, Stated Monthly Income and Loan Status
fig, ax = plt.subplots(figsize=(10, 6))
colors = {'Defaulted':'steelblue','Completed':'orange'}
#plt.figure(figsize = [12, 8])
plt.title('Loan Status by Monthly Income and Loan Amount')
plt.xscale('log')
plt.xlabel('Monthly Income')
plt.ylabel('Loan Original Amount')
plt.xlim(100,100000)
xticks = [100,1000,10000,100000]
ax.set_xticks(xticks)
ax.set_xticklabels(["$%.0f$" % x for x in xticks], fontsize=10)
plt.scatter(data=loan_df_copy.query("LoanStatus == 'Defaulted'"), x='StatedMonthlyIncom
```

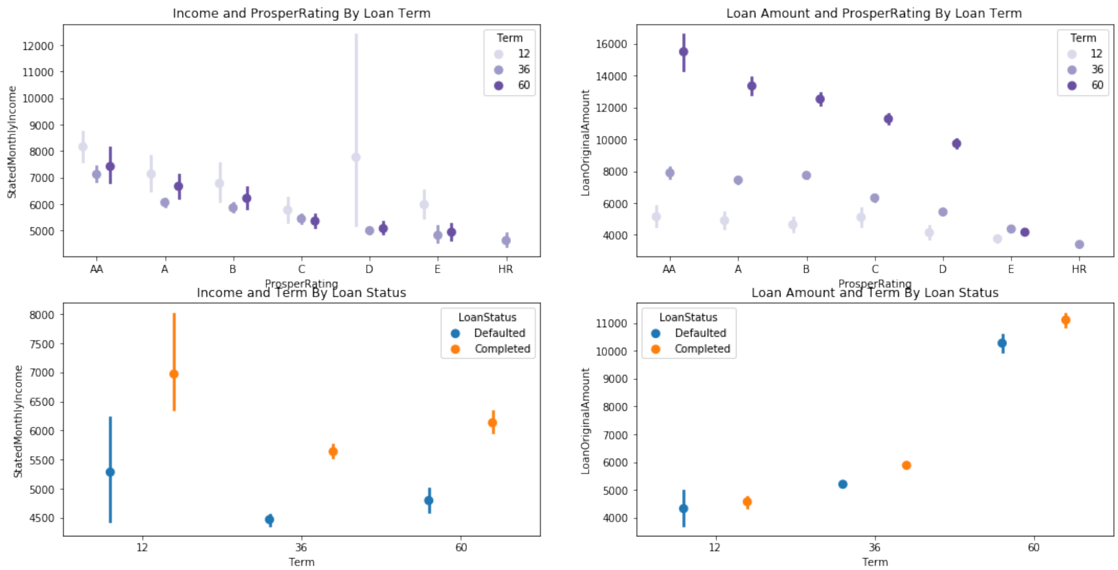
```
plt.scatter(data=loan_df_copy.query("LoanStatus == 'Completed'"), x='StatedMonthlyIncom

# Add legend
plt.legend(["Defaulted" , "Completed"], loc= 'upper right');
```



In [80]:
```
plt.figure(figsize = [12, 8])
plt.title('Loan Status by Income Range and Loan Amount')
sb.violinplot(data=loan_df_copy, x='IncomeRange', y='LoanOriginalAmount', hue='LoanStat
```



In [81]:
```
fig, ax = plt.subplots(ncols=2, nrows=2, figsize=[18,9])
sb.pointplot(data = loan_df_copy, x = 'ProsperRating', y = 'StatedMonthlyIncome', hue =
             palette = 'Purples', linestyles = '', dodge = 0.4, order=xorder, ax=ax[0,0])
sb.pointplot(data = loan_df_copy, x = 'ProsperRating', y = 'LoanOriginalAmount', hue =
             palette = 'Purples', linestyles = '', dodge = 0.4,order=xorder, ax=ax[0,1]).
sb.pointplot(data = loan_df_copy, x = 'Term', y = 'StatedMonthlyIncome', hue = 'LoanSta
             linestyles = '', dodge = 0.4, ax=ax[1,0]).set(title='Income and Term By Loan
sb.pointplot(data = loan_df_copy, x = 'Term', y = 'LoanOriginalAmount', hue = 'LoanStat
             linestyles = '', dodge = 0.4, ax=ax[1,1]).set(title='Loan Amount and Term By
```



1.6.1 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?

ListingCategories Debt Consolidation, Wedding Loans, Baby&Adoption, Business and Home Improvement have Loan Amount with higher ranges of default. Also Income range from 25K to 100K have the highest loan ranges with defaults. Persons with Loan Rating AA and A usually take loans with higher term, persons with Loan Rating D go for short term loans. Lower loan amount between 4k to 5k over a 12 month term tend to default more

1.6.2 Were there any interesting or surprising interactions between features?

Yes, Majority of Loans with Term of 12 months have lower Loans category and less defaults. Another surprising interaction is that most loans with defaults are from employed persons, those with no earnings (0 dollars and not employed) seem to complete their loans. Loans with higher amount over a 60 month term seem to complete but default when the term is shorter even for persons in higher Income Range. Also the number of defaulted loans have reduced after it peaked in the year 2013 most like because the company reduced the number of loans after 2013

1.7 Conclusions

The exploration is all about Loan status and what factors can affect the loan status. The following features have been observed to have effect on the loan status 1. Employment Status 2. Income Range 3. Term 4. BorrowerRate 5. ListingCategory 6. ProsperRating

Most Loans are given to employed persons, but it has been observed through this analysis that most persons within the income range [25,000 to 49,999] seem to default more on their loans, for this kind of persons, it has been observed that when the listing category is for wedding and Baby&Adoption, the default rate is high, the company might need to take this into consideration for other persons requesting for loans. Also, the higher the BorrowerRate, the higher the probabily that the persons will default, hence, due dilligence needs to be carried out to know if the ProsperRating is HR, D and E which seem to be the ProsperRating with more Defaults

In [41]:
```
#Save the wrangled data to the workspace to be used in the slides notebook
loan_df_copy.to_csv('Loan_data_cleaned.csv')
```