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CAPACITY OF NEURAL NETWORKS AND DISCRIMINANT ANALYSIS IN CLASSIFYING POTENTIAL DEBTORS

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Abstract

Identifying potential healthy and unsound customers is an important task. The reduction of loans granted to companies of questionable credibility can influence banks' performance. A prior identification of factors that affect the condition of companies is a vital element. Among the most commonly used methods we can enumerate discriminant analysis (DA), scoring methods, neural networks (NN), etc. This paper investigates the use of different structure NN and DA in the process of the classification of banks' potential clients. The results of those different methods are juxtaposed and their performance compared.

Keywords: credit risk, default, neural networks, discriminant analysis, financial indices

JEL classification: G33; C38; C49

Introduction

Bankruptcy prediction has been an important and widely studied topic in finance because it has a significant impact on the whole economy – lending party, chain of suppliers etc. Identifying potential healthy and unsound customers is an extremely important task, especially in view of a recent recommendation of the Polish Financial Supervision Authority (PFSA; originally KNF – Komisja Nadzoru Bankowego). This recommendation pertains to the widely perceived bank's internal audit which currently is supposed to be separated from risk management. That fact, in turn, can mean that risk is acknowledged as a completely distinct system. Therefore, the reduction of loans granted to companies of questionable creditability is vital, as it can significantly influence and improve banks' performance. The most important element in debtors' classification is the prior identification of factors (input data) that affect the condition of companies. For it is the condition that directly influences the credibility and solvency of a bank customer (company) and, both of these factors result in the low or high probability of default.

Due to increased bankruptcies noted among companies (debtors) banks pay more attention to credit risk control and the better evaluation of a potential debtor's default (Wójcicka, 2012). Unfortunately, analysts often need to choose between the accuracy, efficiency and simplicity of chosen methods. The implementation of various tools should provide banks with the opportunity for a better preselection of companies that are in financial distress (Wójcicka, 2017d). This ought to be prompt and inexpensive, followed by a more thorough analysis.

Ideally, a preselection tool should be uniform for all businesses. However, previous research shows that this goal cannot always be achieved (Wójcicka, 2017a, 2017b, 2017c; Wójciak, Wójcicka 2008, 2009; Wójcicka, Wójtowicz 2009).

Amongst the most commonly used methods assisting the decision-making process we can enumerate discriminant analysis models, scoring methods, and increasingly more and more popular neural networks. However, each method and model has its own advantages and disadvantages.

The main goal of the paper is to investigate the usability of various neural networks architectures (NN) and Discriminant Analysis (DA) models in the process of the classification of entities. This, in practice, is one of the initial steps taken by banks in the process of decision-making in granting or rejecting the application of a potential client (future debtor). Another goal aims at establishing whether a uniform model (regarding the input) is efficient enough in this process or whether the used models should vary depending on the sector. The results of those

different methods and models are juxtaposed and their performance compared in chosen sectors (trade, industry, and construction).

The study can be classified in an applied studies group and the research strategy is descriptive. The neural network technique (also called artificial neural network – ANN) and Discriminant Analysis (DA) – are used.

1. Literature review

The literature on both Discriminant Analysis and Neural Networks is very wide. Multi-factor DA has been present since the 1960s when Altman presented his first model which became a benchmark for all that followed (Altman, 1968). Since that time DA has been improved and tested by many other authors. The choice of DA models (8 – see Table 1) was not random and was dictated by their efficiency of classification reached in previous and on-going research. These models aside, we can enumerate many more, like models by M. Pogodzińska and S. Sojak (1995), A. Hołda (2001), P. Antonowicz (2007), etc.

Neural networks in the scope of credit risk are broadly analysed. Atiya (2001) presents an empirical approach, based on the relationship of default and the characteristics of a firm learnt from the data. The conclusions indicate the superiority of neural networks over other techniques and the need for improvements in training methods, architecture selection, or input. Baesens et al. (2003) investigated neural networks' contribution in helping the credit-risk managers in explaining why a particular applicant is classified as either bad or good. They conclude that neural network rule extraction and decision trees are effective and powerful management tools, allowing for the construction of advanced and user-friendly decision-support systems for credit-risk evaluation.

Also in the work of Pacelli and Azzollini (2011) it is stated that neural networks are particularly suited to analyse and interpret complex and often obscure phenomena and processes.

Still, other research proves that despite the weaknesses, neural networks show good performance when data are noisy or incorrect (see Angelini, Tollo, Roli, 2007; Tollo, 2006). In these studies, the most common NN were analysed. Other structures of neural networks, as well as their comparison with other techniques (Decision Trees, Discriminant Analysis, Regression Function etc.) can be found in the works of e.g. Khemakhem and Boujelbènea (2015), Karaa and Krichene (2012), Huang et al. (2004), Oreski et al. (2012), Ogwueleka et al. (2015), Linder et al. (2004) and many others.

2. Methods and research

The collected data, used in the research, was obtained from a bank operating on the Polish market, the Commercial Court in Poznań, Poland and from NOTORIA SERWIS. The data cover a period of six years (2010–2015). It refers to companies from four sectors (construction, industry, trade, and financial). These sectors cover a wide variety of companies, regarding their legal form, assets value etc. The sample contains the financial statements of companies which include a balance sheet, an income statement, a cash flow statement and a statement of changes in equity. Preliminary, data set was divided into three groups in the following manner:

- learning group (75% of data set),
- testing group (15% of data set),
- independent validation group (10% of data set).

The study was conducted in two parallel ways and in the following stages. Firstly, equipotent sets of objects were determined (healthy and unsound companies). Then, necessary ratios, utilized in DA, were calculated. That input was implemented in both approaches (DA and NN). The appropriate calculations were carried out. Next, the classification results of the DA model and the best NN (with identical input) were compared.

In the successive test, another approach was implemented. DA results for all the tested objects remained the same; however, for the same sample of entities (healthy and unsound) other input sets of ratios were used. That input (sets containing 7–11 ratios) was selected being based on previous research on neural networks (Wójcicka, 2017a, 2017b, 2017c) and varied depending on the sector of the economy.

2.1. Discriminant Analysis

This study concerns only the existing models (8) of various authors. The presented models were created being based on national data which is beneficial as every economy has its own specific character. To implement Discriminant Analysis, two independent sets of samples are necessary. These include unsound and healthy companies. The sample must be balanced.

In the study, unsound companies were matched with healthy businesses similar in assets value and branch of the economy (construction, industry and trade). The models used for the comparison with neural networks are as follows: Gajdka and Stos, Hadasik, Wierzba, Hamrol,[1] Prusak, Mączyńska, Appenzeller and Szarzec, Mączyńska and Zawadzki. The choice of these

[1] The model of M. Hamrol is in the literature also referred to as "poznański".

models was dictated by the interest they still arouse among researchers as well as previous own research. The formulas of the models are presented in Table 1.

Table 1. The formulas of the DA models used in the analysis

Model	Formula	Ratios
Gajdka and Stos	$Z_{G\text{-}S.} = 0.7732059 - 0.0856425X_1 + 0.0007747X_2 + 0.9220985X_3 + 0.6535995X_4 - 0.594687X_5$	X1 – (sale net revenues/average annual value of assets) X2 – (average value of short-term liabilities/cost of sold production × 360), X3 – (net profit/average annual value of assets), X4 – (gross profit/net revenues on sales), X5 – (total liabilities/total assets)
Hadasik	$Z_{H.} = 0.335969X_1 - 0.71245X_2 - 2.476X_5 + 1.46434X_7 + 0.00246069X_9 - 0.0138937X_{12} + 0.0243387X_{17} + 2.59323$	X1 – current assets/current liabilities, X2 – (current assets – stocks)/current liabilities, X5 – total liabilities/total assets, X7 – working capital/total assets, X9 – (average level of receivables/sales revenues) × 365, X12 – (average level of stocks/sales revenues) × 365, X17 – net profit/average level of stocks
Wierzba	Zd.w. = 3.26X1 + 2.16X2 + 0.3X3 + 0.69X4	X1 – (operational activity profit – depreciation)/total assets, X2 – (operational activity profit – depreciation/sale of products, X3 – current assets/total liabilities, X4 – running capital/total assets
Hamrol	$Z_{Pń} = 3.526X_1 + 1.588X_2 + 4.288X_3 + 6.719X_4 - 2.368$	X1 – net profit/total assets, X2 – (current assets – stocks)/short-term liabilities, X3 – fixed capital/total assets, X4 – sales profit/sales revenues
Prusak	$Z_{B.P.} = 1.438X_1 + 0\ .188X_2 + 5.023X_3 - 1.871$	X_1 – (net profit + depreciation)/total liabilities, X_2 – operational costs/current liabilities, X3 – profit on sales/total assets
Mączyńska	$Z_{E.M.} = 1.5X_1 + 0.08X_2 + 10X_3 + 5X_4 + 0.3X_5 + 0.1X_6$	X_1 – (gross profit + depreciation)/total liabilities, X_2 – balance sheet total/total liabilities, X_3 – gross financial result/balance sheet total, X_4 – gross financial result/sales revenues, X_5 – stock/sales revenues, X_6 – sales revenues/balance sheet total
Appenzeller and Szarzec	$Z_{A.\text{-}S.} = 1.286440X_1 - 1.305280X_2 - 0.226330X_3 - 0.005380X_4 + 3.015280X_5 - 0.009430X_6 - 0.66132$	X_1 – current assets/current liabilities, X_2 – (current assets – stock – receivables)/short-term liabilities, X_3 – gross profit/sales revenues, X_4 – (average value of stock/sales revenues) × 360, X_5 – net profit/average assets value, X_6 – (total liabilities + reserves)/(operation activity result + depreciation)
Mączyńska and Zawadzki (model G INE PAN)	$Z_{M.}\text{-}Z. = 9.498X_1 + 3.566X_2 + 2.903X_3 + 0.452X_4 - 1.498$	X_1 – operational result/annual average value of assets, X_2 – own capital/assets, X_3 – (net financial result + depreciation)/total liabilities, X_4 – current assets/short-term liabilities

Source: Gajdka and Stos (1996), Hadasik (1998), Hamrol, Czajka and Piechocki (2004), Prusak (2005), Mączyńska (1994), Mączyńska and Zawadzki (2006), Wierzba (2000), Appenzeller and Szarzec (2004).

In the process of analysis, the necessary ratios were calculated and implemented into chosen, existing models. As this analysis is an ex-post analysis and the condition of the company in the examined period is known (as well as the standing of the company in the following period), checking the actual accuracy of the model is straightforward. We can indicate two types of errors. The type I error means that a specific model classifies a good customer as a bad customer and consequently, based on that results of the model, the bank rejects the application of a potentially healthy client. The type II error means that a model recognises a bad customer as a good customer and therefore the bank accepts the application and grants financing. Such a situation is very likely to lead to a customer's insolvency and bankruptcy and consequently the bank might be forced to incur losses. Table 2 presents the results of the type I and type II error of all of the tested models individually.

Table 2. Type I and II error for the tested Z-score models (%)

Model	Error – type I	Error type II
Gajdka and Stos	6.67	7.33
Hadasik	7.33	6.67
Wierzba	7.33	8.67
Hamrol	5.67	8.67
Prusak	7.33	8.67
Appenzeller and K. Szarzec	5.67	5.67
Mączyńska	6.67	5.67
Mączyńska and M. Zawadzki	6.67	4.33

Source: own calculations.

As type II an error is considered to be more significant for the banks and it is justified to state that the best model is the one by Mączyńska and Zawadzki (4.33%). The next two best were: Appenzeller-Szarzec and Mączyńska (5.67%). The first of these two (A–S) is also characterised by the lowest level of type I error, along with Hamrol. When it comes to the type I error, it is considered to be less harmful for the banks but, anyway, it still is an issue. Due to the rejection of good customers the bank can lose a significant amount of money ("lost opportunities"). Therefore, too high a level of that error also should be a cause for concern.

Generally, all models achieved satisfactory levels, however, this satisfactory level might not always be sufficient in practice as discriminant models usually do not differentiate between various sectors of the economy and, therefore, are inflexible in non-stop changing conditions of functioning. The lack of the possibility of re-adjusting and re-learning and consequently, the

lack of a fast reaction can result in decisions which are not optimal, or simply wrong. Therefore, other alternatives (methods and models) are actively pursued.

2.2. Neural networks

The idea of neural networks as computing processors has its origin in the way the human brain computes and analyses obtained knowledge. Neural networks in the scientific literature can be defined as "(…) a massively parallel distributed processor made up of simple processing units that has a natural propensity for storing experiential knowledge and making it available for use. It resembles the brain in two respects: i) Knowledge is acquired by the network from its environment through a learning process; ii) Interneuron connection strengths, known as synaptic weights, are used to store the acquired knowledge" (Haykin, 2011). A very important issue is the learning algorithm used in a network design which influences the whole structure of NN.

In the literature there are many various topologies of neural networks, amongst which we can list, for instance: Single Layer perceptron, Multi-Layer Perceptron, Recurrent Neural Network, Self-organizing Map, Shared Weights Neural Networks, Learning Vector Quantisation, and Auto-Associative Neural Networks, etc.

The research focuses on investigating and comparing the results of two different structures of neural networks – the most common Multi-Layer Perceptron (MLP) and the Radial Basis Function neural network (RBF). Multi-Layer Perceptron (MLP) is a popular architecture used in ANN. In MLP the data provided in the neurons of the input layer, the neurons in this first layer propagate the weighted data and randomly selected bias through the hidden layers. The MLP can be trained by a back propagation and the algorithm Data is forwarded layer by layer (through the hidden layers) until the activation process at the output layer occurs. In each layer a weight is calculated for each possible connection. Then, a transfer function, which determines the output value for each neuron, is applied. In the research, there are several transfer functions possible. The MLP network is trained with error correction learning, which means that the desired response for the system must be known.

The Radial Basis Function (RBF) is another popular architecture used in ANN. The RBF (multilayer and feed-forward) is often used for strict interpolation in a multi-dimensional space. The term "feed-forward" means that the neurons are organized as layers in a layered neural network. The RBF network is comprised of three layers, i.e. input, hidden and output. The input layer is composed of input data. The hidden layer transforms the data from the input space to the hidden space using a non-linear function. The output layer, which is linear, yields the response of the network. The argument of the activation function of each hidden unit in an

RBF network computes the Euclidean distance between the input vector and the centre of that unit. In the structure of the RBF network, the input data, *x*, is a p-dimensional vector, which is transmitted to each hidden unit. The activation function of the hidden units is symmetric in the input space, and the output of each hidden unit depends only on the radial distance between the input vector, *x*, and the centre for the hidden unit (https://documents.software.dell.com/statistics/textbook/neural-networks#multilayera). The main similarities and differences between the two NN structures are presented in Table 3.

Table 3. Similarities and differences between the MLP and RBF neural networks

	MLP	RBF
Signal transmission	feedforward	feedforward
Process of building the model	one stage	two different, independent stages – at the first stage by means of radial basis functions the probability distribution is established; the network learns the relations between input *x* and output *y* at the second stage. On the contrary to MLP the lag is only visible in RBF in the output layer
Threshold	yes	no
Type of parameters	weights and thresholds	location and width of basis function and weights binding basis functions with output
Functioning time	faster	slower (bigger memory required)
Learning time	slower	faster

Source: own elaboration based on Gaudart et al. (2004), Nigrin (1993), Statistica Help SANN.

The implemented tool is the STATISTICA Neural Networks (SANN). Variables are divided into dependent and independent ones. Independent variables are the financial ratios of various groups:

– ratios used by analysed Z-score models,
– ratios selected in previous research (Wójcicka, 2017a, 2017b, 2017c).

The dependent variable was identified as a "good" (healthy) or "bad" (unsound) company. A "good" company was the one which was (or potentially would be) granted financial resources and, consequently, the "bad" enterprise was the one that was denied funding. However, it must be stressed that the fact that a bank classified the company as a potential good debtor and was willing to grant the financial means is not unequivocal with the final entering into the contract of a loan.

The examined neural networks are the best, the chosen ones based on previous research and they are presented in table 4 in the following manner: chosen architecture (MLP or RBF), X – number of inputs, Y – neurons in the hidden units, and Z – number of outputs (healthy, unsound).

Table 4. Neural networks architectures used in the research

Model	Construction	Industry	Trade	Finance
MLP	MLP 7-11-2	MLP 9-10-2	MLP 8-12-2	MLP 11-13-2
RBF	RBF 10-13-2	RBF 10-11-2	RBF 9-12-2	RBF 11-12-2

Source: own.

3. Results for NN and DA – initial input of ratios from DA

The first phase of the analysis focused on the results of NN when the input consisted of the ratios selected by the Discriminant Analysis. This means that networks learnt on exactly the same sample of data as the other tested models (Z-score models). This experiment was to demonstrate and assess whether the initial input should vary when it comes to the used method or whether it is indifferent. The accuracy results of the best NN (MLP and RBF), with reference to individual DA models, are presented in Table 5.

Table 5. Results of MLP and RBF neural networks quality in %
(input – ratios selected by the chosen DA model)

Models	MLP	RBF
Gajdka and Stos	83.33	87.75
Hadasik	80.00	86.67
Wierzba	80.00	86.67
Hamrol	78.33	87.75
Prusak	76.67	78.33
Appenzeller and Szarzec	87.75	78.33
Mączyńska	86.67	86.67
Mączyńska and Zawadzki	83.33	86.67

Source: own calculations SANN Statistica.

The best results were achieved in the case of three combinations: RBF-Hamrol, RBF-Gajdka/Stos and MLP-Apenzeller/Szarzec (87.75%). It can be noticed that MLP generally, despite the chosen Z-score model, achieved a lower level of accuracy in the classification of objects. The average decrease of classification accuracy between MLP and RBF is almost 3%

However, it should be stressed that none of the neural networks, used on the initial input from the DA models, achieved the level of classification accuracy higher than 87.75% which might be acknowledged as not a sufficient result. It is also worth emphasising that the combinations which reached the lowest level are the ones in combination with the model by Prusak (respectively 76.67 with MLP and 78.33 with RBF). In this case, the input consisted only

of three financial ratios. Previous research on MLP and RBF indicated that the best results are of accuracy are reached in the case of at least seven different ratios that act as the input. The current situation with both combinations (MLP-Prusak, RBF-Prusak) seems to prove that condition of input sufficiency.

4. Results for NN and DA – various input of ratios

In the second phase, another approach was implemented. The DA models still utilised the individual set of input (ratios). However, neural networks used other sets of financial ratios, depending on the sector of the economy they operate in (construction, industry, and trade). The ratios were identified in an iterative approach. The initial set of ratios contained 25 various financial ratios. In the case of the examined sectors selected the ratios are presented in Table 6 (for a detailed description of the data see Wójcicka (Wójcicka, 2017a, 2017b, 2017c).

Table 6. Comparison of the ratios used for the analysis of trade, construction and industrial sectors

No.	Ratios	Trade sector		Construction sector		Industrial sector		Financial sector	
		MLP	RBF	MLP	RBF	MLP	RBF	MLP	RBF
1	Current ratio	x	x	x	x			x	x
2	Receivables ratio			x	x	x	x	x	x
3	Operating activity profitability index			x	x	x	x		
4	Financial surplus rate	x	x	x	x	x	x	x	x
5	Total debt ratio	x	x	x	x	x	x	x	x
6	Costs level ratio			x	x			x	x
7	Assets profitability index			x	x	x	x		
8	Financial leverage	x	x	x	x		x		
9	Operating activity profitability index				x	x	x		
10	Current assets turnover ratio		x		x	x	x		
11	Quick ratio					x	x	x	x
12	Stock turnover ratio								
13	Receivables to liabilities ratio					x	x	x	x
14	Equity profitability index	x	x						x
15	Equity debt ratio	x	x						
16	Sale profitability index	x	x						
17	EBITDA/Financial expenses		x						

Source: own work.

The results of both architectures of NN, based on the sets of data selected for various sectors, are significantly better compared to the sets of data when the input was presented by ratios from DA. The results of the chosen NN (best results) are presented in Table 7.

Table 7. Comparison of MLP and RBF neural networks on input ratios selected for sectors

	Quality (%)			
Model	construction	industry	trade	finance
MLP	96.67	91.67	95.00	93.33
RBF	95.00	91.67	93.33	91.67

Source: own calculations.

The results of NN quality demonstrate the significance of tailor-made input. The differences between both of the tested structures are slender – the highest level is 96.67% for MLP and 91.67% for RBF. It can be interpreted that the previous differences between individual NN architectures disappear if the input is selected in advance according to the line of the business of the examined entity.

Comparing the results of NN and DA it can be noticed that NN do slightly better, though the difference is not very significant. It can be assumed that NN are more flexible than DA models.

Conclusions

Credit risk estimation and the correct classification of customers is a valid, up-to-day, significant issue. Therefore, methods are being constantly developed to improve the process of decision-making and new models are being created. The methods cover a wide range of various approaches. Their utility is checked daily in practice. The objective of the used methods is increased accuracy which means that more creditworthy applicants are granted a loan, thereby increasing bank profits. Consequently, those accounts which are not creditworthy are denied the loan and, thus avoiding unnecessary losses.

The paper analysed two types of neural networks: the Multi-Layer Perceptron (MLP) and the Radial Basis Function (RBF). The choice of those types of neural network architecture was dictated by their popularity.

In the research, they both proved to be highly useful in the credit risk decision-making process, especially when the input was based on previously selected ratios, according to the line of business of the examined entities. The obtained results show that, irrespective of the model and data set, the accuracy is not less than 90% (among the best ones). It can be concluded that the application of the NN approach to company distress prediction is beneficial for the process of credit risk evaluation.

On the basis of the performed experiments a conclusion can be drawn that the prior selection of input data (in this case financial ratios) is vital in e correct classification of healthy and unsound companies – potential clients of a bank.

In the author's opinion, it is essential in further research to implement various methods of including and excluding the variables – preferably, independently for each method and branch of the economy. Moreover, one of the further directions of currently on-going research may lead to broadening the set of exogenous factors which, in the author's opinion, significantly influence credit risk.

The alternative direction of research, with respect to this analysis, is based on the comparative analysis among neural networks and other approaches to categorising clients (classification trees, regression etc.) and amid different types of neural networks as well.

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