Report

Context

Banks play a crucial role in market economies. They decide who can get finance and on what terms and can make or break investment decisions. For markets and society to function, individuals and companies need access to credit.

Credit scoring algorithms, which make a guess at the probability of default, are the method banks use to determine whether or not a loan should be granted. This project aim to improve on the state of the art in credit scoring, by *predicting the probability that somebody will experience financial distress in the next two years*.

Objectives

General

- Improve credit scoring
- Build a model that borrowers and lenders can use to make better financial decisions

Concrete

- Generate delinquency scores for the data provided

Methodology

Given the data provided, the following approach was implemented to get our results.

1. Exploration of data: visual identification of patterns, trends, and extreme values in data
2. Modelling proposal: identification of logistic regression as the model that would potentially yield the best results, given objectives and current data
3. Processing data: imputation of data on empty datapoints with median values
4. Estimating the model: we propose and build three models, then compare the best fit.
5. Evaluating the model: we use accuracy as we believe it is the best measure for evaluating binary responses

Results

The three tested models yielded similar results. The best model has an accuracy of 0.9338. Nevertheless, the other two models performed almost as well. This means

Next steps

- Further iterations of this exercise could include a Linear Probability Model and a Probit regression as different classifiers
- Evaluation should include other measures: mean square error, mean absolute deviation, and entropy among others

Technical appendix

Description	Original header	Relabeling
(None)	(No header)	‘ID’
Has the person experienced past 90 days due delinquency or worse?	'SeriousDlqin2yrs'	‘SD2Y’
Total balance on credit cards and personal lines of credit[1] divided by the sum of credit limits	'RevolvingUtilization OfUnsecuredLines'	‘RUUL’
Age of borrower in years	'age'	‘Age’
Times borrower has been 30-59 days past due but no worse in the last 2 years	'NumberOfTime30-59 DaysPastDueNotWorse'	‘LP30_59’
Monthly debt payments, alimony, and living costs, divided by monthy gross income	'DebtRatio'	‘DR’
Monthly income	'MonthlyIncome'	‘MI’
Number of open loans[2] and lines of credit[3]	'NumberOfOpen CreditLinesAndLoans'	‘OCLL’
Number of times borrower has been 90 days or more past due in the last 2 years	'NumberOfTimes 90DaysLate'	‘LP90_’
Times borrower has been 60-89 days past due but no worse in the last 2 years	'NumberRealEstate LoansOrLines'	‘LP60_90’
Number of mortgage and real estate loans[4]	'NumberOfTime60-89 DaysPastDueNotWorse'	‘MREL’
Number of dependents, excluding themselves	'NumberOfDependents'	‘Deps’

Table 1. Data provided

<u>Notes on methodology</u>

1. Exploration of data
   Running the function go.py will yield several information on data:
   - Descriptive statistics, to get an idea of the distributions of data for each variable
   - Histograms, not as descriptive as the previous statistic, given the numerous ‘extreme’ observations on several variables (e.g. MI > 3,000,000, DR > 5,000)
   - Scatter plots, of variables vs. observation number, to identify potential bins to categorize or group data [5]

2. Modelling proposal
   We use logistic regression, as it is a natural model to fit probabilities.

[1] Except real estate and no installment debt
[2] e.g. installment such as car loan or mortgage
[3] e.g. credit cards
[4] Including home equity lines of credit
[5] Both histograms and scatter plots are avaliable in their corresponding folder for consultation

3. Processing data
   We found missing information in observations of two variables, which were filled with their corresponding median values:
   - Monthly income
   - Dependents in family, excluding oneself

4. Estimating the model and classifying
   The three models are estimated without binning or discretizing any variables.
   - The first model regresses SD2Y with the rest of the covariates (except ID). The classification rule of the logistic regression is as follows:

$$\hat{Y} = \begin{cases} 1, if\ P > 0.5 \\ 0, if\ P\ \leq 0.5 \end{cases}$$

```
Results: Logit
================================================================
Model:              Logit            Pseudo R-squared: 0.069
Dependent Variable: SD2Y             AIC:              68577.0382
Date:               2016-04-12 23:07 BIC:              68676.2221
No. Observations:   150000           Log-Likelihood:   -34279.
Df Model:           9                LL-Null:          -36808.
Df Residuals:       149990           LLR p-value:      0.0000
Converged:          1.0000           Scale:            1.0000
No. Iterations:     7.0000
-----------------------------------------------------------------
              Coef.  Std.Err.     z     P>|z|    [0.025   0.975]
-----------------------------------------------------------------
RUUL        -0.0001    0.0001   -0.8887 0.3742  -0.0002   0.0001
Age         -0.0503    0.0005  -94.5485 0.0000  -0.0514  -0.0493
LP30_59      0.4913    0.0112   43.8688 0.0000   0.4693   0.5132
DR          -0.0000    0.0000   -3.5100 0.0004  -0.0001  -0.0000
MI          -0.0001    0.0000  -16.3768 0.0000  -0.0001  -0.0000
OCLL        -0.0207    0.0026   -8.0156 0.0000  -0.0258  -0.0157
LP90_        0.4196    0.0149   28.0714 0.0000   0.3903   0.4489
LP60_90      0.1034    0.0107    9.7043 0.0000   0.0825   0.1243
MREL        -0.8834    0.0175  -50.4487 0.0000  -0.9178  -0.8491
Deps         0.0383    0.0090    4.2792 0.0000   0.0208   0.0559
================================================================
```

   - The second model takes out the RUUL, as it results statistically insignificant. The classification rule of the logistic regression remains unchanged.

```
Results: Logit
================================================================
Model:              Logit            Pseudo R-squared: 0.069
Dependent Variable: SD2Y             AIC:              68576.0321
Date:               2016-04-12 23:07 BIC:              68665.2976
No. Observations:   150000           Log-Likelihood:   -34279.
Df Model:           8                LL-Null:          -36808.
Df Residuals:       149991           LLR p-value:      0.0000
Converged:          1.0000           Scale:            1.0000
No. Iterations:     7.0000
-----------------------------------------------------------------
              Coef.  Std.Err.     z     P>|z|    [0.025   0.975]
-----------------------------------------------------------------
Age         -0.0503    0.0005  -94.5529 0.0000  -0.0514  -0.0493
LP30_59      0.4913    0.0112   43.8714 0.0000   0.4693   0.5132
DR          -0.0000    0.0000   -3.5176 0.0004  -0.0001  -0.0000
MI          -0.0001    0.0000  -16.3962 0.0000  -0.0001  -0.0000
OCLL        -0.0207    0.0026   -8.0025 0.0000  -0.0258  -0.0156
LP90_        0.4196    0.0149   28.0726 0.0000   0.3903   0.4489
LP60_90      0.1033    0.0107    9.6965 0.0000   0.0825   0.1242
MREL        -0.8835    0.0175  -50.4516 0.0000  -0.9178  -0.8492
Deps         0.0383    0.0090    4.2779 0.0000   0.0208   0.0559
================================================================
```

- The third model keeps the covariates of the second model, but elevates the threshold of the classification rule to *u = 0.9.*

```
                          Results: Logit
=================================================================
Model:              Logit            Pseudo R-squared: 0.069
Dependent Variable: SD2Y             AIC:              68576.0321
Date:               2016-04-12 23:07 BIC:              68665.2976
No. Observations:   150000           Log-Likelihood:   -34279.
Df Model:           8                LL-Null:          -36808.
Df Residuals:       149991           LLR p-value:      0.0000
Converged:          1.0000           Scale:            1.0000
No. Iterations:     7.0000
------------------------------------------------------------------
              Coef.   Std.Err.     z      P>|z|    [0.025   0.975]
------------------------------------------------------------------
Age          -0.0503    0.0005  -94.5529  0.0000  -0.0514  -0.0493
LP30_59       0.4913    0.0112   43.8714  0.0000   0.4693   0.5132
DR           -0.0000    0.0000   -3.5176  0.0004  -0.0001  -0.0000
MI           -0.0001    0.0000  -16.3962  0.0000  -0.0001  -0.0000
OCLL         -0.0207    0.0026   -8.0025  0.0000  -0.0258  -0.0156
LP90_         0.4196    0.0149   28.0726  0.0000   0.3903   0.4489
LP60_90       0.1033    0.0107    9.6965  0.0000   0.0825   0.1242
MREL         -0.8835    0.0175  -50.4516  0.0000  -0.9178  -0.8492
Deps          0.0383    0.0090    4.2779  0.0000   0.0208   0.0559
=================================================================
```

5. Evaluating the model

- Accuracy model 1: 0.9337533333333333
- Accuracy model 2: 0.9337533333333333
- Accuracy model 3: 0.93318

We selected the second model as it has the least covariates and best accuracy of the tested cases.