Project 5 - Exploration_Template

June 28, 2020

1 Udacity Project 5: Communicate Data Findings

1.1 Dataset: Loan Data from prosper

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1.3 Preliminary Wrangling

The dataset contains 113937 entries. Each row includes infomation on the loan status, employment status, borrow's APR, Loan original amount, etc. This investigation will be analyzing the factors which effect a loan's status (Completed or Defaulted).

```
In [56]: # 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
```

```
In [57]: loan = pd.read_csv('prosperLoanData.csv')
```

```
In [58]: loan.head()
```

```
Out[58]:                 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 [59]:
```
loan.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 [60]: #Subset the df by columns of interest
         cols = ['LoanStatus', 'EmploymentStatus','StatedMonthlyIncome', 'BorrowerAPR','Borrower
         loan_sub=loan[cols]
         loan_sub.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 113937 entries, 0 to 113936
Data columns (total 7 columns):
LoanStatus               113937 non-null object
EmploymentStatus         111682 non-null object
StatedMonthlyIncome      113937 non-null float64
BorrowerAPR              113912 non-null float64
BorrowerRate             113937 non-null float64
LoanOriginalAmount       113937 non-null int64
ProsperRating (Alpha)    84853 non-null object
dtypes: float64(3), int64(1), object(3)
memory usage: 6.1+ MB
```

```
In [61]: #Missing values idfentified
         loan_sub.isnull().sum().sum()

Out[61]: 31364
```

```
In [62]: loan_sub = loan_sub.dropna()
         loan_sub.isnull().sum().sum()
```

Out[62]: 0

In [63]:
```
#Number of duplicated data entries
sum(loan_sub.duplicated())
```

Out[63]: 8130

In [64]:
```
loan_sub = loan_sub.drop_duplicates()
sum(loan_sub.duplicated())
```

Out[64]: 0

In [65]:
```
#Rename the column  ProsperRating (Alpha) to ProsperRating
loan_sub.rename(columns={'ProsperRating (Alpha)':'ProsperRating'}, inplace = True)
```

In [66]:
```
loan_sub.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 76723 entries, 1 to 113936
Data columns (total 7 columns):
LoanStatus             76723 non-null object
EmploymentStatus       76723 non-null object
StatedMonthlyIncome    76723 non-null float64
BorrowerAPR            76723 non-null float64
BorrowerRate           76723 non-null float64
LoanOriginalAmount     76723 non-null int64
ProsperRating          76723 non-null object
dtypes: float64(3), int64(1), object(3)
memory usage: 4.7+ MB
```

In [67]:
```
loan_sub.describe()
```

Out[67]:

	StatedMonthlyIncome	BorrowerAPR	BorrowerRate	LoanOriginalAmount
count	7.672300e+04	76723.000000	76723.00000	76723.000000
mean	6.025172e+03	0.224253	0.19382	9077.128710
std	8.610503e+03	0.078926	0.07374	6303.609813
min	0.000000e+00	0.045830	0.04000	1000.000000
25%	3.493750e+03	0.162940	0.13550	4000.000000
50%	5.000000e+03	0.216530	0.18640	7500.000000
75%	7.291667e+03	0.287800	0.25240	13000.000000
max	1.750003e+06	0.423950	0.36000	35000.000000

1.3.1 What is the structure of your dataset?

The data which was used is prosperLoanData.csv. The initial 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.

For simplicity of the visualization I have looked at only a few variables. After filtering the dataset for the variables of our interest and cleaning from the missing values and duplicates, the dataframe consists of 76723 entries and 7 columns: LoanStatus, EmploymentStatus, StatedMonthlyIncome, BorrowerAPR, BorrowerRate, LoanOriginalAmount, ProsperRating.

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

In this project, I want to investigate the best predictor for the LoanStatus-Completed and Defaulted.

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

I expect that the Employment Status and the State Monthly Income would have a positive effect on the Loan Status 'Completed'. The effect of Loan Original Amount on the LoanStatus is expected to have a strong relationship. It is also interesting to investigate the effect of the BorrowerAPR, BorrowerRate and ProsperRating.

In [68]:
```
loan_sub.LoanStatus.value_counts()
```

Out[68]:
```
Current                   49777
Completed                 18784
Chargedoff                 4931
Defaulted                   990
Past Due (1-15 days)        793
Past Due (31-60 days)       359
Past Due (61-90 days)       308
Past Due (91-120 days)      301
Past Due (16-30 days)       262
FinalPaymentInProgress      202
Past Due (>120 days)         16
Name: LoanStatus, dtype: int64
```

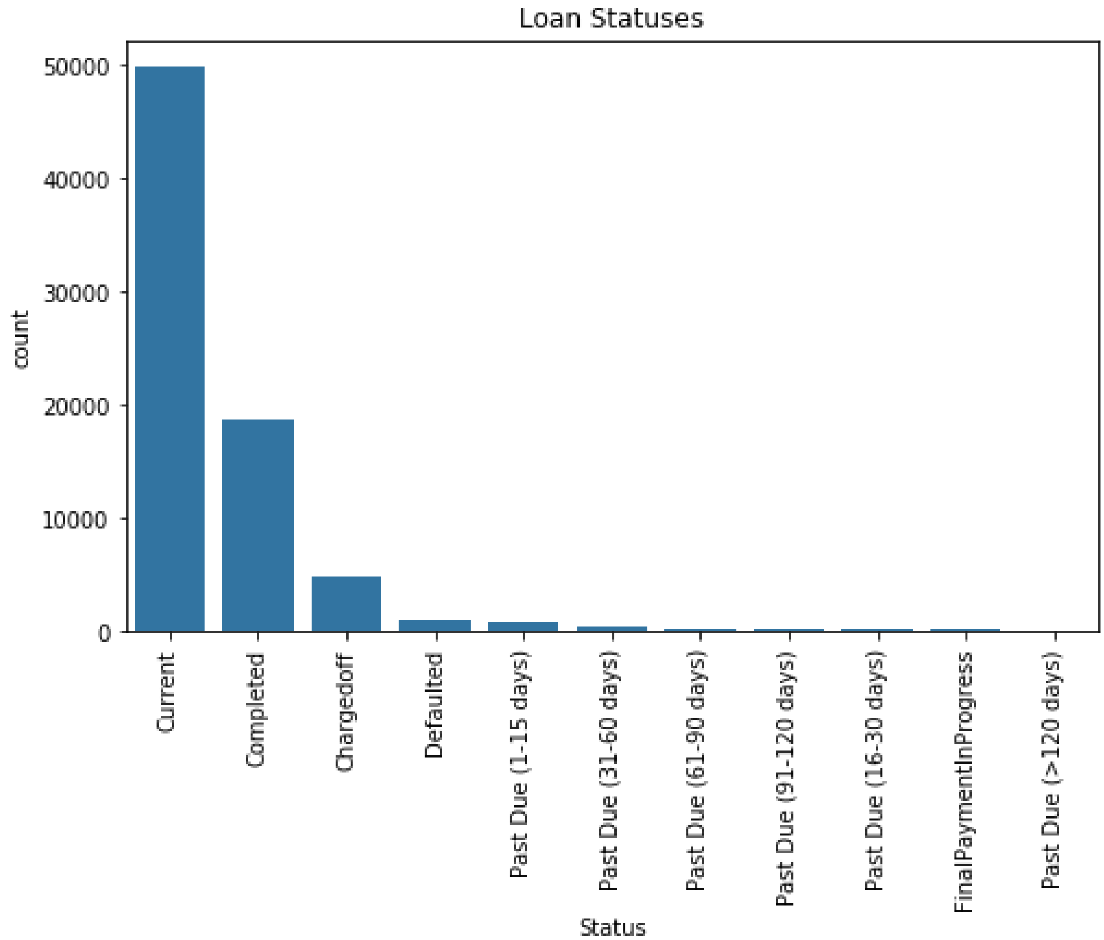
1.4 Univariate Exploration

In this section, I will investigate the variables of my interest individually.

Check the Loan Status.

In [69]:
```
# To check the Loan Status
plt.figure(figsize=[8,5])
status_order = loan_sub['LoanStatus'].value_counts().index
b_color= sb.color_palette()[0]
sb.countplot(data = loan_sub, x='LoanStatus', color=b_color, order =status_order)
plt.xticks(rotation=90)
plt.title('Loan Statuses')
plt.xlabel('Status')
plt.ylabel('count')
```

Out[69]:
```
Text(0,0.5,'count')
```



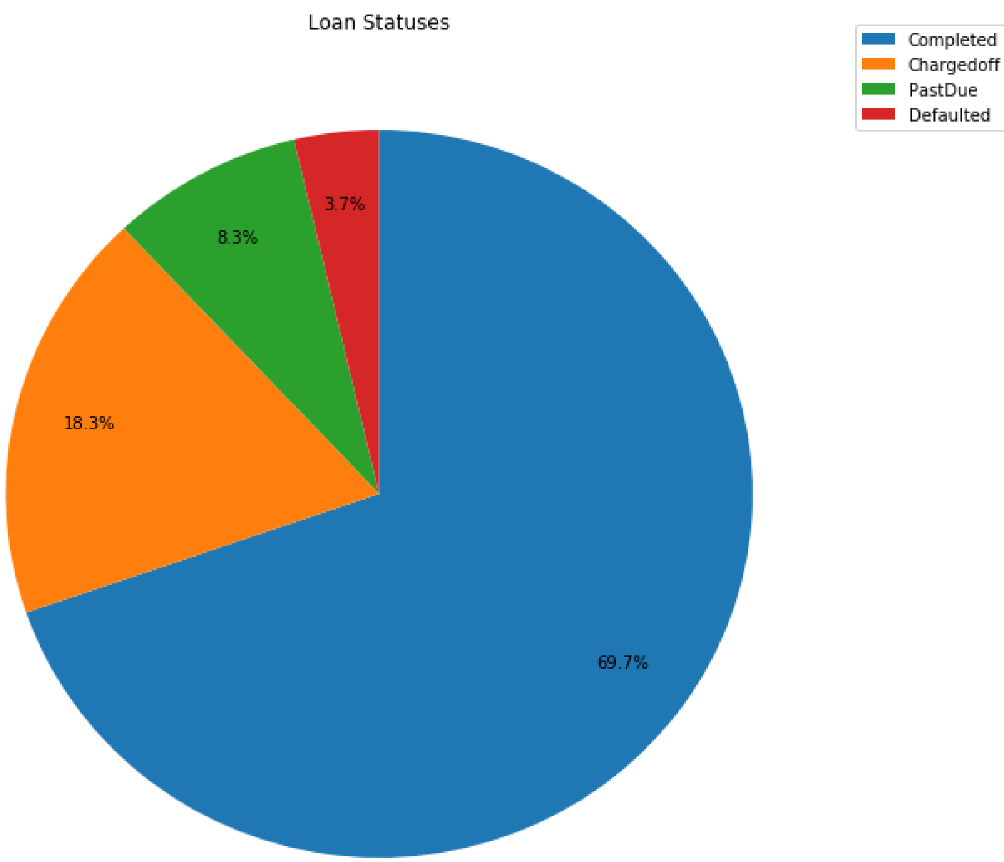
In [70]:
```
#Prepare the relevant information for the pie chart
loan_sub = loan_sub.loc[~loan_sub['LoanStatus'].isin(['Current'])]
Total = loan_sub['LoanStatus'].value_counts().sum()
Current = loan_sub[loan_sub['LoanStatus']== 'Current'].shape[0] *100/Total
Completed = loan_sub[loan_sub['LoanStatus']== 'Completed'].shape[0]  *100/Total
Chargedoff = loan_sub[loan_sub['LoanStatus']== 'Chargedoff'].shape[0]  *100/Total
Defaulted = loan_sub[loan_sub['LoanStatus']== 'Defaulted'].shape[0]  *100/Total
PastDue = loan_sub[(loan_sub['LoanStatus'] == 'Past Due (1-15 days)') |
                 (loan_sub['LoanStatus'] == 'Past Due (31-60 days)') |
                 (loan_sub['LoanStatus'] == 'Past Due (61-90 days)') |
                 (loan_sub['LoanStatus'] == 'Past Due (91-120 days)') |
                 (loan_sub['LoanStatus'] == 'Past Due (16-30 days)') |
                 (loan_sub['LoanStatus'] == 'FinalPaymentInProgress') |
                 (loan_sub['LoanStatus'] == 'Past Due (>120 days)')].shape[0]  *100/Tot
loan_sub.LoanStatus.value_counts()
```

Out[70]:
```
Completed                18784
Chargedoff                4931
```

```
Defaulted                   990
Past Due (1-15 days)        793
Past Due (31-60 days)       359
Past Due (61-90 days)       308
Past Due (91-120 days)      301
Past Due (16-30 days)       262
FinalPaymentInProgress      202
Past Due (>120 days)         16
Name: LoanStatus, dtype: int64
```

In [71]:
```
#Plot the pie chart for the loan status only for Completed, Chargedoff, Defaulted and u
plt.figure(figsize=[10,10])
status_order = [Completed, Chargedoff, PastDue, Defaulted]
labels = [ 'Completed', 'Chargedoff', 'PastDue', 'Defaulted']
plt.pie(status_order, startangle = 90, counterclock= False, autopct='%1.1f%%', pctdista
plt.legend(labels, loc="best", bbox_to_anchor=(1,1.025))
plt.title('Loan Statuses')
```

Out[71]: Text(0.5,1,'Loan Statuses')

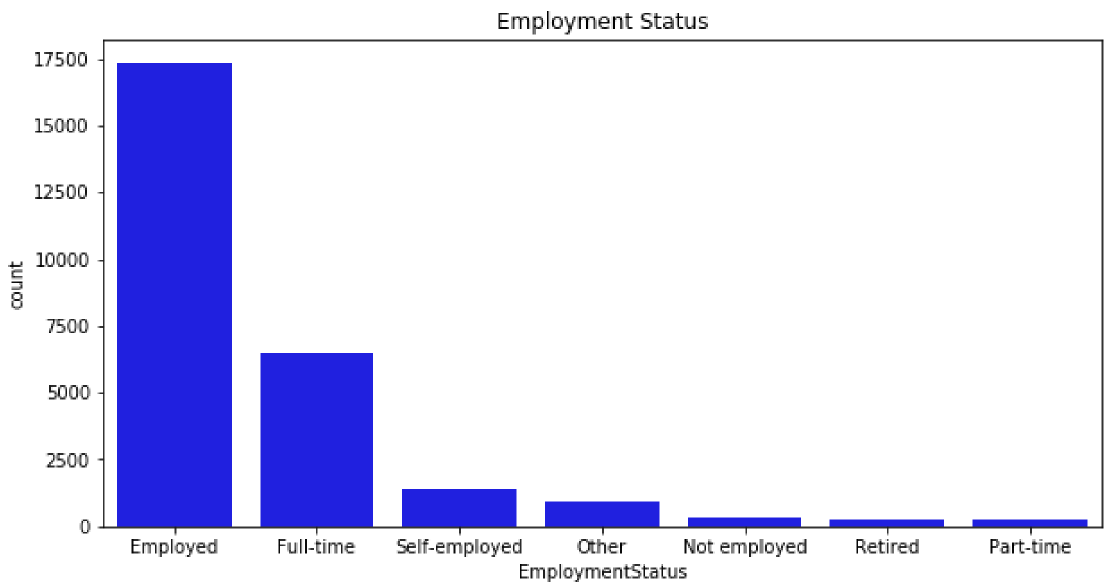


Excluding the loans with status Current, there are 69.7% loans with status 'Completed' and only 3.6% with status 'Defaulted'. The number of completed cases is higher than others.

Check the Employment Status.

In [72]:
```
plt.figure(figsize=[10,5])
order = loan_sub['EmploymentStatus'].value_counts().index
sb.countplot(data = loan_sub, x= 'EmploymentStatus', order = order, color = 'blue')
plt.title('Employment Status')
```

Out[72]: Text(0.5,1,'Employment Status')



According to the graph above, most of the loan takers are Employed and Full-time employed.

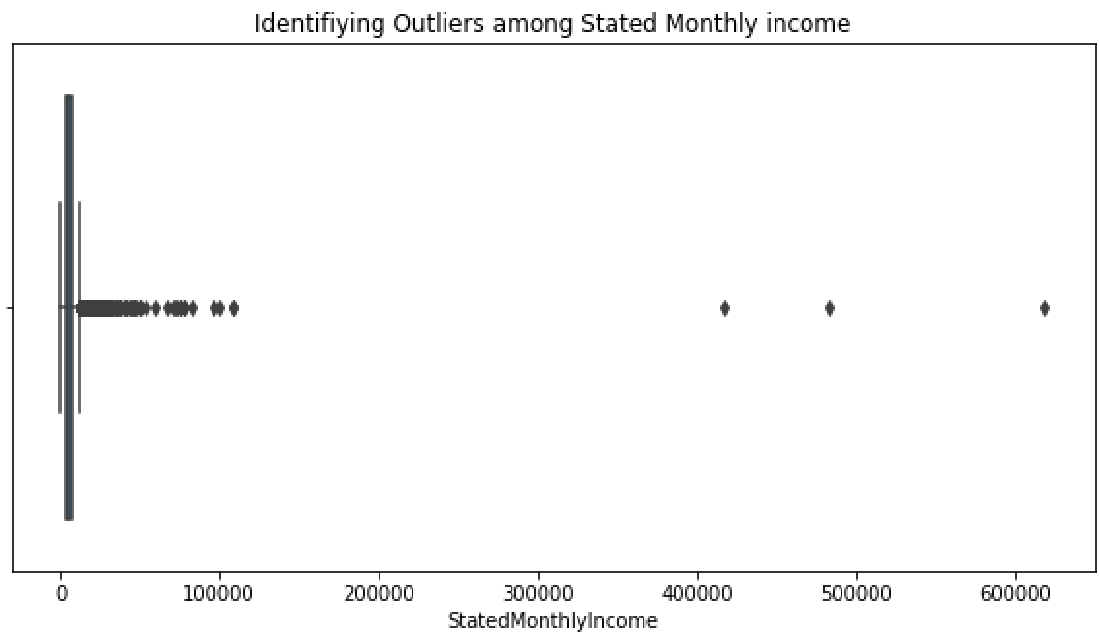
Check the distribution of the Stated Monthly Income.

In [73]:
```
#It seems that the data has outliers
loan_sub.StatedMonthlyIncome.describe()
```

Out[73]:
```
count     26946.000000
mean       5534.869709
std        6758.300905
min           0.000000
25%        3166.666667
50%        4583.333333
75%        6704.791667
max      618547.833333
Name: StatedMonthlyIncome, dtype: float64
```

In [74]:
```
#Identifiyng outliers
#https://towardsdatascience.com/ways-to-detect-and-remove-the-outliers-404d16608dba
plt.figure(figsize=[10,5])
sb.boxplot(x=loan_sub['StatedMonthlyIncome'])
plt.title('Identifiying Outliers among Stated Monthly income')
plt.plot()
```

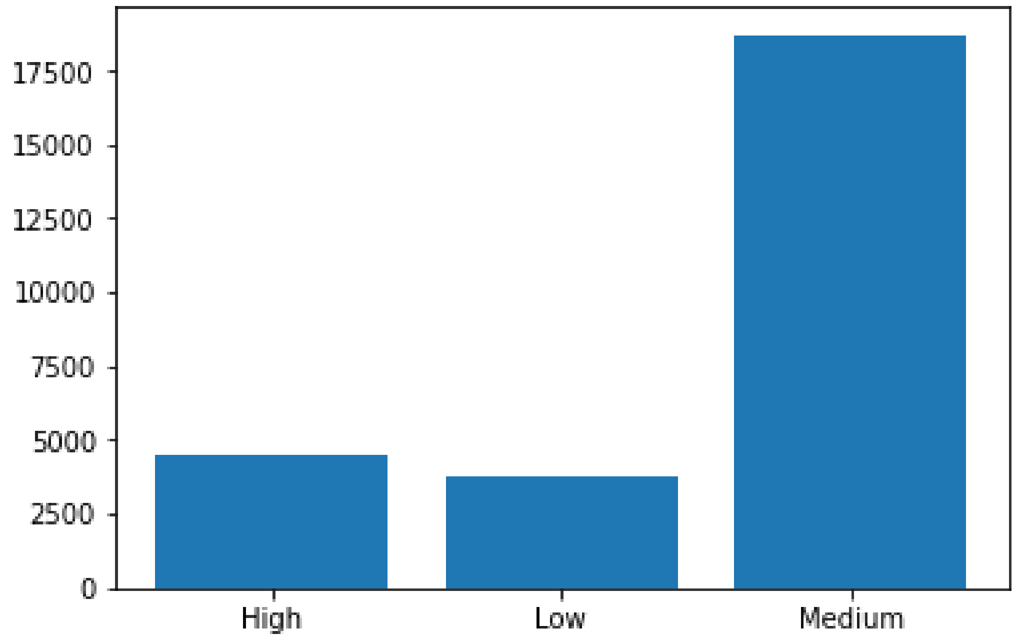
Out[74]: []



In [75]:
```
def classify(row):
    if row["StatedMonthlyIncome"]<2500:
        return 'Low'
    if row["StatedMonthlyIncome"]<8000:
        return 'Medium'
    else:
        return 'High'

loan_sub["WageBracket"] = loan_sub.apply(classify, axis=1);
plt.bar(loan_sub["WageBracket"].value_counts().index,loan_sub["WageBracket"].value_coun
```

Out[75]: <Container object of 3 artists>



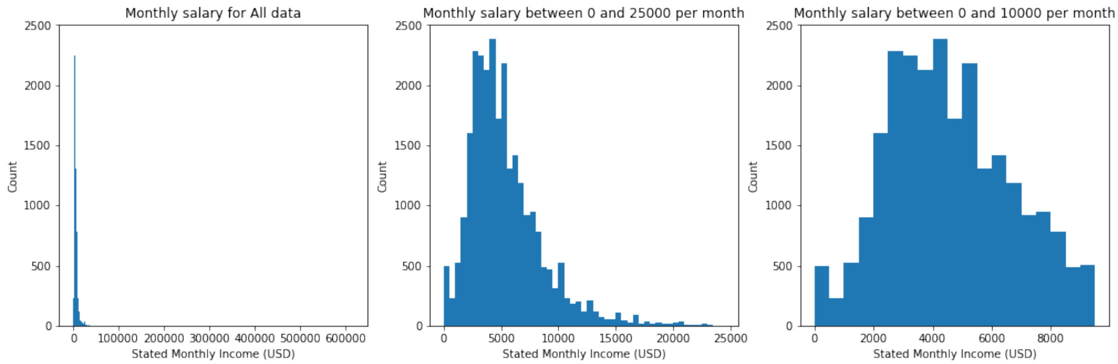
In [76]:
```
# Playng with the bins, i found out the the distribution of the StateMonthlyIncome for
# When we want to take a look only to the group of which salary is less than 10000,
# the distribution look normal with a pick at around 4000 (Average salary)
plt.figure(figsize=[17,5])

plt.subplot(1,3,1)
bins = np.arange(0, 618548, 500)
plt.hist(data =  loan_sub, x= 'StatedMonthlyIncome', bins = bins)
plt.title('Monthly salary for All data')
plt.xlabel('Stated Monthly Income (USD)')
plt.ylabel('Count')

plt.subplot(1,3,2)
bins = np.arange(0, 25000, 500)
plt.hist(data =  loan_sub, x= 'StatedMonthlyIncome', bins = bins)
plt.title('Monthly salary between 0 and 25000 per month')
plt.xlabel('Stated Monthly Income (USD)')
plt.ylabel('Count')

plt.subplot(1,3,3)
bins = np.arange(0, 10000, 500)
plt.hist(data =  loan_sub, x= 'StatedMonthlyIncome', bins = bins)
plt.title('Monthly salary between 0 and 10000 per month')
plt.xlabel('Stated Monthly Income (USD)')
plt.ylabel('Count')
```

Out[76]: Text(0,0.5,'Count')



The Stated Monthly Income is between a min 0 and max 618547 salary range per month. The distribution is right skewed with the mean 5534 and the standard deviation 6758. However, due to the outliers which are presented with the high salaries and based on the bar chart above, we can see that most of the loan payers are in the Medium group with a salary per month from 2500 to 8000. Additionally, there is a normal distribution for a range between 0 and 10000 US Dollars per month.

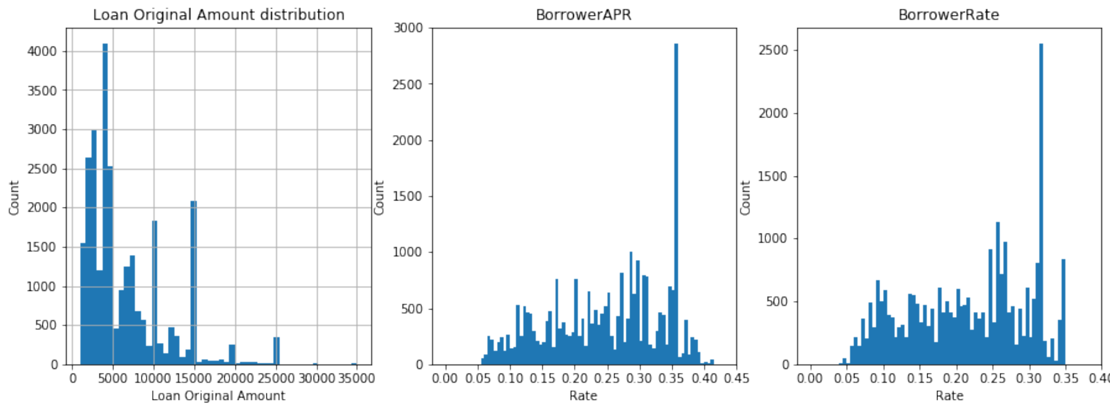
Check the distribution of Loan Original Amount, Borrower APR and Borrower Rate.

In [77]:
```
plt.figure(figsize=[15,5])
# Loan Original Amount distribution is right skewed
plt.subplot(1,3,1)
loan_sub.LoanOriginalAmount.hist(bins = 50)
plt.title('Loan Original Amount distribution')
plt.xlabel('Loan Original Amount')
plt.ylabel('Count')

# BorrowerAPR distribution
plt.subplot(1,3,2)
bins = np.arange(0, loan_sub['BorrowerAPR'].max(), 0.005)
plt.hist(data =  loan_sub, x= 'BorrowerAPR', bins =bins)
plt.title('BorrowerAPR')
plt.xlabel('Rate')
plt.ylabel('Count')
plt.xticks(np.arange(0, loan_sub['BorrowerAPR'].max()+0.05, 0.05));

# BorrowerRate distribution
plt.subplot(1,3,3)
bins = np.arange(0, loan_sub['BorrowerRate'].max(), 0.005)
plt.hist(data =  loan_sub, x= 'BorrowerRate', bins =bins)
plt.title('BorrowerRate')
plt.xlabel('Rate')
```

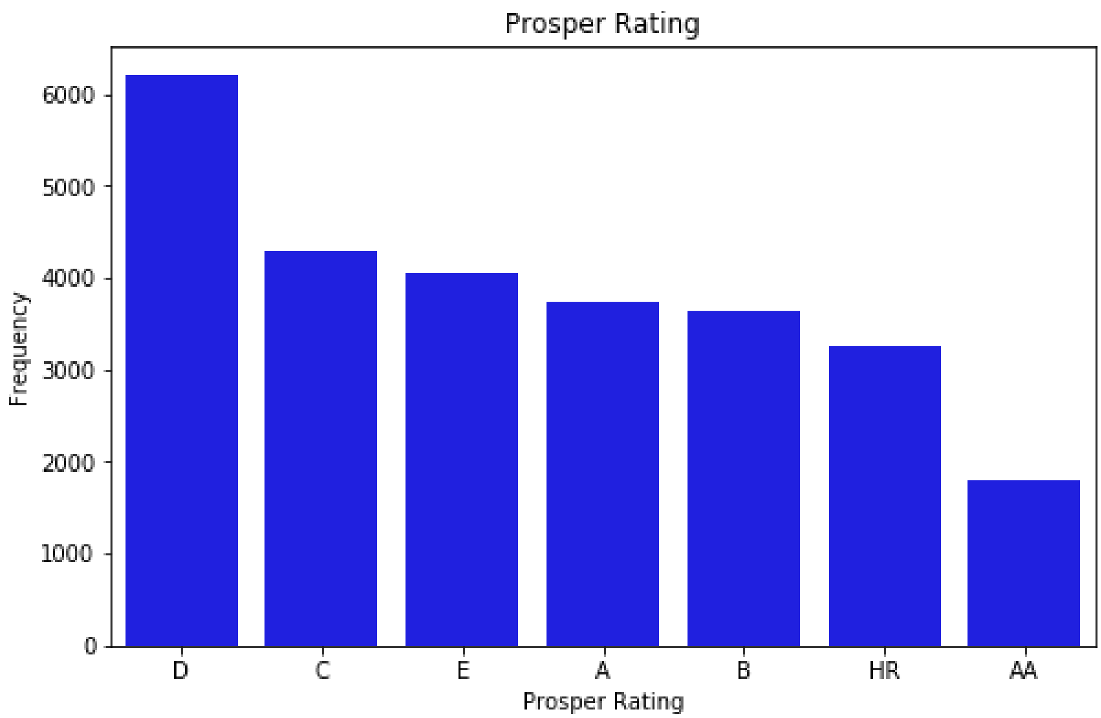
```
plt.ylabel('Count')
plt.xticks(np.arange(0, loan_sub['BorrowerRate'].max()+0.05, 0.05));
```



The Loan Original Amount has a right skewed distribution with the peak at around 4800. The Borrower APR and the Borrower Rate show slightly left skewed distributions with the second spike at 0.37 for Borrower APR and at 0.32 for Borrower Rate. Interestingly, the shape of the Borrower APR and Borrower Rate distributions share some similarities. It's likely that two variables will be correlated with one another.

Check the Prosper Rating

```
In [78]: # ProsperRating (Alpha):  (0 - N/A)  1 - HR, 2 - E, 3 - D, 4 - C, 5 - B, 6 - A, 7 - AA
         # https://www.lendacademy.com/prosper-review/
         plt.figure(figsize=[8,5])
         order = loan_sub['ProsperRating'].value_counts().index
         sb.countplot(data = loan_sub, x= 'ProsperRating', order = order, color = 'blue')
         plt.title('Prosper Rating')
         plt.xlabel('Prosper Rating')
         plt.ylabel('Frequency');
```



Prosper Rating shows that there are less loans with the lowest risk AA and just above 3500 loans for the highest risk rate HR. The most of the loans are with Rating D.

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?

The Loan Status has a high number of current loans as well as high percentage of the completed loans. The distribution of employment shows that the high percentage of the loan takers do have a full-time job or/and Employed.

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?

The variable of interest Loan Status had a very high number of Current loans which was excluded. The goal is to find what effects Completed and Defaulted loans in order to predict the good cases.

Additionally, variable Stated Monthly Income showed the very right skewed distribution of the monthly salary which can be explained with a few high salaries as outliers. However, the most of the salaries are in the range between 0 and 10000 which has a normal distribution.

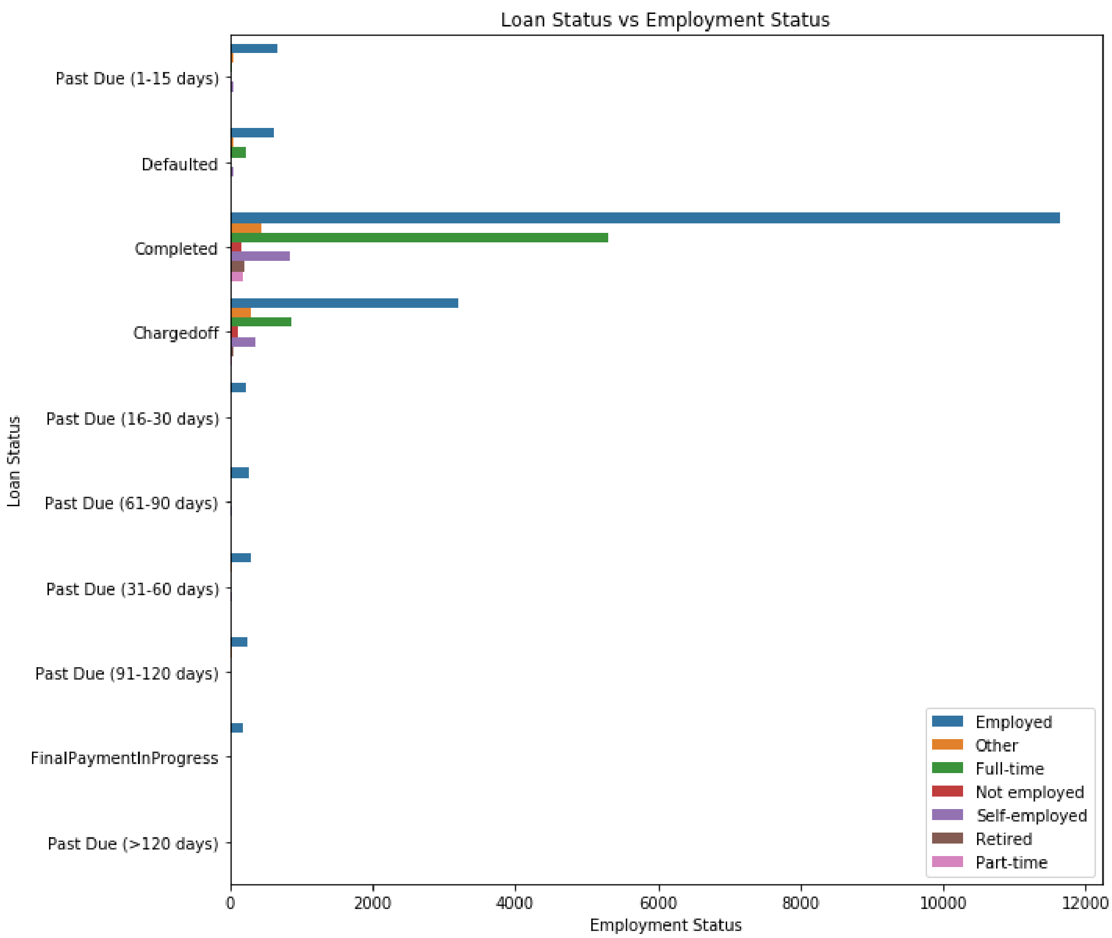
The shape of the Borrower APR and Borrower Rate distributions share some similarities. It's likely that two variables will be correlated with one another.

1.5 Bivariate Exploration

Check Loan Status and Emploament Status (ql vs ql)

```
In [79]: #LoanStatus vs EmploymentStatus - COUNTPLOT
         plt.figure(figsize=[10,10])
         sb.countplot(data = loan_sub, y='LoanStatus', hue='EmploymentStatus')
         plt.legend(loc='lower right')
         plt.title('Loan Status vs Employment Status')
         plt.xlabel('Employment Status')
         plt.ylabel('Loan Status')

Out[79]: Text(0,0.5,'Loan Status')
```



When we investigate the relationship between Loan Status and Employment Status, we can see that only Employed customers show the status as Past Due. It may be due to the postponed Salary. The Status to be Employed also shows a very outstanding level of the loan completion as well as Full-Time employed status.

Loan Status and Stated Monthly Income (ql vs qt) and

Loan status and Loan Original Amount (ql vs qt)

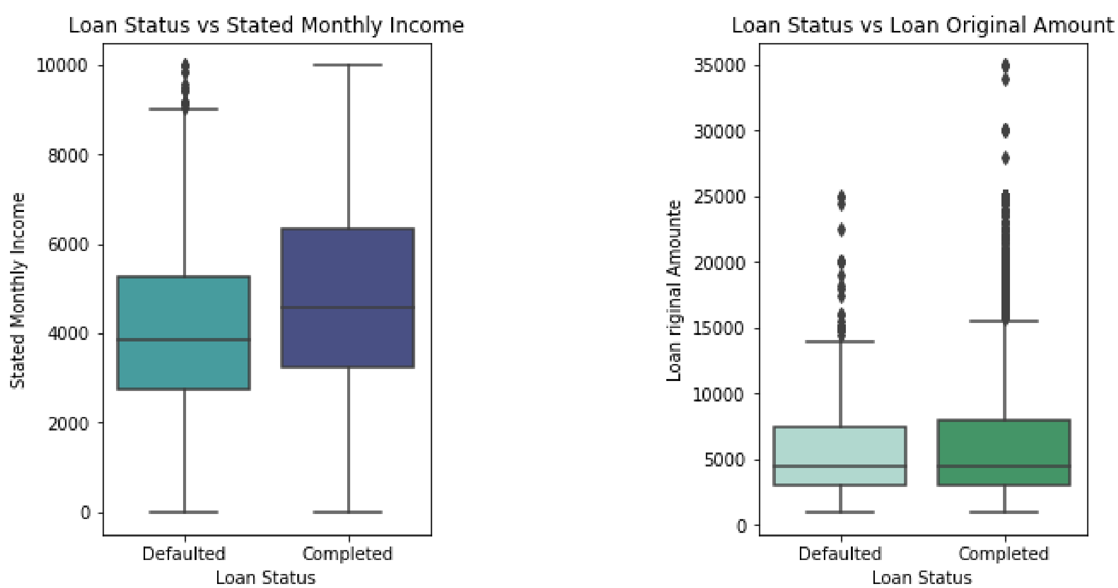
```
In [80]: # filtereing Loan Status for the Completed and Defaulted and without outliers for the m
         loan_sub = loan_sub[(loan_sub['LoanStatus'] == 'Completed') |
                             (loan_sub['LoanStatus'] == 'Defaulted')]
         loan_sub =loan_sub.loc[loan_sub['StatedMonthlyIncome'] <= 10000]
```

```
In [81]: plt.figure(figsize=[10,5])

         #LoanStatus vs StatedMonthlyIncome - BOXPLOT
         plt.subplot(1,2,1)
         plt.subplots_adjust(left=0.1, bottom=0.1, right=0.9, top=0.9 , wspace=1, hspace=0.2)
         sb.boxplot(data = loan_sub, x='LoanStatus', y='StatedMonthlyIncome', palette = 'mako_r'
         plt.title('Loan Status vs Stated Monthly Income')
         plt.ylabel('Stated Monthly Income')
         plt.xlabel('Loan Status')

         #LoanStatus vs LoanOriginalAmount   - BOXPLOT
         plt.subplot(1,2,2)
         plt.subplots_adjust(left=0.1, bottom=0.1, right=0.9, top=0.9 , wspace=1, hspace=0.2)
         sb.boxplot(data = loan_sub, x='LoanStatus', y='LoanOriginalAmount', palette= 'BuGn')
         plt.title('Loan Status vs Loan Original Amount')
         plt.ylabel('Loan riginal Amounte')
         plt.xlabel('Loan Status')
```

```
Out[81]: Text(0.5,0,'Loan Status')
```

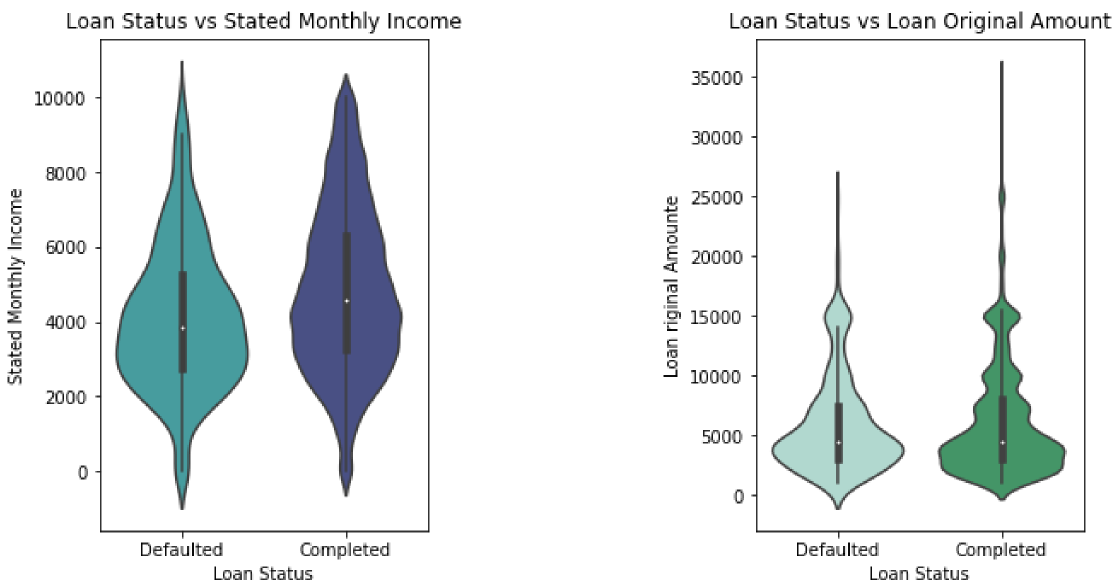



```
In [82]: plt.figure(figsize=[10,5])
```

```
#LoanStatus vs StatedMonthlyIncome - VIOLINPLOT
plt.subplot(1,2,1)
plt.subplots_adjust(left=0.1, bottom=0.1, right=0.9, top=0.9 , wspace=1, hspace=0.2)
sb.violinplot(data = loan_sub, x='LoanStatus', y='StatedMonthlyIncome', palette = 'mako
plt.title('Loan Status vs Stated Monthly Income')
plt.ylabel('Stated Monthly Income')
plt.xlabel('Loan Status')

#LoanStatus vs LoanOriginalAmount - VIOLINPLOT
plt.subplot(1,2,2)
plt.subplots_adjust(left=0.1, bottom=0.1, right=0.9, top=0.9 , wspace=1, hspace=0.2)
sb.violinplot(data = loan_sub, x='LoanStatus', y='LoanOriginalAmount', palette= 'BuGn')
plt.title('Loan Status vs Loan Original Amount')
plt.ylabel('Loan riginal Amounte')
plt.xlabel('Loan Status')
```

Out[82]: Text(0.5,0,'Loan Status')



According to the box plots with Stated Monthly Income, we see that the mean of Completed Loans is slightly higher than the Defaulted, while the original loan amount does not show the differences beetween means of two groups.

According to the violin plots, both groups Completed and Defaulted refer to the Loans with original amount less than 5000 and higher for the Stated monthly Salary between 2000 and 6000.

Loan Status vs Prosper Rating (ql vs ql)

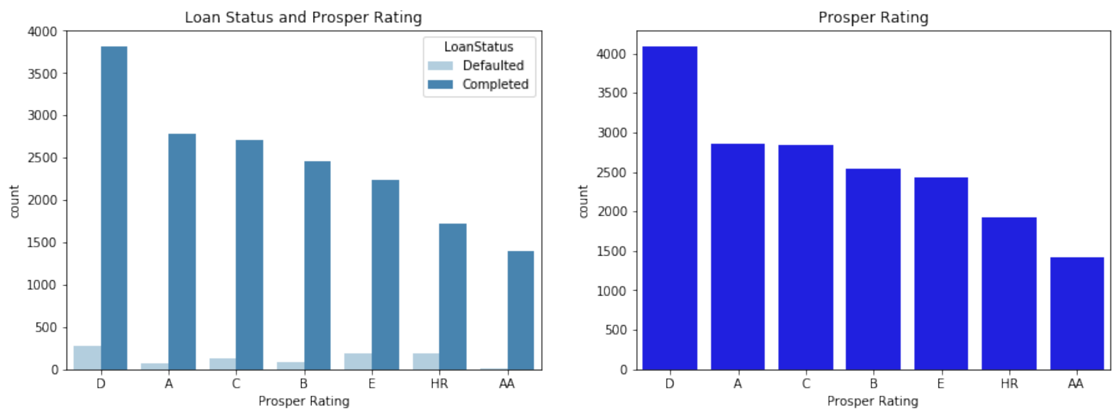
```
In [83]: #LoanStatus vs ProsperRating - COUNTPLOT
         # 0 - N/A, 1 - HR, 2 - E, 3 - D, 4 - C, 5 - B, 6 - A, 7 - AA

         plt.figure(figsize=[15,5])

         plt.subplot(1,2,1)
         order = loan_sub['ProsperRating'].value_counts().index
         sb.countplot(data = loan_sub, x='ProsperRating', hue='LoanStatus', palette= 'Blues', or
         plt.xlabel('Prosper Rating')
         plt.title('Loan Status and Prosper Rating')

         plt.subplot(1,2,2)
         order = loan_sub['ProsperRating'].value_counts().index
         sb.countplot(data = loan_sub, x= 'ProsperRating', order = order, color = 'blue')
         plt.xlabel('Prosper Rating')
         plt.title('Prosper Rating')
```

```
Out[83]: Text(0.5,1,'Prosper Rating')
```

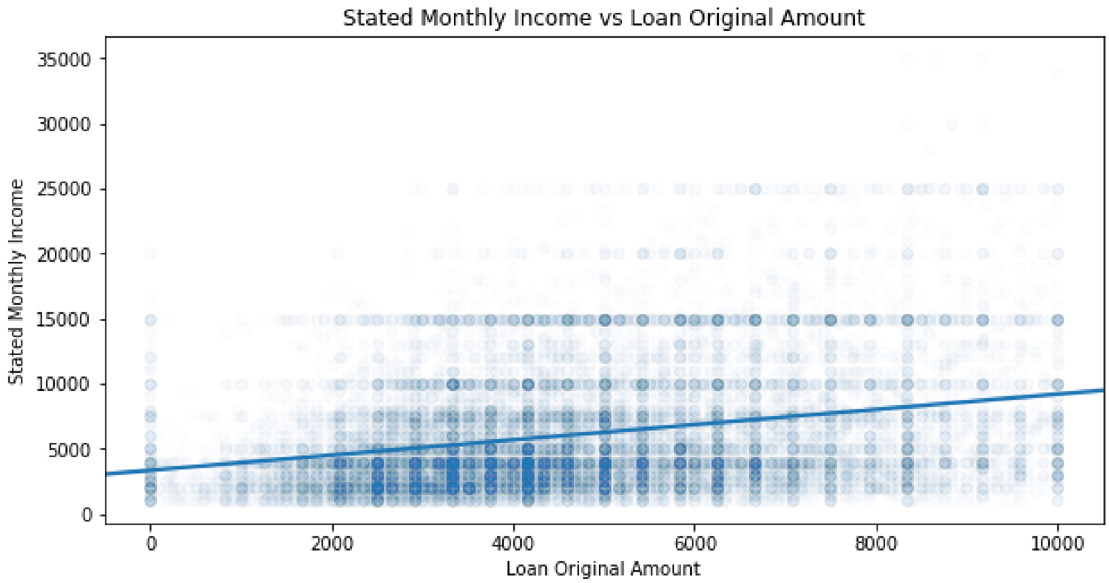


According to the above plots, we can see that only a few borrowers have defaulted loans with a Prosper Rating of AA (lowest risk), while the proportion of defaulted loans in the rating groups HR, E and D (high risk groups) are significantly higher. On the other hand, the highest number of Completed loans also is in the Rating group D.

Stated Monthly Income vs Loan Original Amount (qt vs qt)

```
In [84]: #StatedMonthlyIncome vs LoanOriginalAmount - REGPLOT
         plt.figure(figsize=[10,5])
         sb.regplot(data = loan_sub, x= 'StatedMonthlyIncome', y= 'LoanOriginalAmount', scatter_
         plt.title('Stated Monthly Income vs Loan Original Amount')
         plt.xlabel('Loan Original Amount')
         plt.ylabel('Stated Monthly Income')
```

```
Out[84]: Text(0,0.5,'Stated Monthly Income')
```



The Stated Monthly Income and Loan Original Amount shows a positive correlation.

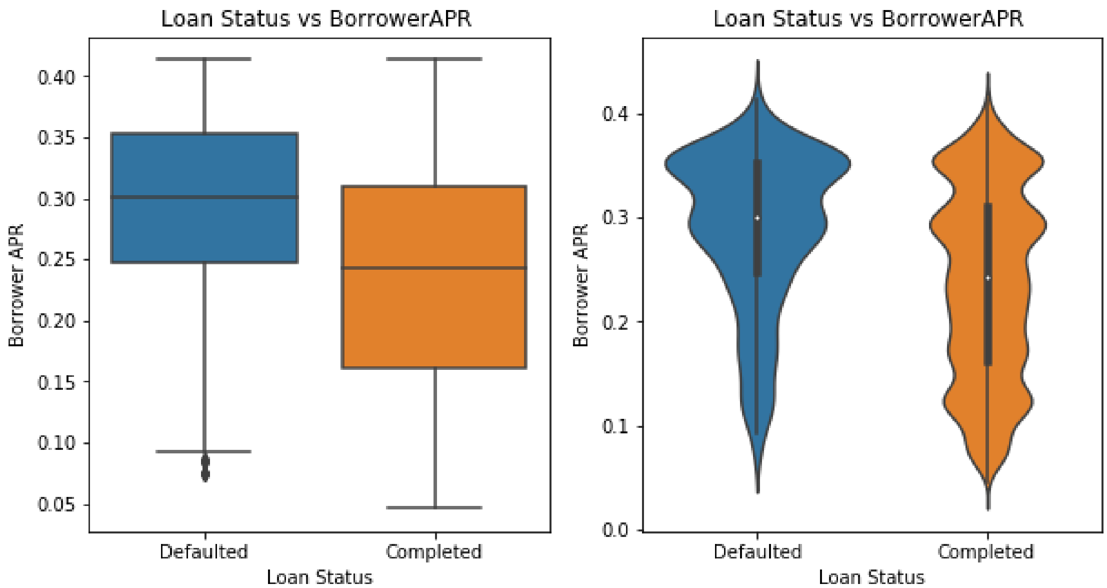
Loan Status and Borrower APR (ql vs qt)

```
In [85]: #LoanStatus vs BorrowerAPR - BOXPLOT and VIOLINPLOT
         plt.figure(figsize=[10,5])

         plt.subplot(1,2,1)
         sb.boxplot(data = loan_sub, x='LoanStatus', y='BorrowerAPR')
         plt.title('Loan Status vs BorrowerAPR ')
         plt.xlabel('Loan Status')
         plt.ylabel('Borrower APR')

         plt.subplot(1,2,2)
         sb.violinplot(data = loan_sub, x='LoanStatus', y='BorrowerAPR')
         plt.title('Loan Status vs BorrowerAPR ')
         plt.xlabel('Loan Status')
         plt.ylabel('Borrower APR')

Out[85]: Text(0,0.5,'Borrower APR')
```



The mean of the Defaulted loans is higher than for the Completed. The most of the loans which were defaulted have Borrower APR higher than 0.25. Conclusively, the higher the Borrower APR, the higher is the possibility for Defaulted loan. On the other hand, from the violinplot we can see that the Completed cases are evenly distributed for the Borrower APR between 0.1 and 0.35 with the mean at 0.25.

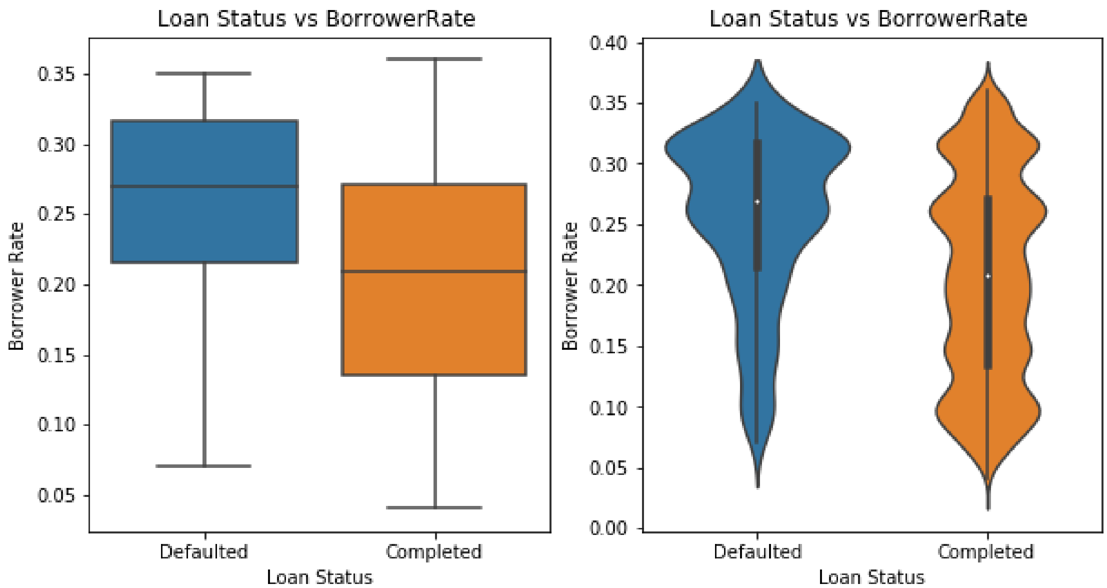
Loan Status and Borrower Rate (ql vs qt)

```
In [86]: #LoanStatus vs BorrowerRate - BOXPLOT and VIOLINPLOT
         plt.figure(figsize=[10,5])

         plt.subplot(1,2,1)
         sb.boxplot(data = loan_sub, x='LoanStatus', y='BorrowerRate')
         plt.title('Loan Status vs BorrowerRate ')
         plt.xlabel('Loan Status')
         plt.ylabel('Borrower Rate')

         plt.subplot(1,2,2)
         sb.violinplot(data = loan_sub, x='LoanStatus', y='BorrowerRate')
         plt.title('Loan Status vs BorrowerRate ')
         plt.xlabel('Loan Status')
         plt.ylabel('Borrower Rate')

Out[86]: Text(0,0.5,'Borrower Rate')
```

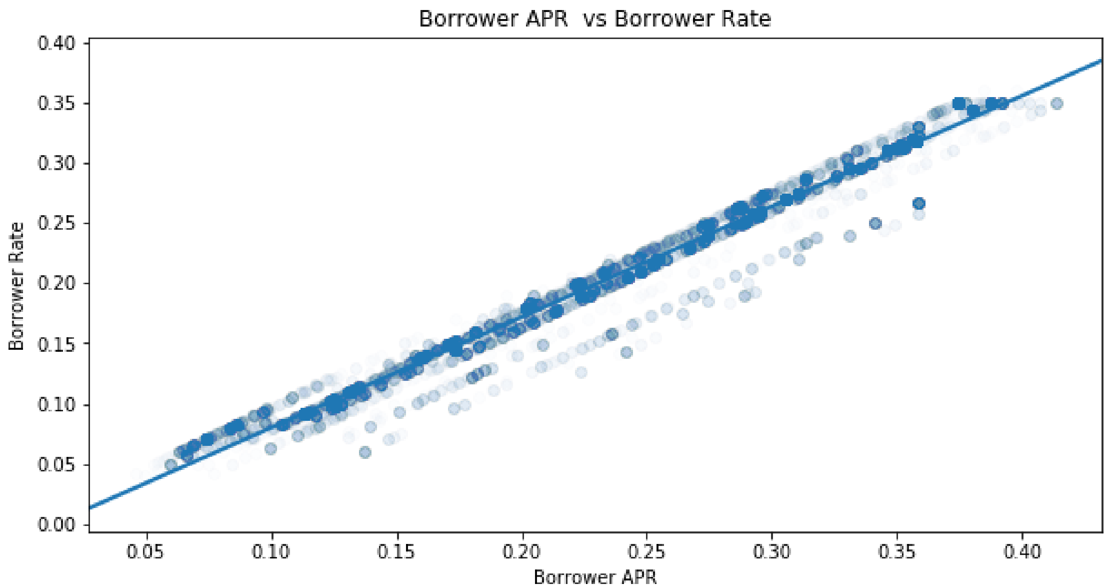


The mean of the Defaulted loans is also higher than for the Completed. The most of the loans which were defaulted have the Borrower rate higher than 0.20. Conclusively, the higher the Borrower Rate, the higher is the possibility for a Defaulted loan. On the other hand, from the violinplot we can see that the Completed cases are also evenly distributed for the Borrower Rate between 0.08 and 0.32 with the mean at 0.21.

Borrower APR and Borrower Rate (qt vs qt)

```
In [87]: # Borrower APR and Borrower Rate - REGPLOT
         plt.figure(figsize=[10,5])
         sb.regplot(data = loan_sub, x= 'BorrowerAPR', y= 'BorrowerRate', scatter_kws={'alpha':0
         plt.title('Borrower APR  vs Borrower Rate')
         plt.xlabel('Borrower APR')
         plt.ylabel('Borrower Rate')

Out[87]: Text(0,0.5,'Borrower Rate')
```



As expected, the Borrower APR and Borrower Rate show a strong positive correlation.

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?

Employment Status does effect the Loan status: the Employed and Full-time statuses cover most of the Completed loans. On the other hand the Post due status for loans also includes the Employed group.

The mean Stated income of loans with status Completed is slightly higher than for the Defaulted.

The original loan amount shows no differences for the mean of two groups: Completed and Defaulted.

Prosper Rating shows effect on the Loan Status: the highest Prosper Rating AA only shows a few defaulted than lower Prosper rating groups. The most of the Completed loans have the rating D.

The higher Borrower APR and/or Borrower Rate, the higher the percentage of the defaulted loans.

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

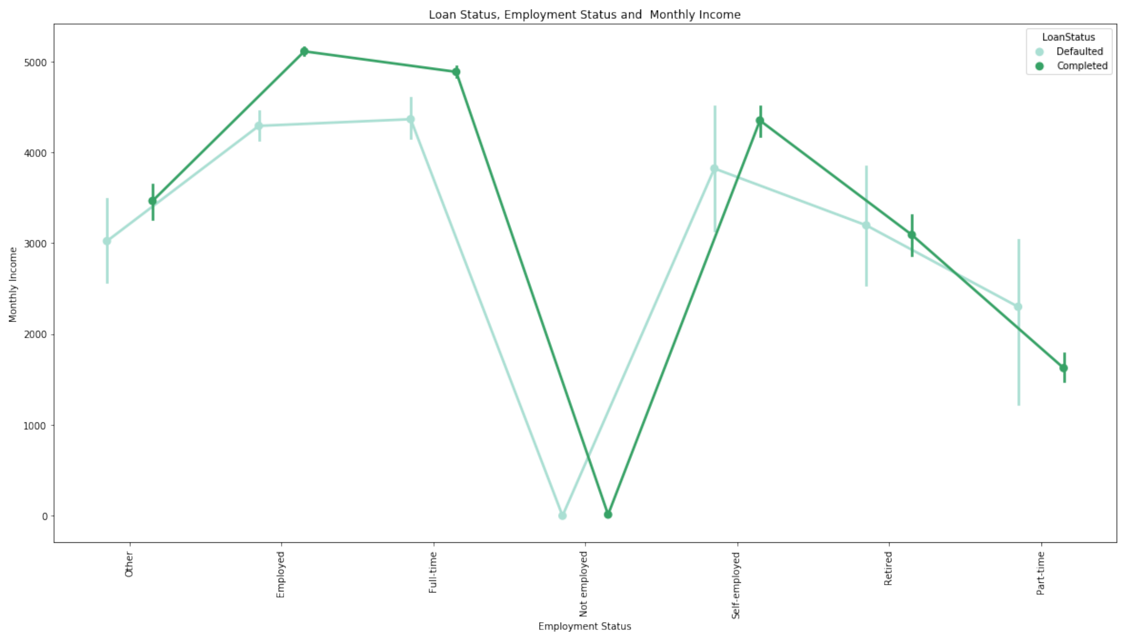
We found a positive correllation between Stated Monthly Income and Loan Original Amount as well as between Borrower APR and Borrower Rate.

1.6 Multivariate Exploration

Loan Status, Employment Status and Stated Monthly Income (ql vs ql vs qt)

```
In [88]: #LoanStatus vs EmploymentStatus vs StatedMonthlyIncome- POINTPLOT
         #https://towardsdatascience.com/data-visualization-using-seaborn-fc24db95a850
         plt.figure(figsize=[20,10])
         sb.pointplot(data = loan_sub, x='EmploymentStatus', y='StatedMonthlyIncome', hue='LoanS
                      dodge=0.3, linestyles= "-", palette = 'BuGn')
         plt.xticks(rotation=90)
         plt.xlabel('Employment Status')
         plt.ylabel('Monthly Income')
         plt.title('Loan Status, Employment Status and  Monthly Income')
```

```
Out[88]: Text(0.5,1,'Loan Status, Employment Status and  Monthly Income')
```

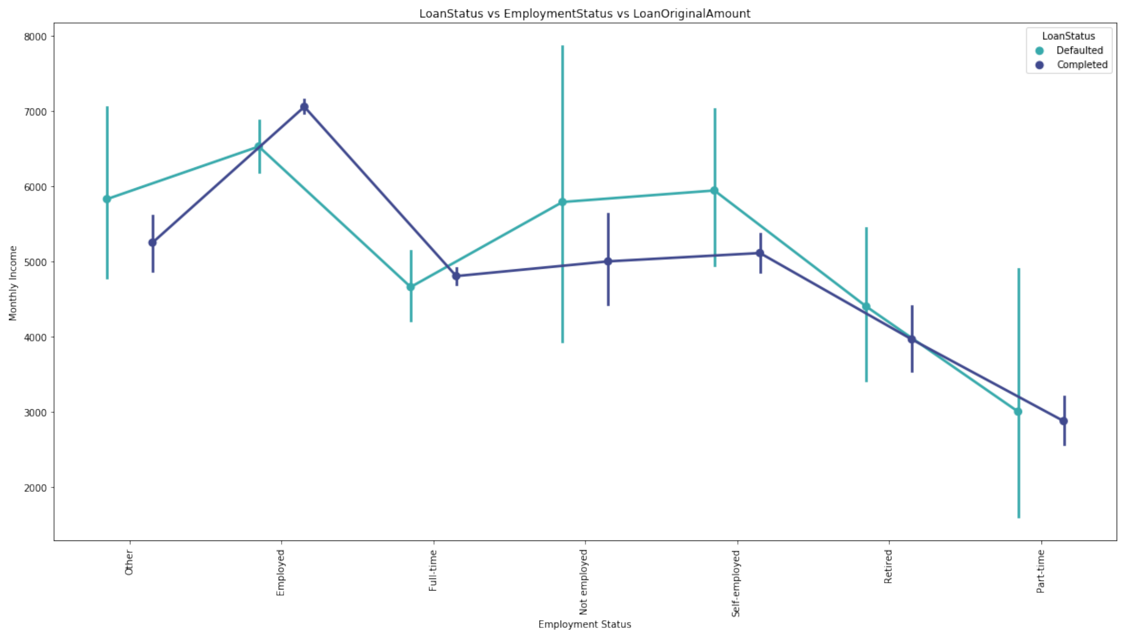


We can see that the top 3 Employment Statuses are Employed, Full-time and Self-Employed show the highest number of Completed as well as Defaulted loans. The data sharply fell for both Completed and Defaulted for the Not Employed which can be explained by that the loans preferably should not be given for unemployed customers.

Loan Status, Employment Status and Loan Original Amount (ql vs qt vs ql)

```
In [89]: #LoanStatus vs EmploymentStatus vs LoanOriginalAmount - POINTPLOT
         plt.figure(figsize=[20,10])
         sb.pointplot(data = loan_sub, x='EmploymentStatus', y='LoanOriginalAmount', hue='LoanSt
         plt.xticks(rotation=90)
         plt.xlabel('Employment Status')
         plt.ylabel('Monthly Income')
         plt.title('LoanStatus vs EmploymentStatus vs LoanOriginalAmount')
```

```
Out[89]: Text(0.5,1,'LoanStatus vs EmploymentStatus vs LoanOriginalAmount')
```

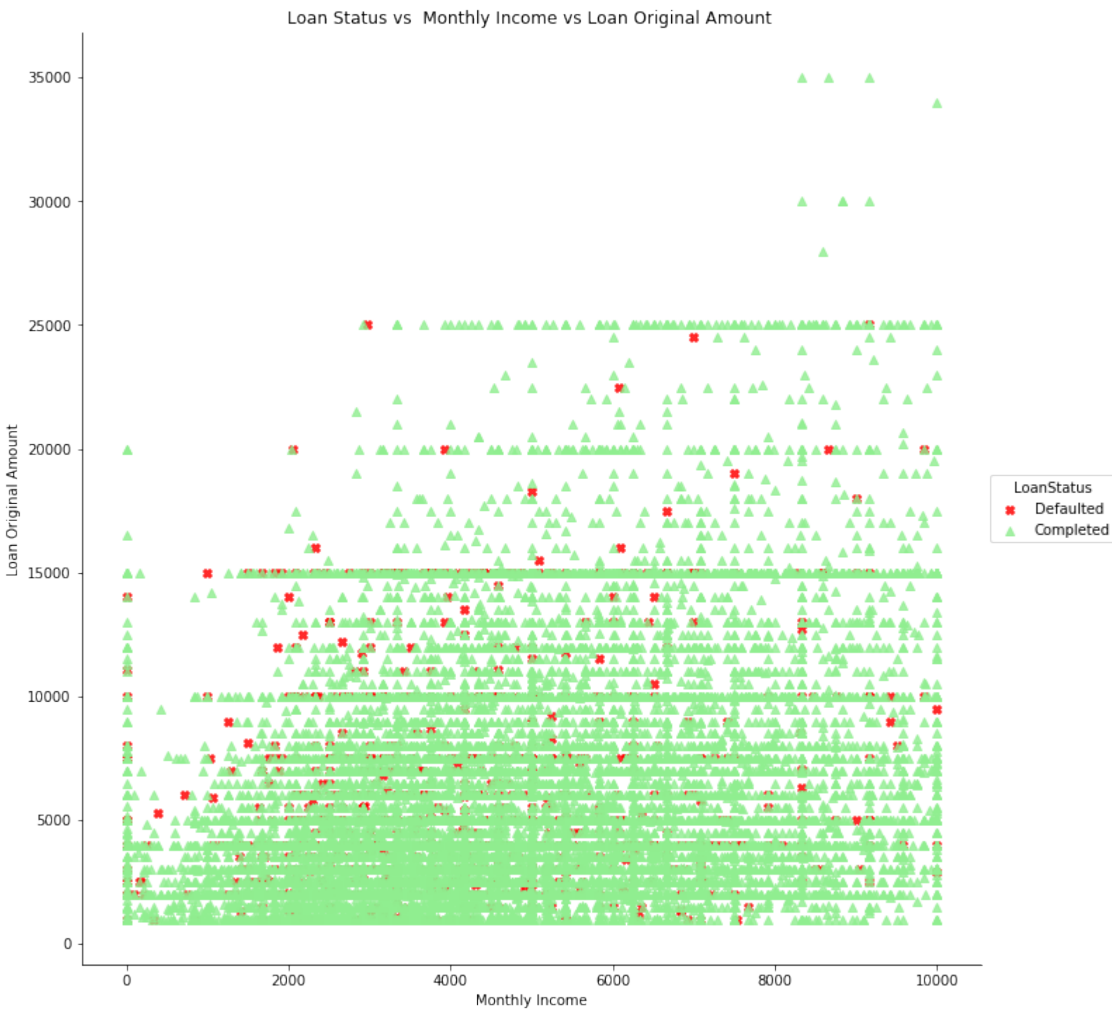


The Employed Status group shows that even with the high Loan original amount as 7000 the loans are completed, while we can observe that for other groups of employments the higher the Loan Amount - the higher the Defaulted cases.

Loan Status, Stated Monthly Income and Loan Original Amount (ql vs qt vs qt)

```
In [90]: #LoanStatus vs StatedMonthlyIncome vs LoanOriginalAmount - LMPLOT
         #https://www.kaggle.com/residentmario/multivariate-plotting
         #https://seaborn.pydata.org/generated/seaborn.lmplot.html
         palette = [ 'r', 'lightgreen']
         sb.lmplot(x='StatedMonthlyIncome', y='LoanOriginalAmount', hue='LoanStatus',
                   data=loan_sub.loc[loan_sub['LoanStatus'].isin(['Completed', 'Defaulted'])],
                   fit_reg=False)
         plt.title('Loan Status vs  Monthly Income vs Loan Original Amount ')
         plt.xlabel('Monthly Income', fontsize=10)
         plt.ylabel('Loan Original Amount', fontsize=10)

Out[90]: Text(28.7235,0.5,'Loan Original Amount')
```



According to the graph above, we can see that the most of the Defaulted loans have less than 15000 Original Loan Amount and less than 7000 Monthly salary. However, the most of the Completed loans are also in the range between 2000 and 5000 monthly Salary and with less than 15000 Loan Amount.

Borrower APR, Stated Monthly Income and Loan Original Amount (qt vs qt vs qt)

In [91]:
```
#Borrower APR vs StatedMonthlyIncome vs LoanOriginalAmount- CORRELATION
#https://seaborn.pydata.org/generated/seaborn.heatmap.html
#https://towardsdatascience.com/formatting-tips-for-correlation-heatmaps-in-seaborn-447
loan_sub_m = loan_sub[["BorrowerAPR", "StatedMonthlyIncome", "LoanOriginalAmount"]]
loan_sub_m.corr()
```

Out[91]:

	BorrowerAPR	StatedMonthlyIncome	LoanOriginalAmount
BorrowerAPR	1.000000	-0.177891	-0.247856
StatedMonthlyIncome	-0.177891	1.000000	0.279661
LoanOriginalAmount	-0.247856	0.279661	1.000000

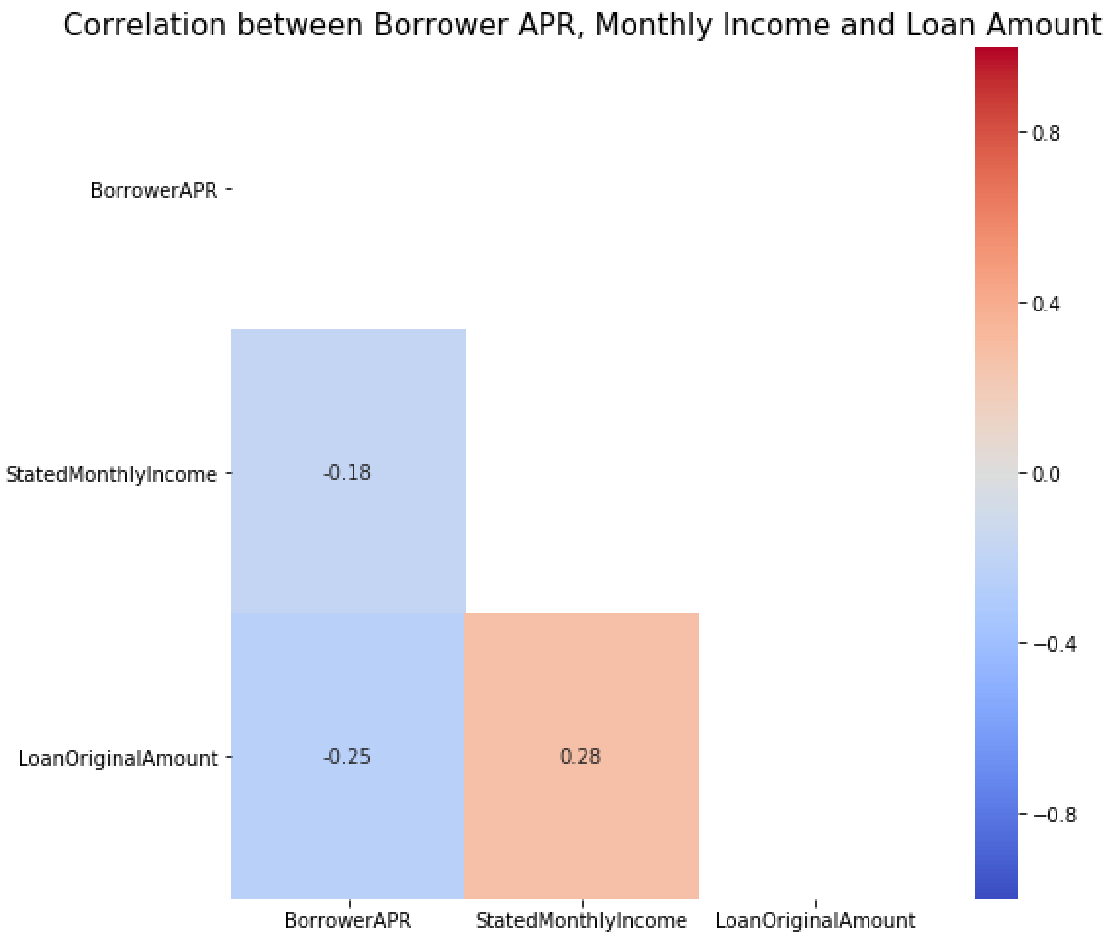
```
In [92]: #Borrower APR vs StatedMonthlyIncome vs LoanOriginalAmount- HEATMAP
         plt.figure(figsize=[8,8])

         mask = np.zeros(loan_sub_m.corr().shape, dtype=bool)
         mask[np.triu_indices(len(mask))] = True

         sb.heatmap(loan_sub_m.corr(), annot=True,cmap='coolwarm', vmin = -1, vmax = 1, center =
         plt.title('Correlation between Borrower APR, Monthly Income and Loan Amount', fontsize=

         plt.yticks(rotation = 0)
```

```
Out[92]: (array([ 0.5,  1.5,  2.5]), <a list of 3 Text yticklabel objects>)
```

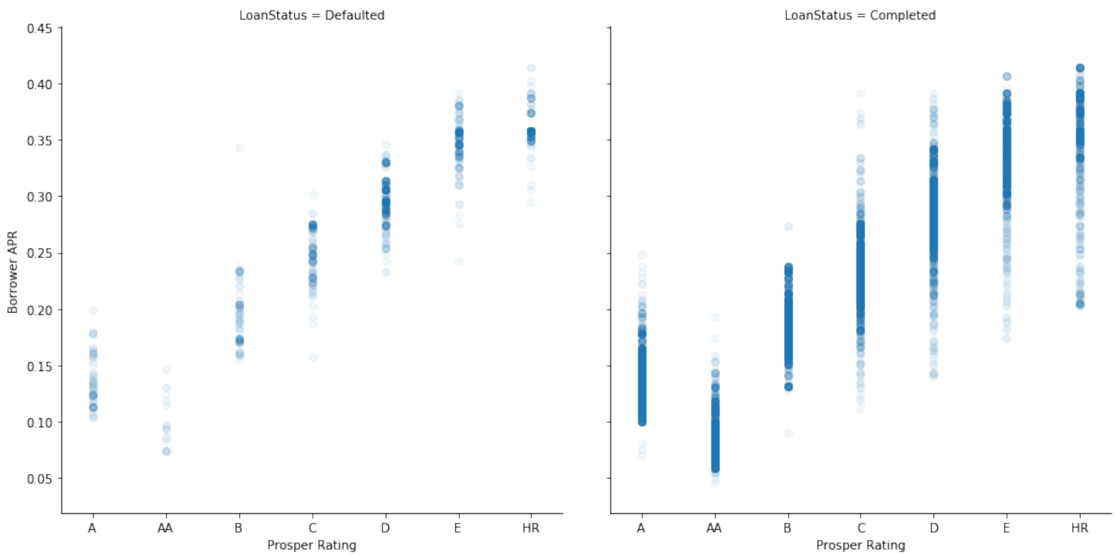


There is a negative correlation of -0.25 between "BorrowerAPR" and "Loan original amount" and -0.18 between "BorrowerAPR" and "StatedMonthlyIncome".

As we have also seen from Bivariate Exploratrion, "Loan original amount" and "StatedMonthlyIncome" have a positive correlation which is 0.28.

Loan Status, ProsperRating and Borrower APR (ql vs ql vs qt)

In [93]:
```
#LoanStatus vs ProsperRating (Alpha) vs Borrower APR - FACETGRID
#https://towardsdatascience.coxm/data-visualization-using-seaborn-fc24db95a850
#https://seaborn.pydata.org/generated/seaborn.FacetGrid.html
g = sb.FacetGrid(data=loan_sub, col='LoanStatus', col_wrap=3)
g = (g.map_dataframe(plt.scatter, 'ProsperRating','BorrowerAPR' ,  alpha=0.05).set_axis
g.fig.set_size_inches(20,8)
```



According to the graphs above, there are less Defaulted cases for the Prosper Rating AA with the Borrower APR around 0.1. We also can observe for the Rating HR - the highest risk - that nevertheless the most of the loans are Completed, there are few Defaulted

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?

The top 3 Employment Statuses are Employed, Full-time and Self-Employed which show the highest number of Completed.

The most of the Defaulted loans are those with the Original Loan Amount less than 15000 and with the Stated Monthly Salary less than 7000.

The most of the Completed loans are also in the range between 2000 and 5000 monthly Salary and with less than 15000 Loan Amount.

We also can see that "Loan original amount" and "StatedMonthlyIncome" have a positive correlation which is 0.28.

There is a negative correlation of -0.25 between "BorrowerAPR" and "Loan original amount" and -0.18 between "BorrowerAPR" and "StatedMonthlyIncome".

There are less Defaulted cases for the Prosper Rating AA with the Borrower APR around 0.1. The most popular Prosper Rating is D which include also most of the Completed loans.

1.6.2 Were there any interesting or surprising interactions between features?

From the top 3 Employed Statuses, there are more Defaulted loans for the Self-employed.

For the Rating HR - the highest risk - we also can observe that nevertheless the most of the loans are Completed, there are a few Defaulted cases.

References:

1. https://towardsdatascience.com/introduction-to-data-visualization-in-python-89a54c97fbed

2. https://towardsdatascience.com/formatting-tips-for-correlation-heatmaps-in-seaborn-4478ef15d87f
3. https://www.lendacademy.com/prosper-review/
4. https://towardsdatascience.com/ways-to-detect-and-remove-the-outliers-404d16608dba
5. https://seaborn.pydata.org/generated/seaborn.heatmap.html
6. https://towardsdatascience.coxm/data-visualization-using-seaborn-fc24db95a850
7. https://seaborn.pydata.org/generated/seaborn.FacetGrid.html
8. https://www.kaggle.com/residentmario/multivariate-plotting
9. https://seaborn.pydata.org/generated/seaborn.lmplot.html


```
In [ ]:
```