Part I - Exploring the Prosper Loan Dataset

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Introduction

> On November 24, 2008, the SEC found Prosper to be in violation of the Securities Act of 1933. As a result of these findings, the SEC imposed a cease and desist order on Prosper ... In July 2009, Prosper reopened their website for lending ("investing") and borrowing after having obtained SEC registration for its loans ("notes"). After the relaunch, bidding on loans was restricted to residents of 28 U.S. states and the District of Columbia. Borrowers may reside in any of 47 states, with residents of three states (Iowa, Maine, and North Dakota) not permitted to borrow through Prosper

> In this notebook, the analysis is done on the Prosper Datatset which is collected from a Loan company. The dataset includes customers who have paid off their

> loans, who have been past due and put into collection without paying back their loan and interests, and who have paid off only after they were put in collection. The original dataset contains 113937 rows and 81 columns out of which 12 features of intrest were selected.

Data Dictionary

The following data dictionary shows each variable of the dataset and the corresponding description:

Variable	
ListingKey	Unique key for each listing, same value as the 'key' used in the listing object in the API.
ListingNumber	The number that uniquely identifies the listing to the public as displayed on the website
ListingCreationDate	The date the listing was created.
CreditGrade	The Credit rating that was assigned at the time the listing went live. Applicable for listin
Term	The length of the loan expressed in months.
LoanStatus	The current status of the loan: Cancelled, Chargedoff, Completed, Current, Defaulted, Fi
ClosedDate	Closed date is applicable for Cancelled, Completed, Chargedoff and Defaulted loan stat
BorrowerAPR	The Borrower's Annual Percentage Rate (APR) for the loan.
BorrowerRate	The Borrower's interest rate for this loan.
LenderYield	The Lender yield on the loan. Lender yield is equal to the interest rate on the loan less th
EstimatedEffectiveYield	Effective yield is equal to the borrower interest rate (i) minus the servicing fee rate, (ii) n
EstimatedLoss	Estimated loss is the estimated principal loss on charge-offs. Applicable for loans origi
EstimatedReturn	The estimated return assigned to the listing at the time it was created. Estimated return
ProsperRating (numeric)	The Prosper Rating assigned at the time the listing was created: 0 - N/A, 1 - HR, 2 - E, 3 -
ProsperRating (Alpha)	The Prosper Rating assigned at the time the listing was created between AA - HR. Appli
ProsperScore	A custom risk score built using historical Prosper data. The score ranges from 1-10, wit
ListingCategory	The category of the listing that the borrower selected when posting their listing: 0 - Not
BorrowerState	The two letter abbreviation of the state of the address of the borrower at the time the Li
Occupation	The Occupation selected by the Borrower at the time they created the listing.
EmploymentStatus	The employment status of the borrower at the time they posted the listing.
EmploymentStatusDuration	The length in months of the employment status at the time the listing was created.
IsBorrowerHomeowner	A Borrower will be classified as a homeowner if they have a mortgage on their credit pro
CurrentlyInGroup	Specifies whether or not the Borrower was in a group at the time the listing was created
GroupKey	The Key of the group in which the Borrower is a member of. Value will be null if the borr
DateCreditPulled	The date the credit profile was pulled.
CreditScoreRangeLower	The lower value representing the range of the borrower's credit score as provided by a c
CreditScoreRangeUpper	The upper value representing the range of the borrower's credit score as provided by a c
FirstRecordedCreditLine	The date the first credit line was opened.
CurrentCreditLines	Number of current credit lines at the time the credit profile was pulled.

Variable	
OpenCreditLines	Number of open credit lines at the time the credit profile was pulled.
TotalCreditLinespast7years	Number of credit lines in the past seven years at the time the credit profile was pulled.
OpenRevolvingAccounts	Number of open revolving accounts at the time the credit profile was pulled.
OpenRevolvingMonthlyPayment	Monthly payment on revolving accounts at the time the credit profile was pulled.
InquiriesLast6Months	Number of inquiries in the past six months at the time the credit profile was pulled.
TotalInquiries	Total number of inquiries at the time the credit profile was pulled.
CurrentDelinquencies	Number of accounts delinquent at the time the credit profile was pulled.
AmountDelinquent	Dollars delinquent at the time the credit profile was pulled.
DelinquenciesLast7Years	Number of delinquencies in the past 7 years at the time the credit profile was pulled.
PublicRecordsLast10Years	Number of public records in the past 10 years at the time the credit profile was pulled.
PublicRecordsLast12Months	Number of public records in the past 12 months at the time the credit profile was pulled
RevolvingCreditBalance	Dollars of revolving credit at the time the credit profile was pulled.
BankcardUtilization	The percentage of available revolving credit that is utilized at the time the credit profile
AvailableBankcardCredit	The total available credit via bank card at the time the credit profile was pulled.
TotalTrades	Number of trade lines ever opened at the time the credit profile was pulled.
TradesNeverDelinquent	Number of trades that have never been delinquent at the time the credit profile was pull
TradesOpenedLast6Months	Number of trades opened in the last 6 months at the time the credit profile was pulled.
DebtToIncomeRatio	The debt to income ratio of the borrower at the time the credit profile was pulled. This v
IncomeRange	The income range of the borrower at the time the listing was created.
IncomeVerifiable	The borrower indicated they have the required documentation to support their income.
StatedMonthlyIncome	The monthly income the borrower stated at the time the listing was created.
LoanKey	Unique key for each loan. This is the same key that is used in the API.
TotalProsperLoans	Number of Prosper loans the borrower at the time they created this listing. This value w
TotalProsperPaymentsBilled	Number of on time payments the borrower made on Prosper loans at the time they crea
OnTimeProsperPayments	Number of on time payments the borrower had made on Prosper loans at the time they
ProsperPaymentsLessThanOneMonthLate	Number of payments the borrower made on Prosper loans that were less than one mon
ProsperPaymentsOneMonthPlusLate	Number of payments the borrower made on Prosper loans that were greater than one m
ProsperPrincipalBorrowed	Total principal borrowed on Prosper loans at the time the listing was created. This value
ProsperPrincipalOutstanding	Principal outstanding on Prosper loans at the time the listing was created. This value w
ScorexChangeAtTimeOfListing	Borrower's credit score change at the time the credit profile was pulled. This will be the
LoanCurrentDaysDelinquent	The number of days delinquent.
LoanFirstDefaultedCycleNumber	The cycle the loan was charged off. If the loan has not charged off the value will be null
LoanMonthsSinceOrigination	Months since the loan originated.
LoanNumber	The number that uniquely identifies the loan to the public as displayed on the website.
LoanOriginalAmount	The original amount of the loan.
LoanOriginationDate	The date the loan originated.
LoanOriginationQuarter	The quarter in which the loan originated.
MemberKey	Unique key for each member. This is the same key that is used in the API.
MonthlyLoanPayment	The monthly payment (principal and interest) the borrower is required to make for this l

Variable	
LP_CustomerPayments	The total payments (principal + interest) that have been made on the loan by the borrow
LP_CustomerPrincipalPayments	The total principal payments that have been made on the loan by the borrower.
LP_InterestandFees	Interest and fees paid by the borrower.
LP_ServiceFees	The servicing fees paid by the borrower.
LP_CollectionFees	The collection fees paid by the borrower.
LP_GrossPrincipalLoss	Gross principal loss on the loan.
LP_NetPrincipalLoss	Net principal loss on the loan.
LP_NonPrincipalRecoverypayments	Non-principal recovery payments on the loan.
PercentFunded	The percentage of the loan that was funded.
Recommendations	Number of recommendations the borrower had at the time they created the listing.
InvestmentFromFriendsCount	Number of investments that were made by friends at the time the listing was created.
InvestmentFromFriendsAmount	The dollar amount of investments that were made by friends at the time the listing was
Investors	The number of investors that funded the loan.

Objectives

1. Loan Performance Analysis

2. Credit Score and Borrower Analysis

3. Geographic and Demographic Analysis

Preliminary Wrangling

- In this section, a preliminary data wrangling is done on the dataset.

```
## import all packages
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

# suppress warnings from final output
import warnings
warnings.simplefilter("ignore")
```

```
c:\Users\SS\AppData\Local\Programs\Python\Python311\Lib\site-packages\scipy\__init__.py:
  warnings.warn(f"A NumPy version >={np_minversion} and <{np_maxversion}"
```

Loading the dataset

> Let's Load in the dataset into a pandas dataframe:

```
df = pd.read_csv("./data/prosperLoanData.csv") ## Load the csv into pandas dataframe
df.sample(10) ## Looking at a random sample of 10 rows.
```

	ListingKey	ListingNumber	ListingCreationDate	CreditGrade	Term
89396	522435803124450551D167F	796219	2013-06-03 18:11:11.817000000	NaN	36
66329	CD2435638856954192AA8E9	682194	2012-12-04 06:24:02.113000000	NaN	36
57866	811B3553828282161FA98C0	616886	2012-07-25 20:22:43.937000000	NaN	36
68993	71C2340109095088293289C	204704	2007-09-21 00:36:36.917000000	AA	36
68782	FDB1357349001237607843C	729927	2013-03-14 16:51:11.260000000	NaN	36
79820	1CB13601952390901F76B99	1172289	2014-01-30 12:50:33.480000000	NaN	36
107870	2260360104242486260A5C5	1142878	2014-02-04 13:01:44.540000000	NaN	60
55104	BD93359101129760282710D0	969276	2013-10-09 19:02:28.670000000	NaN	60
106857	F4533393067041235BB5B50	157991	2007-06-25 16:35:41.160000000	AA	36
44207	5A1735791083505443D330B	785172	2013-05-21 06:09:04.963000000	NaN	60

10 rows × 81 columns

Dataset Structure

```
df.shape ## showing the shape of the dataset
```

```
(113937, 81)
```

> This dataset has 113,937 rows and 81 columns. Which is a relatively big dataset.

Dataset Assessment and Cleaning

Duplicated Records

```
df.duplicated(subset='LoanKey').sum()
```

```
871
```

> Let's identify the duplicated records based on the LoanKey and see if wwe should handle this

```
duplicates = df[df.duplicated(subset='LoanKey', keep=False)]
display(duplicates.head(10))
```

	ListingKey	ListingNumber	ListingCreationDate	CreditGrade	Term	L
8	0F043596202561788EA13D5	1023355	2013-12-02 10:43:39.117000000	NaN	36	
9	0F043596202561788EA13D5	1023355	2013-12-02 10:43:39.117000000	NaN	36	
29	0F5635971610956135174 37	1051243	2013-12-17 09:18:33.220000000	NaN	36	
176	106335993636414276CB477	1119836	2014-01-08 14:27:50.320000000	NaN	36	
313	09233589620788733CFB8CE	930842	2013-09-25 08:03:11.860000000	NaN	36	
349	313635901230654318A9030	931467	2013-09-26 18:50:29.053000000	NaN	36	
442	09AD35918712001025AC1BD	969821	2013-10-24 13:21:31.607000000	NaN	36	
444	09CD3592594126374FB0A7C	986199	2013-10-18 08:28:03.610000000	NaN	36	
455	31C73597152310464749E00	1092437	2013-12-23 13:47:35.500000000	NaN	36	
461	44F2358557406858060EBDE	870200	2013-08-15 07:12:49.410000000	NaN	60	

10 rows × 81 columns

```
df.drop_duplicates(subset='LoanKey', keep='first', inplace=True) ## Dropping the duplicated
```

```
print(df.duplicated(subset='LoanKey').sum()) ## Checking the drop of duplicted
df.shape
```

```
0
(113066, 81)
```

> Let's check for the duplicated records based on the `ListingKey` based on teh documentation it has to be unique too.

```
df.duplicated(subset='ListingKey').sum() ## checking for duliated based on the listing key
```

```
0
```

Data types Validity

- Assessment: Let's look at the data types of these variables and assess them using `.info`:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 113066 entries, 0 to 113936
Data columns (total 81 columns):
 #   Column                               Non-Null Count   Dtype  
---  ------                               --------------   -----  
 0   ListingKey                           113066 non-null  object 
 1   ListingNumber                        113066 non-null  int64  
 2   ListingCreationDate                  113066 non-null  object 
 3   CreditGrade                          28953 non-null   object 
 4   Term                                 113066 non-null  int64  
 5   LoanStatus                           113066 non-null  object 
 6   ClosedDate                           55076 non-null   object 
 7   BorrowerAPR                          113041 non-null  float64
 8   BorrowerRate                         113066 non-null  float64
 9   LenderYield                          113066 non-null  float64
 10  EstimatedEffectiveYield              83982 non-null   float64
 11  EstimatedLoss                        83982 non-null   float64
 12  EstimatedReturn                      83982 non-null   float64
 13  ProsperRating (numeric)              83982 non-null   float64
 14  ProsperRating (Alpha)                83982 non-null   object 
 15  ProsperScore                         83982 non-null   float64
 16  ListingCategory (numeric)            113066 non-null  int64  
 17  BorrowerState                        107551 non-null  object 
 18  Occupation                           109537 non-null  object 
 19  EmploymentStatus                     110811 non-null  object 
 20  EmploymentStatusDuration             105441 non-null  float64
 21  IsBorrowerHomeowner                  113066 non-null  bool   
 22  CurrentlyInGroup                     113066 non-null  bool   
 23  GroupKey                             13339 non-null   object 
 24  DateCreditPulled                     113066 non-null  object 
 25  CreditScoreRangeLower                112475 non-null  float64
 26  CreditScoreRangeUpper                112475 non-null  float64
 27  FirstRecordedCreditLine              112369 non-null  object 
 28  CurrentCreditLines                   105462 non-null  float64
 29  OpenCreditLines                      105462 non-null  float64
 30  TotalCreditLinespast7years           112369 non-null  float64
 31  OpenRevolvingAccounts                113066 non-null  int64  
 32  OpenRevolvingMonthlyPayment          113066 non-null  float64
 33  InquiriesLast6Months                 112369 non-null  float64
 34  TotalInquiries                       111907 non-null  float64
 35  CurrentDelinquencies                 112369 non-null  float64
 36  AmountDelinquent                     105444 non-null  float64
 37  DelinquenciesLast7Years              112076 non-null  float64
 38  PublicRecordsLast10Years             112369 non-null  float64
 39  PublicRecordsLast12Months            105462 non-null  float64
 40  RevolvingCreditBalance               105462 non-null  float64
 41  BankcardUtilization                  105462 non-null  float64
```

```
 42  AvailableBankcardCredit              105522 non-null  float64
 43  TotalTrades                          105522 non-null  float64
 44  TradesNeverDelinquent (percentage)   105522 non-null  float64
 45  TradesOpenedLast6Months              105522 non-null  float64
 46  DebtToIncomeRatio                    104594 non-null  float64
 47  IncomeRange                          113066 non-null  object
 48  IncomeVerifiable                     113066 non-null  bool
 49  StatedMonthlyIncome                  113066 non-null  float64
 50  LoanKey                              113066 non-null  object
 51  TotalProsperLoans                    21923 non-null   float64
 52  TotalProsperPaymentsBilled           21923 non-null   float64
```

> We have the columns of `ClosedDate`, `LoanOriginationDate`, `DateCreditPulled`, and the `ListingCreationDate` has an object type and it has to be a datetime type.

```
## listing the date columns
date_columns = ['ClosedDate', 'LoanOriginationDate', 'DateCreditPulled', 'ListingCreationDat

### Loopong through the list and coverting to datetime data type
for col in date_columns:
    df[col] = pd.to_datetime(df[col], format='mixed') ## using the format as mixed to infer

df.info() ### check if that is successful
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 113066 entries, 0 to 113936
Data columns (total 81 columns):
 #   Column                               Non-Null Count   Dtype
---  ------                               --------------   -----
 0   ListingKey                           113066 non-null  object
 1   ListingNumber                        113066 non-null  int64
 2   ListingCreationDate                  113066 non-null  datetime64[ns]
 3   CreditGrade                          28953 non-null   object
 4   Term                                 113066 non-null  int64
 5   LoanStatus                           113066 non-null  object
 6   ClosedDate                           55076 non-null   datetime64[ns]
 7   BorrowerAPR                          113041 non-null  float64
 8   BorrowerRate                         113066 non-null  float64
 9   LenderYield                          113066 non-null  float64
 10  EstimatedEffectiveYield              83982 non-null   float64
 11  EstimatedLoss                        83982 non-null   float64
 12  EstimatedReturn                      83982 non-null   float64
 13  ProsperRating (numeric)              83982 non-null   float64
 14  ProsperRating (Alpha)                83982 non-null   object
 15  ProsperScore                         83982 non-null   float64
 16  ListingCategory (numeric)            113066 non-null  int64
 17  BorrowerState                        107551 non-null  object
 18  Occupation                           109537 non-null  object
 19  EmploymentStatus                     110811 non-null  object
 20  EmploymentStatusDuration             105441 non-null  float64
 21  IsBorrowerHomeowner                  113066 non-null  bool
```

```
 22  CurrentlyInGroup                     113066 non-null  bool
 23  GroupKey                             13339 non-null   object
 24  DateCreditPulled                     113066 non-null  datetime64[ns]
 25  CreditScoreRangeLower                112475 non-null  float64
 26  CreditScoreRangeUpper                112475 non-null  float64
 27  FirstRecordedCreditLine              112369 non-null  object
 28  CurrentCreditLines                   105462 non-null  float64
 29  OpenCreditLines                      105462 non-null  float64
 30  TotalCreditLinespast7years           112369 non-null  float64
 31  OpenRevolvingAccounts                113066 non-null  int64
 32  OpenRevolvingMonthlyPayment          113066 non-null  float64
 33  InquiriesLast6Months                 112369 non-null  float64
 34  TotalInquiries                       111907 non-null  float64
 35  CurrentDelinquencies                 112369 non-null  float64
 36  AmountDelinquent                     105444 non-null  float64
 37  DelinquenciesLast7Years              112076 non-null  float64
 38  PublicRecordsLast10Years             112369 non-null  float64
 39  PublicRecordsLast12Months            105462 non-null  float64
 40  RevolvingCreditBalance               105462 non-null  float64
 41  BankcardUtilization                  105462 non-null  float64
 42  AvailableBankcardCredit              105522 non-null  float64
 43  TotalTrades                          105522 non-null  float64
 44  TradesNeverDelinquent (percentage)   105522 non-null  float64
 45  TradesOpenedLast6Months              105522 non-null  float64
 46  DebtToIncomeRatio                    104594 non-null  float64
 47  IncomeRange                          113066 non-null  object
 48  IncomeVerifiable                     113066 non-null  bool
 49  StatedMonthlyIncome                  113066 non-null  float64
 50  LoanKey                              113066 non-null  object
 51  TotalProsperLoans                    21923 non-null   float64
```

> Now the rest of the data types of the variables are valid.

Data Completness

```
def get_percent_null(df):
    """
    Args:
        - df (pd.Dataframe)
    Returns:
        - The percentages of missing values
    """
    null_counts = df.isnull().sum()
    null_counts = null_counts[null_counts > 0].sort_values()
    return (null_counts/df.shape[0])*100
```

```
get_percent_null(df)
```

```
BorrowerAPR                              0.022111
CreditScoreRangeUpper                    0.522704
```

```
CreditScoreRangeLower                  0.522704
PublicRecordsLast10Years               0.616454
CurrentDelinquencies                   0.616454
InquiriesLast6Months                   0.616454
TotalCreditLinespast7years             0.616454
FirstRecordedCreditLine                0.616454
DelinquenciesLast7Years                0.875595
TotalInquiries                         1.025065
EmploymentStatus                       1.994410
Occupation                             3.121186
BorrowerState                          4.877682
AvailableBankcardCredit                6.672209
TradesOpenedLast6Months                6.672209
TradesNeverDelinquent (percentage)     6.672209
TotalTrades                            6.672209
CurrentCreditLines                     6.725276
OpenCreditLines                        6.725276
PublicRecordsLast12Months              6.725276
RevolvingCreditBalance                 6.725276
BankcardUtilization                    6.725276
AmountDelinquent                       6.741195
EmploymentStatusDuration               6.743849
DebtToIncomeRatio                      7.492969
ProsperRating (Alpha)                 25.723029
ProsperRating (numeric)               25.723029
ProsperScore                          25.723029
EstimatedLoss                         25.723029
EstimatedEffectiveYield               25.723029
EstimatedReturn                       25.723029
ClosedDate                            51.288628
CreditGrade                           74.392833
TotalProsperLoans                     80.610440
TotalProsperPaymentsBilled            80.610440
OnTimeProsperPayments                 80.610440
ProsperPaymentsLessThanOneMonthLate   80.610440
ProsperPaymentsOneMonthPlusLate       80.610440
ProsperPrincipalBorrowed              80.610440
ProsperPrincipalOutstanding           80.610440
ScorexChangeAtTimeOfListing           83.273486
LoanFirstDefaultedCycleNumber         85.006987
GroupKey                              88.202466
dtype: float64
```

> There are many columns that has null values, some of which have a very high count of null values. The following columns were the highest percentage of null such as higher than 50%. These columns are droppped.

```
high_missing_percent = ['CreditGrade', 'ScorexChangeAtTimeOfListing', 'LoanFirstDefaultedCyc
 'TotalProsperPaymentsBilled', 'OnTimeProsperPayments', 'ProsperPaymentsLessThanOneMonthLate
 'ProsperPrincipalBorrowed', 'ProsperPrincipalOutstanding'] ## list of columns with missing
```

```
df.drop(columns= high_missing_percent, inplace=True) ## Drop the list of high percentage col
```

```
df.shape ## Check if the dropping was successful
```

```
(113066, 70)
```

> The drop is checked now that the variables went from 81 to 70.

Handling the other null values by dropping NA values and rows:

```
get_percent_null(df)
```

```
BorrowerAPR                             0.022111
CreditScoreRangeUpper                   0.522704
CreditScoreRangeLower                   0.522704
TotalCreditLinespast7years              0.616454
CurrentDelinquencies                    0.616454
FirstRecordedCreditLine                 0.616454
PublicRecordsLast10Years                0.616454
InquiriesLast6Months                    0.616454
DelinquenciesLast7Years                 0.875595
TotalInquiries                          1.025065
EmploymentStatus                        1.994410
Occupation                              3.121186
BorrowerState                           4.877682
AvailableBankcardCredit                 6.672209
TradesOpenedLast6Months                 6.672209
TotalTrades                             6.672209
TradesNeverDelinquent (percentage)      6.672209
PublicRecordsLast12Months               6.725276
RevolvingCreditBalance                  6.725276
BankcardUtilization                     6.725276
CurrentCreditLines                      6.725276
OpenCreditLines                         6.725276
AmountDelinquent                        6.741195
EmploymentStatusDuration                6.743849
DebtToIncomeRatio                       7.492969
ProsperScore                           25.723029
ProsperRating (Alpha)                  25.723029
ProsperRating (numeric)                25.723029
EstimatedReturn                        25.723029
EstimatedLoss                          25.723029
EstimatedEffectiveYield                25.723029
GroupKey                               88.202466
dtype: float64
```

> These columns are identifiers, mostly unique between each loan.They are irrelevant for the task and therefore they should be dropped too.

```
df.columns
```

```
Index(['ListingKey', 'ListingNumber', 'ListingCreationDate', 'Term',
       'LoanStatus', 'BorrowerAPR', 'BorrowerRate', 'LenderYield',
       'EstimatedEffectiveYield', 'EstimatedLoss', 'EstimatedReturn',
       'ProsperRating (numeric)', 'ProsperRating (Alpha)', 'ProsperScore',
       'ListingCategory (numeric)', 'BorrowerState', 'Occupation',
       'EmploymentStatus', 'EmploymentStatusDuration', 'IsBorrowerHomeowner',
       'CurrentlyInGroup', 'GroupKey', 'DateCreditPulled',
       'CreditScoreRangeLower', 'CreditScoreRangeUpper',
       'FirstRecordedCreditLine', 'CurrentCreditLines', 'OpenCreditLines',
       'TotalCreditLinespast7years', 'OpenRevolvingAccounts',
       'OpenRevolvingMonthlyPayment', 'InquiriesLast6Months', 'TotalInquiries',
       'CurrentDelinquencies', 'AmountDelinquent', 'DelinquenciesLast7Years',
       'PublicRecordsLast10Years', 'PublicRecordsLast12Months',
       'RevolvingCreditBalance', 'BankcardUtilization',
       'AvailableBankcardCredit', 'TotalTrades',
       'TradesNeverDelinquent (percentage)', 'TradesOpenedLast6Months',
       'DebtToIncomeRatio', 'IncomeRange', 'IncomeVerifiable',
       'StatedMonthlyIncome', 'LoanKey', 'LoanCurrentDaysDelinquent',
       'LoanMonthsSinceOrigination', 'LoanNumber', 'LoanOriginalAmount',
       'LoanOriginationDate', 'LoanOriginationQuarter', 'MemberKey',
       'MonthlyLoanPayment', 'LP_CustomerPayments',
       'LP_CustomerPrincipalPayments', 'LP_InterestandFees', 'LP_ServiceFees',
       'LP_CollectionFees', 'LP_GrossPrincipalLoss', 'LP_NetPrincipalLoss',
       'LP_NonPrincipalRecoverypayments', 'PercentFunded', 'Recommendations',
       'InvestmentFromFriendsCount', 'InvestmentFromFriendsAmount',
       'Investors'],
      dtype='object')
```

```
## List of identifiers and other irrelevant columns
identifiers = ["ListingKey", "ListingNumber", "GroupKey", "LoanKey", "LoanNumber", "MemberKe
df.drop(columns= identifiers, axis= 1, inplace= True ) ## Dropping irrelevant columns
```

```
df.shape ##
```

```
(113066, 63)
```

> The drop is done, since the features count went down to 63.

```
get_percent_null(df)
```

```
BorrowerAPR                    0.022111
CreditScoreRangeUpper          0.522704
CreditScoreRangeLower          0.522704
InquiriesLast6Months           0.616454
TotalCreditLinespast7years     0.616454
FirstRecordedCreditLine        0.616454
PublicRecordsLast10Years       0.616454
CurrentDelinquencies           0.616454
DelinquenciesLast7Years        0.875595
```

```
TotalInquiries                        1.025065
EmploymentStatus                      1.994410
Occupation                            3.121186
BorrowerState                         4.877682
AvailableBankcardCredit               6.672209
TradesOpenedLast6Months               6.672209
TotalTrades                           6.672209
TradesNeverDelinquent (percentage)    6.672209
PublicRecordsLast12Months             6.725276
RevolvingCreditBalance                6.725276
BankcardUtilization                   6.725276
OpenCreditLines                       6.725276
CurrentCreditLines                    6.725276
AmountDelinquent                      6.741195
EmploymentStatusDuration              6.743849
DebtToIncomeRatio                     7.492969
ProsperScore                         25.723029
ProsperRating (Alpha)                25.723029
ProsperRating (numeric)              25.723029
EstimatedReturn                      25.723029
EstimatedLoss                        25.723029
EstimatedEffectiveYield              25.723029
dtype: float64
```

> Let's handle the lower percentages by only dropping the NA values instead of the whole columns.

```
df.dropna(inplace=True)
```

```
get_percent_null(df)
```

```
Series([], dtype: float64)
```

> No missing NA values left.

```
df.shape
```

```
(75486, 63)
```

> After handling missing values and dropping unneccary columns the shape of the data is 76,216 rows and 63 columns

> wWe want to create a simplified version of this columns, since there are multiple values for the Due Past values.

```
df['LoanStatus'].unique()
```

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

```
df['SimplifiedLoanStatus'] = df['LoanStatus'].apply(lambda x: 'Past Due' if 'Past Due' in x
df.head(10)
```

	ListingCreationDate	Term	LoanStatus	BorrowerAPR	BorrowerRate	LenderYield	Estim
1	2014-02-27 08:28:07.900	36	Current	0.12016	0.0920	0.0820	
3	2012-10-22 11:02:35.010	36	Current	0.12528	0.0974	0.0874	
4	2013-09-14 18:38:39.097	36	Current	0.24614	0.2085	0.1985	
5	2013-12-14 08:26:37.093	60	Current	0.15425	0.1314	0.1214	
6	2013-04-12 09:52:56.147	36	Current	0.31032	0.2712	0.2612	
7	2013-05-05 06:49:27.493	36	Current	0.23939	0.2019	0.1919	
8	2013-12-02 10:43:39.117	36	Current	0.07620	0.0629	0.0529	
10	2012-05-10 07:04:01.577	60	Current	0.27462	0.2489	0.2389	
12	2013-12-15 20:01:10.757	36	Past Due (1-15 days)	0.17969	0.1435	0.1335	
13	2013-07-15 16:28:28.087	36	Current	0.13138	0.1034	0.0934	

10 rows × 64 columns

Main Features of interest

- All the left columns are the features of intrest they will be devided based on the objective into three subsets.

- Objective 1: Loan Performance

```
loan_performance_columns = [ 'LoanStatus','SimplifiedLoanStatus' , 'LoanCurrentDaysDelinquer
    'LoanOriginalAmount', 'BorrowerAPR', 'DebtToIncomeRatio', 'CreditScoreRangeLower','Credi
    'ProsperScore', 'EmploymentStatus','IsBorrowerHomeowner']

loan_performance_df = df[loan_performance_columns]
print(loan_performance_df.shape)
loan_performance_df.head()
```

(75486, 12)

	LoanStatus	SimplifiedLoanStatus	LoanCurrentDaysDelinquent	LoanMonthsSinceOriginat:
1	Current	Current	0	
3	Current	Current	0	
4	Current	Current	0	
5	Current	Current	0	
6	Current	Current	0	

- Objective 2: Credit Score and Borrower Analysis

```
credit_borrower_columns = [ 'CreditScoreRangeLower', 'CreditScoreRangeUpper', 'ProsperRating
    'ProsperRating (Alpha)','ProsperScore','IncomeRange','EmploymentStatus','IsBorrowerHomec
    'BorrowerAPR', 'LoanOriginalAmount']

credit_borrower_df = df[credit_borrower_columns]
print(credit_borrower_df.shape)
credit_borrower_df.head()
```

(75486, 10)

	CreditScoreRangeLower	CreditScoreRangeUpper	ProsperRating (numeric)	ProsperRating (Alpha)	ProsperS
1	680.0	699.0	6.0	A	
3	800.0	819.0	6.0	A	
4	680.0	699.0	3.0	D	
5	740.0	759.0	5.0	B	
6	680.0	699.0	2.0	E	

- Objective 3: Geographic and Demographic Analysis

```
geo_demo_columns = [ 'BorrowerState', 'Occupation', 'EmploymentStatus', 'IncomeRange',
    'IsBorrowerHomeowner', 'LoanOriginalAmount', 'ProsperRating (Alpha)', 'CreditScoreRangeL
    'CreditScoreRangeUpper']

geo_demo_df = df[geo_demo_columns]
print(geo_demo_df.shape)
geo_demo_df.head()
```

```
(75486, 9)
```

	BorrowerState	Occupation	EmploymentStatus	IncomeRange	IsBorrowerHomeowner	LoanOr
1	CO	Professional	Employed	$50,000-74,999	False	
3	GA	Skilled Labor	Employed	$25,000-49,999	True	
4	MN	Executive	Employed	$100,000+	True	
5	NM	Professional	Employed	$100,000+	True	
6	KS	Sales - Retail	Employed	$25,000-49,999	False	

Store the cleaned dataset

```
df.to_csv('./data/prosperLoanDataCleaned.csv') ## Load the csv into pandas dataframe
```

Univariate Exploration

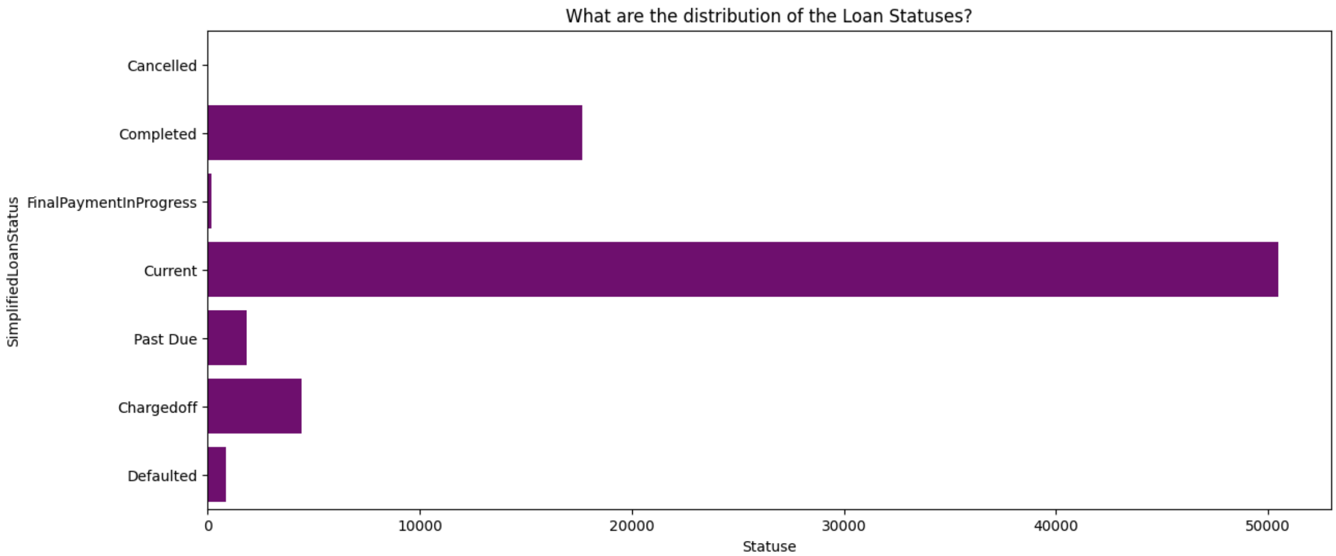
> In this section, we are investigating distributions of individual variables. To see unusual points or outliers, take a deeper look to clean things up and prepare yourself to look at relationships between variables. the "Question-Visualization-Observations" framework is used throughout the exploration, it involves asking a question from the data, creating a visualization to find answers, and then recording observations after each visualisation.

1. Loan Status

Question: What are the distribution of the Loan Statuses?

```
## add orderring to the loan status and include the cancelled ones
loan_status_order = ['Cancelled', 'Completed', 'FinalPaymentInProgress', 'Current',
                     'Past Due', 'Chargedoff', 'Defaulted']


plt.figure(figsize=(14, 6))
sns.countplot(data = loan_performance_df, y = 'SimplifiedLoanStatus', color = 'purple', orde
plt.xlabel('Statuse')
plt.title('What are the distribution of the Loan Statuses?');
```



> It seems that the majority status among the loan statuses is the `current` which is 50462, While the completed are success story they are `17675`. The chargedoff however are 4444 cases they are failed loans. While the `deafulted` are the cases in danger of `chargedoff` they reach 885. And the past due are slightly larger 1835 but still not in danger of charge off.

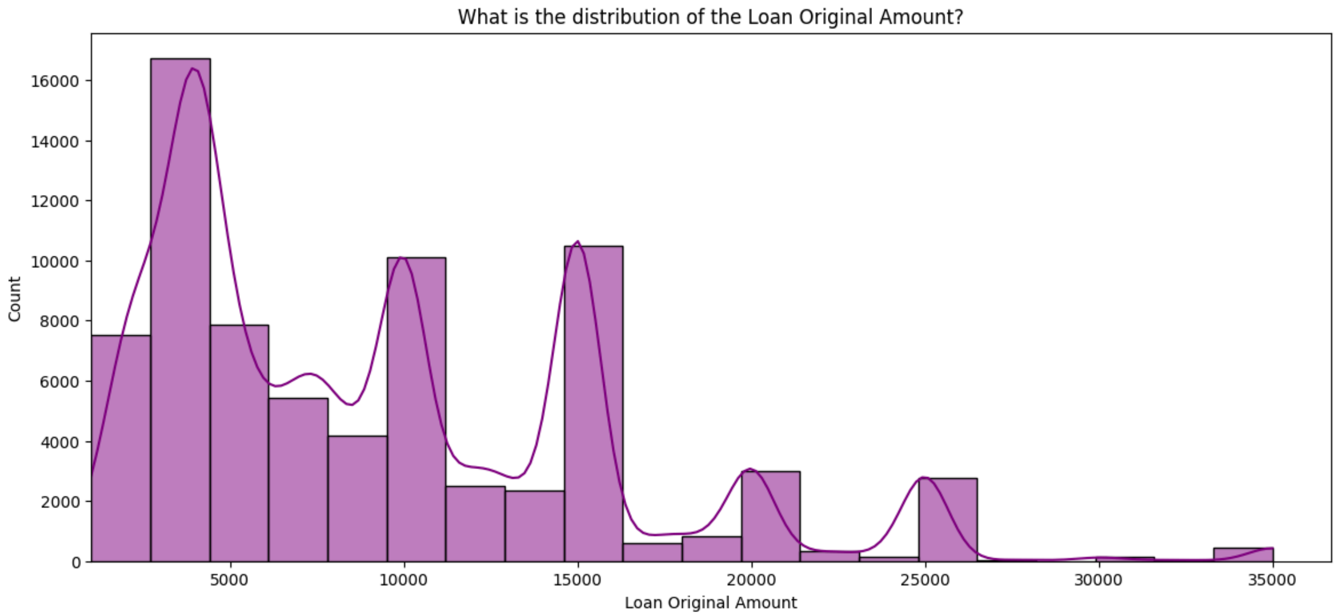
> The chraged off and the deafulted represntts the actual risks for these loans.

> Nothing unusual with this distribution.

2. The Loan Original Amount

Let's take a look into the Loan Original Amounts.

```
plt.figure(figsize=(14, 6))
sns.histplot(data= credit_borrower_df,  x = 'LoanOriginalAmount', bins=20, kde= True, color
plt.title('What is the distribution of the Loan Original Amount?')
plt.ylabel('Count')
plt.xlim(1000)
plt.xlabel('Loan Original Amount');
```



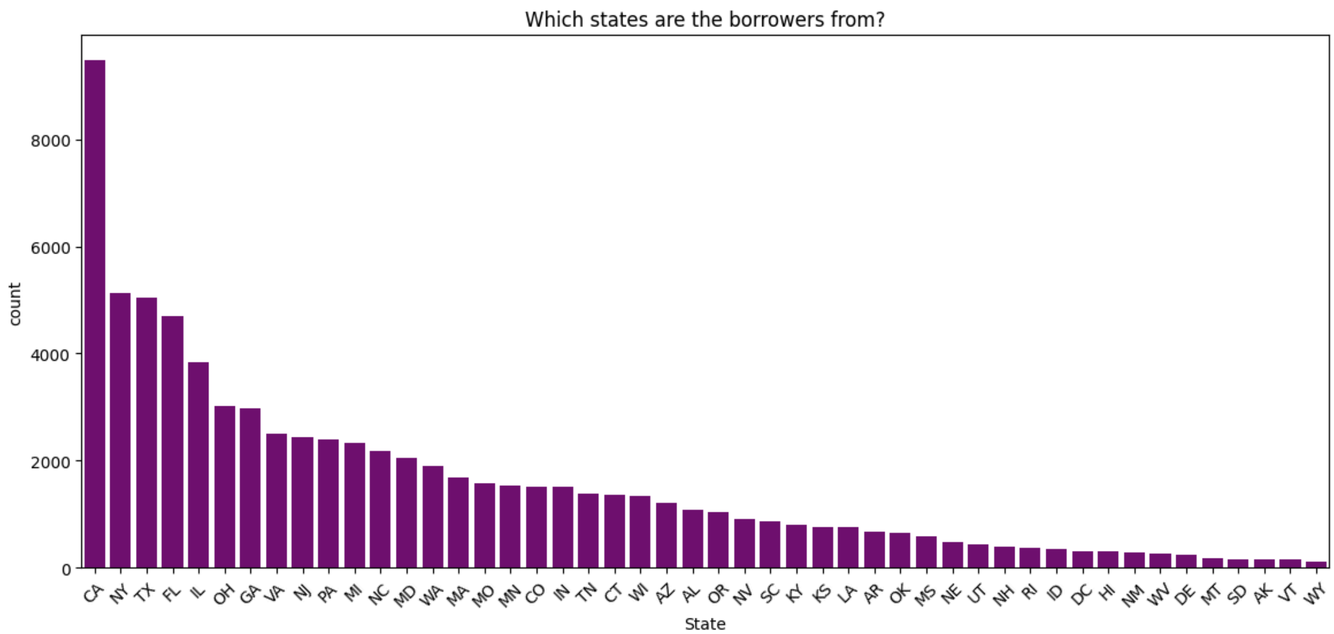
> The distribution of the Loan Original Amount is right skewed, with multiple peaks suggesting distinct borrower groups. Most loans are relatively small, but there are outliers indicating larger, less frequent loan amounts. However these are numerical outliers but valid values for a given loan amount, so doesn't need to be handled.

3. Borrower State

Which states are the borrowers from?

```
borrower_states_counts = geo_demo_df['BorrowerState'].value_counts()


plt.figure(figsize=(14, 6))
ax = sns.barplot(borrower_states_counts, color = 'purple')
plt.title('Which states are the borrowers from?')
plt.xlabel('State')
plt.xticks(rotation = 45);
```



> California boasts the highest number of borrowers among all US states, followed closely by Texas, New York, and Florida. On the other end of the spectrum, states like South Dakota, Alaska, Vermont, and Wyoming have significantly lower borrower counts.

> California is an unpper bound outlier, however this is numerically and valid values that will not be handled.

Bivariate Exploration

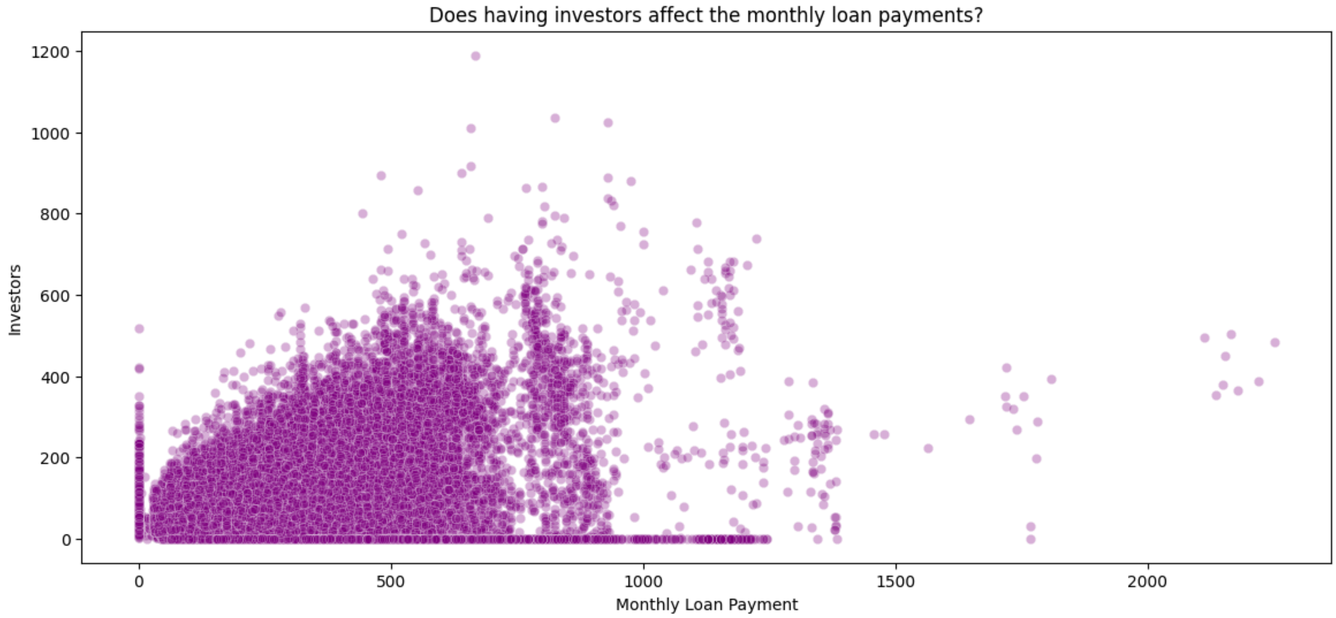
> In this section, relationships between pairs of variables in the data are investigated.
> The variables of intreset that have been introduced in the previous sections.
> Questions are asked.

Question: Does having investors affect the monthly loan payments?

```
df['Investors'].corr(df['MonthlyLoanPayment'])
```

```
0.30761429000108165
```

```
plt.figure(figsize=(14, 6))
sns.scatterplot(data= df, x='MonthlyLoanPayment', y='Investors', alpha=0.3, color = 'purple'
plt.title('Does having investors affect the monthly loan payments?')
plt.xlabel('Monthly Loan Payment')
plt.ylabel('Investors');
```



> There is a positive correlation between the number of investors and the monthly loan payments, with a correlation coefficient of 0.3. This indicates that as the number of investors increases, the monthly loan payments also tend to increase.

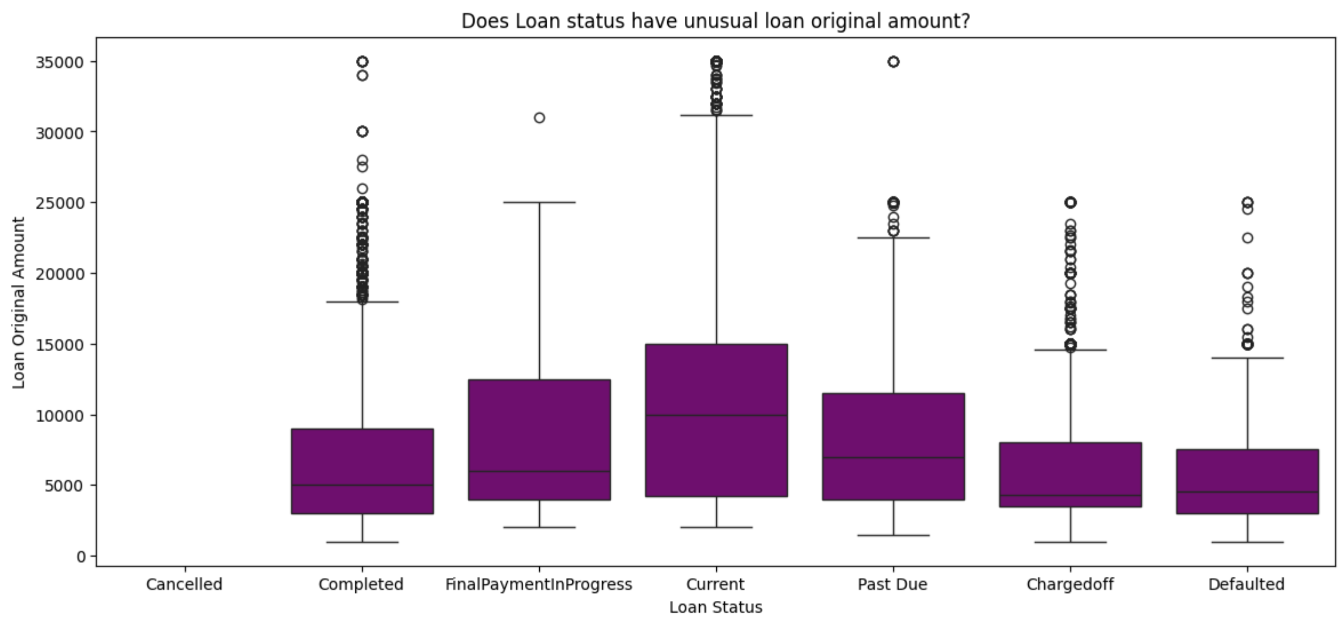
> Some outliers are observed, with loans having over 600 investors and monthly payments exceeding 1000.

> A few loans with very high monthly payments (above 2000) are also present, indicating significant loan amounts or terms.

> The plot shows a dense cluster of points with fewer than 200 investors and monthly payments below 500, suggesting this is the most common scenario.

Question: Does Loan status have unusual loan original amount?

```
plt.figure(figsize=(14, 6))
sns.boxplot(data=loan_performance_df, x='SimplifiedLoanStatus', y='LoanOriginalAmount', colc
plt.title('Does Loan status have unusual loan original amount?')
plt.xlabel('Loan Status')
plt.ylabel('Loan Original Amount');
```



> All loan statuses have outliers, indicating some loans are significantly larger than most others in their respective categories.

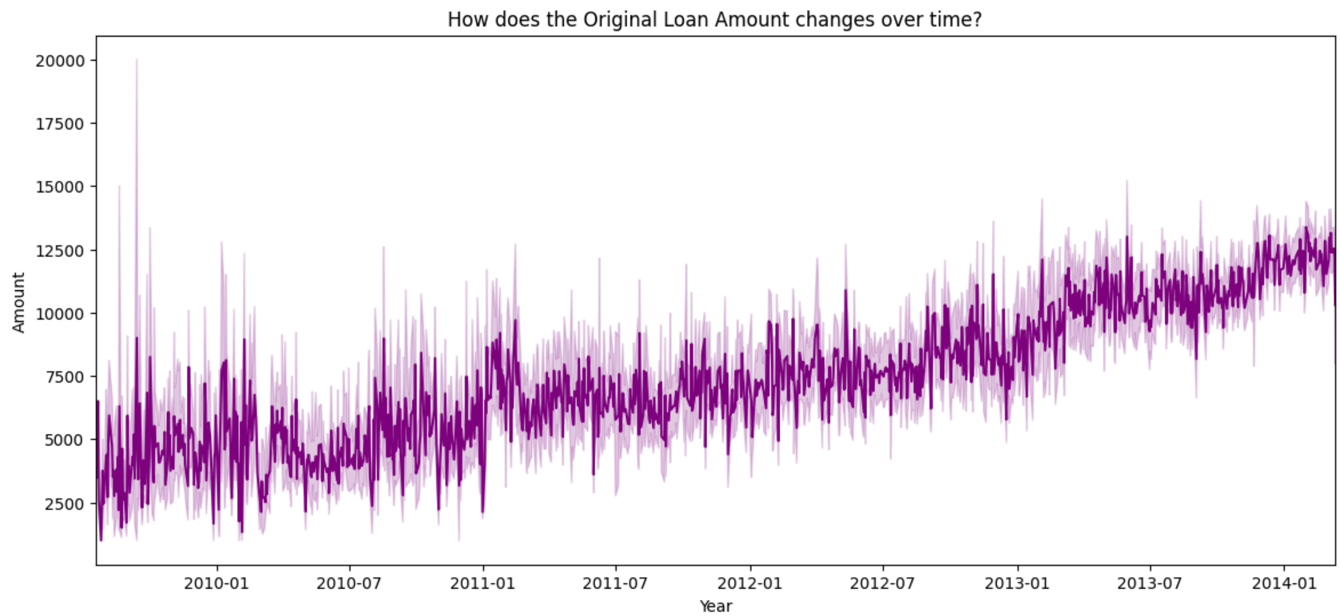
> Completed loans exhibit the most outliers, suggesting a wide variation in loan amounts within this category.

> Charged-off loans also show a considerable number of outliers.

> Current Loans, The highest upper outliers are observed in the current loan status, indicating some very large loans are currently active.

Question: How does the Original Amount of Loan change over time?

```
plt.figure(figsize=(14, 6))
sns.lineplot(data= df, x = 'LoanOriginationDate', y ='LoanOriginalAmount', color = 'purple')
plt.ylabel('Amount')
plt.xlabel('Year')
plt.xlim(pd.to_datetime('2009-07-20'), pd.to_datetime('2014-03-12')) ## the max and min date
plt.title('How does the Original Loan Amount changes over time?');
```



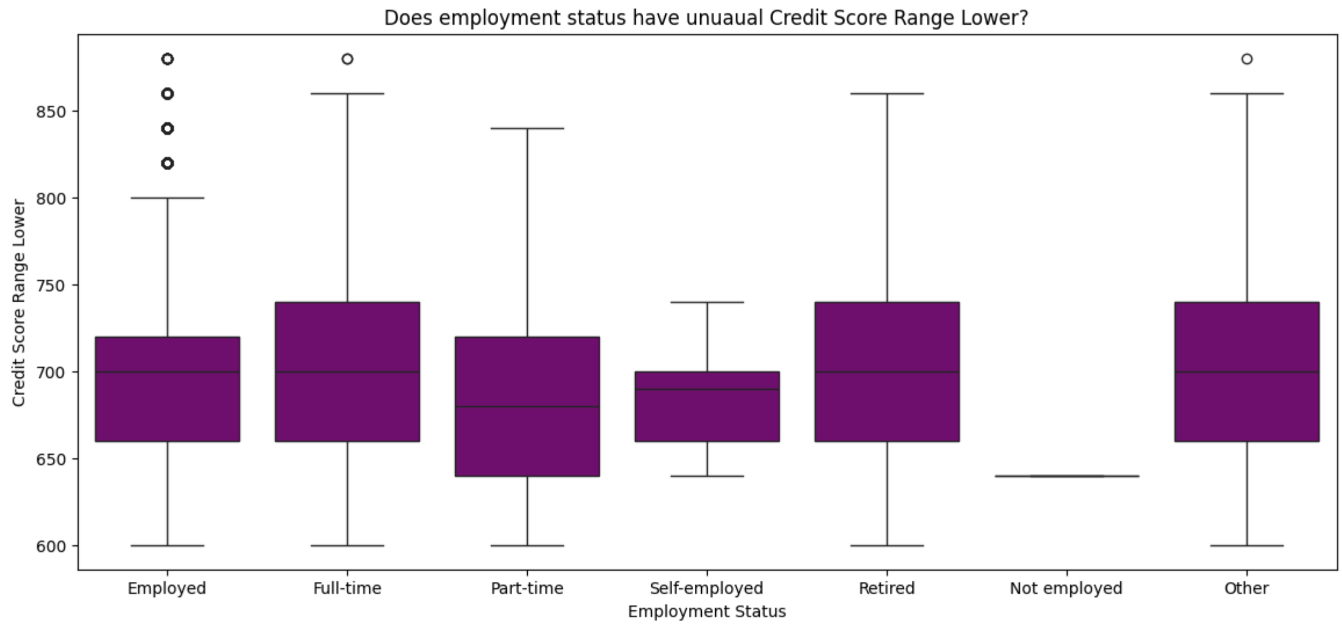
> There is a noticeable increase in loan amounts over the years, suggesting that borrowers have been taking out larger loans as time progresses.

> Interestingly, the year 2009 stands out with some of the highest loan amounts, indicating that during this period, there were notably larger loans compared to other years.

Question: Does employment status have unuaual credit score lower range?

```
employment_status_oredr = ['Employed', 'Full-time', 'Part-time', 'Self-employed', 'Retired',

plt.figure(figsize=(14, 6))
sns.boxplot(data=credit_borrower_df, x='EmploymentStatus', y='CreditScoreRangeLower', color=
plt.title('Does employment status have unuaual Credit Score Range Lower?')
plt.xlabel('Employment Status')
plt.ylabel('Credit Score Range Lower');
```



> Employed borrowers have a wide range of credit scores, with some higher outliers. This indicates that while most employed borrowers have moderate to high credit scores, there are a few with exceptionally high scores.

> Borrowers in the "Other" and "Full-time" categories have similar distributions of credit scores, generally higher than those of employed borrowers. These groups also include some high outliers, suggesting that a subset of these borrowers have excellent credit.

> Self-employed borrowers tend to have lower credit scores compared to other groups, with a narrower range and fewer outliers.

> Not employed borrowers have the lowest and least variable credit scores, indicating financial instability or limited credit history.

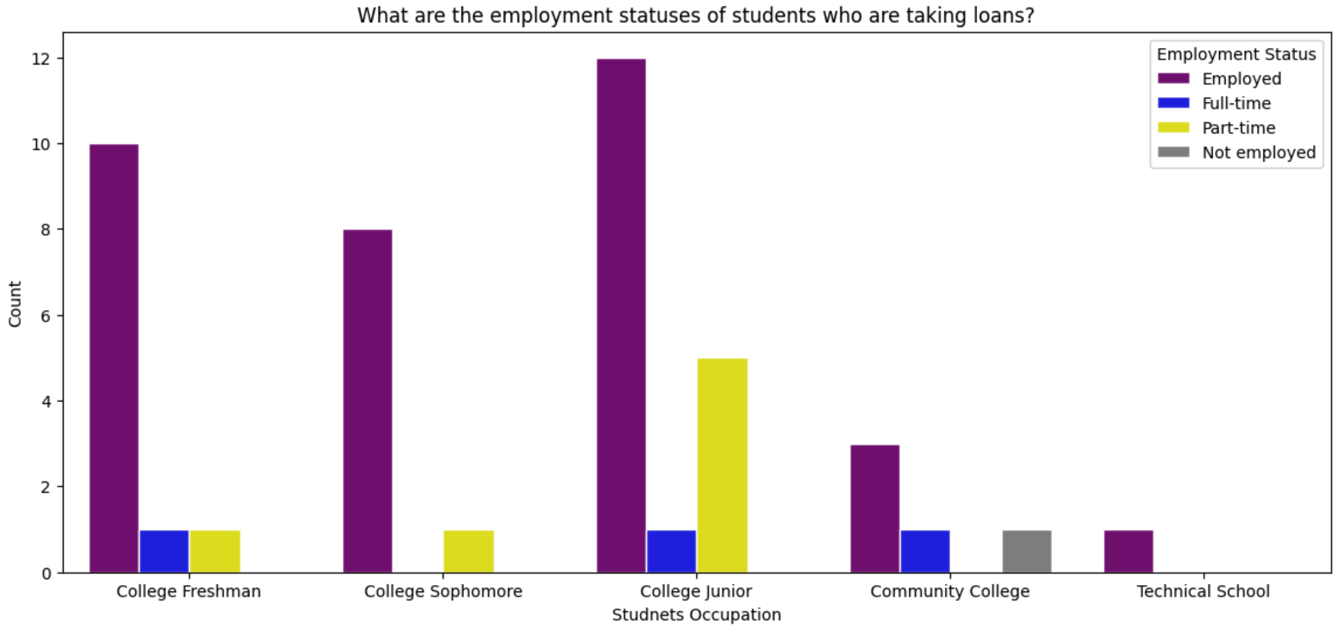
Question: What are the employment statuses of students who are taking loans?

```
## List of students occupations ordered by their natural order
study_occupations = ['Student - College Freshman',  'Student - College Sophomore',  'Student
 'Student - Community College', 'Student - Technical School']

## Labels for the visualization
labels = ['College Freshman', 'College Sophomore', 'College Junior', 'Community College', 'T

## the natural order of employment staus
employment_status_hue_oredr = ['Employed', 'Full-time', 'Part-time', 'Not employed']
```

```
plt.figure(figsize=(14, 6))
sns.countplot(data=geo_demo_df[geo_demo_df['Occupation'].isin(study_occupations)], x='Occupa
              hue='EmploymentStatus', hue_order=employment_status_hue_oredr,  order = study_
plt.title('What are the employment statuses of students who are taking loans?')
plt.xlabel('Studnets Occupation')
plt.ylabel('Count')
plt.xticks(ticks= study_occupations, labels= labels)
plt.legend(title='Employment Status');
```



> Employment is widespread among students taking loans, with the majority falling into the "Employed" category across all educational levels.

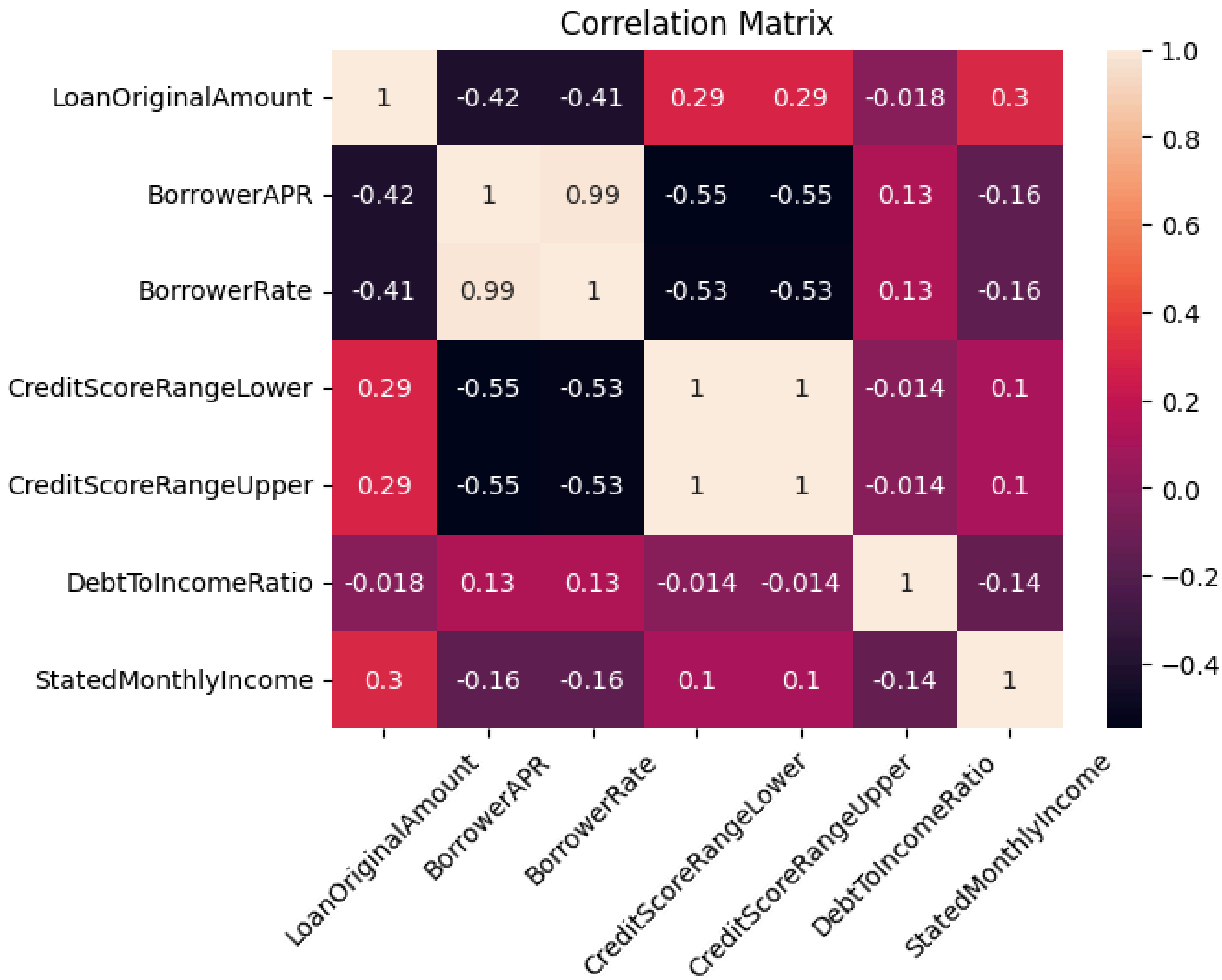
> Part-time work appears to be the most common arrangement, indicated by the higher count of "Part-time" compared to "Full-time" in most categories. Expected since they are students.

> Community college students exhibit a notably higher proportion of full-time employment compared to other groups.

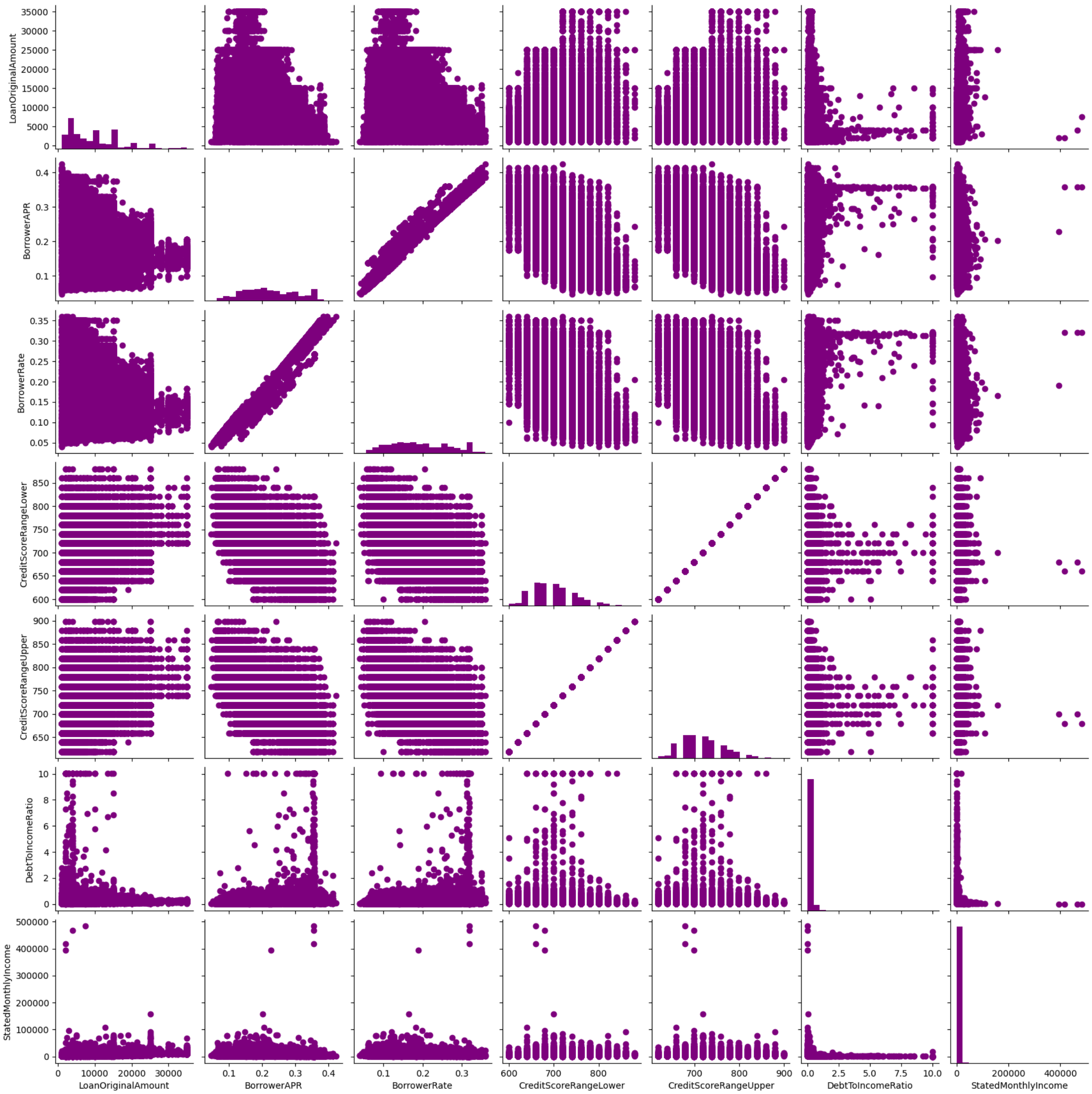
> The "Technical School" category shows a lower overall employment rate and a higher percentage of students who are not employed.

Question: What are intresting relationships between variables in the dataset?

```
intrest_vars = ['LoanOriginalAmount', 'BorrowerAPR', 'BorrowerRate',
    'CreditScoreRangeLower', 'CreditScoreRangeUpper',
    'DebtToIncomeRatio', 'StatedMonthlyIncome']
subset = df[intrest_vars]
sns.heatmap(subset.corr(), annot=True)
plt.xticks(rotation = 45)
plt.title("Correlation Matrix");
```




```
grid = sns.PairGrid(data = df, vars = intrest_vars )
grid.map_diag(plt.hist, bins = 20,color='purple')
grid.map_offdiag(plt.scatter,color='purple')
grid.tight_layout();
```


LoanOriginalAmount
BorrowerAPR
BorrowerRate
CreditScoreRangeLower
CreditScoreRangeUpper
DebtToIncomeRatio
StatedMonthlyIncome

> Positive correlation between `borrowerAPR` and `BorrowerRate`.

> `Debit Income Ratio` has a low positive correlation with bith the `credit scire range lower and the upper range`.

> `LoanOriginalAmount` and `StatedMonthlyIncome` have a moderate positive correlation (0.3). This indicates that individuals with higher incomes tend to borrow larger amounts.

> `BorrowerAPR` and `CreditScoreRangeLower` have a moderate negative correlation (-0.55). This suggests that borrowers with higher credit scores tend to have lower APRs.

> There is no other intresting correlations between the variables.

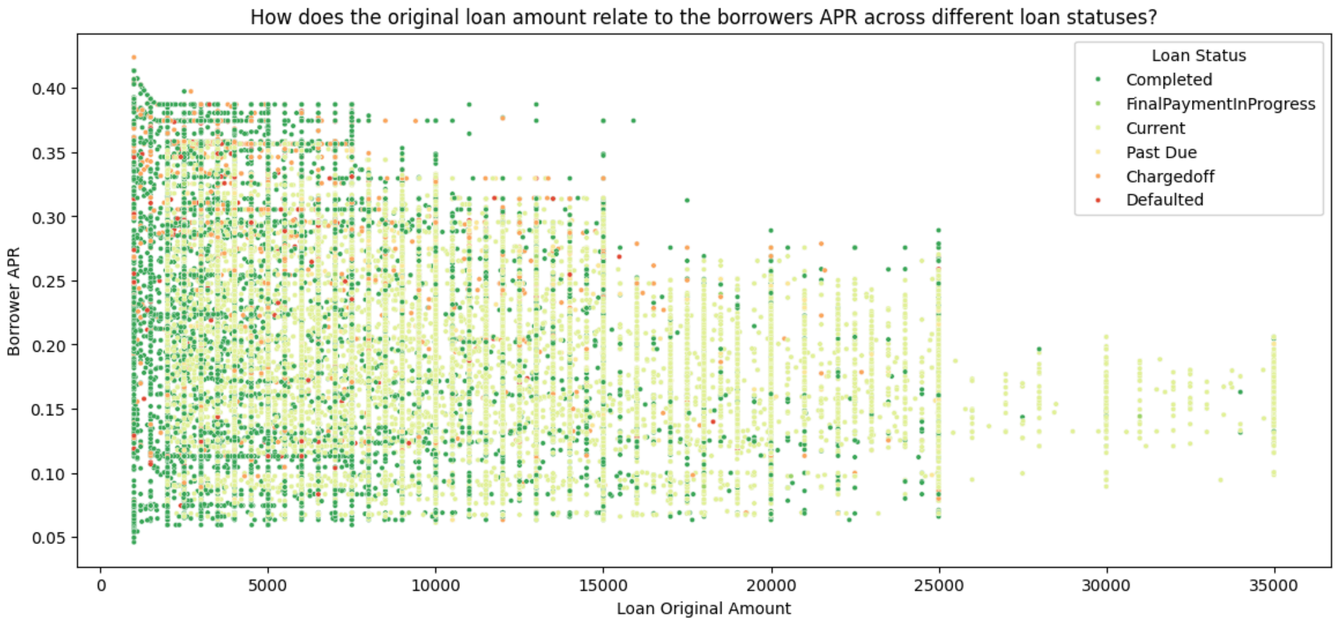
Multivariate Exploration

> In this section, plots of three or more variables are created to investigate the data even further.

Question: How does the original loan amount relate to the borrower's APR across different loan statuses?

```
## this list is the natural order of loan status
loan_status_order = [ 'Completed','FinalPaymentInProgress','Current', 'Past Due','Chargedoff
```

```
## Scatterplot with multiple encodings, color encoding with ordered categories
plt.figure(figsize=(14, 6))
sns.scatterplot(data=df, x='LoanOriginalAmount', y='BorrowerAPR', hue='SimplifiedLoanStatus'
                hue_order=loan_status_order, palette='RdYlGn_r', s = 10)
plt.title('How does the original loan amount relate to the borrowers APR across different lc
plt.ylabel('Borrower APR')
plt.xlabel('Loan Original Amount')
plt.legend(title = 'Loan Status', loc='upper right');
```



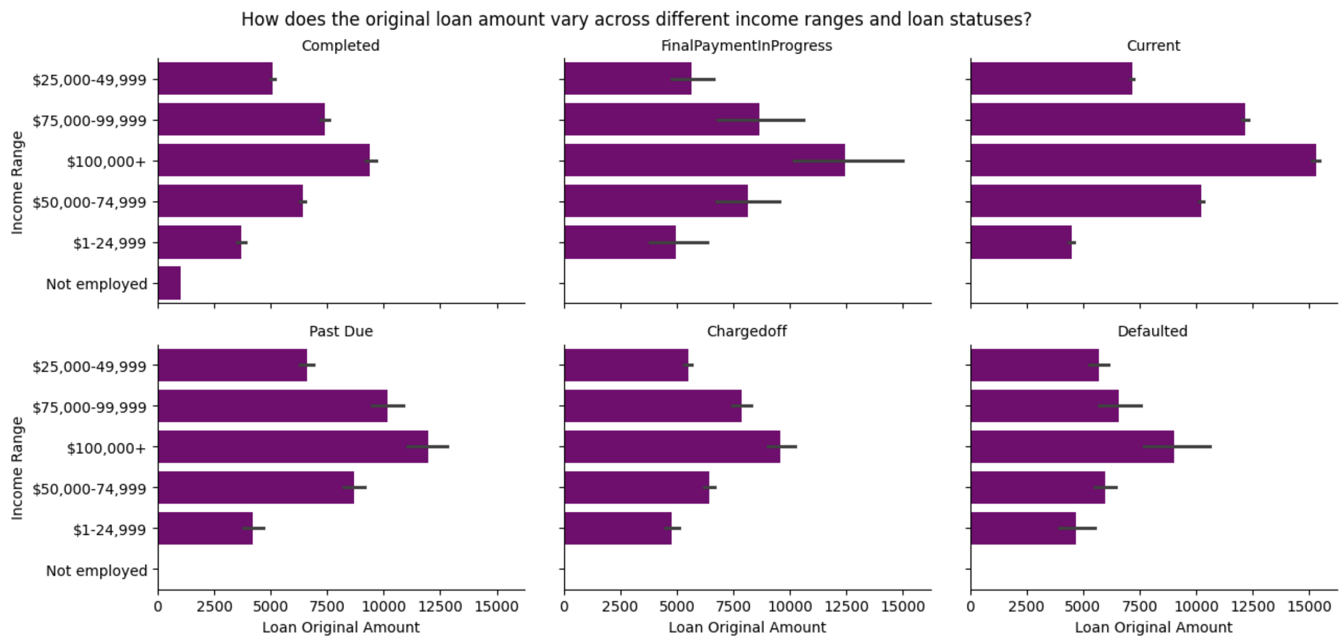
> The majority of data points cluster in the lower left region, indicating that most loans have lower original amounts and APRs.

> A few data points appear as outliers, situated away from the main cluster. These represent loans with significantly higher original amounts or APRs compared to the majority.

> The current loans have different and varying APRs and loan amounts. While most of the completed, dedfaulted, and chargedoff are in the lower region.

Question: How does the original loan amount vary across different income ranges and loan statuses?

```
## Facet Plotting three variables SimplifiedLoanStatus, LoanOriginalAmount and IncomeRange
grid = sns.FacetGrid(data = df, col = 'SimplifiedLoanStatus', col_wrap = 3, col_order= loan_
grid.map(sns.barplot, 'LoanOriginalAmount', 'IncomeRange', color = 'Purple')
grid.set_titles("{col_name}")
grid.set_axis_labels('Loan Original Amount', 'Income Range')
plt.suptitle('How does the original loan amount vary across different income ranges and loar
grid.figure.set_size_inches(14, 6);
```



> As income range increases, the loan original amount also tends to increase. This is evident in the length of the bars across different income ranges.

> The "Current" and "Completed" statuses, where the highest loan original amount is not always associated with the highest income range.

> Higher income ranges might be associated with fewer defaults, which is worth investigating.

> Across all loan statuses, the highest Loans amounts are associated with the 100,000+ income range.

Question: How do different terms group with the selected variables?

```
selected_columns = ['LoanOriginalAmount', 'BorrowerAPR','DebtToIncomeRatio']
```

```
## Plot Matrix
grid = sns.pairplot(data=df, vars=selected_columns, hue='Term', palette=['purple', 'yellow',
plt.suptitle('How do different terms group with the selected variables?', y=1.02)
grid.figure.set_size_inches(14, 6);
```