Capstone Project- GROUP 5

Loan Default Prediction using Machine Learning Techniques

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In [1]:
```
# # This Python 3 environment comes with many helpful analytics libraries installed
# # It is defined by the kaggle/python Docker image: https://github.com/kaggle/docker-python
# # For example, here's several helpful packages to load

# import numpy as np # linear algebra
# import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)

# # Input data files are available in the read-only "../input/" directory
# # For example, running this (by clicking run or pressing Shift+Enter) will list all files under the
input directory

# import os
# for dirname, _, filenames in os.walk('/kaggle/input'):
#     for filename in filenames:
#         print(os.path.join(dirname, filename))

# # You can write up to 20GB to the current directory (/kaggle/working/) that gets preserved as outpu
t when you create a version using "Save & Run All"
# # You can also write temporary files to /kaggle/temp/, but they won't be saved outside of the curre
nt session
```

In [2]:
```
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
import seaborn as sns
%matplotlib inline
from warnings import filterwarnings
filterwarnings('ignore')
```

In [3]:
```
pd.set_option("display.max_columns",None)
```

In [5]:
```
df=pd.read_csv('prosperLoanData.csv')
```

In [6]:
```
df.head()
```

Out[6]:

	ListingKey	ListingNumber	ListingCreationDate	CreditGrade	Term	LoanStatus	ClosedDate	BorrowerAPR
0	1021339766868145413AB3B	193129	2007-08-26 19:09:29.263000000	C	36	Completed	2009-08-14 00:00:00	0.16516
1	10273602499503308B223C1	1209647	2014-02-27 08:28:07.900000000	NaN	36	Current	NaN	0.12016
2	0EE9337825851032864889A	81716	2007-01-05 15:00:47.090000000	HR	36	Completed	2009-12-17 00:00:00	0.28269
3	0EF5356002482715299901A	658116	2012-10-22 11:02:35.010000000	NaN	36	Current	NaN	0.12528
4	0F023589499656230C5E3E2	909464	2013-09-14 18:38:39.097000000	NaN	36	Current	NaN	0.24614

In [7]:
```
df.shape
```

Out[7]:
```
(113937, 81)
```

There are 113937 rows and 81 columns in these dataset.

In [8]:
```
df.dtypes
```

Out[8]:
```
ListingKey                      object
ListingNumber                    int64
ListingCreationDate             object
CreditGrade                     object
Term                             int64
                                 ...
PercentFunded                  float64
Recommendations                  int64
InvestmentFromFriendsCount       int64
InvestmentFromFriendsAmount    float64
Investors                        int64
Length: 81, dtype: object
```

In [9]:
```
df.describe()
```

Out[9]:

	ListingNumber	Term	BorrowerAPR	BorrowerRate	LenderYield	EstimatedEffectiveYield	EstimatedLoss	E:
count	1.139370e+05	113937.000000	113912.000000	113937.000000	113937.000000	84853.000000	84853.000000	
mean	6.278857e+05	40.830248	0.218828	0.192764	0.182701	0.168661	0.080306	
std	3.280762e+05	10.436212	0.080364	0.074818	0.074516	0.068467	0.046764	
min	4.000000e+00	12.000000	0.006530	0.000000	-0.010000	-0.182700	0.004900	
25%	4.009190e+05	36.000000	0.156290	0.134000	0.124200	0.115670	0.042400	
50%	6.005540e+05	36.000000	0.209760	0.184000	0.173000	0.161500	0.072400	
75%	8.926340e+05	36.000000	0.283810	0.250000	0.240000	0.224300	0.112000	
max	1.255725e+06	60.000000	0.512290	0.497500	0.492500	0.319900	0.366000	

In [10]:
```
# Duplicates data entry in loan data
df.duplicated().sum()
```

Out[10]:
```
0
```

There is no redundant values in the dataset.

In [11]:
```
df.isnull().sum().sum()
```

Out[11]:
```
1364086
```

In [12]:
```
df.isnull().sum()
```

Out[12]:
```
ListingKey                        0
ListingNumber                     0
ListingCreationDate               0
CreditGrade                   84984
Term                              0
                              ...
PercentFunded                     0
Recommendations                   0
InvestmentFromFriendsCount        0
InvestmentFromFriendsAmount       0
Investors                         0
Length: 81, dtype: int64
```

In [13]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 113937 entries, 0 to 113936
Data columns (total 81 columns):
 #   Column                               Non-Null Count   Dtype  
---  ------                               --------------   -----  
 0   ListingKey                           113937 non-null  object 
 1   ListingNumber                        113937 non-null  int64  
 2   ListingCreationDate                  113937 non-null  object 
 3   CreditGrade                          28953 non-null   object 
 4   Term                                 113937 non-null  int64  
 5   LoanStatus                           113937 non-null  object 
 6   ClosedDate                           55089 non-null   object 
 7   BorrowerAPR                          113912 non-null  float64
 8   BorrowerRate                         113937 non-null  float64
 9   LenderYield                          113937 non-null  float64
 10  EstimatedEffectiveYield              84853 non-null   float64
 11  EstimatedLoss                        84853 non-null   float64
 12  EstimatedReturn                      84853 non-null   float64
 13  ProsperRating (numeric)              84853 non-null   float64
 14  ProsperRating (Alpha)                84853 non-null   object 
 15  ProsperScore                         84853 non-null   float64
 16  ListingCategory (numeric)            113937 non-null  int64  
 17  BorrowerState                        108422 non-null  object 
 18  Occupation                           110349 non-null  object 
 19  EmploymentStatus                     111682 non-null  object 
 20  EmploymentStatusDuration             106312 non-null  float64
 21  IsBorrowerHomeowner                  113937 non-null  bool   
 22  CurrentlyInGroup                     113937 non-null  bool   
 23  GroupKey                             13341 non-null   object 
 24  DateCreditPulled                     113937 non-null  object 
 25  CreditScoreRangeLower                113346 non-null  float64
 26  CreditScoreRangeUpper                113346 non-null  float64
 27  FirstRecordedCreditLine              113240 non-null  object 
 28  CurrentCreditLines                   106333 non-null  float64
 29  OpenCreditLines                      106333 non-null  float64
 30  TotalCreditLinespast7years           113240 non-null  float64
 31  OpenRevolvingAccounts                113937 non-null  int64  
 32  OpenRevolvingMonthlyPayment          113937 non-null  float64
 33  InquiriesLast6Months                 113240 non-null  float64
 34  TotalInquiries                       112778 non-null  float64
 35  CurrentDelinquencies                 113240 non-null  float64
 36  AmountDelinquent                     106315 non-null  float64
 37  DelinquenciesLast7Years              112947 non-null  float64
 38  PublicRecordsLast10Years             113240 non-null  float64
 39  PublicRecordsLast12Months            106333 non-null  float64
 40  RevolvingCreditBalance               106333 non-null  float64
 41  BankcardUtilization                  106333 non-null  float64
 42  AvailableBankcardCredit              106393 non-null  float64
 43  TotalTrades                          106393 non-null  float64
 44  TradesNeverDelinquent (percentage)   106393 non-null  float64
 45  TradesOpenedLast6Months              106393 non-null  float64
 46  DebtToIncomeRatio                    105383 non-null  float64
 47  IncomeRange                          113937 non-null  object 
 48  IncomeVerifiable                     113937 non-null  bool   
 49  StatedMonthlyIncome                  113937 non-null  float64
 50  LoanKey                              113937 non-null  object 
 51  TotalProsperLoans                    22085 non-null   float64
 52  TotalProsperPaymentsBilled           22085 non-null   float64
 53  OnTimeProsperPayments                22085 non-null   float64
 54  ProsperPaymentsLessThanOneMonthLate  22085 non-null   float64
 55  ProsperPaymentsOneMonthPlusLate      22085 non-null   float64
 56  ProsperPrincipalBorrowed             22085 non-null   float64
 57  ProsperPrincipalOutstanding          22085 non-null   float64
 58  ScorexChangeAtTimeOfListing          18928 non-null   float64
 59  LoanCurrentDaysDelinquent            113937 non-null  int64  
 60  LoanFirstDefaultedCycleNumber        16952 non-null   float64
 61  LoanMonthsSinceOrigination           113937 non-null  int64  
 62  LoanNumber                           113937 non-null  int64  
 63  LoanOriginalAmount                   113937 non-null  int64  
 64  LoanOriginationDate                  113937 non-null  object 
```

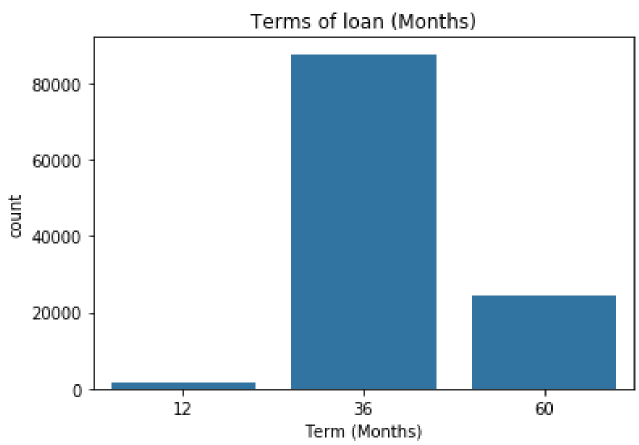
```
 65  LoanOriginationQuarter               113937 non-null  object
 66  MemberKey                            113937 non-null  object
 67  MonthlyLoanPayment                   113937 non-null  float64
 68  LP_CustomerPayments                  113937 non-null  float64
 69  LP_CustomerPrincipalPayments         113937 non-null  float64
 70  LP_InterestandFees                   113937 non-null  float64
 71  LP_ServiceFees                       113937 non-null  float64
 72  LP_CollectionFees                    113937 non-null  float64
 73  LP_GrossPrincipalLoss                113937 non-null  float64
 74  LP_NetPrincipalLoss                  113937 non-null  float64
 75  LP_NonPrincipalRecoverypayments      113937 non-null  float64
 76  PercentFunded                        113937 non-null  float64
 77  Recommendations                      113937 non-null  int64
 78  InvestmentFromFriendsCount           113937 non-null  int64
 79  InvestmentFromFriendsAmount          113937 non-null  float64
 80  Investors                            113937 non-null  int64
dtypes: bool(3), float64(50), int64(11), object(17)
memory usage: 68.1+ MB
```

In [14]:
```
df['LoanOriginationDate'] = pd.to_datetime(df['LoanOriginationDate'])
```

In [15]:
```
df_loan = df.copy()
```

In [16]:
```
## Univariate Data Analysis
```

In [17]:
```
# Loan by term
base_color = sns.color_palette()[0]
sns.countplot(data=df_loan,x= 'Term',color=base_color);
plt.title('Terms of loan (Months)')
plt.xlabel('Term (Months)');
```



Most common term of loans is 36 months

In [18]:
```
type_count = df_loan['LoanStatus'].value_counts()
type_order = type_count.index
```

In [19]:
```
# Count of Loan by Loan Status
n_loan =df_loan.shape[0]
max_type_count = type_count[0]
max_prop = max_type_count/n_loan
```

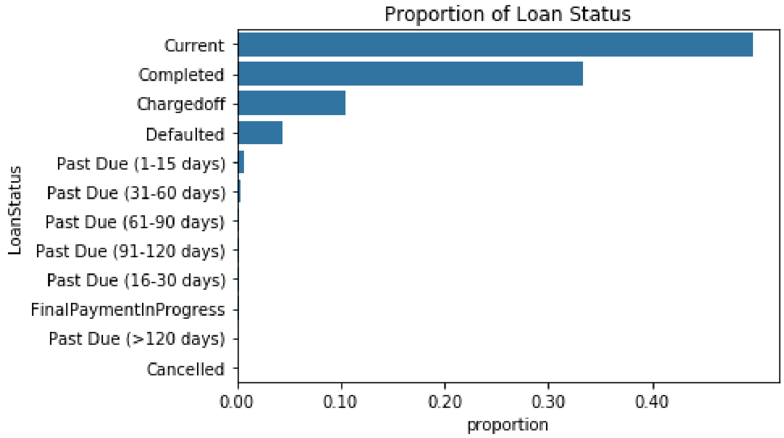
In [20]:
```
tick_props = np.arange(0,max_prop,0.1)
tick_names = ['{:0.2f}'.format(v) for v in tick_props]
```

In [21]:
```
tick_names
```

Out[21]:
```
['0.00', '0.10', '0.20', '0.30', '0.40']
```

In [22]:
```
sns.countplot(data=df_loan,y='LoanStatus',color=base_color,order=type_order);
plt.xticks(tick_props*n_loan,tick_names)
plt.xlabel('proportion');
plt.title('Proportion of Loan Status')
```

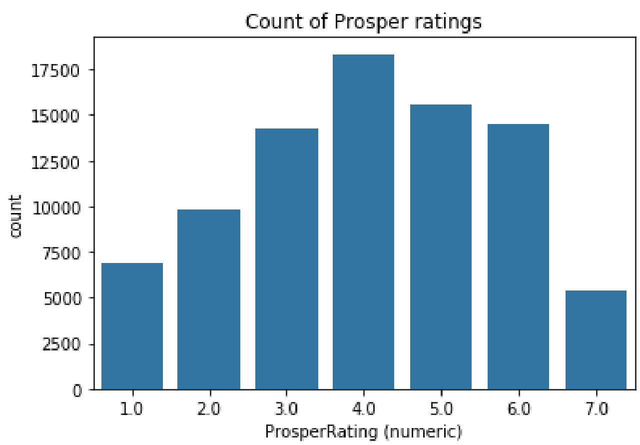
Out[22]:
```
Text(0.5, 1.0, 'Proportion of Loan Status')
```



Around 25% of total loan are completed but still majority of loans are in currentor pending state(around 80%)

In [23]:
```
# Distribution of Prosper rating
sns.countplot(data=df_loan,x='ProsperRating (numeric)',color=base_color);
plt.title('Count of Prosper ratings')
```

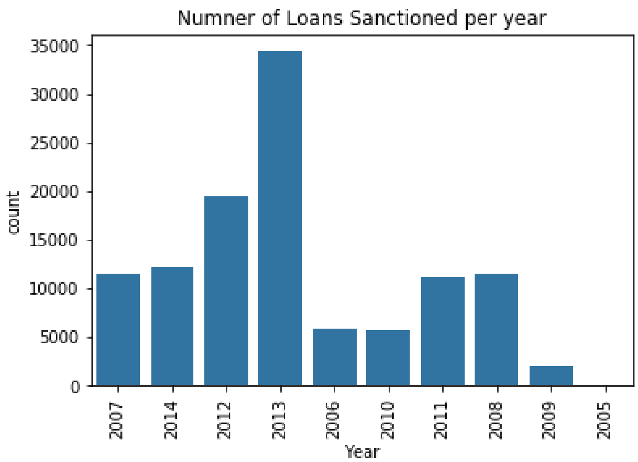
Out[23]:
```
Text(0.5, 1.0, 'Count of Prosper ratings')
```



Most of borrowers has got 4 prosper ratings that means most of borrowers has risk associated on the higher end

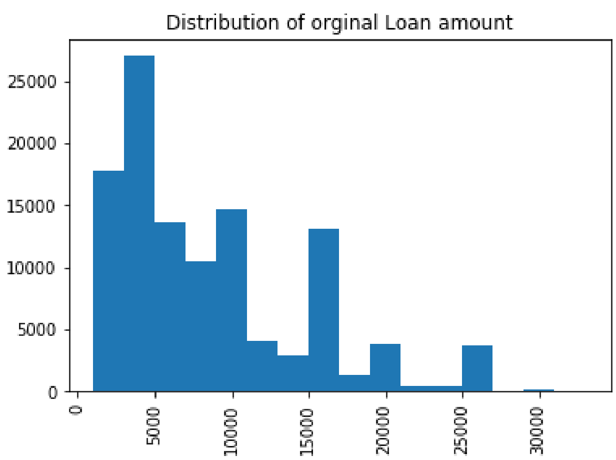
In [24]:
```
df_loan['Year'] = df_loan['LoanOriginationQuarter'].str[-4:]
```

In [25]:
```
# Number of loans per year
sns.countplot(data=df_loan,x='Year',color=base_color);
plt.title('Numner of Loans Sanctioned per year')
plt.xticks(rotation=90);
```

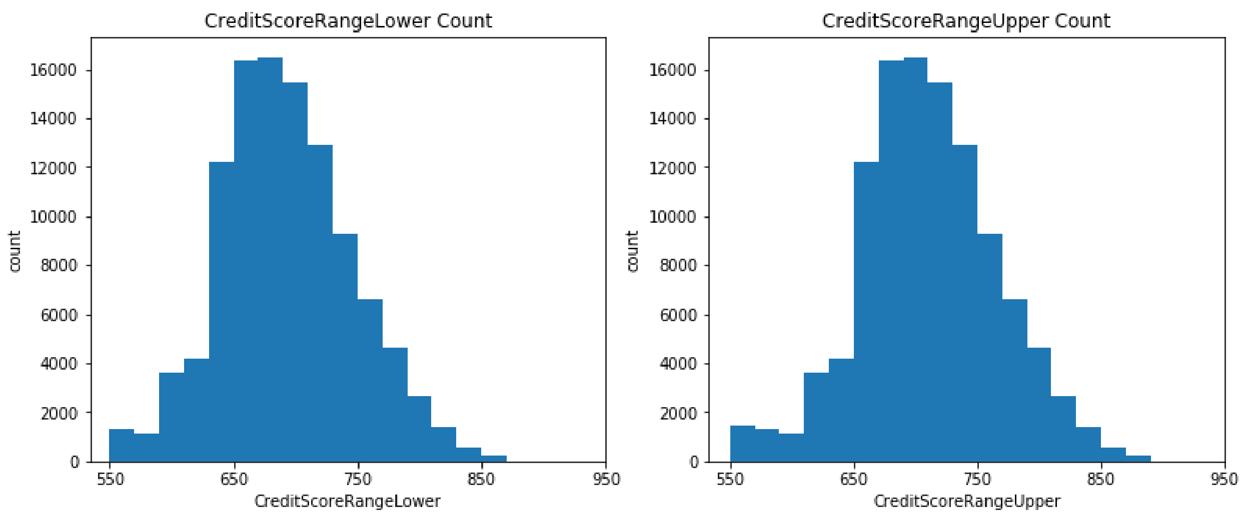


In 2009 there was lowest number of loans sanctioned whereas 2013 has got highest number of loans sanctioned

In [26]:
```
# Distribution of orginal Loan amount
bins = np.arange(1000,35000,2000)
plt.hist(data=df_loan,x='LoanOriginalAmount',color=base_color,bins=bins);
plt.title('Distribution of orginal Loan amount')
plt.xticks(rotation=90);
```

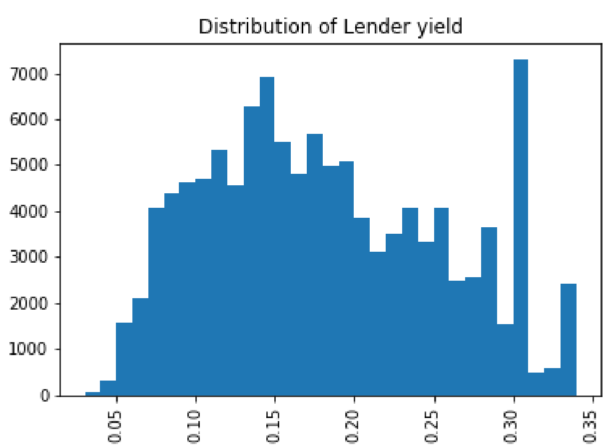


In [27]:
```
# Histogram for Credit Score ranges

plt.figure(figsize = [13, 5])


plt.subplot(1, 2, 1)
bins = np.arange(550, df_loan['CreditScoreRangeLower'].max(), 20)
plt.hist(data = df_loan, x = 'CreditScoreRangeLower', bins = bins)
plt.xticks(np.arange(550, 1000, 100))
plt.title('CreditScoreRangeLower Count')
plt.xlabel('CreditScoreRangeLower')
plt.ylabel('count');

plt.subplot(1, 2, 2)
bins = np.arange(550, df_loan['CreditScoreRangeUpper'].max(), 20)
plt.hist(data = df_loan, x = 'CreditScoreRangeUpper', bins = bins)
plt.xticks(np.arange(550, 1000, 100))
plt.title('CreditScoreRangeUpper Count')
plt.xlabel('CreditScoreRangeUpper')
plt.ylabel('count');
```



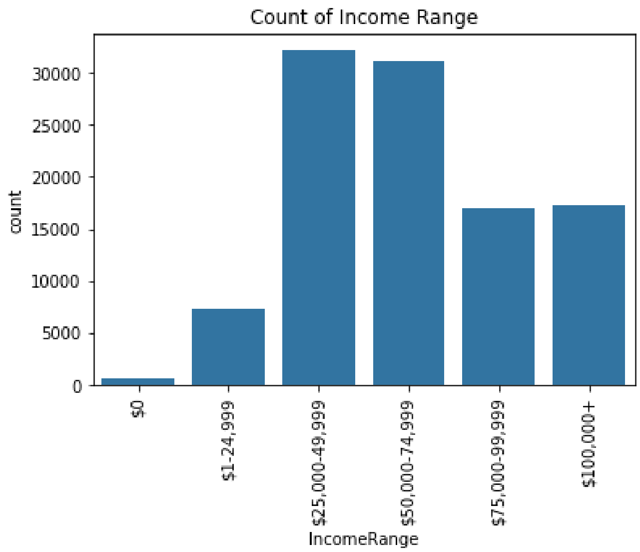
These two histograms shows similar trend. As both the upper and lower score are ranges of credit score

In [28]:
```
# Distribution of Lender yield
bins = np.arange(.03,.34,.01)
plt.hist(data=df_loan,x='LenderYield',color=base_color,bins=bins);
plt.title('Distribution of Lender yield')
plt.xticks(rotation=90);
```



Data is positively skewed, suggests that for investors got good yield for loans. Data is spiked at 34%.

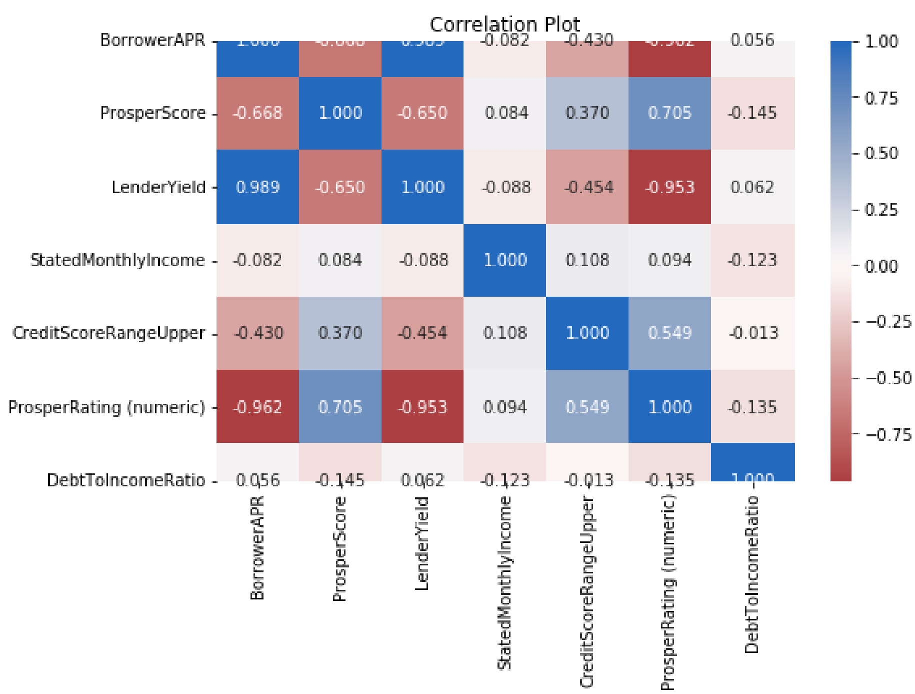
In [29]:
```
# Income range of borrower
order = ['$0','$1-24,999','$25,000-49,999','$50,000-74,999','$75,000-99,999','$100,000+']
sns.countplot(data=df_loan,x='IncomeRange',color=base_color,order=order);
plt.title('Count of Income Range')
plt.xticks(rotation=90);
```



more borrowers has income in the this range $25000-49,999

In [30]:
```
## Bivariate Data Analysis
```

In [31]:
```
# correlation plot

num_vars = ['BorrowerAPR', 'ProsperScore', 'LenderYield',
            'StatedMonthlyIncome',  'CreditScoreRangeUpper','ProsperRating (numeric)','DebtToIncomeRa
tio']
plt.figure(figsize = [8, 5])
sns.heatmap(df_loan[num_vars].corr(), annot = True, fmt = '.3f',
           cmap = 'vlag_r', center = 0)
plt.title('Correlation Plot')
plt.show()
```



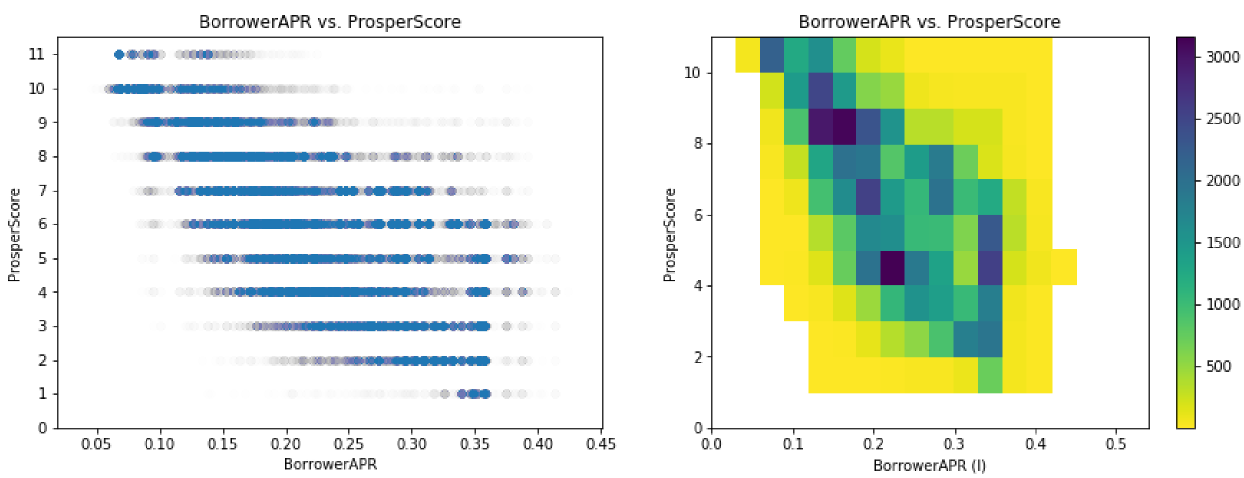
Strong positive correlations between Lender yield and Borrower APR. prosper score and prosper rating are also positive correlation .Credit score upper range has also some weak +ve correlation with prosper score. Negative correlation between prosper score & APR, and prosper

score & Lender yield. Negative correlation between prosper ratings & APR, and prosper score & Lender yield.

In [32]:
```
# plot matrix: only 300 random loans are used to see the pattern more clearer

# sns.pairplot(df_loan)
```

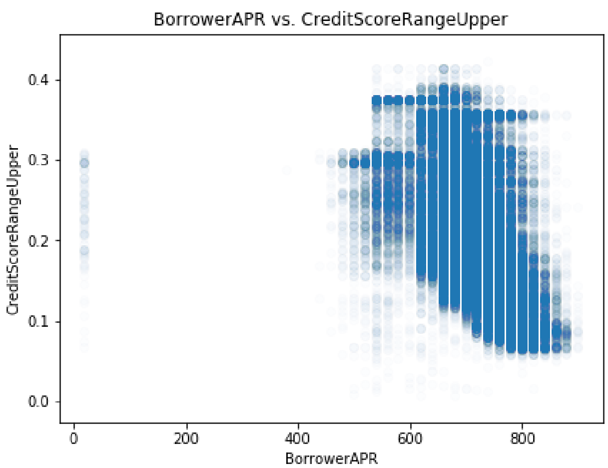
Borrower APR is negatively related with prosper score and credit upper score. However borrower APR and lending yield are postively correlated as higher the APR will be, higher will be yield for lender. Prosper score is negatively related with Borrower APR and lender yield Debt To Income Ratio and Monthly income is not seems to be related with any variable.

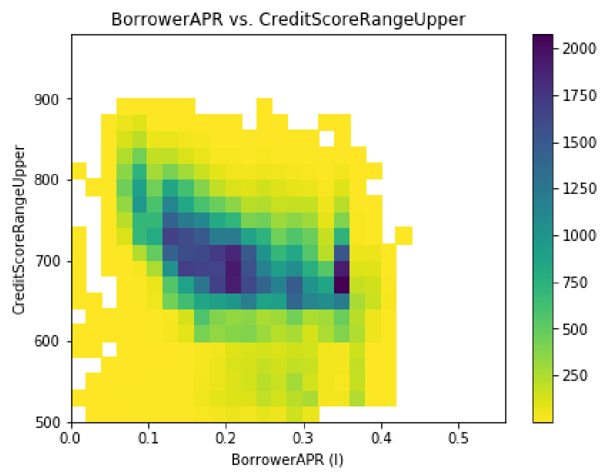
In [33]:
```
# scatter and heat plot for comparing ProsperScore and BorrowerAPR.
plt.figure(figsize = [15, 5])

plt.subplot(1, 2, 1)
plt.scatter(data = df_loan, x = 'BorrowerAPR', y = 'ProsperScore', alpha =  0.005)
plt.yticks(np.arange(0, 12, 1))
plt.title('BorrowerAPR vs. ProsperScore')
plt.xlabel('BorrowerAPR')
plt.ylabel('ProsperScore')


plt.subplot(1, 2, 2)
bins_x = np.arange(0, df_loan['BorrowerAPR'].max()+0.05, 0.03)
bins_y = np.arange(0, df_loan['ProsperScore'].max()+1, 1)
plt.hist2d(data = df_loan, x = 'BorrowerAPR', y = 'ProsperScore', bins = [bins_x, bins_y],
               cmap = 'viridis_r', cmin = 0.5)
plt.colorbar()
plt.title('BorrowerAPR vs. ProsperScore')
plt.xlabel('BorrowerAPR (l)')
plt.ylabel('ProsperScore');
```



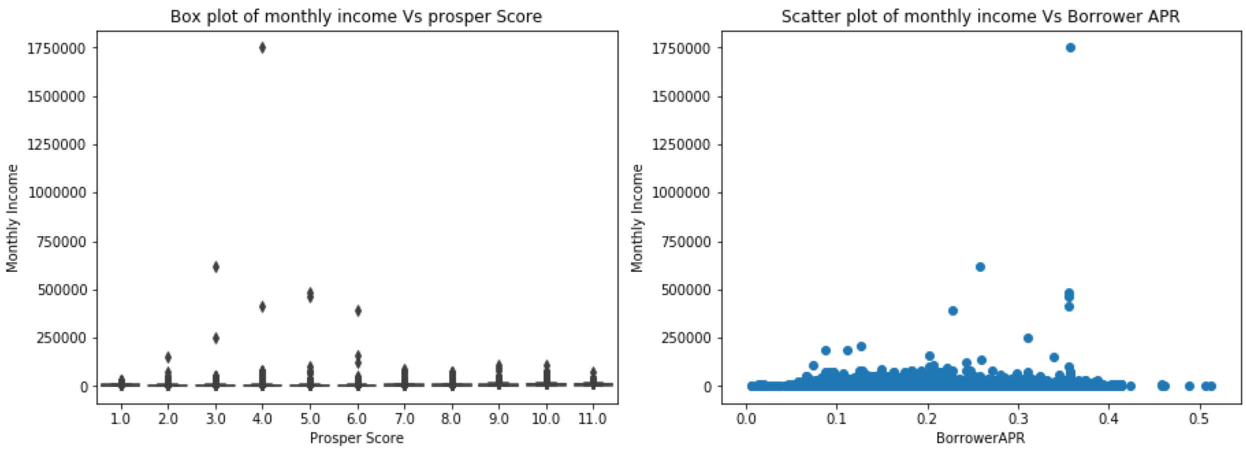
Here the relationship is evident, higher the prosper score is lower is Borrower APR and this makes sense because lower the risk attached with the borrower lower will be the APR.

In [34]:
```
# scatter and heat plot for comparing BorrowerAPR and credit score upper range.
plt.figure(figsize = [15, 5])

plt.subplot(1, 2, 1)
plt.scatter(data = df_loan, x = 'CreditScoreRangeUpper', y = 'BorrowerAPR', alpha = 0.01)
plt.title('BorrowerAPR vs. CreditScoreRangeUpper')
plt.xlabel('BorrowerAPR')
plt.ylabel('CreditScoreRangeUpper');


plt.subplot(1, 2, 2)
bins_x = np.arange(0, df_loan['BorrowerAPR'].max()+0.05, 0.02)
bins_y = np.arange(500, df_loan['CreditScoreRangeUpper'].max()+100, 20)
plt.hist2d(data = df_loan, x = 'BorrowerAPR', y = 'CreditScoreRangeUpper', bins = [bins_x, bins_y],
               cmap = 'viridis_r', cmin = 0.5)

plt.colorbar()
plt.title('BorrowerAPR vs. CreditScoreRangeUpper')
plt.xlabel('BorrowerAPR (l)')
plt.ylabel('CreditScoreRangeUpper');
```

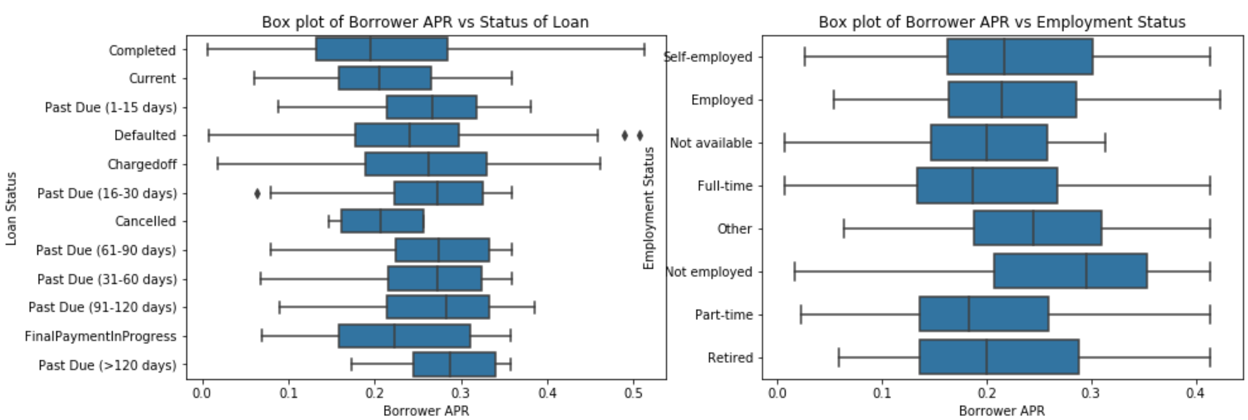




In [35]:
```
# Stated MonthlyIncome vs Prosper Rating
plt.figure(figsize = [15, 5])

plt.subplot(1, 2, 1)
sns.boxplot(data=df_loan,x='ProsperScore',y='StatedMonthlyIncome',color=base_color);
plt.xlabel('Prosper Score');
plt.ylabel('Monthly Income');
plt.title('Box plot of monthly income Vs prosper Score');

plt.subplot(1, 2, 2)
plt.scatter(data=df_loan,x='BorrowerAPR',y='StatedMonthlyIncome',color=base_color);
plt.xlabel('BorrowerAPR');
plt.ylabel('Monthly Income');
plt.title('Scatter plot of monthly income Vs Borrower APR');
```



In [36]:
```
# Borrower APR vs Status of Loan and  Borrower APR vs Employment status
plt.figure(figsize = [15, 5])

plt.subplot(1, 2, 1)
sns.boxplot(data=df_loan,x='BorrowerAPR',y='LoanStatus',color=base_color);
plt.xlabel('Borrower APR');
plt.ylabel('Loan Status');
plt.title('Box plot of Borrower APR vs Status of Loan');

plt.subplot(1, 2, 2)
sns.boxplot(data=df_loan,x='BorrowerAPR',y='EmploymentStatus',color=base_color);
plt.xlabel('Borrower APR');
plt.ylabel('Employment Status');
plt.title('Box plot of Borrower APR vs Employment Status');
```

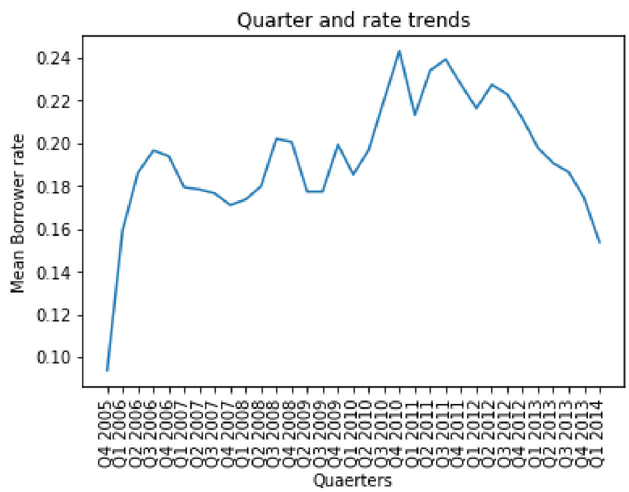


The median borrower APR of current, completed and Final payment in process are the lowest, with few low outliers of APR rate in charged off. Whereas charged off loans and defaulted are with the highest median of borrower rate. Median borrower APR is lowest for employed and highest for not employed because of high risk attached with unemployed people

In [37]:
```
df_series = df_loan['BorrowerRate'].groupby(df_loan['LoanOriginationQuarter']).mean().reset_index()
```

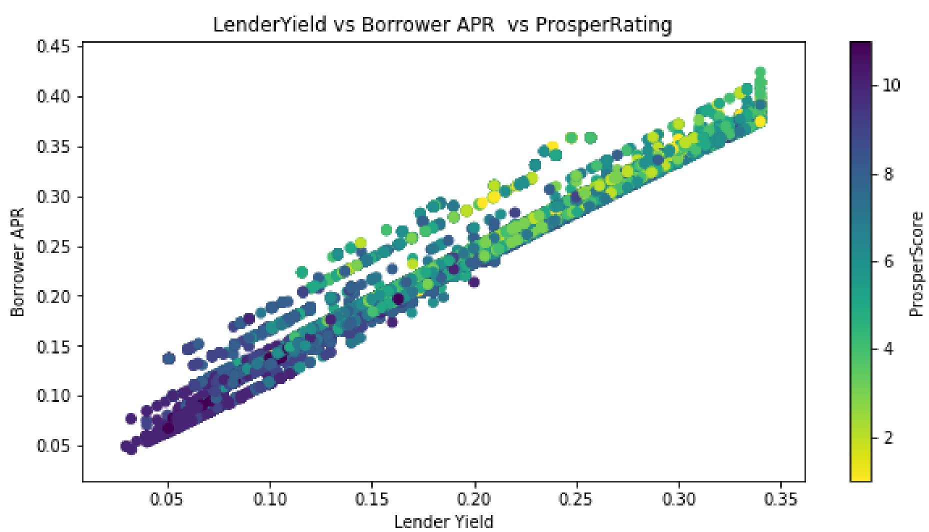
In [38]:
```
df_series.LoanOriginationQuarter = pd.Categorical(df_series.LoanOriginationQuarter, sorted(df_series.
LoanOriginationQuarter, key=lambda x: x.split(' ')[-1]), ordered = True)
df_series.sort_values('LoanOriginationQuarter', inplace=True)
```

In [39]:
```
# Mean Borrower rate over time
plt.errorbar(data=df_series,x='LoanOriginationQuarter',y='BorrowerRate');
plt.xticks(rotation = 90);
plt.xlabel('Quaerters');
plt.ylabel('Mean Borrower rate');
plt.title('Quarter and rate trends');
```



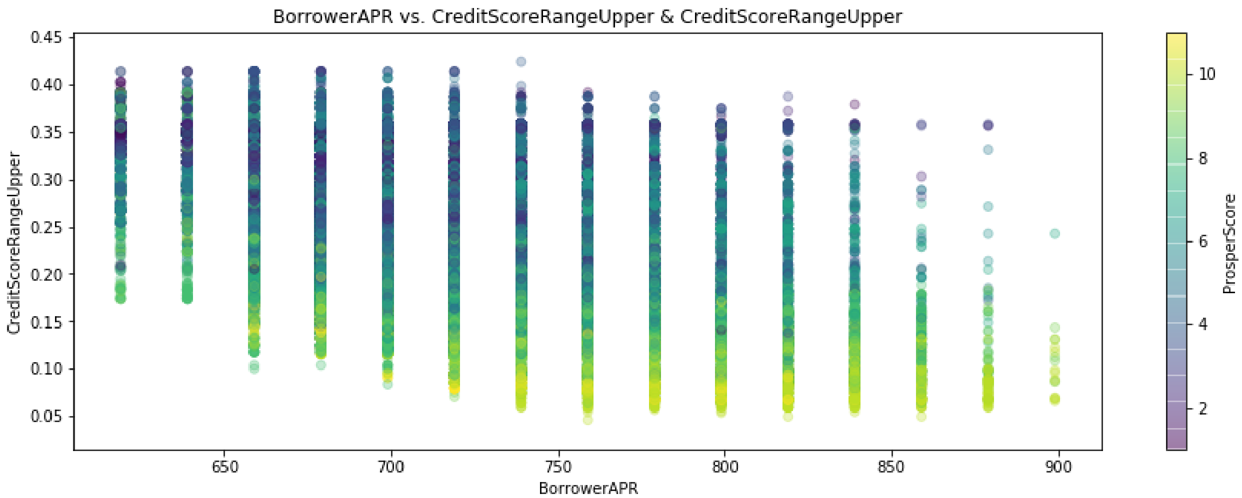
Multivariate Data Analysis

In [40]:
```
# LenderYield vs Borrower APR  vs ProsperRating
plt.figure(figsize = [10, 5])
plt.scatter(data=df_loan,x='LenderYield',y = 'BorrowerAPR',c='ProsperScore',cmap = 'viridis_r')
plt.colorbar(label = 'ProsperScore');
plt.xlabel('Lender Yield')
plt.ylabel('Borrower APR')
plt.title('LenderYield vs Borrower APR  vs ProsperRating');
```



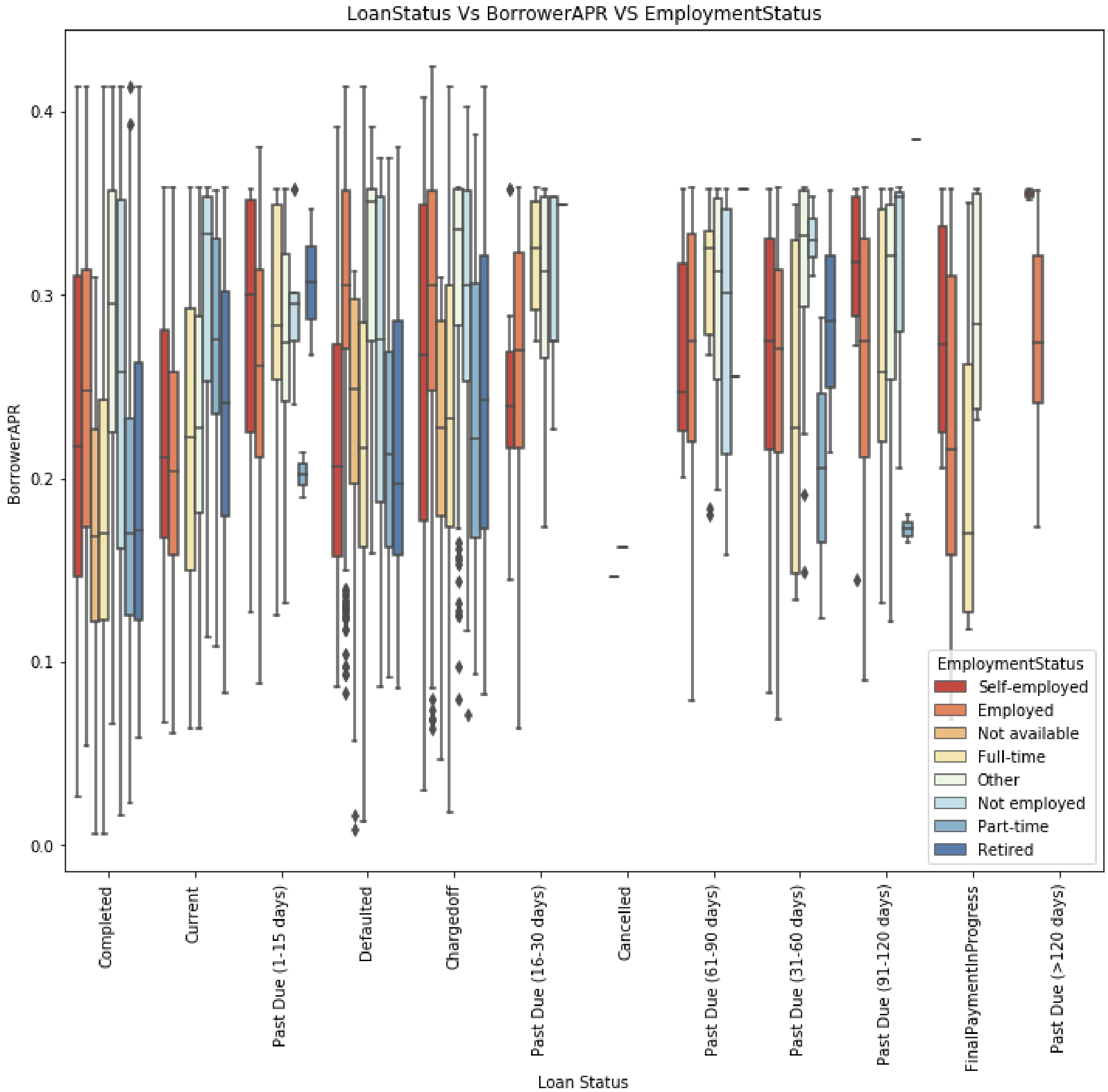
This graphs clearly shows the relationship between all variables. Borrower APR and Lender yield are directly positively correlated as more the interest borrowers pays,more will be yield for lender. For the prosper score, higher the prosper score lower will be the risk attached hence lower will be the APR and that further lowers down the yield.

In [41]:
```
# BorrowerAPR vs. CreditScoreRangeUpper & CreditScoreRangeUpper
plt.figure(figsize = [15, 5])
plt.scatter(data = df_loan, x = 'CreditScoreRangeUpper', y = 'BorrowerAPR', c ='ProsperScore', alpha
= 0.3)
plt.colorbar(label = 'ProsperScore')
plt.title('BorrowerAPR vs. CreditScoreRangeUpper & CreditScoreRangeUpper')
plt.xlabel('BorrowerAPR')
plt.ylabel('CreditScoreRangeUpper');
```



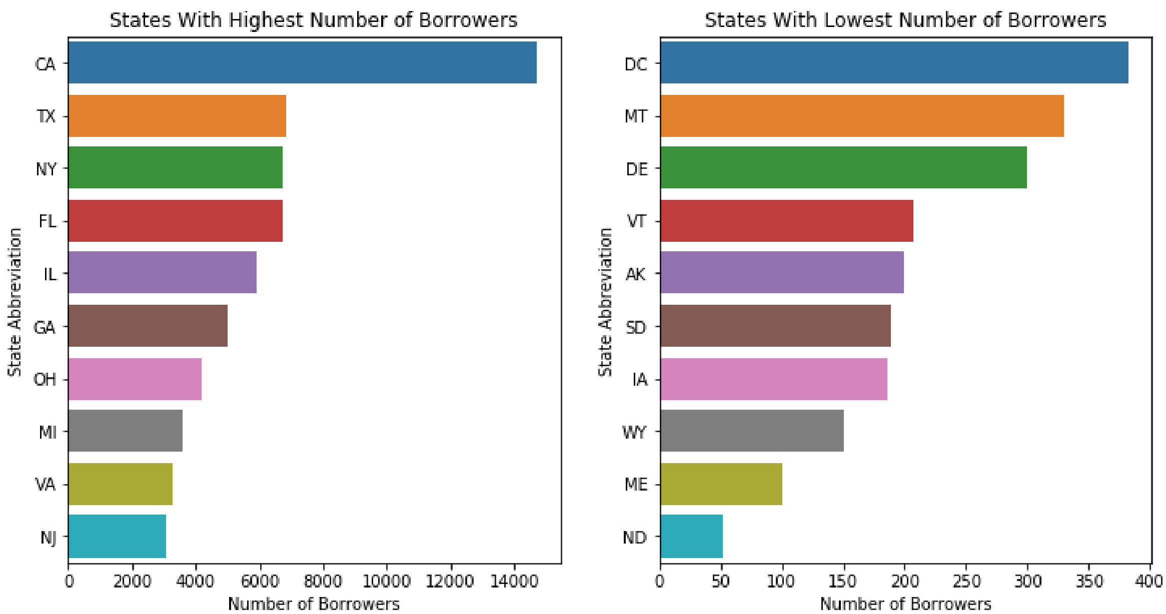
Credit score range upper and prosper score are positively correlated. However the high credit score upper range and borrower APR are negatively correlated.By adding ProsperScore to color encodings, BorrowerAPR decreases as ProsperScore increases. This proves the point that CreditScoreRangeUpper and ProsperScore negatively correlated to BorrowerAPR.

In [42]:
```
# LoanStatus Vs BorrowerAPR VS EmploymentStatus
plt.figure(figsize=[12,10])
sns.boxplot(x="LoanStatus", y="BorrowerAPR", hue="EmploymentStatus", data=df_loan, palette="RdYlBu");
plt.xticks(rotation = 90);
plt.xlabel('Loan Status');
plt.ylabel('BorrowerAPR');
plt.title('LoanStatus Vs BorrowerAPR VS EmploymentStatus');
```



For each category of loan status, the lowest APR is for Employed and Full-time. Whereas highest APR is for Not employed.

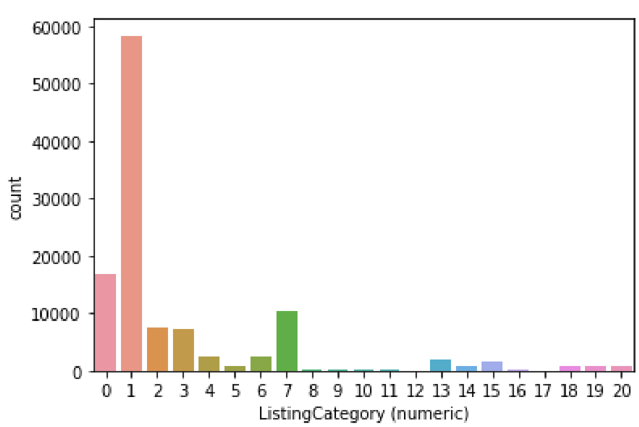
In [43]:
```
most_state_list = df_loan['BorrowerState'].value_counts()[:10].index.tolist()
most_state_count = df_loan['BorrowerState'].value_counts()[:10].values.tolist()

least_state_list = df_loan['BorrowerState'].value_counts()[-10:].index.tolist()
least_state_count = df_loan['BorrowerState'].value_counts()[-10:].values.tolist()

f,(ax1,ax2) = plt.subplots(ncols=2, sharey=False, sharex=False,
                          figsize=(12,6))

sns.barplot(x=most_state_count, y=most_state_list, ax=ax1)
ax1.set_title('States With Highest Number of Borrowers')
ax1.set_xlabel('Number of Borrowers')
ax1.set_ylabel('State Abbreviation')

sns.barplot(x=least_state_count, y=least_state_list, ax=ax2)
ax2.set_title('States With Lowest Number of Borrowers')
ax2.set_xlabel('Number of Borrowers')
ax2.set_ylabel('State Abbreviation')
plt.show()
```



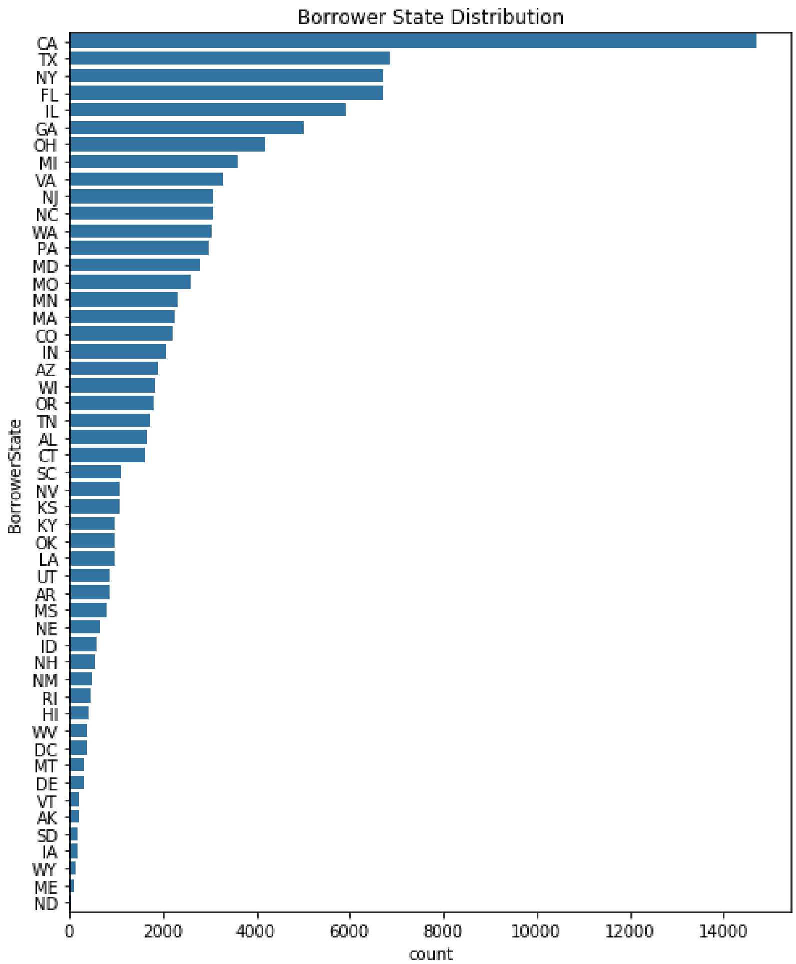
The state of California, is the state with the most number of borrowers, and California, Texas and New York are the top 3 states with the most number of borrowers. The state of North Dakota is the state with the least number of borrowers, and Wyoming, Maine and North Dakota are the 3 states with the least number of borrowers.

In [44]:
```
# fig = plt.figure(figsize=(12,6))
sns.countplot(df_loan["ListingCategory (numeric)"])
```

Out[44]: <matplotlib.axes._subplots.AxesSubplot at 0x165dfb40288>



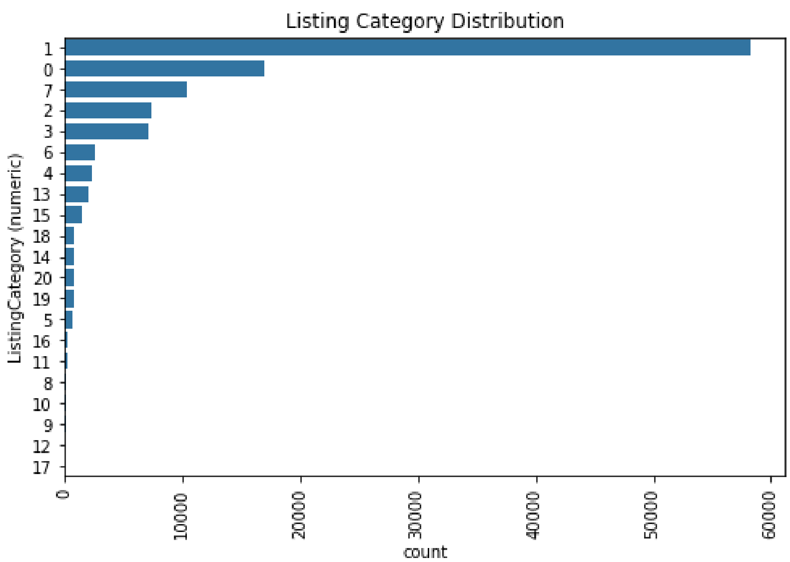
In [45]:
```
#Borrower State Distrobution
cat_order = df_loan.BorrowerState.value_counts().index
plt.figure(figsize=[8, 10])
sns.countplot(data=df_loan,y='BorrowerState',color=base_color, order=cat_order);
plt.title('Borrower State Distribution');
```



States California, Texas and New York have the 3 biggest numbers of loans originated in that period of time

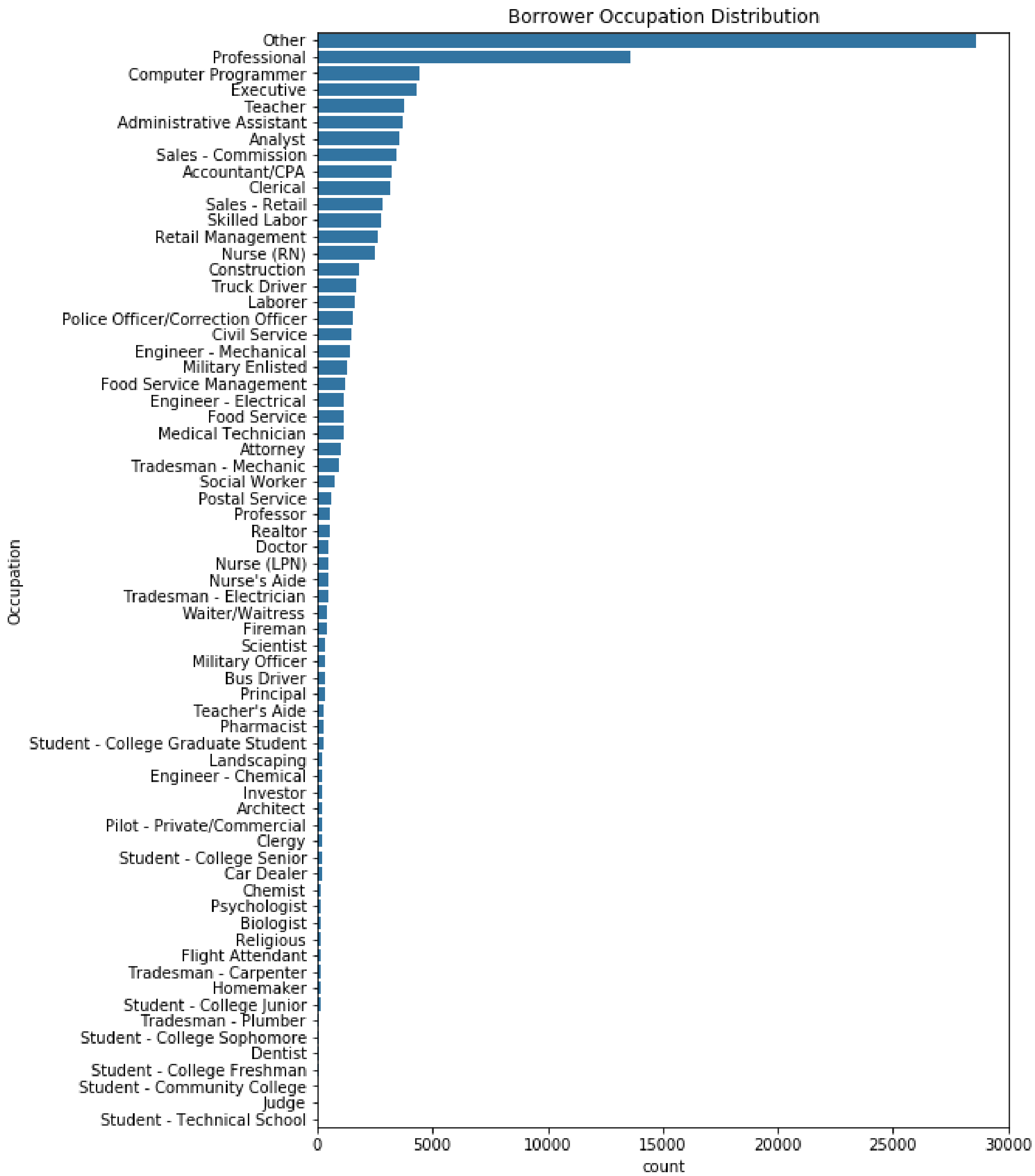
In [46]:
```
#Listing Category Distrobution
cat_order = df_loan["ListingCategory (numeric)"].value_counts().index
plt.figure(figsize=[8, 5])
sns.countplot(data=df_loan,y='ListingCategory (numeric)',color=base_color, order=cat_order);
plt.title('Listing Category Distribution')
plt.xticks(rotation=90)

# add annotations
# n_points = df_loan.shape[0]
# cat_counts = df_loan['ListingCategory (numeric)'].value_counts()
# locs, labels = plt.yticks() # get the current tick locations and labels

# # 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 = cat_counts[label.get_text()]
#     pct_string = '{:0.0f}%'.format(100*count/n_points)

#     # print the annotation just below the top of the bar
#     plt.text(count+1400, loc+0.3,  pct_string, ha = 'center', color = 'black');
```

Out[46]:
```
(array([    0., 10000., 20000., 30000., 40000., 50000., 60000., 70000.]),
 <a list of 8 Text xticklabel objects>)
```



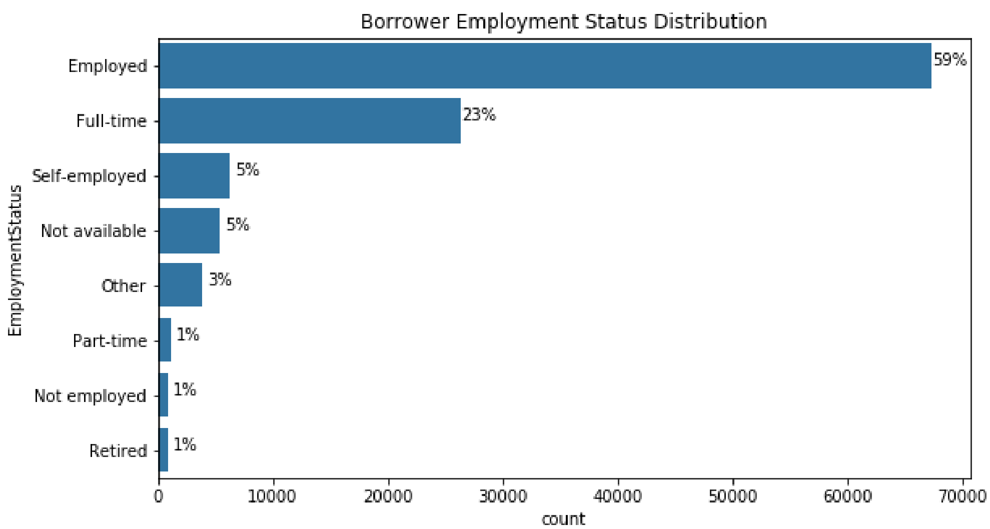
many people have take ListingCategory (numeric) 1

In [47]:
```
#Borrower Occupation Distrobution
cat_order = df_loan.Occupation.value_counts().index
plt.figure(figsize=[8, 13])
sns.countplot(data=df_loan,y='Occupation',color=base_color, order=cat_order);
plt.title('Borrower Occupation Distribution');
```



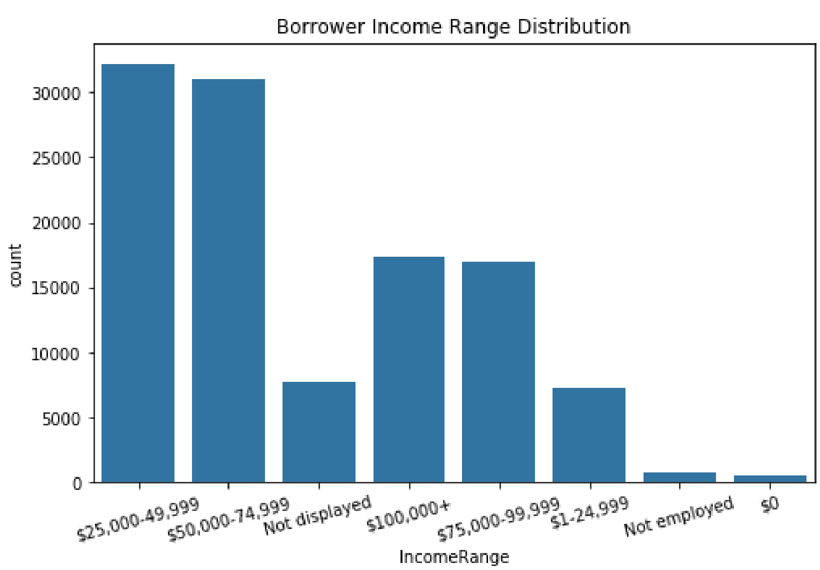
Most borrowers' occupations (excluding the others group) are: Professional, Computer Engineer and Executive It is interesting to see that Students, Judges, Dentists and Biologists are the least occupations taking loans

In [48]:
```
#Borrower Employment Status Distrobution
cat_order = df_loan.EmploymentStatus.value_counts().index
plt.figure(figsize=[9, 5])
sns.countplot(data=df_loan,y='EmploymentStatus',color=base_color, order=cat_order);
plt.title('Borrower Employment Status Distribution')

# add annotations
n_points = df_loan.shape[0]
cat_counts = df_loan['EmploymentStatus'].value_counts()
locs, labels = plt.yticks() # get the current tick locations and labels

# 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 = cat_counts[label.get_text()]
    pct_string = '{:0.0f}%'.format(100*count/n_points)

    # print the annotation just below the top of the bar
    plt.text(count+1600, loc,  pct_string, ha = 'center', color = 'black');
```



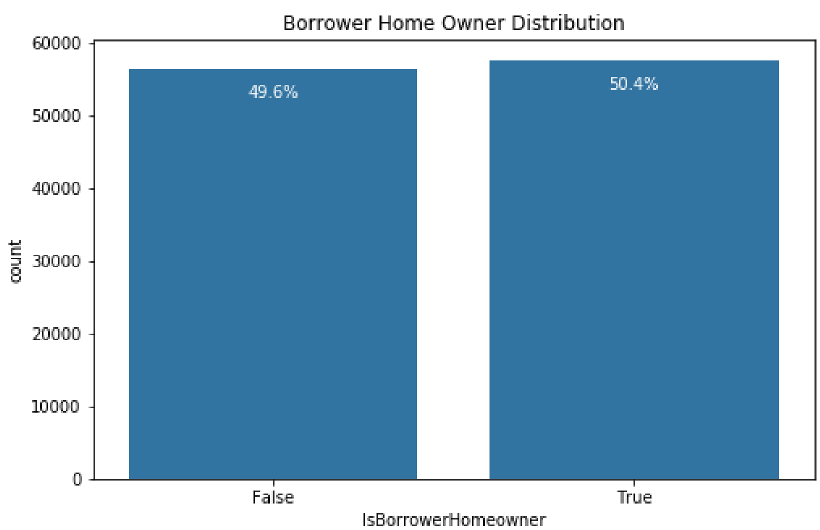
Most loan takers are employed

In [49]:
```
#Borrower Income Range Status Distrobution
plt.figure(figsize=[8, 5])
sns.countplot(data=df_loan,x='IncomeRange',color=base_color);
plt.title('Borrower Income Range Distribution')
plt.xticks(rotation=15);
```



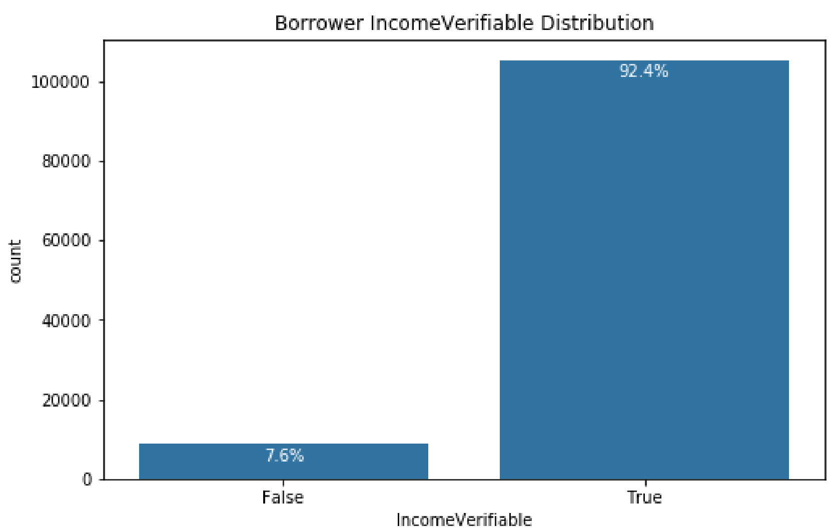
It is clear that people with yearly income range of $25,000-49,999 are the most taking loans

In [50]:
```
#Is Borrower-Homeowner Status Distrobution
plt.figure(figsize=[8, 5])

def str2bool(v):
    return str(v).lower() in ("yes", "true", "True", "1")

base_color = sns.color_palette()[0]
sns.countplot(data = df_loan, x = 'IsBorrowerHomeowner', color = base_color)

# add annotations
n_points = df_loan.shape[0]
cat_counts = df_loan['IsBorrowerHomeowner'].value_counts()
locs, labels = plt.xticks() # get the current tick locations and labels

# 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 = cat_counts[str2bool(label.get_text())]
    pct_string = '{:0.1f}%'.format(100*count/n_points)

    # print the annotation just below the top of the bar
    plt.text(loc, count-4000, pct_string, ha = 'center', color = 'w')

plt.title('Borrower Home Owner Distribution');
```

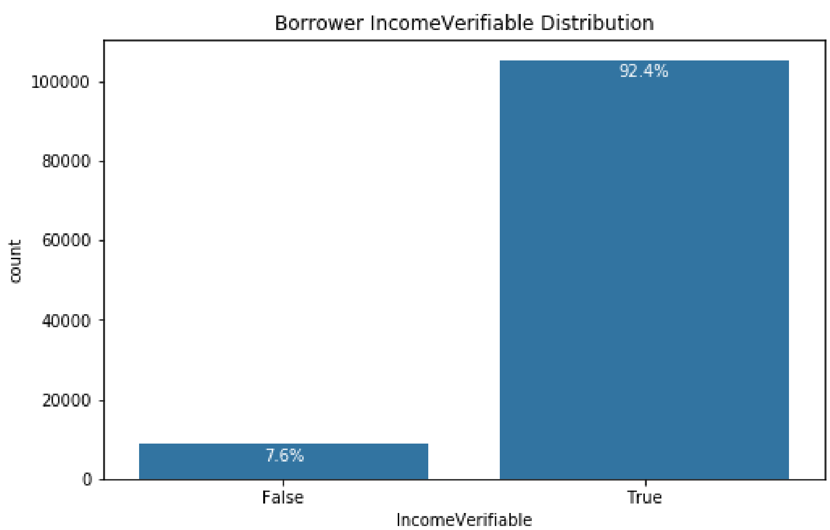


it seems that owning a house or not has no effect to taking loans

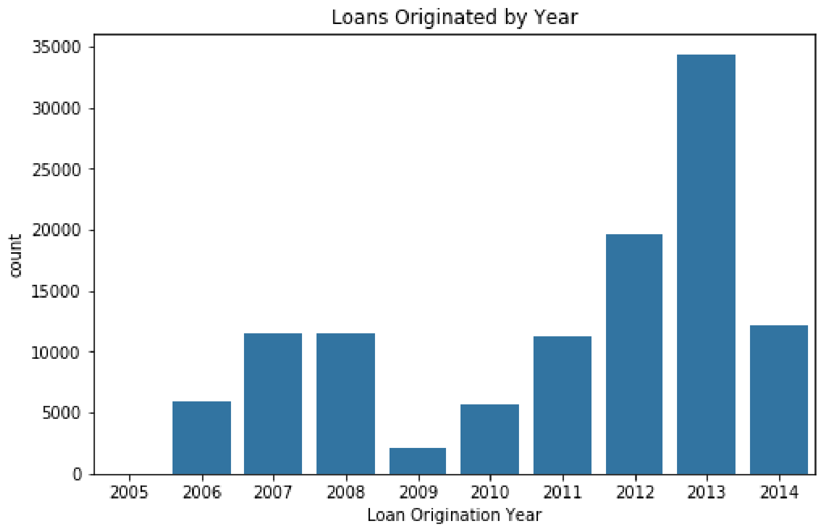
In [51]:
```
#Is Income-Verifiable Status Distrobution
plt.figure(figsize=[8, 5])

def str2bool(v):
    return str(v).lower() in ("yes", "true", "True", "1")

base_color = sns.color_palette()[0]
sns.countplot(data = df_loan, x = 'IncomeVerifiable', color = base_color)

# add annotations
n_points = df_loan.shape[0]
cat_counts = df_loan['IncomeVerifiable'].value_counts()
locs, labels = plt.xticks() # get the current tick locations and labels

# 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 = cat_counts[str2bool(label.get_text())]
    pct_string = '{:0.1f}%'.format(100*count/n_points)

    # print the annotation just below the top of the bar
    plt.text(loc, count-4000, pct_string, ha = 'center', color = 'w')

#sb.countplot(data=df_loans_clean,x='IsBorrowerHomeowner',color=base_color);
plt.title('Borrower IncomeVerifiable Distribution');
```



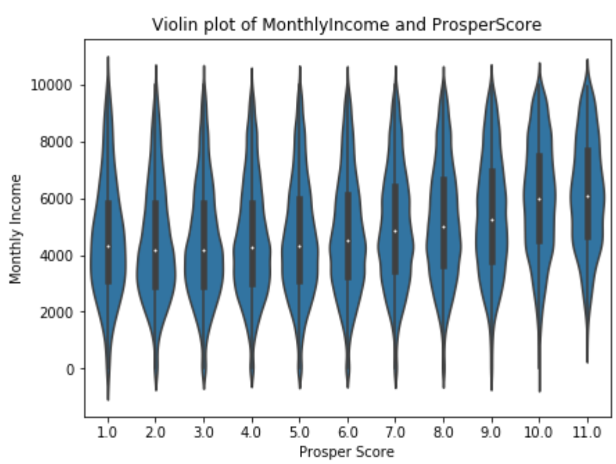
In [52]:
```
#Is Income-Verifiable Status Distrobution
plt.figure(figsize=[8, 5])

def str2bool(v):
    return str(v).lower() in ("yes", "true", "True", "1")

base_color = sns.color_palette()[0]
sns.countplot(data = df_loan, x = 'IncomeVerifiable', color = base_color)

# add annotations
n_points = df_loan.shape[0]
cat_counts = df_loan['IncomeVerifiable'].value_counts()
locs, labels = plt.xticks() # get the current tick locations and labels

# 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 = cat_counts[str2bool(label.get_text())]
    pct_string = '{:0.1f}%'.format(100*count/n_points)

    # print the annotation just below the top of the bar
    plt.text(loc, count-4000, pct_string, ha = 'center', color = 'w')

#sb.countplot(data=df_loans_clean,x='IsBorrowerHomeowner',color=base_color);
plt.title('Borrower IncomeVerifiable Distribution');
```



In [53]:
```
# Loan Origination by Year
plt.figure(figsize=[8, 5])
sns.countplot(data=df_loan,x=df_loan['LoanOriginationDate'].dt.year,color=base_color)
plt.title('Loans Originated by Year')
plt.xlabel('Loan Origination Year');
```

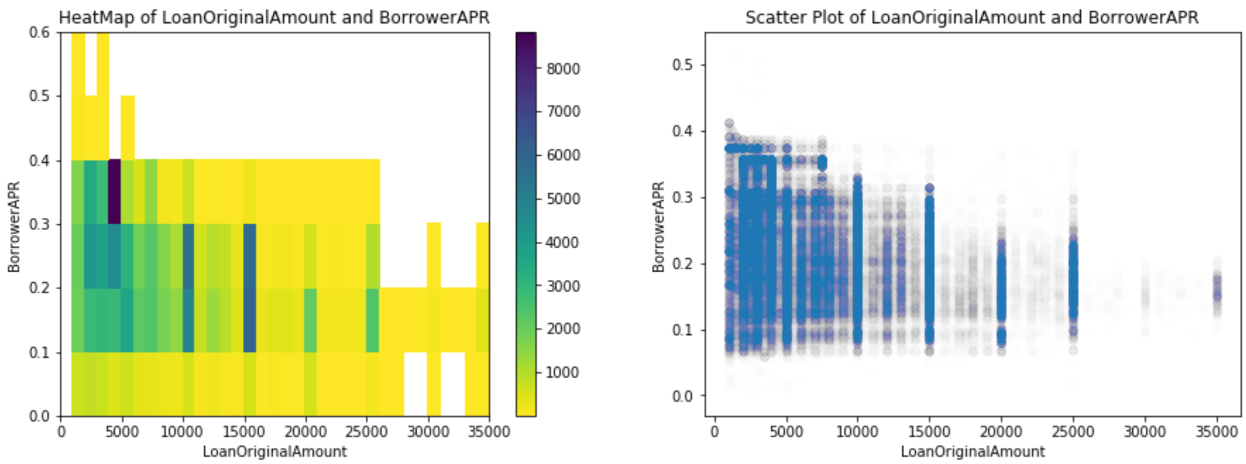


In [54]:
```
# Stated MonthlyIncome  Prosper Rating
# Since 75% of the data has StatedMonthlyIncome less than 6825, we can plot data within this range
df_wo_outlier=df_loan[df_loan['StatedMonthlyIncome'] < 10000]

plt.figure(figsize = [15, 5])
plt.subplot(1, 2, 1)
sns.violinplot(data=df_wo_outlier,x='ProsperScore', y='StatedMonthlyIncome',color=base_color);
plt.xlabel('Prosper Score');
plt.ylabel('Monthly Income');
plt.title('Violin plot of MonthlyIncome and ProsperScore');

plt.subplot(1, 2, 2)
plt.scatter(data=df_wo_outlier,x='BorrowerAPR', y='StatedMonthlyIncome',color=base_color, alpha =  0.
005);
plt.xlabel('BorrowerAPR');
plt.ylabel('Monthly Income');
plt.title('Scatter plot of MonthlyIncome and BorrowerAPR');
```



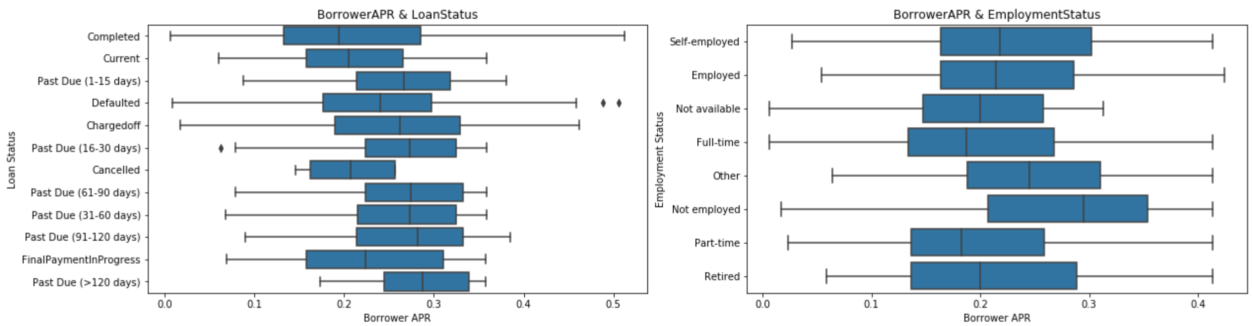
violin plots show that higher prosper scores have higher mean income sactter plot shows that the higher the income, the lower the borrower rate

In [55]:
```
# Checking the relation between ProsperScore and StatedMonthlyIncome

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


plt.subplot(1, 2, 1)
bins_x = np.arange(0, df_loan['LoanOriginalAmount'].max()+1000, 1000)
bins_y = np.arange(0, df_loan['BorrowerAPR'].max()+0.1, 0.1)
plt.hist2d(data = df_loan, x = 'LoanOriginalAmount', y = 'BorrowerAPR', bins = [bins_x, bins_y],
               cmap = 'viridis_r', cmin = 0.5)
plt.xlabel('LoanOriginalAmount')
plt.ylabel('BorrowerAPR')
plt.title('HeatMap of LoanOriginalAmount and BorrowerAPR')

plt.colorbar()


plt.subplot(1, 2, 2)
plt.scatter(data = df_loan, x = 'LoanOriginalAmount', y = 'BorrowerAPR',  alpha =  0.005)
plt.yticks(np.arange(0, 0.6, 0.1))
plt.title('Scatter Plot of LoanOriginalAmount and BorrowerAPR')
plt.xlabel('LoanOriginalAmount')
plt.ylabel('BorrowerAPR');
```



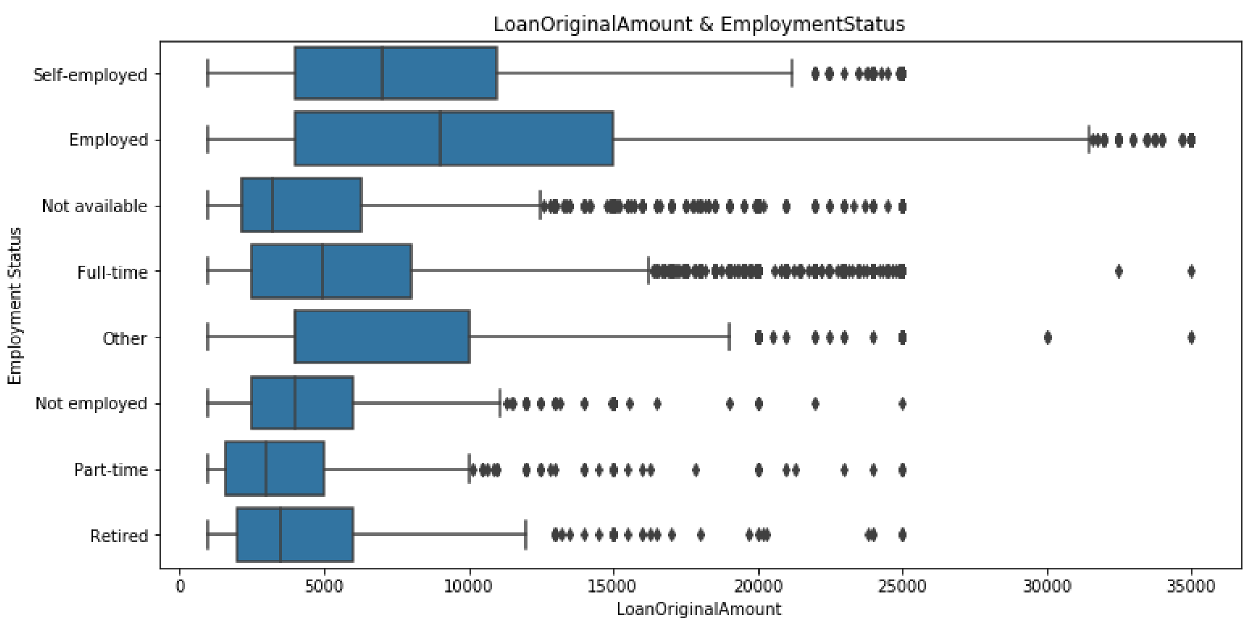
This shows a negative relationship, means large loans have relatively less interest rate.

In [56]:
```
# Borrower APR vs Status of Loan and  Borrower APR vs Employment status
plt.figure(figsize = [20, 5])

plt.subplot(1, 2, 1)
sns.boxplot(data=df_loan,x='BorrowerAPR',y='LoanStatus',color=base_color);
plt.xlabel('Borrower APR');
plt.ylabel('Loan Status');
plt.title('BorrowerAPR & LoanStatus');

plt.subplot(1, 2, 2)
sns.boxplot(data=df_loan,x='BorrowerAPR',y='EmploymentStatus',color=base_color);
plt.xlabel('Borrower APR');
plt.ylabel('Employment Status');
plt.title('BorrowerAPR & EmploymentStatus');
```



Current and completed loans have lower rate than the past-due loans and Employed people have lower rates than not employed

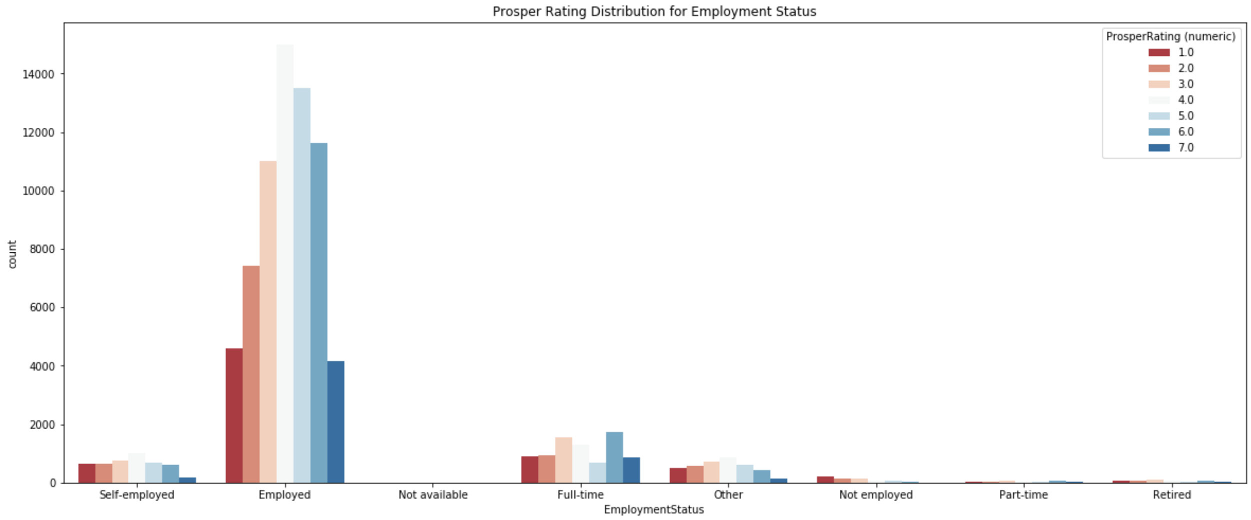
In [57]:
```
plt.figure(figsize = [12, 6])
sns.boxplot(data=df_loan,x='LoanOriginalAmount',y='EmploymentStatus',color=base_color);
plt.xlabel('LoanOriginalAmount');
plt.ylabel('Employment Status');
plt.title('LoanOriginalAmount & EmploymentStatus');
```



Employed people can get larger loan amounts compared to all other categories

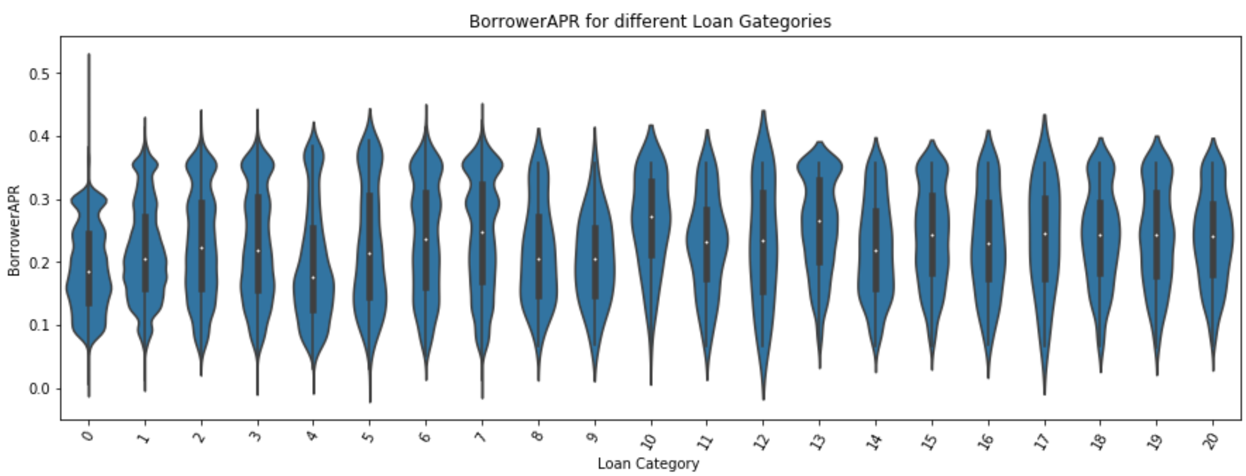
In [58]:
```
plt.figure(figsize = [20, 8])
sns.countplot(data = df_loan, x = 'EmploymentStatus', hue = 'ProsperRating (numeric)', palette='RdB
u')
plt.title('Prosper Rating Distribution for Employment Status')
```

Out[58]: Text(0.5, 1.0, 'Prosper Rating Distribution for Employment Status')



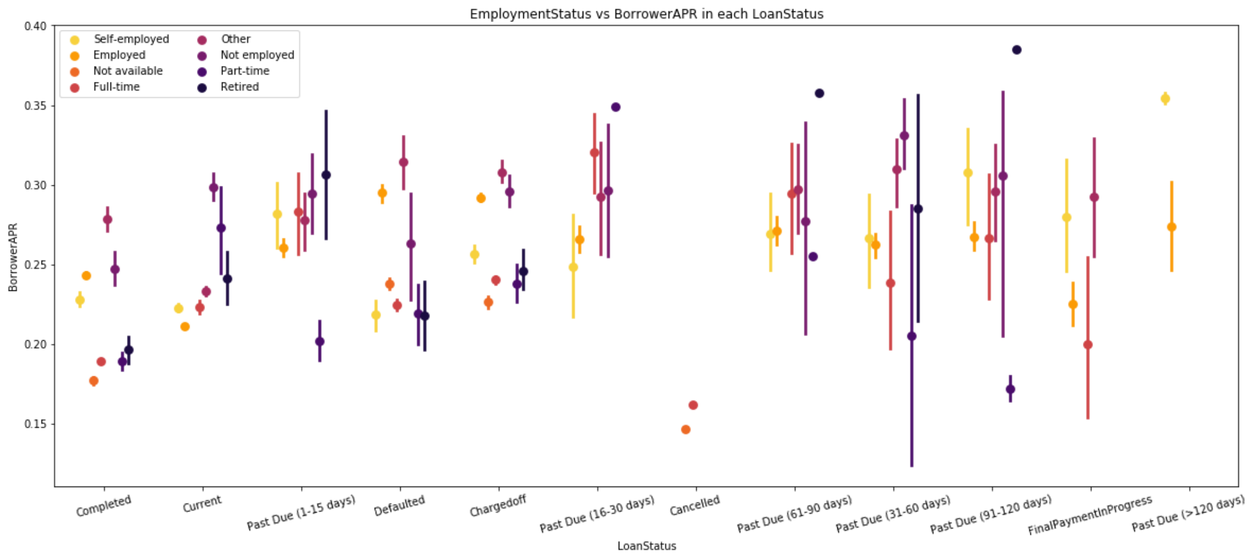
It is noticed that Employed people get rating C or above while Not Employed recieve mostly HR means High Risk and this makes sense

In [59]:
```
plt.figure(figsize = [15, 5])
sns.violinplot(data=df_loan,x='ListingCategory (numeric)', y='BorrowerAPR',color=base_color);
plt.xlabel('Loan Category ');
plt.ylabel('BorrowerAPR');
plt.title('BorrowerAPR for different Loan Gategories')
plt.xticks(rotation=60);
```



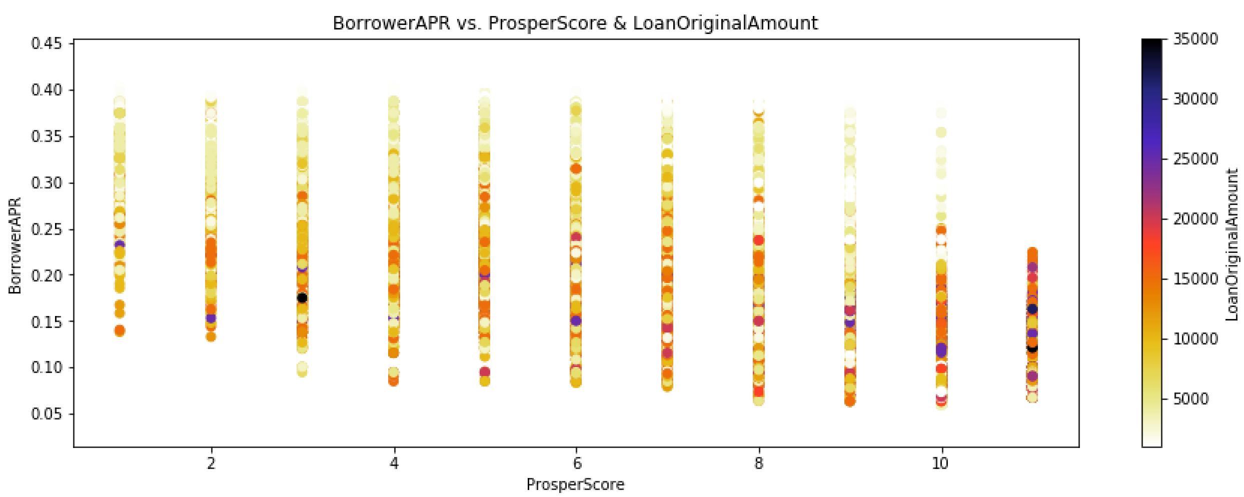
It is noticed that mostly listing category 5 are given higer interest rates

In [60]:
```
fig = plt.figure(figsize = [20,8])
ax = sns.pointplot(data = df_loan, x = 'LoanStatus', y = 'BorrowerAPR', hue = 'EmploymentStatus', lin
estyles = "",
                   dodge = 0.5, palette = 'inferno_r')
plt.title('EmploymentStatus vs BorrowerAPR in each LoanStatus')
plt.ylabel('BorrowerAPR')
plt.xticks(rotation=15)
plt.legend(ncol=2)
plt.show();
```



Past Due loans generally have higher interest rates in all employment statuses

In [61]:
```
# BorrowerAPR vs. CreditScoreRangeUpper & CreditScoreRangeUpper
plt.figure(figsize = [15, 5])
cm = plt.cm.get_cmap('CMRmap_r')
plt.scatter(data = df_loan[df_loan['StatedMonthlyIncome'] <20000],\
            x = 'ProsperScore', y = 'BorrowerAPR', c ='LoanOriginalAmount', cmap=cm)
plt.colorbar(label = 'LoanOriginalAmount')
plt.title('BorrowerAPR vs. ProsperScore & LoanOriginalAmount')
plt.xlabel('ProsperScore')
plt.ylabel('BorrowerAPR');
```



the chart shows most of the loans with higher amounts (>$20,000) are taken by people with higher prosper score (10 and above)

Data Preprocessing

In [62]:
```
df['Term'] = df['Term'].astype('object')
df['ProsperScore'] = df['ProsperScore'].astype('object')
```

In [63]:
```
percent_missing = (df.isnull().sum() * 100 / len(df)).round(2)
missing_value_df = pd.DataFrame({'column_name': df.columns,
                                 'percent_missing': percent_missing})
missing_value_df["no_ofmissing_values"]=df.isnull().sum()
```

In [64]:
```
missing_value_df.sort_values(by = 'percent_missing', ascending = False)[0:30]
```

Out[64]:

	column_name	percent_missing	no_ofmissing_values
GroupKey	GroupKey	88.29	100596
LoanFirstDefaultedCycleNumber	LoanFirstDefaultedCycleNumber	85.12	96985
ScorexChangeAtTimeOfListing	ScorexChangeAtTimeOfListing	83.39	95009
ProsperPrincipalOutstanding	ProsperPrincipalOutstanding	80.62	91852
ProsperPrincipalBorrowed	ProsperPrincipalBorrowed	80.62	91852
ProsperPaymentsOneMonthPlusLate	ProsperPaymentsOneMonthPlusLate	80.62	91852
ProsperPaymentsLessThanOneMonthLate	ProsperPaymentsLessThanOneMonthLate	80.62	91852
OnTimeProsperPayments	OnTimeProsperPayments	80.62	91852
TotalProsperLoans	TotalProsperLoans	80.62	91852
TotalProsperPaymentsBilled	TotalProsperPaymentsBilled	80.62	91852
CreditGrade	CreditGrade	74.59	84984
ClosedDate	ClosedDate	51.65	58848
ProsperRating (Alpha)	ProsperRating (Alpha)	25.53	29084
ProsperScore	ProsperScore	25.53	29084
EstimatedReturn	EstimatedReturn	25.53	29084
ProsperRating (numeric)	ProsperRating (numeric)	25.53	29084
EstimatedLoss	EstimatedLoss	25.53	29084
EstimatedEffectiveYield	EstimatedEffectiveYield	25.53	29084
DebtToIncomeRatio	DebtToIncomeRatio	7.51	8554
EmploymentStatusDuration	EmploymentStatusDuration	6.69	7625
AmountDelinquent	AmountDelinquent	6.69	7622
CurrentCreditLines	CurrentCreditLines	6.67	7604
BankcardUtilization	BankcardUtilization	6.67	7604
PublicRecordsLast12Months	PublicRecordsLast12Months	6.67	7604
OpenCreditLines	OpenCreditLines	6.67	7604
RevolvingCreditBalance	RevolvingCreditBalance	6.67	7604
TotalTrades	TotalTrades	6.62	7544
TradesOpenedLast6Months	TradesOpenedLast6Months	6.62	7544
TradesNeverDelinquent (percentage)	TradesNeverDelinquent (percentage)	6.62	7544
AvailableBankcardCredit	AvailableBankcardCredit	6.62	7544

In [65]:
```
df=df.drop(["ListingKey",'ListingNumber','ListingCreationDate','ClosedDate',"ProsperRating (Alph
a)",'GroupKey','CurrentlyInGroup','DateCreditPulled','LoanKey','LoanNumber','LoanOriginationDate','Me
mberKey','LP_CollectionFees','LP_GrossPrincipalLoss','LP_NetPrincipalLoss','LP_NonPrincipalRecoverypa
yments','PercentFunded','Recommendations','InvestmentFromFriendsCount','InvestmentFromFriendsAmoun
t','FirstRecordedCreditLine','LoanOriginationQuarter', 'BorrowerState'],axis=1)
```

In [66]:
```
df.shape
```

Out[66]:
```
(113937, 58)
```

Categorizing Target Variable

In [67]:
```
df["LoanStatus"].value_counts()
```

Out[67]:
```
Current                   56576
Completed                 38074
Chargedoff                11992
Defaulted                  5018
Past Due (1-15 days)        806
Past Due (31-60 days)       363
Past Due (61-90 days)       313
Past Due (91-120 days)      304
Past Due (16-30 days)       265
FinalPaymentInProgress      205
Past Due (>120 days)         16
Cancelled                     5
Name: LoanStatus, dtype: int64
```

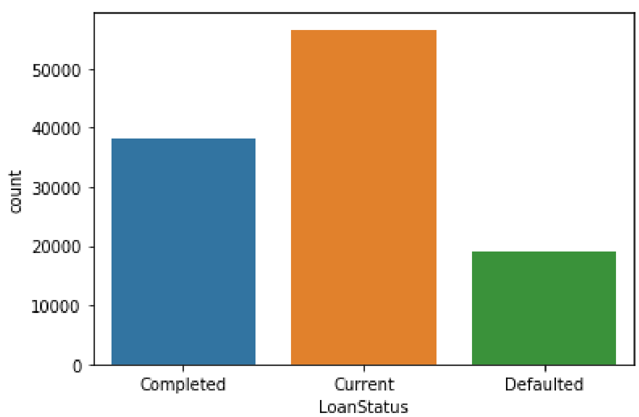
In [68]:
```
df['LoanStatus'] = df['LoanStatus'].replace(['Chargedoff', 'Defaulted', 'Past Due (1-15 days)', 'Past
Due (31-60 days)',
                                             'Past Due (61-90 days)','Past Due (91-120 days)','Past D
ue (16-30 days)',
                                             'Past Due (>120 days)'],'Defaulted')
df['LoanStatus'] = df['LoanStatus'].replace('FinalPaymentInProgress','Completed')
print(df.LoanStatus.value_counts())
```

```
Current      56576
Completed    38279
Defaulted    19077
Cancelled        5
Name: LoanStatus, dtype: int64
```

In [69]:
```
df = df.drop(df[df['LoanStatus'] == 'Cancelled'].index)
```

In [70]:
```
df = df.reset_index()
```

In [72]:
```
sns.countplot(df['LoanStatus']);
```



Dropping Missing Values

In [73]:
```
df=df.dropna(thresh=df.shape[0]*0.5,how="all",axis=1)
```

In [74]:
```
df.shape
```

Out[74]:
```
(113932, 49)
```

In [75]:
```
cateogry_columns=df.select_dtypes(include=['object']).columns.tolist()
integer_columns=df.select_dtypes(include=['int64','float64']).columns.tolist()
bool_columns=df.select_dtypes(include=['bool']).columns.tolist()
```

Filling Missing Values

In [76]:
```
for column in df:
    if df[column].isnull().any():
        if(column in cateogry_columns):
            df[column]=df[column].fillna(df[column].mode()[0])
        else:
            df[column]=df[column].fillna(df[column].mean())
```

In [77]:
```
df.isnull().sum().sum()
```

Out[77]: 0

In [78]:
```
percent_missing = (df.isnull().sum() * 100 / len(df)).round(2)
missing_value_df = pd.DataFrame({'column_name': df.columns,
                                 'percent_missing': percent_missing})
missing_value_df["no_of_missing_values"]=df.isnull().sum()
```

In [79]:
```
missing_value_df[:20]
```

Out[79]:

	column_name	percent_missing	no_of_missing_values
index	index	0.0	0
Term	Term	0.0	0
LoanStatus	LoanStatus	0.0	0
BorrowerAPR	BorrowerAPR	0.0	0
BorrowerRate	BorrowerRate	0.0	0
LenderYield	LenderYield	0.0	0
EstimatedEffectiveYield	EstimatedEffectiveYield	0.0	0
EstimatedLoss	EstimatedLoss	0.0	0
EstimatedReturn	EstimatedReturn	0.0	0
ProsperRating (numeric)	ProsperRating (numeric)	0.0	0
ProsperScore	ProsperScore	0.0	0
ListingCategory (numeric)	ListingCategory (numeric)	0.0	0
Occupation	Occupation	0.0	0
EmploymentStatus	EmploymentStatus	0.0	0
EmploymentStatusDuration	EmploymentStatusDuration	0.0	0
IsBorrowerHomeowner	IsBorrowerHomeowner	0.0	0
CreditScoreRangeLower	CreditScoreRangeLower	0.0	0
CreditScoreRangeUpper	CreditScoreRangeUpper	0.0	0
CurrentCreditLines	CurrentCreditLines	0.0	0
OpenCreditLines	OpenCreditLines	0.0	0

In [80]:
```
cat_col=df[cateogry_columns].copy()
```

In [81]:
```
cat_col.head()
```

Out[81]:

	Term	LoanStatus	ProsperScore	Occupation	EmploymentStatus	IncomeRange
0	36	Completed	4.0	Other	Self-employed	$25,000-49,999
1	36	Current	7.0	Professional	Employed	$50,000-74,999
2	36	Completed	4.0	Other	Not available	Not displayed
3	36	Current	9.0	Skilled Labor	Employed	$25,000-49,999
4	36	Current	4.0	Executive	Employed	$100,000+

In [82]:
```
final_cat_col=cat_col[['Term','ProsperScore','LoanStatus','Occupation','EmploymentStatus','IncomeRang
e']]
```

In [83]:
```
final_cat_col.head()
```

Out[83]:

	Term	ProsperScore	LoanStatus	Occupation	EmploymentStatus	IncomeRange
0	36	4.0	Completed	Other	Self-employed	$25,000-49,999
1	36	7.0	Current	Professional	Employed	$50,000-74,999
2	36	4.0	Completed	Other	Not available	Not displayed
3	36	9.0	Current	Skilled Labor	Employed	$25,000-49,999
4	36	4.0	Current	Executive	Employed	$100,000+

In [84]:
```
df['LoanStatus'].value_counts()
```

Out[84]:
```
Current      56576
Completed    38279
Defaulted    19077
Name: LoanStatus, dtype: int64
```

In [85]:
```
df["Occupation"].value_counts()
```

Out[85]:
```
Other                          32201
Professional                   13628
Computer Programmer             4478
Executive                       4311
Teacher                         3759
                               ...
Dentist                           68
Student - College Freshman        41
Student - Community College       28
Judge                             22
Student - Technical School        16
Name: Occupation, Length: 67, dtype: int64
```

In [86]:
```
df["EmploymentStatus"].value_counts()
```

Out[86]:
```
Employed         69574
Full-time        26354
Self-employed     6134
Not available     5346
Other             3806
Part-time         1088
Not employed       835
Retired            795
Name: EmploymentStatus, dtype: int64
```

In [87]:
```
df['IncomeRange'].value_counts()
```

Out[87]:
```
$25,000-49,999    32191
$50,000-74,999    31050
$100,000+         17337
$75,000-99,999    16916
Not displayed      7737
$1-24,999          7274
Not employed        806
$0                  621
Name: IncomeRange, dtype: int64
```

In [88]:
```
def ordinal_encoder(final_cat_col, feats):
    for feat in feats:
        feat_val = list(1+np.arange(final_cat_col[feat].nunique()))
        feat_key = list(final_cat_col[feat].sort_values().unique())
        feat_dict = dict(zip(feat_key, feat_val))
        final_cat_col[feat] = final_cat_col[feat].map(feat_dict)
    return final_cat_col

final_cat_col = ordinal_encoder(final_cat_col, final_cat_col.drop(['LoanStatus'],axis=1).columns)
final_cat_col.shape
```

Out[88]: (113932, 6)

In [89]:
```
final_cat_col.head()
```

Out[89]:

	Term	ProsperScore	LoanStatus	Occupation	EmploymentStatus	IncomeRange
0	2	4	Completed	36	8	4
1	2	7	Current	42	1	5
2	2	4	Completed	36	3	7
3	2	9	Current	51	1	4
4	2	4	Current	20	1	3

In [90]:
```
df=df.drop(['LoanStatus','Occupation','EmploymentStatus','IncomeRange','Term','ProsperScore'],axis=1)
```

In [91]:
```
df=pd.concat([df,final_cat_col],axis=1)
```

In [92]:
```
df.head()
```

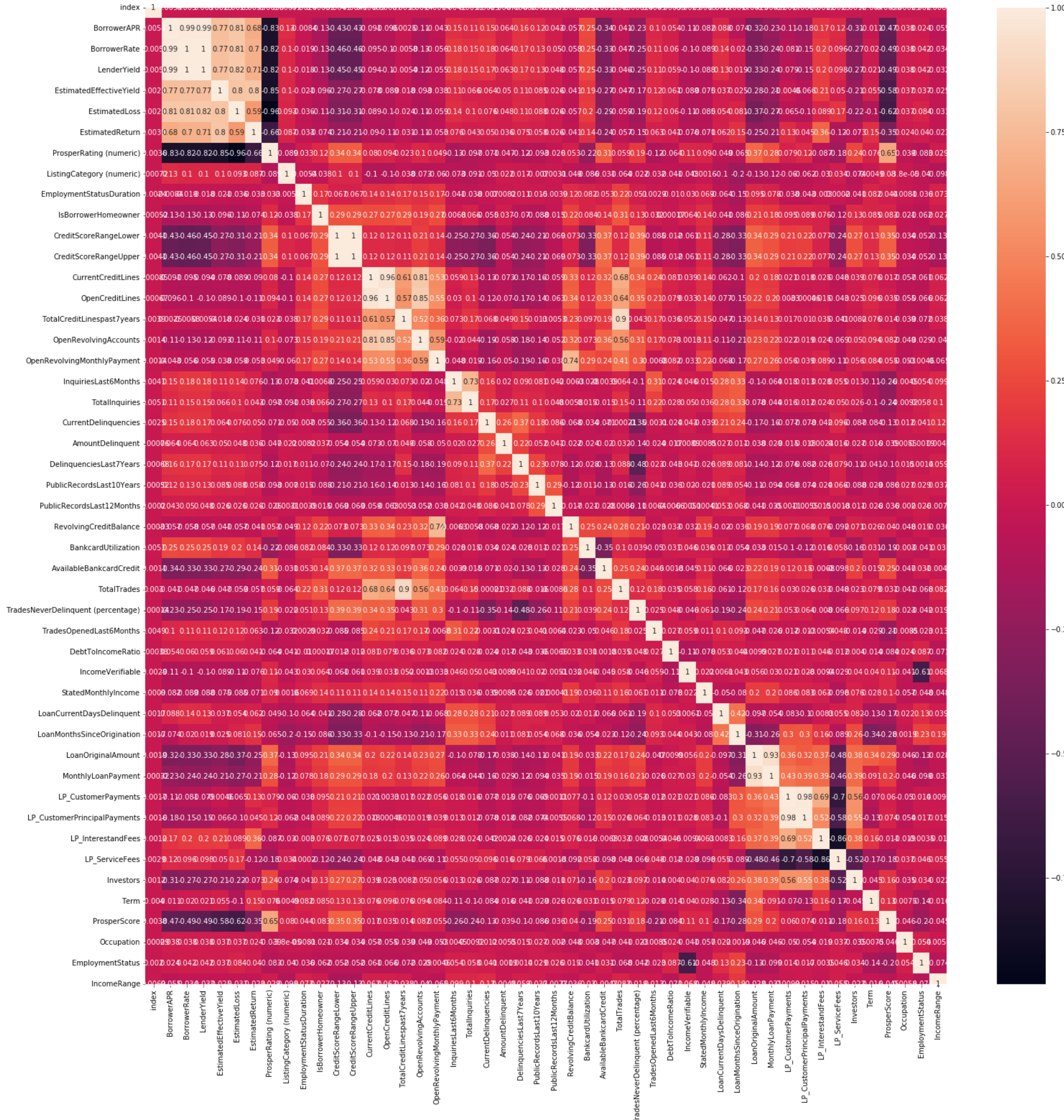
Out[92]:

	index	BorrowerAPR	BorrowerRate	LenderYield	EstimatedEffectiveYield	EstimatedLoss	EstimatedReturn	ProsperRating (numeric)	I
0	0	0.16516	0.1580	0.1380	0.168661	0.080306	0.096068	4.072243	
1	1	0.12016	0.0920	0.0820	0.079600	0.024900	0.054700	6.000000	
2	2	0.28269	0.2750	0.2400	0.168661	0.080306	0.096068	4.072243	
3	3	0.12528	0.0974	0.0874	0.084900	0.024900	0.060000	6.000000	
4	4	0.24614	0.2085	0.1985	0.183160	0.092500	0.090660	3.000000	

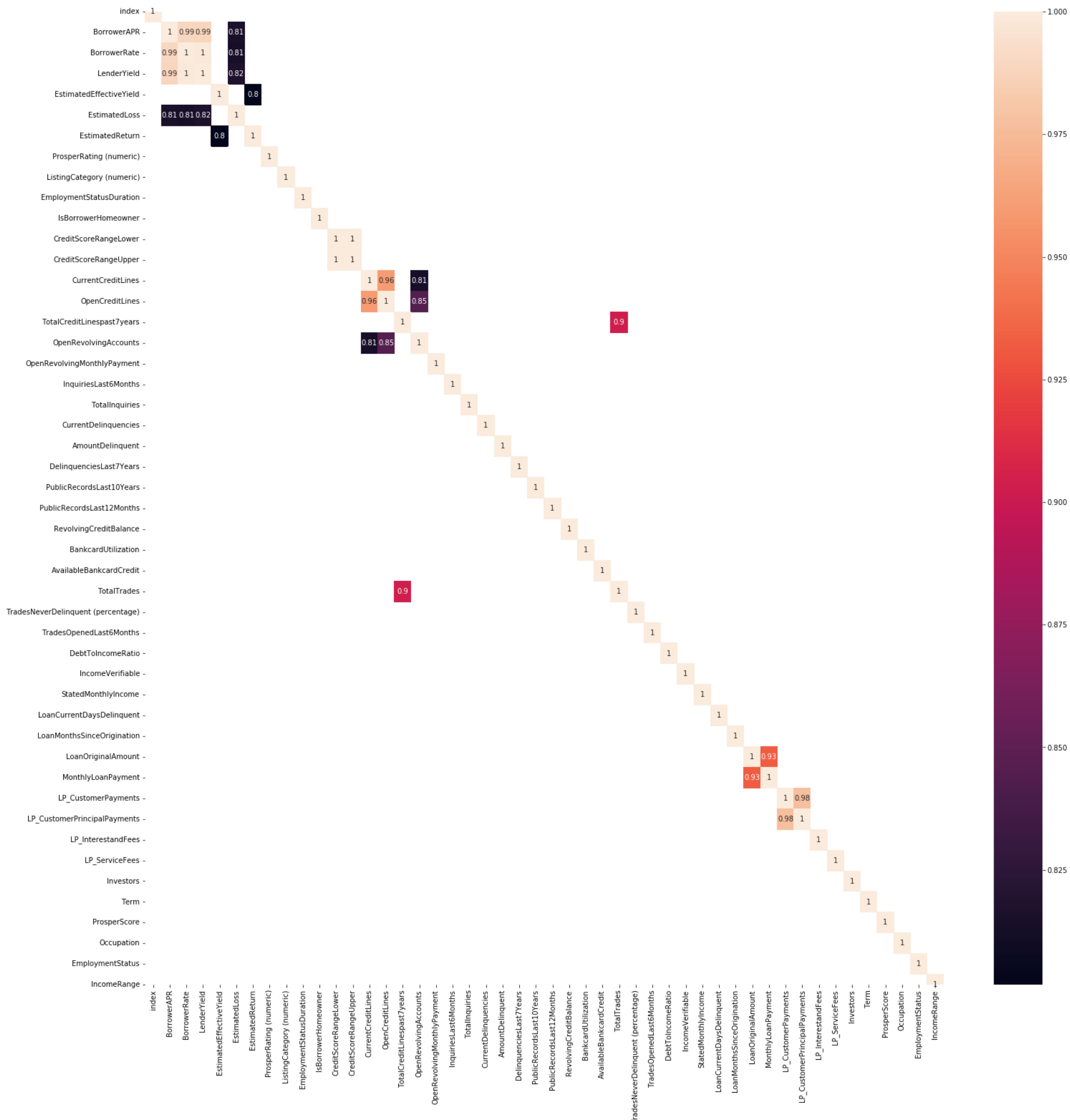
In [93]:
```
df.shape
```

Out[93]: (113932, 49)

In [94]:
```
plt.figure(figsize = (25, 25))
sns.heatmap(df.corr(), annot = True)
plt.show()
```



In [95]:
```
plt.figure(figsize = (25, 25))
sns.heatmap(df.corr()[df.corr() > 0.8], annot = True)
plt.show()
```



In [96]:
```
df = df.drop(['BorrowerAPR', 'LenderYield', 'EstimatedLoss', 'CreditScoreRangeLower', 'OpenCreditLines',
              'OpenRevolvingAccounts', 'TotalCreditLinespast7years', 'LP_CustomerPrincipalPayments',
              'LoanMonthsSinceOrigination'], axis = 1)
```

In [97]:
```
df.shape
```

Out[97]: (113932, 40)

In [98]:
```
from sklearn.model_selection import train_test_split
X= df.drop(['LoanStatus'], axis=1)
y = df['LoanStatus']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)
print('X_train :', X_train.shape)
print('X_test :', X_test.shape)
print('y_train :', y_train.shape)
print('y_test :', y_test.shape)
```

```
X_train : (79752, 39)
X_test : (34180, 39)
y_train : (79752,)
y_test : (34180,)
```

In [99]:
```
from sklearn.metrics import (accuracy_score,
                             classification_report,
                             recall_score, precision_score, f1_score,
                             confusion_matrix)
from xgboost import XGBClassifier
from sklearn.ensemble import ExtraTreesClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.neighbors import NearestNeighbors
from sklearn.tree import DecisionTreeClassifier
```

In [100]:
```
def modelling(X_train, y_train, X_test, y_test, **kwargs):
    scores = {}
    models = []
    if 'dtf' in kwargs.keys() and kwargs['dtf']:
        dtf=DecisionTreeClassifier()
        dtf.fit(X_train,y_train)
        y_pred = dtf.predict(X_test)
        scores['dtf'] = [accuracy_score(y_test, y_pred)]
#         scores['extree']['roc_auc'] = roc_auc_score(y_test, y_pred)
    return scores
```

In [101]:
```
modelling(X_train,y_train, X_test, y_test, dtf=True)
```

Out[101]:
```
{'dtf': [0.9811878291398478]}
```

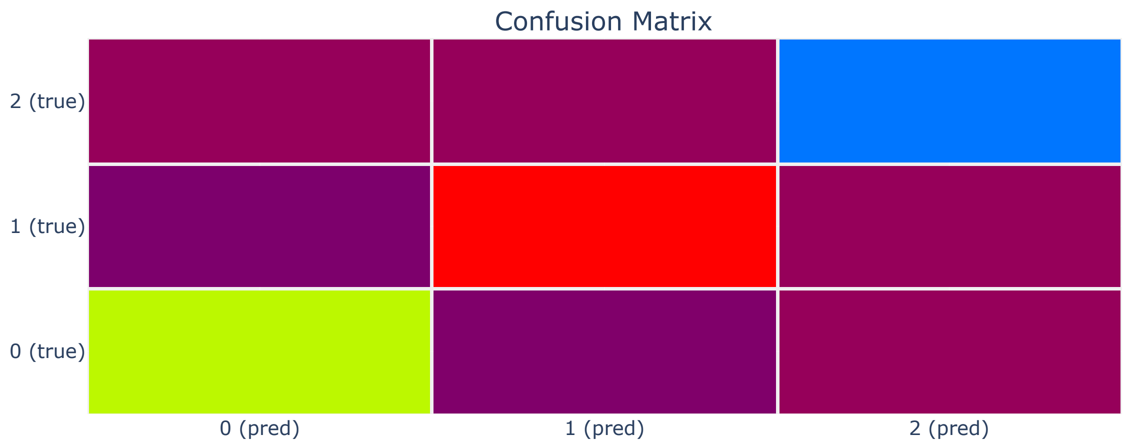
In [102]:
```
import plotly.graph_objs as go
import plotly.tools as tls
import plotly.figure_factory as ff

import plotly.express as px
import plotly.offline as py
def model_performance(model, y_test, y_hat) :
    conf_matrix = confusion_matrix(y_test, y_hat)
    trace1 = go.Heatmap(z = conf_matrix  ,x = ["0 (pred)","1 (pred)", "2 (pred)"],
                        y = ["0 (true)","1 (true)", "2 (true)"],xgap = 2, ygap = 2,
                        colorscale = 'Rainbow', showscale  = False)

    #Show metrics
    Accuracy  =  accuracy_score(y_test, y_hat)
    Precision =  precision_score(y_test, y_pred, average= 'weighted')
    Recall    =  recall_score(y_test, y_pred, average= 'weighted')
    F1_score  =  f1_score(y_test, y_pred, average= 'weighted')

    show_metrics = pd.DataFrame(data=[[Accuracy , Precision, Recall, F1_score]])
    show_metrics = show_metrics.T

    colors = ['gold', 'lightgreen', 'lightcoral', 'lightskyblue']
    trace2 = go.Bar(x = (show_metrics[0].values),
                   y = ['Accuracy', 'Precision', 'Recall', 'F1_score'], text = np.round_(show_metrics
[0].values,4),
                    textposition = 'auto',
                   orientation = 'h', opacity = 0.8,marker=dict(
            color=colors,
            line=dict(color='#000000',width=1.5)))


    #plots
    model = model

    #Subplots
    fig = tls.make_subplots(rows=2, cols=1, print_grid=False,
                          subplot_titles=('Confusion Matrix',
                                        'Metrics',
                                        ))

    fig.append_trace(trace1,1,1)
    fig.append_trace(trace2,2,1)

    fig['layout'].update(showlegend = False, title = '<b>Model performance report</b><br>'+str(mode
l),
                        autosize = True, height = 800,width = 800,
                        plot_bgcolor = 'rgba(240,240,240, 0.95)',
                        paper_bgcolor = 'rgba(240,240,240, 0.95)',
                        # margin = dict(b = 100)
                        )
    fig.layout.titlefont.size = 14

    py.iplot(fig)
```

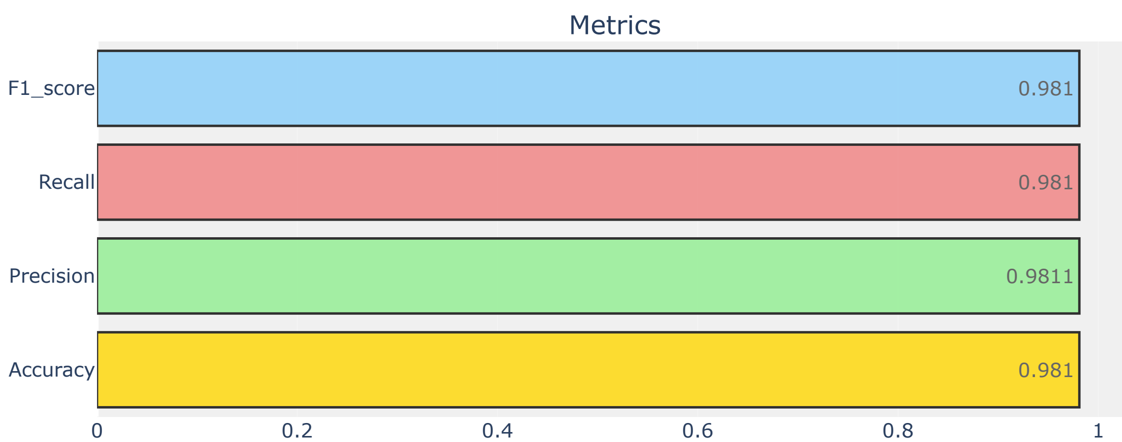
In [103]:
```
dtf=DecisionTreeClassifier()
dtf.fit(X_train,y_train)
# dtf.score(X_test,y_test)
y_pred = dtf.predict(X_test)
```

In [104]:
```
model_performance(dtf,y_test, y_pred)
```

```
C:\Users\Owner\Anaconda3\lib\site-packages\plotly\tools.py:465: DeprecationWarning:

plotly.tools.make_subplots is deprecated, please use plotly.subplots.make_subplots instead
```

Model performance report
DecisionTreeClassifier()





In [105]:
```
print('Train accuracy: ', dtf.score(X_train, y_train))
```

```
Train accuracy:  1.0
```

In [106]:
```
print('Test accuracy: ', dtf.score(X_test, y_test))
```

```
Test accuracy:  0.9810415447630193
```

In [107]:
```
y_pred=dtf.predict(X_train)
```

In [108]:
```
print(classification_report(y_train,y_pred))
```

```
              precision    recall  f1-score   support

   Completed       1.00      1.00      1.00     26810
     Current       1.00      1.00      1.00     39556
   Defaulted       1.00      1.00      1.00     13386

    accuracy                           1.00     79752
   macro avg       1.00      1.00      1.00     79752
weighted avg       1.00      1.00      1.00     79752
```

In [109]:
```
y_pred=dtf.predict(X_test)
```

In [110]:
```
print(classification_report(y_test,y_pred))
```

```
              precision    recall  f1-score   support

   Completed       0.97      0.97      0.97     11469
     Current       0.98      0.98      0.98     17020
   Defaulted       1.00      1.00      1.00      5691

    accuracy                           0.98     34180
   macro avg       0.98      0.98      0.98     34180
weighted avg       0.98      0.98      0.98     34180
```

In [112]:
```
from sklearn.model_selection import GridSearchCV

tuned_parms = {'criterion' : ['entropy', 'gini'],
              'max_depth' : range(2, 10),
              'min_samples_split' : range(5, 10, 15)}
dtf = DecisionTreeClassifier(random_state = 10)
grid = GridSearchCV(estimator = dtf, param_grid = tuned_parms, cv = 5, scoring = 'roc_auc')
grid_model = grid.fit(X_train, y_train)
```

In [113]:
```
grid_model.best_params_
```

Out[113]:
```
{'criterion': 'entropy', 'max_depth': 2, 'min_samples_split': 5}
```

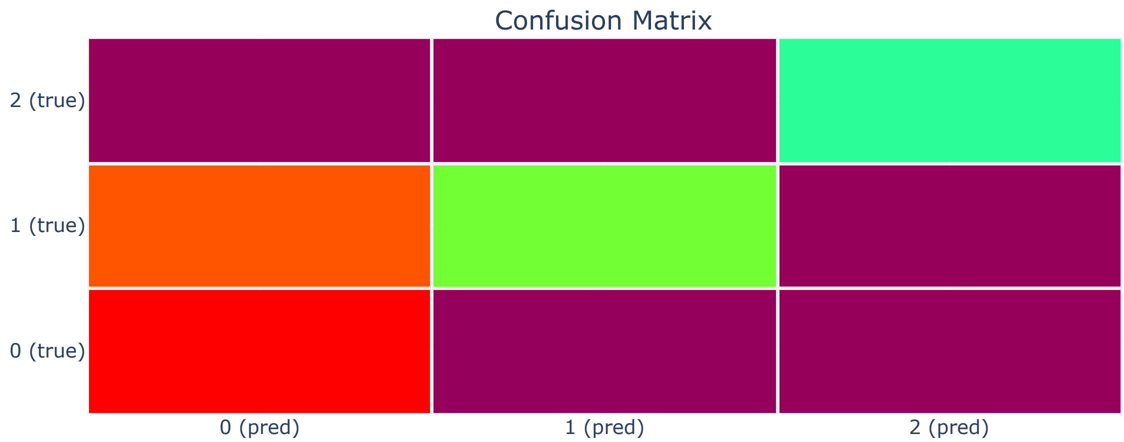
In [114]:
```
dt_best = DecisionTreeClassifier(criterion = 'entropy', max_depth = 2, min_samples_split = 2)
dt_best.fit(X_train, y_train)
```

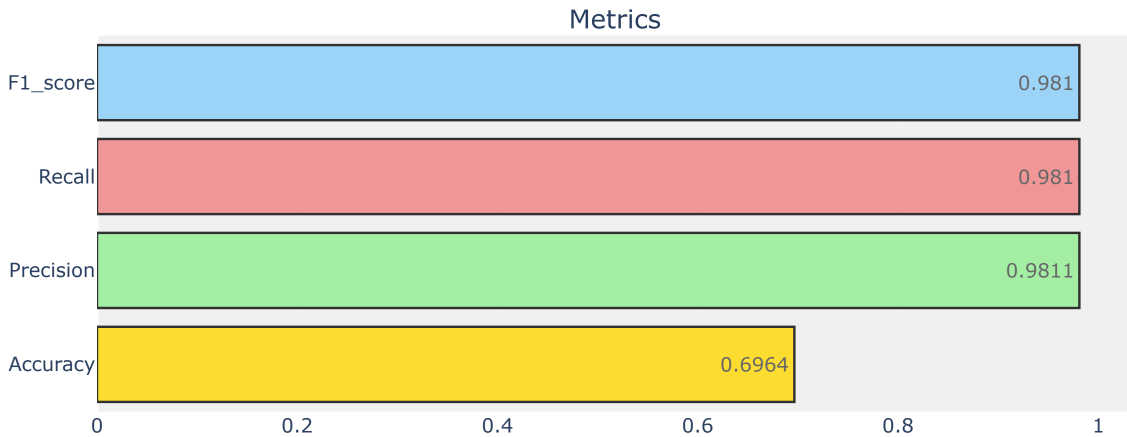
Out[114]:
```
DecisionTreeClassifier(criterion='entropy', max_depth=2)
```

In [115]:
```
y_test_pred = dt_best.predict(X_test)

model_performance(dt_best, y_test, y_test_pred)
```

```
C:\Users\Owner\Anaconda3\lib\site-packages\plotly\tools.py:465: DeprecationWarning:

plotly.tools.make_subplots is deprecated, please use plotly.subplots.make_subplots instead
```

Model performance report
DecisionTreeClassifier(criterion='entropy', max_depth=2)





In [116]:
```
feat_imp=pd.DataFrame(dt_best.feature_importances_,index=X_train.columns,columns=['Importance'])
feat_imp=feat_imp.reset_index().sort_values('Importance',ascending=False)
```

In [117]:
```
feat_imp
```

Out[117]:

	index	Importance
27	LoanCurrentDaysDelinquent	0.796333
30	LP_CustomerPayments	0.203667
29	MonthlyLoanPayment	0.000000
22	TradesNeverDelinquent (percentage)	0.000000
23	TradesOpenedLast6Months	0.000000
24	DebtToIncomeRatio	0.000000
25	IncomeVerifiable	0.000000
26	StatedMonthlyIncome	0.000000
28	LoanOriginalAmount	0.000000
0	index	0.000000
20	AvailableBankcardCredit	0.000000
31	LP_InterestandFees	0.000000
32	LP_ServiceFees	0.000000
33	Investors	0.000000
34	Term	0.000000
35	ProsperScore	0.000000
36	Occupation	0.000000
37	EmploymentStatus	0.000000
21	TotalTrades	0.000000
19	BankcardUtilization	0.000000
1	BorrowerRate	0.000000
9	CurrentCreditLines	0.000000
2	EstimatedEffectiveYield	0.000000
3	EstimatedReturn	0.000000
4	ProsperRating (numeric)	0.000000
5	ListingCategory (numeric)	0.000000
6	EmploymentStatusDuration	0.000000
7	IsBorrowerHomeowner	0.000000
8	CreditScoreRangeUpper	0.000000
10	OpenRevolvingMonthlyPayment	0.000000
18	RevolvingCreditBalance	0.000000
11	InquiriesLast6Months	0.000000
12	TotalInquiries	0.000000
13	CurrentDelinquencies	0.000000
14	AmountDelinquent	0.000000
15	DelinquenciesLast7Years	0.000000
16	PublicRecordsLast10Years	0.000000
17	PublicRecordsLast12Months	0.000000
38	IncomeRange	0.000000

In [ ]:

In [118]:
```
y_xgb = y.replace({'Completed' : 0, 'Current' : 1, 'Defaulted' : 2})
```

In [119]:
```
X_train, X_test, y_xgb_train, y_xgb_test = train_test_split(X, y_xgb, test_size = 0.3, random_state = 10)

print('X_train :', X_train.shape)
print('X_test :', X_test.shape)
print('y_xgb_train :', y_xgb_train.shape)
print('y_xgb_test :', y_xgb_test.shape)
```

```
X_train : (79752, 39)
X_test : (34180, 39)
y_xgb_train : (79752,)
y_xgb_test : (34180,)
```

In [120]:
```
def modelling(X_train, y_train, X_test, y_test, **kwargs):
    scores = {}
    models = []
    if 'xgb' in kwargs.keys() and kwargs['xgb']:
        xgb = XGBClassifier()
        xgb.fit(X_train._get_numeric_data(), np.ravel(y_train, order='C'))
        y_pred = xgb.predict(X_test._get_numeric_data())
        scores['xgb']= [accuracy_score(y_test, y_pred)]
#         scores['xgb']['roc_auc'] = roc_auc_score(y_test, y_pred)
    return scores
```

In [121]:
```
modelling(X_train, y_xgb_train, X_test, y_xgb_test, xgb=True)
```

```
[19:32:10] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.5.1/src/learner.cc:111
5: Starting in XGBoost 1.3.0, the default evaluation metric used with the objective 'multi:softprob'
was changed from 'merror' to 'mlogloss'. Explicitly set eval_metric if you'd like to restore the old
behavior.
```

Out[121]:
```
{'xgb': [0.9935634874195436]}
```

In [122]:
```
xgb = XGBClassifier()
xgb.fit(X_train._get_numeric_data(), np.ravel(y_xgb_train, order='C'))
y_xgb_pred_test = xgb.predict(X_test)
y_xgb_pred_train = xgb.predict(X_train)
```

```
[19:33:39] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.5.1/src/learner.cc:111
5: Starting in XGBoost 1.3.0, the default evaluation metric used with the objective 'multi:softprob'
was changed from 'merror' to 'mlogloss'. Explicitly set eval_metric if you'd like to restore the old
behavior.
```

In [123]:
```
print(classification_report(y_xgb_test, y_xgb_pred_test))
```

```
              precision    recall  f1-score   support

           0       0.99      1.00      0.99     11363
           1       1.00      0.99      0.99     17069
           2       1.00      1.00      1.00      5748

    accuracy                           0.99     34180
   macro avg       0.99      1.00      0.99     34180
weighted avg       0.99      0.99      0.99     34180
```

In [124]:
```
print(classification_report(y_xgb_train,y_xgb_pred_train))
```

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     26916
           1       1.00      1.00      1.00     39507
           2       1.00      1.00      1.00     13329

    accuracy                           1.00     79752
   macro avg       1.00      1.00      1.00     79752
weighted avg       1.00      1.00      1.00     79752
```

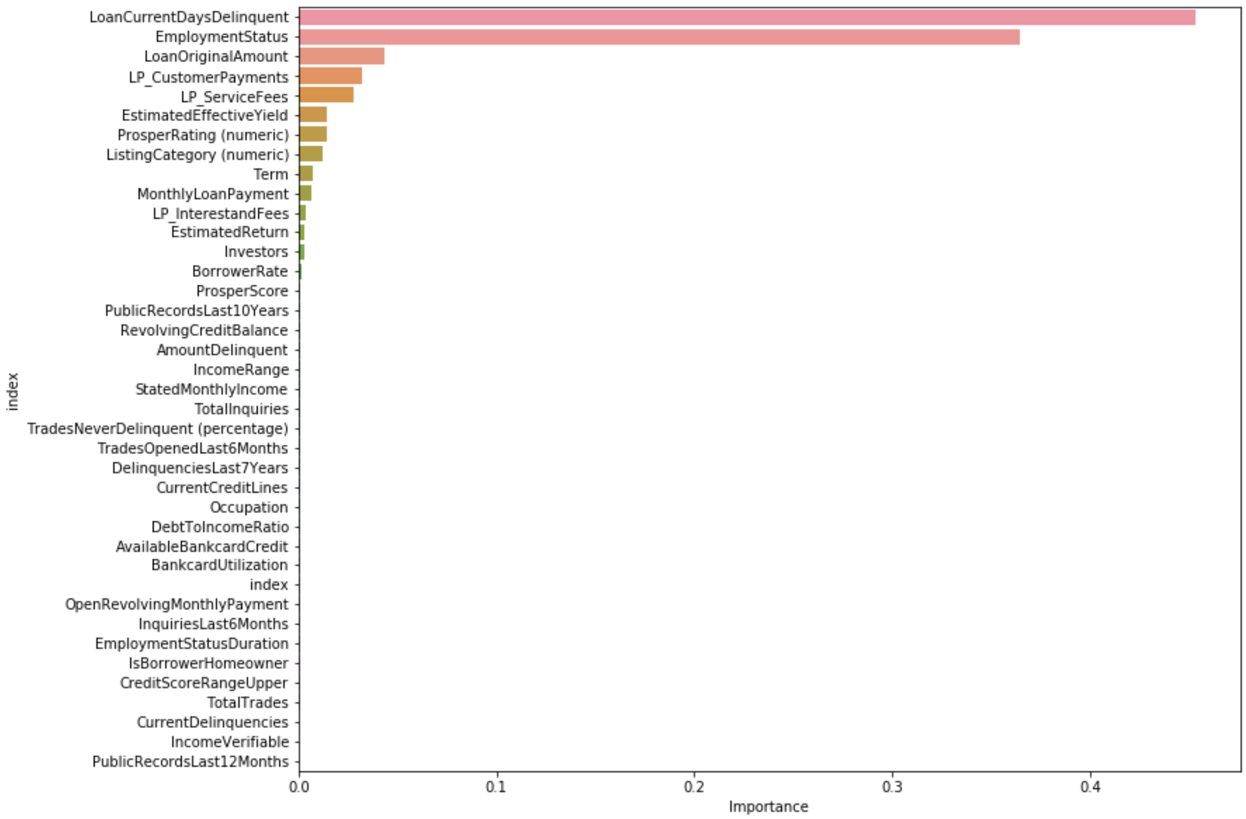
In [125]:
```
feat_imp=pd.DataFrame(xgb.feature_importances_,index=X_train.columns,columns=['Importance'])
feat_imp=feat_imp.reset_index().sort_values('Importance',ascending=False)
```

In [126]:
```
feat_imp
```

Out[126]:

	index	Importance
27	LoanCurrentDaysDelinquent	0.453034
37	EmploymentStatus	0.364620
28	LoanOriginalAmount	0.043328
30	LP_CustomerPayments	0.031854
32	LP_ServiceFees	0.027439
2	EstimatedEffectiveYield	0.014475
4	ProsperRating (numeric)	0.014210
5	ListingCategory (numeric)	0.012160
34	Term	0.007198
29	MonthlyLoanPayment	0.006741
31	LP_InterestandFees	0.003451
3	EstimatedReturn	0.002802
33	Investors	0.002677
1	BorrowerRate	0.001557
35	ProsperScore	0.000870
16	PublicRecordsLast10Years	0.000802
18	RevolvingCreditBalance	0.000711
14	AmountDelinquent	0.000709
38	IncomeRange	0.000697
26	StatedMonthlyIncome	0.000686
12	TotalInquiries	0.000684
22	TradesNeverDelinquent (percentage)	0.000673
23	TradesOpenedLast6Months	0.000669
15	DelinquenciesLast7Years	0.000669
9	CurrentCreditLines	0.000621
36	Occupation	0.000615
24	DebtToIncomeRatio	0.000613
20	AvailableBankcardCredit	0.000610
19	BankcardUtilization	0.000600
0	index	0.000595
10	OpenRevolvingMonthlyPayment	0.000592
11	InquiriesLast6Months	0.000562
6	EmploymentStatusDuration	0.000560
7	IsBorrowerHomeowner	0.000506
8	CreditScoreRangeUpper	0.000501
21	TotalTrades	0.000489
13	CurrentDelinquencies	0.000245
25	IncomeVerifiable	0.000177
17	PublicRecordsLast12Months	0.000000

In [128]:
```
plt.figure(figsize=(12,10))
sns.barplot(data=feat_imp,x='Importance',y='index')
plt.show()
```



In [119]:
```
from sklearn.experimental import enable_halving_search_cv
from sklearn.model_selection import HalvingGridSearchCV

params = {'n_estimators' : [100, 120, 150],
'learning_rate' : [0.1, 0.01, 0.001, 0.15, 0.015],
'gamma' : [2, 3, 4, 5, 6],
'max_depth' : [2, 3, 4, 5, 6]}

xgb = XGBClassifier()
grid = HalvingGridSearchCV(estimator = xgb, param_grid = params, cv = 5)
grid_model = grid.fit(X_train, y_xgb_train)
```

In [120]:
```
grid_model.best_params_
```

Out[120]:
```
{'gamma': 2, 'learning_rate': 0.15, 'max_depth': 4, 'n_estimators': 100}
```

In [130]:
```
def modelling(X_train, y_train, X_test, y_test, **kwargs):
    scores = {}
    models = []
    if 'xgb' in kwargs.keys() and kwargs['xgb']:
        xgb = XGBClassifier(n_estimators = 100, learning_rate = 0.15, gamma = 2, max_depth = 4)
        xgb.fit(X_train._get_numeric_data(), np.ravel(y_train, order='C'))
        y_pred = xgb.predict(X_test._get_numeric_data())
        scores['xgb']= [accuracy_score(y_test, y_pred)]
#         scores['xgb']['roc_auc'] = roc_auc_score(y_test, y_pred)
    return scores
```

In [131]:
```
modelling(X_train, y_xgb_train, X_test, y_xgb_test, xgb=True)
```

Out[131]:
```
{'xgb': [0.9923639555295495]}
```

In [132]:
```
print(classification_report(y_xgb_test, y_xgb_pred_test))
```

```
              precision    recall  f1-score   support

           0       0.99      1.00      0.99     11363
           1       1.00      0.99      0.99     17069
           2       1.00      1.00      1.00      5748

    accuracy                           0.99     34180
   macro avg       0.99      1.00      0.99     34180
weighted avg       0.99      0.99      0.99     34180
```

In [133]:
```
print(classification_report(y_xgb_train,y_xgb_pred_train))
```

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     26916
           1       1.00      1.00      1.00     39507
           2       1.00      1.00      1.00     13329

    accuracy                           1.00     79752
   macro avg       1.00      1.00      1.00     79752
weighted avg       1.00      1.00      1.00     79752
```

In [135]:
```
def modelling(X_train, y_train, X_test, y_test, **kwargs):
    scores = {}
    models = []
    if 'rf' in kwargs.keys() and kwargs['rf']:
        rf = RandomForestClassifier(n_estimators=200)
        rf.fit(X_train, y_train)
        y_pred = rf.predict(X_test)
        scores['rf']= [accuracy_score(y_test, y_pred)]
#         scores['rf']['roc_auc'] = roc_auc_score(y_test, y_pred)
    return scores
```

In [123]:
```
rf = RandomForestClassifier()
rf.fit(X_train, y_train)
y_pred_test = rf.predict(X_test)
y_pred_train = rf.predict(X_train)
```

In [124]:
```
print(classification_report(y_test, y_pred_test))
```

```
              precision    recall  f1-score   support

   Completed       0.34      0.10      0.16     11469
     Current       0.50      0.90      0.64     17020
   Defaulted       0.19      0.00      0.00      5691

    accuracy                           0.48     34180
   macro avg       0.34      0.33      0.27     34180
weighted avg       0.39      0.48      0.37     34180
```

In [125]:
```
print(classification_report(y_train, y_pred_train))
```

```
              precision    recall  f1-score   support

   Completed       1.00      1.00      1.00     26810
     Current       1.00      1.00      1.00     39556
   Defaulted       1.00      1.00      1.00     13386

    accuracy                           1.00     79752
   macro avg       1.00      1.00      1.00     79752
weighted avg       1.00      1.00      1.00     79752
```

In [126]:
```
params = {'criterion' : ['entropy', 'gini'],
'n_estimators' : [90, 100, 150, 200],
'max_depth' : [10, 15, 20],
'min_samples_split' : [2, 5, 8]}

rf = RandomForestClassifier()
grid = HalvingGridSearchCV(estimator = rf, param_grid = params, cv = 5)
grid_model = grid.fit(X_train, y_train)
```

In [128]:
```
grid_model.best_params_
```

Out[128]:
```
{'criterion': 'entropy',
 'max_depth': 10,
 'min_samples_split': 8,
 'n_estimators': 200}
```

In [138]:
```
rf = RandomForestClassifier(criterion = 'entropy', max_depth = 10, min_samples_split = 8, n_estimator
s = 200)
rf.fit(X_train, y_train)
y_pred_test = rf.predict(X_test)
y_pred_train = rf.predict(X_train)
```

In [139]:
```
print(classification_report(y_test, y_pred_test))
```

```
              precision    recall  f1-score   support

   Completed       0.00      0.00      0.00     11469
     Current       0.50      1.00      0.66     17020
   Defaulted       0.00      0.00      0.00      5691

    accuracy                           0.50     34180
   macro avg       0.17      0.33      0.22     34180
weighted avg       0.25      0.50      0.33     34180
```

In [140]:
```
print(classification_report(y_train, y_pred_train))
```

```
              precision    recall  f1-score   support

   Completed       1.00      0.00      0.00     26810
     Current       0.50      1.00      0.66     39556
   Defaulted       1.00      0.00      0.00     13386

    accuracy                           0.50     79752
   macro avg       0.83      0.33      0.22     79752
weighted avg       0.75      0.50      0.33     79752
```

•Conclusion:

Based on the results, it can be concluded that this model can predict loan defaulters with an accuracy of 99%. Companies can employ similar models and potentially avoid giving loans to applicants who are highly likely to default. Doing so will reduce risk and financial loss for lending companies. As with all predictive models, data should be monitored and re-evaluated on a regular basis.

Though XGB predicts better than Decision Tree, however, in the banking industry, as per the government regulations and compliance requirements, one should be able to interpret the model results and clearly explain the reason for declining the loans to the clients. Hence Decision tree should be used to build the real model for deploying the same in production. Decision Tree is simple which is a score that is a combination of coefficients multiplied by features. It can be interpreted as probabilities. If users are declined the features where their scores were low can be identified and the account holder can be told how to improve their score

In [ ]: