CS156 - ASSIGNMENT 2

LENDING CLUB DATA REPORT

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Project Aim

The goal of this project is to build a model that predicts the largest loan amount that will be successfully funded on the Lending Club platform for any given individual given the Lending club data provided in the assignment prompt. The data was provided in the form of two separate csvs, with one containing data on loan application rejections and the other containing much less data on loan application acceptances. Hence, both datasets had to be merged for the eventual process of model building.

Variables Chosen for Modeling

Using the column descriptions for both datasets as provided in the assignment prompt, variables that appeared to exist in both datasets were manually determined.

Variable Determination process:

- Given the rejected dataset has a lot less variables (9 variables), it was used as a starting point for variable selection. Then for each variable in the rejected stats sheet, the following steps were repeated:
  - Get a relevant keyword from the variable name (e.g. 'policy' in 'Policy Code')
  - Search for this keyword in the LoanStats (Accepted) sheet
- Doing so, I deduced the following columns (in the RejectStats sheet) to be the only ones consistent in both dataframes:

Variable Name	Variable Name in Rejected Dataframe	Variable Name in LoanStats (Accepted Dataframe)
Amount Requested	Amount Requested	loan_amnt
Application Date	Application Date	issue_d
Loan Title	Loan Title	title
Debt-to-Income Ratio	Debt-to-Income Ratio	dti
Zip Code	Zip Code	zip_code
State	State	addr_state
Employment Length	Employment Length	emp_length

Policy Code	Policy Code	policy_code

Table 1: Table showing variables present in both the rejected and accepted loans dataframes. The rows in red indicate variables that were excluded from the modeling process

The rows in red denote variables that were excluded from the eventual model. These were done for the following reasons:

- **Loan Title:** I drop this column as factoring it adequately into the model might require text (pre)processing, which deviates from the learning outcomes of this assignment.
- **Zip Code & State:** I drop these two columns because I don't believe location reasonably affects the acceptance status of a loan. If I did include a location factor, I would probably keep State and drop Zip Code. Since the Zip Code isn't full, we find that it is highly duplicated across rows for the same state.

A few assumptions were made for some of the variables included in the model:

- *loan_amnt* (the loan amount applied for by the borrower) in the accepted dataframe is assumed to be equal to the amount requested i.e. the individual will not be lent more or less money than they asked for on the platform.
- *issue_d* (the month which the loan was funded) in the accepted dataframe was assumed to be the same as the loan application date in the rejected dataframe. This is based on the following statement from Lending Club (2021): “Most members are approved within 24 hours and receive their money from LendingClub Bank in as little as a few days”. Here there is an implicit assumption that this statement on the website has stayed the same for most of the years.
- Although, I don't feel the application date should be a big factor in acceptance vs. rejection, I do not drop it as it might be interesting to see if the month an individual applies in could influence the acceptance status e.g. due to high loan requests, for example, just before a school semester. Hence, the month of application will be extracted from the application date.

Data Cleaning

Based on the variables decided on for merging (as seen in Table1 above), the following data cleaning processes were carried out before concatenation:

- Deletion of unimportant columns in both datasets (e.g. Risk score in Rejected loan dataframe, etc.)

- Renaming of the columns in the accepted loans dataframe to those of the rejected loans dataframe to allow for easy concatenating
- Removal of '%' symbols in the Debt-to-Income Ratio column. This column is subsequently converted to decimal form percentages

After concatenating both data frames to form a larger dataframe, rows with NAs were dropped from the larger dataframe. These rows constituted 3.67% of the entire dataset (6.52% of the total rows in accepted and 3.44% of the total rows in rejected loans subset), a small portion of the data, and so shouldn't influence results greatly.

Note: When concatenating the two dataframes, an indicator was assigned for accepted (1) and rejected (0) records. This was done to help with the eventual problem of classifying individuals as accepted or rejected for loans given their data.

<u>Data Transformation</u>

- **Extracting month from Application Date column:** In line with my interest in seeing if the months people apply for loans could influence acceptance and other factors, I respecified the application dates column to month of application by extracting the months from each application date. Hence the values in this column were restricted to numerics from 1 to 12, where 1 is January and 12 is December.
- **One-hot encoding of Application Date:** To not mislead the model into thinking one month is more important than another, I one-hot encoded the months after the process discussed in the above bullet.
- **Encoding employment years:** However, for employment years, I take the opposite approach to that which I take with Application Date. From a loan perspective, someone who has a longer employment length might suggest more stability and so we might want an ordinal relationship (where higher employment lengths mean more favourable outcomes) to exist. Hence I extract and assign the numeric value (year) from the categories (e.g. 1 year, 2 year, etc.) as a means to encode the categories . Here, <1 year was changed to 0 and 10+ years was changed to 10.

<u>Model Building: Logistic Regression</u>

For this classification problem I decided to use a logistic regression model. This is because in this scenario we are trying to predict a binary outcome: accepted or not accepted, which logistic regression is generally known to tackle well. A logistic regression model also better models my view on the loan acceptance predictions through its use of probabilities: you can't always say for certain based on an individual's factors, if they will get a loan or not, you could however assign a probability to reflect some of that uncertainty. Lastly, a logistic regression model is a probabilistic model, and these have the added benefit that they tend to do well with imbalanced datasets (like ours in this case).

Training procedure (a means to avoid overfitting)

After deciding on a model to implement, I split the merged dataset into a training and test set with 75:25 split. This was done to avoid overfitting in the form of testing the model on data it has already seen and trained on. By setting aside a test set, we can later test the trained model on unseen data to evaluate if it is generalizable to new observations.

As a means to further reduce the chance of overfitting, I conducted a cross-validation with 5 folds with the training set. Cross-validation is beneficial as it gives the model the opportunity to train on multiple train-test splits (unlike in hold-out), again providing a better indication on how well the model might perform on unseen data[1].

Model settings

More specifically, I conducted a cross-validated grid search where I experimented with two parameters:

- C (inverse of regularization strength) = [1.0, 0.1, 0.01]
- Solver (Algorithm used for optimization problem) = ['lbfgs', 'sag', 'saga'][2]

As indicated above, this helps reduce the chance of overfitting, but it also optimizes the performance of the sklearn logistic regression model by trying to pick the most optimal set of parameters.

Following the grid search, the best estimator returned was a Logistic regression model with C = 1.0 and an lbfgs solver. This estimator resulted in an average validation set accuracy of 98.8%.

Note: The grid search was conducted on a random 1% sample of the original dataset (close to 300,000 rows of data). This was done to save time as experimenting with the

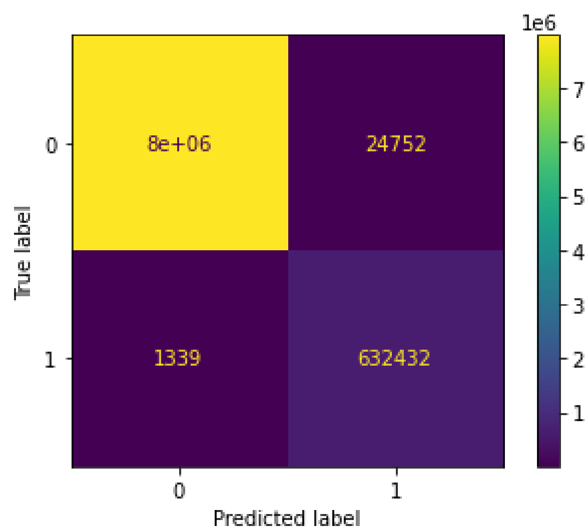
[1] **#overfitting:** I outline two approaches I take to avoid overfitting: splitting to training-test set and cross validation, indicating why these combat overfitting: they allow the model to be evaluate on unseen data thus providing a measure of how well the model is generalizable to new data

[2] Sag and saga were experimented with as solvers as they are faster for large datasets (Sklearn, 2021)

different parameters on the entire dataset (or even a magnitude of 10 higher) was found to take an impractical amount of time.

Model Evaluation

After determining the optimal set of parameters for the model, the entire dataset was split into a training and test set, and the model was then trained on the training set with the optimal parameters. Following training, the model was used to predict the test data, yielding the following results:

Accuracy: 99.7% **Avg Precision:** 96%	

From the confusion matrix our model struggles the most with false positives (top right sector), the metric we might want to especially minimize (see discussion below). Nonetheless, it doesn't do an extremely poor job as hinted at by the 96% precision (the ability of the classifier not to label as positive a sample that is negative)

Discussion of metrics

It is unclear (to me) which of a false rejection or false acceptance is more costly for a loan application.

For a false acceptance, the individual could end up wasting time compiling documents and applying but not getting the loan and that appears to be the major con: wastage of time. A failed loan application, even if it wastes time, does not affect your credit score unless you apply to many loans in quick succession (Bieber, 2021).

Meanwhile, a false rejection would mean you forgo the potential loan you could get from the Lending club and instead look elsewhere (which might not have as good rates).

For the purpose of this assignment, I assume a false acceptance is more costly than a false rejection because you waste time applying and waiting for the response from the Lending Club, and this time might have been substituted applying for another loan instead.

Hence, in this scenario we are interested in the precision (the ability of the classifier not to label as positive a sample that is negative) especially, which the Logistic Regression model does pretty good at[3].

Predicting the maximum loan amount an individual can apply for

Going back to our main goal in this assignment: predicting the largest loan amount that will be successfully funded on the Lending Club platform for any given individual, this maximum value was determined from my classification model thus:

- The user is asked to input data considered pertinent to the loan (here, the model parameters): debt, annual income, employment length, policy code, month of application.
- The inputted debt and annual income are used to calculate the debt-to-income ratio
- We start of with a requested amount of $100
- All these variables are then passed into the model to predict whether the loan application will be accepted or rejected
- As long as the model predicts an acceptance, we:
    - Increment the loan amount by $100
    - Feed in the new data with the increased amount into the model to make a new prediction on the acceptance status
- Repeating this process gets us closer and closer to the decision boundary i.e. where the difference between a rejection and acceptance is very tight.

[3] **#modelmetrics:** I discussed the outcome variables in the classification problem, situating them in the real-world context. This enabled me to decide what outcome would be more costly in a realistic sense and then map a metric (precision especially) to these outcomes. I subsequently compute and evaluated my model based on my chosen metrics.

<u>Concerns with my model</u>
When predicting the maximum values an individual could apply for, my model predicts extremely huge sums once an individual indicates favourable factors (e.g. long employment length, more income than debt, etc.). Sometimes these values far outweigh the individual's annual income (e.g. a prediction of $300,000 for someone earning $2000 per annum). This is definitely unrealistic. As a quick fix to the problem, I set a threshold that the maximum value cannot be 6 times more than the individual's income.

Another concern with my model is that it implements a variable 'policy code' which I really do not know how to interpret. This variable has really high correlation with the acceptance and so could potentially sway the decision from one side to the other.

A clear report explaining:

- which variables you included in the model
- any cleaning or transformations that you carried out on the data
- the type of model you used and any settings that the model required
- the training method you used, and any techniques that you used to avoid overfitting the data
- an estimate of how well the model will perform on unseen data

cs156-modelmetrics: Be able to carefully define and correctly apply the range of common model performance metrics (eg. classification accuracy, recall, precision) and choose metrics appropriate to the task at hand

cs156-overfitting: Be able to succinctly identify and explain why and when overfitting occurs. Also be able to adopt strategies when appropriate to avoid such pathologies

cs156-regressionalgorithm: Apply and interpret regression methods for a supervised learning task

cs156-classification: Apply and interpret classification methods for a supervised learning task

Assignment 2 – Lending Club

October 8, 2021

1 CS156 Assignment 2

Lending Club Data | By Korede Akande

1.1 1. Library Importation

[154]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import missingno
from pandas_profiling import ProfileReport
import warnings
warnings.simplefilter(action='ignore')
```

1.2 2. Loading the datasets

[194]:
```
#Load the full data for accepted and rejected applications
accepted_df = pd.read_csv('accepted.csv', low_memory=False)
rejected_df = pd.read_csv('rejected.csv', low_memory=False)
```

def sample_generator(filename,pct_of_file= 0.1):

```
"""
Return a sample of the file, where the sample size is determined by the % specified

Inputs:
    - filename (str): Name of the file to read
    - pct_of_file (float): Percentage of the original file to sample

Output:
    - df (pandas Dataframe): Return the random sample

"""

#Load a sample of the dataset
#If randomly generated probability is greater than pct_of_file, the row will be skipped
```

```
df = pd.read_csv(filename,
                 skiprows = lambda l: l>0 and np.random.random() > pct_of_file,
                 low_memory=False)
```

```
return df
```

#Load samples of the datasets for accepted and rejected applications accepted_df = sample_generator('accepted.csv', 0.5) rejected_df = sample_generator('rejected.csv', 0.5)

1.3 3. Previewing the datasets

1.3.1 a. Accepted Loans Dataframe

[196]:
```
#Quick preview of the accepted loans dataset
accepted_df.head()
```

[196]:
```
         id  member_id  loan_amnt  funded_amnt  funded_amnt_inv        term  \
0  68407277        NaN     3600.0       3600.0           3600.0   36 months
1  68355089        NaN    24700.0      24700.0          24700.0   36 months
2  68341763        NaN    20000.0      20000.0          20000.0   60 months
3  66310712        NaN    35000.0      35000.0          35000.0   60 months
4  68476807        NaN    10400.0      10400.0          10400.0   60 months

   int_rate  installment grade sub_grade  … hardship_payoff_balance_amount  \
0     13.99       123.03     C        C4  …                            NaN
1     11.99       820.28     C        C1  …                            NaN
2     10.78       432.66     B        B4  …                            NaN
3     14.85       829.90     C        C5  …                            NaN
4     22.45       289.91     F        F1  …                            NaN

  hardship_last_payment_amount disbursement_method  debt_settlement_flag  \
0                          NaN                Cash                     N
1                          NaN                Cash                     N
2                          NaN                Cash                     N
3                          NaN                Cash                     N
4                          NaN                Cash                     N

  debt_settlement_flag_date settlement_status settlement_date  \
0                       NaN               NaN             NaN
1                       NaN               NaN             NaN
2                       NaN               NaN             NaN
3                       NaN               NaN             NaN
4                       NaN               NaN             NaN

  settlement_amount settlement_percentage settlement_term
0               NaN                   NaN             NaN
1               NaN                   NaN             NaN
```

```
2              NaN                     NaN              NaN
3              NaN                     NaN              NaN
4              NaN                     NaN              NaN

[5 rows x 151 columns]
```

[197]:
```
accepted_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2260701 entries, 0 to 2260700
Columns: 151 entries, id to settlement_term
dtypes: float64(113), object(38)
memory usage: 2.5+ GB
```

1.3.2 b. Rejected Loans Dataframe

[198]:
```
#Quick preview of the rejected loans dataset
rejected_df.head()
```

[198]:
```
   Amount Requested Application Date                        Loan Title  \
0            1000.0       2007-05-26  Wedding Covered but No Honeymoon
1            1000.0       2007-05-26                Consolidating Debt
2           11000.0       2007-05-27       Want to consolidate my debt
3            6000.0       2007-05-27                           waksman
4            1500.0       2007-05-27                            mdrigo

   Risk_Score Debt-To-Income Ratio Zip Code State Employment Length  \
0       693.0                  10%    481xx    NM           4 years
1       703.0                  10%    010xx    MA          < 1 year
2       715.0                  10%    212xx    MD            1 year
3       698.0               38.64%    017xx    MA          < 1 year
4       509.0                9.43%    209xx    MD          < 1 year

   Policy Code
0          0.0
1          0.0
2          0.0
3          0.0
4          0.0
```

[199]:
```
rejected_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 27648741 entries, 0 to 27648740
Data columns (total 9 columns):
 #   Column                Dtype
---  ------                -----
```

```
 0   Amount Requested      float64
 1   Application Date      object
 2   Loan Title            object
 3   Risk_Score            float64
 4   Debt-To-Income Ratio  object
 5   Zip Code              object
 6   State                 object
 7   Employment Length     object
 8   Policy Code           float64
dtypes: float64(3), object(6)
memory usage: 1.9+ GB
```

1.4 4. Data Cleaning

Using the column descriptions for both datasets as provided in the assigment prompt, variables that appeared to exist in both datasets were manually determined.

Determination process:

- Given the rejected dataset has a lot less variables (9 variables), it was used as a starting point. Then for each variable in the rejected stats sheet, the following steps were repeated:
  - Get a relevant keyword from the variable name (e.g. 'policy' in 'Policy Code')
  - Search for this keyword in the LoanStats (Accepted) sheet

Doing so, I deduced the following columns (in the RejectStats sheet) to be the only ones consistent in both dataframes: *Amount Requested, Application Date, Loan Title, Debt-To-Income Ratio, Zip Code, State, Employment Length* and *Policy Code*.

Assumptions: - *loan_amnt* in the accepted dataframe is assumed to equal to the amount requested: the individual will not be lent more or less money than they asked for on the platform. - *issue_d* in the accepted dataframe was assumed to be (roughly) the same as the loan application date in the rejected dataframe. This is based on the following statement from the Lending Club official website: "*Most members are approved within 24 hours and receive their money from LendingClub Bank in as little as a few days*". Here there is an implicit assumption that this statement on the website has stayed the same for most of the years.

- **State:**
  - Rejected: State
  - Accepted: addr_state
- **Application Date:**
  - Rejected: Application Date
  - Accepted: issue_d
- **Zip code:**
  - Rejected: Zip Code
  - Accepted: zip_code
- **Employment Length:**
  - Rejected: Employment Length
  - Accepted: emp_length
- **Debt-To-Income Ratio:**

    - Rejected: Debt-To-Income Ratio
    - Accepted: dti
- **Policy Code:**
    - Rejected: Policy Code
    - Accepted: policy_code
- **Loan Title:**
    - Rejected: Loan Title
    - Accepted: title
- **Amount Requested:**
    - Rejected: Amount Requested
    - Accepted: loan_amnt

Where 'Rejected' is the rejected loans dataset and 'Accepted' is the accepted loans dataset

- I drop the Loan Title column as factoring it into the model might require text (pre)processing. This will be considered as a potential extension to the model if accuracy is low.
- Drop Zip Code and State as I don't believe location should affect the acceptance status of a loan. If I do include a location factor, I would probably keep State and drop Zip Code. Since the Zip Code isn't full, I would expect it to be highly duplicated across rows for the same state (this is infact the case)
- Although, I don't feel the Application Date should be a big factor in acceptance vs. rejectance, I do not drop it as it might be interesting to see if the month an individual applies in could influence the acceptance status e.g. due to high loan requests, for example, just before a school semester.

Variables I consider a priority are in line with this article

1.4.1 a. Getting the relevant subset of the accepted dataset

[200]:
```
#Subset the accepted dataframe based on the columns listed in the markdown above
accepted_loans =␣
↪accepted_df[['loan_amnt','issue_d','dti','emp_length','policy_code']]

accepted_loans.head()
```

[200]:
```
   loan_amnt   issue_d    dti emp_length  policy_code
0     3600.0  Dec-2015   5.91  10+ years          1.0
1    24700.0  Dec-2015  16.06  10+ years          1.0
2    20000.0  Dec-2015  10.78  10+ years          1.0
3    35000.0  Dec-2015  17.06  10+ years          1.0
4    10400.0  Dec-2015  25.37    3 years          1.0
```

1.4.2 b. Renaming columns in the accepted dataset for concatenating

[201]:
```python
#Rename columns to for easy understanding and concatenating
accepted_loans = accepted_loans.rename(columns={'loan_amnt': 'Amount Requested',
                                                'issue_d': 'Application Date',
                                                'dti': 'Debt-To-Income Ratio',
                                                'emp_length': 'Employment␣
 ↪Length',
                                                'policy_code': 'Policy Code'})

accepted_loans.head()
```

[201]:
```
   Amount Requested Application Date  Debt-To-Income Ratio Employment Length  \
0            3600.0         Dec-2015                  5.91         10+ years
1           24700.0         Dec-2015                 16.06         10+ years
2           20000.0         Dec-2015                 10.78         10+ years
3           35000.0         Dec-2015                 17.06         10+ years
4           10400.0         Dec-2015                 25.37           3 years

   Policy Code
0          1.0
1          1.0
2          1.0
3          1.0
4          1.0
```

1.4.3 c. Dropping columns in the rejected dataset that are unavailable in the accepted dataset

[202]:
```python
rejected_loans = rejected_df.drop(columns = ['Risk_Score', 'Loan Title', 'Zip␣
 ↪Code', 'State'])
rejected_loans.head()
```

[202]:
```
   Amount Requested Application Date Debt-To-Income Ratio Employment Length  \
0            1000.0       2007-05-26                  10%           4 years
1            1000.0       2007-05-26                  10%          < 1 year
2           11000.0       2007-05-27                  10%            1 year
3            6000.0       2007-05-27               38.64%          < 1 year
4            1500.0       2007-05-27                9.43%          < 1 year

   Policy Code
0          0.0
1          0.0
2          0.0
3          0.0
4          0.0
```

1.4.4 d. Add indicator for loan acceptance to both dataframes

Here 1 indicates an acceptance and 0 represents a rejection

[203]:
```
#Indicate in the relevant dataframes if the loan application was accepted or␣
↪rejected
accepted_loans['Accepted'] = 1
rejected_loans['Accepted'] = 0
```

1.4.5 e. Concatenate the dataframes into one big dataframe

[204]:
```
#Join the two datasets into one big df and shuffle records around
loan_df = pd.concat([accepted_loans, rejected_loans]).sample(frac=1,␣
↪random_state=1).reset_index(drop=True)

#Print summary of the dataframe
print(loan_df.info())

loan_df.head()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 29909442 entries, 0 to 29909441
Data columns (total 6 columns):
 #   Column                Dtype
---  ------                -----
 0   Amount Requested      float64
 1   Application Date      object
 2   Debt-To-Income Ratio  object
 3   Employment Length     object
 4   Policy Code           float64
 5   Accepted              int64
dtypes: float64(2), int64(1), object(3)
memory usage: 1.3+ GB
None
```

[204]:
```
   Amount Requested Application Date Debt-To-Income Ratio Employment Length  \
0            1000.0       2018-02-15                20.3%          < 1 year
1           13000.0         Jul-2018                16.37           6 years
2           20000.0       2015-10-14               11.25%               NaN
3           17000.0       2015-03-21               38.82%          < 1 year
4            3000.0       2013-08-02                7.85%          < 1 year

   Policy Code  Accepted
0          0.0         0
1          1.0         1
2          0.0         0
```

```
3              0.0           0
4              0.0           0
```

1.4.6 f. Data Type Conversion

Looking at the preview of the data and the output of .info(), we see that Application Date and Debt-to-Income (dti) ratio have the wrong data type. They should be datetime and float/percentage, respectively for more accurate manipulation. Additionally, we note that the dates from the accepted and rejected datasets differ in terms of format: the accepted dataset is formatted as M-Y, while the rejected is formatted as Y-M-D. These are all corrected below:

> Debt-to-Income Ratio

[205]:
```
#Remove percentage symbols from dti values and convert to percentage (float)
loan_df['Debt-To-Income Ratio'] = loan_df['Debt-To-Income Ratio'].astype(str)\
                                                                  .str.
 ↪replace('%','')\
                                                                  .astype(float)/
 ↪100
```

[206]:
```
#Get descriptive stats
loan_df['Debt-To-Income Ratio'].describe().round(3)
```

[206]:
```
count    2.990770e+07
mean     1.339000e+00
std      1.013340e+02
min     -1.000000e-02
25%      8.600000e-02
50%      1.970000e-01
75%      3.510000e-01
max      5.000003e+05
Name: Debt-To-Income Ratio, dtype: float64
```

We note that there are some unreasonable/incorrect dti value (we see the minimum is a negative percentage which is not possible). Thus we explore strange and large dti values. A DTI of 43% is typically the highest ratio a borrower can have and still get qualified for a mortgage, but lenders generally seek ratios of no more than 36% (Investopedia).

> Application Date

[211]:
```
#Convert date column to datetime objects, extract the months, and convert to␣
 ↪integers (1-Jan to 12-Dec)
loan_df['Application Date'] = pd.to_datetime(loan_df['Application Date']).dt.
 ↪month.astype('Int64')
```

[212]:
```
loan_df.head()
```

```
[212]:    Amount Requested  Application Date  Debt-To-Income Ratio Employment Length  \
0               1000.0                 2                0.2030          < 1 year
1              13000.0                 7                0.1637           6 years
2              20000.0                10                0.1125               NaN
3              17000.0                 3                0.3882          < 1 year
4               3000.0                 8                0.0785          < 1 year

   Policy Code  Accepted
0          0.0         0
1          1.0         1
2          0.0         0
3          0.0         0
4          0.0         0
```

1.4.7 h. Drop rows with NAs

I instead opt to drop the rows with missing NAs (most of which are employment length variables) because these represent a small portion of the data (for both accepted and rejected) as shown below, thus deletion shouldn't influence results very greatly.

```
[213]: #What percentage of rows will we be dropping if we dropped na rows from the␣
        ↪accepted dataframe
       na_pct_of_accepted = (accepted_loans.shape[0] - accepted_loans.dropna().
        ↪shape[0])/accepted_loans.shape[0]
       print(f"{round(na_pct_of_accepted*100,2)}% of the rows in accepted contain NAs")
```

```
6.5% of the rows in accepted contain NAs
```

```
[214]: #What percentage of rows will we be dropping if we dropped na rows from the␣
        ↪rejected dataframe
       na_pct_of_rejected = (rejected_loans.shape[0] - rejected_loans.dropna().
        ↪shape[0])/rejected_loans.shape[0]
       print(f"{round(na_pct_of_rejected*100,2)}% of the rows in rejected contain NAs")
```

```
3.44% of the rows in rejected contain NAs
```

```
[215]: print("Number of rows before dropping NAs:", loan_df.shape[0])
       cleaned_loan_df = loan_df.dropna(how='any', axis=0)
       print("Number of rows after dropping NAs:", cleaned_loan_df.shape[0])
       print("Number of rows dropped: ", loan_df.shape[0] - cleaned_loan_df.shape[0])
```

```
Number of rows before dropping NAs: 29909442
Number of rows after dropping NAs: 28810215
Number of rows dropped:  1099227
```

```
[216]: #What percentage of rows were dropped
       (549324/14957444)*100
```

[216]: 3.6725793524615566

1.5 5. Data Transformation

Given a Logistic Regression model is intended for use, scaling the data should not change the performance of the model. This is because if there are predictor variables with large ranges that do not effect the dependent variable of interest, the algorithm makes their coefficients small so that they do not greatly influence predictions. Hence, most of my data transformations in this case are encoding:

1.5.1 Encoding Categorical Variables

To not mislead the model in thinking one category is more important than another, I one-hot encode categorical variables. However, for employment years, I take the opposite approach as from a loan perspective, someone who has a longer employment length might suggest more stability, hence I extract the year (numeric value) from the category and assign as a column value

[217]:
```
#Extract numeric value from the Employment Length
cleaned_loan_df['Employment Length'] = cleaned_loan_df['Employment Length'].
↪replace('< 1 year', '0 years')
cleaned_loan_df['Employment Length'] = cleaned_loan_df['Employment Length'].str.
↪extract(r'([0-9]+)')
cleaned_loan_df['Employment Length'] = pd.
↪to_numeric(cleaned_loan_df['Employment Length'])
```

[218]:
```
#One-hot encode Application month and State
encoded_df = pd.get_dummies(cleaned_loan_df, columns = ['Application Date'])
```

[219]:
```
encoded_df.head()
```

[219]:
```
   Amount Requested  Debt-To-Income Ratio  Employment Length  Policy Code  \
0            1000.0                0.2030                  0          0.0
1           13000.0                0.1637                  6          1.0
3           17000.0                0.3882                  0          0.0
4            3000.0                0.0785                  0          0.0
5            8500.0                0.2361                  0          0.0

   Accepted  Application Date_1  Application Date_2  Application Date_3  \
0         0                   0                   1                   0
1         1                   0                   0                   0
3         0                   0                   0                   1
4         0                   0                   0                   0
5         0                   0                   0                   1

   Application Date_4  Application Date_5  Application Date_6  \
```

```
0                         0                         0                         0
1                         0                         0                         0
3                         0                         0                         0
4                         0                         0                         0
5                         0                         0                         0

   Application Date_7  Application Date_8  Application Date_9  \
0                   0                   0                   0
1                   1                   0                   0
3                   0                   0                   0
4                   0                   1                   0
5                   0                   0                   0

   Application Date_10  Application Date_11  Application Date_12
0                    0                    0                    0
1                    0                    0                    0
3                    0                    0                    0
4                    0                    0                    0
5                    0                    0                    0
```

1.6 6. Modeling & Evaluation

I decide to use a logistic regression model because in this scenario we are trying to predict a binary outcome: (accepted or not accepted), which logistic regression is generally know to tackle. It also better models my (realistic) view on the loan acceptance prediction through its use of probabilities: you can't always say for certain based on an individual's factors if they will get a loan or not, you could however assign a probability to reflect some of that uncertainty. A logistic regression model is also a probablistic model, and these have the added benefit that they tend to do well with imbalanced datasets (like ours in this case).

[231]:
```
from sklearn.model_selection import train_test_split,GridSearchCV
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, plot_confusion_matrix,␣
↪classification_report, precision_score
```

1.6.1 a. Split data into training and test set

[221]:
```
#Specify the predictor variables
X = encoded_df.drop(columns=['Accepted'])

#Specify the target variable
y = encoded_df['Accepted']

#Split to training and test set with a 70:30 split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3)
```

1.6.2 b. Fit model on training data on predict on test set

Note: Optimal model parameters for the logisitic regression were determined via a grid search cv (see Appendix A)

[225]:
```
#Initialize Logistic Regression model with the optimal parameters determined␣
↪from a grid search cross-validation
#on a smaller dataset which should have roughly the same distribution  (see␣
↪Appendix)
clf = LogisticRegression(C=1.0, solver= 'lbfgs')

#Fit the model on the train data
clf.fit(X_train, y_train)

#Predict on the test data
y_preds = clf.predict(X_test)
```

1.6.3 c. Model Evaluation

It is unclear which of a false rejection or false acceptance is more costly. For a false prediction of acceptance, the individual could end up wasting time compiling documents and applying but not getting the loan and that appears that be the major con: wastage of time. A failed loan application does not affect your credit score unless you apply to many loans in quick succession.

Meanwhile, a false rejection would mean you forgo the potential loan you could get from the Lending club and have to look elsewhere (which might not have as good rates).

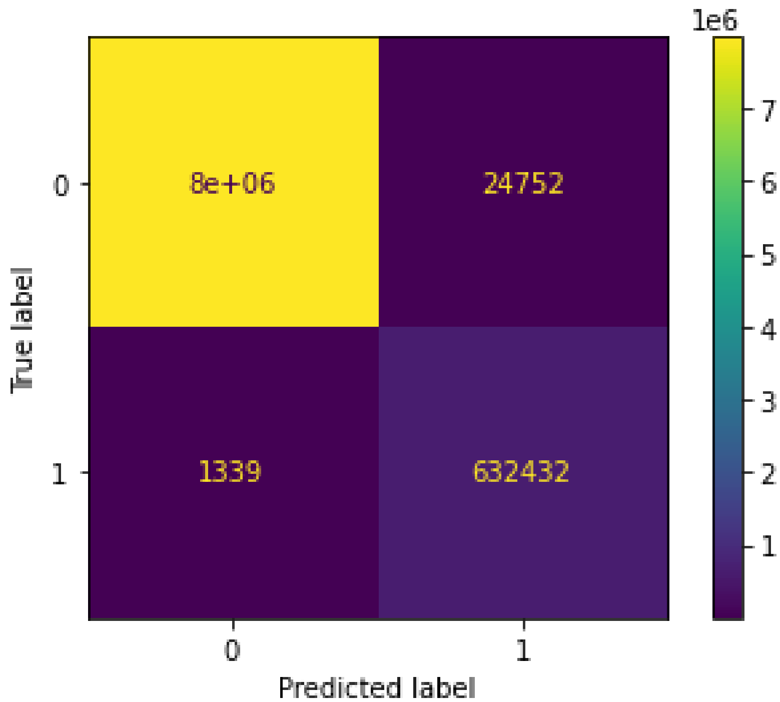
For the purpose of this assignment, I assume a false acceptance is more costly than a false rejection because you waste time applying and waiting for the response from the Lending Club, which might have been substituted applying for another loan instead.

Hence, in this scenario we are interested in the **precision** (the ability of the classifier not to label as positive a sample that is negative) in addition to the general accuracy

[233]:
```
test_accuracy = accuracy_score(y_test, y_preds)
print("Precision score: {}".format(precision_score(y_test,y_preds)))
print("Test set accuracy: ", test_accuracy)
```

```
Precision score: 0.9623362711204169
Test set accuracy:  0.9969812792105578
```

[227]:
```
plot_confusion_matrix(clf, X_test, y_test)
plt.show()
```



[228]:
```
print("Coefficients for predictor variables: ")
variables = X.columns
coefficients = clf.coef_

for var, coef in zip(variables, coefficients[0]):

    if 'Application Date_' in var:

        print('- ', 'Month ' + str(var.replace('Application Date_','')),'=',␣
 ↪coef)

    else:
        print('- ',var ,'=', coef)
```

```
Coefficients for predictor variables:
-  Amount Requested = -2.3389538928349764e-05
-  Debt-To-Income Ratio = -4.134642041212085
-  Employment Length = 0.20929938612153554
-  Policy Code = 7.690682047875009
-  Month 1 = -0.3425296506195545
-  Month 2 = -0.23171713149534146
-  Month 3 = -0.2387149725593726
-  Month 4 = -0.3287164542309141
-  Month 5 = -0.3890069496679627
```

```
- Month 6 = -0.49423773024412576
- Month 7 = -0.46953731500870427
- Month 8 = -0.48002751229679025
- Month 9 = -0.47591355468563484
- Month 10 = -0.3179987890600234
- Month 11 = -0.37192974617726465
- Month 12 = -0.485366783165484
```

[229]:
```python
print(classification_report(y_test,␣
↪y_preds,target_names=['Rejected','Accepted']))
```

```
              precision    recall  f1-score   support

    Rejected       1.00      1.00      1.00   8009294
    Accepted       0.96      1.00      0.98    633771

    accuracy                           1.00   8643065
   macro avg       0.98      1.00      0.99   8643065
weighted avg       1.00      1.00      1.00   8643065
```

From the classification report above we see that the model does really well on accuracy (1.00) as well as precision (0.96) for the test set, increasing our confidence that it is generalizable to new data

1.7 7. Predicting Largest Loan Amount that will be funded for any given individual

[ ]:
```python
def max_loan_amount_predictor(step_size = 100):

    #Initialize the max requestable amount to 0, this will be increased␣
↪interatively to determine the
    #true max acceptable value
    max_requestable = 0

    print("Please enter your information below: ")
    application_month = int(input("What month are you applying in?␣
↪(Jan-1,Feb-2,..Dec-12) "))
    debt = float(input("How much are you currently owing in total? "))
    income = float(input("What is your annual income? "))
    employment_length = int(input("How many years have you been at your current␣
↪job? (Enter 0 if < 1 year) "))
    policy_code = float(input("What's your policy code? (0, 1 or 2) "))

    #Assume no loaning to someone without income
    if income <= 0:
        return max_requestable
```

```
    #Compute the individual's dti
    dti = debt/income

    #If the individual has worked more than 10 years, cap at 10 given our model
    if employment_length > 10:
        employment_length = 10

    #Note the month the individual is applying in
    application_month_array = np.zeros(12)
    application_month_array[application_month-1] = 1

    #New request - next amount to request, we increment by step size
    next_request = max_requestable + step_size

    #Create data which will be passed into the model
    data = pd.DataFrame([next_request, dti, employment_length, policy_code,␣
↪*application_month_array]).T

    #While the amount requested is accepted and not more than 6 times your␣
↪annual salary
    while (best_estimator.predict(data)  == 1) and (next_request <= 6*income):

        #Update the max requestable amount
        max_requestable = next_request

        #Increase the amount
        next_request += step_size

        #And check if the loan is still accepted with the increased amount
        data = pd.DataFrame([next_request, dti, employment_length, policy_code,␣
↪*application_month_array]).T

    if max_requestable > 0:
        return (f"The maximum loan amount you could apply for is␣
↪${max_requestable - 100} ")
    else:
        return (f"The maximum loan amount you could apply for is ${0}")
```

1.7.1 Sample Runs

a. Loan Acceptance

[249]:
```
max_loan_amount_predictor()
```

```
Please enter your information below:
What month are you applying in? (Jan-1,Feb-2,..Dec-12) 5
How much are you currently owing in total? 100
What is your annual income? 2000
How many years have you been at your current job? (Enter 0 if < 1 year) 3
What's your policy code? (0, 1 or 2) 1
```

[249]: 'The maximum loan amount you could apply for is $11900 '

a. Loan Rejection

[250]:
```
max_loan_amount_predictor()
```

```
Please enter your information below:
What month are you applying in? (Jan-1,Feb-2,..Dec-12) 5
How much are you currently owing in total? 10000
What is your annual income? 200
How many years have you been at your current job? (Enter 0 if < 1 year) 4
What's your policy code? (0, 1 or 2) 0
```

[250]: 'The maximum loan amount you could apply for is $0'

1.8 Appendix

1.8.1 a. Cross-validation code on smaller dataset (with results)

!!! Be careful re-running! You lose the results shown below

[ ]:
```
#Load samples of the datasets for accepted and rejected applications
accepted_df = sample_generator('accepted.csv', 0.01)
rejected_df = sample_generator('rejected.csv', 0.01)
```

[111]:
```
#Specify the predictor variables
X = encoded_df.drop(columns=['Accepted'])

#Specify the target variable
y = encoded_df['Accepted']

#Split to training and test set with a 70:30 split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3)

#Initialize Logistic Regression model
clf = LogisticRegression()

#Create parameter list for optimization trial
#C: Inverse of regularization strength, smaller values specify stronger␣
↪regularization.
```

```
#solver: Try default solver as well as Sag and Saga. The latter are faster for␣
↪larger datasets (Sklearn)
param_grid = [{'C': [1.0, 0.1, 0.01] ,'max_iter': [500], 'solver': ['lbfgs',␣
↪'sag', 'saga']}]

#Run grid search to find best parameters
#I run on a subset because running on a sample of like 2M rows was still␣
↪running after 2 hrs
grid_search = GridSearchCV(clf, param_grid = param_grid)
grid_search.fit(X_train[:round(len(X_train)/10)], y_train[:round(len(X_train)/
↪10)])
```

[111]:
```
GridSearchCV(estimator=LogisticRegression(),
             param_grid=[{'C': [1.0, 0.1, 0.01], 'max_iter': [500],
                          'solver': ['lbfgs', 'sag', 'saga']}])
```

[112]:
```
#Get the best params from the grid search
print(f"The best parameters from the grid search were {grid_search.
↪best_params_}")

#Get the best estimator
best_estimator = grid_search.best_estimator_

#Predict class using best parameters
y_gs_pred = best_estimator.predict(X_test)
```

```
The best parameters from the grid search were {'C': 1.0, 'max_iter': 500,
'solver': 'lbfgs'}
```

[118]:
```
print(f"There were {len(X_train)} rows of data for the training set")
print(f"There were {len(X_test)} rows of data for the test set")
```

```
There were 209600 rows of data for the training set
There were 89829 rows of data for the test set
```

[113]:
```
print("Coefficients for predictor variables: ")
variables = X.columns
coefficients = best_estimator.coef_

for var, coef in zip(variables, coefficients[0]):

    if 'Application Date_' in var:

        print('- ', 'Month ' + str(var.replace('Application Date_','')),'=',␣
↪coef)

    else:
```

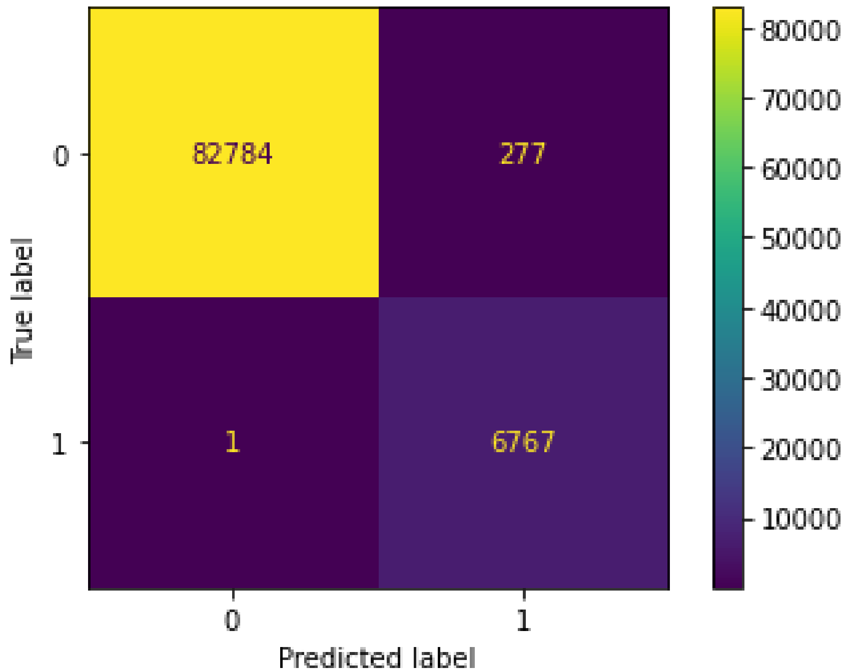
```
        print('- ',var ,'=', coef)
```

```
Coefficients for predictor variables:
-  Amount Requested = -7.751546020776982e-06
-  Debt-To-Income Ratio = -0.5928399401149207
-  Employment Length = 0.2172891753086878
-  Policy Code = 7.376147136393904
-  Month 1 = -0.7072266495572977
-  Month 2 = -0.29281914176963736
-  Month 3 = -0.2759858238401665
-  Month 4 = -0.3548141812721871
-  Month 5 = -0.7590970179993761
-  Month 6 = -0.4203981759560921
-  Month 7 = -0.7747375074208613
-  Month 8 = -0.3442879425663216
-  Month 9 = -0.7338211336834859
-  Month 10 = 0.17016120000009421
-  Month 11 = 0.2513773620748405
-  Month 12 = -0.43807488865019395
```

[114]:
```
avg_train_accuracy = grid_search.best_score_
test_accuracy = accuracy_score(y_test, y_gs_pred)
print("Mean validation set accuracy: ", avg_train_accuracy)
print("Test set accuracy: ", test_accuracy)
```

```
Mean validation set accuracy:  0.9882633587786259
Test set accuracy:  0.9969052310501063
```

[115]:
```
plot_confusion_matrix(best_estimator, X_test, y_test)
plt.show()
```


82784
277
1
6767
0
1
True label
0
1
Predicted label
80000
70000
60000
50000
40000
30000
20000
10000