Credit Scoring for German Credit Data

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German credit data

Abstract

Credit scoring can be defined as a technique that helps credit providers decide whether to grant credit to consumers or customers. Its increasing importance can be seen from the growing popularity and application of credit scoring in consumer credit. There are advantages not only to construct effective credit scoring models to help improve the bottom-line of credit providers, but also to combine models to yield a better performing combined model. This paper has two objectives. First, it illustrates the use of data mining techniques to construct credit scoring models. Second, it illustrates the combination of credit scoring models to give a superior final model.

Introduction

The data set for the illustration is taken from the UCI Machine Learning Repository [Blake and Merz, 1998]. The data related to a credit screening application in a German bank. For this two datasets are provided. The original data set, in the form provided by Prof. Hofmann, contains categorical/symbolic attribute. There are 20 attributes (7 numerical and 13 categorical) and a binary outcome.

For algorithms that need numerical attributes, Strathclyde University produced the file “german.data-numeric". This file has been edited and several indicator variables added to make it suitable for algorithms which cannot cope with categorical variables. Several attributes that are ordered categorical (such as attribute 17) have been coded as integer.

Among the 1000 observations, 700 (or 70.0%) are good credit risk and 300 (30.0%) are bad credit risk. The 20 attributes available for constructing credit scoring models including demographic characteristics (e.g., gender and age) and credit details (e.g., credit history and credit amount)

We want to develop a credit scoring rule that can be used to determine if a new applicant is a good credit risk or a bad credit risk, based on values for one or more of the predictor variables.

Problem statement

The aim of this project is to construct a model using data mining techniques to perform credit scoring, is defined as technique that helps credit providers decide whether to grant credit to customers. Here we are suing German Credit Data Set (source::UCI Machine Learning Repository), is a classification problem.

Credit Scoring

Credit scoring can be formally defined as a statistical (or quantitative) method that is used to predict the probability that a loan applicant or existing borrower will default or become fail to pay credit amount. This helps to determine whether credit should be granted to a borrower or not. Credit scoring can also be defined as a systematic method for evaluating credit risk that provides a consistent analysis of the factors that have been determined to cause or affect the level of risk. The objective of credit scoring is to help credit providers quantify and manage the financial risk involved in providing credit so that they can make better lending decisions quickly and more objectively.

Benefits of Credit Scoring

- Increased Credit Availability
  The use of credit scores gives lenders a much better understanding of risk than previously, giving them the confidence to offer credit to more people. Lenders who use credit scoring can approve more loans, because credit scoring gives them more information upon which they can base their decisions to make loans. In addition, lenders can tailor a range of loans to different risk levels and offer a whole range of credit options.
- Lower Credit Rates
  With more credit available the cost of credit for borrowers has decreased. Automated credit processes, including credit scoring, make the credit process more efficient and thus less costly for lenders, who pass savings on to their customers. In addition, lenders can more effectively control their losses using credit scoring systems, again, allowing them to offer lower overall rates.
- Fairer Credit Decisions
  Credit scoring is an automated mathematical process that utilizes technology to determine suitability for loans. It considers only factors related to credit risk, removing from the lending process the risk of human bias based on race, religion nationality or marital status.
- Faster Credit Decisions
  Technology that utilizes scoring systems allows lenders to make instant credit decisions. This is notable in virtually all areas where a consumer seeks credit, from a retail store to an auto dealership to buying a home. In the personal loan and mortgage lending industry, applications can be approved in hours rather than weeks for borrowers who score above a lender's score cut-off.
- Opportunities to Improve Credit Rating
  Before the advent of credit scoring, so-called “knock out rules” meant that lenders often turned away borrowers based on a past problem in their file. Credit scoring considers all credit-related information, good and bad, in a person’s credit report. With credit scoring systems past credit problems fade as time passes and as recent good payment patterns are established.

Applications of Credit Scoring

TOOLS USED

- KNIME
- WEKA

Techniques Used

- Support Vector Machine
- Decision Tree
- Logistic regression
- Multilayer Perceptron
- RProp Multilayer Perceptron
- Probabilistic Neural Network

Variable Description

Var.#	Variable name	Variable type	Variable type
1	OBS#	Categorical	Observation No.
2	CHK_ACCT	Categorical	Checking account status
3	DURATION	Numerical	Duration of credit in months
4	HISTORY	Categorical	Credit history
5	NEW_CAR	Binary	Purpose of credit
6	USED_CAR	Binary	Purpose of credit
7	FURNITURE	Binary	Purpose of credit
8	RADIO/TV	Binary	Purpose of credit
9	EDUCATION	Binary	Purpose of credit
10	RETRAINING	Binary	Purpose of credit
11	AMOUNT	Numerical	Credit amount
12	SAV_ACCT	Categorical	Average balance in savings account
13	EMPLOYMENT	Categorical	Present employment since
14	INSTALL_RATE	Numerical	Instalment rate as % of disposable income
15	MALE_DIV	Binary	Applicant is male and divorced
16	MALE_SINGLE	Binary	Applicant is male and single
17	MALE_MAR_WID	Binary	Applicant is male and married or a widower
18	CO-APPLICANT	Binary	Application has a co-applicant
19	GUARANTOR	Binary	Applicant has a guarantor
20	PRESENT_RESIDENT	Categorical	Present resident since - years
21	REAL_ESTATE	Binary	Applicant owns real estate
22	PROP_UNKN_NONE	Binary	Applicant owns no property (or unknown)
23	AGE	Numerical	Age in years
24	OTHER_INSTALL	Binary	Applicant has other instalment plan credit
25	RENT	Binary	Applicant rents
26	OWN_RES	Binary	Applicant owns residence
27	NUM_CREDITS	Numerical	Number of existing credits at this bank
28	JOB	Categorical	Nature of job
29	NUM_DEPENDENTS	Numerical	Number of people for whom liable to provide maintenance
30	TELEPHONE	Binary	Applicant has phone in his or her name
31	FOREIGN	Binary	Foreign worker
32	RESPONSE	Binary	Credit rating is good

Model Description

Decision Tree (DT):

The decision tree is a structure that includes root node, branch and leaf node. Each internal node denotes a test on attribute, each branch denotes the outcome of test and each leaf node holds the class label. The topmost node in the tree is the root node.

The decision making can be either nominal or numerical.

- Numeric splits are always binary (two outcomes), dividing the domain in two partitions at a given split point.
- Nominal splits can be either binary (two outcomes) or they can have as many outcomes as nominal values.

In the case of a binary split the nominal values are divided into two subsets. The algorithm provides two quality measures for split calculation; the gini index and the gain ratio. Further, there exist a post pruning method to reduce the tree size and increase prediction accuracy. The pruning method is based on the minimum description length principle.

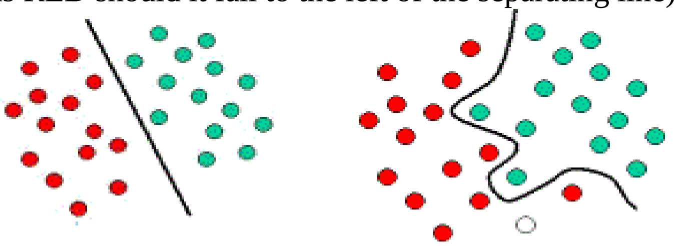
The algorithm can be run in multiple threads, and thus, exploit multiple processors or cores.

Advantages:

- It does not require any domain knowledge.
- It is easy to assimilate by human.
- Learning and classification steps of decision tree are simple and fast.

Support Vector Machine (SVM):

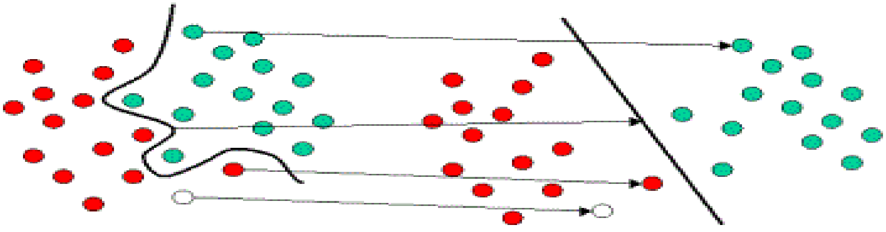
Support Vector Machines are based on the concept of decision planes that define decision boundaries. A decision plane is one that separates between a set of objects having different class memberships. A schematic example is shown in the illustration below. In this example, the objects belong either to class GREEN or RED. The separating line defines a boundary on the right side of which all objects are GREEN and to the left of which all objects are RED. Any new object (white circle) falling to the right is labelled, i.e., classified, as GREEN (or classified as RED should it fall to the left of the separating line).



Linear SVM Non-Linear SVM

The above is a classic example of a linear classifier, i.e., a classifier that separates a set of objects into their respective groups (GREEN and RED in this case) with a line. Most classification tasks, however, are not that simple, and often more complex structures are needed in order to make an optimal separation, i.e., correctly classify new objects (test cases) on the basis of the examples that are available (train cases). This situation is depicted in the illustration below. Compared to the previous schematic, it is clear that a full separation of the GREEN and RED objects would require a curve (which is more complex than a line). Classification tasks based on drawing separating lines to distinguish between objects of different class memberships are known as hyper plane classifiers. Support Vector Machines are particularly suited to handle such tasks.

The illustration below shows the basic idea behind Support Vector Machines. Here we see the original objects (left side of the schematic) mapped, i.e., rearranged, using a set of mathematical functions, known as kernels. The process of rearranging the objects is known as mapping (transformation). Note that in this new setting, the mapped objects (right side of the schematic) is linearly separable and, thus, instead of constructing the complex curve (left schematic), all we have to do is to find an optimal line that can separate the GREEN and the RED objects.



Multilayer perceptron (MLP):

A **multilayer perceptron** (MLP) is a feed forward artificial neural network model that maps sets of input data onto a set of appropriate outputs. A MLP consists of multiple layers of nodes in a directed graph, with each layer fully connected to the next one. Except for the input nodes, each node is a neuron (or processing element) with a nonlinear activation function. MLP utilizes a supervised learning technique called back propagation for training the network. MLP is a modification of the standard linear perceptron and can distinguish data that are not linearly separable.

Based on a trained Multilayer Perceptron-model given at the model, the expected output values are computed. If the output variable is nominal, the output of each neuron and the class of the winner neuron are produced. Otherwise, the regression value is computed. Filter out missing values before using this node.

Activation function:

If a multilayer perceptron has a linear activation function in all neurons, that is, a linear function that maps the weighted inputs to the output of each neuron, then it is easily proved with linear algebra that any number of layers can be reduced to the standard two-layer input-output model. What makes a multilayer perceptron different is that each neuron uses a *nonlinear* activation function which was developed to model the frequency of action potentials, or firing, of biological neurons in the brain. This function is modelled in several ways.

The two main activation functions used in current applications are both sigmoid, and are described by

$$y(v_i) = \tanh(v_i) \quad \text{and} \quad y(v_i) = (1 + e^{-v_i})^{-1}$$

Layers:

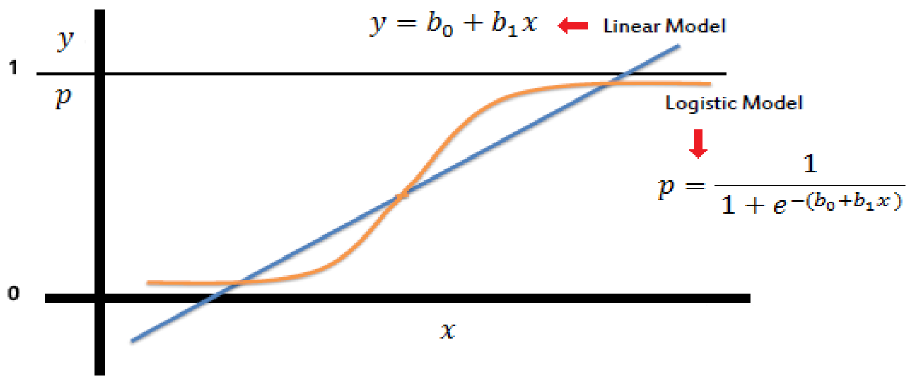
The multilayer perceptron consists of three or more layer of nonlinearly-activating nodes. Each node in one layer connects with a certain weight w_{ij} to every node in the following layer. Some people do not include the input layer when counting the number of layers and there is disagreement about whether w_{ij} should be interpreted as the weight from i to j or the other way around.

Logistic Regression (LR):

Logistic regression predicts the probability of an outcome that can only have two values (i.e. a dichotomy). The prediction is based on the use of one or several predictors (numerical and categorical). A linear regression is not appropriate for predicting the value of a binary variable for two reasons:

- A linear regression will predict values outside the acceptable range (e.g. predicting probabilities outside the range 0 to 1).
- Since the dichotomous experiments can only have one of two possible values for each experiment, the residuals will not be normally distributed about the predicted line.

On the other hand, a logistic regression produces a logistic curve, which is limited to values between 0 and 1. Logistic regression is similar to a linear regression, but the curve is constructed using the natural logarithm of the "odds" of the target variable, rather than the probability. Moreover, the predictors do not have to be normally distributed or have equal variance in each group.



In the logistic regression the constant (b_0) moves the curve left and right and the slope (b_1) defines the steepness of the curve.

Probabilistic Neural Network (PNN):

Probabilistic Neural Network (PNN) based on the DDA (Dynamic Decay Adjustment) method on labelled data using Constructive Training of Probabilistic Neural Networks as the underlying algorithm.

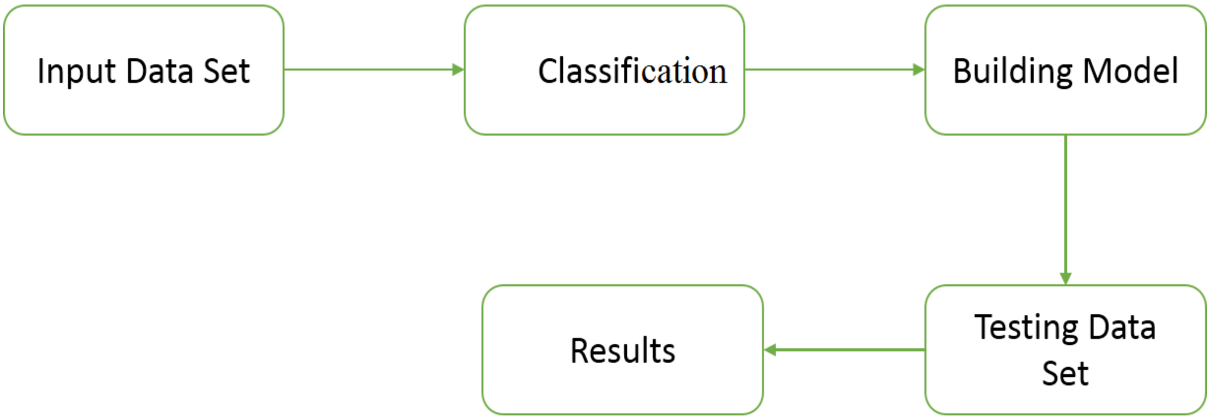
This algorithm generates rules based on numeric data. Each rule is defined as high-dimensional Gaussian function that is adjusted by two thresholds, theta minus and theta plus, to avoid conflicts with rules of different classes. Each Gaussian function is defined by a centre vector (from the first covered instance) and a standard deviation which is adjusted during training to cover only non-conflicting instances. The selected numeric columns of the input data are used as input data for training and additional columns are used as classification target, either one column holding the class information or a number of numeric columns with class degrees between 0 and 1 can be selected. The data output contains the rules after execution along with a number of rule measurements. The model output port contains the PNN model, which can be used for prediction in the PNN Predictor node.

Rprop Multilayer perceptron (Rprop MLP):

Rprop, short for resilient back propagation, is a learning heuristic for supervised learning in feed forward artificial neural networks. This is a first-order optimization algorithm.

Rprop takes into account only the sign of the partial derivative over all patterns (not the magnitude), and acts independently on each "weight". For each weight, if there was a sign change of the partial derivative of the total error function compared to the last iteration, the update value for that weight is multiplied by a factor η^-, where $\eta^- < 1$. If the last iteration produced the same sign, the update value is multiplied by a factor of η^+, where $\eta^+ > 1$. The update values are calculated for each weight in the above manner, and finally each weight is changed by its own update value, in the opposite direction of that weight's partial derivative, so as to minimise the total error function. η^+ is empirically set to 1.2 and η^- to 0.5.

Basic Data mining method



Input Data:

Here we are giving the data as input to the classifier after data cleaning process.

Classification:

Classification consists of assigning a class label to a set of unclassified cases.

- .Supervised Classification

  The set of possible classes is known in advance.
- Unsupervised Classification

  Set of possible classes is not known. After classification we can try to assign a name to that class. Unsupervised classification is called clustering.

Classification methods:

- Genetic Algorithms
- Rough Set Approach
- Fuzzy Set Approaches

Building Model:

Building a mining model is part of a larger process that includes everything from asking questions about the data and creating a model to answer those questions, to deploying the model into a working environment.

A model may be either opaque (it works but we aren't exactly sure how or why) or transparent (we understand exactly how the model arrives at any prediction). Either may be acceptable, depending upon the application. An opaque model that predicts production defect rates is perfectly acceptable if our interest is limited to production planning, but we would certainly prefer a transparent model if we were interested in increasing productivity.\

Testing Data Set:

We have to compare the predictions to the known answers. Data is also known as *test data* or *evaluation data*. This technique is called testing a model, which measures the model's predictive accuracy.

Results:

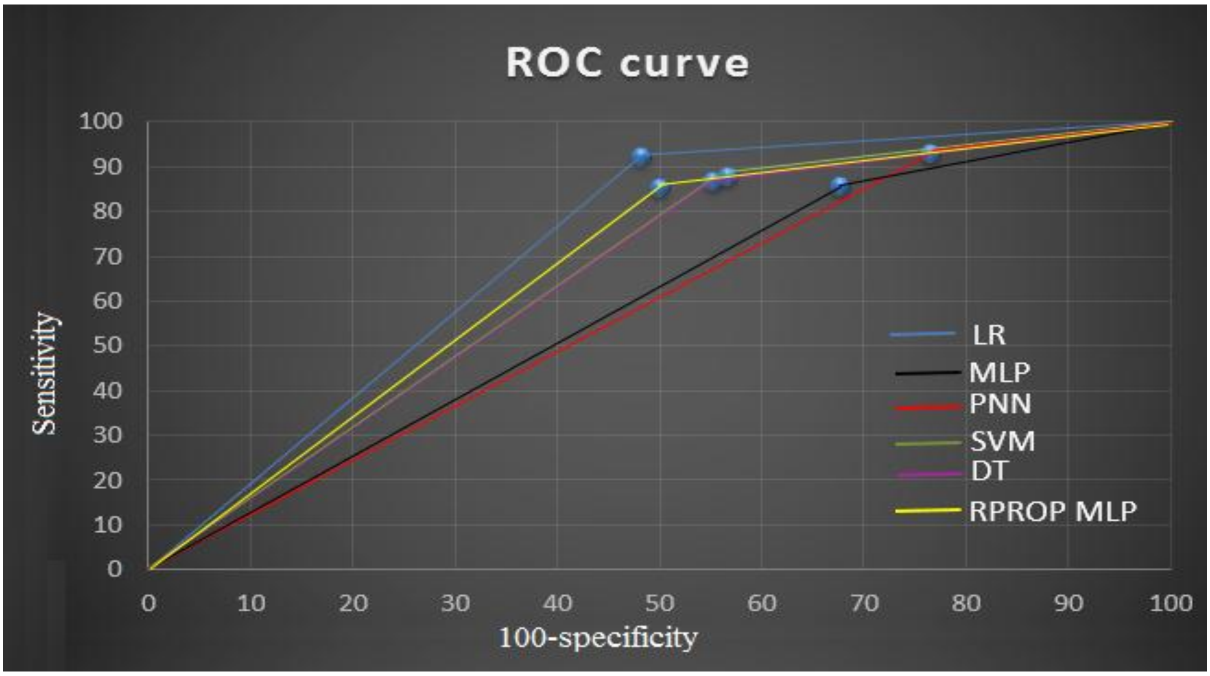
The results those we have achieved after comparing the data with learned knowledge data by the model.

Results

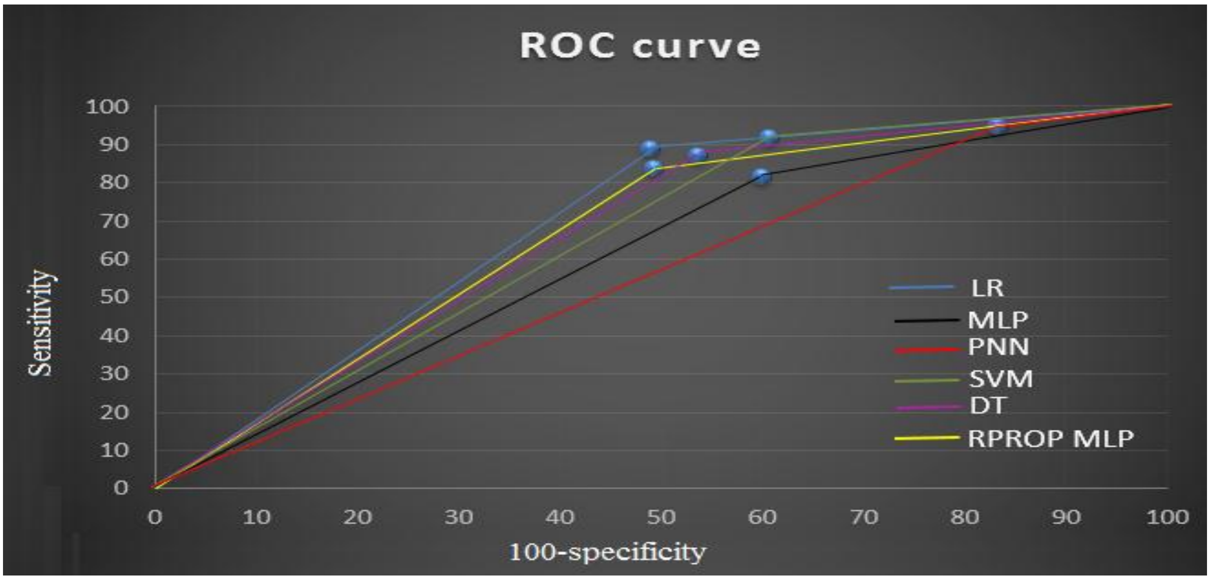
S.NO.	Model	Sensitivity (%)	Specificity (%)	Accuracy (%)
1	Support Vector Machine + PCA	87.85714286	43.333333	74.5
2	Decision Tree	86.66666667	44.615384	73
3	Logistic regression	92.14285714	51.666666	80
4	Multilayer Perceptron	85.50724638	32.258064	69
5	Probabilistic Neural Network	92.85714286	23.333333	72
6	Rprop Multilayer Perceptron	85.15625	50	72.5

Comparing Models

Using ROC curve (Hold-Out results)



Using ROC curve (10 Fold Cross validation)



Using T-Test (based on sensitivity)

Comparing	T-Test		Comparing	T-Test
LR vs DT	3.5		SVM vs DT	14.2
LR vs MPL	12.5		SVM vs MLP	15.4
LR vs SVM	19.06		SVM vs PNN	4.9
LR vs PNN	7.88		SVM vs Rprop	22.6
LR vs Rprop	14.40		SVM vs LR	19.06

Using T-Test (based on Accuracy)

Comparing	T-Test
LR vs DT	1.225
LR vs MPL	4.42
LR vs SVM	3.586
LR vs PNN	3.82
LR vs Rprop	2.1

Conclusion

This paper discusses and illustrates the use of data mining techniques in the construction and combination of credit scoring models.

- LR gave better results than other models.
- According to the T-Test based on the accuracy LR, DT and Rprop MLP significantly same.
- According to the T-Test based on the accuracy LR, SVM and PNN significantly not same
- So according to the ROC curve and accuracy statics we can prefer LR model
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References

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