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Estimation of Credit Risk by Artificial Neural Networks Models

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Credits mostly form a considerable part of banks assets and is one of the most risky types of them. Credits for banks are not only the source of income but also they can be the main reason of loss. The main risk that banks meet with lending money is credit risk. It is risk that debtor will not be able to repay his obligations due to certain reasons. Seeking to reduce potential loss due to crediting not reliable clients banks must be able to measure credit risk of each client properly. One of possible methods is using of internal credit risk estimation models.

Due to the importance of credit risk analysis, many methods were widely applied to credit risk measurement tasks: linear discriminant analysis, logit analysis, probit analysis, linear programming, integer programming, k-nearest neighbour, classification tree, artificial neural networks (ANN), genetic algorithm, support vector machine, some hybrid models ant other. An increasing field of research in artificial neural networks is the one mainly concerned with interactions between economics and computer science, studying their potential applications to economics. Artificial neural networks represent an easily customizable tool for modelling learning behaviour of agents and for studying a lot of problems very difficult to analyze with standard economic models (Gallo, 2006).

ANN have many advantages over conventional methods of analysis. According to Shachmurove (2002), they have the ability to analyze complex patterns quickly and with a high degree of accuracy. Artificial neural networks make no assumptions about the nature of the distribution of the data. Since time-series data are dynamic in nature, it is necessary to have non-linear tools in order to discern relationships among time-series. ANN are best at discovering these types of relationships. Also neural networks perform well with missing or incomplete data. Compared with an econometric model, it is easier to use ANN where a forecast needs to be obtained in a shorter period of time.

The purpose of this research is to define the rates of classification accuracy and to measure the classification accuracy of artificial neural networks credit risk estimation models. The methods of the research are analysis of scientific publications about credit risk estimation models and analysis of artificial neural networks credit risk estimation models classification accuracy.

One important component needed to accomplish credit risk evaluation is to seek an accurate classifier in order to categorize new applicants or existing customers as good or bad (Lai, Yu, Wang, Zhou, 2006). In this paper rates of credit risk estimation models accuracy and their calculation were described: correct classification and misclassification rates, false negative and false positive rates, model sensitivity and specificity, positive and negative predictive values, F-measure, ROC analysis. Analysis of scientific publications about credit risk estimation models has shown that the most efficient of the most commonly used methods are logistic regression and artificial neural networks. Less reliable methods are decision trees and discriminant analysis. Also artificial neural networks models (multilayer perceptrons) were constructed for the analysis of Lithuanian enterprises credit risk. Calculation of models accuracy rates has shown that the most efficient model analyses data about clients is of 3 years. Experiments have shown that analyzing data of 4 and 5 years classification accuracy decreases due to high quantity of input information and neural network's overlearning. Models accuracy rates allowed to estimate risk of client misclassification and other characteristics. Also they helped to make the decision which model is to be used in practice in order to measure credit risk successfully.

Keywords: *artificial neural networks, classification of banks clients, credit risk, model accuracy rates.*

Introduction

Usually loan interest makes a significant share of banks' income (Macerinskiene, Ivaskeviciute, 2008). It is very important for commercial banks to choose such performance strategy that would reduce credit, liquidity, interest-rate related risk and would balance risk, profitability, liquidity and security (Lileikiene, 2008). Naturally, specifics of commercial bank services demands for special and well-defined measures for risk management (Zukauskas, Neverauskas, 2008). Effective risk valuation for commercial bank increases its value on the market and confidence between potential investors (Aniunas, Nedzveckas, Krusinskas, 2009). Financial decisions are related to the necessity to investigate prospective consequences of decisions made under uncertainty conditions according to the possible risk (Christauskas, Stunguriene, 2007). Proper risk management can reduce the probability of serious problems in banks (Rutkauskas, Stankeviciene, 2006).

Financial institutions are transforming themselves in response to fundamental changes in regulation and technology (Deltuvaite, Vaskelaitis, Pranckeviciute, 2007). Statistical decision theory is of major importance for the development of management science (Martisius, Martisius, 2008). In order to predict possible insolvency of companies in future, scientists and strategists of financial institutions demonstrate high interest in research of companies insolvency indicators. They construct and develop early warning systems of potential insolvency. By internal credit risk estimation models banks analyze data of credit applicants. The results of analysis help to make decision conserning crediting of clients. Commonly the purpose of quantitative credit risk estimation models is the measurement of client's probability of default (Hamerle, Liebig, Rosch, 2003). For this reason the bank must have information about clients and their reliability in the past (training set). Every credit applicant must be characterized by a set of variables $x_1, x_2, ..., x_n$. And these indicators must be able to discriminate different groups of clients, i.e. measure their credit risk. Training set consists of data of reliable and not reliable clients.

In recent years artificial neural networks (ANN) are widely used for credit risk measurement. The theory of ANN is based on the principles of biological neural networks and allow to analyze complex dynamic non-linear systems. Mostly in scientific publications where ANN are compared with other statistical models predicting insolvency of companies is affirmed that ANN are more preeminent than statistical models (Sookhnaphibarn, Polsiri, Choensawat, Lin, 2007, Lai, Yu, Wang, Zhou, 2006, Yim, Mitchel, 2005 and others). However, sometimes researchers present opposite results where ANN reached less classification accuracy than the analysis of the same data by other statistical models. For example Bastos (2008), Yun, Jianyingn, Lin (2007) higher accuracy reached by decision trees. ANN could be improved combining them with other statistical data analysis methods. This idea was implemented by Hsieh, Liu, Hsieh (2007), Lai, Yu, Wang, Zhou (2006), Yim, Mitchel (2005), Yegorova, Andrews, Jensen, Smoluk, Walczak (2001). In their models ANN were combined with other statistical methods. The results of their researches has shown that hybrid ANN models are very effective predicting bankruptcy of companies. Yim, Mitchell (2005) maintained that ANN have very high potential as an instrument for the prediction of companies insolvency and their proper integration with other statistical analysis methods can improve the results of enterprises classification.

The object of this research – artificial neural networks models for the estimation of credit risk.

The purpose of research is to define the rates of classification accuracy and to measure the classification accuracy of artificial neural networks credit risk estimation models.

The methods of the research:

1. Analysis of scientific publications about credit risk estimation models.
2. Analysis of artificial neural networks credit risk estimation models classification accuracy.

Artificial neural networks models

Artificial neural networks (ANN) are calculable structures consisting of a number of the same types elements, which execute relatively simple functions. Processes in ANS sometimes are associated with ones, which take place in the nervous system of living organisms (Shunin, 2005). Tal (2003) defines ANN as a mathematical model made of a great number of elements organized in levels. One of the most useful and successful applications of neural networks to data analysis is the multilayer perceptron model (MLP). Multilayer perceptron models are non-linear neural network models that can be used to approximate almost any function with a high degree of accuracy (Shachmurove, 2002). Vojtek, Kocenda (2006) also mantain that multilayer perceptron is especially suitable for classification and is widely used in practice.

The key difference between neural networks and other problem-solving methods is that neural networks in a real sense learn by example rather than having to be programmed with specific, preconceived rules. In other words, neural networks can be seen as a non-parametric statistical procedure that uses the observed data to estimate the unknown function (Tal, 2003).

The most important feature of neural networks is their ability to learn. Just like human brain, neural networks can learn by example and dynamically modify themselves to fit the data presented. Furthermore, neural models are also able to learn from very noisy, distorted, or incomplete sample data, which render other methods useless (Handzic, Tjandrawibawa, Yeo, 2003).

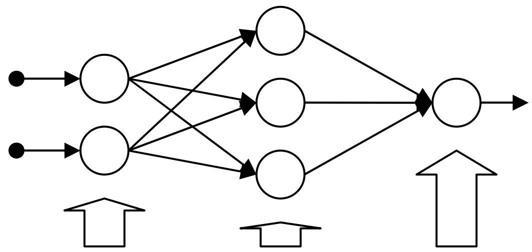

Figure 1. Typical neural network

An artificial neural network consists of an input layer, the inner (hidden) layers and an output layer (Figure 1). The input layer serves the purpose of taking in information (e.g. specific indicator values) and passing it on to the downstream neurons via the connections shown in Figure 1. These links are assigned weights in an artificial neural network and thus control the flow of information (Thonabauer, Nosslinger, 2004).

The base unit of any neural network is the neuron (processor). Each unit or neuron has a number of inputs that are combined to produce a single output (Nguyen, 2005). Model of computing neuron is illustrated in Figure 2 (Handzic, Tjandrawibawa, Yeo, 2003). Each neuron is able to sum many inputs, whether these inputs are from a database or from other neurons, with each input modified by an adjustable weight w_i. The sum of these weighted inputs s is added to an adjustable threshold for the neuron and then passed through a modifying (transfer) function f that determines the final output y (Tal, 2003).

Typical activation functions in neural networks are shown in Table 1 (Gallo, 2006).

The hidden layer is the series of relationships calculated in the network's training process. There is no theoretical limit on the number of hidden layers in a given network. Typically there will be one or two (Tal, 2003).

The deviation of the calculated output o_d from the actual output t_d is measured using an error function. The sum-of-squares error function is frequently used in this form:

$$e = \frac{1}{2}\sum_d \left(t_d - o_d\right)^2 \quad (1)$$

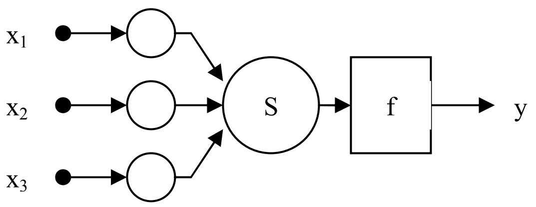

Figure 2. Model of computing neuron

The calculated error can be back-propagated and used to adjust the relevant weights. This process begins at the output layer and ends at the input layer (Thonabauer, Nosslinger, 2004).

In most real world problems, the neural network is never 100% correct. ANN are programmed to learn up to a given threshold of error. After the neural network learns up to the error threshold, the weight adaptation mechanism is turned off, and the net is tested on known cases it has not seen before. The application of the neural network to unseen cases gives the true error rate. In a well-trained neural network, the error threshold and the true error should be identical (Shachmurove, 2002).

Table 1

Activation functions in neural networks

Function	Calculation
Logistic	$f(x) = \frac{1}{1+e^{-x}}$
Symmetric logistic	$f(x) = \left(\frac{2}{1+e^{-x}}\right)^{-1}$
Hyperbolic tangent	$f(x) = \frac{e^{x}-e^{-x}}{e^{x}+e^{-x}}$
Corrected tangent	$f(x) = \tanh(c \cdot x)$
Sinusoidal	$f(x) = \sin(x)$
Gaussian	$f(x) = e^{-x^2}$
Inverse Gaussian	$f(x) = 1 - e^{-x^2}$

Models classification accuracy rates

The very significant importance of credit risk in financial sector determines demand to reach as high as possible credit risk estimation accuracy. That is possible only by using complex quantitative credit risk measurement methods (Vasiliauskaite, Cvilikas, 2008). When creating credit risk estimation models, it is very important to evaluate rates of classification accuracy. The evaluation of models quality becomes possible having training set, i.e. data about banks clients and their reliability in the past. For this purpose, models classification results are compared with actual clients reliability.

When estimating models classification accuracy, it is necessary to make classification matrix (Table 2). In this matrix information about clients reliability is encoded following: "0" – company has repayed its financial obligations (client is reliable), "1" – company had solvency problems (client is not reliable).

Table 2

Classification matrix

Model	Actual	
	1	0
1	True Positive (TP)	False Positive (FP)
0	False Negative (FN)	True Negative (TN)

Using data of the classification matrix, classification accuracy rates that are given in Table 3 can be calculated. Meaning of rates is:

- Correct Classification Rate (CCR) – correctly classified companies, where N is the number of analyzed companies.
- Misclassification Rate (MCR) – incorrectly classified companies.
- False Negative Rate (Type I error) (α) – not reliable companies classified as reliable.
- False Positive Rate (Type II error) (β) – reliable companies classified as not reliable.
- Sensitivity (Se) – correctly classified not reliable companies.
- Specificity (Sp) – correctly classified reliable companies.
- Positive Predictive Value (PPV) – percentage of companies classified as not reliable actually are not reliable.
- Negative Predictive Value (NPV) – percentage of companies classified as reliable actually are reliable.

As a single measure of performance of the test the *F*-measure can be used. The *F*-measure is the harmonic mean of precision and recall (positive predictive value is called precision, and sensitivity is called recall).

Table 3

Classification accuracy rates

Rate	Calculation
Correct classification rate	CCR = (TP+TN)/N
Misclassification rate	MCR = (FP+FN)/N
False negative rate	α = FN/(FN+TP)
False positive rate	β = FP/(FP+TN)
Sensitivity	Se = TP/(TP+FN)
Specificity	Sp = TN/(TN+FP)
Positive predictive value	PPV = TP/(TP+FP)
Negative predictive value	NPV = TN/(TN+FN)
F-measure	$F = \frac{2 \cdot PPV \cdot Se}{PPV + Se}$

For the estimation of credit risk models accuracy graphic analysis also is used. ROC (receiver operator characteristics) curve is often used to evaluate results of the objects classification to two groups when having training set (Figure 4). In the case of perfect credit risk model ROC curve reaches the top left corner of the graph. This means that all (100%) not reliable companies were classified correctly, i.e. the sensitivity of model is maximum. In this case the incorrectly classified part of companies is equal to 0. So the closer curve to the top left corner of graph, the more precise is the model. And conversely, the less arched curve the closer it is to the diagonal, the model is less effective. The diagonal of the graph reflects worthless model – the absolute impossibility to discriminate classes. These ROC curves allow to compare efficiency of different models. The closer is the ROC curve to the top left corner of the graph, the better is the model. If ROC curves of different models are very close to each other and they intersect, it is very difficult to evaluate the efficiency of models visually. Then areas under ROC curves (AUC) are compared. The area is in the range from 0 to 1. However, model is useful only if its ROC curve is above diagonal, so the efficiency of models commonly is evaluated in the range from 0,5 (worthless model) to 1 (perfect model). These values can be calculated estimating the area under the ROC curve.

Comparison of ANN classification accuracy with other methods

In order to estimate the efficiency of the most commonly used methods for credit risk measurement, 77 models published in 30 scientific publications were analyzed: Abdou (2009), Fantazzini, Figini (2009), Zhou, Lai, Yu (2009), Bastos (2008), Liou (2008), Lieu, Lin, Yu (2008), Marinakis, Marinaki, Doumpos, Matsatsinis, Zopounidis (2008), Yu, Wang, Wen, Lai, He (2008), Bandyopadhyay (2007), Yun, Jianying, Lin (2007), Altman, Sabato (2007), Wang, Li (2007), Bandyopadhyay (2006), Kumar, Bhattacharya (2006), Lai, Yu, Wang, Zhou (2006), Peter, Peter (2006), Ugurlu, Aksoy (2006), Witkowska (2006), Yim, Mitchell (2005) and others. The most often used methods are artificial neural networks (ANN) – 63.3%, logistic regression (LR) – 53.3%, discriminant analysis (DA) – 36.7%, decision trees (DT) – 23.3%. Various other methods were adapted for companies classification in 33.3% publications.

The general accuracy of models was evaluated: what proportion of companies was classified correctly (CCR). Objects illustrated in Figure 3 have such meaning: middle line is mean, top and bottom lines of rectangles – mean ± standard deviation (Mean±SD), the top and bottom lines of objects – the highest and lowest values (Min-Max).

The analysis results indicate that credit risk is estimated most precisely by logistic regression and artificial neural networks. Average accuracy of these methods is almost the same – 86.78% and 86.77%. The less reliable methods are decision trees and discriminant analysis. Their average accuracy is 82.7% and 77.38% respectively. Very important indicator is standard deviation of CCR which reflects the variation of analyzed rates, i.e. average deviation from mean. Although averages of CCR are almost the same of ANN and LR models (difference is only 0.01%), the variation of of ANN models is less. It indicates that average CCR of ANN is more reliable characteristic. Evaluating every model separately, the highest accuracy was reached by logistic regression (99.2%). In analyzed models the highest CCR reached by artificial neural networks is 98.35%.

Comparison of analysis methods demonstrates that artificial neural networks and logistic regression models allow to reach very good banks clients credit risk measurement results.

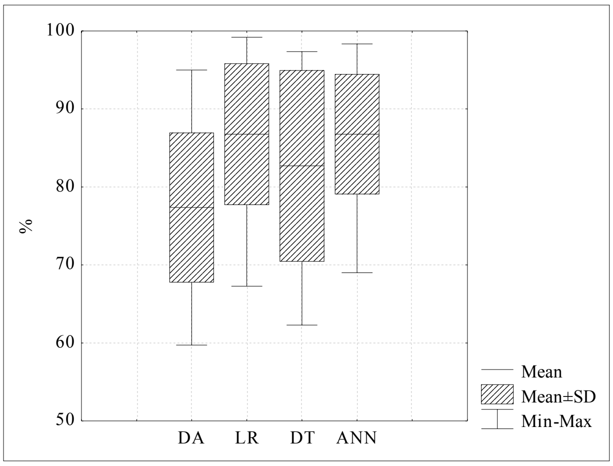

Figure 3. Comparison of models classification accuracy

Data sample and the models

Data sample consists of two groups of Lithuanian enerprises: successful (50) and bankrupted (50). For the analysis 3 criterions were estimated to determine if the company is successful:

1. Liquidity: curent ratio, quick ratio, cash to current liabilities, working capital to total assets.

2. Profitability: gross profitability, net profitability, net profit to total assets, net profit to equity.

3. Leverage: total liabilities to total assets.

60 variables (20 financial ratios of 3 years) were used as inputs in the models. These ratios were the following.

1. Liquidity rates: 1.1. Curent ratio, 1.2. Quick ratio, 1.3. Cash to current liabilities, 1.4. Working capital to total assets.

2. Profitability rates: 2.1. Gross profitability, 2.2. Net profitability, 2.3. Net profit to total assets.

3. Leverage rates: 3.1. Total liabilities to total assets, 3.2. Total debt to equity, 3.3. Long term debt to equity, 3.4. Equity to total assets.

4. Activity rates: 4.1. Sales to total assets, 4.2. Sales to long term assets.

5. Other rates: 5.1. Cash to total assets, 5.2. Current assets to total assets, 5.3. Unappropriate balance to total assets, 5.4. Working capital to sales, 5.5. Activity profit to total assets, 5.6. Activity profit to sales.

In this case MLP network solved a supervised learning problem. It was given a training set of input-output pairs (data about companies) to the network and the network learned to model the dependency between them. The training means adapting the weights in neural networks. The number of input variables by neural networks was reduced. The number of these variables and neurons in hidden layers of constructed networks is given in Table 4.

Table 4

Neural networks characteristics

	Data (years)	Variables	Neurons in hidden layer
Model 1	1	15	13
Model 2	2	37	16
Model 3	3	50	23

Models classification accuracy

The classification accuracy rates of created artificial neural networks models are calculated in Table 5.

Table 5

Rates of classification accuracy

Rate	Model 1	Model 2	Model 3
CCR	0.8587	0.9222	0.9551
MCR	0.1413	0.0778	0.0449
α	0.2143	0.1220	0.0976
β	0.0800	0.0408	0.0000
Se	0.7857	0.8780	0.9024
Sp	0.9200	0.9592	1.0000
PPV	0.8919	0.9474	1.0000
NPV	0.8364	0.9038	0.9231
F	0.8476	0.9168	0.9487
AUC	0.8876	0.9567	0.9906

The lengthened period of the analyzed data from 1 to 3 years values of CCR are constantly increasing. The higgest classification accuracy was reached analyzing 3 years data of companies (95.5%). Other experiments also have shown that analyzing 4 and 5 years data classification accuracy (CCR) decreases to 85.4% and 86.2% accordingly due to the high quantity of input information and neural network‘s overlearning.

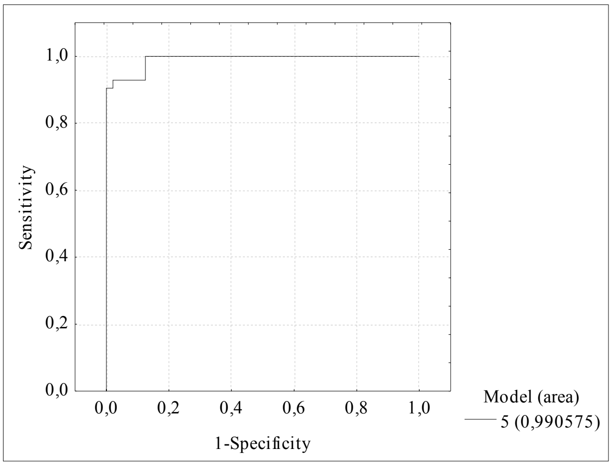

Figure 4. ROC curve of model 3

Values of *F*-measures also approved that Model 3 was the most accurate. Increasing the period of data for analysis to 3 years, False negative classification rate (type I error) and False positive classification rate (type II error) which indicate portion of clients classified incorrectly, decreased. Table 5 demonstrates that the model 3 correctly classified all reliable companies (Sp = 1) and 90.2% of not reliable (Se = 0.9024).

ROC curve of the best model 3 is illustrated in Figure 4. Area under the curve (AUC) is 0.9906.

Credit ratings

By using created artificial neural networks models 4 ratings were attributed to every company according to the output of neural netwoks. These outputs indicate possibility of default. Scale of ratings is illustrated in Figure 5.

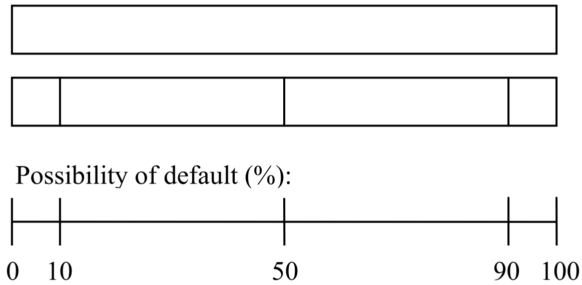

Figure 5. Possibility of default and credit ratings

These ratings evaluate the possibility of default in one year.

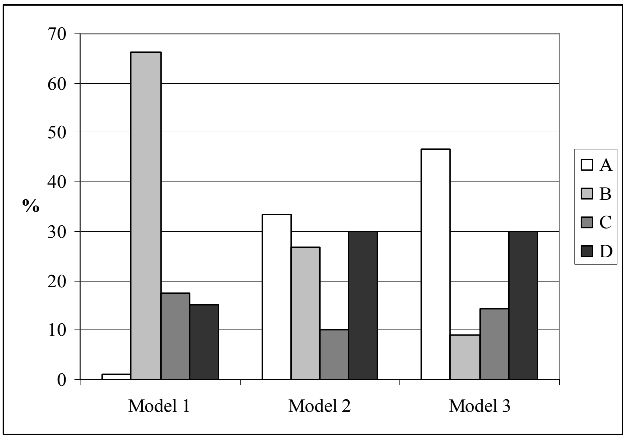

Figure 6. Distribution of credit ratings (percentage of companies)

Distribution of ratings corresponding to the outputs of ANN models is illustrated in Figure 6. Meanings of ratings are: A – reliable clients, very low possibility of default (0% - 10%). B – less reliable clients, possible insolvency of financial obligations, possibility of default is not high (10% - 50%). C – high possibility of default (50% - 90%). D – default (90 - 100%).

Default rates were calculated for every rating:

$$DR = (D_j \cdot 100\%) / R_j \quad (2)$$

D_j – number of companies defaulted in each group (rating);

R_j – number of companies in group (rating).

Default rates corresponding to different ratings for developed models are shown in Table 6.

Table 6

Default rates (%)

Rating:	A	B	C	D
Model 1	0	21.31	93.75	100
Model 2	3.33	20.83	88.89	100
Model 3	0	37.5	92.31	100

In all models companies to which ratings D were attributed actually bankrupted. In rating C this rate differs from 88.89% to 93.75%, in rating B actually defaulted 20.83% - 37.5% of companies. In the group of reliable clients (rating A) no companies actually defaulted in model 1 and model 3. This default rate in model 2 is 3.33%.

Characteristics of every rating according to financial ratios for the model 3 are described in Table 7.

Table 7

Model 3 average financial ratios

Rating:	A	B	C	D
Liquidity:				
-CR	3.9279	1.6307	0.9575	0.9276
-QR	2.7002	0.8448	0.4623	0.6128
-WA	0.3002	0.1496	-0.5038	-0.8860
Profitability:				
-GP	0.4246	0.3776	0.2434	0.1795
-NP	0.0876	0.0610	-0.3520	-0.6591
-PA	0.1078	0.0520	-0.2245	-0.6555
Leverage:				
-LA	0.4533	0.6999	1.2829	1.6850

Liqudity ratios. Average current ratio (CR) for companies attributed of rating A is 3.93, quick ratio (QR) – 2.70, working capital to total assets (WA) is 0.30. All these averages decrease when credit ratings decrease, except QR in which average of rating D is higher than rating C.

Profitability ratios. Average gross profitability (GP) for rating A is 42.5%, net profitability (NP) is 8.8%, net profit to total assets (PA) is 10.8%. Decreasing credit ratings averages of all above mentioned ratios constantly decrease.

Leverage ratio. Total liabilities to total assets (LA) indicate what portion of company‘s assets were obtained using loan capital. Average ratio in rating A is 0.45 and with decreasing credit rating this ratio increases to 1.69.

Calculated classification accuracy rates of credit risk estimation models, accomplished rating of companies allowed to evaluate risk of incorrect classification and other characteristics. In conformity with these rates credit analysts can make decision which model is worth to use in banking for the measurement of clients credit risk. This research also confirmed that artificial neural networks are an efficient method for the estimation of credit risk in banks.

Conclusions

1. Rates of classification accuracy are very important in the estimation of quality of credit risk models. They allow to evaluate parameters of models efficiency, compare different models and make decision which model should be used in banks.
2. The analysis of scientific publications revealed that the most efficient methods widely used for credit risk measurement are artificial neural networks and logistic regression.
3. Created ANN models showed that the rates of classification accuracy become higher when increasing time period of the data analyzed from 1 to 3 years. The highest accuracy was reached by the model that analyzed data of 3 years. The analysis of 4 years and more data reduced the value of the correct classification rate due to the network‘s overlearning.
4. Analyzing 3 year data of companies, 95.51% companies were classified correctly, the highest sensitivity reached by the model 90.24%, specificity – 100%.
5. This research confirmed that artificial neural networks are an efficient method for the estimation of credit risk in banks.

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Kredito rizikos vertinimas dirbtinių neuronų tinklų modeliais

Santrauka

Pagrindinė rizika, su kuria susiduria bankai skolindami pinigus, yra kredito rizika. Tai rizika, kad banko skolininkas dėl tam tikrų priežasčių negalės įvykdyti savo prisiimtų finansinių įsipareigojimų bankui. Bankai, norėdami sumažinti galimus nuostolius dėl kreditų suteikimo, turi sugebėti tinkamai šią riziką įvertinti.

Tam, kad būtų galima numatyti įmonių nemokumą ateityje, mokslininkai ir finansinių institucijų strategai labai susidomėję įmonių nemokumo indikatorių tyrinėjimu ir galimo nemokumo išankstinio perspėjimo sistemų kūrimu ir plėtojimu. Taikant banko vidaus kredito rizikos įvertinimo modelius, analizuojami dėl kredito besikreipiančių įmonių duomenys, o šios analizės rezultatai padeda priimti sprendimą dėl kredito suteikimo. Dažniausiai kiekybinių kredito rizikos vertinimo modelių paskirtis – nustatyti banko kliento finansinių įsipareigojimų nevykdymo tikimybę. Tam reikia turėti mokymo imtį, t. y. informaciją apie klientus ir jų patikimumą praeityje. Mokymo imtį turi sudaryti patikimų ir nepatikimų klientų duomenys. Kredito prašanti įmonė turi būti apibūdinama tam tikrų ją nusakančių kintamųjų visuma. Klientus apibūdinantys požymiai turi leisti atskirti skirtingas klientų grupes, t. y. įvertinti jų kredito riziką.

Šiuo metu kredito rizikai vertinti plačiai taikomi dirbtinių neuronų tinklai (toliau – DNT). DNT teorija yra grindžiama biologinių neuronų tinklų veikimo principais ir leidžia atlikti sudėtingų netiesinių dinaminių sistemų analizę. Daugelyje mokslinių straipsnių, kuriuose DNT lyginami

su statistiniais duomenų analizės modeliais prognozuojant įmonių nemokumą, teigiama, kad DNT yra pranašesni už statistinius modelius. Tačiau kartais gaunami priešingi tyrimų rezultatai, kur taikant DNT modelius pasiekiamas mažesnis tikslumas, nei analizuojant tuos pačius duomenis kitais statistiniais modeliais. Mokslininkų buvo iškelta idėja, kad DNT galėtų būti pagerinti jiems priskiriant statistinius duomenų analizės metodus. Taip būtų pagerinti DNT pateikiami rezultatai. Įvairių autorių sudaryti DNT modeliai derinami su kitais statistiniais duomenų analizės metodais. Jų tyrimų rezultatai parodė, kad hibridiniai DNT modeliai yra labai veiksmingi prognozuojant įmonių bankrotą. Teigiama, jog DNT labai pajėgi priemonė įmonių nemokumui prognozuoti, o jų tinkamas sujungimas su kitais statistiniais duomenų analizės metodais gali dar labiau pagerinti įmonių klasifikavimo rezultatus.

Tyrimo tikslas – nustatyti kredito rizikos vertinimo modelių klasifikavimo tikslumą apibūdinančius rodiklius ir įvertinti sudarytų DNT modelių klasifikavimo tikslumą.

Tyrimo metodai:

- Mokslinių publikacijų, kuriose aprašyti kredito rizikos vertinimo modeliai, analizė.
- Sudarytų DNT kredito rizikos vertinimo modelių klasifikavimo tikslumo analizė.

Norint nustatyti kredito rizikos vertinimo modelių tikslumą, turi būti skaičiuojami tam tikri kiekybiniai rodikliai. Šie rodikliai leidžia tarpusavyje palyginti ir išrinkti geriausią modelį, kurį taikant banko klientų patikimumas gali būti nustatytas tiksliausiai. Straipsnyje pateikti šie kredito rizikos vertinimo modelių tikslumą apibūdinantys rodikliai ir jų skaičiavimas: teisingo ir klaidingo klasifikavimo rodikliai, I ir II rūšies klaidos, modelių jautrumas ir specifiškumas, *F* įvertis, ROC kreivė.

Siekiant nustatyti dažniausiai taikomų kredito rizikos vertinimo metodų tikslumą, buvo analizuojamos mokslinės publikacijos, kuriose aprašyti įvairių autorių sudaryti kredito rizikos vertinimo modeliai. Atlikus analizę nustatyta, kad tiksliausiai banko klientų kredito rizika įvertinama logistinės regresijos ir neuronų tinklų metodais. Vidutinis šių metodų tikslumas yra beveik vienodas – 86,78 ir 86,77 proc. Mažiau patikimi metodai yra sprendimų medžiai ir diskriminantinė analizė, kurių vidutinis tikslumas atitinkamai yra 82,7 ir 77,38 proc. Labai svarbus rodiklis yra modelių tikslumo standartinis nuokrypis, atspindintis analizuotų reikšmių variaciją, t. y. vidutinį nuokrypį nuo vidurkio. Nors logistinės regresijos ir neuronų tinklų tikslumo vidurkiai yra beveik vienodi (skirtumas tik 0,01 proc.), tačiau neuronų tinklų tikslumo variacija yra mažesnė. Tai rodo, kad neuronų tinklų vidurkis yra patikimesnė vidutinio modelių tikslumo charakteristika. Tačiau vertinant kiekvieną modelį atskirai, didžiausias tikslumas buvo pasiektas naudojant logistinę regresiją (99,2 proc.). Iš analizuotų modelių neuronų tinklais pasiektas maksimalus tikslumas – 98,35 proc.

Darbe buvo sudaryti kredito rizikos vertinimo modeliai (dirbtinių neuronų tinklai), kuriuos taikant analizuoti Lietuvoje veikiančių įmonių duomenys. Apskaičiavus šių modelių efektyvumo rodiklius, nustatyta, kad didžiausias įmonių klasifikavimo tikslumas pasiekiamas analizuojant 3 metų duomenis.

Daugėjant analizuojamiems metams nuo 1 iki 3, sudarytų dirbtinių neuronų tinklų modelių teisingo klasifikavimo rodiklio (CCR) reikšmė didėja. Didinant analizuojamų duomenų kiekį, I ir II rūšies klaidos, parodančios, kokia klientų dalis taikant modelį klasifikuojama klaidingai, mažėja. Taikant 3 metų duomenis analizuojantį modelį, teisingai klasifikuotos visos patikimos įmonės (Sp = 1) ir 90,2 proc. nepatikimų. Šio modelio plotas po ROC kreive (AUC) lygus 0,9906. Atlikti tyrimai taip pat parodė, kad padidinus duomenų kiekį, apimantį 4 ir 5 metų laikotarpį, teisingo klasifikavimo rodiklio reikšmė sumažėja atitinkamai iki 85,4 ir 86,2 proc. Tai galima paaiškinti neuronų tinklo persimokymu dėl didelio įvedamų į tinklą duomenų kiekio.

Taikant sudarytus kredito rizikos vertinimo modelius, buvo reitinguojamos įmonės. Įmonėms buvo priskiriami reitingai pagal jų finansinių įsipareigojimų nevykdymo per ateinančius metus galimybę:

A – visiškai patikimos įmonės, įsipareigojimų nevykdymo galimybė labai maža (0 – 10 proc.).

B – mažiau patikimos įmonės, galimas finansinių įsipareigojimų nevykdymas (10 – 50 proc.).

C – didelė įsipareigojimų nevykdymo galimybė (50 – 90 proc.).

D – visiškas įmonės nemokumas (90 – 100 proc.).

Vertinant reitingų vidutinius likvidumo rodiklius nustatyta, kad A reitingo įmonių vidutinis bendrasis padengimo koeficientas yra 3,93, skubaus padengimo koeficientas – 2,70, grynojo apyvartinio kapitalo santykis su turtu – 0,30. Visi šie rodikliai, mažėjant kredito reitingui, tolygiai mažėja, išskyrus skubaus padengimo koeficientą, kurio vidurkis D reitingo grupėje yra didesnis nei C reitingo.

Analizuojant pelningumo rodiklius nustatyta, kad A reitingo įmonių vidutinis bendrasis pelningumas siekia 42,5 proc., grynasis pelningumas – 8,8 proc., turto pelningumas – 10,8 proc. Mažėjant įmonių kredito reitingui, šių pelningumo rodiklių vidutinės reikšmės mažėja.

Analizuojant įmonių finansų struktūrą, vertinamas įsiskolinimo koeficientas, kuris parodo, kokia įmonės turto dalis įsigyta už skolintas lėšas. A grupėje šis rodiklis sudaro 0,45. Mažėjant kredito reitingui vidutinė jo reikšmė didėja iki 1,69.

Priskyrus įmonėms reitingus, buvo apskaičiuotos kiekvienos įmonių grupės (reitingo) įsipareigojimų nevykdymo tikimybės. Visų modelių D reitingą gavusios įmonės bankrutavo. C grupėje šis rodiklis siekia 88,89 – 93,75 proc., o B grupėje įsipareigojimų nevykdymo dalis yra 20,83 – 37,5 proc. Patikimų įmonių grupėje nei vienai bankrutavusiai įmonei taikant 1 ir 3 modelius nebuvo priskirtas reitingas A, o 2 modelio A reitingo įsipareigojimų nevykdymo tikimybė yra 3,33 proc.

Straipsnyje pateikti kredito rizikos vertinimo modelių tikslumo rodikliai leido įvertinti įmonių klaidingo klasifikavimo riziką ir kitas klasifikavimo charakteristikas. Remiantis šiais rodikliais galima objektyviai priimti sprendimą, ar bankų vidaus kredito reitingų modelis yra tinkamas taikyti vertinant klientų kredito riziką. Tyrimas parodė, kad DNT yra veiksminga priemonė banko klientų kredito rizikai vertinti.

Raktažodžiai: *dirbtinių neuronų tinklai (DNT), klasifikavimas, kredito rizika, modelių tikslumas.*

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