assginment_2

February 11, 2022

[ ]:
```python
import gzip
import pandas as pd

accept = pd.read_csv('accepted_2007_to_2018Q4.csv.gz')
reject = pd.read_csv('rejected_2007_to_2018Q4.csv.gz')
```

```
/Users/swimmingcircle/Library/Python/3.9/lib/python/site-
packages/IPython/core/interactiveshell.py:3457: DtypeWarning: Columns
(0,19,49,59,118,129,130,131,134,135,136,139,145,146,147) have mixed
types.Specify dtype option on import or set low_memory=False.
  exec(code_obj, self.user_global_ns, self.user_ns)
```

0.1 Data Inspection

[ ]:
```python
accept.shape, reject.shape
```

[ ]:
```
((2260701, 151), (27648741, 9))
```

[ ]:
```python
accept.columns, reject.columns
```

[ ]:
```
(Index(['id', 'member_id', 'loan_amnt', 'funded_amnt', 'funded_amnt_inv',
        'term', 'int_rate', 'installment', 'grade', 'sub_grade',
        ...
        'hardship_payoff_balance_amount', 'hardship_last_payment_amount',
        'disbursement_method', 'debt_settlement_flag',
        'debt_settlement_flag_date', 'settlement_status', 'settlement_date',
        'settlement_amount', 'settlement_percentage', 'settlement_term'],
       dtype='object', length=151),
 Index(['Amount Requested', 'Application Date', 'Loan Title', 'Risk_Score',
        'Debt-To-Income Ratio', 'Zip Code', 'State', 'Employment Length',
        'Policy Code'],
       dtype='object'))
```

[ ]:
```python
accept.head()
```

[ ]:
```
         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]
```

[ ]:
```
accept.describe()
```

[ ]:
```
       member_id     loan_amnt   funded_amnt  funded_amnt_inv      int_rate  \
count        0.0  2.260668e+06  2.260668e+06     2.260668e+06  2.260668e+06
mean         NaN  1.504693e+04  1.504166e+04     1.502344e+04  1.309283e+01
std          NaN  9.190245e+03  9.188413e+03     9.192332e+03  4.832138e+00
min          NaN  5.000000e+02  5.000000e+02     0.000000e+00  5.310000e+00
25%          NaN  8.000000e+03  8.000000e+03     8.000000e+03  9.490000e+00
50%          NaN  1.290000e+04  1.287500e+04     1.280000e+04  1.262000e+01
75%          NaN  2.000000e+04  2.000000e+04     2.000000e+04  1.599000e+01
max          NaN  4.000000e+04  4.000000e+04     4.000000e+04  3.099000e+01

        installment    annual_inc           dti   delinq_2yrs  fico_range_low  \
count  2.260668e+06  2.260664e+06  2.258957e+06  2.260639e+06    2.260668e+06
mean   4.458068e+02  7.799243e+04  1.882420e+01  3.068792e-01    6.985882e+02
```

std	2.671735e+02	1.126962e+05	1.418333e+01	8.672303e-01	3.301038e+01
min	4.930000e+00	0.000000e+00	-1.000000e+00	0.000000e+00	6.100000e+02
25%	2.516500e+02	4.600000e+04	1.189000e+01	0.000000e+00	6.750000e+02
50%	3.779900e+02	6.500000e+04	1.784000e+01	0.000000e+00	6.900000e+02
75%	5.933200e+02	9.300000e+04	2.449000e+01	0.000000e+00	7.150000e+02
max	1.719830e+03	1.100000e+08	9.990000e+02	5.800000e+01	8.450000e+02

	...	deferral_term	hardship_amount	hardship_length	hardship_dpd	\
count	...	10917.0	10917.000000	10917.0	10917.000000	
mean	...	3.0	155.045981	3.0	13.743886	
std	...	0.0	129.040594	0.0	9.671178	
min	...	3.0	0.640000	3.0	0.000000	
25%	...	3.0	59.440000	3.0	5.000000	
50%	...	3.0	119.140000	3.0	15.000000	
75%	...	3.0	213.260000	3.0	22.000000	
max	...	3.0	943.940000	3.0	37.000000	

	orig_projected_additional_accrued_interest	\
count	8651.000000	
mean	454.798089	
std	375.385500	
min	1.920000	
25%	175.230000	
50%	352.770000	
75%	620.175000	
max	2680.890000	

	hardship_payoff_balance_amount	hardship_last_payment_amount	\
count	10917.000000	10917.000000	
mean	11636.883942	193.994321	
std	7625.988281	198.629496	
min	55.730000	0.010000	
25%	5627.000000	44.440000	
50%	10028.390000	133.160000	
75%	16151.890000	284.190000	
max	40306.410000	1407.860000	

	settlement_amount	settlement_percentage	settlement_term
count	34246.000000	34246.000000	34246.000000
mean	5010.664267	47.780365	13.191322
std	3693.122590	7.311822	8.159980
min	44.210000	0.200000	0.000000
25%	2208.000000	45.000000	6.000000
50%	4146.110000	45.000000	14.000000
75%	6850.172500	50.000000	18.000000
max	33601.000000	521.350000	181.000000

```
[8 rows x 113 columns]
```

[ ]:
```
reject.head()
```

[ ]:
```
   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
```

[ ]:
```
# #Understand risk score's influence on reject data
# import matplotlib.pyplot as plt
# import seaborn as sns
# sns.histplot(reject['Risk_Score'], stat = 'percent')
# plt.title('Risk score distribution for rejected data')
```

0.2 Data Cleaning

0.2.1 Choice of variables

In order to use both reject and accept data, I only choose the columns that exists in both dataset. The table below is the columns that have been chosen.

Accept data/Reject data:Column Description

- loan_amnt/Amount Requested:The listed amount of the loan applied for by the borrower. If at some point in time, the credit department reduces the loan amount, then it will be reflected in this value.
- title/Loan Title: The loan title provided by the borrower
- dti/Debt-To-Income Ratio: A ratio calculated using the borrower's total monthly debt payments on the total debt obligations, excluding mortgage and the requested LC loan, divided by the borrower's self-reported monthly income.
- addr_state/State: The state provided by the borrower in the loan application

- emp_length/Employment Length:Employment length in years. Possible values are between 0 and 10 where 0 means less than one year and 10 means ten or more years.
- policy_code/Policy Code:products publicly available policy_code=1, new products not publicly available policy_code=2

[ ]:
```python
#Create the dataframe for modeling
accept_cols = ['loan_amnt','title', 'dti','addr_state','emp_length',␣
 ↪'policy_code' ]
accept_df = accept.loc[:, accept_cols]
accept_df.head()
```

[ ]:
```
   loan_amnt               title    dti addr_state emp_length  policy_code
0     3600.0  Debt consolidation   5.91         PA  10+ years          1.0
1    24700.0            Business  16.06         SD  10+ years          1.0
2    20000.0                 NaN  10.78         IL  10+ years          1.0
3    35000.0  Debt consolidation  17.06         NJ  10+ years          1.0
4    10400.0      Major purchase  25.37         PA    3 years          1.0
```

[ ]:
```python
reject_df = reject.drop(columns = ['Application Date', 'Zip Code',␣
 ↪'Risk_Score'])
reject_df.head()
```

[ ]:
```
   Amount Requested                        Loan Title Debt-To-Income Ratio  \
0            1000.0  Wedding Covered but No Honeymoon                  10%
1            1000.0                Consolidating Debt                  10%
2           11000.0       Want to consolidate my debt                  10%
3            6000.0                           waksman               38.64%
4            1500.0                            mdrigo                9.43%

  State Employment Length  Policy Code
0    NM           4 years          0.0
1    MA          < 1 year          0.0
2    MD            1 year          0.0
3    MA          < 1 year          0.0
4    MD          < 1 year          0.0
```

[ ]:
```python
#Encode accept and reject status in the data
reject_df['pass'] = 0
accept_df['pass'] = 1


#concact two data together
reject_df.columns = list(accept_df)
df = pd.concat([accept_df,reject_df])
print(df.shape)
df.head()
```

```
(29909442, 7)
```

[ ]:   loan_amnt   title   dti addr_state emp_length policy_code \
```
0     3600.0  Debt consolidation   5.91         PA  10+ years          1.0
1    24700.0            Business  16.06         SD  10+ years          1.0
2    20000.0                 NaN  10.78         IL  10+ years          1.0
3    35000.0  Debt consolidation  17.06         NJ  10+ years          1.0
4    10400.0      Major purchase  25.37         PA    3 years          1.0

   pass
0     1
1     1
2     1
3     1
4     1
```

[ ]:
```
#columns that contain nan in df
df.isnull().sum()

# drop rows that contain NA
df.dropna(inplace=True)
```

[ ]:
```
#Check dataframe types
print(df.dtypes)

#convert strings to numerical values
df['dti'] = df['dti'].astype(str).str.extract('(\d+)').astype(float)
df['emp_length'] = df['emp_length'].str.extract('(\d+)').astype(int)

#deep copy
df_copy = df.copy()
```

```
loan_amnt      float64
title           object
dti             object
addr_state      object
emp_length      object
policy_code    float64
pass             int64
dtype: object
```

Note: `'(\d+)'`This is a Regular Expression pattern is a regex pattern for digit + is a regex pattern for at least (one or more) since they are enclosed in a ( ) that means the group that you want to capture. - \d+: 1, 12, 123

[ ]:
```
#understand 'policy_code'
print(df['policy_code'].value_counts())
```

```
0.0    26613303
1.0     2093538
2.0       81939
Name: policy_code, dtype: int64
```

policy_code variable contains lots of 0. Since there isn't an explanation of it, we will drop when it is 0.

[ ]:
```
df = df[df['policy_code'] !=0]
```

0.3 Exploratory Data Analysis

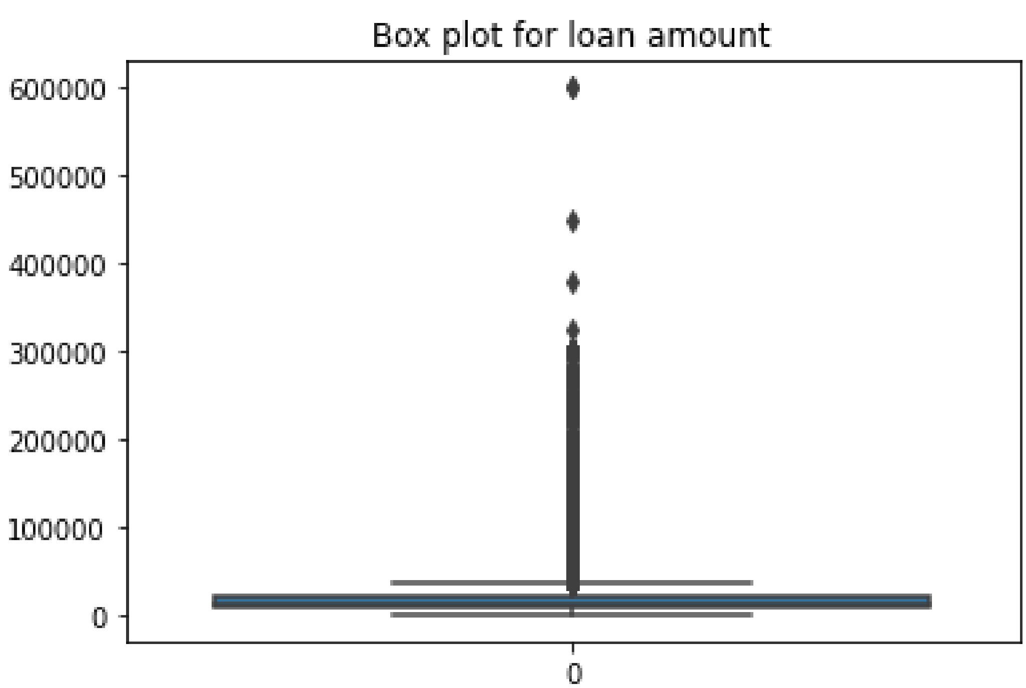
[ ]:
```
#stats for all columns
df.describe()
```

[ ]:

	loan_amnt	dti	emp_length	policy_code	pass
count	2.175477e+06	2.175477e+06	2.175477e+06	2.175477e+06	2.175477e+06
mean	1.557046e+04	1.837936e+01	5.971460e+00	1.037665e+00	9.623352e-01
std	1.201160e+04	1.472063e+01	3.596680e+00	1.903844e-01	1.903844e-01
min	5.000000e+02	0.000000e+00	1.000000e+00	1.000000e+00	0.000000e+00
25%	8.000000e+03	1.100000e+01	2.000000e+00	1.000000e+00	1.000000e+00
50%	1.302500e+04	1.700000e+01	6.000000e+00	1.000000e+00	1.000000e+00
75%	2.000000e+04	2.400000e+01	1.000000e+01	1.000000e+00	1.000000e+00
max	6.000000e+05	9.999000e+03	1.000000e+01	2.000000e+00	1.000000e+00

[ ]:
```
import seaborn as sns
import matplotlib.pyplot as plt

sns.boxplot(data=df['loan_amnt'])
plt.title('Box plot for loan amount')
```

[ ]: Text(0.5, 1.0, 'Box plot for loan amount')

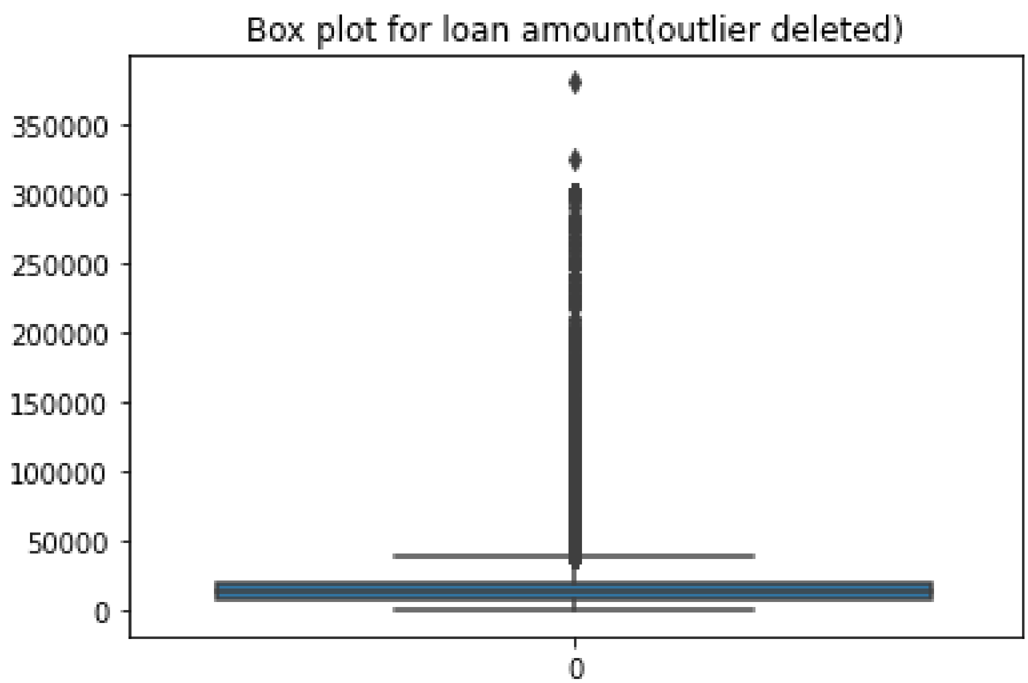


```
[ ]: #outliers in loan amout
     df.loc[df['loan_amnt'] >400000]
```

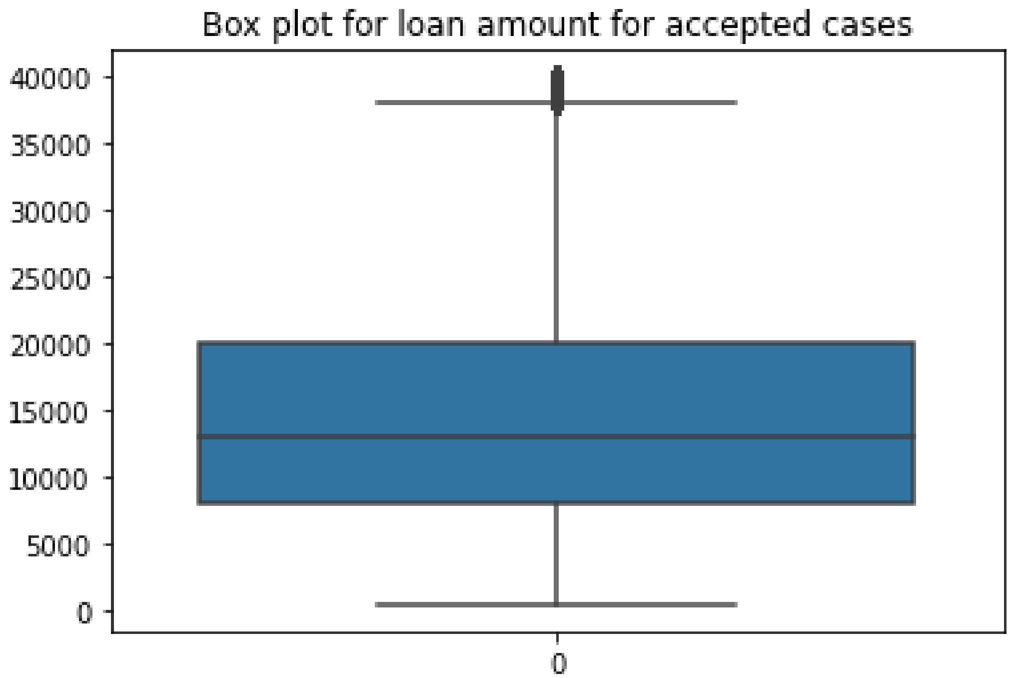
```
[ ]:           loan_amnt          title  dti addr_state  emp_length  policy_code  \
     9604094    600000.0  Business Loan  1.0         CA           1          2.0
     9618307    600000.0  Business Loan  1.0         MN           1          2.0
     21915082   450000.0  Business Loan  1.0         MA           1          2.0

               pass
     9604094      0
     9618307      0
     21915082     0
```

```
[ ]: #Delete outlier
     df  = df.loc[df['loan_amnt'] <=400000]
     sns.boxplot(data=df['loan_amnt'])
     plt.title('Box plot for loan amount(outlier deleted)')
```

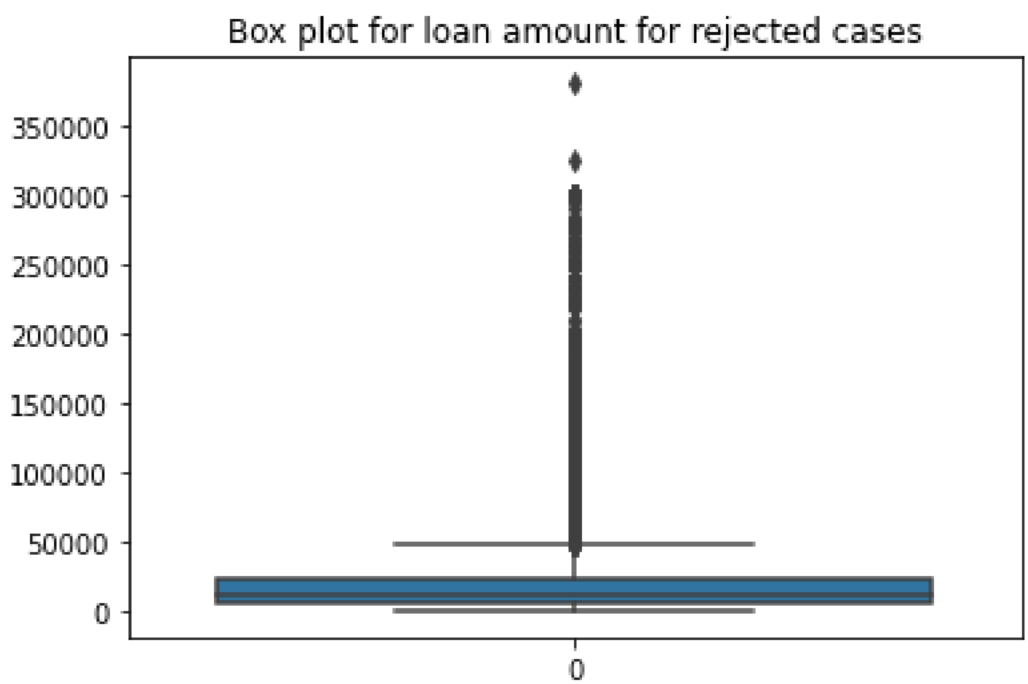
```
[ ]: Text(0.5, 1.0, 'Box plot for loan amount(outlier deleted)')
```




```
[ ]: accept_loan_amt =  df.loc[df['pass'] == 1]
     reject_loan_amt =  df.loc[df['pass'] == 0]
     sns.boxplot(data=accept_loan_amt['loan_amnt'])
     plt.title('Box plot for loan amount for accepted cases')
     plt.show()
```



[ ]:
```
sns.boxplot(data= reject_loan_amt['loan_amnt'].values)
plt.title('Box plot for loan amount for rejected cases')
plt.show()
```

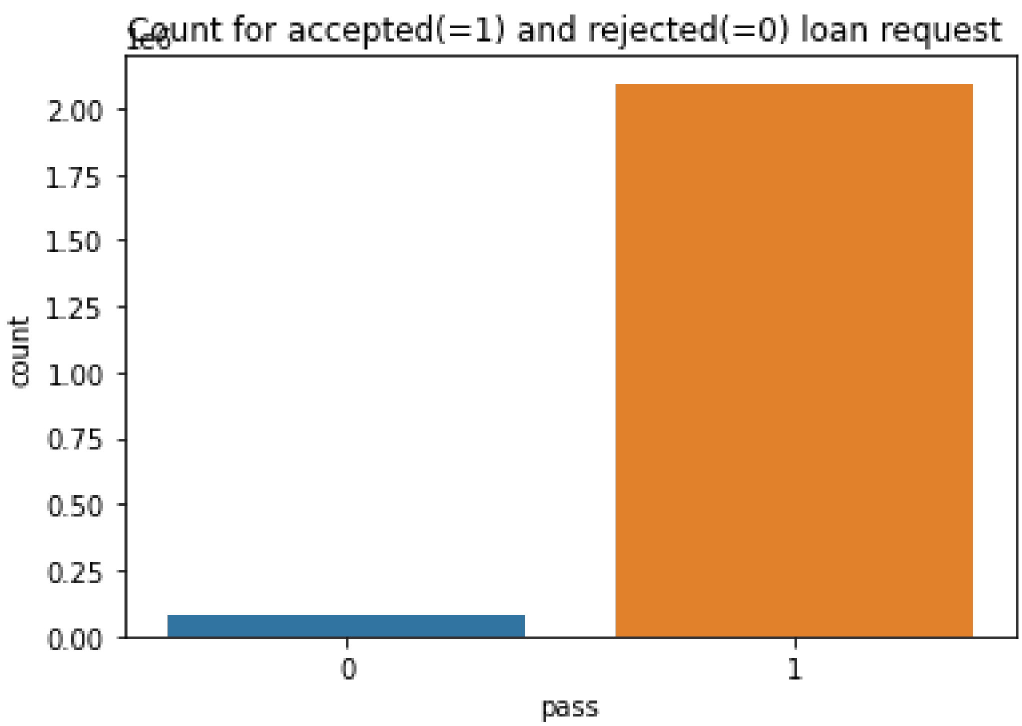


[ ]:
```
#stats specifically for categorical columns
df.describe(include = ['O'])
```

[ ]:
```
                        title addr_state
count                 2175474    2175474
unique                  60962         51
top        Debt consolidation         CA
freq                  1107332     305414
```

[ ]:
```
#Percentage of pass vs not pass
sns.countplot(x="pass", data=df)
plt.title('Count for accepted(=1) and rejected(=0) loan request ')
```

[ ]:
```
Text(0.5, 1.0, 'Count for accepted(=1) and rejected(=0) loan request ')
```



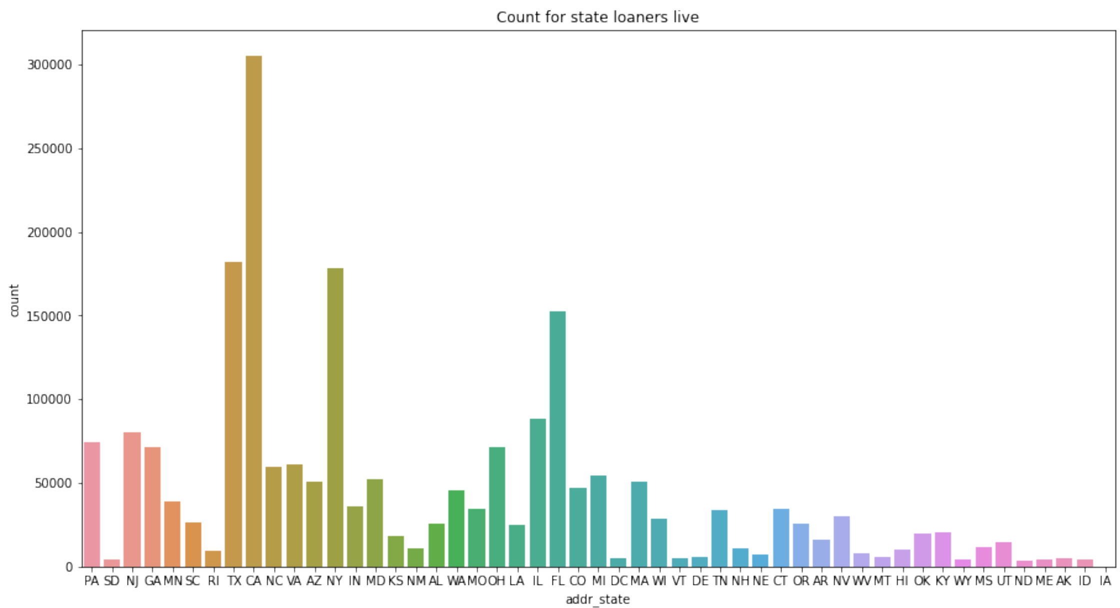
[ ]:
```
#Understand the variable, title
df['title'].value_counts()
```

[ ]:
```
Debt consolidation              1107332
Credit card refinancing          460527
Home improvement                 129089
Other                            119946
Major purchase                    42990
                                  ...
Debt Consolidation loan.              1
```

```
EASYDAY                              1
Dodge                                1
Credit Card Refineance               1
Business assets acquisition          1
Name: title, Length: 60962, dtype: int64
```

[ ]:
```
plt.figure(figsize=(15,8))
sns.countplot(x="addr_state", data=df)
plt.title('Count for state loaners live')
```

[ ]:
```
Text(0.5, 1.0, 'Count for state loaners live')
```



0.3.1 Some obeservation

- Most requests in our data frame are accepted, which might bias our classification model.
- Most loaners live in CA, T, NY, or FL.
- From the boxplot, we can see more variance in loan amount exist the rejected loan, and rejected loan has much more outlier in comparison to accepted loan. Since we have much more accpeted loan, we will decide not to delete the outliers from rejected loan amount to so the data won't be even more unblanaced.

0.4 Feature engineering

0.4.1 Encode cateogrical data

Others: encoder understanding Label encoder only turns the data into a list of ordinal values e.g.[1112213] while one hot encoder will change it into multiple dummy variables e.g. [[010][001][100]] To perform the encoding, we will needs to reshape the data.

to reshape the data

```
import numpy as np
cat = np.array(["cold","hot","warm"]).reshape(1,3) #format for onehotencoding
cat_wrong = np.array(["cold","hot","warm"]) #wrong format
cat.shape, cat_wrong.shape
```

label encoder

```
le = LabelEncoder()
X_type = le.fit_transform(X['type'])
print(X_type)
```

onehot encoder We will need to reshape the categorical column, one hot encode, make it a dataframe so we can piece it we are original dataset.

```
ohe = OneHotEncoder()
X_type = np.array(X['type']).reshape(-1, 1)

X_type = pd.DataFrame(ohe.fit_transform(X_type).toarray(), columns=['Link', 'Photo', 'Status',
X_type
```

Problem of One-Hot Encoding: Dummy Variable Trap

- Dummy Variable Trap is a scenario in which variables are highly correlated to each other.
- multicollinearity: Multicollinearity occurs where there is a dependency between the independent features.

When to use one hot encoding or label encoding? We apply One-Hot Encoding when:

- The categorical feature is not ordinal (like countries)
- The number of categorical features is less so one-hot encoding can be effectively applied

We apply Label Encoding when:

- The categorical feature is ordinal (like Jr. kg, Sr. kg, Primary school, high school)
- The number of categories is quite large as one-hot encoding can lead to high memory consumption

Conclusion for our dataset Since states and title aren't ordinal data, we will use one hot encoder to process our categorical data.

[ ]:
```
#one-hot encoding for addr_state variable

from sklearn.preprocessing import OneHotEncoder
import numpy as np


addr_state = df['addr_state']
```

```
ohe = OneHotEncoder()
addr_state = np.array(addr_state).reshape(-1, 1)

addr_state = pd.DataFrame(ohe.fit_transform(addr_state).toarray(), columns=ohe.
 ↪categories_, index=df.index)
addr_state
```

[ ]:
```
           AK   AL   AR   AZ   CA   CO   CT   DC   DE   FL  ...   SD   TN  \
0         0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  ...  0.0  0.0
1         0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  ...  1.0  0.0
3         0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  ...  0.0  0.0
4         0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  ...  0.0  0.0
5         0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  ...  0.0  0.0
...       ...  ...  ...  ...  ...  ...  ...  ...  ...  ...  ...  ...  ...
27637988  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  ...  0.0  0.0
27638313  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  ...  0.0  0.0
27639468  0.0  1.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  ...  0.0  0.0
27640181  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  ...  0.0  0.0
27641336  0.0  0.0  0.0  0.0  1.0  0.0  0.0  0.0  0.0  0.0  ...  0.0  0.0

           TX   UT   VA   VT   WA   WI   WV   WY
0         0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0
1         0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0
3         0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0
4         0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0
5         0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0
...       ...  ...  ...  ...  ...  ...  ...  ...
27637988  1.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0
27638313  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0
27639468  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0
27640181  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0
27641336  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0

[2175474 rows x 51 columns]
```

[ ]:
```
#flatten multi-index
addr_state.columns = addr_state.columns.get_level_values(0)
addr_state.columns
```

[ ]:
```
Index(['AK', 'AL', 'AR', 'AZ', 'CA', 'CO', 'CT', 'DC', 'DE', 'FL', 'GA', 'HI',
       'IA', 'ID', 'IL', 'IN', 'KS', 'KY', 'LA', 'MA', 'MD', 'ME', 'MI', 'MN',
       'MO', 'MS', 'MT', 'NC', 'ND', 'NE', 'NH', 'NJ', 'NM', 'NV', 'NY', 'OH',
       'OK', 'OR', 'PA', 'RI', 'SC', 'SD', 'TN', 'TX', 'UT', 'VA', 'VT', 'WA',
       'WI', 'WV', 'WY'],
      dtype='object')
```

[ ]:
```
# One hot encode policy_code

policy_code = df['policy_code']
```

```
ohe = OneHotEncoder()
policy_code = np.array(policy_code).reshape(-1, 1)

policy_code = pd.DataFrame(ohe.fit_transform(policy_code).toarray(), columns=␣
↪['policy_1', 'policy_2'], index=df.index)
policy_code

#flatten multi-index
policy_code.columns = policy_code.columns.get_level_values(0)
policy_code.columns
```

[ ]:
```
Index(['policy_1', 'policy_2'], dtype='object')
```

[ ]:
```
#Concat two data together
full_df = pd.concat([df,addr_state, policy_code], axis = 1)
full_df.drop(columns= ['addr_state', 'policy_code'], inplace = True)
```

[ ]:
```
full_df.head()
```

[ ]:
```
   loan_amnt                title   dti  emp_length  pass   AK   AL   AR   AZ  \
0     3600.0   Debt consolidation   5.0          10     1  0.0  0.0  0.0  0.0
1    24700.0             Business  16.0          10     1  0.0  0.0  0.0  0.0
3    35000.0   Debt consolidation  17.0          10     1  0.0  0.0  0.0  0.0
4    10400.0       Major purchase  25.0           3     1  0.0  0.0  0.0  0.0
5    11950.0   Debt consolidation  10.0           4     1  0.0  0.0  0.0  0.0

    CA  ...   TX   UT   VA   VT   WA   WI   WV   WY  policy_1  policy_2
0  0.0  ...  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0       1.0       0.0
1  0.0  ...  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0       1.0       0.0
3  0.0  ...  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0       1.0       0.0
4  0.0  ...  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0       1.0       0.0
5  0.0  ...  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0       1.0       0.0

[5 rows x 58 columns]
```

0.4.2 Balancing the target variable -- pass

From the bar plot, we can see much more accepted cases in the dataset. We want to create a more balanced dataset to imporve the prediction, so we random sample the the same number of rejected cases for the accepted cases.

[ ]:
```
reject_count = len(full_df[full_df['pass']==0])
accept_count = len(full_df[full_df['pass']==1])
print('total count of rejected cases', reject_count)
print('total count of accepted cases', accept_count)

accept_samples = full_df[full_df['pass']==1].sample(n= reject_count,␣
↪replace=True, random_state=1)
print('total count of the accepted samples', len(accept_samples))
```

```
full_df = pd.concat([accept_samples,full_df[full_df['pass']==0]])
print('total count of the balanced dataset', len(full_df))
```

```
total count of rejected cases 81936
total count of accepted cases 2093538
total count of the accepted samples 81936
total count of the balanced dataset 163872
```

[ ]:
```
print('total count of rejected cases', len(full_df[full_df['pass']==0]))
print('total count of accepted cases', len(full_df[full_df['pass']==1]))
```

```
total count of rejected cases 81936
total count of accepted cases 81936
```

0.5 Modeling & Evaluation

[ ]:
```
X = full_df.drop(columns= ['pass', 'title'])
y = full_df['pass']
```

Split the training and testing data

[ ]:
```
from sklearn.metrics import classification_report
from sklearn.model_selection import train_test_split

X_train, X_test,y_train,y_test = train_test_split(X, y, test_size=0.25,␣
 ↪random_state=123)
print(X_train.shape,X_test.shape,y_train.shape,y_test.shape)
```

```
(122904, 56) (40968, 56) (122904,) (40968,)
```

[ ]:
```
y_train.value_counts()
```

[ ]:
```
0    61465
1    61439
Name: pass, dtype: int64
```

[ ]:
```
#Use LogisticRegressionCV becuase it allows cross validation
from sklearn.linear_model import LogisticRegressionCV

model = LogisticRegressionCV(cv=5, random_state=0).fit(X_train, y_train)
```

```
/Users/swimmingcircle/Library/Python/3.9/lib/python/site-
packages/sklearn/linear_model/_logistic.py:814: ConvergenceWarning: lbfgs failed
to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.
```

```
Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-
regression
  n_iter_i = _check_optimize_result(
```

[ ]:
```python
#logistic regression model
result = model.fit(X_train,y_train)
predictions = model.predict(X_test)
print(classification_report(y_test,predictions))
```

```
/Users/swimmingcircle/Library/Python/3.9/lib/python/site-
packages/sklearn/linear_model/_logistic.py:814: ConvergenceWarning: lbfgs failed
to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-
regression
  n_iter_i = _check_optimize_result(
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     20471
           1       1.00      1.00      1.00     20497

    accuracy                           1.00     40968
   macro avg       1.00      1.00      1.00     40968
weighted avg       1.00      1.00      1.00     40968
```

[ ]:
```python
coeff_parameter = pd.DataFrame(np.array(model.coef_).reshape(-1,1), X_train.
 ↪columns,columns=['Coefficient'])
coeff_parameter.loc['intercept', :] = model.intercept_
coeff_parameter
```

[ ]:

	Coefficient
loan_amnt	-0.000010
dti	-0.005435
emp_length	0.043533
AK	0.001765
AL	-0.000351
AR	0.000839
AZ	-0.005295

CA	0.002608
CO	0.001753
CT	0.018115
DC	-0.002000
DE	-0.003239
FL	0.011748
GA	-0.013595
HI	0.002142
IA	0.000000
ID	-0.002878
IL	0.002329
IN	0.002983
KS	0.004816
KY	0.002815
LA	0.007832
MA	0.009882
MD	-0.006057
ME	-0.003285
MI	-0.006458
MN	0.001855
MO	-0.010153
MS	0.006703
MT	0.001468
NC	-0.003667
ND	-0.002161
NE	-0.006945
NH	-0.004961
NJ	0.013369
NM	-0.007145
NV	0.007325
NY	0.017542
OH	-0.004531
OK	0.008591
OR	0.002645
PA	-0.001018
RI	-0.010219
SC	-0.005493
SD	-0.002838
TN	-0.009821
TX	-0.010372
UT	0.002534
VA	0.014815
VT	-0.003547
WA	-0.000539
WI	-0.007766
WV	0.000906
WY	0.006291

```
policy_1        7.005768
policy_2       -6.986429
intercept       0.054702
```

0.5.1 Interpret the coefs in logsitic model

logit(p) = a+ bX + cX (Equation **)

logit(p) is log(p/1-p), indicating the log-odds ratio. We can say that 1 unit increase in X will result in b increase in logit(p). Therefore we want to maximize logit(p) to find the highest amount of loan we can rent.

0.5.2 Some observations

- add_state: For the state address, since one person can only have one state address, and NY have the highest positive ceofficient, 0.017 for state address, we will assign NY to a person to get the highest loan as possible.
- dti: As expected, depth to income ratio is -0.005, showcasing that it has a negative effect on amount of loan you can borrow.
- emp_length: The longer the emp_length, the more loan you can borrow, which is also within expectation.
- loan_amnt: It is really small, -0.00001, but it still has a negative effect, which is also plausible.
- policy_code: We can see that policy_1, borrowing a products publicly available, is around 7.005, which is much better than policy_2, borrowing a products that isn't publicly available. Therefore, we should also assign policy_1 = 1, policy_2 = 0.

0.5.3 Hypothesize to find the highest loan

To find the highest loan, we will assign values to the variables below, - NY = 1, other state address code = 0 - policy_1 = 1, policy_2 = 0 - emp_length: 45. We assume on average, a person will start working at 20, and retire at 65 if he/she doesn't change a compay. The max emp_length is 45 years. - dti: 0. We assume that person never has a depth yet.

[ ]:
```
fill = [0 for _ in range(len(X_train.columns)-3)]
fill
#randomly set default loan as 100000
best_person = [100000, 0, 25]+ fill

#Put NY as 1
best_person[37] = 1
best_person = np.array(best_person).reshape(1,-1)
predictions = model.predict(best_person)
predictions
```

```
/Users/swimmingcircle/Library/Python/3.9/lib/python/site-
packages/sklearn/base.py:450: UserWarning: X does not have valid feature names,
but LogisticRegressionCV was fitted with feature names
  warnings.warn(
```

[ ]: array([1])

0.5.4 Use a step wise function to calculate the highest amount of loan one can borrow

[ ]:
```
def step_wise(best_person, model):
    prediction = 1
    for _ in range(1000):
        best_person[0][0] += 1000
        prediction = model.predict(best_person)
        if prediction != 1:
            break

    return best_person[0][0]

step_wise(best_person, model)
```

```
/Users/swimmingcircle/Library/Python/3.9/lib/python/site-
packages/sklearn/base.py:450: UserWarning: X does not have valid feature names,
but LogisticRegressionCV was fitted with feature names
  warnings.warn(
/Users/swimmingcircle/Library/Python/3.9/lib/python/site-
packages/sklearn/base.py:450: UserWarning: X does not have valid feature names,
but LogisticRegressionCV was fitted with feature names
  warnings.warn(
/Users/swimmingcircle/Library/Python/3.9/lib/python/site-
packages/sklearn/base.py:450: UserWarning: X does not have valid feature names,
but LogisticRegressionCV was fitted with feature names
  warnings.warn(
/Users/swimmingcircle/Library/Python/3.9/lib/python/site-
packages/sklearn/base.py:450: UserWarning: X does not have valid feature names,
but LogisticRegressionCV was fitted with feature names
  warnings.warn(
/Users/swimmingcircle/Library/Python/3.9/lib/python/site-
packages/sklearn/base.py:450: UserWarning: X does not have valid feature names,
but LogisticRegressionCV was fitted with feature names
  warnings.warn(
/Users/swimmingcircle/Library/Python/3.9/lib/python/site-
packages/sklearn/base.py:450: UserWarning: X does not have valid feature names,
but LogisticRegressionCV was fitted with feature names
  warnings.warn(
/Users/swimmingcircle/Library/Python/3.9/lib/python/site-
packages/sklearn/base.py:450: UserWarning: X does not have valid feature names,
but LogisticRegressionCV was fitted with feature names
  warnings.warn(
/Users/swimmingcircle/Library/Python/3.9/lib/python/site-
packages/sklearn/base.py:450: UserWarning: X does not have valid feature names,
but LogisticRegressionCV was fitted with feature names
```

```
  warnings.warn(
/Users/swimmingcircle/Library/Python/3.9/lib/python/site-
packages/sklearn/base.py:450: UserWarning: X does not have valid feature names,
but LogisticRegressionCV was fitted with feature names
  warnings.warn(
/Users/swimmingcircle/Library/Python/3.9/lib/python/site-
packages/sklearn/base.py:450: UserWarning: X does not have valid feature names,
but LogisticRegressionCV was fitted with feature names
  warnings.warn(
/Users/swimmingcircle/Library/Python/3.9/lib/python/site-
packages/sklearn/base.py:450: UserWarning: X does not have valid feature names,
but LogisticRegressionCV was fitted with feature names
  warnings.warn(
/Users/swimmingcircle/Library/Python/3.9/lib/python/site-
packages/sklearn/base.py:450: UserWarning: X does not have valid feature names,
but LogisticRegressionCV was fitted with feature names
  warnings.warn(
/Users/swimmingcircle/Library/Python/3.9/lib/python/site-
packages/sklearn/base.py:450: UserWarning: X does not have valid feature names,
but LogisticRegressionCV was fitted with feature names
  warnings.warn(
/Users/swimmingcircle/Library/Python/3.9/lib/python/site-
packages/sklearn/base.py:450: UserWarning: X does not have valid feature names,
but LogisticRegressionCV was fitted with feature names
  warnings.warn(
/Users/swimmingcircle/Library/Python/3.9/lib/python/site-
packages/sklearn/base.py:450: UserWarning: X does not have valid feature names,
but LogisticRegressionCV was fitted with feature names
  warnings.warn(
/Users/swimmingcircle/Library/Python/3.9/lib/python/site-
packages/sklearn/base.py:450: UserWarning: X does not have valid feature names,
but LogisticRegressionCV was fitted with feature names
  warnings.warn(
/Users/swimmingcircle/Library/Python/3.9/lib/python/site-
packages/sklearn/base.py:450: UserWarning: X does not have valid feature names,
but LogisticRegressionCV was fitted with feature names
  warnings.warn(
/Users/swimmingcircle/Library/Python/3.9/lib/python/site-
packages/sklearn/base.py:450: UserWarning: X does not have valid feature names,
but LogisticRegressionCV was fitted with feature names
  warnings.warn(
```

[ ]: 118000

We can run the stepwise function in a more granular level, but it consume more computational power. For now, I use 1000 as a step, and find that the highest amount of loan a person can receive is around 118000.

[2]:
```python
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

[8]:
```
!cp "./drive/My Drive/Assignment/CS156/assginment_2.ipynb" ./
!jupyter nbconvert --to pdf 'assginment_2.ipynb'
```

```
[NbConvertApp] Converting notebook assginment_2.ipynb to pdf
[NbConvertApp] Support files will be in assginment_2_files/
[NbConvertApp] Making directory ./assginment_2_files
[NbConvertApp] Making directory ./assginment_2_files
[NbConvertApp] Making directory ./assginment_2_files
[NbConvertApp] Making directory ./assginment_2_files
[NbConvertApp] Making directory ./assginment_2_files
[NbConvertApp] Making directory ./assginment_2_files
[NbConvertApp] Writing 89853 bytes to ./notebook.tex
[NbConvertApp] Building PDF
[NbConvertApp] Running xelatex 3 times: [u'xelatex', u'./notebook.tex',
'-quiet']
[NbConvertApp] Running bibtex 1 time: [u'bibtex', u'./notebook']
[NbConvertApp] WARNING | bibtex had problems, most likely because there were no
citations
[NbConvertApp] PDF successfully created
[NbConvertApp] Writing 126947 bytes to assginment_2.pdf
```

[ ]:
```

```