Predictive Analytics: Application in the Credit Risk Domain Case Study Teaching (CST)-Vignette in cheat sheet style ("group project cover sheet")

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1 Contextualization: Credit risk management domain - Specification

1.1 Methodological and linguistic overview

1.1.1 Empirical research methodology in the credit risk management domain

Two predicting models will be of special importance, i.e. Generalized Linear Models (glm) and Score Card Models (scm). As will be shown, the scm-models add two special concepts to the glm-models, i.e. the

1. **Classing/Binning/Grouping** concept, where the predictor variables are partioned into bins
2. **Weight-of-Evidence (woe)** concept for evaluating the predictive importance of the variables' bins (attributes)

The empirical research methodology deals with the construction, calibration and validation of credit scoring models.

Hint: "Risk Model Management" lecture at the TU Wien by Dr. Thomas Lederer, where the focus lies on the **construction, calibration and validation (CCV)** framework for predictive analytics in the risk management domain.

1.1.2 Credit risk management domain language

'Vocabulary and Syntax' of domain language, i.e. key domain concepts are

- Credit scoring model: **Scorecard model**, **logistic regression model**, decision tree model...
- Model **construction** step
  - Distinction between **binary response** (dependent) vs. **interval/nominal/ordinal predictor** (independent) variable
  - **Classing** predictor variables via **binning** interval (numeric) variables and **grouping** nominal (categorical/ordinal) variables
  - Using the **Weight-of-Evidence (woe)** metric in the predictor variables' classing
- Model **calibration** step: Stastistical **estimation of the models parameters** and statistical **testing of the model fit** via test statistics (e.g. Akaike Information Criteria abbreviated as **AIC**)
- Model **validation** step: Statistical **testing of the fitted models prediction accuracy** via in-sample and out-of-sample forecast accuracy tests (e.g. Area Under Curve abbreviated as **AUC** and **Gini** coefficient)

1.2 Literature References

Weight-of-Evidence (woe): Origins

- **?**
- **?**

Scorecard Model: Up-to-date article

Yap/Ong/Husain: Using data mining to improve assessment of credit worthiness via credit scoring models, Expert Systems with Applications, 38, 2011, 13274–13283

Scorecard Model - Reference Manual: Package 'scorecard', April 13, 2024

- https://cran.r-project.org/web/packages/scorecard/scorecard.pdf

Scorecard Model - Vignette: Developing a Credit Scorecard (Shichen Xie, Michael Thomas)

- https://cran.r-project.org/web/packages/scorecard/vignettes/demo.html

Credit Scoring Development Using R, Ng Yong Kad, 11/9/2020:

- https://rpubs.com/ngyongkad/scorecard

WoE, IV and Scorecards in Credit Risk Modelling, OEB, March 2018:

- https://rstudio-pubs-static.s3.amazonaws.com/376828_032c59adbc984b0ab892ce0026370352.html

Credit scorecard using Logistic Regression on R:

- https://stats.stackexchange.com/questions/419160/credit-scorecard-using-logistic-regression-on-r

2 Use Case Preparation: Loading and preparing data

2.1 Loading libraries: scorecard, tidyverse, knitr

```
library(scorecard)
library(tidyverse)
library(knitr)
```

2.2 Loading external data: germancredit

The variables are distinguished among predictor (feature, independent) variables and response (label, dependent) variables.

```
data("germancredit")
```

Variables: Names

```
germancredit %>% names()
```

```
##  [1] "status.of.existing.checking.account"
##  [2] "duration.in.month"
##  [3] "credit.history"
##  [4] "purpose"
##  [5] "credit.amount"
##  [6] "savings.account.and.bonds"
##  [7] "present.employment.since"
##  [8] "installment.rate.in.percentage.of.disposable.income"
##  [9] "personal.status.and.sex"
## [10] "other.debtors.or.guarantors"
## [11] "present.residence.since"
## [12] "property"
## [13] "age.in.years"
## [14] "other.installment.plans"
## [15] "housing"
## [16] "number.of.existing.credits.at.this.bank"
## [17] "job"
## [18] "number.of.people.being.liable.to.provide.maintenance.for"
## [19] "telephone"
## [20] "foreign.worker"
## [21] "creditability"
```

2.3 Selecting response and predictor variables for the use case: data.df

For demonstrating special considerations the following variables from the germancredit data are chosen:

- Response variable is (as always): **creditability** (binary)
- Five predictor variables:
  - **credit.amount** (numeric)
  - **duration.in.month** (numeric)
  - **credit.history** (factor)
  - **purpose** (character)
  - **property** (factor)

Hint: Consider the different primitive data types in R, i.e. numeric (num), factor (Factor), character (chr) and integer (int).

Selecting the response and the five predictor variables

```
data.df <- germancredit %>% select(
creditability,
status.of.existing.checking.account,
duration.in.month,
credit.history,
savings.account.and.bonds,
purpose
)


iv.df <- iv(data.df, y = "creditability")
```

Hint: Consider the different data types applied in R, i.e. vector, matrix, array, data frame (df) and list. Theses types will be indicated in the names of the variables, e.g. data.df is a data frame that contains the data.

Exemplarily showing the variables' contents

```
data.df %>%
  select(
    creditability,
    status.of.existing.checking.account,
    duration.in.month,
    credit.history,
    savings.account.and.bonds,
    purpose
  ) %>%
  head()
```

```
##   creditability status.of.existing.checking.account duration.in.month
## 1          good                          ... < 0 DM                 6
## 2           bad                   0 <= ... < 200 DM                48
## 3          good                 no checking account                12
## 4          good                          ... < 0 DM                42
## 5           bad                          ... < 0 DM                24
## 6          good                 no checking account                36
##                                               credit.history
## 1 critical account/ other credits existing (not at this bank)
## 2                   existing credits paid back duly till now
## 3 critical account/ other credits existing (not at this bank)
## 4                   existing credits paid back duly till now
```

Table 1: data.df

creditability	status.of.existing.checking.account	duration.in.month
good	... < 0 DM	6
bad	0 <= ... < 200 DM	48
good	no checking account	12
good	... < 0 DM	42
bad	... < 0 DM	24
good	no checking account	36

```
## 5                              delay in paying off in the past
## 6                     existing credits paid back duly till now
##     savings.account.and.bonds             purpose
## 1 unknown/ no savings account    radio/television
## 2                ... < 100 DM    radio/television
## 3                ... < 100 DM           education
## 4                ... < 100 DM furniture/equipment
## 5                ... < 100 DM           car (new)
## 6 unknown/ no savings account           education
```

The following chunk contains the code for generating Table **??**.

```
data.df[,1:3] %>%
  head() %>%
  kable(align = 'lccc',
        digits = 2,
        caption = "data.df")
```

```
data.df %>%
  select(creditability,
         status.of.existing.checking.account) %>%
  head()
```

```
##   creditability status.of.existing.checking.account
## 1          good                        ... < 0 DM
## 2           bad                 0 <= ... < 200 DM
## 3          good               no checking account
## 4          good                        ... < 0 DM
## 5           bad                        ... < 0 DM
## 6          good               no checking account
```

```
data.df %>%
  select(creditability,
         duration.in.month) %>%
  head()
```

```
##   creditability duration.in.month
## 1          good                 6
## 2           bad                48
## 3          good                12
## 4          good                42
## 5           bad                24
## 6          good                36
```

For checking the statistical relevance of the five predictor variables in the use case their information value is calclulated

```
data.df %>% iv(y="creditability")
```

```
##                             variable info_value
##                               <char>      <num>
## 1: status.of.existing.checking.account  0.6660115
## 2:                    duration.in.month  0.3345035
## 3:                       credit.history  0.2932335
## 4:             savings.account.and.bonds  0.1960096
## 5:                              purpose  0.1691951
```

Hint: All predictor variable have info_value > 0.02 so that they have relevance in predicting creditability

2.4 Filtering data and transforming data types: data_f.df

For filtering missing values, information values and identical values the var_filter() function is applied

```
data_f.df <- data.df %>%
  var_filter("creditability")
```

```
## v Variable filtering on 1000 rows and 5 columns in 00:00:00
## v 0 variables are removed in total
```

Exemplarily showing the variables' contents

```
data_f.df %>%
  select(
    creditability,
    status.of.existing.checking.account,
    duration.in.month,
    credit.history,
    savings.account.and.bonds,
    purpose
  ) %>%
  head()
```

```
##    creditability status.of.existing.checking.account duration.in.month
##            <int>                               <fctr>             <num>
## 1:             0                           ... < 0 DM                 6
## 2:             1                    0 <= ... < 200 DM                48
## 3:             0                  no checking account                12
## 4:             0                           ... < 0 DM                42
## 5:             1                           ... < 0 DM                24
## 6:             0                  no checking account                36
##                                                credit.history
##                                                        <fctr>
## 1: critical account/ other credits existing (not at this bank)
## 2:                   existing credits paid back duly till now
## 3: critical account/ other credits existing (not at this bank)
## 4:                   existing credits paid back duly till now
## 5:                               delay in paying off in the past
## 6:                   existing credits paid back duly till now
##      savings.account.and.bonds             purpose
##                         <fctr>              <char>
## 1: unknown/ no savings account    radio/television
## 2:                 ... < 100 DM    radio/television
## 3:                 ... < 100 DM           education
```

```
## 4:                  ... < 100 DM furniture/equipment
## 5:                  ... < 100 DM           car (new)
## 6: unknown/ no savings account           education
```

Hint: Consider the change of the data type of creditability from "factor" to "integer". This is important as now the **language of data science and machine learning** is applied, where the occurrence of the event is labeled with the number "1" as positive. Think of a medical test. A positive event means that something unwanted was found, so the positive test result is interpreted as "bad". The same reasoning applies in the credit risk context, where a positive occurrence of the default event is interpreted as "bad".

2.5 Splitting filtered data into train and validate samples: data_f.list

For having two independent samples for training and evaluation the filtered data frame is split into a list that contains two data frames, i.e. for the train and the validate samples

```r
data_f.list <- data_f.df %>%
  split_df("creditability",
           ratios = c(0.75,0.25),
           name_dfs = c('train','validate'))
```

Hint: For the use case the splitting is set to 75/25 % and the splitted samples are named **train** and **evaluate** instead of **test** for making clear that it belongs to the **validation step** of the risk model management process.

Hint: By default the splitting is 70/30 % for the train/validate samples, i.e. the argument is ratios=c(0.7,0.3) in the split_df() function. The standard names for the splitted samples are train and test in the function's argument name_dfs=c('train','test').

Exemplarily showing the content of the data_f.list

```r
data_f.list %>% class()
```

```
## [1] "list"
```

```r
data_f.list %>% lapply(class)
```

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

```r
data_f.list %>% lapply(dim)
```

```
## $train
## [1] 727   6
##
## $validate
## [1] 273   6
```

```r
data_f.list$train %>% str()
```

```
## Classes 'data.table' and 'data.frame':   727 obs. of  6 variables:
##  $ status.of.existing.checking.account: Factor w/ 4 levels "... < 0 DM","0 <= ... < 200 DM",..: 1 1 
##  $ duration.in.month                  : num  6 42 24 36 24 12 30 12 15 24 ...
##  $ credit.history                     : Factor w/ 5 levels "no credits taken/ all credits paid back 
##  $ savings.account.and.bonds          : Factor w/ 5 levels "... < 100 DM",..: 5 1 1 5 3 4 1 1 1 2 ..
##  $ purpose                            : chr  "radio/television" "furniture/equipment" "car (new)" "e
##  $ creditability                      : int  0 0 1 0 0 0 1 1 0 1 ...
```

```
##  - attr(*, ".internal.selfref")=<externalptr>
```

2.6 Specifying dummy variable for credit defaults: default.list

For being able to statistically analyze and test the results from the scorecard the default.list is established that contains the default values of the response variable

```
default.list <- data_f.list %>%
  lapply(function(x) x$creditability)
```

Hint: The default.list is needed for calculating the population stability indes (PSI) with the function perf_psi() and the gains table with the function gains_table().

Exemplarily showing the content of the default.list

```
default.list %>% str()
```

```
## List of 2
##  $ train   : int [1:727] 0 0 1 0 0 0 1 1 0 1 ...
##  $ validate: int [1:273] 1 0 0 1 0 1 1 0 0 1 ...
```

3 Weight-Of-Evidence (WoE)-based transformation of predictor variables

3.1 WoE-based binning of train and validate samples: bins.list

WoE-based classing, i.e. binning and grouping of predictor variables

```
bins.list <- data_f.list$train %>%
  woebin("creditability")
```

```
## v Binning on 727 rows and 6 columns in 00:00:10
```

Hint: The default binning method is method="width". Other methods are

- "frequ" that support numerical variables as well as
- "tree" and "chimerge" supporting both, i.e. numerical and categorical variables which are used in the optimal binning approach.

```
bins.list %>% names()
```

```
## [1] "status.of.existing.checking.account" "duration.in.month"
## [3] "credit.history"                      "savings.account.and.bonds"
## [5] "purpose"
```

Plotting the bins (including bin statistics)

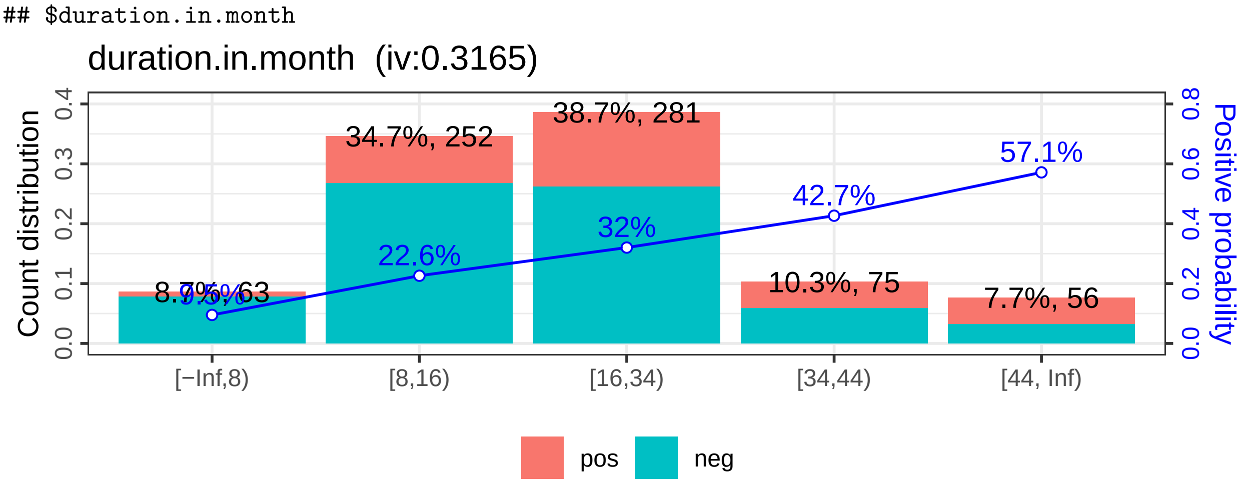
```
bins.list$credit.amount %>%
  woebin_plot()
```

```
## list()
```

Hint: credit.amount does not have an acceptable structure of the default rates (positive probability) over the bins like e.g. a linear or u-curve structure; hence it should not be included in the scorecard model!

```
bins.list$duration.in.month %>%
  woebin_plot()
```

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



Hint: duration.in.month has lineare structure of the default rates; hence it should be included in the scorecard model!

Excursion: Manual bin-adjustments

Bins can be altered manually by

1. Saving the bin list generated in the woebin() function via e.g. save_as="breaks2410.list"
2. Loading the saved R-file "breaks2410.list.R", editing the breaks as needed and storing the file
3. Sourcing the edited and stored "breaks2410.list.R" file with the "source(…)$value" function
4. Binning the data again with the "woebin()" function with the additional argument "break_list"

ad 1)

```
bins.list <- data_f.list$train %>%
  woebin("creditability",
         save_as = "breaks2410.list")
```

ad 3)

```
breaksList <- source("breaks2410.list.R")$value
```

ad 4)

```
bins.list <- data_f.list$train %>%
  woebin("creditability",
         breaks_list = "breaksList")
```

Hint: The above code chunks are not yet evaluated, as they are performed only when the original binning does not deliver beneficial results.

3.2 WoE-based transforming of predictor variables: data_woe.list

3.2.1 WoE-based transforming of train and validate data: data_woe.list

Transforming splitted sample: Needed for train/validate analysis

```
data_woe.list <- data_f.list %>%
  lapply(function(x) woebin_ply(x, bins.list))
```

```
## v Woe transformating on 727 rows and 5 columns in 00:00:10
## v Woe transformating on 273 rows and 5 columns in 00:00:10
```

```
data_woe.list %>% lapply(class)
```

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

```
data_woe.list %>% lapply(dim)
```

```
## $train
## [1] 727   6
##
## $validate
## [1] 273   6
```

```
#data_woe.list$train %>%
#  select(creditability, credit.amount_woe, duration.in.month_woe) %>%
#  head()
```

4 Generalized linear model (glm): Regressing predictors against responses

4.1 Logistic regression of WoE-transformed predictors: glm(.,data_woe.list$train)

The WoE-based logistic regression is the preferred regression approach as it delivers the most compact regression models.

4.1.1 Constructing and calibrating the WoE-based logistic regression model

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

4.1.2 Investigating the fitted regression model

```
data_woe.glm$aic
```

```
## [1] 711.2915
```

Summary of regression: summary()

```
data_woe.glm %>% summary()
```

```
##
## Call:
## glm(formula = creditability ~ ., family = binomial(), data = data_woe.list$train)
##
## Coefficients:
##                                       Estimate Std. Error z value Pr(>|z|)
## (Intercept)                           -0.84422    0.09532  -8.857  < 2e-16
## status.of.existing.checking.account_woe  0.83286    0.12266   6.790 1.12e-11
## duration.in.month_woe                  0.96608    0.17657   5.471 4.46e-08
## credit.history_woe                     0.78853    0.16945   4.653 3.26e-06
## savings.account.and.bonds_woe          0.86020    0.24723   3.479 0.000503
## purpose_woe                            0.94490    0.22095   4.277 1.90e-05
##
## (Intercept)                           ***
## status.of.existing.checking.account_woe ***
## duration.in.month_woe                 ***
## credit.history_woe                    ***
## savings.account.and.bonds_woe         ***
## purpose_woe                           ***
## ---
## 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: 699.29  on 721  degrees of freedom
## AIC: 711.29
##
## Number of Fisher Scoring iterations: 5
```

4.2 Logistic regression of original predictors: glm(.,data_f.list$train)

```
#data_f.glm <- glm(creditability ~ .,
 #                 family = binomial(),
  #                data = data_f.list$train %>%
   #                 select(creditability,
     #                      credit.amount,
    #                       duration.in.month,
   #                        credit.history))
```

Hint: For simplicity only three original predictors are included in the logistic regression model

```
#data_f.glm$aic
```

```
#data_f.glm$xlevels
```

For getting a compact summary the function summary() is customized and formatted

```
formatSummary <- function(model_summary) {
  aux_coeff <- model_summary$coefficients[, 1]
  aux_prob <- model_summary$coefficients[, 4]
  aux_stars <- symnum(aux_prob,
                      corr = FALSE,
                      na = FALSE,
                      cutpoints = c(0, 0.001, 0.01, 0.05, 0.1, 1),
                      symbols = c("***", "**", "*", ".", " "))
  names(aux_coeff) <- str_trunc(names(aux_coeff),
                               width = 40)
  aux_result <- data.frame(Estimate = aux_coeff,
                          Prob_z = aux_prob,
                          "Stars" = aux_stars)
  return(aux_result)
}
```

```
#summary(data_f.glm) %>% formatSummary()
```

5 Building scorecard-models (scm) and calculating scorepoints

Scorepoints are calculated by combing scorecard-model, which combines bin and glm information, with individual data

5.1 Building scm-models: Combining bins.list & data_woe.glm in scorecard()

Building the scorecard via bin and glm information resulting from train sample

```
scorecard.scm <- bins.list %>% scorecard(data_woe.glm)
```

```
scorecard.scm %>% names()
```

```
## [1] "basepoints"                           "status.of.existing.checking.account"
## [3] "duration.in.month"                    "credit.history"
## [5] "savings.account.and.bonds"            "purpose"
```

Investigating the content of the "woe-based" scorecard model

```
scorecard.scm$basepoints
```

```
##      variable    bin    woe points
##        <char> <lgcl> <lgcl>  <num>
## 1: basepoints     NA     NA    449
```

```
scorecard.scm$duration.in.month[,1:8]
```

```
##             variable       bin count count_distr   neg   pos   posprob
##               <char>    <char> <int>       <num> <int> <int>     <num>
## 1: duration.in.month  [-Inf,8)    63  0.08665750    57     6 0.0952381
## 2: duration.in.month    [8,16)   252  0.34662999   195    57 0.2261905
## 3: duration.in.month   [16,34)   281  0.38651994   191    90 0.3202847
## 4: duration.in.month   [34,44)    75  0.10316369    43    32 0.4266667
## 5: duration.in.month [44, Inf)    56  0.07702889    24    32 0.5714286
##           woe
##         <num>
## 1: -1.3967784
## 2: -0.3754349
## 3:  0.1020496
## 4:  0.5590492
## 5:  1.1421954
```

```
scorecard.scm$duration.in.month[,c(1,9:13)]
```

```
##             variable      bin_iv  total_iv breaks is_special_values points
##               <char>       <num>     <num> <char>            <lgcl>  <num>
## 1: duration.in.month 0.117489928 0.3165171      8             FALSE     97
## 2: duration.in.month 0.044932100 0.3165171     16             FALSE     26
## 3: duration.in.month 0.004106144 0.3165171     34             FALSE     -7
## 4: duration.in.month 0.035304912 0.3165171     44             FALSE    -39
## 5: duration.in.month 0.114683977 0.3165171    Inf             FALSE    -80
```

5.2 Calculating scorepoints: Combinig individual data.df & scm-model in scorecard_ply()

Generating a score list

```
score.list <- data_f.list %>%
  lapply(function(x) scorecard_ply(x, scorecard.scm))
```

Hint: The only_total_score=TRUE (= default argument) has to be used for providing two compatible lists for further processing. If scores to the different predictors are of interest, the two separate, i.e. train and validate samples have to analyzed individually with the argument only_total_score=FALSE.

```
score.list %>% names()
```

```
## [1] "train"    "validate"
```

```
score.list$train %>%
  head()
```

```
##    score
##    <num>
## 1:   633
## 2:   351
## 3:   351
## 4:   477
## 5:   553
## 6:   625
```

```
score.list$validate %>%
  head()
```

```
##    score
##    <num>
## 1:   349
## 2:   531
## 3:   390
## 4:   287
## 5:   455
## 6:   408
```

6 WoE-based predicting (forecasting) of probabilities and score-points

6.1 Predicting probabilities: Combining data_woe.list & data_woe.glm in predict()

```
predProb.list <- data_woe.list %>%
  lapply(function(x) predict(data_woe.glm,
                              type = 'response',
                              x))
```

Hint: Due to the fact that the data_woe.glm was calibrated for the train sample two different types of prediction can be destinguished, i.e. the in-sample (IS) prediction by using the train sample in the predict()-function, and the out-of-sample (OoS) prediction by using the test sample in the predict()-function.

```
predProb.list %>% names()
```

```
## [1] "train"    "validate"
```

```
predProb.list$train %>% head() # In-Sample prediction
```

```
##          1          2          3          4          5          6
## 0.03257030 0.62644835 0.62511261 0.22923725 0.09405324 0.03635829
```

```
predProb.list$validate %>% head() # Out-of-Sample prediction
```

```
##         1         2         3         4         5         6
## 0.6293632 0.1222070 0.4915309 0.8008039 0.2815743 0.4315283
```

6.2 Predicting scorepoints: Retrieving predictions from score.list generated in scorecard_ply()

The prediction of the scorepoints is alread incorported in the built scorecard.

```
score.list$train %>%
  head()
```

```
##    score
##    <num>
## 1:   633
## 2:   351
## 3:   351
## 4:   477
## 5:   553
## 6:   625
```

```
score.list$validate %>%
  head()
```

```
##    score
##    <num>
## 1:   349
## 2:   531
## 3:   390
## 4:   287
## 5:   455
## 6:   408
```

7 Scorecard Validation: Statistical testing of forecasting accuracy

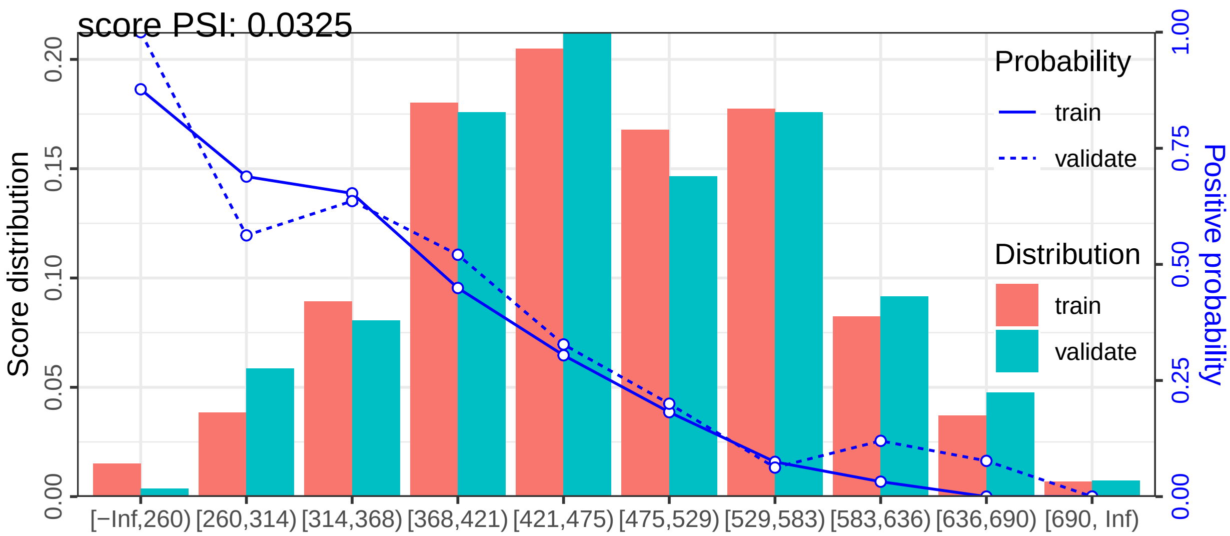
7.1 Checking stability of score and probility distributions: Population Stability Index (PSI)

```
psi.list <- perf_psi(score = score.list,
                     label = default.list,
                     return_distr_dat = TRUE)
```

Hint: More details of per_psi() function are given @ https://www.rdocumentation.org/packages/scorecard/versions/0.1.9/topics/perf_psi

```
psi.list$pic
```

```
## $score
```




```
psi.list %>% names()
```

```
## [1] "pic" "psi" "dat"
```

```
psi.list$dat %>% names()
```

```
## [1] "score"
```

```
psi.list$dat$score[,1:9] %>% head()
```

```
## Key: <datset>
##    datset        bin count cum_count   neg   pos cum_neg cum_pos count_distr
##    <fctr>     <fctr> <int>     <int> <int> <int>   <int>   <int>       <num>
## 1:  train [-Inf,260)    11        11     1    10       1      10      0.0151
## 2:  train  [260,314)    28        39     8    20       9      30      0.0385
## 3:  train  [314,368)    65       104    21    44      30      74      0.0894
## 4:  train  [368,421)   131       235    70    61     100     135      0.1802
## 5:  train  [421,475)   149       384   102    47     202     182      0.2050
## 6:  train  [475,529)   122       506    99    23     301     205      0.1678
```

```
psi.list$psi
```

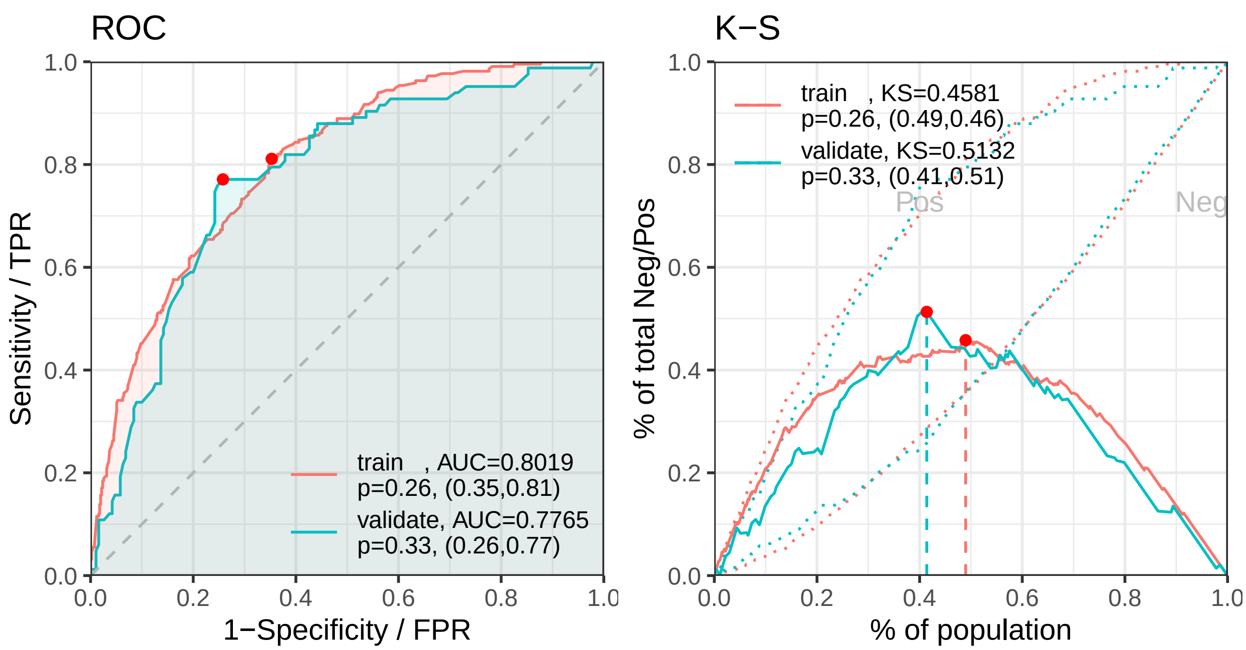
```
##    variable        dataset        psi
##      <char>         <char>      <num>
## 1:    score train_validate 0.03247355
```

```r
perf_psi(score, label = NULL, title = NULL, x_limits = NULL,
  x_tick_break = 50, show_plot = TRUE, seed = 186,
  return_distr_dat = FALSE)
# e.g. # x_limits = c(250, 700),
#      # x_tick_break = 50,
```

7.2 IS & OoS testing probability prediction accuracy: perf_eva(.,predProb.list)

probability prediction accuracy

```r
ProbPredAccuracy <- perf_eva(pred = predProb.list,
                             label = default.list,
                             binomial_metric = c("rmse","auc","gini"),
                             show_plot=c("roc","ks"),
                             confusion_matrix = TRUE)
```




```r
names(ProbPredAccuracy)
```

```
## [1] "binomial_metric"  "confusion_matrix" "pic"
```

```r
ProbPredAccuracy$binomial_metric
```

```
## $train
##         RMSE       AUC      Gini
##        <num>     <num>     <num>
## 1: 0.3998542 0.8018569 0.6037137
##
## $validate
##         RMSE      AUC     Gini
##        <num>    <num>    <num>
## 1: 0.4150501 0.776506 0.553012
```

```r
ProbPredAccuracy$confusion_matrix
```

```
## $train
```

```
##     label pred_0 pred_1     error
##    <char>  <num>  <num>     <num>
## 1:      0    330    180 0.3529412
## 2:      1     41    176 0.1889401
## 3:  total    371    356 0.3039890
##
## $validate
##     label pred_0 pred_1     error
##    <char>  <num>  <num>     <num>
## 1:      0    122     68 0.3578947
## 2:      1     17     66 0.2048193
## 3:  total    139    134 0.3113553
```

Excursion

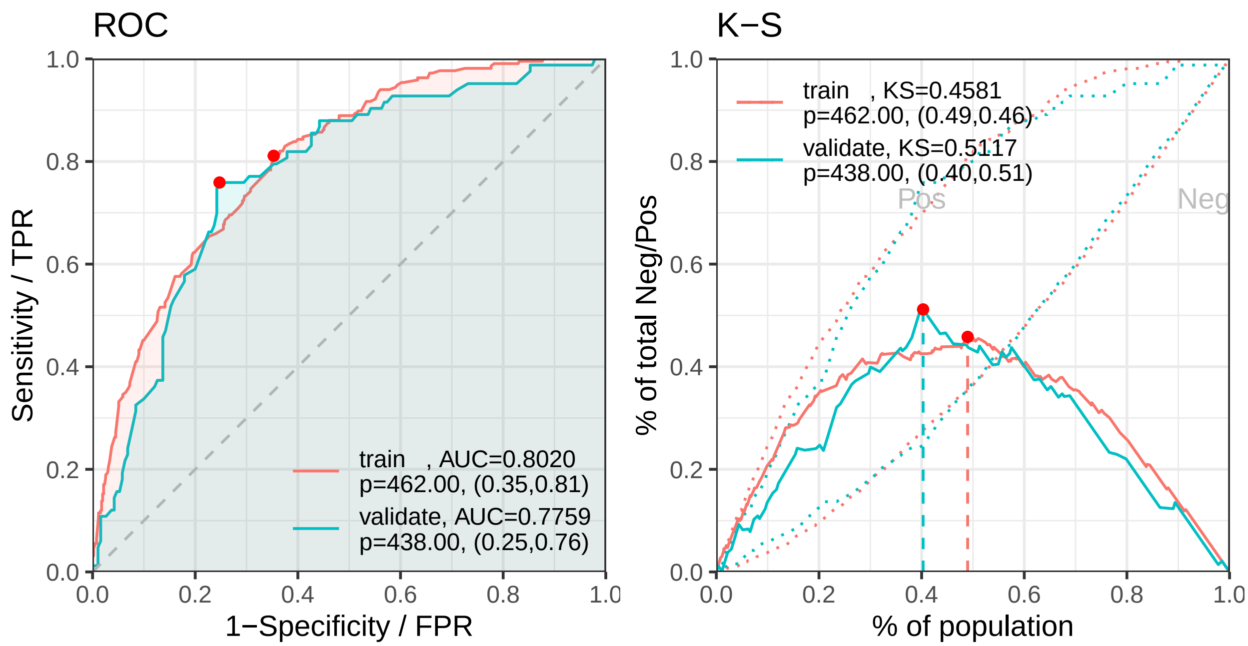
```r
perf_eva(pred = predProb.list,
         label = default.list,
         binomial_metric = c("rmse","auc","gini"),
         show_plot= FALSE,
         confusion_matrix = FALSE)
```

```
## $binomial_metric
## $binomial_metric$train
##         RMSE       AUC      Gini
##        <num>     <num>     <num>
## 1: 0.3998542 0.8018569 0.6037137
##
## $binomial_metric$validate
##         RMSE      AUC     Gini
##        <num>    <num>    <num>
## 1: 0.4150501 0.776506 0.553012
```

7.3 IS & OoS testing scorepoint prediction accuracy: perf_eva(.,score.list)

scorepoint prediction accuracy

```r
ScorePredAccuracy <- perf_eva(pred = score.list,
                              label = default.list,
                              binomial_metric = c("rmse","auc","gini"),
                              show_plot=c("roc","ks"),
                              confusion_matrix = TRUE)
```




```r
names(ScorePredAccuracy)
```

```
## [1] "binomial_metric"  "confusion_matrix" "pic"
```

```r
ScorePredAccuracy$binomial_metric
```

```
## $train
##          AUC      Gini
##        <num>     <num>
## 1: 0.8019563 0.6039125
##
## $validate
##          AUC      Gini
##        <num>     <num>
## 1: 0.7759036 0.5518072
```

```r
ScorePredAccuracy$confusion_matrix
```

```
## $train
##     label pred_0 pred_1     error
##    <char>  <num>  <num>     <num>
## 1:      0    330    180 0.3529412
## 2:      1     41    176 0.1889401
## 3:  total    371    356 0.3039890
##
## $validate
##     label pred_0 pred_1     error
##    <char>  <num>  <num>     <num>
## 1:      0    122     68 0.3578947
## 2:      1     17     66 0.2048193
## 3:  total    139    134 0.3113553
```

8 Appendix

8.1 Appendix: Essay style with formulas in LaTeX language

Group project assignment: Write a scholarly essay with full sentences, correct citations and LaTeX formulas.

Example essay style: From a statistical perspective the transition from the MPS to the VaR framework is related to switching the perspective from considering moments (parameters) of random variables, i.e. μ and σ, to considering the quantiles and corresponding probabilities of these variables. Specifically, the VaR measure specifies the risk of a random variable ($\tilde{P}$) via the threshold quantile (VaR) that is exceeded into the negative direction (i.e. $P \leq VaR$) with the loss probability (α) or respectively, is exceeded into the positive direction (i.e. $P > VaR$) with the complementary probability, i.e. the confidence level $(1 - \alpha)$.

8.2 Appendix: Generating tables, figures, cross references and citations

```
data.df[1:100,2:3] %>% plot()
```

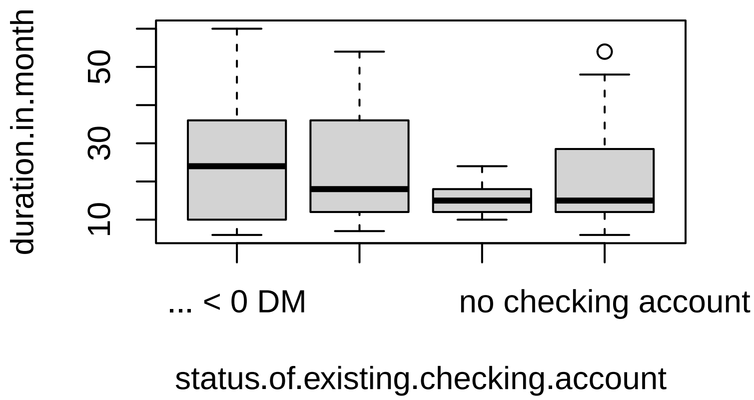


Figure 1: Amount vs. Duration

Figure **??** is a sample figure where the credit.amount is scatter plotted against the duration.in.month.

Formulas without numbering

$$\Pr\{\tilde{P} \leq VaR\} = \alpha$$

Formulas with numbering (and labeling which is needed for referencing)

$$\Pr\{\tilde{P} \leq VaR\} = \alpha \tag{1}$$

Formula (**??**) is a sample formula defining the Value at Risk.

Always cite original literature to avoid plagiarism: e.g. **?** or (**?**). Don't forget to cite page numbers as well for literal citations, e.g. (**?**, p. 100).