Predictive Analytics: Credit Risk Scorecard Application Case Study: Group 15

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Abstract

Credit scorecards are crucial tools in the credit assessment process. They are based on the prior performance of clients that share the same traits as a new client. Consequently, the goal of a credit scorecard is to estimate risk because credit scorecards are based on the past behavior of clients that share the same qualities as a prospective client. Therefore, the primary purpose of it is to either approve or reject a new client's loan request. The scorecard's function is to support this option. In this assignment, we'll compare and contrast the binning techniques known as weight-of-evidence (woe) binning and group binning. That's why we have been using the existing scorecard. Moreover, certain model changes and binning splits will be made as a result of the addition of the 7 variables. To evaluate the effectiveness of the scorecard, the Gini coefficient is used. The major results of this research were to: demonstrate that group binning outperforms woe binning in out-of-sample predictions as measured by the Gini coefficient. The dependent variable, credibility, may be predicted more precisely when more independent variables are included.

Contents

Abstract

Credit scorecards are crucial tools in the credit assessment process. They are based on the prior performance of clients that share the same traits as a new client. Consequently, the goal of a credit scorecard is to estimate risk because credit scorecards are based on the past behavior of clients that share the same qualities as a prospective client. Therefore, the primary purpose of it is to either approve or reject a new client's loan request. The scorecard's function is to support this option. In this assignment, we'll compare and contrast the binning techniques known as weight-of-evidence (woe) binning and group binning. That's why we have been using the existing scorecard. Moreover, certain model changes and binning splits will be made as a result of the addition of the 7 variables. To evaluate the effectiveness of the scorecard, the Gini coefficient is used. The major results of this research were to: demonstrate that group binning outperforms woe binning in out-of-sample predictions as measured by the Gini coefficient. The dependent variable, credibility, may be predicted more precisely when more independent variables are included.

1 Introduction

In the form of a score and a likelihood of default, credit scoring models and scorecards estimate the risk that a borrower won't return a loan.

For instance, a credit scorecard may award a borrower points based on the following table for their age and income. As previously noted, a single dependent variable, credibility, was predicted using seven independent variables. As a binning strategy, the Weight-of-Evidence technique was adopted.

Therefore, group binning will be used as an extra binning strategy for this project's execution. To increase the model's Gini coefficient of prediction, a seventh independent variable was added, and the binning breaks were modified.

2 Predictive Analytics Research Methodology

2.1 Predictor Variable Transformation

Transforming predictor variables with the Weight of Evidence (WOE) approach. The WOE describes how well an independent variable may predict the outcome of a dependent variable.

The WOE cannot be determined until the data has been separated into bins. This value is used for future calculations in place of the original value once the WOE has been located. As a result, upon transformation, the WOE will be the same for all lines that include the variable in the same bin.

If the WOE is greater than one, then the Distribution of the Goods is greater than the Bads, if the WOE is smaller than one, then the Distribution of the Goods is less than the Distribution of the Bads.

There are benefits to this transformation: Because the data is categorized with the simple treatment of the missing values, outliers are no longer a concern. Additionally, it supports categorical and continuous numbers.

Using the two functions in R:

woebin: This function determines the best binning.

woebin_ply: This function applies the provided binning information to convert the values in the original data to WOE values.

There will be some drawbacks for WOE as well. One is that binning may result in information loss. Another is the possibility of an unresearched link between the independent variables.

$$WOE = \frac{Distribution of Goods}{Distribution of Bads} \tag{1}$$

2.2 Logistic Regression Analysis

Logistic Regression (also known as Logit-Model) is a statistical Model that can estimate probability of a certain event happening based on one or more independent variables. Its application is widespread in various statistical methods, especially in classification problems and prediction analyses. Contrary to linear regression, the predicted variable in logistic regression is a Bernoulli variable, i.e. a binary random variable k with:

$$k \in \{0, 1\} \tag{2}$$

Formally, the logistic regression model estimates probability p of the Bernoulli k being 1, corresponding the the event in question happening. The logistic function defining $p(x)$ takes on the form:

$$p(k) = \frac{e^{\beta_0 + \beta_1 k}}{1 + e^{\beta_0 + \beta_1 k}} = \frac{1}{1 + e^{-}(\beta_0 + \beta_1 k)} \tag{3}$$

Figure TODO depicts the logistic regression for two examplary attributes.

In the domain of Credit Scoring, logistic regression is one of the most widely used statistical models. (Bolton u. a., 2009, p. 19)

2.3 Building Scorecards

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2.4 Forecasting Scorepoints and default Probabilities

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2.5 Forecasting Accuracy Testing

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3 Empirical results

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3.1 Loading external data

requesting the loading of the "germancredit" built-in data set while creating the scorecard, we may leverage a variety of variables in our project to forecast creditability based on a subset of these variables.

```
# Importing of library and data
library(scorecard)
data("germancredit")
```

In order to achieve the aim of predicting creditability, we will take into account 7 variables from the "germancredit" data and determine which one has the most influence on the precision of a predicted desired value. Considering the Filtering of variables with >= iv_limit = 0.02, <= missing_limit = 0.95 and <= identical_limit_limit = 0.95.

```
data_f.df = var_filter(germancredit, y="creditability")
```

```
## v Variable filtering on 1000 rows and 20 columns in 00:00:00
## v 7 variables are removed
```

3.2 Splitting filtered data into train and test samples

It is essential to draw conclusions from historical data and use the information gained to make precise predictions about credibility in order to have a scorecard that can be relied upon. As a result, we must divide the data into two sets that we loaded and filtered in the earlier phases. The sets consist of a training set and a test set, with the training set accounting for 75% and the test set for 25% of the total.

```
data_f.list = split_df(data_f.df,"creditability",ratio=c(0.75,0.25))
```

The model can make a forecast that is as accurate as feasible since there is enough training data available. To determine if the learning process was sufficiently effective, the test set is employed.

3.3 Weight-Of-Evidence (WOE)-Binning

Using the two functions in R: woebin & woebin_ply. As shown below:

- WOE-Binning of predictor variables (used method: “width”):

```
bins.list = woebin(data_f.list$train,
                   "creditability",
                   save_breaks_list = "breaks.list")
```

```
## v Binning on 727 rows and 14 columns in 00:00:03
```

```
head(bins.list)
```

```
## $status.of.existing.checking.account
##                              variable
## 1: status.of.existing.checking.account
## 2: status.of.existing.checking.account
## 3: status.of.existing.checking.account
##                                                  bin count count_distr neg
## 1:                          ... < 0 DM%,%0 <= ... < 200 DM   398  0.54745530 224
## 2: ... >= 200 DM / salary assignments for at least 1 year    46  0.06327373  34
## 3:                                       no checking account   283  0.38927098 252
##    pos   posprob        woe      bin_iv  total_iv
## 1: 174 0.4371859  0.6019226 0.218273774 0.6562879
## 2:  12 0.2608696 -0.1869405 0.002124977 0.6562879
## 3:  31 0.1095406 -1.2409285 0.435889174 0.6562879
##                                                 breaks is_special_values
## 1:                          ... < 0 DM%,%0 <= ... < 200 DM             FALSE
## 2: ... >= 200 DM / salary assignments for at least 1 year             FALSE
## 3:                                       no checking account             FALSE
##
## $duration.in.month
##             variable       bin count count_distr neg pos   posprob        woe
## 1: duration.in.month  [-Inf,8)    63  0.08665750  57   6 0.0952381 -1.3967784
## 2: duration.in.month    [8,16)   252  0.34662999 195  57 0.2261905 -0.3754349
## 3: duration.in.month   [16,34)   281  0.38651994 191  90 0.3202847  0.1020496
## 4: duration.in.month   [34,44)    75  0.10316369  43  32 0.4266667  0.5590492
## 5: duration.in.month [44, Inf)    56  0.07702889  24  32 0.5714286  1.1421954
##         bin_iv  total_iv breaks is_special_values
## 1: 0.117489928 0.3165171      8             FALSE
## 2: 0.044932100 0.3165171     16             FALSE
## 3: 0.004106144 0.3165171     34             FALSE
## 4: 0.035304912 0.3165171     44             FALSE
## 5: 0.114683977 0.3165171    Inf             FALSE
```

```
##
## $credit.history
##         variable
## 1: credit.history
## 2: credit.history
## 3: credit.history
## 4: credit.history
##                                                                              bin
## 1: no credits taken/ all credits paid back duly%,%all credits at this bank paid back duly
## 2:                                              existing credits paid back duly till now
## 3:                                                       delay in paying off in the past
## 4:                            critical account/ other credits existing (not at this bank)
##    count count_distr neg pos   posprob         woe      bin_iv  total_iv
## 1:    64  0.08803301  25  39 0.6093750  1.29919919 0.169810394 0.3238461
## 2:   382  0.52544704 262 120 0.3141361  0.07366061 0.002892645 0.3238461
## 3:    63  0.08665750  41  22 0.3492063  0.23198376 0.004869416 0.3238461
## 4:   218  0.29986245 182  36 0.1651376 -0.76597438 0.146273629 0.3238461
##                                                                           breaks
## 1: no credits taken/ all credits paid back duly%,%all credits at this bank paid back duly
## 2:                                              existing credits paid back duly till now
## 3:                                                       delay in paying off in the past
## 4:                            critical account/ other credits existing (not at this bank)
##    is_special_values
## 1:             FALSE
## 2:             FALSE
## 3:             FALSE
## 4:             FALSE
##
## $purpose
##    variable                                        bin count count_distr neg
## 1:  purpose retraining%,%car (used)%,%radio/television   284  0.39064649 228
## 2:  purpose              furniture/equipment%,%repairs   144  0.19807428 100
## 3:  purpose car (new)%,%domestic appliances%,%business   253  0.34800550 157
## 4:  purpose                          education%,%others    46  0.06327373  25
##    pos   posprob         woe       bin_iv  total_iv
## 1:  56 0.1971831 -0.54948057 0.1038486990 0.1853448
## 2:  44 0.3055556  0.03353282 0.0002242187 0.1853448
## 3:  96 0.3794466  0.36261576 0.0487911020 0.1853448
## 4:  21 0.4565217  0.68015999 0.0324807583 0.1853448
##                                        breaks is_special_values
## 1: retraining%,%car (used)%,%radio/television             FALSE
## 2:              furniture/equipment%,%repairs             FALSE
## 3: car (new)%,%domestic appliances%,%business             FALSE
## 4:                         education%,%others             FALSE
##
## $credit.amount
##         variable         bin count count_distr neg pos   posprob         woe
## 1: credit.amount [-Inf,1400)   197  0.27097662 141  56 0.2842640 -0.06889483
## 2: credit.amount [1400,4000)   349  0.48005502 268  81 0.2320917 -0.34202445
## 3: credit.amount [4000,5000)    42  0.05777166  19  23 0.5476190  1.04556861
## 4: credit.amount [5000,9600)   102  0.14030261  67  35 0.3431373  0.20516881
## 5: credit.amount [9600, Inf)    37  0.05089409  15  22 0.5945946  1.23750562
##         bin_iv  total_iv breaks is_special_values
## 1: 0.001268083 0.2204009   1400             FALSE
```

```
## 2: 0.052062383 0.2204009   4000             FALSE
## 3: 0.071868080 0.2204009   5000             FALSE
## 4: 0.006138194 0.2204009   9600             FALSE
## 5: 0.089064175 0.2204009    Inf             FALSE
##
## $savings.account.and.bonds
##                     variable
## 1: savings.account.and.bonds
## 2: savings.account.and.bonds
## 3: savings.account.and.bonds
##                                                                   bin count
## 1:                                                       ... < 100 DM   431
## 2:                                                100 <= ... < 500 DM    78
## 3: 500 <= ... < 1000 DM%,%... >= 1000 DM%,%unknown/ no savings account   218
##    count_distr neg pos   posprob         woe       bin_iv  total_iv
## 1:   0.5928473 277 154 0.3573086  0.26744847 0.0445409119 0.1593706
## 2:   0.1072902  54  24 0.3076923  0.04358316 0.0002055698 0.1593706
## 3:   0.2998624 179  39 0.1788991 -0.66931079 0.1146240838 0.1593706
##                                                                breaks
## 1:                                                       ... < 100 DM
## 2:                                                100 <= ... < 500 DM
## 3: 500 <= ... < 1000 DM%,%... >= 1000 DM%,%unknown/ no savings account
##    is_special_values
## 1:             FALSE
## 2:             FALSE
## 3:             FALSE
```

```
# woebin_plot (bins.list)
```

- Transformation of predictor variables WOE and GRP:

```
data_woe.list = lapply(data_f.list, function(x) woebin_ply(x, bins.list))
```

```
## v Woe transformating on 727 rows and 13 columns in 00:00:01
## v Woe transformating on 273 rows and 13 columns in 00:00:01
```

```
lapply(data_woe.list, class)
```

```
## $train
## [1] "data.table" "data.frame"
##
## $test
## [1] "data.table" "data.frame"
```

```
lapply(data_woe.list, dim)
```

```
## $train
## [1] 727  14
##
## $test
## [1] 273  14
```

```
data_grp.list = lapply(data_f.list, function(x)
woebin_ply(x, bins.list, to = 'bin'))
```

```
## v Woe transformating on 727 rows and 13 columns in 00:00:01
## v Woe transformating on 273 rows and 13 columns in 00:00:01
```

```r
lapply(data_grp.list, class)
```

```
## $train
## [1] "data.table" "data.frame"
##
## $test
## [1] "data.table" "data.frame"
```

```r
lapply(data_grp.list, dim) ## Generalized linear model (glm): Regressing response w.r.t. predictors
```

```
## $train
## [1] 727  14
##
## $test
## [1] 273  14
```

3.3.1 Logistic regression w.r.t. WOE-transformed predictors (data_woe.list$train)

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3.3.2 Logistic regression w.r.t. GRP-transformed predictors (data_grp.list$train)

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3.4 Building the scorecard-model

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3.4.1 Calculating scorepoints for the splitted sample (train and test)

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3.5 Predicting probabilities and scorepoints

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3.6 Testing prediction accuracy

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4 Summary

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References

[Bolton u. a. 2009] Bolton, C. ; Mathematics, University of Pretoria. Department o. ; Mathematics, Applied: *Logistic Regression and Its Application in Credit Scoring*. University of Pretoria, 2009 https://books.google.at/books?id=K7B3MwEACAAJ