Part I - Loan Data from Prosper Dataset Exploration

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Introduction

Loan Data from Prosper is a dataset with over 110,000 loan entries on 81 variables. In this document though, it is modified to have only 14,882 loan entries on 13 variables. The selected variables are TermMonths (originally "Term", but renamed "TermMonths"), LoanStatus, BorrowerAPR, BorrowerRate, ListingCategory, BorrowerState, Occupation, EmploymentStatus, IsBorrowerHomeowner, IncomeRange, and LoanOriginalAmount. Two other variables, JobStatus and Term, will also be created during the analysis of the dataset, making up the 13 variables of the modified dataset in this document.

- TermMonths is the length of the loan in months
- Term states the term each month length represents (short term, mid term, and long term)
- LoanStatus means the status of the loan which could be completed, current, charged off, defaulted, cancelled, final payment in progress, or past due. Past due usually includes the range in which the number of days for which the loan is past due falls into in parentheses.

> During the analysis, the rows with "Current" values will be removed from our dataset as they will not be needed.

- ListingCategory contains the listing category that the borrower selected when posting their listing for the loan.
- BorrowerAPR is the borrower's Annual Percentage Rate, which is the totality of all the cost of a loan to a borrower (including the interest rate) in a year expressed in percentage.
- BorrowerRate is the interest rate a borrower gets for a loan.
- IsHomeonwer contains a boolean value (True/False) for whether the borrower owns a home.
- Occupation, EmploymentStatus, and IncomeRange contain the occupation, employment status and income range of the borrower respectively.
- BorrowerState is the state of residence of borrower

- LoanOriginalAmount is the original amount loaned to the borrower.
- JobStatus states if the borrower is working or not.

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Preliminary Wrangling

In this section, the dataset is assessed and issues found are cleaned. The cleaning process would involve the removal of variables not necessary for this analysis.

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

%matplotlib inline
```

In [2]:
```
#load dataset into a dataframe
prosper_loans = pd.read_csv("prosperLoanData.csv")
```

In [3]:
```
def drop_unwanted_cols(df, list_of_cols_to_keep):
    """This function selects out unwanted columns in a dataframe
    and drops them"""
    new_list = []
    for col in df.columns:
        if col not in list_of_cols_to_keep:
            new_list.append(col)
    return df.drop(new_list, axis = 1)
```

In [4]:
```
#create a list of wanted columns
wanted_cols = ["Term","LoanOriginalAmount", "LoanStatus", "BorrowerAP

#apply the drop_unwanted_cols function to the dataframe
prosper_loans = drop_unwanted_cols(prosper_loans, wanted_cols)
```

Assess data

In [5]:
```
#view random rows of dataframe
prosper_loans.sample(15)
```

Out[5]:

	Term	LoanStatus	BorrowerAPR	BorrowerRate	ListingCategory (numeric)	BorrowerState	Occ
65127	36	Current	0.24205	0.2045	1	CA	
61714	36	Completed	0.14207	0.1350	2	GA	Trad M
24023	36	Completed	0.17160	0.1499	7	WI	Account
13513	36	Completed	0.23428	0.2193	0	NaN	
9649	60	Completed	0.28160	0.2557	1	LA	Profe
91966	36	Current	0.22712	0.1899	1	MI	Skille
70108	36	Chargedoff	0.35797	0.3177	6	NC	Admin A
68080	36	Current	0.17611	0.1400	1	GA	C Prog
11300	60	Current	0.18222	0.1585	1	NY	
91288	60	Current	0.31159	0.2849	1	TX	Truc
47140	36	Chargedoff	0.33973	0.2999	15	AL	Skille
110234	36	Chargedoff	0.29776	0.2900	0	TX	
34957	60	Current	0.22140	0.1970	1	CO	Account
78809	36	Current	0.23131	0.1940	1	MD	
68712	36	Completed	0.36716	0.3400	1	MO	Account

In [6]:
```
#check number of rows and columns of dataframe
prosper_loans.shape
```

Out[6]: (113937, 11)

In [7]:
```
#check summarized info of dataset
prosper_loans.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 113937 entries, 0 to 113936
Data columns (total 11 columns):
 #   Column                     Non-Null Count   Dtype  
---  ------                     --------------   -----  
 0   Term                       113937 non-null  int64  
 1   LoanStatus                 113937 non-null  object 
 2   BorrowerAPR                113912 non-null  float64
 3   BorrowerRate               113937 non-null  float64
 4   ListingCategory (numeric)  113937 non-null  int64  
 5   BorrowerState              108422 non-null  object 
 6   Occupation                 110349 non-null  object 
 7   EmploymentStatus           111682 non-null  object 
 8   IsBorrowerHomeowner        113937 non-null  bool   
 9   IncomeRange                113937 non-null  object 
 10  LoanOriginalAmount         113937 non-null  int64  
dtypes: bool(1), float64(2), int64(3), object(5)
memory usage: 8.8+ MB
```

Note

The listing category is present in the dataset in numeric form as **ListingCategory (numeric)** variable. Each number has a word meaning and would be converted to the meaning in word during cleaning.

In [8]:
```
#check for duplicated rows
prosper_loans.duplicated().sum()
```

Out[8]:
```
1742
```

In [9]:
```
#check for the unique values in Term column
prosper_loans.Term.unique()
```

Out[9]:
```
array([36, 60, 12])
```

In [10]:
```
#check for the unique values in the LoanStatus column
prosper_loans.LoanStatus.unique()
```

Out[10]:
```
array(['Completed', 'Current', 'Past Due (1-15 days)', 'Defaulted',
       'Chargedoff', 'Past Due (16-30 days)', 'Cancelled',
       'Past Due (61-90 days)', 'Past Due (31-60 days)',
       'Past Due (91-120 days)', 'FinalPaymentInProgress',
       'Past Due (>120 days)'], dtype=object)
```

In [11]:
```
#check values count for loan status variable
prosper_loans.LoanStatus.value_counts()
```

Out[11]:
```
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 [12]:
```
#check for the unique values in the EmploymentStatus column
prosper_loans.EmploymentStatus.unique()
```

Out[12]:
```
array(['Self-employed', 'Employed', 'Not available', 'Full-time', 'O
ther',
       nan, 'Not employed', 'Part-time', 'Retired'], dtype=object)
```

In [13]:
```
#check for number of null values in each column
prosper_loans.isnull().sum()
```

Out[13]:
```
Term                            0
LoanStatus                      0
BorrowerAPR                    25
BorrowerRate                    0
ListingCategory (numeric)       0
BorrowerState                5515
Occupation                   3588
EmploymentStatus             2255
IsBorrowerHomeowner             0
IncomeRange                     0
LoanOriginalAmount              0
dtype: int64
```

In [14]:
```
#check for the unique values in the IncomeRange column
prosper_loans.IncomeRange.unique()
```

Out[14]:
```
array(['$25,000-49,999', '$50,000-74,999', 'Not displayed', '$100,00
0+',
       '$75,000-99,999', '$1-24,999', 'Not employed', '$0'], dtype=o
bject)
```

In [15]:
```
#check employment status of people with $0 income range values
prosper_loans[prosper_loans["IncomeRange"] == "$0"]["EmploymentStatus
```

Out[15]:
```
array(['Full-time', 'Self-employed', 'Retired', 'Employed', 'Part-ti
me',
       'Not employed'], dtype=object)
```

In [16]:
```
#obtain unique values for ListingCategory
prosper_loans["ListingCategory (numeric)"].unique()
```

Out[16]:
```
array([ 0,  2, 16,  1,  7, 13,  6, 15, 20, 19,  3, 18,  8,  4, 11, 1
4,  5,
        9, 17, 10, 12])
```

In [17]:
```
#obtain value counts of each unique value in ListingCategory (numeric
prosper_loans["ListingCategory (numeric)"].value_counts().sort_values
```

Out[17]:
```
17       52
12       59
9        85
10       91
8       199
11      217
16      304
5       756
19      768
20      771
14      876
18      885
15     1522
13     1996
4      2395
6      2572
3      7189
2      7433
7     10494
0     16965
1     58308
Name: ListingCategory (numeric), dtype: int64
```

Issues Noticed

- Too many variations of "Past Due" values in **LoanStatus** column
- Listing category in numbers
- **ListingCategory (numeric)** column name
- "Not Available" values in **EmploymentStatus** column
- **IncomeRange** values of "Not Displayed"
- "Not employed" **IncomeRange** values
- Rows with $0 income range for borrowers with a job (that is borrowers with full-time or part-time or employed or self-employed employment status)
- Rows with "Current" loan status (**LoanStatus**)

- Rows with "Other" value in **EmploymentStatus** column
- Job status column needed
- **Term** column name
- A column depicting term in words needed
- **TermMonths**, **Term** and **IncomeRange** datatypes
- Null rows

Clean data

In [18]:
```
#make copy of dataset to clean
loans_clean = prosper_loans.copy()
```

First, the duplicate rows noticed in the assessment phase will be dropped.

In [19]:
```
#drop duplicated rows
loans_clean.drop_duplicates(inplace = True)
```

During the assessment of the **LoanStatus** column, various variations of "Past Due" values were noticed. This is as the "Past Due" values were recorded with a range of the number of days for which the loan was past due in parentheses.

Below, each of these variations will be modified into simply "Past Due".

In [20]:
```
def rename_pastdue(x):
    """The function renames every variation of "Past Due" values
    to just "Past Due\"""

    if "Past Due" in x:
        return "Past Due"
    else:
        return x
```

In [21]:
```
#apply rename_pastdue on LoanStatus column
loans_clean["LoanStatus"] = loans_clean["LoanStatus"].apply(rename_pa

#confirm
loans_clean.LoanStatus.unique()
```

Out[21]:
```
array(['Completed', 'Current', 'Past Due', 'Defaulted', 'Chargedof
f',
       'Cancelled', 'FinalPaymentInProgress'], dtype=object)
```

Below, **ListingCategory (numeric)** values will be converted to their various meanings in words and the column will be renamed.

Note

Each number in the **ListingCategory (numeric)** column and its meaning:

0 - Not Available, 1 - Debt Consolidation, 2 - Home Improvement, 3 - Business, 4 - Personal Loan, 5 - Student Use, 6 - Auto, 7 - Other, 8 - Baby&Adoption, 9 - Boat, 10 - Cosmetic Procedure, 11 - Engagement Ring, 12 - Green Loans, 13 - Household Expenses, 14 - Large Purchases, 15 - Medical/Dental, 16 - Motorcycle, 17 - RV, 18 - Taxes, 19 - Vacation, 20 - Wedding Loans

In [22]:
```
#obtain value counts of each unique value in ListingCategory (numeric
loans_clean["ListingCategory (numeric)"].value_counts().sort_values()
```

Out[22]:
```
17       52
12       58
9        85
10       91
8       196
11      214
16      304
5       756
20      762
19      764
14      863
18      882
15     1507
13     1984
4      2393
6      2568
3      7145
2      7379
7     10427
0     16518
1     57247
Name: ListingCategory (numeric), dtype: int64
```

In [23]:
```
def list_category(x):
    """This function changes each numeric value in the "ListingCatego
    to its appropriate word meaning"""

    cat_listing = {0 : "Not Available", 1 : "Debt Consolidation", 2 :
                   3 : "Business", 4 : "Personal Loan", 5 : "Student
                   7 : "Other", 8 : "Baby & Adoption", 9 : "Boat", 10
                   11 : "Engagement Ring", 12 : "Green Loans", 13 : "
                   14 : "Large Purchases", 15 : "Medical/Dental", 16
                   18 : "Taxes", 19 : "Vacation", 20 : "Wedding Loans
    for key, value in cat_listing.items():
        if x == key:
            return cat_listing[key]
```

In [24]:

```
#apply function
loans_clean["ListingCategory (numeric)"] = loans_clean["ListingCatego

#check
loans_clean["ListingCategory (numeric)"].value_counts().sort_values()
```

Out[24]:

```
RV                      52
Green Loans             58
Boat                    85
Cosmetic Procedure      91
Baby & Adoption        196
Engagement Ring        214
Motorcycle             304
Student Use            756
Wedding Loans          762
Vacation               764
Large Purchases        863
Taxes                  882
Medical/Dental        1507
Household Expenses    1984
Personal Loan         2393
Auto                  2568
Business              7145
Home Improvement      7379
Other                10427
```

In [25]:

```
#Rename the "ListingCategory (numeric)" column
loans_clean.rename(columns = {"ListingCategory (numeric)" : "ListingC

#confirm
loans_clean.head(1)
```

Out[25]:

	Term	LoanStatus	BorrowerAPR	BorrowerRate	ListingCategory	BorrowerState	Occupation	E
0	36	Completed	0.16516	0.158	Not Available	CO	Other	

For some columns (e.g **EmploymentStatus**, **ListingCategory** and **IncomeRange**), values such as "Not Available", "Not available" or "Not Displayed" are given. First, a function will be created to capitalize only the first letters of each word in a string and applied to **EmploymentStatus** and **IncomeRange** columns. Afterwards, another function would be created to convert the above-listed values to null values, and the function would be applied to the data frame.

In [26]:

```
def make_title(x):
    """This function capitalizes the first letter of each
    word in a string"""
    if type(x) == str:
        return x.title()
    else:
        return x
```

In [27]:

```python
#apply function on dataframe
loans_clean["EmploymentStatus"] = loans_clean["EmploymentStatus"].app
loans_clean["IncomeRange"] = loans_clean["IncomeRange"].apply(make_ti

#view random rows
print(loans_clean.EmploymentStatus.unique())
loans_clean.IncomeRange.unique()
```

```
['Self-Employed' 'Employed' 'Not Available' 'Full-Time' 'Other' nan
 'Not Employed' 'Part-Time' 'Retired']
```

Out[27]:

```
array(['$25,000-49,999', '$50,000-74,999', 'Not Displayed', '$100,00
0+',
       '$75,000-99,999', '$1-24,999', 'Not Employed', '$0'], dtype=o
bject)
```

In [28]:

```python
def change_to_null(x):
    """The function changes "Not Available" and "Not
    Displayed" values in a column to null values"""

    if x == "Not Available" or x == "Not Displayed":
        return np.nan
    else:
        return x
```

In [29]:

```python
#apply on dataframe
loans_clean = loans_clean.applymap(change_to_null)

#confirm
loans_clean.query('EmploymentStatus == "Not Available" or IncomeRange
```

Out[29]:

Term	LoanStatus	BorrowerAPR	BorrowerRate	ListingCategory	BorrowerState	Occupation	En

During the assessment, it was noted that some rows having $0 income range also belonged to borrowers with jobs. That is borrowers with full-time, self-employed, employed, and part-time employment statuses.

The $0 income range record for those borrowers may have been an error. Therefore, rows with such entries (rows having $0 **IncomeRange** value and full-time or self-employed or employed or part-time **EmploymentStatus**) will be removed.

In [30]:

```python
#select out rows with zero dollars income range
zero_dollars_df = loans_clean.query('IncomeRange == "$0"')

#filter out rows that belong to people with jobs
zero_with_job = zero_dollars_df.query('EmploymentStatus == "Full-Time
```

In [31]:
```
#drop rows in zero_with_job
loans_clean.drop(zero_with_job.index, inplace = True)
```

In [32]:
```
#confirm for "Full-Time" EmploymentStatus
loans_clean.query('IncomeRange == "$0" & EmploymentStatus == "Full-Ti
```

Out[32]:

Term	LoanStatus	BorrowerAPR	BorrowerRate	ListingCategory	BorrowerState	Occupation	En

In [33]:
```
#confirm for "Self-Employed" EmploymentStatus
loans_clean.query('IncomeRange == "$0" & EmploymentStatus == "Self-Em
```

Out[33]:

Term	LoanStatus	BorrowerAPR	BorrowerRate	ListingCategory	BorrowerState	Occupation	En

In [34]:
```
#confirm for "Employed" EmploymentStatus
loans_clean.query('IncomeRange == "$0" & EmploymentStatus == "Employe
```

Out[34]:

Term	LoanStatus	BorrowerAPR	BorrowerRate	ListingCategory	BorrowerState	Occupation	En

In [35]:
```
#confirm for "Part-Time" EmploymentStatus
loans_clean.query('IncomeRange == "$0" & EmploymentStatus == "Part-Ti
```

Out[35]:

Term	LoanStatus	BorrowerAPR	BorrowerRate	ListingCategory	BorrowerState	Occupation	En

As seen during assessment, some rows have "Not Employed" values in the **IncomeRange** column, which means the borrowers to whom those row records belong have no job. Therefore, those "Not Employed" values will be replaced with "$0" values.

In [36]:
```
def zero_dollar(x):
    """This function replaces every "Not Employed"
    value with a "$0" value"""
    if x == "Not Employed":
        return "$0"
    else:
        return x
```

In [37]:
```
#apply the zero_dollar function on IncomeRange column
loans_clean["IncomeRange"] = loans_clean["IncomeRange"].apply(zero_do

#confirm
loans_clean.IncomeRange.unique()
```

Out[37]:
```
array(['$25,000-49,999', '$50,000-74,999', nan, '$100,000+',
       '$75,000-99,999', '$1-24,999', '$0'], dtype=object)
```

For this analysis, current loan entries will not be needed. Therefore, rows with "Current" values in the **LoanStatus** column will be dropped.

In [38]:
```
#filter out rows with "Current" loan status
current_loans = loans_clean.query('LoanStatus == "Current"')

#drop rows with "Current" loan status
loans_clean.drop(current_loans.index, inplace = True)

#confirm
loans_clean.query('LoanStatus == "Current"')
```

Out[38]:

Term	LoanStatus	BorrowerAPR	BorrowerRate	ListingCategory	BorrowerState	Occupation	En

Below, rows for which the value in **EmploymentStatus** are "Other" will be dropped as they have no clear interpretation and will not be useful in this analysis.

In [39]:
```
#select out rows with "Other" value in employment status column
other_status = loans_clean[loans_clean["EmploymentStatus"] == "Other"

#drop the rows
loans_clean.drop(other_status.index, inplace = True)

#confirm
loans_clean[loans_clean["EmploymentStatus"] == "Other"]
```

Out[39]:

Term	LoanStatus	BorrowerAPR	BorrowerRate	ListingCategory	BorrowerState	Occupation	En

The **EmploymentStatus** variable has 6 unique values: "Full-Time", "Part-Time", "Self-Employed", "Employed", "Not Employed", and "Retired".

Of the 6 unique variables, 4 ("Full-Time", "Part-Time", "Self-Employed", and "Employed") represent borrowers who work or have a job, and only 2 ("Not Employed" and "Retired") represent borrowers without jobs.

Below, a new column will be created for job status with values stating if a borrower is working or not.

In [40]:

```
def job_status(col_name):
    """This function returns a list containing values
    of "Working" or "Not Working" for a borrower's job
    status"""
    status_list = []
    for x in col_name:
        if x == "Not Employed" or x == "Retired":
            status_list.append("Not Working")

        else:
            status_list.append("Working")
    return status_list
```

In [41]:

```
#apply the function to the EmploymentStatus column
#and assign the list returned to a new variable
job_status_list = job_status(loans_clean.EmploymentStatus)


#create new column for job status in clean loans dataframe
loans_clean["JobStatus"] = job_status_list
```

In [42]:

```
#confirm for borrowers with "Full-Time" employment status
loans_clean.query('EmploymentStatus == "Full-Time" & JobStatus == "No
```

Out[42]:

Term	LoanStatus	BorrowerAPR	BorrowerRate	ListingCategory	BorrowerState	Occupation	En

In [43]:

```
#confirm for borrowers with "Part-Time" EmploymentStatus
loans_clean.query('EmploymentStatus == "Part-Time" & JobStatus == "No
```

Out[43]:

Term	LoanStatus	BorrowerAPR	BorrowerRate	ListingCategory	BorrowerState	Occupation	En

In [44]:

```
#confirm for borrowers with "Self-Employed" EmploymentStatus
loans_clean.query('EmploymentStatus == "Self-Employed" & JobStatus ==
```

Out[44]:

Term	LoanStatus	BorrowerAPR	BorrowerRate	ListingCategory	BorrowerState	Occupation	En

In [45]:

```
#confirm for borrowers with "Employed" EmploymentStatus
loans_clean.query('EmploymentStatus == "Employed" & JobStatus == "Not
```

Out[45]:

Term	LoanStatus	BorrowerAPR	BorrowerRate	ListingCategory	BorrowerState	Occupation	En

In [46]:

```
#confirm for borrowers with "Not Employed" EmploymentStatus
loans_clean.query('EmploymentStatus == "Not Employed" & JobStatus ==
```

Out[46]:

Term	LoanStatus	BorrowerAPR	BorrowerRate	ListingCategory	BorrowerState	Occupation	En

In [47]:

```
#confirm for borrowers with "Retired" EmploymentStatus
loans_clean.query('EmploymentStatus == "Retired" & JobStatus == "Work
```

Out[47]:

Term	LoanStatus	BorrowerAPR	BorrowerRate	ListingCategory	BorrowerState	Occupation	En

The **Term** variable in the dataset is given in terms of the number of months. There are three groups: 12 months, 36 months and 60 months.

To represent them in "Term" (Short Term, Mid Term, and Long Term), a new feature will be created. But first, the initial **Term** variable will be renamed as **TermMonths** and the new feature to be created will be named **Term**.

In [48]:

```
#Rename Term variable
loans_clean.rename(columns = {"Term" : "TermMonths"}, inplace = True)

#confirm
loans_clean.head(1)
```

Out[48]:

	TermMonths	LoanStatus	BorrowerAPR	BorrowerRate	ListingCategory	BorrowerState	Occupa
0	36	Completed	0.16516	0.158	NaN	CO	O

In [49]:

```
def term_words(col_name):
    """This function returns a list of the term
    (in words) each loan belongs in"""
    term_list = []
    for x in col_name:
        if x == 12:
            term_list.append("Short Term")
        elif x == 36:
            term_list.append("Mid Term")
        else:
            term_list.append("Long Term")
    return term_list
```

In [50]:
```python
#apply function to TermMonths column
term_words_list = term_words(loans_clean.TermMonths)

#create a new variable for the term in words
loans_clean["Term"] = term_words_list
```

In [51]:
```python
#confirm by viewing random rows
print(loans_clean.TermMonths.value_counts())

loans_clean.Term.value_counts()
```

```
36    49535
60     4276
12     1505
Name: TermMonths, dtype: int64
```

Out[51]:
```
Mid Term      49535
Long Term      4276
Short Term     1505
Name: Term, dtype: int64
```

TermMonths, **IncomeRange**, and **Term** variables are ordinal variables, that is, their unique values are sequential. Therefore, their datatype should be "category", showing that they are ordered.

Hence, below the datatype for each of the variables are changed into "category" by specifying the order of their unique values.

In [52]:
```python
#create loop to change TermMonths, IncomeRange and Term datatypes to
ord_data_dict = {"TermMonths": [12, 36, 60],
            "IncomeRange": ["$0", "$1-24,999", "$25,000-49,999"
                            "$50,000-74,999", "$75,000-99,999", "$10
                "Term": ["Short Term", "Mid Term", "Long Term"]
                }

for ord_data in ord_data_dict:
    ord_cat = pd.api.types.CategoricalDtype(ordered = True, categorie
    loans_clean[ord_data] = loans_clean[ord_data].astype(ord_cat)
```

In [53]:
```
#confirm
loans_clean.dtypes
```

Out[53]:
```
TermMonths              category
LoanStatus                object
BorrowerAPR              float64
BorrowerRate             float64
ListingCategory           object
BorrowerState             object
Occupation                object
EmploymentStatus          object
IsBorrowerHomeowner         bool
IncomeRange             category
LoanOriginalAmount         int64
JobStatus                 object
Term                    category
dtype: object
```

Lastly, null rows were also noticed during the assessment of the dataset. Below, the null rows will be dropped.

In [54]:
```
#drop null values
loans_clean.dropna(inplace = True)
```

In [55]:
```
#obtain number of rows and columns of clean dataset
loans_clean.shape
```

Out[55]:
```
(14882, 13)
```

What is the structure of your dataset?

The clean Loan Data from Prosper dataset `loans_clean` has 14,882 loan entries on 13 variables (14,882 rows and 13 columns). It consists of numeric, nominal categorical, and ordinal categorical variables.

The **numeric variables** are: BorrowerAPR, BorrowerRate, and LoanOriginalAmount.

The **nominal categorical variables** are: LoanStatus, ListingCategory, Occupation, EmploymentStatus, BorrowerState, IsBorrowerHomeowner, and JobStatus.

The **ordinal categorical variables** are: TermMonths, and IncomeRange, and Term.

Below, the unique values in each of the variables are arranged in increasing order.

(smallest --> greatest)
TermMonths: 12, 36, 60
IncomeRange: $0, $1-24,999, $25,000-49,999, $50,000-74,999, $75,000-99,999, $100,000+
Term: Short Term, Mid Term, Long Term

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

I am mainly interested in determining the features that affect loan status, the features that tell the proportion of loans taken for student use that was completed, and how the length of a loan affects the interest rate. I am also interested in the features that determine if loan amount increases with increasing income range, if higher loan amounts are usually associated with longer loan length, and if borrowers who take loan for debt consolidation are mostly high income earners?

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

The following features: **LoanStatus**, **Term**, **ListingCategory**, **LoanOriginalAmount**, **IncomeRange**, and **BorrowerRate** will be useful in determining the outcome of my investigation into the features of interest stated above.

<\a>

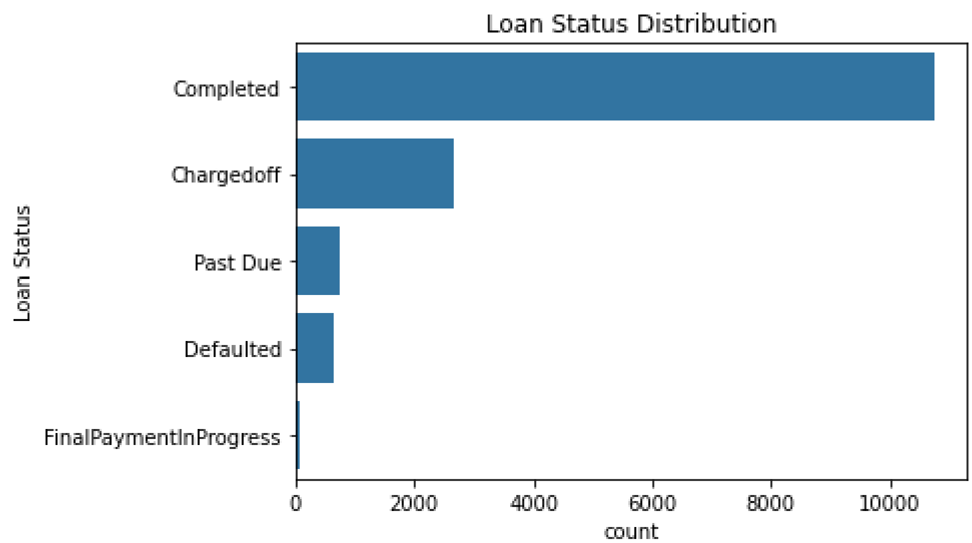
Univariate Exploration

This section involves investigation of distributions of individual variables in the dataset.

What is the status of most loans?

In [56]:

```
#visualize loan status variable
#choose color of bars
base_color = sb.color_palette()[0]

#create order for values from highest to least count
group_order = loans_clean.LoanStatus.value_counts().index

#plot
sb.countplot(data = loans_clean, y = "LoanStatus", color = base_color
plt.ylabel("Loan Status")
plt.title("Loan Status Distribution");
```



Observations

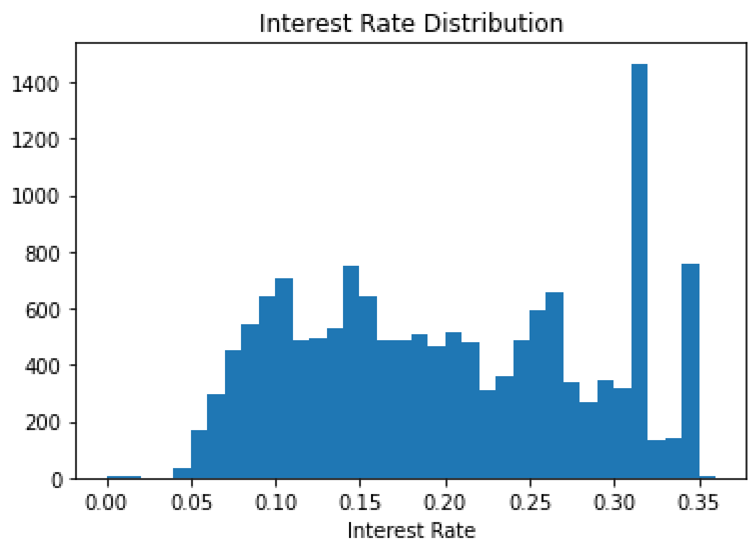
- Most borrowers complete their loans.
- There are more borrowers whose loans are charged off than there are those with their loans past due.
- The number of borrowers who defaulted on their loans is only slightly less than those for whom their loans are past due.
- Borrowers with their final payment in progress are the least.

How are the interest rates distributed?

In [57]:
```python
#summary statistics on borrower rate
loans_clean.BorrowerRate.describe()
```

Out[57]:
```
count    14882.000000
mean         0.201281
std          0.085881
min          0.000000
25%          0.128825
50%          0.194500
75%          0.271200
max          0.360000
Name: BorrowerRate, dtype: float64
```

In [58]:
```python
#visualize borrow rate variable
#create bin edges
bins = np.arange(0, loans_clean.BorrowerRate.max() + 0.01, 0.01)

#plot
plt.hist(data = loans_clean, x = "BorrowerRate", bins = bins)

plt.xlabel("Interest Rate");
#plt.xlim(0.03, 0.37)
plt.title("Interest Rate Distribution");
```



Observations

- It is multi-modal
- The highest peak is for interest rate between 0.31 and 0.32
- There are outliers between 0.00 and 0.02, also between 0.35 and 0.36

In [59]:

```
#investigate outliers
#check rows with interest rate betwee  0 and 0.02
low_rates = loans_clean.query('BorrowerRate >= 0.00 & BorrowerRate <
low_rates
```

Out[59]:

	TermMonths	LoanStatus	BorrowerAPR	BorrowerRate	ListingCategory	BorrowerState
15993	36	Chargedoff	0.01823	0.0100	Debt Consolidation	NY
37201	36	Completed	0.02998	0.0100	Student Use	CA
50251	36	Completed	0.01325	0.0001	Debt Consolidation	AR
78920	36	Completed	0.01987	0.0000	Debt Consolidation	NJ
105191	36	Chargedoff	0.02998	0.0100	Personal Loan	NY
112717	36	Completed	0.01315	0.0000	Other	CA

In [60]:

```
#obtain summary statistics for rows with interest rate between 0.35 a
high_rates = loans_clean.query('BorrowerRate >= 0.35 & BorrowerRate <
high_rates.LoanOriginalAmount.describe()
```

Out[60]:

```
count      554.000000
mean      3342.194946
std       3047.936633
min       1000.000000
25%       1500.000000
50%       2525.500000
75%       4000.000000
max      25000.000000
Name: LoanOriginalAmount, dtype: float64
```

In [61]:

```
#obtain maximum original loan amount value
loans_clean.LoanOriginalAmount.max()
```

Out[61]: 35000

For interest rates between 0 and 0.02:
There are two loan entries or rows with 0 value interest rates and an original loan amount of $25,000 and $3,000 respectively.
A third loan entry with an original loan amount of $5,000 has an interest rate of 0.0001 which is lower than the interest rate for a loan amount of $1,500.
The two other loan entries with original loan amounts of $1,500 and $2,000 have relatively low interest rates compared to other loans of the same amount.

For interest rates between 0.35 and 0.36:
Interest rates in this range are relatively high and seeing how no rows with original loan amounts of $35,000 have an interest rate in that range, it is possible that the record of interest rates for these rows is erroneous.

To be safe, these rows will be dropped, and a new plot will be created for the **BorrowerRate** variable.

In [62]:
```
#drop BorrowerRate outlier rows
loans_clean.drop(low_rates.index, inplace = True)
loans_clean.drop(high_rates.index, inplace = True)

#confirm
#for low interest rates
loans_clean.query('BorrowerRate >= 0.00 & BorrowerRate < 0.02')
```

Out[62]:

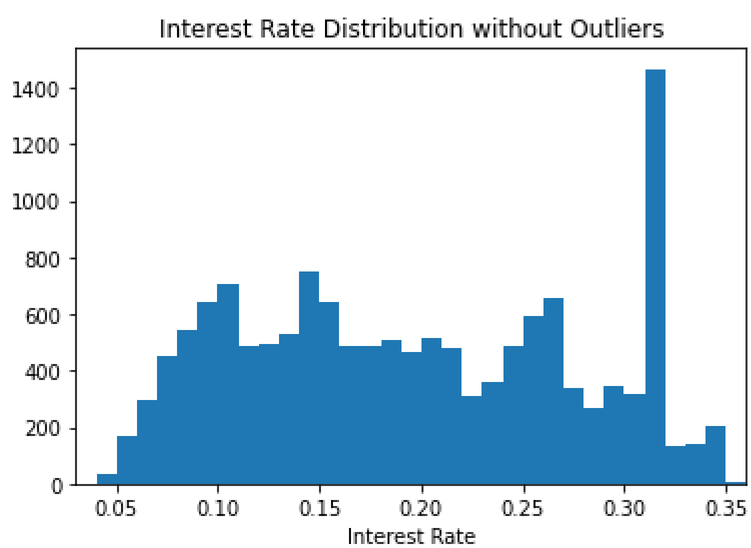
TermMonths	LoanStatus	BorrowerAPR	BorrowerRate	ListingCategory	BorrowerState	Occupati

In [63]:
```
#for high interest rates
loans_clean.query('BorrowerRate >= 0.35 & BorrowerRate < 0.36')
```

Out[63]:

TermMonths	LoanStatus	BorrowerAPR	BorrowerRate	ListingCategory	BorrowerState	Occupati

In [64]:
```
#revisualize borrow rate variable
#create bin edges
bins = np.arange(0, loans_clean.BorrowerRate.max() + 0.01, 0.01)

#plot
plt.hist(data = loans_clean, x = "BorrowerRate", bins = bins)
plt.xlabel("Interest Rate");
plt.xlim(0.03, 0.36)
plt.title("Interest Rate Distribution without Outliers");
```

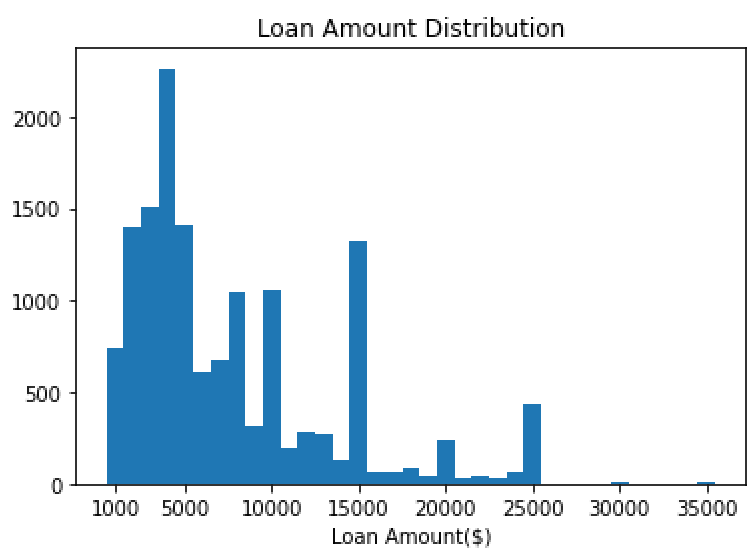


How is loan amount distributed?

In [65]:
```
#obtain summary statistics for LoanOriginalAmount variable
loans_clean.LoanOriginalAmount.describe()
```

Out[65]:
```
count    14322.000000
mean      7540.879067
std       5885.548949
min       1000.000000
25%       3200.000000
50%       5000.000000
75%      10000.000000
max      35000.000000
Name: LoanOriginalAmount, dtype: float64
```

In [66]:
```
#create bin edges
bins = np.arange(500, 35500 + 1000, 1000)

#plot
plt.hist(data = loans_clean, x = "LoanOriginalAmount", bins = bins)

#create tick labels
ticks = [1000, 5000, 10000, 15000, 20000, 25000, 30000, 35000]
tick_labels = ["{}".format(tick) for tick in ticks]

plt.xticks(ticks, tick_labels)
#plt.xlim(0, 25500)
plt.xlabel("Loan Amount($)")
plt.title("Loan Amount Distribution");
```



Observations

- The data distribution is multimodal
- There are outliers having values of 30,000 and 35,000

In [67]:

```python
#investigate outliers
loans_clean.query('LoanOriginalAmount > 27000 and LoanOriginalAmount
```

Out[67]:

	TermMonths	LoanStatus	BorrowerAPR	BorrowerRate	ListingCategory	Borr
2636	36	Past Due	0.17754	0.1414	Debt Consolidation	
10825	36	Completed	0.13138	0.1034	Business	
15459	36	Completed	0.20053	0.1639	Debt Consolidation	
41694	60	Completed	0.14760	0.1249	Debt Consolidation	
44659	60	Completed	0.16294	0.1399	Debt Consolidation	
46741	36	Completed	0.15833	0.1299	Debt Consolidation	
49022	36	Completed	0.20462	0.1679	Motorcycle	
50066	60	Completed	0.16294	0.1399	Debt Consolidation	
51770	36	Past Due	0.17601	0.1399	Vacation	
56440	36	Completed	0.19645	0.1599	Debt Consolidation	
61917	60	Completed	0.15783	0.1349	Debt Consolidation	
62729	36	Completed	0.14348	0.1153	Debt Consolidation	
65984	36	Past Due	0.14857	0.1203	Debt Consolidation	
79411	36	Completed	0.12274	0.0949	Business	
81597	60	Completed	0.20593	0.1819	Business	
82248	36	Completed	0.14857	0.1203	Debt Consolidation	
83858	36	Completed	0.12081	0.0930	Debt Consolidation	
90748	36	Past Due	0.20053	0.1639	Debt Consolidation	
94875	60	Completed	0.13227	0.1099	Business	
96715	60	Past Due	0.17522	0.1519	Debt Consolidation	
101601	36	Completed	0.14409	0.1159	Debt Consolidation	

	TermMonths	LoanStatus	BorrowerAPR	BorrowerRate	ListingCategory	Borr
108637	36	FinalPaymentInProgress	0.14409	0.1159	Other	

These outliers are quite valid, and so will not be dropped.

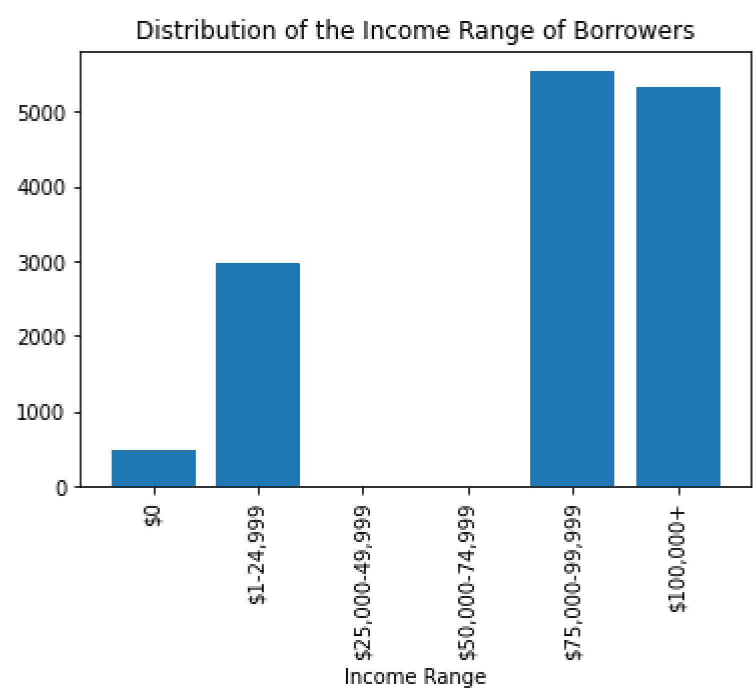
What income range do most borrowers belong in?

In [68]:

```
#obtain number of count for each income range
range1 = loans_clean.query('IncomeRange == "$0"').IncomeRange.count()
range2 = loans_clean.query('IncomeRange == "$1-24,999"').IncomeRange.
range3 = loans_clean.query('IncomeRange == "$25,000-49,999"').IncomeR
range4 = loans_clean.query('IncomeRange == "$50,000-74,999"').IncomeR
range5 = loans_clean.query('IncomeRange == "$75,000-99,999"').IncomeR
range6 = loans_clean.query('IncomeRange == "$100,000+"').IncomeRange.
```

In [69]:

```
#visualize the income range variable
x_num = np.arange(6)
y_values = [range1, range2, range3, range4, range5, range6]
x_labels = ["$0", "$1-24,999", "$25,000-49,999", "$50,000-74,999", "$


#plot
plt.bar(x_num, y_values, tick_label = x_labels)
plt.xticks(rotation = 90)
plt.xlabel("Income Range")
plt.title("Distribution of the Income Range of Borrowers") ;
```



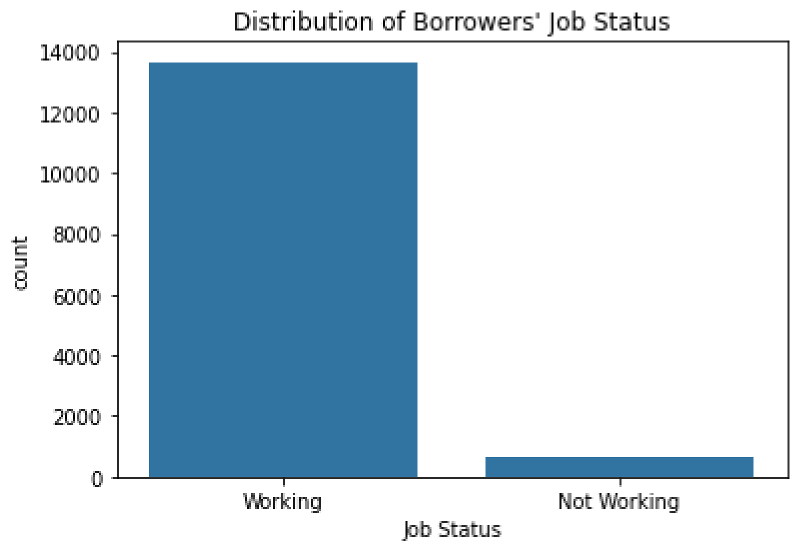
Observations

- Most of the borrowers have an income range of $75,000-99,999. This is closely followed by borrowers in the $100,000+ income range.
- Borrowers in the $0 income range are the least.
- There are more borrowers in the $1-24,999 income range than there are in $0 income range, but they are less than those in $100,000+ income range.
- Lastly, there are no borrowers in the $25,000-49,999 and $50,000-74,999 income range.

Are there more borrowers with job than there are those without?

In [70]:

```
#visualize the job status variable
sb.countplot(data = loans_clean, x = "JobStatus", color = base_color)

plt.xlabel("Job Status")
plt.title("Distribution of Borrowers' Job Status");
```



Observations

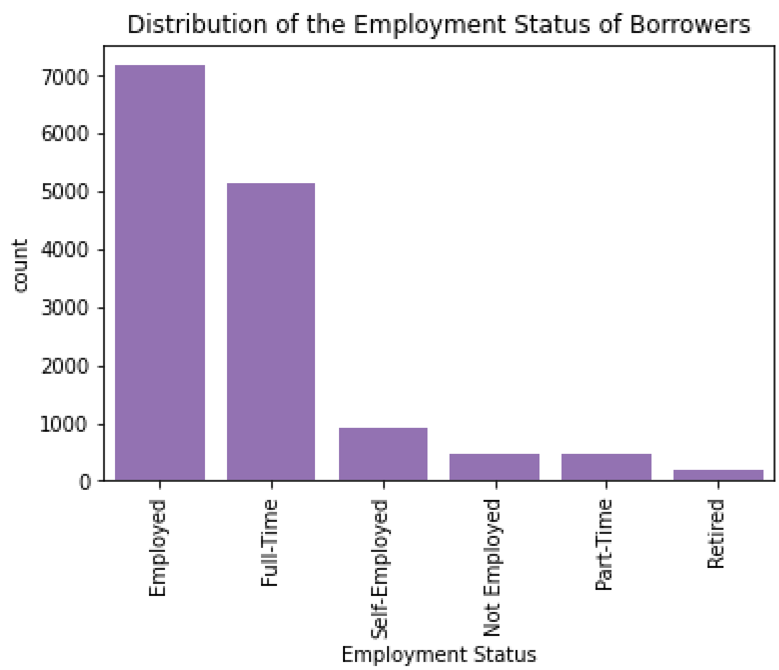
- There are only a few borrowers without a job.
- There is a large difference in number between borrowers with job and borrowers without jobs.

Below, the **EmploymentStatus** variable will be visualized to further explain the reason for the large difference between borrowers that are working and those not working.

What employment status has the highest frequency?

In [71]:

```
#visualize employment status
#choose color of bars
color5 = sb.color_palette()[4]

#create order from highest to least
group_order = loans_clean.EmploymentStatus.value_counts().index

#plot
sb.countplot(data = loans_clean, x = "EmploymentStatus", color = colo
plt.xticks(rotation = 90)
plt.xlabel("Employment Status")
plt.title("Distribution of the Employment Status of Borrowers");
```



Observations

- The highest employment status count belongs to borrowers with "Employed" status, followed by those with "Full-Time" status.
- The count of borrowers with "Self-Employed", "Not-Employed", "Part-Time", and "Retired" statuses are relatively less than the count of borrowers with "Employed" and "Full-Time" employment statuses.
- There are more self-employed borrowers than not employed and part-time borrowers.
- The "Not Employed" bar looks almost equal / slightly less than the "Part-Time" status bar.
- Retired borrowers are the least.

This explains the large difference between the number of borrowers with jobs and those without.

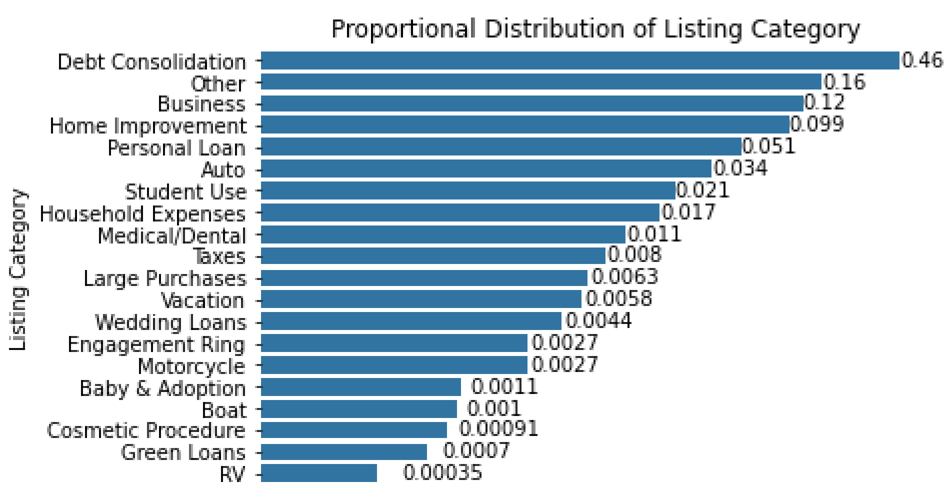
What listing category has the highest proportion?

In [72]:
```
#assign value counts of ListingCategory column to a variable
col_count = loans_clean.ListingCategory.value_counts()

#obtain total sum of values in ListingCategory column
total_sum = col_count.sum()
```

In [73]:
```
#create group order from highest count of values to least
group_order = loans_clean.ListingCategory.value_counts().index

#create tick marks and labels for x-axis
ticks = [1, 2, 5, 10, 20, 50, 100, 200, 500, 1000, 2000, 5000, 10000]
x_labels = ['{}'.format(tick) for tick in ticks]
```

In [74]:

```
#visualize proportion of each listing category
#plot a horizontal bar chart
ax = sb.countplot(data = loans_clean, y = "ListingCategory", color =

#rescale the x-axis in logarithm
plt.xscale("log")

plt.xticks(ticks, x_labels)
plt.xticks(rotation = 90)
plt.ylabel("Listing Category");

#turn off top, bottom, right, and left spine
ax.spines["top"].set_visible(False)
ax.spines["bottom"].set_visible(False)
ax.spines["right"].set_visible(False)
ax.spines["left"].set_visible(False)

#turn off x-axis
ax.get_xaxis().set_visible(False)

#include the proportion of each listing category as text om their app
for i in range(col_count.shape[0]):
    count = col_count[i]
    count_str = "{:0.2}".format(count / total_sum)
    plt.text(count + 2, i, count_str, va = "center")

plt.title("Proportional Distribution of Listing Category");
```



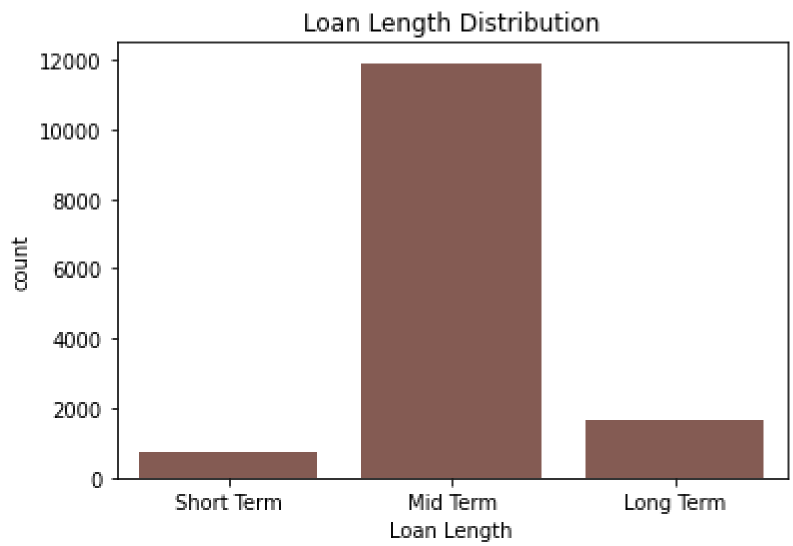
Observations

- Almost half the listings are for debt consolidation.
- Only approximately 2% of listings are for student use.

Are there more loans with longer loan lengths?

In [75]:

```
#visualize Term variable
#choose color of bars
color6 = sb.color_palette()[5]

#plot
sb.countplot(data = loans_clean, x = "Term", color = color6)

plt.xlabel("Loan Length")
plt.title("Loan Length Distribution");
```



Observations

- There are by far more mid term loans than there are long term and short term loans.
- Short term loans are the fewest

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

The loan status was unevenly distributed across completed, charged off, past due, defaulted, and final payment in progress. The majority of the loans were completed, and this was followed by loans charged off. Loans with final payment in progress had the least number of counts or frequency, and there was only a small difference between the number of loans past due and the number of defaulted loans.

There were more borrowers with an income range of $75,000-99,999, and this was closely followed by borrowers with an income range of $100,000+. Fewer borrowers were in the $0 income range, and the borrowers in the $1-24,999 income range were greater than those in the $0 range by a wide margin but less than those in the $100,00+ range.

The frequency of borrowers working in the job status variable was by far more than those not working.

Almost half the values in the listing category were "Debt Consolidation", with the least being "RV" with only a percentage proportion of 0.035%. Also, only approximately 2% of the listings were for "Student Use".
The scale of the x-axis (axis representing count/frequency) was transformed to a log scale because of the large values its large range of values.

Compared to mid term loans, there were only a few long and short term loans, as more than half the loans were mid term. Short term loans were the least in number.

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

In the interest rate variable (**BorrowerRate**), there were some outliers on both extremes (high and low). The interest rate values were considered either too high or too low when compared with the trend of interest rate for their loan amount, and the rows were dropped to be safe.

Outliers were also present in the loan amount variable (**LoanOriginalAmount**), but these rows were not dropped as they were considered valid.

<\a>

Bivariate Exploration

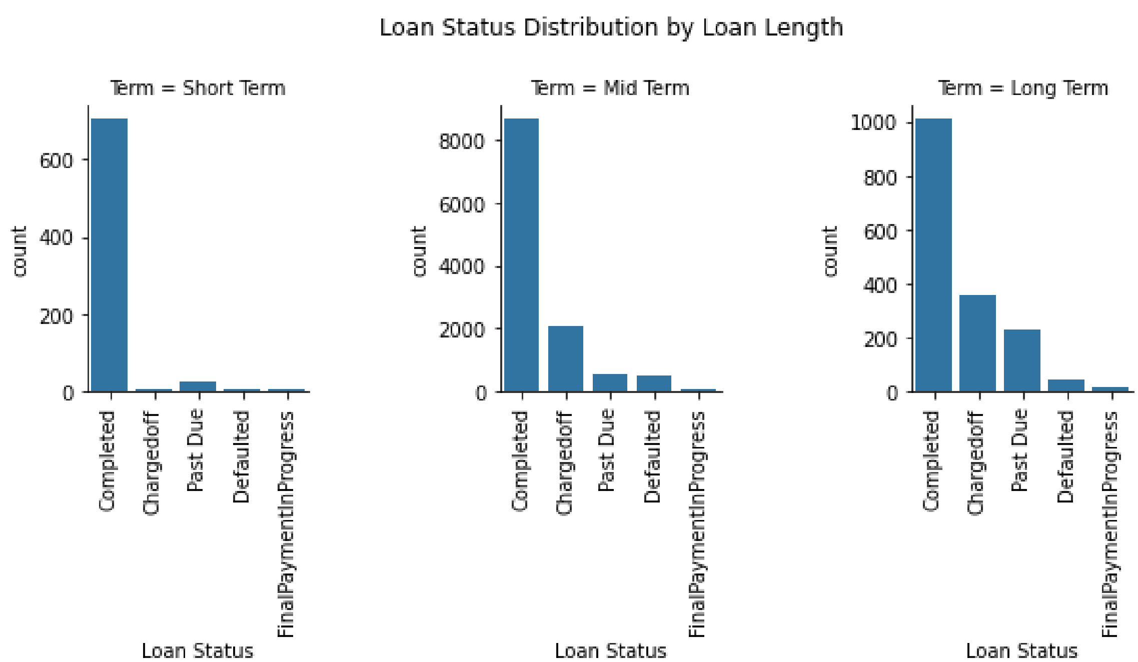
In this section, relationships between pairs of variables in the dataset will be investigated.

Does loan length affect loan status?

In [76]:

```
#visualize
g = sb.FacetGrid(data = loans_clean, col = "Term", sharey = False)
g.map(sb.countplot, "LoanStatus");

for ax in g.axes.flat:
    label = ax.get_xticklabels()
    ax.set_xticklabels(label, rotation = 90)
    ax.set_xlabel("Loan Status");

#set title of figure
plt.suptitle("Loan Status Distribution by Loan Length", y = 1.1);
```

```
/data/user/0/ru.iiec.pydroid3/files/aarch64-linux-android/lib/python
3.9/site-packages/seaborn/axisgrid.py:670: UserWarning: Using the co
untplot function without specifying `order` is likely to produce an
incorrect plot.
  warnings.warn(warning)
```



Observations

Short Term

- Most loans are completed.
- Only a very few loans are charged off or defaulted or have their final payment in progress.
- The amount of loans past due are more that those charged off, defaulted, or that have their final payment in progress, but is by far less than completed loans.

Mid Term

- The majority of the loans are completed, and only a very few have their final payment in progress.
- An amount of the loans far less than that of loans that are completed, but greater than those of loans that are past due, defaulted, and have their final payment in progress are charged off.
- Loans that are past due are present in the same amount as defaulted loans.

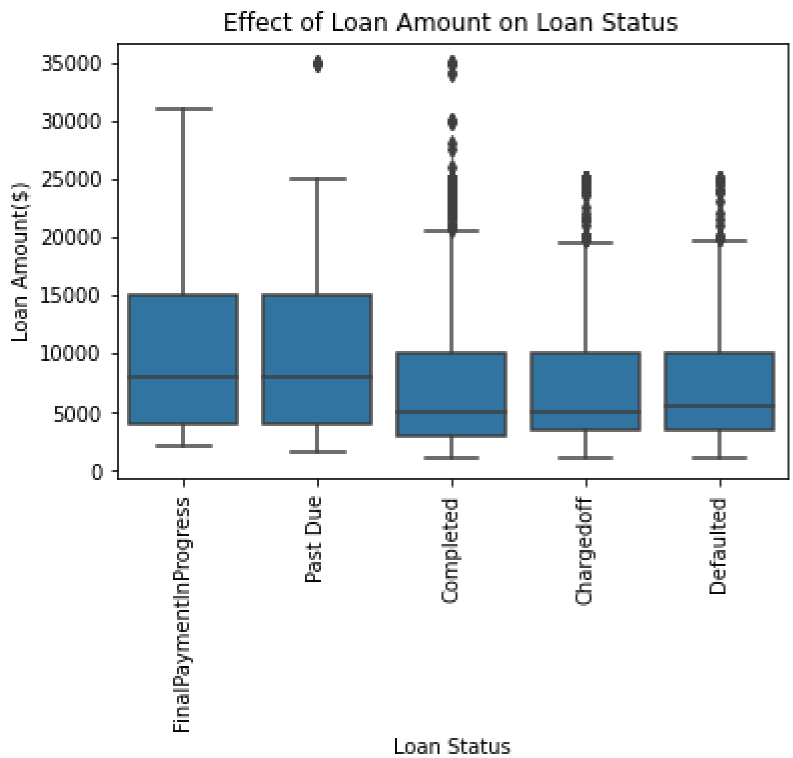
Long Term

- More loans are completed than charged off or past due or defaulted.
- Less than half the loans are charged off.
- There is a slight decrease from the number of loans charged off to the number of loans past due.
- Only a very few loans are defaulted, and fewer have their final payment in progress.

What is the effect of loan amount on loan status?

In [77]:

```
sb.boxplot(data = loans_clean, x = "LoanStatus", y = "LoanOriginalAmo
              color = base_color, order = ["FinalPaymentInProgress",
                                           "Completed", "Chargedoff",

plt.xticks(rotation = 90)
plt.xlabel("Loan Status")
plt.ylabel("Loan Amount($)")
plt.title("Effect of Loan Amount on Loan Status");
```



Observations

- Generally, as the loan amount decreases, it goes from final payment in progress to past due to completed and then to defaulted and chargedoff.
- There are high outlier loan amounts with past due and completed statuses.

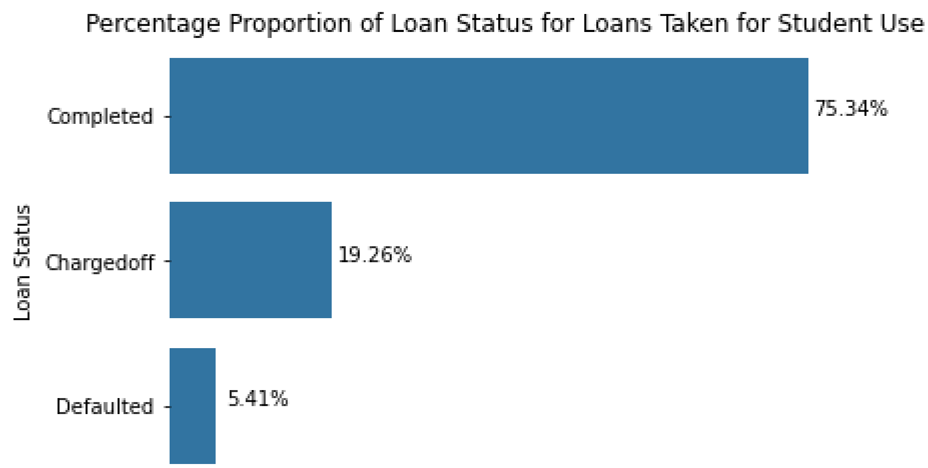
What percentage of loans taken for student use gets completed?

In [78]:

```
#select out rows with listing category as Student Use
student_use = loans_clean.query('ListingCategory == "Student Use"')

#get the count for each loan status
loan_stats_count = student_use.LoanStatus.value_counts()

#get the total number of loan status values
total_student_stats = loan_stats_count.sum()

#obtain status order for the student use data
stat_order = loan_stats_count.index
```

In [79]:

```
#visualize
g = sb.countplot(data = student_use, y = "LoanStatus", color = base_c
             order = stat_order)

#input percentage of each status as texts on their respective bars
for i in range(loan_stats_count.shape[0]):
    count = loan_stats_count[i]
    pct_text = "{:0.2f}%".format(100 * (count/total_student_stats))
    plt.text(count + 15, i , pct_text, ha = "center");

#remove spines
g.spines["top"].set_visible(False)
g.spines["right"].set_visible(False)
g.spines["left"].set_visible(False)
g.spines["bottom"].set_visible(False)

#remove y-axis
g.get_xaxis().set_visible(False)

plt.ylabel("Loan Status")
plt.title("Percentage Proportion of Loan Status for Loans Taken for S
```



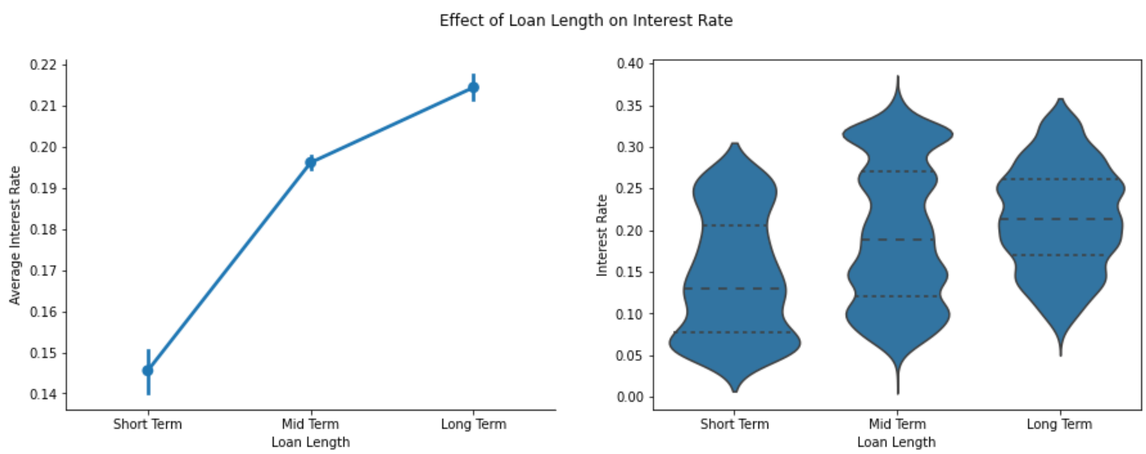
Observations

- More than half the loans are completed
- A few percent of the loans were charged off and defaulted, with charged-off loans being more than defaulted loans.

How does the length of a loan affect interest rate?

In [80]:

```python
#set fig size
plt.figure(figsize = (15, 5))

#subplot for point plot
plt.subplot(1, 2, 1)
g = sb.pointplot(data = loans_clean, x = "Term", y = "BorrowerRate",
             color = base_color);
#remove top and right spines
g.spines["top"].set_visible(False)
g.spines["right"].set_visible(False)
plt.xlabel("Loan Length")
plt.ylabel("Average Interest Rate")



#subplot for violin plot
plt.subplot(1, 2, 2)
sb.violinplot(data = loans_clean, x = "Term", y = "BorrowerRate",
              color = base_color, inner = "quartile");
plt.xlabel("Loan Length")
plt.ylabel("Interest Rate")

#set title of figure
plt.suptitle("Effect of Loan Length on Interest Rate");
```

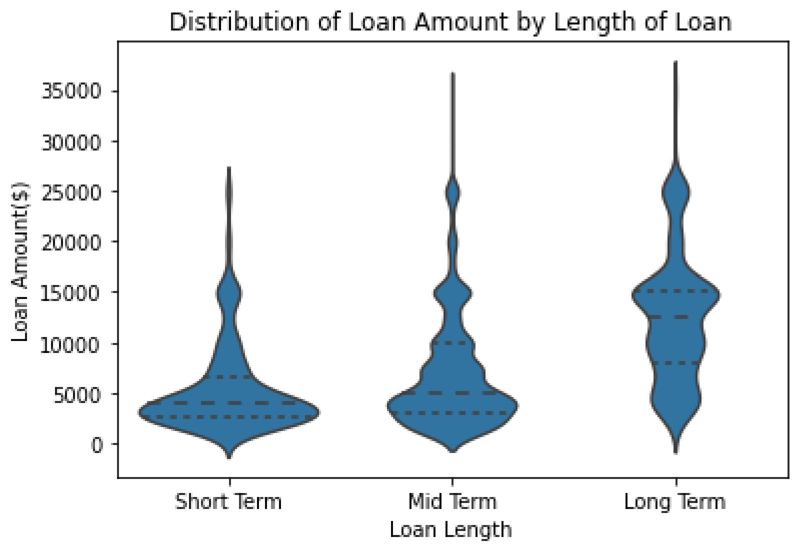


Observations

- There is a positive relationship between both variables.
- The distributions are multimodal.
- Generally, there is an increase in interest rate from short term to long term.
- Most of the interest rate values for long term loans are between 0.15 and 0.27.

Are higher loan amount usually associated with long loan length?

In [81]:
```
#visualize
sb.violinplot(data = loans_clean, x = "Term", y = "LoanOriginalAmount
              color = base_color, inner = "quartile");


plt.xlabel("Loan Length")
plt.ylabel("Loan Amount($)")
plt.title("Distribution of Loan Amount by Length of Loan");
```



Observations

- The relationship is positive. There is an increase in loan amount as loan length increases.
- The distributions are multimodal.
- Most short term loans are less than $5,000.
- Long term loans has its highest distribution of loan amount at about $15,000.

Does loan amount increase with increasing income range?

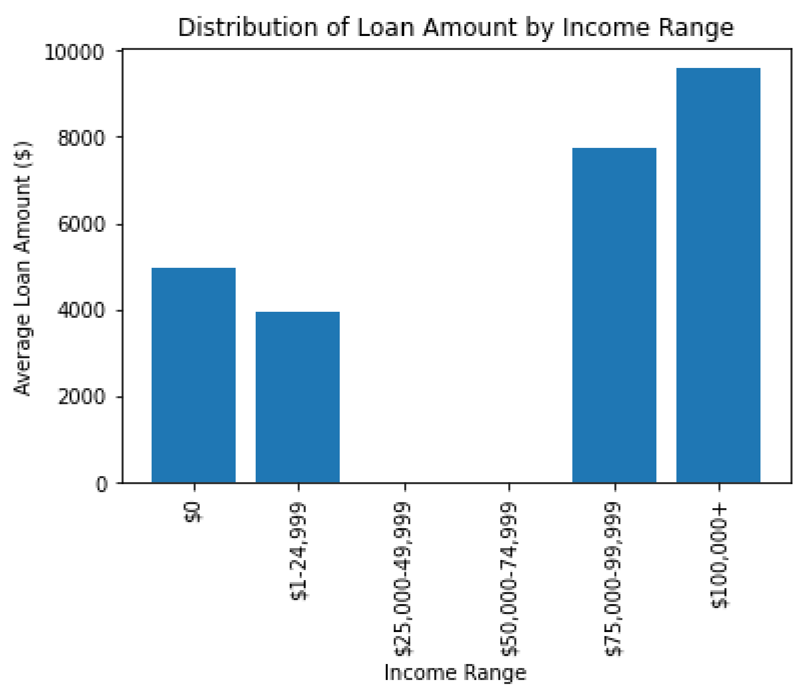
In [82]:
```
#obtain the average loan amount for each income range values
range1_mean = loans_clean[loans_clean["IncomeRange"] == "$0"].LoanOri
range2_mean = loans_clean[loans_clean["IncomeRange"] == "$1-24,999"].
range3_mean = loans_clean[loans_clean["IncomeRange"] == "$25,000-49,9
range4_mean = loans_clean[loans_clean["IncomeRange"] == "$50,000-74,9
range5_mean = loans_clean[loans_clean["IncomeRange"] == "$75,000-99,9
range6_mean = loans_clean[loans_clean["IncomeRange"] == "$100,000+"].
```

In [83]:

```
#set parameters for bar plot
x_num = np.arange(6)
y_values = [range1_mean, range2_mean, range3_mean, range4_mean, range
            range6_mean]
labels = ["$0", "$1-24,999", "$25,000-49,999",
          "$50,000-74,999", "$75,000-99,999",
          "$100,000+"]
```

In [84]:

```
#plot bar plot
plt.bar(x_num, y_values, tick_label = labels)
plt.xticks(rotation = 90)
plt.xlabel("Income Range")
plt.ylabel("Average Loan Amount ($)");
plt.title("Distribution of Loan Amount by Income Range");
```



Observations

- The average loan amount of the $1-24,999 income range is slightly less than that of the $0 income range.
- Generally, there is an increase in loan amount from the $0 income range to $100,000+.

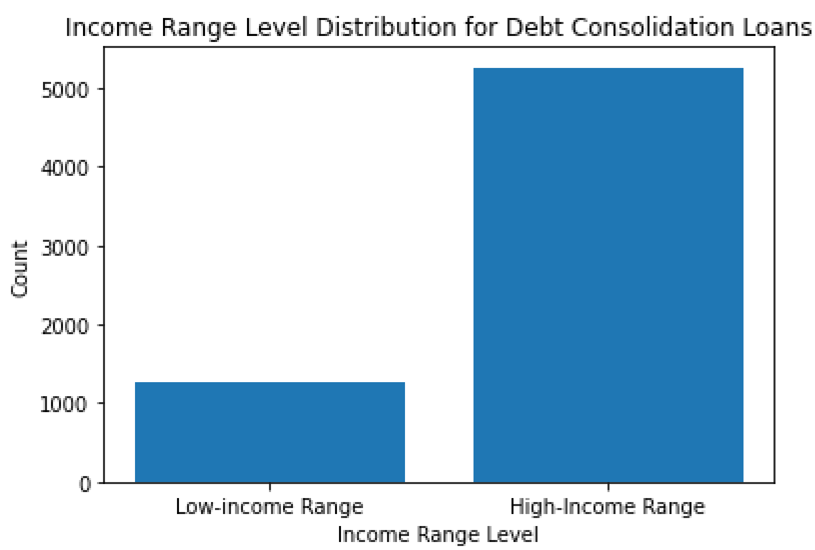
Are borrowers who take loans for debt consolidation mostly high-income earners?

From the univariate exploration of this dataset, it has been established that there are no borrowers in the $25,000-49,999 and $50,000-74,999 income range. Hence the low-income range in this analysis will only consist of the $0 and $1-24,999 income ranges, and the high-income ranges are $75,000-99,999 and $100,000+.

In [85]:
```
#filter out debt consolidation rows
debt_cons = loans_clean[loans_clean["ListingCategory"] == "Debt Conso

#select out the count of each income range
cons_inc1 = debt_cons[debt_cons["IncomeRange"] == "$0"].IncomeRange.c
cons_inc2 = debt_cons[debt_cons["IncomeRange"] == "$1-24,999"].Income
cons_inc3 = debt_cons[debt_cons["IncomeRange"] == "$25,000-49,999"].I
cons_inc4 = debt_cons[debt_cons["IncomeRange"] == "$50,000-74,999"].I
cons_inc5 = debt_cons[debt_cons["IncomeRange"] == "$75,000-99,999"].I
cons_inc6 = debt_cons[debt_cons["IncomeRange"] == "$100,000+"].Income
```

In [86]:
```
#get total value for low income earners
#sum of count for income range $0 - $74,999
total_low_inc = cons_inc1 + cons_inc2


#get total value for higher income earners
#sum of count for income range $75,000-99,999
#and $100,0000+
total_high_inc = cons_inc5 + cons_inc6
```

In [87]:
```
#set bar chart parameters
x_num = np.arange(2)
y_values = [total_low_inc, total_high_inc]
labels = ["Low-income Range", "High-Income Range"]

#plot
plt.bar(x_num, y_values, tick_label = labels)
plt.xlabel("Income Range Level")
plt.ylabel("Count")
plt.title("Income Range Level Distribution for Debt Consolidation Loa
```



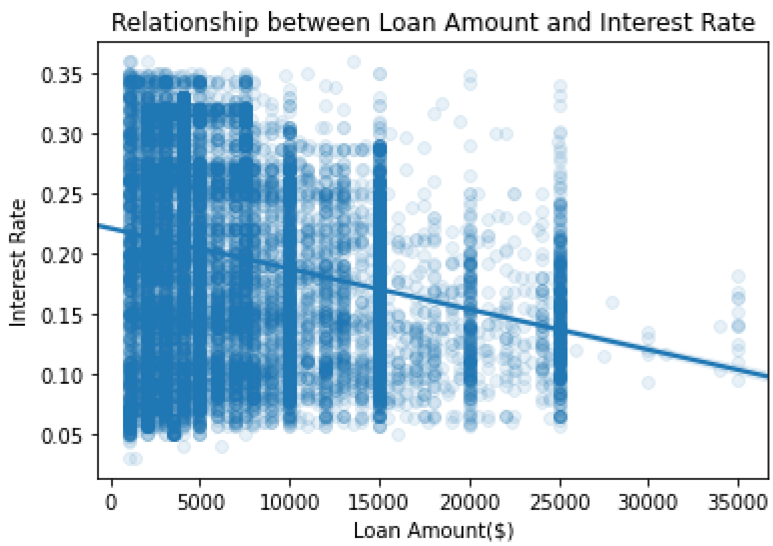
Observations

- There is a higher number of high-income earners.

Does interest rate increase with an increase in loan amount?

In [88]:

```
#visualize
sb.regplot(data = loans_clean, x = "LoanOriginalAmount", y = "Borrowe
           truncate = False, scatter_kws = {"alpha" : 1/10});

plt.xlabel("Loan Amount($)")
plt.ylabel("Interest Rate")
plt.title("Relationship between Loan Amount and Interest Rate");
```



Observations

- The relationship is negative.
- There is a decrease in interest rate as loan amount increases.

Talk about some of the relationships you observed in this part of the investigation. How did the feature(s) of interest vary with other features in the dataset?

One interesting relationship was seen between loan length and interest rate. The bivariate visualization of both variables showed a positive relationship, as the interest rate increased with increasing loan length, from short to long term.

A positive relationship was also noticed between loan amount and loan length. As loan amount increased, there was also an increase in loan length with progression from short to mid, and then to long term.

Another relationship noticed was that between income range, and loans listed in the debt consolidation category. From the visualization created, there were by far more high-income earners who took loans for debt consolidation than there were low-income earners.

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

An interesting relationship was noticed between loan amount and interest rate. The visualization of the relationship showed a decrease in interest rate as loan amount increased.

<\a>

Multivariate Exploration

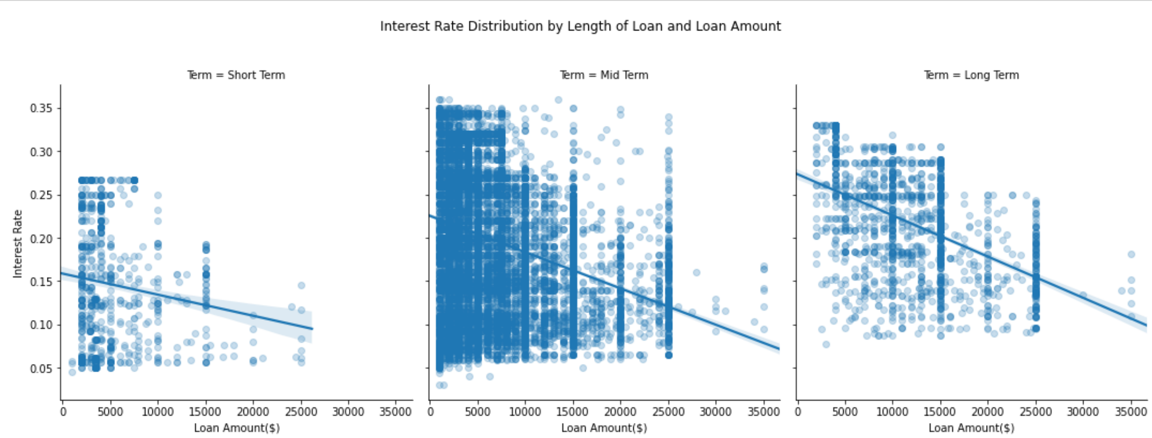
Here, the relationship between interest rates, loan amount and loan length, as well as that between loan amount/interest rate, loan status and loan length will be visualized.

During the bivariate exploration of the dataset, separate visualizations were created between different pairs of these variables, but a single visualization combining some of the different pairs will help us gain a better understanding of the data.

What is the relationship between interest rates, loan amount and loan length?

In [89]:

```
#visualize
g = sb.FacetGrid(data = loans_clean, col = "Term",
                 height = 5)
g.map(sb.regplot, "LoanOriginalAmount", "BorrowerRate",
      truncate = False, scatter_kws = {"alpha" : 1/4});

#set x-axis label for each plot in the facet grid
for ax in g.axes.flat:
    ax.set_xlabel("Loan Amount($)")
    ax.set_ylabel("Interest Rate")

#set y-axis label and title of figure
plt.suptitle("Interest Rate Distribution by Length of Loan and Loan A
```



Observations

- Generally, there is an increase in loan amount as loan length increases.
- As the loan amount increases, the interest rate decreases.
- Also, there is a general increase in interest rate from short to long term (loan length).

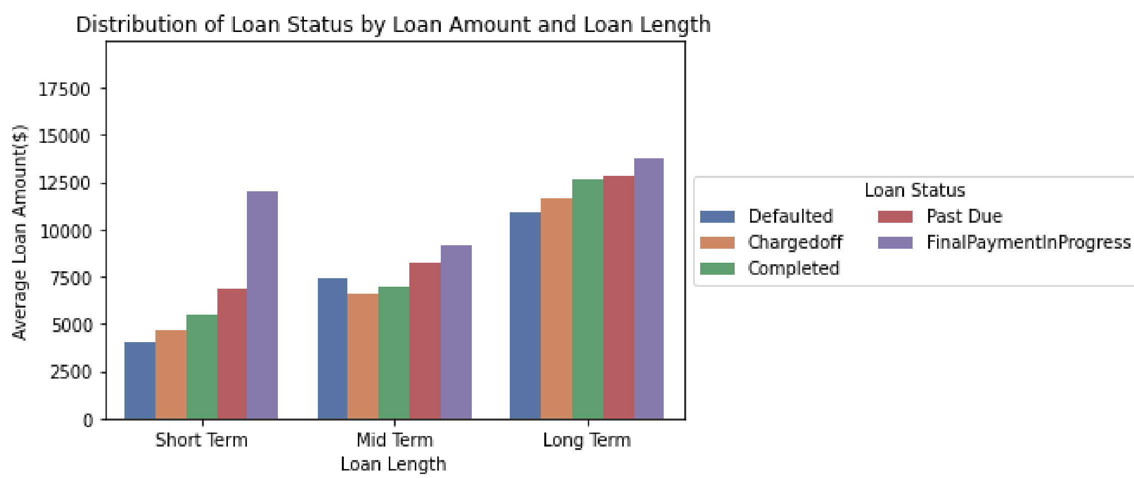
What trend does loan status follow with increasing loan amount and loan length?

In [90]:

```
#create order by which the hue is created
order_hue = ["Defaulted", "Chargedoff", "Completed",
              "Past Due", "FinalPaymentInProgress"]
```

In [91]:

```
#visualize
sb.barplot(data = loans_clean, x = "Term", y = "LoanOriginalAmount",
           hue = "LoanStatus", hue_order = order_hue, palette = "deep
           errwidth = 0);

plt.legend(title = "Loan Status", ncol = 2, loc = 6, bbox_to_anchor =
plt.xlabel("Loan Length")
plt.ylabel("Average Loan Amount($)")
plt.title("Distribution of Loan Status by Loan Amount and Loan Length
```



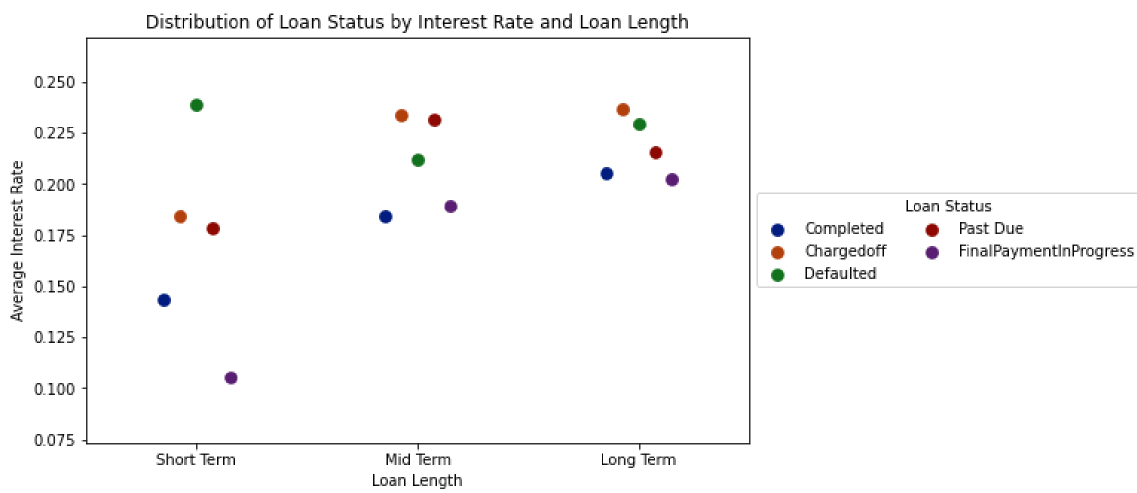
Observations

- Generally, as loan amount increases, there is an increase in loan length.
- Each term has loan statuses distributed across "Defaulted", "Chargedoff", "Completed", "Past Due", and "FinalPaymentInProgress".
- Generally, as loan amount increases, loan status goes from defaulted to charged off to completed to past due and to final payment in progress in each loan length.
- There is an exception with mid term loans where increasing loan amount causes loan status to go from charged off to completed to defaulted to past due, and finally to final payment in progress.

What trend does loan status follow with increasing interest rate and loan length?

In [92]:

```
#set figure
plt.figure(figsize = (8,5))

#visualise
sb.pointplot(data = loans_clean, x = "Term", y = "BorrowerRate",
             hue = "LoanStatus", palette = "dark",
               dodge = 0.3, linestyles = "", errwidth = 0);

#set legend
plt.legend(title = "Loan Status", ncol = 2, loc = 6, bbox_to_anchor =

plt.xlabel("Loan Length")
plt.ylabel("Average Interest Rate")
plt.title("Distribution of Loan Status by Interest Rate and Loan Leng
```



Observations

- Generally, there is an increase in interest rates from short to long term (loan length).
- Loans with high-interest rates are usually past due, defaulted, or charged off.
- Each term has its loan status spread across final payment in progress, completed, past due, defaulted, and charged off.
- For short term loans, as interest rate increases, loan status goes from final payment in progress to completed to past due to charged off to defaulted.
- For mid term loans, as interest rate increases, loan status goes from completed to final payment in progress to defaulted to past due to charged off.
- For long term loans, as interest rate increases, loan status goes from final payment in progress to completed to past due to defaulted to charged off with increasing interest rate.

Talk about some of the relationships you observed in this part of the investigation. Were there features that strengthened each other in terms of looking at your feature(s) of interest?

The distribution of loan status by loan amount followed the same pattern in the short and long term loan lengths, although, for the short term loan length, loans with their final payment in progress had a much higher average loan amount than the loans with other statuses. For the mid term loan length though, defaulted loans had a higher average loan amount than charged off and completed loans.

The visualization of the relationship between loan amount, loan status and loan length allowed for a better understanding of the distribution of the various loan statuses by loan amount, across the different loan lengths. In the same way, the visualization of the relationship between interest rate, loan status and loan length provided a better understanding of the distribution of the various loan statuses by interest rate, across the different loan lengths.

Were there any interesting or surprising interactions between features?

In the visualization of the relationship between loan amount, interest rate and loan length, it was seen that increasing loan amount is associated with a decrease in interest rate across the three loan lengths.

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Conclusions

In the exploration of the modified Loan Data from Prosper dataset, various visualizations were created to find relationships between variables. First relationships were created in pairs, and then multiple pairs were combined for a better understanding of the relationship between some variables. The results of the exploration showed that:

75.34% of loans taken for student use are usually completed. Only 19.26% of the loans are charged off, and only an even smaller percentage, 5.41%, are defaulted.

Across each loan length, from short to long term, interest rates as well as loan amount, increases, and higher loan amounts usually have a lower interest rate. This could be a result of other factors/variables which were not included in this analysis such as the borrower's credit risk rating, as high-risk borrowers usually get high-interest rates.

Loans are mostly taken for debt consolidation, and these debt consolidation loans are usually taken by borrowers with high incomes ($75,000-100,000+). Also, generally, loan amounts increase with an increase in income range.

Lastly, irrespective of loan length, loans with high-interest rates, are usually either not paid in time, become defaulted or are charged off, and lower loan amounts are likely to become defaulted or charged off. This reiterates the effect of increasing loan amounts on interest rates.

In [ ]: