

# Methods for Evaluating the Creditworthiness of Borrowers

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**Abstract.** The Internal Rating Based Approach (IRB) of the Basel Capital Accord allows banks to use their own rating models for the estimation of probabilities of default (PD). The objective of this research is to present mathematical-statistical methods of creditworthiness evaluation usage at banks, describe technical issues of scoring model development for each of methods, and analyse their advantages and disadvantages. The most widely used models to forecast default include parametric methods such as discriminatory analysis, regression analysis and non-parametric methods such as decision trees, neural networks, expert systems, support vector machines and others. The authors are trying to classify all kinds of methods used for credit risk evaluation. This article opens all technical issues of each method and shows the difference in practical applications, but it does not attempt to evaluate which method is better. The authors have used a comparative analysis to show that in practice it is possible to use other methods excluding regression and discriminant analyses. The advantage of credit scoring models certainly will help banks meet the next wave in Latvian's consumer loans and mitigate default risks.

**Keywords:** probability of default, parametric and non-parametric models, credit scoring, IRB approach, Basel Capital Accord.

## I. INTRODUCTION

Credit risk management is one of the leading topics in modern finance and a central task for commercial banks. The key variable in quantifying credit risk is the probability of default (PD). Under the proposed internal rating based (IRB) approach in the Basel Capital Accord (Basel, 2006), the Basel Committee on Banking Supervision allows banks to access the regulatory capital charges to cover their credit risks based on bank internal credit risk ratings for their exposures. The IRB banks are responsible for determining PD and demonstrating the appropriateness of techniques used for measuring PD to banking supervisors. In practice, the PD models are necessary not only for regulatory capital calculation as PD models or credit scoring models can be used effectively to control risk selection, manage credit losses, evaluate new loan programs, reduce loan approval processing time, ensure that the existing credit criteria are sound and consistently applied, increase profitability and minimize acquisition costs.

The process of credit scoring is very important for banks as they need to discriminate a "good customer" from a "bad customer" in terms of their creditworthiness.

Credit scoring model is a mechanism used to quantify the risk factors relevant to an obligor's ability and willingness to pay. The aim of the credit score models is to build a single aggregate risk indicator for a set of risk factors. The risk indicator indicates the ordinal or cardinal credit risk level of

the obligor. The result is an index of creditworthiness expressed as a numerical score, which indirectly measures the borrower's probability of default.

Statistical theory offers a variety of methods for building and estimation scoring models (or PD). Such methods have become increasingly important with the dramatic growth in consumer credit in recent years. The complexity and flexibility of statistical methods and advanced computing technology has made such credit scoring possible in business lending.

These models can be grouped into parametric and non-parametric or data mining models (see Fig.1). Also following the research of Kiss (2003), looking at credit scoring processes, it is possible to split scoring methods by groups from a knowledge management perspective [31].

Historically, the most popular parametric models are the linear discriminant analysis (DA) and the logistic regression. Both have the merits of being conceptually straightforward and widely available in statistical software packages. Linear discriminant analysis was the first parametric technique suggested for credit scoring purposes. This approach has attracted criticism due to the categorical nature of the data and the fact that the covariance matrices of the good credit and bad credit groups are typically distinct. The logistic regression allows overcoming these deficiencies, and it has become a common credit scoring tool of practitioners. Non-parametric techniques applied to credit scoring include the neural networks, genetic programming, and expert systems, support vector machines, nearest neighbour approach and decision trees [11].

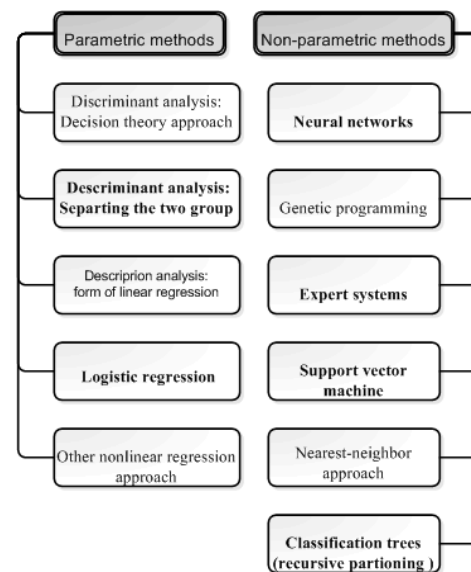


Fig. 1. Classification of scoring methods

The authors of the article will summarize some methods of each classification group, giving describing of their use from the credit scoring literature and analyse their advantages and disadvantages [28].

## II. LITERATURE SURVEY

The techniques underlying credit-scoring models were devised in the 1930s by such authors as Fisher (1936) [24] and Durand (1941) [18], who showed that the discriminant analysis method could produce good predictions of credit repayment. The decisive boost to the development and spread of these models came after the 1960s, which were studied by Beaver (1966) [12], Altman (1968) [2]. Eisenbeis (1977) [20] presented a critical assessment of use of discriminant analysis in finance and economics in general. Other accounts of the use of discriminant analysis in credit scoring are given by Lane (1972) [34], Apilado (1974) [6], Grablowsky and Talley (1981) [27]. Myers and Forgy (1963) [38] used discriminant and regression analyses to predict credit risk using retail credit application data. They found that the most predictive variables, using equal weights, yielded similar results as the weights obtained from LDA or a multiple regression analysis. [28]. Altman (1968) [2] published his famous "Z-Score" model for predicting bankruptcy of commercial firms. Scherr (1982) [46] has criticized Altman's model for not including variables representing firm size, firm age, and economic conditions because it is well known that younger firms are more prone to failure.

The discriminant analysis model to assess insolvency of Latvian enterprises was built by Šorin and Voronova (1998) [48]; the authors have used Altman's "Z-Score" model and adopted it for the Latvian enterprises.

Wiginton (1980) [51] was one of the first, who published research about the use of a logistic regression method in credit scoring. He concluded that the logistic method gave excellent classification results. Genriha, Voronova and Pettere (2011) [25], based on the logistic regression analysis, created a 3-factor model to predict the probability of default of Latvian enterprises.

Decision trees were developed by Raiffa and Schlaifer (1961) [40] in the 1960s, and later Sparks (1972) used this method to build a credit scoring model. Also applications of decision tree method are described by Mehta (1968) [37], Makowski (1985) [35], Coffman (1986) [17].

Research into neural networks began in 1943 with the publication written by McCulloch and Pittb (1943) [36] about a logical calculus of the ideas immanent in nervous activity. Baesens, R. Setino, C. Mues, S. Viaene and J. Vanthienen (2001) [9] evaluated and contrasted three neural network rule extraction techniques and decision tables. They also described how it is possible to use decision tables that can be easily verified by a human expert, in combination with neural network rule extraction, for building advanced credit-risk evaluation expert systems. Also Rosenbeg and Gleit (1994) [42] described several applications of neural networks to corporate credit decisions.

Experiments using SVM for credit scoring are relatively new, they started to be widely used since 2000. Baesens (2003) [10] applied SVMs along with other classifiers to several data sets. They reported that SVMs performed well in comparison with other algorithms, but did not always give the best performance. Schebesch and Stecking (2005) [45] applied SVM to a database of applicants for a building and loan credit. They concluded that SVMs performed slightly better than LR.

## III. PARAMETRIC METHODS

### A. Discriminant Analysis (DA)

Discriminant analysis is a classification method, which uses data obtained from a sample of customers to draw a boundary, based on discriminant function, which separates the group of insolvent customers from the group of reliable ones. Figure 2 shows how the discriminant function used only two variables  $x_1$  and  $x_2$  to separate a group A from a group B.

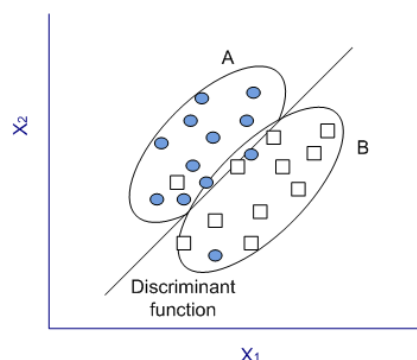


Fig. 2. Example of linear discriminant analysis

Discriminant function determines which variables discriminate more effectively between groups and whether groups are significantly different from each other with respect to the mean of given variables. If the mean of a variable significantly differs from the value of different groups, then this variable discriminates between the groups [14].

In general, there are three types of discriminant analysis:

- ✓ Univariate: only one variable is used as the determinant between groups;
- ✓ Multivariate [common covariance]: more than one variable is used as the determinant between groups. The covariance is the same;
- ✓ Multivariate [different covariance]: more than one variable is used as the determinant between groups. The covariance differs.

Multivariate discriminant analysis is the most widely used statistical method to build credit scoring or to predict probability of default. This method allows dividing all customers into two groups: solvent and insolvent or high risk and low risk customers.

Model building started from the evaluation of all potential variables to determine which contributes the most to discrimination between groups. The variable selection is purely based on the statistical fit. Discriminant analysis tries to find the linear combination of independent variables that will

better discriminate between groups, in our case discriminate between solvent and insolvent customers. This is achieved by the statistical decision rule of maximising the between-group variance relative to the within-group variance.

In more general terms, given  $n$  independent variables and each financial ratio or factor becomes a variable,  $X$ , and gets its own coefficient,  $V$ . This leads to the following formula, which calculates a sample's  $Z$ -score:

$$Z = \sum_{i=1}^n V_i X_i \quad (1)$$

The average  $Z$ -Score,  $\bar{Z}$ , and the average  $Z$ -Score,  $\bar{Z}_g$ , in each group  $g$  are given by the following equations:

$$\bar{Z} = \frac{1}{n} \sum_{i=1}^n V_i X_i \quad (2) \quad \bar{Z}_g = \frac{1}{N_g} \sum_{p=1}^{N_g} Z_{pg} \quad (3)$$

The goal of the Multivariate Discriminant analysis is to maximize the sum of the square among the groups,  $SS_{among}$  and minimize the sum of the square across the group,  $SS_{across}$ , which are given by the following equations:

$$SS_{among} = \sum_{g=1}^G N_g [\bar{Z}_g - \bar{Z}]^2 \quad (4)$$

$$SS_{across} = \sum_{g=1}^G \sum_{p=1}^{N_g} [Z_{pg} - \bar{Z}_g]^2 \quad (5)$$

The aim of analysis is to maximize the ratio of  $SS_{among}$  and  $SS_{across}$  [14].

*Advantages* of Discriminant Analysis are the following:

- ✓ multiple dependent variables;
- ✓ reduced error rates;
- ✓ easier interpretation of between-group differences: each discriminant function measures something unique and different.

*Disadvantages* of Discriminant Analysis are the following:

- ✓ a mystical interpretation of the discriminant functions, such as identifying factors in a factor analysis;
- ✓ each discriminant function is assumed to show approximately equal variances in each group.
- ✓ patterns of correlations between variables are assumed to be equivalent from one group to another;
- ✓ the relationships between variables are assumed to be linear in all groups;
- ✓ independent variable may be perfectly correlated to a linear combination of other variables (Multicollinearity);
- ✓ discriminant analysis is extremely sensitive to outliers.

#### B. Logistic Regression Analysis (RA)

Logistic regression aims to assign the dependent variable to two groups (0;1); in our case one group represents solvent customers and another group – insolvent ones. Therefore, the logistic method allows us to predict probabilities. This method is used to predict binary (i.e., good or bad) outcomes from independent variables by using the following log equation:

$$\ln\left(\frac{p}{1-p}\right) = \alpha + \beta x + \varepsilon, \quad (6)$$

where  $p$  is the probability (i.e., PD) that the event  $Y$  occurs,  $p=1$ ,  $p/(1-p)$  is the “odds ratio” and  $\ln(p/(1-p))$  is the log odds ratio or “logit”. The logistic distribution constrains the estimated probabilities to lie between 0 and 1. Converting the above expression, the PD is given by

$$PD = \frac{1}{1 + e^{-(\alpha + \beta x)}} \quad (7)$$

To obtain the estimates of the parameters, the non-linear maximum likelihood (ML) estimation procedure is used. ML is a way of finding the smallest possible deviation between the observed and predicted values.

The *advantage* of the logistic regression method is that it does not assume multivariate normality and equal covariance matrices as discriminant analysis, but incorporates non-linear effects, and uses the logistical cumulative function in predicting a default [14].

The *disadvantage* of the logistic regression is that it is difficult to use ML to estimate the weights, because this requires non-linear optimising techniques using iterative procedures [14].

## IV. NON-PARAMETRIC METHODS

### A. Classification and Regression Trees / Decision Trees (DT)

Decision tree or recursive partitioning is a non-parametric approach and consists of several layers of nodes: the first layer consists of a root node and the last layer consists of leaf nodes [32].

The algorithm of model building begins with a root node containing a sample of good and bad credit applicants. Then, the algorithm loops over all possible binary splits in order to find the attribute  $x$  and corresponding cut-off value  $c$ , which gives the best separation into good and bad credits. The figure of merit is optimized when the data in the root node is split between instances with attribute  $x_i \geq c_i$  and those with  $x_i < c_i$ . This procedure is then repeated for the new daughter nodes until a stopping criterion is satisfied. Defining the purity  $p$  of a node as the fraction of good credit instances in it, the splitting attribute and cut-off value are those that minimize the sum of the Gini indices  $p(1-p)$  of the created daughter nodes. If, for any attribute or cut-off value, the sum of the Gini indices of the daughter nodes is higher than the Gini index of the parent node, the parent node is not split. Since the Gini index is a measure of the statistical dispersion or diversity of the population in a node, minimizing the Gini index results in daughter nodes that are more homogeneous than the parent nodes [11].

Non-split nodes are denoted by leaves that are classified according to the most prevalent class in them. A leaf is called “good credit” if it contains more good credit applicants than bad credit applicants and otherwise.

Frequently in practice the resulting trees are quite large, because a decision tree could be grown until all leaves contain only good credit instances or only bad credit instances. However, such a tree would be over-fitted, in such a situation,

the generalization performance may be improved if the tree will be cut in order to get rid of statistically insignificant nodes [11,15].

Two types of decision trees are the most widely used. Classification Trees are used if the target variable is categorical. To predict the category value of the target variable using a classification tree, use the values of the predictor variables to move through the tree until you reach a terminal (leaf) node, then predict the category shown for that node. Regression Trees are used if the target variable is continuous. To predict the value of the target variable, the mean value of the target variable of the rows falling in a leaf node is the estimated value.

The *advantage* of decision trees:

- ✓ representing and reasoning about relations amongst symbolic objects; this facilitates the task of generating explanations about objects and about inferences on the relations amongst objects.

The *disadvantage* of decision trees:

- ✓ the relations embedded in their knowledge base are pre-defined and their maintenance can become a tedious task.

### B. Neural Networks (NN)

Neural Network consists of a large number of elements, called neurons, which are arranged in layers. Each neuron is connected to another by synaptic relations. A neuron receives inputs from other neurons and produces an output which is transmitted to other destination neurons. Every single input is multiplied by the weight on the corresponding link, and all these values are summed up. Then, the activation is evaluated by applying a particular function (linear, step, sigmoid) to the weighted sum of inputs. One of the key characteristics of MLPs is that all neurons and layers are arranged in a feed forward manner and no feedback connections are allowed.

Figure 3 [9] provides an example of an MLP with one hidden layer and two output neurons for a binary classification problem.

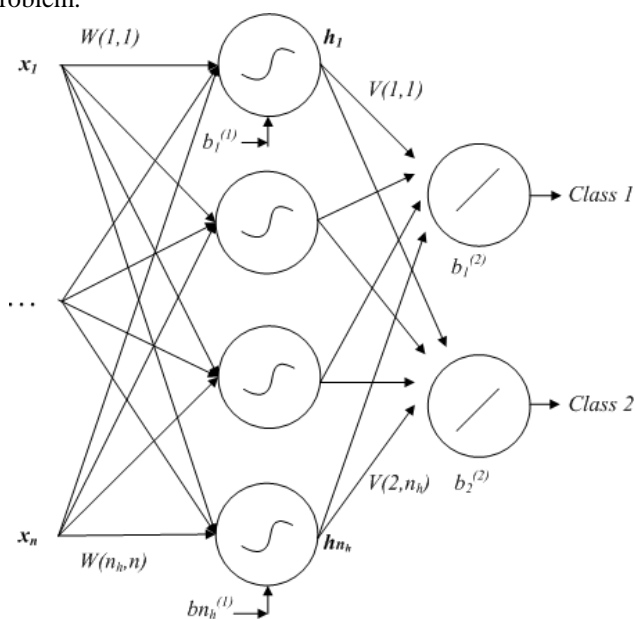


Fig. 3. Example of Neural Network system

The output of hidden neuron  $i$  is computed by processing the weighted inputs and its bias term  $b_i^{(1)}$  as follows [9]:

$$h_i = f^{(1)}\left(b_i^{(1)} + \sum_{j=1}^n W(i,j)x_j\right) \quad (8)$$

$W$  is a weight matrix, whereby  $W(i,j)$  denotes the weight connecting input  $j$  to hidden unit  $i$ . In an analogous way, the output of the output neurons is computed [9]:

$$z_i = f^{(2)}\left(b_i^{(2)} + \sum_{j=1}^{n_h} V(i,j)h_j\right) \quad (9)$$

with  $n_h$  – the number of hidden neurons and  $V$  – a weight matrix, whereby  $V(i,j)$  denotes the weight connecting hidden unit  $j$  to output unit  $i$ . The bias inputs play a role analogous to that of the intercept term in a classical linear regression model. The class is then assigned according to the output neuron with the highest activation value (the winner-take-all learning). The transfer functions  $f^{(1)}$  and  $f^{(2)}$  allow the network to model nonlinear relationships in the data [9]. Examples of transfer functions that are commonly used are the sigmoid

$$f(x) = \frac{1}{1 + \exp(-x)}. \quad (10)$$

The hyperbolic tangent

$$f(x) = \frac{\exp(x) - \exp(-x)}{\exp(x) + \exp(-x)} \quad (11)$$

and the linear transfer function  $f(x) = x$  [9].

The weights  $W$  and  $V$  are the crucial parameters and need to be estimated during a training process, which is usually based on gradient descent learning to minimize some kind of error function over a set of training observations (Bishop 1995).

Note that multiple hidden layers might be used, but theoretical works have shown that one hidden layer is sufficient to approximate any continuous function to any desired degree of accuracy (Bishop 1995).

The output of credit scoring is a classification of borrowers into groups, usually two; therefore, only two outputs are obtained from neural networks.

The *advantages* of neural networks are the following:

- ✓ they are able to analyse complex patterns quickly and with a high accuracy level and without any programmed knowledge;
- ✓ without any restrictive statistical assumptions, non-numeric data can be used and data can be non-linear that is a substantial advantage over the discriminant analysis;
- ✓ perfectly suited to work with “noisy data”, e.g., incomplete annual account data;
- ✓ more precise, powerful and robust, especially in case of small sample size.

Neural networks perform better if the number of independent variables is larger [14].

The *disadvantages* of neural networks are the following:

- ✓ the black box problem cannot be “applied”;
- ✓ variables must be carefully selected initially;
- ✓ a risk of over-fitting exists;
- ✓ a long process of time is requested;

✓ a possibility of illogical network behaviour exists [14].

### B. Expert Systems

The expert system is a computer system, which stores and manages the expert's knowledge, as well as handles it in a manner so that users can be given the targeted information or certain tasks are performed alone. Expert systems contain three main components: knowledge, decision machine and user interface.

Knowledge base contains all the data, facts and rules to process the data and facts. Rules are expressed in terms of mathematical and logical equations. The knowledge base has building blocks of "if-then" rules. The rules need to be sequential, and the matching of facts to rules is complex.

Decision machine, which combines the facts and rules to obtain conclusions, has a series of facts that are matched with the rules to provide recommended actions.

User interface must ensure easy and efficient use, data capture and error detection. Interface needs to allow users to understand the reasoning behind a decision and add or update information online.

Expert system has four key characteristics:

- ✓ the system is based on a knowledge base;
- ✓ the system has the tools to maintain and expand the knowledge base;
- ✓ the system can draw conclusions;
- ✓ the system can explain its decisions that can be particularly important given the legal requirements for credit scores to provide reasons for rejecting applicants.

The *advantages* of the expert system are the following:

- ✓ the system can take qualitative variables;
- ✓ the system does not assume any specific statistical distribution of the data;
- ✓ the system builds a number of if-then rules, which can easily be applied to new cases for a classification decision.

The *disadvantages* of the expert system are the following:

- ✓ it is very difficult to program the intuition of the expert system and to determine which heuristics must be used;
- ✓ the process of extracting the knowledge into rules is very time consuming and expensive;
- ✓ systems are unable to use inductive learning to adapt the if-then rules to changing situations;
- ✓ the data input quality has to be good and the system is not capable of working with incomplete, noisy data or input information with errors [14].

### C. Support Vector Machine (SVM)

The support vector machines are capable of extracting useful information from financial data, although extensive data sets are required in order to fully utilize their classification power. SVMs produce better classification results than parametric methods and such a widely used nonparametric technique as neural networks, which is deemed to be one of the most accurate [29].

Support vector machine is a new technique suitable for binary classification tasks, which is related to and contains elements of non-parametric applied statistics, neural networks

and machine learning. Like classical techniques, SVM also classifies customers as solvent or insolvent according to its score value, which is a function of selected factors. The authors are limited in the case of a linear description of SVM, where the score function is linear and parametric, will first be introduced, in order to clarify the concept of margin maximization. Also in practice, the non-linear and non-parametric SVM are used; in this case the score is calculated based on kernel transformation. This characteristic makes SVM a useful tool for credit scoring, in the case the distribution assumptions of input data cannot be made or their relation to the PD is non-monotone [8].

Assume that there is a new customer  $j$ , who has to be classified as solvent or insolvent according to the SVM score. In the case of a linear SVM, the score looks like a Discriminant analysis or Logistic regression score, which is a linear combination of relevant factors  $x_j = (x_{j1}, x_{j2}, \dots, x_{jd})$ , where  $x_j$  is a vector with  $d$  factors and  $x_{jk}$  is the value of the factor number  $k$  for the customer  $j$ ,  $k=1, \dots, d$ . So  $z_j$ , the score of customer  $j$ , can be expressed as:

$$z_j = w_1 x_{j1} + w_2 x_{j2} + \dots + w_d x_{jd} + b, \quad (12)$$

$$z_j = x_j^T w + b \quad (13)$$

where  $w$  is a vector, which contains the weights of the  $d$  factors and  $b$  is a constant. Calculating the value of the parameters  $w$  and  $b$  means looking for a hyperplane that best separates solvent from insolvent customers according to a certain criterion. The criterion used by SVMs is based on margin maximization between solvent and insolvent customer groups. The threshold separating customers is the line in the middle between the two margin boundaries, which are canonically represented as  $x^T w + b = 1$  and  $x^T w + b = -1$ .

Let  $y_i$  be an indicator of the state of the customer, where in the case of solvency  $y_i = -1$ , and in the case of insolvency  $y_i = 1$ . By imposing the constraint that no observation may lie within the margin except some classification errors  $\xi_i$ , SVMs require that either  $x_i^T w + b \geq 1 - \xi_i$  or  $x_i^T w + b \leq -1 + \xi_i$ , which can be summarized with:

$$y_i (x_i^T w + b) \geq 1 - \xi_i. \quad (14)$$

The optimization problem for the calculation of  $w$  and  $b$  can thus be expressed by:

$$\min_w \frac{1}{2} \|w\|^2 + C \sum_{i=1}^n \xi_i \quad (15)$$

$C$  – "capacity" is a tuning parameter, which weights in-sample classification errors and thus controls the generalization ability of an SVM. The higher  $C$  is, the higher the weight given to in-sample misclassifications is and the lower the generalization of the machine is. Low generalisation means that the machine can work well on the training set. Bad generalization may be a result of overfitting, for example, if the sample shows some untypical and non-repeating data structure. By choosing a low  $C$ , the risk of overfitting an SVM is reduced [8].

Solving the above-mentioned constrained optimization problem of calibrating an SVM means searching for the minimum of the following Lagrange function:

$$L(w, b, \xi, \alpha, \nu) = \frac{1}{2} w^T w + C \sum_{i=1}^n \xi_i - \sum_{i=1}^n \alpha_i \{y_i (w^T x_i + b) - 1 + \xi_i\} - \sum_{i=1}^n \nu_i \xi_i, \quad (16)$$

where  $\alpha_i \geq 0$  are the Lagrange multipliers for the inequality constraint (14) and  $\nu_i \geq 0$  are the Lagrange multipliers for the condition  $\xi_i \geq 0$ . This is an optimization problem with inequality constraints, which is solved by application of the Kuhn-Tucker sufficiency theorem. The solution of this optimization problem is given by the saddle-point of the Lagrangian, minimized with respect to  $w$ ,  $b$ , and  $\xi$  and maximized with respect to  $\alpha$  and  $\nu$ . Calculating  $\alpha_i$ , we are able to calculate the parameters of the linear SVM model according to the following formulas:

$$w = \sum_{i=1}^n y_i \alpha_i x_i, \quad (17)$$

$$b = \frac{1}{2} (x_{+1}^T + x_{-1}^T) w \quad (18)$$

As can be seen from (17),  $\alpha_i$ , which must be positive, weighs different customers of the sample. The customers, whose  $\alpha_i$  are not equal to zero, are called support vectors and are the relevant ones for the calculation of  $w$ . Support vectors lie on the margin boundaries or, for non-perfectly separable data, within the margin. By substituting (17) into the score (13), we obtain the score  $z_j$  as a function of the scalar product of the factors of the customer to be classified and the factors of the support vectors, of  $\alpha_i$ , and of  $y_i$ . By comparing  $z_j$ , it is possible to estimate whether a customer has to be classified as solvent or insolvent [8].

$$z_j = \sum_{i=1}^n y_i \alpha_i \langle x_i, x_j \rangle + b. \quad (19)$$

The *advantages* of the SVM are the following:

- ✓ SVM method is chosen if distribution assumptions of input data are not regularly distributed or have an unknown distribution or their relation to the PD is non-monotone;
- ✓ SVMs provide a good out-of-sample generalization, if the parameter  $C$  is appropriately chosen. It means that, by choosing an appropriate generalization grade, SVMs can be robust, even when the training sample has some bias;
- ✓ SVMs deliver a unique solution, since the optimality problem is convex. This is an advantage compared to Neural Networks, which have multiple solutions associated with a local minimum and for this reason may not be robust over different samples;
- ✓ SVMs are easily adjusted with only few parameters, and SVMs are based on very few restrictive assumptions and can reveal effects overlooked by many other methods [29].

The *disadvantages* of SVMs are the following:

- ✓ the lack of transparency of results. SVMs cannot represent the score of all customers as a simple parametric function of the factors (financial ratios), since its dimension may be very high. It is neither a linear combination of single financial ratios nor has it another simple functional form;

- ✓ SVMs are better suited for processing large data sets [29].

## V. COMPARISON OF METHODS

The selection of a modelling method for credit scoring is a challenging problem, because an appropriate choice given the available data can significantly help improving the accuracy in credit scoring practices. The question of “which method is the best?” cannot be answered conclusively. Unfortunately no study has systematically compared the performance of all the different models, because various factors determine diverse aspects of modelling and performance issue, and each model addresses different issues.

The following factors are the determinants of the predictive power:

- ✓ data sample quality;
- ✓ time horizon;
- ✓ definition of default;
- ✓ theoretical basis for choice of variable;
- ✓ number of independent variables;
- ✓ assumptions about distribution of “good” and “bad”;
- ✓ over-fitting.

Nevertheless, the authors try to keep some information about each method and its predictive power. Having studied about 50 publications on the widely used credit risk modelling methods elaborated by different researchers over different time periods, the authors have summarized all observations in the table (Table 1).

TABLE 1  
PREDICTIVE POWERS OF CREDIT RISK MODELS

Researchers	+	DA	RA	NN	DT	SVM
Altman (1968)	-	85.0	-	-	-	-
Srinivisan (1987)	DT	-	89.3	-	93.2	86.1 (LP)
Dutta (1988)	NN	-	64.7	88.3	-	-
Odom (1990)	RA	59.3	83.3	77.8	-	-
Boyle (1992)	DT	-	-	-	75.0	74.7 (LP)
Salchenberger (1992)	NN	-	83.3	91.7	-	-
Coats (1993)	DA	83.7	-	81.9	-	-
Kerling (1994)	DA	85.7	-	85.3	-	-
Wilson (1994)	NN	88.0	-	97.0	-	-
Henley (1995)	DT	-	43.3	-	43.8	-
Alici (1995)	NN	65.6	66.0	69.5	-	-
Desai (1997)	RA	-	67.3	66.4	-	-
Yobas (1997)	DT	-	-	62.0	62.3	-
Zhang (1999)	NN	-	78.6	88.2	-	-
Fan (2000)	SV	59.8	-	66.1	-	70.4
Baesans (2001)	-	-	-	76.1	-	-
Gestel (2003)	SV	66.4	63.5	67.4	-	75.1
Aragon (2004)	-	94.2	-	-	-	-
Bastos (2008)	DT	-	-	78.3	81.1	79.9
Simha (2006)	DT	-	83.0	-	92.0	-
Belotti (2007)	SV	78.1	77.9	-	-	78.3
Koçenda (2009)	RA	-	83.2	-	83.0	-

Table 1 shows predictive powers calculated by different researchers. Comparison should be made only horizontally, because the researchers have used different definitions of "good" borrowers and conducted studies on different populations and samples. The table demonstrates the percentage of correctly classified customers. The purpose of these studies was to compare the effectiveness of different methods. Thus, it should not be concluded that these figures show the effectiveness of scoring systems in general.

Having performed a comparative analysis of the results of the studies conducted by the above-mentioned researchers (Table 1), the following conclusions are made:

- ✓ 2 out of 8 researchers conclude that Discriminant Analysis method is more precise (25%);
- ✓ 3 out of 12 researchers conclude that Regression method is more precise (25%);
- ✓ 5 out of 13 researchers conclude that Neural Network method is more precise (39%);
- ✓ 6 out of 7 researchers conclude that Decision Tree method is more precise (86%);
- ✓ 3 out of 6 researchers conclude that Support Vector Machine method is more precise (50%).

Based on the above-mentioned facts, the authors have concluded that the non-parametric models in the majority of cases have a greater predictive power, which suggests that there is no need to restrict the use of parametric methods such as discriminant or regression analysis.

## VI. CONCLUSIONS

In the 1960s, the use of statistical methods for credit risk modelling was limited in favour of the use of discriminant analysis. In turn, the 1970s was a period of widespread experimentation with scoring, and the 1980s have seen a limited theoretical progress on scoring modelling methods such as neural networks, expert systems, decision trees. Now in the 21st century, there are written a lot of different publications about credit risk prediction methods. This task still is very popular in risk management, because the technology and economy do not mark time, and every day we have some new possibilities to expand our knowledge. In this article, the authors have tried to open or at least reveal capabilities of scoring modelling. There are described and compared many popular methods that still are used in credit risk assessment. In the article, there are also shown advantages and disadvantages of each method that will help users understand which kind of method will be more suitable, following recommendations of the authors for the use of each method.

The authors of the article have studied many publications written in different time periods, in which some methods were compared and the predictive power of each method was evaluated. Based on the above-mentioned publications, the authors have also concluded that under the impact of Basel Capital Accord, in the world's scientific literature there has appeared a positive trend of development of new methods and approaches to the prediction of risk.

Intense competition, strong growth in consumer credit market and especially sad experience of lending in the period 2006–2009 in our country call for adequate and rapid risk assessment. The more predictable the credit risk will be, the less insolvent people in our country will be in future. Thus, this fact only emphasizes the relevance of this topic. The authors have shown that the credit risk assessment is quite a difficult process that requires knowledge, resources and time. Consumer lending must be a circumspect step, based on the advanced mathematical and statistical methods.

## REFERENCES

- [1] Y. Alici, "Neural networks in corporate failure prediction: The UK experience," in Proc. Third Int. Conf. Neural Networks in the Capital Markets, Eds. London, UK, pp. 393–406, 1995.
- [2] E.I. Altman, "Financial Ratios, Discriminant Analysis, and the prediction of Corporate Bankruptcy", *Journal of Finance* no.23, 589-609,1968.
- [3] E. Altman, G. Marco, and F. Varetto, "Corporate distress diagnosis: Comparisons using linear discriminant analysis and neural networks", *Journal of Banking and Finance*, vol. 18, pp. 505–529, 1994.
- [4] E. Angelini, G. di Tollo and A. Roli, "A neural network approach for credit risk evaluation", *The Quarterly Review of Economics and Finance*, 2007.
- [5] A. Aker, "Discriminant Analysis of Default Risk", MPRA Paper No. 1002, 2007. Available: <http://mpa.ub.uni-muenchen.de/1002/> [Accessed September 1, 2011].
- [6] V.P. Apilado, D.C. Warner and J.J. Dauten, "Evaluative Techniques in Consumer Finance", Experiments Results and Policy Implications for Financial Institutions, *J. Fin. and Quant. Anal.*, 275-283, 1974.
- [7] A.F. Atiya, "Bankruptcy Prediction for Credit Risk Using Neural Networks: A Survey and New Results", *IEEE transactions of neural networks*, Vol. 12, no. 4, 2001.
- [8] L. Auria and R.A. Moro, "Support Vector Machines (SVM) as a Technique for Solvency Analysis", German Institute for Economic Research, Berlin 2008. Available: [http://www.diw.de/english/products/publications/discussion\\_papers/27539.html](http://www.diw.de/english/products/publications/discussion_papers/27539.html) [Accessed September 1, 2011].
- [9] B. Baesens, R. Setino, C. Mues, S. Viaene and J. Vanthienen, "Building credit-risk evaluation expert systems using neural network rule extraction and decision tables", Twenty-Second International Conference on Information Systems, 2001.
- [10] B. Baesens, T. Gestel, S. Viaene, M. Stepanova, J. Suykens and J. Vanthienen, "Benchmarking state-of-the-art classification algorithms for credit scoring", *Journal of the Operational Research Society* 54: 1082-1088. 2003.
- [11] J. Bastos, "Credit Scoring with boosted decision trees", CEMAPRE, School of Economics and Management (ISEG), Technical University of Lisbon, 2008. Available: <http://mpa.ub.uni-muenchen.de/8156/> [Accessed September 1, 2011].
- [12] R. Beaver, "Financial ratios as predictors of failure," Empirical Research in Accounting: Selected Studies 1966, *J. Accounting Research*, vol. 4, pp. 71–111, 1966.
- [13] T. Belotti and J. Crook, "Support vector machines for credit scoring and discovery of significant features", Quantitative Financial Risk Management Centre, 2007.
- [14] M. Bhatia, *Credit Risk Management & Basel II*. London: Haymarket House, 2006.
- [15] L. Breiman, J.H. Friedman, R.A. Olshen, and C.J. Stone, "Classification and regression trees", Wadworth International Group, Belmont, California, 1984.
- [16] P. Coats and L. Fant, "Recognizing financial distress patterns using a neural network tool", *Financial Management*, vol. 22, pp. 142–155, 1993.
- [17] J.Y. Coffman, "The proper role of tree analysis in forecasting the risk behavior of borrowers", MDS Reports 3,4,7,9. Management Decision Systems, Atlanta, 1986.
- [18] D. Durand, "Risk Elements in Consumer Installment Lending", National Bureau of Economic Research, New York, Vol.8,1941.

- [19] S. Dutta and S. Shekhar, "Bond Rating: A Non-Conservative Application of Neural Networks", In Proceedings IEEE International Conference on Neural Networks, 443-450, 1988.
- [20] R.A. Eisenbejs, "Pitfalls in the Application of Discriminant Analysis in Business, Finance and Economics", *J.Fin.* 32, 875-900, 1977.
- [21] A. Fan and M. Palaniswami, "A new approach to corporate loan default prediction from financial statements", in Proc. Computational Finance/Forecasting Financial Markets Conf. CF/FFM-2000, London(CD), UK, May 2000.
- [22] D.Fantazzini and S. Figini, "Default Forecasting for Small-Medium Enterprises: Does Heterogeneity Matter?", University of Pavia, Italy.
- [23] D.Fantazzini and S. Figini, "Random Survival Forest models for SME Credit Risk Measurement", University of Pavia, Italy.
- [24] R.A. Fisher, "The use of Multiple Measurements in Taxonomic Problems", *Annals of Eugenics*, 7 pp.179-188,1936.
- [25] I. Genriha, I.Voronova and G. Pettere, "Entrepreneurship insolvency risk management: case Latvia", *International Journal of Banking, Accounting And Finance Vol.3 No.1*, 2011.
- [26] T.V. Gestel, B.Baesens, J. Garcia and P.V. Dijke, "A Support Vector Machine Approach to Credit Scoring", 2003. Available: [http://www.defaultrisk.com/pp\\_score\\_25.htm](http://www.defaultrisk.com/pp_score_25.htm) [Accessed September 1, 2011].
- [27] B.J. Grablowsky and W.K. Talley, "Probit and discriminant functions for classifying credit applicants: a comparison", *J.Econ. Bus.*,33,254-261, 1981.
- [28] D.J. Hand and W.E. Henley, "Statistical classification methods in consumer credit scoring: A review", *Journal of the Royal Statistical Society, Series A* 160, 523-541, 1997.
- [29] W. Hardle, R.A. Moro and D. Schafer, "Predicting Bankruptcy with Support Vector Machine", SFB 649 Discussion Paper 2005-009, 2005.
- [30] M. Kerling and T. Poddig, "Klassifikation von Unternehmen mittels KNN", in *Neuronale Netze in der Ökonomie*, Germany, 1994.
- [31] F. Kiss, "Credit scoring processes from a knowledge management perspective", Budapest University of Technology and Economics, *Periodica Polytechnica ser.soc.man.sci.vol.11,no.1*, pp.95-110, 2003.
- [32] E. Kočenda and M. Vojtek, "Default Predictors and Credit Scoring Models for Retail Banking", *CESIFO WORKING PAPER NO.2862*,2009.
- [33] S. Kotsiantis, D. Tzelepis, E. Koumanakos and V. Tampakas, "Efficiency of Machine Learning Techniques in Bankruptcy Prediction", 2nd International Conference on Enterprise Systems and Accounting (ICESAcc'05) Greece,2005.
- [34] S. Lane, "Submarginal Credit Risk Classification", *J.Finan. and Quant. Anal.* 7, 1379-1385, 1972.
- [35] P. Makowski, "Credit Scoring branches out", *Credit Wrldd*, 75, 30-37,1985.
- [36] W. McCullock and W. Pitts, "A Logical Calculus of the Ideas Immanent in Nervous activity", *Bulletin of Mathematical Biophysics*, 7, 115-133,1943.
- [37] D. Mehta, "The Formulation of Credit Policy Models", *Mgmt.sci.* 15,30-50, 1968.
- [38] J.H. Myers and E.W. Forgy, "The Development of Numerical Credit Evaluation Systems", *J.Am.Statist.Assoc.* 58, 799-806, 1963.
- [39] M. Odom and R. Sharda, "A neural network model for bankruptcy prediction", in Proc. Int. Joint Conf. Neural Networks, San Diego, CA,1990.
- [40] H. Raiffa and R. Schlaifer, "Applied Statistical Decision Theory", Colonial Press, Mass, 1961.
- [41] A. Resti and A. Sironi, "Risk Management and Shareholders' Value in Banking", From Risk Measurement Models to Capital Allocation Policies. England: John Wiley & Sons, Ltd, 2007.
- [42] E. Rosenberg and A. Gleit, "Quantitative Methods in Credit Management: A Survey", *Operations Research, Volume 42, Issue 4*, 589-613,1994.
- [43] G. Sabato, "Credit Risk Scoring Models", Group Credit Risk, RBS; University of Rome, 2010. Available: <http://ssrn.com/abstract=1546347> [Accessed September 1, 2011].
- [44] L. Salchenberger, E. Cinar, and N. Lash, "Neural networks: A new tool for predicting thrift failures", *Decision Sciences*, vol. 23, pp. 899-916,1992.
- [45] K.B. Schebesch and R. Stecking, "Support vector machines for classifying and describing credit applicants: detecting typical and critical regions", *Journal of the Operational Research Society* 56:1082-1088, 2005.
- [46] F.C. Scherr, "Estimating and Using Failure-Forecasting Functions:Some Problems and Some Proposed Solutions", *Baylor Bus.Studies* 12, 19-33, 1982.
- [47] J.B. Simha and S.S. Satchidananda, "Comparing decision trees with logistic regression for credit risk analysis", SAS Apaugc, Mumbai,2006.
- [48] R. Šorins, and I. Voronova, "Uzņēmuma maksātspējas novērtējums". In: *Ekonomiskās problēmas uzņēmējdarbībā*, pp.125 -131, Rīga: RTU, 1998.
- [49] L.C. Thomas, D.B. Edelman and J.N. Crook, *Credit Scoring and its Applications*, Society for Industrial and Applied Mathematics: Philadelphia, 2002;
- [50] M.B. Yobas, J.N. Crook and P.Ross, "Credit scoring using neural and evolutionary techniques", *IMA Journal of Mathematics Applied in Business and Industry*, 11,111-125, 2000.
- [51] J.C. Wiginton, "A Note on the Comparison of Logit and Discriminant Models of Consumer Credit Behavior", *J.Finan. and Quan.Anal.* 15, 757-768, 1980.
- [52] R.Wilson and R. Sharda, "Bankruptcy prediction using neural networks", *Decision Support Systems*, vol. 11, pp. 431-447, 1994.
- [53] G. Zhang, M. Hu, and B. Patuwo et al., "Artificial neural networks in bankruptcy prediction: General framework and cross-validation analysis", *European J. Oper. Res.*, vol. 116, pp. 16-32, 1999.



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**Irina Genriha, Irina Voronova. Aizņēmēju maksātspējas novērtēšanas metodes**

Balstoties uz Basel Capital Accord un Internal Rating Based (IRB) pieeju, komercbankām ieteikts izmantot savus iekšējos reitinga modeļus, lai novērtētu saistību nepildīšanas varbūtību (PD). Savukārt, praksē PD izmantota ne tikai, lai aprēķinātu iekšējā kapitāla prasības, bet arī, lai pieņemtu lēmumu par kredīta izsniegšanu, lai novērtētu potenciālā aizņēmēja maksātspēju. PD ir iespējams aprēķināt izmantojot matemātiskus modeļus, kurus sauc par skoringa modeļiem. Šī pētījuma mērķis ir sniegt atvērtu analīzi par matemātiski-statistiskām metodēm maksātspējas novērtēšanai, aprakstīt aprēķināšanas metodoloģiju katrai no metodei, un analizēt priekšrocības un trūkumus. Vēsturiski visplašāk izmantotie modeļi, maksātspējas novērtēšanai bija tādas parametriskas metodes kā dispersijas un regresijas analīze. Bet finanšu matemātikas attīstības gaitā sāk rasties jaunas neparametriskas metodes tādas kā lēmumu koki, neironu tīkli, ekspertu sistēmas, vektora mašīnas un daudzi citi. Autori klasificē metodes, kas bija pieejamas zinātņu literatūrā un kas tika izmantotas, lai novērtētu aizņēmēja maksātspēju. Izanalizējot ap 50 zinātnieku rakstus, autori, izmantojot salīdzinošas analīzes paņēmieni, izveidojuši tabulu, kurā tika salīdzinātas 5 visbiežāk izmantotās metodes. Balstoties uz to autori secinājuši, ka neparametriskas metodes biežāk uzrāda lielāku novērtēšanas precizitāti nekā parametriskas metodes, tāpēc ir vērts izmantot ne tikai tādas pazīstamas parametriskas metodes kā regresijas un dispersijas analīze, bet arī neparametriskas metodes. Autori uzskata, ka pilnveidotie skoringa modeļi palīdzēs Latvijas komercbankām būt gatavām strādāt ar nākamo kredītēšanas vilni, jo ar skoringa modeļiem ir iespējams pareizi novērtēt un regulēt potenciālo aizņēmēju plūsmu, kā arī vienlaicīgi samazināt saistību nepildīšanas varbūtību.

**Ирина Генрих, Ирина Воронова. Методы оценки платежеспособности заемщиков**

На основании Базельского соглашения (Basel Capital Accord) и подхода на основе Внутренних Рейтингов (Internal Rating Based (IRB)), коммерческим банкам предлагается использовать свои внутренние модели рейтинга для оценки вероятности дефолта (PD). На практике PD используются не только для расчета требований по внутреннему капиталу, но и для принятия решений о выдаче кредита, осуществляя оценку платежеспособности потенциального заемщика. PD можно вычислить с помощью математических моделей, известных как скоринговые модели. Это исследование направлено на обеспечение открытого анализа математико-статистических методов для оценки платежеспособности, на освещении методики расчета каждого из методов, а также анализе их преимуществ и недостатков. Исторически наиболее широко используемые методы для оценки платежеспособности были такие параметрические методы как дисперсионный и регрессионный анализы. Но с развитием финансовой математики стали появляться новые непараметрические методы, такие как, деревья решений, нейронные сети, экспертные системы, вектор машины и многие другие. Авторы классифицируют методы, которые были доступны в научной литературе и которые были использованы для оценки платежеспособности заемщика, на две группы. Проанализировав около 50 научных статей, авторы, используя метод сравнительного анализа, выявили пять наиболее часто используемых методов. На основании этого авторы обнаружили, что непараметрические методы часто приводят к более высокой оценке точности, чем параметрические методы. Основываясь на проведенном анализе, авторы советуют использовать при построении скоринговых моделей не только известные параметрические методы (дисперсионный и регрессионный анализ), но и непараметрических методов. Авторы считают, что усовершенствованные модели скоринга, помогут латвийским коммерческим банкам, быть готовым для работы с новой волной кредитования, так как скоринговые модели дают возможность правильно оценить и регулировать поток потенциальных заемщиков, одновременно уменьшая вероятность дефолта.