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

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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

lorem impsum

2.4 Forecasting Scorepoints and default Probabilities

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2.5 Forecasting Accuracy Testing

Include test-train split

3 Empirical results

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3.1 Loading and Preparing the Data

We're using a predefined dataset "germancredit" from the libaray "scorecard". Below the import process is shown. The "germancredit" data has 21 variables, 7 will remain for our scorecard model. In the following we will use the explained theoretical approach to filter out the 7 most significant predictor variables, relevant for the credibility of a possible customer.

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

```
## [1] 21
```

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.

```
# 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")
```

3.2 Splitting the 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.

```
# Splitting data into train and test data with ratio 0.75
data_f.list = split_df(data_f.df,"creditability",ratio=c(0.75,0.25))
class(data_f.list)
lapply(data_f.list,class)
lapply(data_f.list, dim)
```

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.

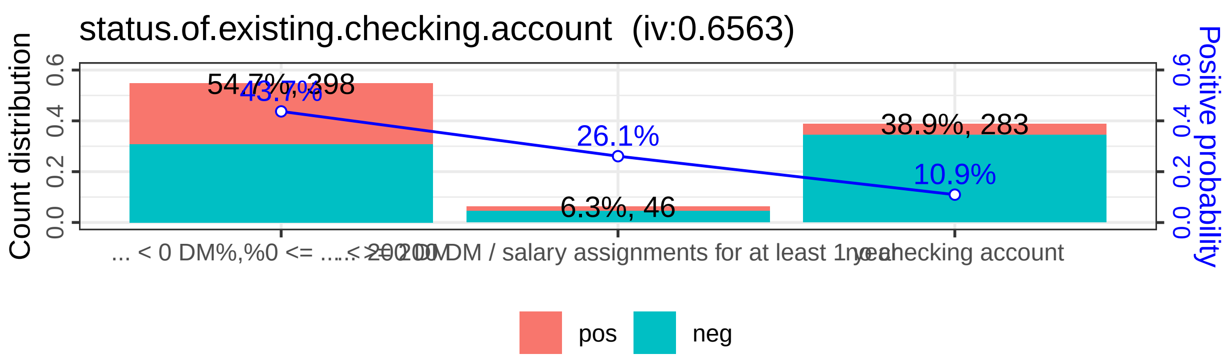
3.3 Weight-Of-Evidence Binning

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

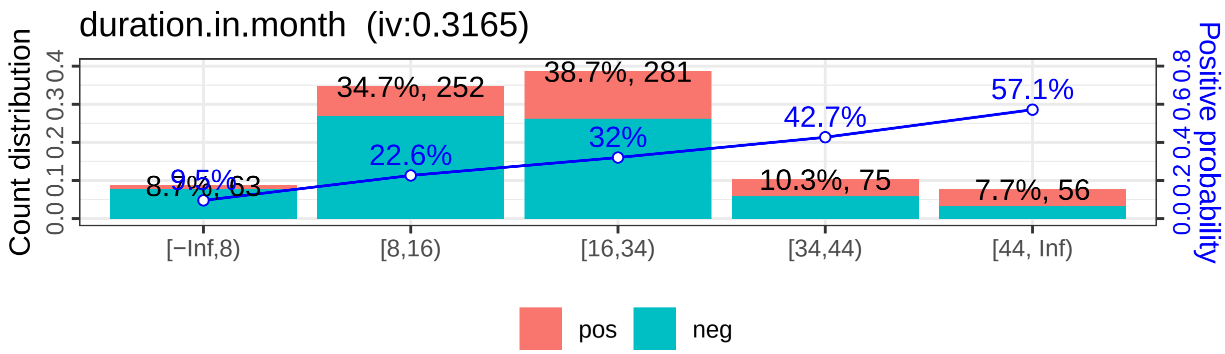
- WOE-Binning of predictor variables (used method: “width”):

```
# Binning of train data
# breaks.list is saved and imported seperately
bins.list = woebin(data_f.list$train,
                   "creditability",
                   save_breaks_list = "breaks.list")
```

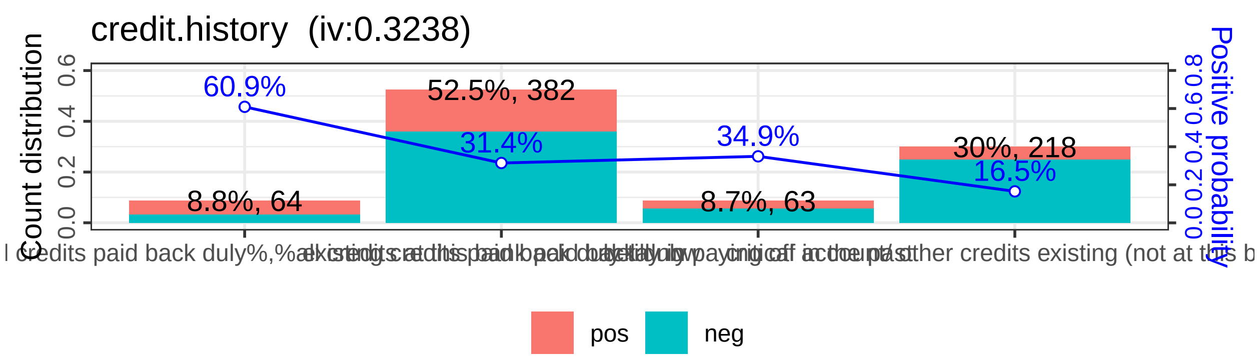
```
## $status.of.existing.checking.account
```



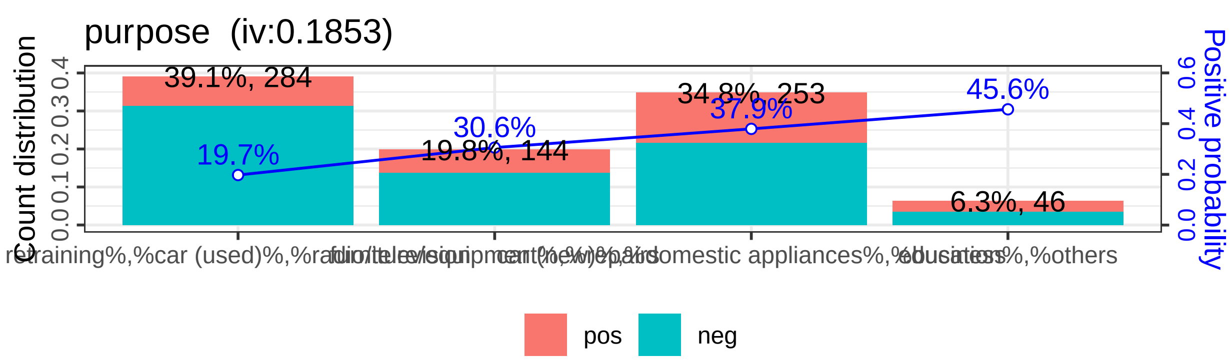

```
##
## $duration.in.month
```



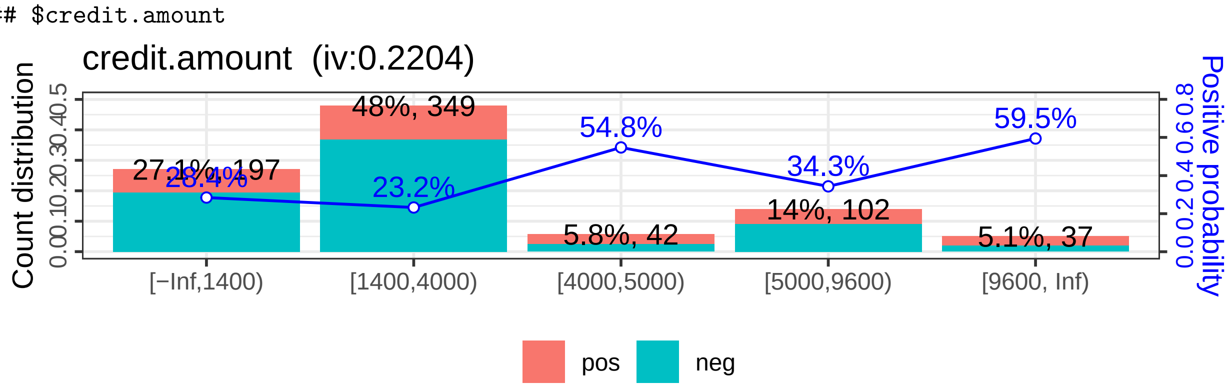

```
##
## $credit.history
```




```
##
## $purpose
```

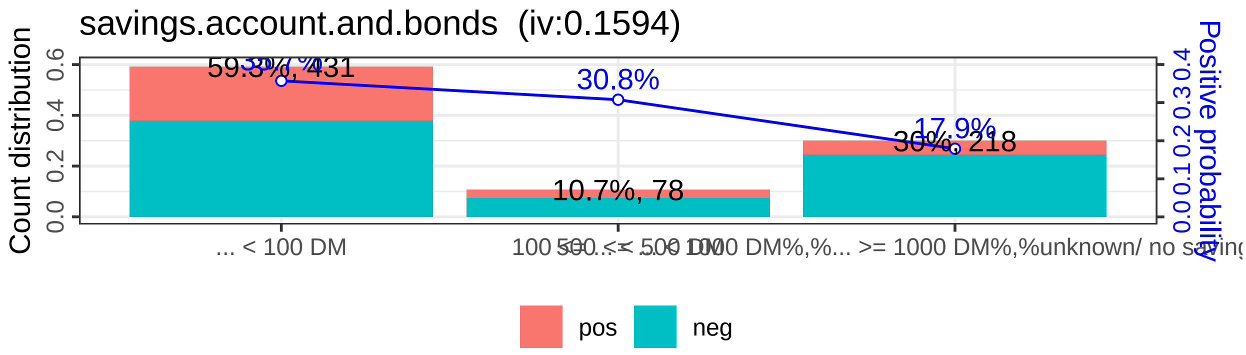



```
##
## $credit.amount
```

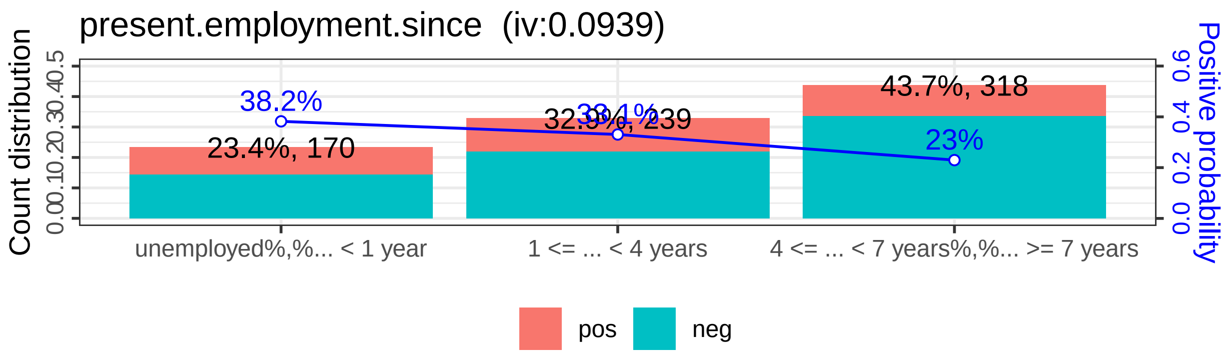



```
##
```

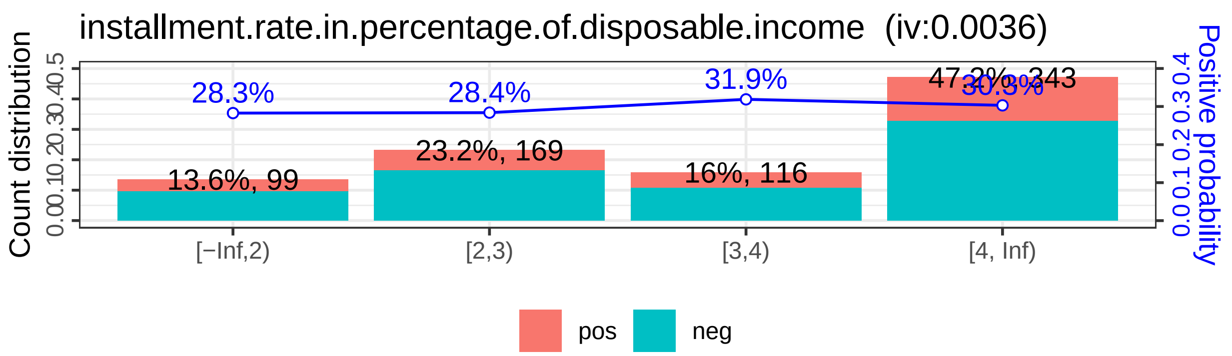
```
## $savings.account.and.bonds
```



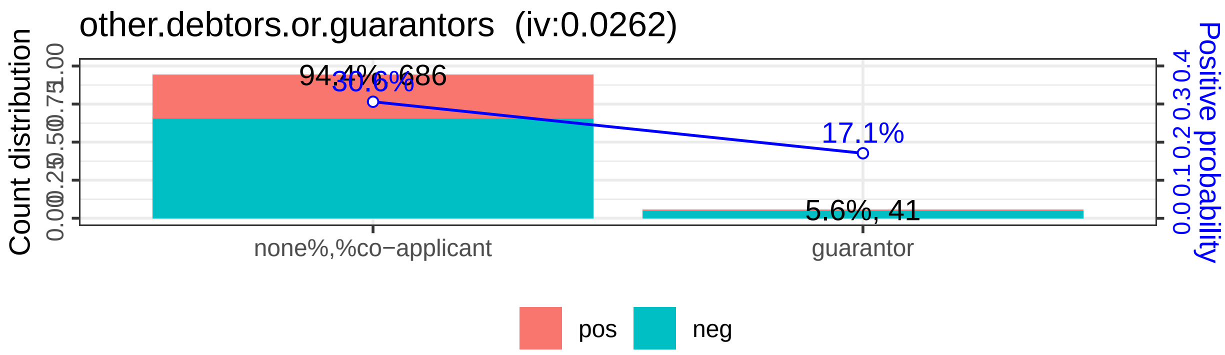

```
##
## $present.employment.since
```



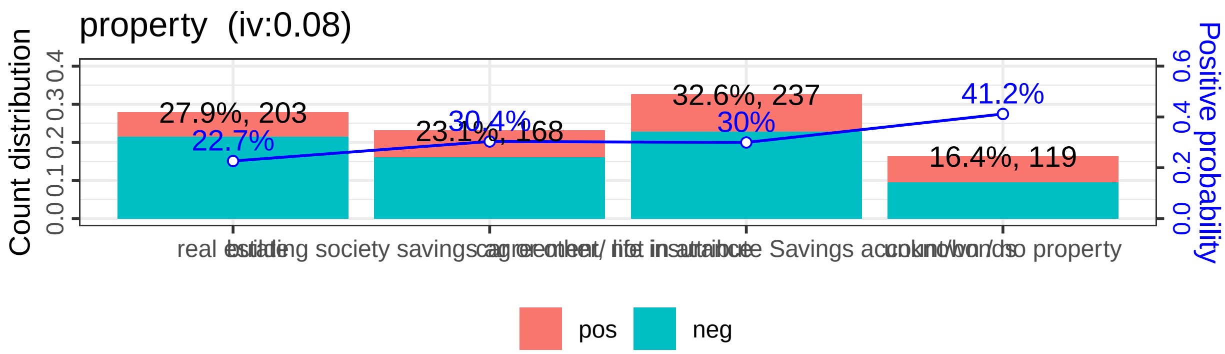

```
##
## $installment.rate.in.percentage.of.disposable.income
```



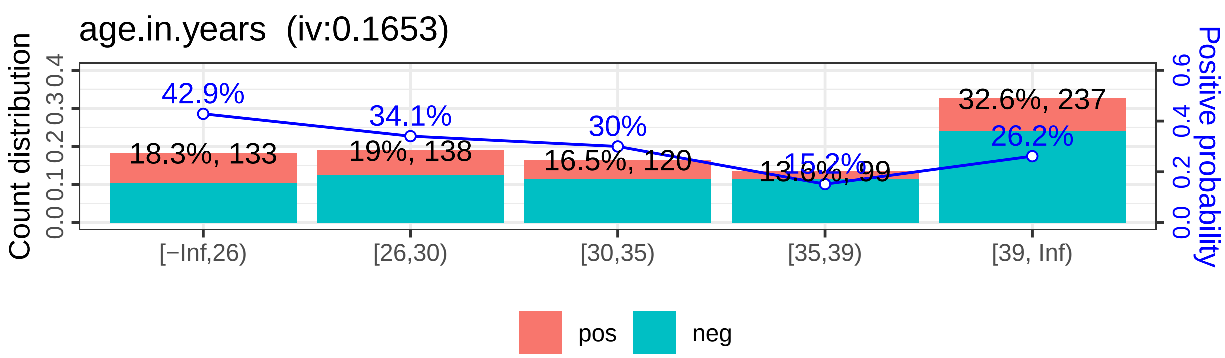

```
##
## $other.debtors.or.guarantors
```



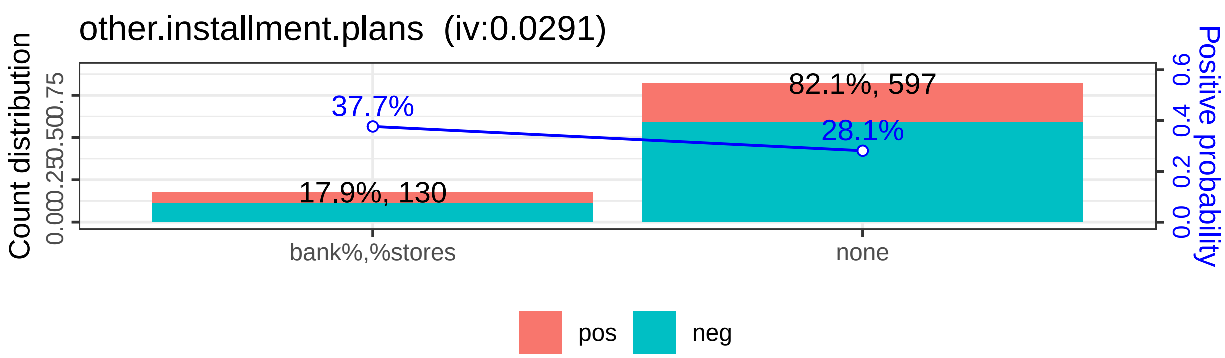

```
##
## $property
```




```
##
## $age.in.years
```

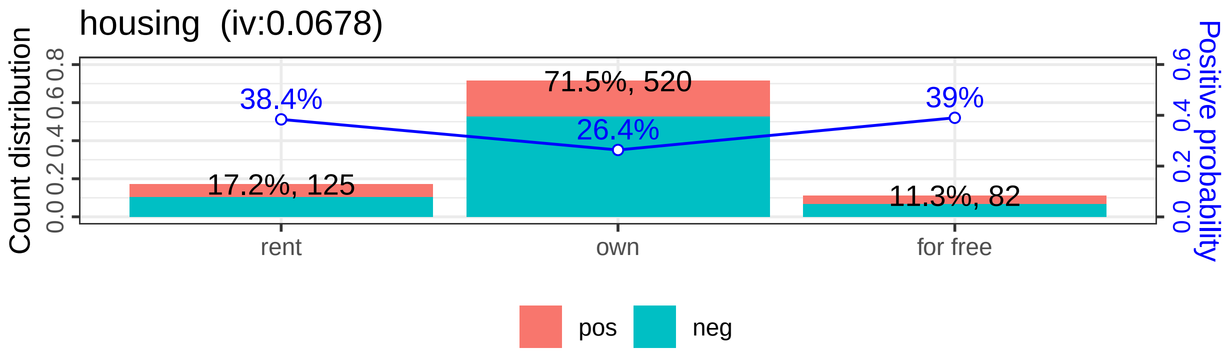



```
##
## $other.installment.plans
```




```
##
```

```
## $housing
```



- Transformation of predictor variables WOE and GRP:

```
# WOE-Transformation of train and test data
data_woe.list = lapply(data_f.list,
                       function(x) woebin_ply(x, bins.list))
lapply(data_woe.list, class)
lapply(data_woe.list, dim)

# Bin-Group (GRP) Transformation of train and test data
data_grp.list = lapply(data_f.list,
                       function(x) woebin_ply(x, bins.list, to = 'bin'))
lapply(data_grp.list, class)
lapply(data_grp.list, dim)
```

3.4 Generalized linear model (glm): Regressing response w.r.t. predictors

In this section, the logistic regression models are built. These models are used to select the seven most significant variables and subsequently to build the scorecard model with the chosen variables.

3.4.1 Selection of seven variables with Logistic regression w.r.t. WOE-transformed predictors

In order to select the seven most significant variables, a logistic regression is performed on the WOE-transformed predictor variables of the train data. The seven predictor variables which have the lowest significance value, are selected.

```
data_woe_first_iteration.glm <- glm(creditability ~ .,
                                    family = binomial(),
                                    data = data_woe.list$train)
summary(data_woe_first_iteration.glm)
```

```
##
## Call:
## glm(formula = creditability ~ ., family = binomial(), data = data_woe.list$train)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -2.0742  -0.6943  -0.3671   0.7495   2.4750
##
## Coefficients:
##                                                           Estimate Std. Error
## (Intercept)                                               -0.85979    0.09958
## status.of.existing.checking.account_woe                    0.82357    0.12779
```

```
## duration.in.month_woe                                     0.77204    0.19631
## credit.history_woe                                        0.66714    0.18079
## purpose_woe                                               1.01485    0.23555
## credit.amount_woe                                         0.73487    0.21701
## savings.account.and.bonds_woe                             0.80377    0.26016
## present.employment.since_woe                              0.59775    0.33021
## installment.rate.in.percentage.of.disposable.income_woe  2.95015    1.62616
## other.debtors.or.guarantors_woe                           1.17259    0.60659
## property_woe                                              0.12139    0.39847
## age.in.years_woe                                          0.96868    0.26093
## other.installment.plans_woe                               0.62812    0.58047
## housing_woe                                               0.37643    0.40013
##                                                          z value Pr(>|z|)
## (Intercept)                                               -8.634  < 2e-16 ***
## status.of.existing.checking.account_woe                    6.445 1.16e-10 ***
## duration.in.month_woe                                      3.933 8.40e-05 ***
## credit.history_woe                                         3.690 0.000224 ***
## purpose_woe                                                4.308 1.64e-05 ***
## credit.amount_woe                                          3.386 0.000708 ***
## savings.account.and.bonds_woe                              3.089 0.002005 **
## present.employment.since_woe                               1.810 0.070265 .
## installment.rate.in.percentage.of.disposable.income_woe   1.814 0.069650 .
## other.debtors.or.guarantors_woe                            1.933 0.053226 .
## property_woe                                               0.305 0.760642
## age.in.years_woe                                           3.712 0.000205 ***
## other.installment.plans_woe                                1.082 0.279215
## housing_woe                                                0.941 0.346826
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 886.32  on 726  degrees of freedom
## Residual deviance: 658.56  on 713  degrees of freedom
## AIC: 686.56
##
## Number of Fisher Scoring iterations: 5
```

The following seven predictor variables are selected as they have the lowest significance value (<0.01) and are therefore selected:

- status.of.existing.checking.account
- duration.in.month
- credit.history
- purpose
- credit.amount
- savings.account.and.bonds
- age.in.years

3.4.2 Logistic regression w.r.t. selected WOE-transformed predictors

The logistic regression model with the seven selected WOE-transformed predictor variables is built on the train data and saved in "data_woe_second_iteration.glm".

```
data_woe_second_iteration.glm <- glm(creditability ~ status.of.existing.checking.account_woe
                                     +duration.in.month_woe
                                     +credit.history_woe+purpose_woe+credit.amount_woe
                                     +savings.account.and.bonds_woe+age.in.years_woe,
                                    family = binomial(),
                                    data = data_woe.list$train)
```

3.4.3 Logistic regression w.r.t. selected GRP-transformed predictors

The logistic regression model with the seven selected GRP-transformed predictor variables is built on the train data and saved in "data_grp_second_iteration.glm".

```
data_grp_second_iteration.glm <- glm(creditability ~ status.of.existing.checking.account_bin
                                     +duration.in.month_bin
                                     +credit.history_bin+purpose_bin+credit.amount_bin
                                     +savings.account.and.bonds_bin+age.in.years_bin,
                                     family = binomial(),
                                     data = data_grp.list$train)
```

3.5 Building the scorecard-model

3.5.1 Scorecard-model w.r.t. WOE-transformed predictors

The scorecard is built with the logistic regression model of the seven WOE-transformed variables and is saved in "scorecard_woe_second_iteration.scm".

```
scorecard_woe_second_iteration.scm <- scorecard(bins.list,
                                               data_woe_second_iteration.glm)
```

The scores for the entire "germancredit" data are calculated and saved in "score_woe_second_iteration.df"

```
score_woe_second_iteration.df = scorecard_ply(germancredit,
                                             scorecard_woe_second_iteration.scm,
                                             only_total_score = FALSE)
```

The scores for the splitted "germancredit" data (train and test) are calculated and saved in "score_woe_second_iteration.list".

```
score_woe_second_iteration.list <- lapply(data_f.list,
                                         function(x) scorecard_ply(x,
                                            scorecard_woe_second_iteration.scm))
```

A report is generated for the scorecard model that includes information on the dataset, model coefficients, model performance, WOE binning, scorecard, population stability, and gains.

```
# Report of Scoreboard with WOE-transformed predictor variables
y<-"creditability"
x<-c("status.of.existing.checking.account","duration.in.month","credit.history",
      "purpose","credit.amount","savings.account.and.bonds",
      "age.in.years")

report(data_f.list,
       y,
       x,
```

```
        breaks.list,
        seed = NULL,
        save_report = "Report_WOE_second_iteration")
```

3.5.2 Scorecard-model w.r.t. GRP-transformed predictors

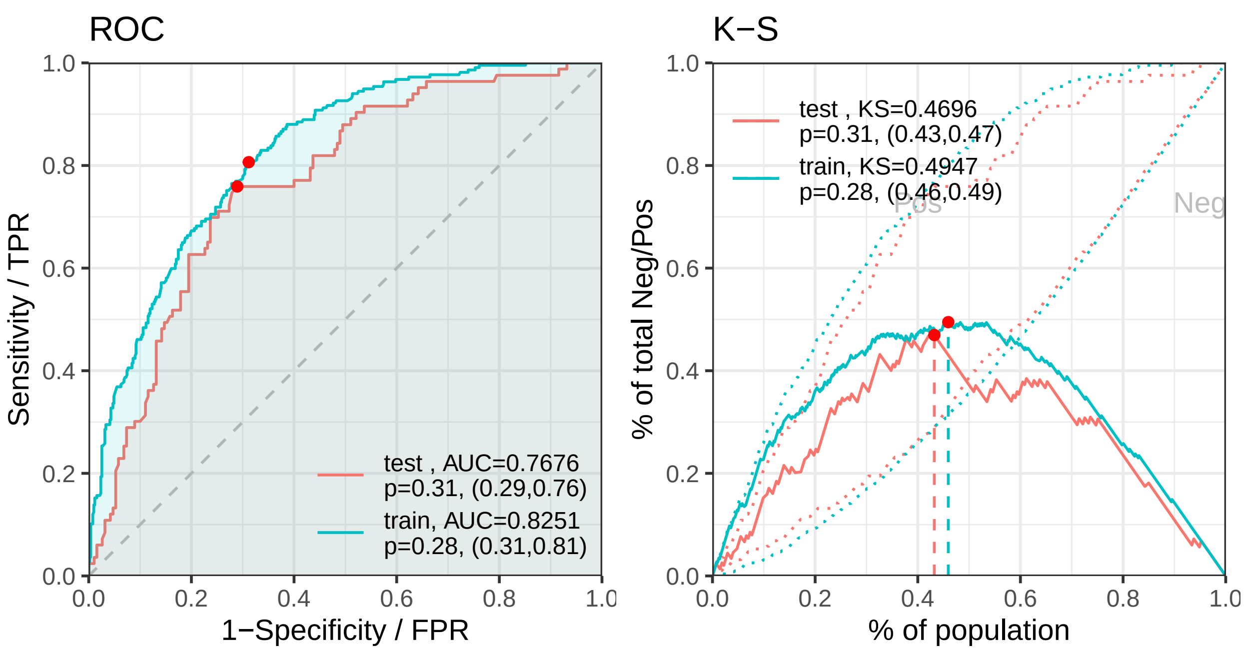
Building a scorecard with GRP-transformed predictor variables is unfortunately not supported by the "scorecard" library. Therefore, no report can be created as well. Nevertheless, the performance of the logistic model of the GRP-transformed predictor variables is compared with the logistic model of the WOE-transformed predictor variables in the next section.

3.6 Predicting (forecasting) probabilities and scorepoints

todo

3.7 Gini Coefficient In-Sample and Out-of-Sample

```
## [INFO] The threshold of confusion matrix is 0.2756.
```




```
## $binomial_metric
## $binomial_metric$train
##         Gini       AUC        R2      RMSE
## 1: 0.6502033 0.8251017 0.2775988 0.3889285
##
## $binomial_metric$test
##         Gini       AUC        R2      RMSE
## 1: 0.5352568 0.7676284 0.1618554 0.4211266
##
##
## $confusion_matrix
## $confusion_matrix$train
##    label pred_0 pred_1     error
## 1:     0    351    159 0.3117647
## 2:     1     42    175 0.1935484
```

```
## 3: total    393    334 0.2764787
##
## $confusion_matrix$test
##    label pred_0 pred_1     error
## 1:     0    128     62 0.3263158
## 2:     1     20     63 0.2409639
## 3: total    148    125 0.3003663
##
##
## $pic
## TableGrob (1 x 2) "arrange": 2 grobs
##   z     cells    name           grob
## 1 1 (1-1,1-1) arrange gtable[layout]
## 2 2 (1-1,2-2) arrange gtable[layout]
```

4 Summary

TODO

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