Yang, Steven. Assignment 2

February 19, 2022

${f 1}$ Assignment ${f 2}$

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1.1.1 Lending Club Data

The Lending Club has made an anonymized set of data available for anyone to study here or if you do not have a lending club account the data is also available on Kaggle here. Descriptions of the columns can be found here under 'LoanStats' and 'RejectStats'.

The Lending Club is a platform which allows the crowdfunding of various loans. Various investors are able to browse the profiles of people applying for loans and decide whether or not to help fun them.

In this assignment you will build a model that predicts the largest loan amount that will be successfully funded for any given individual. This model can then be used to advise the applicants on how much they could apply for.

Detailed Instructions Tools Jupyter Notebook, pandas, sklearn

1.1.2 Variables:

Below table are the columns that exist in both data set.

Accepted	Rejected
emp_length	Employment Length
policy_code	Policy Code
zip_code	Zip Code
dti	Debt-To-Income Ratio
$addr_state$	State
loan_amnt	Amount Requested
title	Loan Title

Risk score is not present in the accepted data set but I use FICO credit score's mean of high/low values. As credit score's purpose is to tell how much an individual is reliable, I think this is the great way to have risk score on accepted data.

As policy code strictly means accepted/rejected, I drop that. Using State address is more relavant that having zip code as it's more intuitive.

Thus the final variables I use are: - Employment Length - Loan Amount - Risk Score - DTI - State

```
[1]: import numpy as np
     import pandas as pd
     pd.set_option('max_rows', 50)
     import matplotlib.pyplot as plt
     %matplotlib inline
     # Define Data Frames
     accepted = pd.read_csv('accepted_data.csv')
     rejected = pd.read csv('rejected data.csv')
    /Library/Frameworks/Python.framework/Versions/3.8/lib/python3.8/site-
    packages/IPython/core/interactiveshell.py:3444: 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)
[2]: # To see if accepted data is loaded.
     accepted.head()
                                         funded amnt
                                                       funded amnt inv
[2]:
                  member id
                              loan amnt
                                                                                term
                         NaN
                                 3600.0
                                               3600.0
                                                                 3600.0
                                                                          36 months
        68407277
     1
        68355089
                         NaN
                                24700.0
                                              24700.0
                                                                24700.0
                                                                          36 months
                                              20000.0
                                                                          60 months
     2 68341763
                         NaN
                                20000.0
                                                                20000.0
     3 66310712
                         NaN
                                35000.0
                                              35000.0
                                                                35000.0
                                                                          60 months
     4 68476807
                                              10400.0
                                                                10400.0
                                                                          60 months
                         NaN
                                10400.0
        int_rate
                  installment grade sub_grade
                                                ... hardship_payoff_balance_amount
     0
           13.99
                        123.03
                                   C
                                             C4
                                                                                NaN
     1
           11.99
                        820.28
                                   С
                                             C1
                                                                                NaN
     2
           10.78
                        432.66
                                   В
                                             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
                                                     Cash
                                 NaN
                                                                                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
```

NaN

NaN

NaN

4

```
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]
[3]: # To see if rejected data is loaded.
    rejected.head()
[3]:
       Amount Requested Application Date
                                                             Loan Title \
                                        Wedding Covered but No Honeymoon
                1000.0
    Λ
                             2007-05-26
    1
                1000.0
                             2007-05-26
                                                      Consolidating Debt
    2
                11000.0
                             2007-05-27
                                             Want to consolidate my debt
                6000.0
    3
                             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
                                                             4 years
                                                 NM
                                        010xx
            703.0
                                  10%
    1
                                                            < 1 year
                                                 MA
    2
            715.0
                                  10%
                                        212xx
                                                 MD
                                                              1 year
    3
            698.0
                               38.64%
                                        017xx
                                                            < 1 year
                                                 MA
            509.0
    4
                                9.43%
                                        209xx
                                                 MD
                                                            < 1 year
       Policy Code
    0
               0.0
    1
               0.0
    2
               0.0
    3
               0.0
    4
               0.0
[4]: # These are the columns that I'll use
    final_columns = ["emp_length", "loan_amnt", "risk_score", "dti", "addr_state"]
[5]: # New column for risk score in accepted data frame
    accepted["risk_score"] = accepted[['fico_range_high', 'fico_range_low']].
     →mean(axis=1)
    # Rename Columns in Rejected Data Frame
    rejected = rejected.rename(columns={'Amount Requested': 'loan_amnt', __
     'Zip Code': 'zip_code', 'State': 'addr_state', 'Employment Length':
```

settlement_amount settlement_percentage settlement_term

```
# Drop all rows in N/A
     rejected = rejected[final_columns].dropna()
     accepted = accepted[final_columns].dropna()
[6]: #Create New column says accepted or not
     accepted["accepted"] = 1
     accepted.head()
[6]:
       emp_length
                   loan_amnt
                               risk_score
                                              dti addr_state
                                                               accepted
        10+ years
                       3600.0
                                    677.0
                                             5.91
                                                           PA
                                                                      1
        10+ years
                      24700.0
                                    717.0 16.06
                                                           SD
     1
                                                                      1
     2 10+ years
                      20000.0
                                    697.0
                                           10.78
                                                           IL
                                                                      1
     3 10+ years
                      35000.0
                                    787.0
                                                           NJ
                                                                      1
                                           17.06
          3 years
                      10400.0
                                    697.0 25.37
                                                           PA
                                                                      1
[7]: #Create New column says accepted or not
     rejected["accepted"] = 0
     rejected.head()
[7]:
       emp_length
                   loan_amnt
                               risk_score
                                               dti addr_state
                                                                accepted
          4 years
                       1000.0
                                    693.0
                                               10%
                                                                       0
                                                            NM
         < 1 year
                                                                       0
     1
                       1000.0
                                    703.0
                                               10%
                                                            MA
     2
           1 year
                      11000.0
                                    715.0
                                               10%
                                                            MD
                                                                       0
     3
         < 1 year
                       6000.0
                                    698.0
                                            38.64%
                                                            MA
                                                                       0
         < 1 year
                       1500.0
                                    509.0
                                             9.43%
                                                            MD
                                                                       0
[8]: # Combine two data in one data frame
     data = pd.concat([accepted, rejected], ignore index=True)
     data.head()
[8]:
       emp_length
                   loan_amnt
                                              dti addr_state
                                                               accepted
                               risk_score
     0 10+ years
                       3600.0
                                    677.0
                                             5.91
                                                          PA
                                                                      1
       10+ years
                                                           SD
     1
                      24700.0
                                    717.0 16.06
                                                                      1
     2 10+ years
                      20000.0
                                    697.0
                                           10.78
                                                           IL
                                                                      1
       10+ years
                                                           NJ
     3
                      35000.0
                                    787.0
                                           17.06
                                                                      1
     4
          3 years
                      10400.0
                                    697.0
                                            25.37
                                                           PA
                                                                      1
```

Data Cleaning and Transformation All rows with missing data are removed because they potentially affect the model in falwed way. This is a safe choice as the dataset is huge enough and missing some data should not affect the whole model.

Some data includes string variable and they were all converted to the float variables except states.

As combining data, I added the accepted column to differentiate accepted or rejected loans.

Model Selection Here, I try multiple models and will choose the one has the best accuracy among the other models.

I tried: Logistic Regression, LDA, and LogisticRegressionCV.

As LDA performs the best based on the following results, I use LDA as a final model.

1.1.3 Training Method

To avoid the overfitting, I splitted data into training and testing data. I tried different threshold to find the best ratio to split. According to the report, having 40% of test data and 60% of training data shows the best accuracy and I chose to do so. However, I could not test every threshold but did 0.05 discretely. To imporve the model, trying more threshold should benefit.

```
[9]: numbers = ['0', '1', '2', '3', '4', '5', '6', '7', '8', '9', '10', '.']
      # Clean string variables to float variables
      def str_to_float(x):
          if type(x) == str:
              num = ""
              for i in x:
                  if i in numbers:
                      num += i
              return float(num)
          else:
              return x
      assert (str_to_float("13.35!") == 13.35)
      # Change str columns to float columns
      data['emp_length'] = data['emp_length'].map(lambda x: str_to_float(x))
      data['dti'] = data['dti'].map(lambda x: str_to_float(x))
[10]: # Y as a resultant vector
      Y = data["accepted"]
      # Other variables used for prediction to be X
      X = pd.concat([data[['loan_amnt', 'risk_score', 'dti', 'emp_length']], pd.

→get_dummies(data['addr_state'])], axis = 1)
      Х
「10]:
                                                                                    \
                           risk score
                                               emp length
                                                            ΑK
                                                                AL
                                                                    AR
                                                                        ΑZ
                                                                             CA
                                                                                 CO
                loan amnt
                                          dti
      0
                   3600.0
                                 677.0
                                         5.91
                                                      10.0
                                                                 0
                                                                      0
                                                                          0
                                                                              0
                                                                                  0
      1
                                 717.0 16.06
                                                                          0
                                                                                  0
                  24700.0
                                                      10.0
                                                             0
                                                                 0
                                                                      0
                                                                              0
      2
                  20000.0
                                 697.0 10.78
                                                      10.0
                                                             0
                                                                 0
                                                                     0
                                                                          0
                                                                              0
                                                                                  0
      3
                  35000.0
                                 787.0 17.06
                                                      10.0
                                                             0
                                                                     0
                                                                          0
                                                                 0
                                                                              0
                                                                                  0
      4
                  10400.0
                                 697.0
                                        25.37
                                                                 0
                                                                      0
                                                                          0
                                                                              0
                                                                                  0
                                                       3.0
                                                             0
                  30000.0
      11106219
                                 681.0
                                        55.15
                                                       1.0
                                                             0
                                                                 0
                                                                      1
                                                                          0
                                                                              0
                                                                                  0
      11106220
                   1000.0
                                 531.0 31.31
                                                       1.0
                                                             0
                                                                      0
                                                                          0
                                                                              0
                                                                                  0
                                                                 0
      11106221
                  10000.0
                                 590.0 41.26
                                                       1.0
                                                                     0
                                                                          0
                                                                              0
                                                                                  0
                                                                                  0
      11106222
                   1200.0
                                 686.0 10.26
                                                       1.0
                                                             0
                                                                     0
                                                                          0
                                                                              1
      11106223
                  15000.0
                                 684.0
                                        10.58
                                                       1.0
                                                             0
                                                                      0
                                                                          0
                                                                              0
                                                                                  0
                          TX UT VA VT WA WI WV WY
                   SD
                      TN
```

```
0
        0
           0
             0 0 0 0 0
                          0 0 0
                0 0
                               0
1
        1
           0
             0
                     0
                        0
2
           0 0 0 0
                        0 0 0
                                0
       0
             0 0 0
           0
                                0
                                0
           0
             0
                0 0
                          0
11106219 ... 0
                     0
                        0
                            0
                               0
11106220 ...
        0
           0 1 0 0
                        0
                               0
11106221 ... 0
           0 0 0 0 0 0 0
                                0
11106222 ... 0
           0 0 0 0 0 0 0
                                0
11106223 ...
           0
                0 0
                        0 0 0
                                0
        0
```

[11106224 rows x 55 columns]

```
[11]: from sklearn.linear_model import LogisticRegression
     from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
     from sklearn.model_selection import train_test_split
     from sklearn.metrics import classification_report
      # Test different thresholds to optimize the accuracy
     thresholds = [0.1, 0.15, 0.2, 0.25, 0.3, 0.35, 0.4, 0.45, 0.5, 0.55, 0.6, 0.65]
      40.7, 0.75, 0.8, 0.85, 0.9, 0.95
     threshold = 0
     max_accuracy = 0
      # Generate Train/Test sets
      (train_inputs, test_inputs, train_classes, test_classes) = train_test_split(X,_
      (train_clf_inputs, val_inputs, train_clf_classes, val_classes) =__
      strain_test_split(train_inputs, train_classes, \
         test_size=0.5, shuffle=True)
     clf = LogisticRegression(max_iter=400)
     clf.fit(train_clf_inputs, train_clf_classes)
     for i in thresholds:
          # Try different Thresholds to see what's the optimal threshold
         predictions = np.where(clf.predict_proba(val_inputs)[:,1] > i, 1, 0)
         report = classification_report(val_classes, predictions, output_dict=True)
         if report['accuracy'] > max_accuracy:
             threshold = i
             max_accuracy = report['accuracy']
     print("Optimal threshold", threshold)
     print("Max Accuracy", max_accuracy)
```

Optimal threshold 0.4 Max Accuracy 0.8836364186423756

```
recall f1-score
              precision
                                               support
           0
                   0.90
                             0.94
                                        0.92
                                               2247250
           1
                   0.68
                             0.55
                                        0.61
                                                529306
    accuracy
                                        0.87
                                               2776556
                   0.79
                             0.75
                                        0.76
                                               2776556
  macro avg
weighted avg
                                               2776556
                   0.86
                             0.87
                                        0.86
```

```
[13]: # Using a Linear Discriminant Analysis model and comparing accuracy with the Logistic Regression model

lda = LinearDiscriminantAnalysis()

lda.fit(train_inputs, train_classes)

predictions = lda.predict(test_inputs)

print(classification_report(test_classes, predictions))
```

	precision	recall	f1-score	support
0	0.90	0.96	0.93	2247250
1	0.75	0.56	0.65	529306
accuracy			0.88	2776556
macro avg	0.83	0.76	0.79	2776556
weighted avg	0.87	0.88	0.88	2776556

The report shows that the LDA model has a .88 accuracy. Thefore, I expect that the model is 88% accurate for unseen data.

```
# Keep increase the loan amount and try
                   loan += 500
                   x[0, 0] = loan
                   prediction = lda.predict(x)
               return loan - 500
           elif prediction == 0:
               while prediction == 0 and loan >= 0:
                   # Keep decrease the loan amount and try
                   loan -= 500
                   x[0, 0] = loan
                   prediction = lda.predict(x)
               return loan + 500
[142]: #Testing on some data
      customer = test_inputs.sample(1)
      print(customer)
      print(customer.index)
      print("Maximum Loan Predicted for a Sampled Customer:", maximum loan(customer))
               loan_amnt risk_score
                                       dti emp_length AK
                                                            \mathsf{AL}
                                                                AR AZ CA
      1619796
                 19475.0
                               677.0
                                      10.8
                                                    5.0
                                                          0
                                                                          0
                                                                              0
                      TX UT
                               VA VT
                                      WA WI
      1619796
                0
                    0
                            0
                                0
                                    0
                                        1
                                            0
                                                0
      [1 rows x 55 columns]
      Int64Index([1619796], dtype='int64')
      Largest Loan that will be successfully funded: 23000
      /Library/Frameworks/Python.framework/Versions/3.8/lib/python3.8/site-
      packages/sklearn/base.py:450: UserWarning: X does not have valid feature names,
      but LinearDiscriminantAnalysis was fitted with feature names
        warnings.warn(
      /Library/Frameworks/Python.framework/Versions/3.8/lib/python3.8/site-
      packages/sklearn/base.py:450: UserWarning: X does not have valid feature names,
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```

```
/Library/Frameworks/Python.framework/Versions/3.8/lib/python3.8/site-
     packages/sklearn/base.py:450: UserWarning: X does not have valid feature names,
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       warnings.warn(
     /Library/Frameworks/Python.framework/Versions/3.8/lib/python3.8/site-
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     packages/sklearn/base.py:450: UserWarning: X does not have valid feature names,
     but LinearDiscriminantAnalysis was fitted with feature names
       warnings.warn(
[14]: #Function that computes the largest loan a person can take that will be
       →successfully funded
      def maximum loan clf(x):
          loan = 5000
          x["loan_amnt"] = loan
          x = np.array(x).reshape(1, -1)
          prediction = clf.predict(x)
          if prediction == 1:
              while prediction == 1:
```

warnings.warn(

```
#Continue increasing the loan amount until it reaches the decision_
       \hookrightarrow boundary
                  loan += 500
                  x[0, 0] = loan
                  prediction = clf.predict(x)
              return loan - 500
          elif prediction == 0:
              while prediction == 0 and loan >= 0:
                  #Continue decreasing the loan amount until it reaches the decision_
       ⇔boundary or gets to 0
                  loan -= 500
                  x[0, 0] = loan
                  prediction = clf.predict(x)
              return loan + 500
[15]: #Testing on some data
      customer = test_inputs.sample(1)
      print(customer)
      print(customer.index)
      print("Maximum Loan Predicted for a Sampled Customer:", __
       →maximum_loan_clf(customer))
              loan amnt
                        risk_score
                                        dti emp_length AK
                                                             ΑL
                                                                 AR AZ CA
                                                                              CO
     6968635
                10000.0
                               487.0
                                      24.96
                                                    1.0
                                     VT
                                        WA WI
                                                      WY
                 SD
                     TN
                        TX UT
                                 VA
                                                  WV
                      0
                          0
                               0
                                       0
                                           0
                                               0
     6968635
                                   1
                                                   0
     [1 rows x 55 columns]
     Int64Index([6968635], dtype='int64')
     Maximum Loan Predicted for a Sampled Customer: 0
     /Library/Frameworks/Python.framework/Versions/3.8/lib/python3.8/site-
     packages/sklearn/base.py:450: UserWarning: X does not have valid feature names,
     but LogisticRegression was fitted with feature names
       warnings.warn(
     /Library/Frameworks/Python.framework/Versions/3.8/lib/python3.8/site-
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     but LogisticRegression was fitted with feature names
       warnings.warn(
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     /Library/Frameworks/Python.framework/Versions/3.8/lib/python3.8/site-
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     but LogisticRegression was fitted with feature names
       warnings.warn(
```

```
/Library/Frameworks/Python.framework/Versions/3.8/lib/python3.8/site-
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packages/sklearn/base.py:450: UserWarning: X does not have valid feature names,
but LogisticRegression was fitted with feature names
  warnings.warn(
```

1.1.4 Based on the test result above:

One individual who makes \$19475.0 can maximum of \$23,000 of loan as maximum.

```
from sklearn.linear_model import LogisticRegressionCV

# randomize and split to reduce overusage of data but preserving data_
characteristics

X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size = 0.95,_
random_state = 123)

# initiate classification model with cross-validation parameters to allow for_
best parameter choice

cla = LogisticRegressionCV(max_iter=400)
```

p	recision	recall	f1-score	support
0	0.90	0.96	0.93	809352
1	0.77	0.54	0.63	190648
accuracy			0.88	1000000
macro avg	0.83	0.75	0.78	1000000
weighted avg	0.87	0.88	0.87	1000000

[]: