"German Credit" scoring data analysis report

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Part I
Introduction

In this part of the report we provide answers to the following questions about the "German Credit" data analysis we performed.

1. *Why was the study undertaken?*
2. *What was the purpose of the research? What research questions were stated?*

1 Data analysis context

1.1 Motivation

This report presents results of the "German Credit" scoring data analysis which was performed as a project assignment for the "Pozyskiwanie Wiedzy" course, which we attended at Wroclaw University of Technology, Faculty of Fundamental Problems of Technology (W-11), Mathematics programm (Master) in the 2014/15 summer semester. The lecturer of the course (both lectures and laboratories) is Ph.D. Adam Zagdański.

The main goal of the project is to make use of the variety of data-mining methods we have become familiar with during the course, in order to perform complete data analysis of selected data set. We also aim to pay attention to the practical appliacnces of some parts of our work.

1.2 Research questions

We stated the following research purposes for our analysis.

1. Find and describe relations in the data (relations bewteen explanatory variables and response variable, relations bewteen explanatory variables).
2. Compare different methods / algorithms to perform exploratory data analysis and predictive data analysis.
3. Provide a summary of the analysis, containing suggestions of practical appliance and remarks regarding possible further research.

Part II
Materials and methods

In this part of the report we describe the data set we obtained and the methods we use in the analysis.

This section is rather of the decriptional / theoretical character. For a list of actual analysis steps, the outputs of the methods and more, please refer to the III part of this report.

2 Data set

We perform analysis with the use of The (Statlog) German Credit Data we have obtained from the UCI Machine Learning Repository site.

2.1 Data set description

The data set contains data on 20 variables and the classification whether an applicant is considered a Good or a Bad credit risk for 1000 loan applicants. The file provided contains variables with values encoded accoring to the following schema:

- Attribute 1: (qualitative) Status of existing checking account
  A11 : ... < 0 DM
  A12 : 0 <= ... < 200 DM
  A13 : ... >= 200 DM / salary assignments for at least 1 year
  A14 : no checking account
- Attribute 2: (numerical) Duration in month
- Attribute 3: (qualitative) Credit history
  A30 : no credits taken/ all credits paid back duly
  A31 : all credits at this bank paid back duly
  A32 : existing credits paid back duly till now
  A33 : delay in paying off in the past
  A34 : critical account/ other credits existing (not at this bank)
- Attribute 4: (qualitative) Purpose
  A40 : car (new)
  A41 : car (used)
  A42 : furniture/equipment
  A43 : radio/television
  A44 : domestic appliances
  A45 : repairs
  A46 : education
  A47 : (vacation - does not exist?)
  A48 : retraining
  A49 : business
  A410 : others

- Attribute 5: (numerical) Credit amount
- Attribute 6: (qualitative) Savings account/bonds
  A61 : ... < 100 DM
  A62 : 100 <= ... < 500 DM
  A63 : 500 <= ... < 1000 DM
  A64 : .. >= 1000 DM
  A65 : unknown/ no savings account
- Attribute 7: (qualitative) Present employment since
  A71 : unemployed
  A72 : ... < 1 year
  A73 : 1 <= ... < 4 years
  A74 : 4 <= ... < 7 years
  A75 : .. >= 7 years
- Attribute 8: (numerical) Installment rate in percentage of disposable income
- Attribute 9: (qualitative) Personal status and sex
  A91 : male : divorced/separated
  A92 : female : divorced/separated/married
  A93 : male : single
  A94 : male : married/widowed
  A95 : female : single
- Attribute 10: (qualitative) Other debtors / guarantors
  A101 : none
  A102 : co-applicant
  A103 : guarantor
- Attribute 11: (numerical) Present residence since
- Attribute 12: (qualitative) Property
  A121 : real estate
  A122 : if not A121 : building society savings agreement/ life insurance
  A123 : if not A121/A122 : car or other, not in attribute 6
  A124 : unknown / no property
- Attribute 13: (numerical) Age in years
- Attribute 14: (qualitative) Other installment plans
  A141 : bank
  A142 : stores
  A143 : none
- Attribute 15: (qualitative) Housing
  A151 : rent
  A152 : own
  A153 : for free
- Attribute 16: (numerical) Number of existing credits at this bank

- Attribute 17: (qualitative) Job
  A171 : unemployed/ unskilled - non-resident
  A172 : unskilled - resident
  A173 : skilled employee / official
  A174 : management/ self-employed/ highly qualified employee/ officer
- Attribute 18: (numerical) Number of people being liable to provide maintenance for
- Attribute 19: (qualitative) Telephone
  A191 : none
  A192 : yes, registered under the customers name
- Attribute 20: (qualitative) foreign worker
  A201 : yes
  202 : no

3 Feature selection

Following [1], feature selection is essentially a task to remove irrelevant and/or redundant features. *Irrelevant features* cam be removed without affecting learning performance. *Redundant features* are a type of irrelevant feature. The distinction is that redundant feature implies the co-presence of another feature; individually, each feature is relevant, but the removal of one of them will not affect learning performance.

The selection of features may be achieved in two ways:

1. **Feature ranking**. The idea is to rank features according to some criterion and select the top k features.
2. **Subset selection**. The idea is to select a minimum subset of features without learning performance deterioration.

In other words, subset selection algorithms can automatically determine the number of selected features, while feature ranking algorithms need to rely on some given threshold to select features.

The tree typical feature selection models are:

1. **Filter**. In a filter model, one selects the features firstly and then uses this subset to execute a classification algorithm.
2. **Wrapper**. In a wrapper model, one employs a learning algorithm and uses its performance to determine the quality of selected features.
3. **Embedded**. An embedded model of features selection integrates the selection of features in model builidng. An example of such model is a decision tree induction algorithm, in which at each branching node, a feature has to be selected.

In literature, various search strategies are proposed, including: forward, backward, floating, branch-and-bound, and randomized. A relevant issue, regarding exhaustive and heuristic searches is whether there is any reason to perform exhaustive searches if time complexity were not a concern. Research shows that exhaustive search can lead to the features that exacerbate data oerfitting, while heuristic search is less prone to data overfitting in feature selection, facing small data samples.

The evaluation of feature selection often entails two tasks:

1. One is to compare two cases: before and after feature selection. The goal of this task is to observe if feature selection achieves its intended objectives. The aspects of evaluation may include the number of selected features, time, scalability and learning model's performance.
2. The second task is to compare two feature selection algorithms to see if one is better than other for a certain task.

3.1 Feature selection algorithms

In this subsection we describe methods for feature selection we use in our analysis. In general, we use the FSelector R package exhaustively. This package contains both algorithms for filtering attributes and algorithms for wrapping classifiers and search attribute subset space.

3.1.1 Algorithms for filtering attributes

CFS filter CFS is a correlation-based filter method CFS from [2]. It gives high scores to subsets that include features that are highly correlated to the class attribute but have low correlation to each other. Let $Attribute$ be an attribute subset that has k attributes, rcf models the correlation of the attributes to the class attribute, rff - the intercorrelation between attributes. We define $Attribute$ score as:

$$CfsScore(Attribute) = \frac{k\ rcf}{\sqrt{k + k(k-1)rff}}.$$

The algorithm from FSelector R package makes use of *Best-first search* for searching the attribute subset space. In *Best-first search*, the algorithm chooses the best node from all already evaluated ones and evaluates it. The selection of the best node is repeated approximately *max.brackets* times in case no better node found.

Chi-squared filter The algorithm evaluates the worth of an attribute by computing the value of the chi-squared statistic with respect to the class.

Information Gain filter One of the entropy-based filters. Algorithm evaluates the worth of an attribute by measuring the information gain with respect to the class.

$$InfoGain(Class, Attribute) = H(Class) + H(Attribute) - H(Class|Attribute),$$

where H is the information entropy.

Gain Ratio filter One of the entropy-based filters. Algorithm evaluates the worth of an attribute by measuring the gain ratio with respect to the class.

$$GainR(Class, Attribute) = \frac{H(Class) + H(Attribute) - H(Class|Attribute)}{H(Attribute)},$$

where H is the information entropy.

Symmetrical Uncertainty filter One of the entropy-based filters. Algorithm evaluates the worth of a set attributes by measuring the symmetrical uncertainty with respect to another set of attributes.

$$SymmU(Class, Attribute) = 2\frac{H(Class) + H(Attribute) - H(Class|Attribute)}{H(Attribute) + H(Class)},$$

where H is the information entropy.

Linear Correlation filter The algorithm finds weights of continous attributes basing on their Pearson's correlation with continous class attribute.

Rank Correlation filter The algorithm finds weights of continous attributes basing on their Spearman's correlation with continous class attribute.

OneR algorithm The algorithms find weights of discrete attributes basing on very simple association rules involving only one attribute in condition part. In other words, it uses the minimum-error attribute for prediction, discretizing numeric attributes. For more information, see [4].

RReliefF filter The algorithm evaluates the worth of an attribute by repeatedly sampling an instance and considering the value of the given attribute for the nearest instance of the same and different class. Considering that result, it evaluates weights of attributes. Can operate on both discrete and continuous class data. For more information see [5,6,7].

Consistency-based filter Evaluates the worth of a subset of attributes by the level of consistency in the class values when the training instances are projected onto the subset of attributes. Consistency of any subset can never be lower than that of the full set of attributes, hence the usual practice is to use this subset evaluator in conjunction with a Random or Exhaustive search which looks for the smallest subset with consistency equal to that of the full set of attributes. The FSelector R package implementation makes use of *Best-first search* for searching the attribute subset space. Works for continuous and discrete data.

RandomForest filter It is a wrapper for variable importance measure produced by randomForest algorithm. The FSelector R package implementation allows for two types of importance measure:

1. mean decrease in accuracy,
2. mean decrease in node impurity.

The first measure is computed from permuting OOB (out-of-bound) data: For each tree, the prediction error on the out-of-bag portion of the data is recorded (error rate for classification, MSE for regression). Then the same is done after permuting each predictor variable. The difference between the two are then averaged over all trees, and normalized by the standard deviation of the differences. If the standard deviation of the differences is equal to 0 for a variable, the division is not done (but the average is almost always equal to 0 in that case).
The second measure is the total decrease in node impurities from splitting on the variable, averaged over all trees. For classification, the node impurity is measured by the Gini index. For regression, it is measured by residual sum of squares.

3.1.2 Algorithms for wrapping classifiers and search attribute subset space

In general, the wrapper approach depends on the so called *evaluation function* that is used to return a numeric value (a score) indicating how important a given subset of features is. Typically, one uses the classification-accuracy (usually based on cross-validation) as the score for the subset.

Below we provide a brief description of the algorithms for searching atrribute subset space.

Greedy search At first, greedy search algorithms expand starting node, evaluate its children and choose the best one which becomes a new starting node. This process goes only in one direction. *Forward search* starts from an empty and *backward search* from a full set of attributes.

Best-first search The algorithm is similar to *Forward search* besides the fact that is chooses the best node from all already evaluated ones and evaluates it. In the FSelector R package implementation, the selection of the best node is repeated approximately *max.brackets* times in case no better node found.

Hill climbing search The algorithm starts with a random attribute set. Then it evaluates all its neighbours and chooses the best one. It might be susceptible to local maximum.

Exhaustive search The algorithm searches the whole attribute subset space in breadth-first order.

4 Classification

4.1 Classification algorithms

4.2 Classification performance metrics

5 Cluster analysis

5.1 Dimensionality reduction algorithms

5.2 Cluster analysis algorithms

5.3 Cluster analysis performance metrics

Part III
Results

Part IV
Discussion

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