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# ENTERPRISE CREDIT RISK ASSESSMENT ANALYZING THE DATA OF SHORT TERM ACTIVITY PERIOD

**Ričardas Mileris**
*Kaunas University of Technology*

**Abstract**

This research investigates the possibility to classify the companies into default and non-default groups analyzing the financial data of 1 year. The developed statistical model enables banks to predict the default of new companies that have no sufficient financial information for the credit risk assessment using other models. The classification and regression tree predicts the default of companies with the 96 % probability. The complementary analysis the financial data of 2 years by probit model allows to increase the classification accuracy to 99 %.

Key words: bank, classification, credit risk, statistical analysis.

## Introduction

The international financial supervisors and authorities require banks to monitor their credit risk because the proper risk management has a positive effect not only on bank performance, but also on whole economy. This fact is evident in times of financial crises, when financial institutions can suffer high losses due to unpaid credits. In recent years, credit risk has been a frequent object of the scientific researches, mainly due to the international financial crisis that has considerably affected a large number of financial institutions. The commercial banks seek to increase the amount of credits without increasing the proportion of failures in the loan portfolio extremely. The ability to develop the reliable computational credit risk assessment models is the key to successful credit operations. The problem can be summarized as finding a function that relates the default possibility as the dependent variable with the set of explanatory variables. Credit scoring models generally aims to classify credit applicants into two groups (approved and disapproved) according to the particular properties of the applicants. The statistical approaches use the credit history and external data to build the predictors for the credit risk assessment of new loan applicants. The independent variables usually are the economic and financial information: the company‘s size, liquidity, solvency, profitability, debt, etc. Instead of relying on a single classifier, banks can construct a composite model that combines the predictions of multiple classifiers in order to improve the definitive classification results.

The object of this research is the credit risk of enterprises.

The aim of this research is to develop the enterprises credit risk assessment model analyzing the financial data of short term activity.

The tasks of the research:

1. To analyze the principles of credit riska assessment using the credit scoring models.
2. To develop the enterprises classification model for the assessment of credit risk analyzing the financial data of short term activity.

The methods of the research:

1. The analysis of scientific publications.
2. The classification and regression tree, probit analysis of enterprises financial data.

The developed classification model in this research allows to predict the possible insolvency of companies after 1 year and bankruptcy after 2 years.

## Credit scoring models in credit risk assessment

Credit risk evaluation is a very important task for banks to classify the loan applicants into the different risk classes and to predict their default probabilities. In the credit risk management it is important for banks to decide if the loan can be given to the customer or if the credit request has to be rejected. It is crucial to select the correct principle or model for credit applications evaluation and bankruptcy prediction as well as to decide which data and which factors are important. Decision rules can be derived using many statistical techniques and can be used to solve classification, regression or forecasting tasks, including identification of risk classes or probabilities of default (Danenas, Garsva, Gudas, 2011). Usually the data about loan applicants is complex and it is impossible for decision makers, even highly specialized banks, to achieve full information about the objective risk properties of borrowers. Thus, decision-makers develop decisional rules that abstract the complex information and rely on a reduced subset of data. After an evolutionary process, only those rules survive that enable high classification accuracy (Ramskogler, 2011).

The traditional credit risk measures are credit ratings that are concerned with repayment risk. The ratings signal the likelihood that a specific debt obligation will be paid on time. Solvency of a debtor is among the main drivers of traditional risk ratings (Beisland, Mersland, 2012). The credit rating scales usually separate the loan applicants into 8 or more risk classes and allow to estimate the minimum capital requirement according to the default probabilities of debtors. But for the decision making of financing or rejecting the loan application the credit scoring models can be used.

Credit scoring is the term used to describe formal statistical methods for classifying the loan applicants into two classes: creditworthy and no credit. The former class has great possibilities to repay financial obligations, and the latter has high possibilities of defaulting (Chen, Xiang, Liu, Wang, 2012). Thus, the primary problem of any lender is to differentiate between "good" and "bad" debtors prior to granting credit and to determine the likelihood that credit applicant will default on his credit obligation. The advantages of credit scoring include reducing the cost of credit analysis, enabling faster credit decisions, closer monitoring of existing accounts, and prioritizing collections. Credit scoring problems are basically in the scope of classification agenda that is a commonly encountered decision making task in businesses, and it is a typical classification problem to categorize an object into one of predefined groups or classes based on a number of observed attributes related to that object (Bahrammirzaee, Ghatari, Ahmadi, Madani, 2011). The various statistical and artificial intelligence methods can be applied developing the credit scoring models by bankers and researchers for the credit admission decision. However, irrespective of the varying nature of techniques used, credit scoring is invariably used to answer one key question – what is the probability of default within a fixed period, usually 12 months. Credit scoring can be divided into application scoring and behavior scoring, based on the information used when modeling. Application scoring uses only the information provided in application, while behavior scoring uses both the application information, and past behavior information (Dong, Lai, Yen, 2010).

Typically, the quality of a developed credit scoring model is estimated and verified by the procedure of cross-validation. The procedure usually requires a large sample that can be divided into an analysis group and a holdout group – the analysis group is used to estimate a prediction model and the holdout group is used to validate its predictive ability. Limited by a small sample size, it can be difficult to have a holdout group to test the predictive abilities of the developed model. Obtaining the numbers from the estimation procedure, the performance of a model commonly is evaluated by the predictive accuracy, Type I and Type II errors (Lin, Wang, 2011). The most costly misclassification error is incorrect classification of a defaulter as a nondefaulter (Type I), which increases exposure to a loss of funds and profits. A less costly error occurs when nondefaulters are misclassified as defaulters (Type II), creating an opportunity cost of not extending credit to worthy applicants. While a model cannot eliminate both errors, a small percentage improvement in accuracy can materially impact the lending institution's profit (Trinkle, Baldwin, 2007).

This research is related with the commercial and industrial loans – the category of loans that covers lending to business firms. Banks set the particular lending standards for companies that are the criteria by which banks determine and rank loan applicants' risks of loss due to default, according to which banks then make the lending decisions (Gorton, He, 2008). Banks must develop a screening technology to find out the quality of an entrepreneur's project analyzing private or public information (Hakenes, Schnabel, 2010). Zambaldi, Aranha, Lopes and Politi (2011) distinguish between two types of lending decision processes: relationship banking and statement (ratio) lending. A relationship loan depends on both objective and subjective information about borrowers, which the bank obtains through its relationships with customers, while a ratio loan relies on objective procedures such as credit score and loan securitization. Relationship banking may increase credit availability to small firms dealing with one bank and gives banks informational advantage over competitors since their customer's credit behavior remains private. Despite the benefits of relationship banking, the more important are lending techniques with automatic procedures that may reduce screening costs and avoid default. Ratio borrowers usually establish their credit reputation and encounter standard underwriting procedures for obtaining credit (Zambaldi, Aranha, Lopes, Politi, 2011).

In credit scoring the independent variables for the analysis can be selected by banks. Financial ratios have received particular attention as a means of detecting firm operating or financial difficulties. Several studies have concluded that failing firms have significantly more varied financial ratios than other firms. In addition to the quantitative measures of company performance, banks established to supply qualitative information for assessing the credit-worthiness of loan applicants (Chen, Ho, Lin, Tsai, 2012). Although their practical importance, often the development of empirical credit risk models has been hindered by the limited availability of credit data. In fact, historical default data can be insufficient and inadequate for the purpose of statistical modelling. So the supplementary information on credit risk can be inferred from financial market data or macroeconomic indicators (Giammarino, Barrieu, 2009).

The credit risk assessment models relying only on the financial data have also been criticised for assuming naively that the risk factor distribution in times of crisis is the same as usual (Breuer, Jandacka, Mencia, Summer, 2012). With minimum capital requirements based on risk, banks are more likely to become capital constrained during economic downturns as loan losses rise and capital is depleted. If banks raise their lending standards, then some borrowers are cut off from credit, that should have negative macroeconomic implications. Because risk-based capital standards explicitly link banks' minimum required capital to asset risk and place higher capital requirements on loans, capital constrained banks are likely to reduce lending thereby exacerbating the economic downturn (Jacques, 2010). Bank loan portfolio growth before the economic downturn leads to higher bank risk, including a worsening of the risk-return structure and decreasing bank solvency (Nijskens, Wagner, 2011). This is the reason why the interest rates can increase because banks can require a higher compensation for default risk on loans (Gefang, Koop, Potter, 2011). The credit risk of companies not only can be assessed analyzing the macroeconomic indicators, but also conversely the conditions of an economy can be evaluated by the loan portfolio quality in banks of a country. According to Wong, Wong and Leung

(2010), an economy at time *t* is classified as a distress economy if at least one of the following four conditions is satisfied:

- The nonperforming loan ratio in the banking sector is larger than 10%.
- The rescuing costs of the banking sector are larger than or equal to 2% of the GDP.
- There is a significant large-scale nationalization of banks in response to banking problems.
- A systemic bank run takes place or emergency measures are enacted for rescuing systemic banking problems (Wong, Wong, Leung, 2010).

A study by Thiagarajan, Ayyappan and Ramachandran (2011) revealed that various macroeconomic and bank specific factors such as growth in GDP, rapid credit expansion, bank size and capital adequacy ratio influence the amount of non-performing loans. An inverse relationship between bank size and the non-performing loans was found because large banks have better risk management strategies that usually translate into more superior loan portfolios than their smaller counterparts. Also it was found that the banks with higher government ownership have lower non-performing loans (Thiagarajan, Ayyappan, Ramachandran, 2011).

The recent studies have employed various statistical and artificial intelligence data analysis methods for the classification of companies into default and non-default groups. The methods employed and the overall accuracy of the classification models developed by different researchers are given below. These models analyze the financial data of 1 year.

- Wang, Ma (2012): logistic regression (LR) – 71,69%, decision tree (DT) – 69,06%, artificial neural networks (ANN) – 71,52%, linear support vector machine (SVM) – 68,02%, polynomial SVM – 73,84%.
- Kim, Ahn (2012): discriminant analysis (DA) – 65,03%, LR – 67,12%, ANN – 69,55%.
- Yu, Yao, Wang, Lai (2011): *k*-nearest neighbour classifier (KNN) – 70,70%, linear DA – 74,60%, quadratic DA – 71,00%, LR – 74,60%, linear programming (LP) – 71,90%, naive Bayes classifier (NB) – 72,20%, tree augmented naive Bayes classifier (TAN) – 72,50%, DT – 74,60%, feedforward neural networks (FNN) – 73,70%, multilayer perceptron (MLP) – 73,28%, radial basis function network (RBFN) – 74,60%.
- Derelioglu, Gurgen (2011): KNN – 80,66%, MLP – 76,17%, SVM – 75,78%.
- Zhou, Jiang, Shi, Tian (2011): linear SVM – 84,78%, RBF SVM – 85,65%, linear kernel affine subspace nearest point (KASNP) – 85,81%, RBF KASNP – 86,27%.
- Khashman (2011): ANN – 91,16%.
- Peng, Wang, Kou, Shi (2011): NB – 86,45%, Bayesian network – 91,11%, SVM – 98,13%, LR – 98,09%, KNN – 97,23%, RBFN – 98,13%.
- Zhou, Jiang, Shi (2010): nearest subspace (NS) – 70,04%, ANN – 63,46%, linear SVM – 67,81%, RBF SVM – 68,37%.
- Yu, Wang, Lai (2008): LR – 70,77%, ANN – 73,63, SVM – 77,84%.
- Liou (2008): LR – 99,05%, ANN – 95,82%, DT – 98,15%.

The average overall accuracy of 43 analyzed models is 78,6%. It can be concluded that analyzing the data of short term activity the ability to classsify companies correctly is not high. The advantage of such models for banks is the wide application because the models need the financial data of only 1 year. The banks can apply these models for the credit risk assessment of new companies that have not the financial information of long period. But the main imperfection in this case is the low classification accuracy. So in the empirical research the statistical model will be developed trying to extract more valuable information from the limited financial data and to reach the higher classification accuracy.

## The enterprises classification model

The previous researches (Mileris, Boguslauskas, 2011) allowed to develop enterprises classification models that analyze the financial data of different periods. The highest classification accuracy (97%) was reached by the logistic regression model analyzing the data of 3 years and the statistical credit rating model was developed. But in this case the model cannot assess the credit risk of a company if it works only 1 or 2 years. Because of the lack of financial data banks must rely on expert opinion or deny the credit application if a company is new. The not successful activity and high credit risk can be seen in financial report of a company if it has negative profitability, low solvency and indebted capital structure ratios. The statistical analysis of 200 Lithuanian companies has shown that financial ratios of bankrupted and profitable companies differ significantly at last year before bankruptcy (Figure 1). The average net profit margin (NPM) of profitable companies is 29,8% while the activity of bankrupted companies 1 year before the bankruptcy was loss making. The average return on assets (ROA) of the profitable companies was 12,2% while the bankrupted companies had this ratio negative. The average current ratios (CR) indicate that the current assets of profitable companies was 3,173 times higher than current liabilities. This solvency parameter of bankrupted companies in the last year of their activity was 0,944. The debt ratios (DR) indicate that the average indebtedness of profitable companies is 51,4% but the liabilities of bankrupted companies are 6,905 times higher than their assets. So if a company is in bad financial condition and the bankruptcy in next financial year is very probable, the bank will not lend the money.

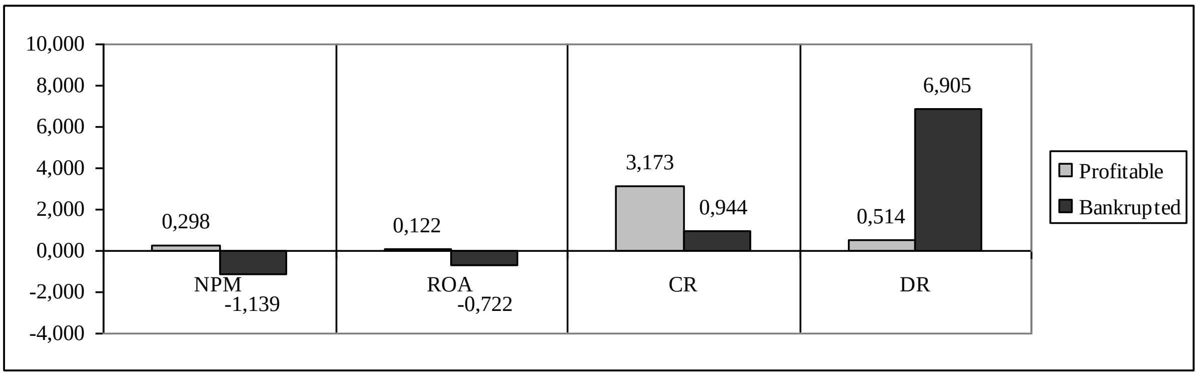


**Fig. 1. The average financial ratios**

The problem of this research is to find the methods to classify companies if their financial condition is not apparently bad. For this purpose the financial data was used about 150 profitable companies and 50 bankrupted companies 2 years prior to bankruptcy. Having the company‘s financial data of year $y_0$ the developed model allows to classify a company into two groups:

- The group of profitable and continuing activity companies in years $y_1 – y_2$.
- The group of loss making companies in year $y_1$ and bankrupted companies in year $y_2$ (Figure 2).

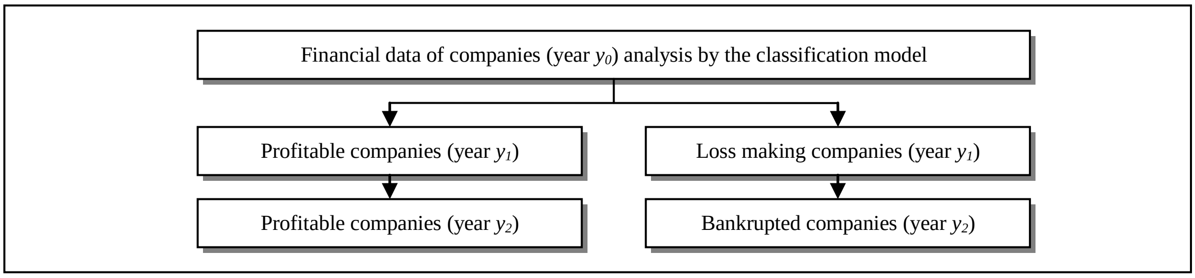


**Fig. 2. The classification of companies by the developed model**

The analyzed financial data sample of bankrupted companies indicated that 2 years prior to the bankruptcy the financial condition of these companies is better than before 1 year. The graph in Figure 3 is divided into 4 parts reflecting the solvency and profitability of bankrupted companies in the sample. 23,9% of companies were solvent and profitable (CR ≥ 1, NPM ≥ 0), 21,7% – solvent but loss making (CR ≥ 1, NPM < 0), 13,1% – insolvent but profitable (CR < 1, NPM ≥ 0), 41,3% – insolvent and loss making (CR < 1, NPM < 0).

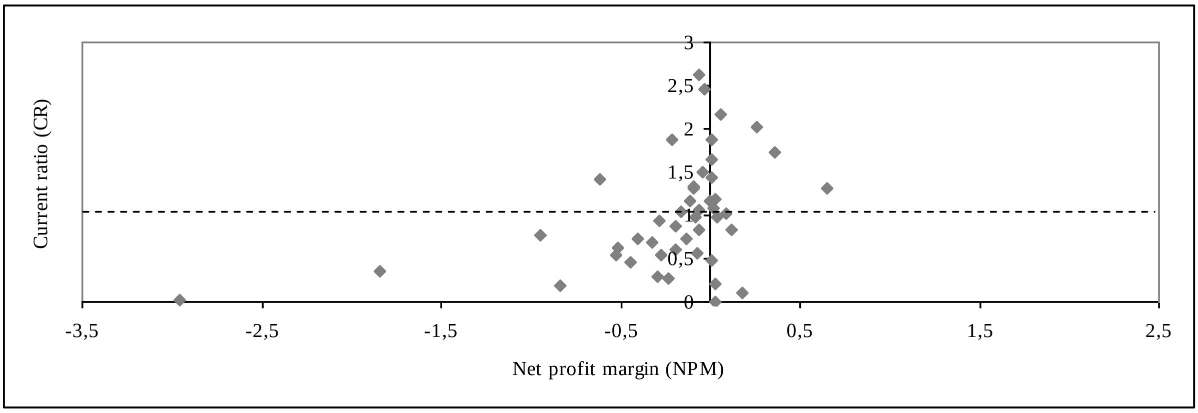


**Fig. 3. The profitability and solvency of bankrupted companies 2 years prior to the bankruptcy**

The classification and regression tree (CART) model was developed for the classification of companies (Figure 4). 7 financial ratios of year $y_0$ are being analyzed in this model:

- Return on assets (ROA) = Net income / Total assets.
- Current ratio (CR) = Current assets / Current liabilities.
- Gross profit margin (GPM) = Gross profit / Net sales.
- Quick ratio (QR) = (Current assets – (Inventories + Prepayments)) / Current liabilities.

- Cash ratio (CSR) = Cash and marketable securities / Current liabilities.
- Fixed assets turnover ratio (FTA) = Net sales / Fixed assets.

The *ID* in the developed CART model is the node number, *N* is the size of node, *Mu* is the average of the dependent variable. The financial conditions and the classification thresholds are in brackets. The end nodes are highlighted in grey.

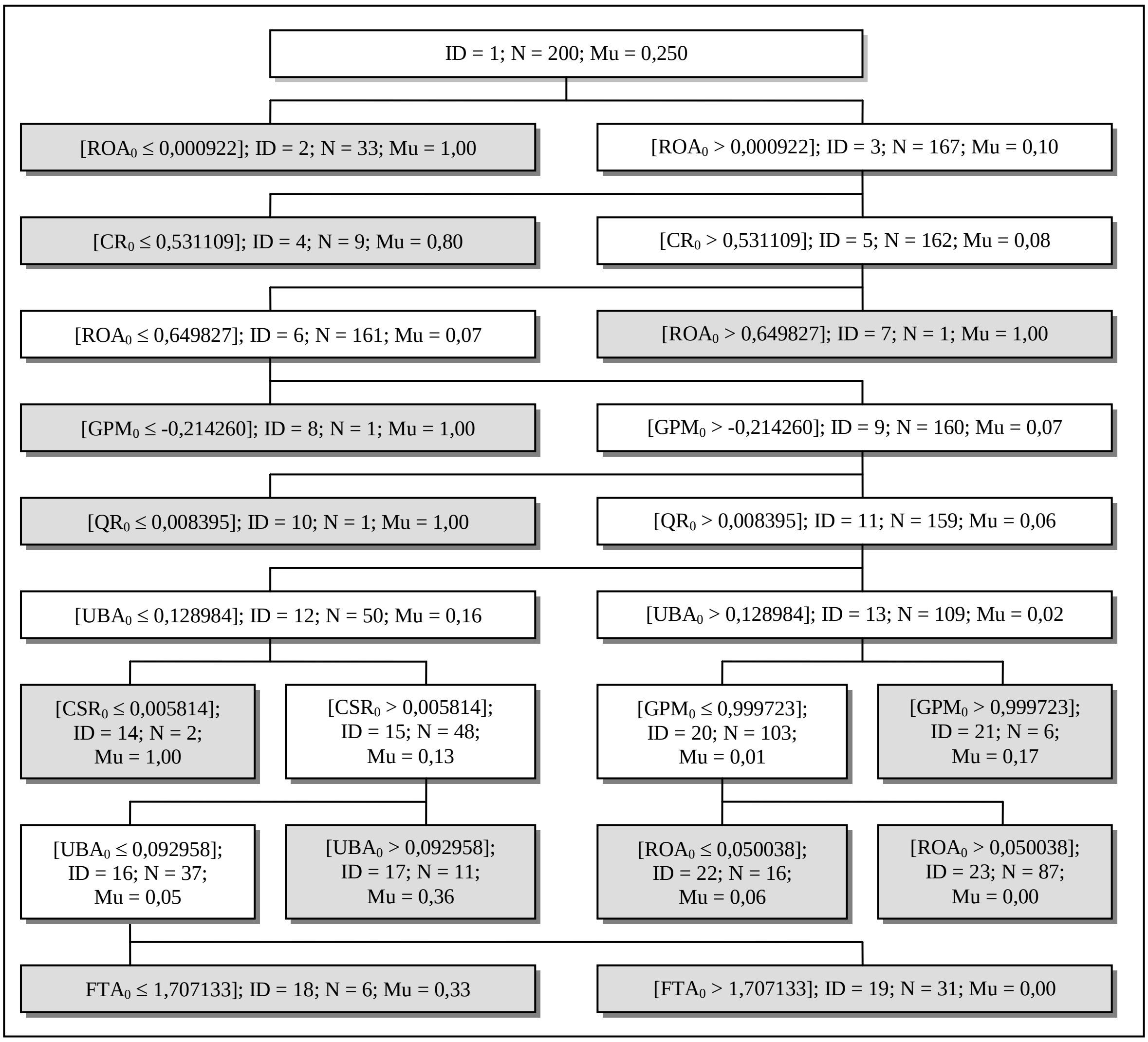


**Fig. 4. The CART model for the classification of companies**

The classification of companies in the CART model:

- If *Mu* < 0,5 a company is classified into the profitable group.
- If *Mu* ≥ 0,5 a company is classified into the bankrupted group.

The classification results of analyzed data sample are given in the classification matrix (Predicted CART in Table 1). In this matrix „0“ means the group of profitable companies, „1“ means the group of bankrupted companies.

**Table 1. The classification matrix**

| Observed | Predicted CART | | Predicted CART + Probit | |
|---|---|---|---|---|
| | 0 | 1 | 0 | 1 |
| 0 | $TN_1 = 150$ | $FP_1 = 0$ | $TN_2 = 150$ | $FP_2 = 0$ |
| 1 | $FN_1 = 8$ | $TP_1 = 42$ | $FN_2 = 2$ | $TP_2 = 48$ |

The correct classification rate of the CART model indicated that correctly were classified 96% of companies:

$$CCR = \frac{TN_1 + TP_1}{TN_1 + TP_1 + FN_1 + FP_1} = \frac{150 + 42}{150 + 42 + 8 + 0} = 0{,}96 = 96\% \tag{1}$$

The sensitivity of model reflects the ability to classify correctly the bankrupted companies. This rate is 84%:

$$Se = \frac{TP_1}{TP_1 + FN_1} = \frac{42}{42+8} = 0{,}84 = 84\% \quad (2)$$

The specificity of model reflects the ability to classify correctly the profitable companies. This rate is 100%:

$$Sp = \frac{TN_1}{TN_1 + FP_1} = \frac{150}{150+0} = 1 = 100\,\% \quad (3)$$

In order to increase the ability to classify correctly the bankrupted companies, the probit model was developed. The data sample for probit model consists of 158 companies that were classified as profitable by the CART model: 150 observed as profitable and 8 observed as bankrupted. The bank will classify companies by CART model using the financial data of year $y_0$. Next year, if a company by CART model was classified as profitable and this company is continuing the activity, the financial data of year $y_1$ must be used for the further classification by probit model. In addition to GPM, ROA, CR, QR, CSR and FTA, the other 9 financial ratios are the independent variables in the probit model:

- Main activity profit margin (APM) = (Sales – (Cost of goods sold + Operating Expenses)) / Net sales.
- Net profit margin (NPM) = Net income / Net sales.
- Return on equity (ROE) = Net income / Shareholders‘ equity.
- Working capital to total assets (WCA) = (Current assets – Current liabilities) / Total assets.
- Solvency ratio (SR) = Shareholders‘ equity / Total liabilities.
- Debt ratio (DR) = Total liabilities / Total assets.
- Long-term debt ratio (LDR) = Long-term debt / (Long-term debt + Shareholders‘ equity).
- Asset turnover (AT) = Net sales / Total assets.
- Unappropriate balance to total assets (UBA) = Unappropriate balance / Total assets.

The probit model:

$$P = -16{,}9233 - 6{,}3824 \cdot GPM_1 + 10{,}3425 \cdot APM_1 + 14{,}0876 \cdot NPM_1 - 19{,}6914 \cdot ROA_1 + 1{,}4493 \cdot ROE_1 + 0{,}9370 \cdot CR_1 + 0{,}0572 \cdot QR_1 - 1{,}1442 \cdot CSR_1 - 6{,}1835 \cdot WCA_1 + 8{,}5869 \cdot SR_1 + 27{,}8547 \cdot DR_1 - 6{,}0973 \cdot LDR_1 + 0{,}0076 \cdot FTA_1 - 1{,}2500 \cdot AT_1 + 26{,}0383 \cdot UBA_1 \quad (4)$$

The classification of companies in the probit model:

- If $P \geq 0{,}5$ a company is classified into the profitable group.
- If $P < 0{,}5$ a company is classified into the bankrupted group.

The classification results combining the CART and probit models are given in Table 1 (Predicted CART + Probit). The overall classification accuracy increased by 3% (CCR = 99%) and the sensitivity increased by 12% (Se = 96%). So this research affirmed the ability of statictical analysis techniques to predict the insolvency and bankruptcy of companies analyzing the short term financial data. The developed model can improve the credit risk assessment process in the commercial banks supporting the instruments used in decision making of financing the business clients.

## Conclusions

1. In credit risk assessment of new business clients banks often meet with the data lack problem for the analysis process. Banks must have the instruments for the analysis of different situations because the decision making of credit experts is more objective using the quantitative models. The research results can improve the credit risk assessment in banks and increase the possibilities to get credit for new companies.

2. The analysis of scientific literature has shown that various statistical and artificial intelligence methods were applied for the classification of companies analyzing the 1 year financial data. The highest overall classification accuracy of estimated 43 models was 99,05%, but the average accuracy is not high (78,6%). So the results of new researches that are above this average can have a valuable information for banks.

3. The developed CART model analyzing the 1 year financial information classifies companies with the 96% accuracy. Having the data of next year the non-default companies can be analyzed by probit model which raises the accuracy to 99%. The research affirmed that the increase of period in financial information analysis enables to extract more valuable information in credit risk assessment.

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## ĮMONIŲ KREDITO RIZIKOS VERTINIMAS ANALIZUOJANT TRUMPO VEIKLOS LAIKOTARPIO DUOMENIS

**Ričardas Mileris**
*Kauno Technologijos universitetas*

### Santrauka

Įmonių kredito rizikos vertinimo procese komerciniai bankai susiduria su duomenų analizei trūkumu, jei dėl paskolos besikreipiančios įmonės veiklos laikotarpis yra trumpas. Esant nepatenkinamai įmonių finansinei būklei, finansinių įsipareigojimų nevykdymo ir bankroto rizika atsispindi finansiniuose rodikliuose. Tačiau egzistuoja problema, kaip įžvelgti šią riziką, jei įmonės finansiniai rodikliai nėra žemi. Tokiais atvejais greta kokybinio ekspertinio vertinimo bankams naudinga turėti ir kiekybinius modelius, leidžiančius klasifikuoti įmones į patikimų ir nepatikimų klientų grupes. Mokslinės literatūros analizės rezultatai parodė, kad analizuojant 1 metų įmonių duomenis pasiektas didžiausias klasifikavimo tikslumas yra 99,05 %, tačiau teisingo klasifikavimo rodiklio vidurkis siekia tik 78,6 %. Šiame tyrime sudarytas klasifikavimo ir regresijos medis, kuriuo analizuojami įmonių 7 santykiniai finansiniai rodikliai. Modelis leidžia prognozuoti įmonių finansinių įsipareigojimų nevykdymą ir bankrotą su 96 % tikimybe. Veikiančių įmonių vėlesnių metų 15 santykinių rodiklių analizė sudarytu tiesiniu tikimybiniu modeliu padidina klasifikavimo tikslumą iki 99 %.

Prasminiai žodžiai: bankas, klasifikavimas, kredito rizika, statistinė duomenų analizė.