ACTA SCIENTIARUM POLONORUM Oeconomia 7 (1) 2008, 45–58

PREDICTION OF LOAN REDEMPTION IN A TRANSITION COUNTRY: A COMPARISON OF LOGIT MODELS AND ARTIFICIAL NEURAL NETWORKS

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Abstract. Banks provide a financial intermediary service by channeling funds efficiently between borrowers and lenders. Bank lending is subject to credit risk when loans are not paid back on a timely basis or are in default. The ability or possessing a methodology to evaluate the creditworthiness of a borrower is therefore crucial to managing the bank's risk management and profitability. In transition countries like Poland, creditworthiness evaluation is especially difficult due to the transitional nature of the financial markets. This paper looks at a comparison of using logit models and artificial neural networks models to evaluate a borrower's credit risk. In particular, this paper shows that artificial neural networks model is a better predictive tool than logit models of credit risk.

Key words: loan redemption, classification, logit model, artificial neural networks

INTRODUCTION

The fundamental risk of making bank loans is credit risk and its redemption in a timely manner, particularly in a transitioning country like Poland. Poland's financial system has undergone tremendous reforms and changes for over a decade and a half in adapting to a market economy. However, the Polish financial system is still primarily a banking based system, lacking in depth and width comparable with older European Union member

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countries. In an effort to improve the financial system, foreign banks participation is encouraged with the result that there are now only 3 banks that can be called Polish: PKO BP SA and BOŚ, listed on the Warsaw Stock Exchange, and BGŻ. Other Polish banks are foreign owned, for example, WBK Bank Zachodni (Irish), Kredytbank (Austrian) and Citibank and Bank Handlowy w Warszawie (USA) to name a few.

Small and medium size business ventures are still mainly dependent on bank for financing. The greater risk and uncertainty associated with an emerging transition business environment means that the Polish banks are extremely cautious and reluctant in their loan lending. Although the foreign owned Polish banks brought improved management skills and much needed current technology into the Polish banking system, the Polish bank market is different from the western developed market and the application of western norms in the evaluation of credit risk may not be applicable, resulting in fewer loans being made. The loan amounts tend to be small, often between five to forty thousand dollars. Firms find it relatively difficult to obtain a credit from the banks, while individual clients find it easier with smaller loans. A loan credit procedure and evaluation that is more suited to a transition market like the Polish market may be more appropriate.

Banks have two different approaches to credit evaluation of potential borrowers. Credit evaluation of firms consists of firm performance (asset turnover, profit, credit history, etc) while individual client evaluation consists of income and demographic indicators characteristics: gender, age, place of living, labour market status, level of education, monthly incomes, family size, etc. For small seasonal and holiday loans (Christmas, Easter, vacation loans) of USD 500 to USD 3.000, individual client credibility is seldom investigated.

This paper focus on individual client loan lending by Polish bank, given that most Polish banks focus on primarily small loans to individual clients. The use of traditional discriminant analysis to classify individual client credit indicators is not valid, given the poor nature of the factors and some of the factors are qualitative. This paper discusses the different models and problems associated with dependent dichotomous variables that can only take on two values. The paper uses logit models and artificial neural networks to dichotomous the classification of individual client indicators based on actual data of loan redemption obtained from the regional bank of Poland. Developing a reliable and systematic risk evaluation method usable and applicable to credit officers in a transition country like Poland will encourage greater loan lending, contributing to the growth and expansion of the business sector.

DISCRETE CHOICE MODELS

Many dependent variables of interest in economic and social sciences can only take on two values. The two possible outcomes are usually denoted by zero and one. Such variables are called dummy or dichotomous variables. Examples of some binary choice situations are:

- evaluation of potential borrowers as credit worthy clients,
- prediction of bankruptcy,
- the labour market status of a person (employed and unemployed),
- voting behaviour of a person (i.e. voting in favour or otherwise).

The above problems can usually be solved by applying binary response models such as discriminant analysis, logit and probit models, or artificial neural networks. These models describe the relationship between a dependent variable *Y* and one or more independent variables *X*. The dependent variable *Y* is a discrete (binary) variable that represents a choice or category. Thus, the solution of the binary response model classifies the object, the bank client, the company, employee, or the person in terms of his creditworthiness, potential for firm bankruptcy, labour market status or voting preference to one of two pre-defined classes. The independent variables are presumed to affect the choice or category, and represent *a priori* beliefs about the causal or associative elements important in the choice or classification process.

In the case of client creditworthy evaluation, the input of the classifier could be the information (in the database) that describes the situation of the credit applicant. And the classifier produces the output in terms of evaluating the creditworthiness of the client (Fig. 1).

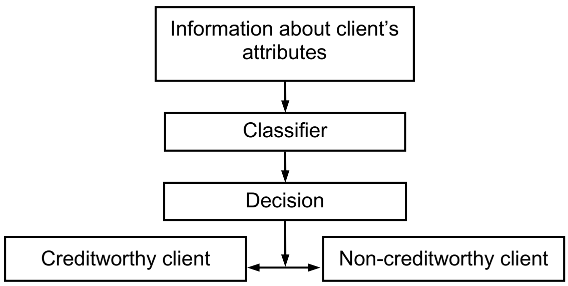

Fig. 1. Creditworthiness evaluation as a classification problem
Rys. 1. Ocena wiarygodności kredytowej jako zadanie klasyfikacji
Source: Witkowska, Mazur, Staniec 2005.
Źródło: Witkowska, Mazur, Staniec 2005.

The application of binary response models to bankruptcy prediction, firm performance evaluation or creditworthiness determination have been carried out by many studies. Altman (1968) made the first attempt to apply linear discriminant analysis to evaluate potential bankruptcy by employing financial ratio indicators; his further works [(1971), (1988), (1993)] develop this idea further. Back, Laitinen, Sere and van Wazel (1995) compare bankruptcy prediction methods using discriminant analysis, logit model and genetic algorithm. Ohlson (1980) uses logit models in the probabilistic prediction of bankruptcy. Johnsen and Melicher (1994) apply logit models to bankruptcy prediction and financial distress. Lennox (1999) compares logit and probit models in bankruptcy prediction. Later studies like Cramer (2001), (2003) also uses logit models in credit evaluation.

Theodossiou, Kahya, Saidi and Philippatos (1996) carry out an empirical study of financial distress while Kaiser (2001) applies logit models to predict financial distress. Bernhandsen (2001), Neophytou, Charitou and Charambolis (2000) perform an empirical study of corporate bankruptcy in UK while Barniv, Agarwal and Leach's (2002) study looks at bankruptcy prediction. Gruszczyński (2001) presents econometric models constructed for binary variables and their application in finance.

Bankruptcy prediction using artificial neural networks are carried out by various studies like Rahimian, Singh, Thammachote and Virmani (1993), Odom and Sharda (1993), Raghupathi, Schkade and Raju (1993) and Rehkugler and Schmidt-von Rhein (1993). Baetge and Krause (1993) apply artificial neural networks to the risk classification of companies while Witkowska (1999), (2002), **Witkowska, Kaminski, Kompa, Staniec** (2004) and Witkowska, Mazur, Staniec (2005) apply neural networks to simulate the decisions made by the credit officers about the credit granting.

Alfaro (2005) compares neural networks to combining classifiers in corporate failure prediction in Spain while Chrzanowska, Witkowska (2007) employ aggregated classification trees, binary regression and Bayesian discriminant analysis to the individual borrowers recognition.

In summary, the various studies indicate that any evaluation of a client's credit worthiness has to apply a formal statistical method. In studies where a comparison is made it shows that the application of artificial neural nets usually gives better results than linear discriminant analysis. It is possible to find the economic interpretation parameters of the discriminant and logit models while weights in neural networks cannot be interpreted. The fundamental problem in the application all these models is to select the set of diagnostic variables because of the strong correlation of most financial ratios used.

LOGIT MODELS

Logit model is the most popular model of dichotomous classification. Let us assume that there is a set of n observations of grouping variable: $Y=[y_1 \quad y_2 \quad \ldots \quad y_n]$, where y_i equals 1 or y_i equals 0, $i = 1, 2,\ldots, n$. To describe the probability that $y_i = 1$, the following logit model is used:

$$p_i = \frac{e^{y_i}}{e^{y_i}+1} \tag{1}$$

where: p_i – the probability that y_i takes the value 1, $p_i \in (0,1)$,

$$y_i = \mathbf{b}^T \mathbf{x}_i + \varepsilon_i \tag{2}$$

where: $\mathbf{x}_i$ – vector of k discriminant variables that describe the i-th object: $\mathbf{x}_i = [x_{i1}\ x_{i2} \ldots x_{ik}]^T$,
$\mathbf{b}$ – vector of regression function (2) parameters: $\mathbf{b} = [b_0\ b_1\ b_2 \ldots b_k]^T$ ε_i – random coefficient.

The model (1) uses the logistic distribution function. To estimate parameters $b_0, b_1, b_2,\ldots, b_k$ the maximum likelihood method is applied[1]. To evaluate the accuracy of the model, likelihood ratio (L) is used:

$$L = -2(\log LR - \log LUR) \tag{3}$$

where: LUR – the likelihood function value that is evaluated for the model with (k + 1) parameters, i.e. the model:

[1] To maximize the likelihood function the quasi Newton method is used.

$$\hat{y}_i = \hat{\mathbf{b}}^T \mathbf{x}_i \tag{4}$$

where: $\hat{y}_i$ – theoretical values, $\hat{\mathbf{b}} = [\hat{b}_0\ \hat{b}_1\ \hat{b}_2 ... \hat{b}_k]^T$ – the vector of parameter estimates, LR – the likelihood function value that is evaluated for the model with intercept $\hat{b}_0$ only.

The L statistic is distributed chi – squared with k degrees of freedom (k – number of independent variables in the model). Other measures that are used to evaluate the logit model are:

- correlation coefficient $cor(y, \hat{y})$ that is used to evaluate the relationship between real y_i and theoretical value $\hat{y}_i$ ($i = 1, 2, \ldots, n$),
- Wald statistic: $$W = \left(\frac{\hat{b}_i}{S\left(\hat{b}_i\right)} \right)^2 \tag{5}$$

where: $S\left(\hat{b}_i\right)$ – standard error of parameter estimates $\hat{b}_i$, to investigate if the independent (discriminant) variables $x_1, x_2, ..., x_k$ are statistically significant.

ARTIFICIAL NEURAL NETWORKS

The computational structure of artificial neural networks (ANN) has attractive characteristics such as graceful degradation, robust recall with noisy and fragmented data, parallel distributed processing, generalization to patterns outside of the training set, nonlinear modeling, and learning.

There are numerous artificial neural networks architecture designs. However, they can be classified on the basis of the techniques used to train the free parameters (weights) in the network[2]. Azoff (1994), Bishop (1995), Schurmann (1996) distinguish two learning methods: supervised and unsupervised learning. Applying unsupervised learning, the network does not know the correct answers and is to find out the classification patterns (these are the so-called self-organizing networks). Employing supervised learning, sample inputs and desired outputs must be given (the entire collection of cases learned is called a training set). During the training procedure the computed output is compared to the desired output. If the computed output is incorrect, then the weights are adjusted so as to make the computed output closer to the known output.

In our study of Polish client creditworthiness we apply supervised learning networks such as multilayer perceptron (MLP)[3] and radial basis function network (RBF) since the data set contains patterns of borrower classification.

Multilayer perceptron (Fig. 2) is usually formed by a cascading group of single layers. There is an input layer, an output layer, and hidden layers. The neurons of different layers are densely interconnected through direct links. At the input layers, the neurons receive the values of input variables and multiply them through the network, layer by layer.

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[2] The initial weights of the connections can be chosen randomly.

[3] In our experiments MLP parameters (weights) are estimated (trained) employing back propagation algorithm.

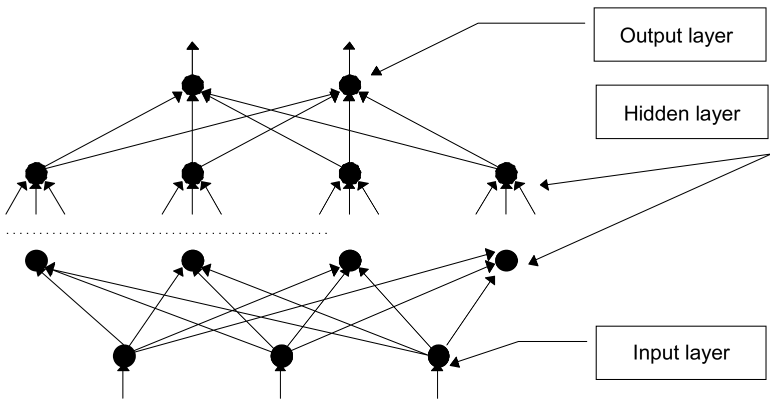

Fig. 2. Multilayer perceptron
Rys. 2. Perceptron wielowarstwowy
Source: Witkowska 2002.
Źródło: Witkowska 2002.

Assuming that there are (L – 1) hidden layers and each of them contains K^l neurons (l = 1, 2,…, L – 1), the output of the j-th neuron in the l-th hidden layer (l = 2, 3,…, L – 1) equals:

$$h_j^l = F_l\left(\sum_{k=0}^{K^{l-1}} w_{jk}^l h_k^{l-1}\right) \tag{6}$$

For the first hidden layer output of the j-th neuron is:

$$h_j^1 = F_1\left(\sum_{i=0}^{n} w_{ji}^1 x_i\right) \tag{7}$$

The output of the j-th neuron in the output layer equals:

$$y_j = F_L\left(\sum_{k=0}^{K^{L-1}} w_{jk}^L h_k^{L-1}\right) \tag{8}$$

where: h_k^l is the output of the k-th neuron in the l-th hidden layer (k = 1, 2,… K^l), x_i is the input of the i-th neuron in the output layer, y_j is the output of the j-th neuron in the output layer (j = 1, 2,…, m), F_l is the activation (transfer) function defined for the l-th hidden layer, and for the output layer, $w_{jk}^l, w_{ji}^1, w_{jk}^L$ are the weights estimated for each element in all layers (i.e. l = 1 for the input layer, l = 2, 3,…, L – 1 for hidden layers and $l = L$ for the output layer). Index k (k = 1, 2,…, K^l) denotes numbers of neurons being inputs of the hidden layers (l = 2, 3,…, L – 1) and the output layer ($l = L$).

The hidden layer neurons are often characterized as feature-detectors. The number of hidden layers and the number of neurons in each hidden layer is selected arbitrarily.

The number of neurons in input and output layers is determined by the problem that is to be solved by ANN, for instance, applying neural systems to the classification, the input neurons represent discriminant variables, and output neurons represent the pre-defined classes (as it is shown in Fig. 1).

The total transfer function of the RBF network is given by:

$$y = \sum_{k=1}^{M} w_k \Phi_k (\|\mathbf{x} - c_k\| / \delta_k) \tag{9}$$

where: y – the network output, $\mathbf{x} = [x_1 x_2 ... x_n]$ – the vector of inputs, w_k – the network adjustable weights connecting the network hidden nodes with the network output, $\Phi_k (\|\mathbf{x} - c_k\| / \delta_k)$ – radially-symmetric transfer functions with centers $c_k \in R^N$ ($k = 1,..., M$), δ_k – the scaling factor, $\|\cdots\|$ denotes the Euclidean distance.

Note that in RBF network (Fig. 3), the only adaptable weights (i.e. parameters w_k in (9)) are located between the hidden and the output network layers. These weights determine linear combination of basis functions values, and together with the chosen basis functions centers c_k, determine the shape of the generated mapping function (Kaminski and Strumillo 1997). In our study, the basis functions centers are selected by applying *k*-means method.

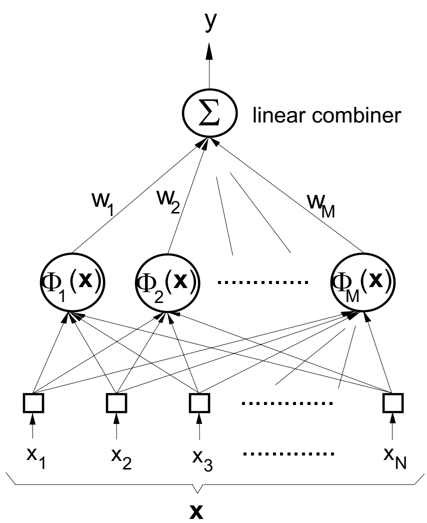

Fig. 3. Radial basis function network
Rys. 3. Siec o radialnych funkcjach bazowych
Source: Kaminski, Strumillo 1997.
Źródło: Kaminski, Strumillo 1997.

Applying supervised learning the data set is divided into three usual subsets: training set, the validation set, and the testing set. In our research, the elements of the training, validation, and testing sets are chosen randomly. The training set is used to “teach” the network while the validation set is employed to evaluate the accuracy of the training. And the testing set is used to evaluate the accuracy of prediction or classification. This accuracy is usually measured by root mean squared error (*RMS*):

$$RMS = \sqrt{\frac{\sum_{i=1}^{n} \rho_i}{n}} \tag{10}$$

where: ρ_i – the absolute error, i.e. the difference between desired and generated output, evaluated for the i-th object, n – number of elements in the training, validation (or testing) set.

DATA DESCRIPTION

The empirical study is carried out using data that contain information of 100 individual borrowers from regional Polish bank who had obtained "Christmas" credit loans for December 2002. The value of "Christmas" loans varied from USD 550 to USD 2.500. In March 2004 the bank reported that 37 of the borrowers are in default. Thus, the structure of our sample is as following:

Table 1. Structure of the sample
Tabela 1. Struktura próby

Total number of borrowers	Number of borrowers who paid back the loan	Number of borrowers who defaulted
100	63	37

Source: Based on the data set.
Źródło: Opracowanie własne na podstawie danych.

To construct the binary response model, the dependent variable $y_i = 1$ denotes the borrower who paid back the loan, and $y_i = 0$ otherwise. Each borrower is described by eight credit evaluation characteristics:

- X_1 – age (in years),
- X_2 – period of loan repayment (in quarters),
- X_3 – incomes,
- X_4 – level of education,
- X_5 – place of resident,
- X_6 – gender,
- X_7 – information if the borrower is an existing or potential bank client,
- X_8 – amount of the loan.

Attributes: X_1, X_2, X_3 and X_8 are measurable characteristics while the remaining four X_4, X_5, X_6 and X_7 are qualitative characteristics. The letters are binary coded to form the model. Hence, there are eight potential input variables x_j ($j = 1, 2,..., k$).

MODEL CONSTRUCTION

The first step of the model building is to investigate the correlation among the variables y and x_j (j = 1, 2,..., 8). We employ the following methods to distinguish independent variables for the models:

- Yule coefficient for the pairs of binary variables (i.e. Y and one of variables: X_4 – X_7),
- t – Student statistic test for the pairs consisting of binary and continuous variable,
- Pearson correlation coefficient if both variables are quantitative.

Investigation of mutual relationships between the grouping and the discriminant variables as well as the relationships among independent variables shows that the value of the loan, income, the place of resident, and gender should be omitted in the models. Finally we defined five sets of independent variables as follow:

a) x_1 (age), and x_4 (level of education),
b) x_1 (age), x_4 (level of education), and x_2 (period of repayment),
c) x_1 (age), x_4 (level of education), and x_7 (an existing or potential bank client)
d) x_1 (age) and x_2 (period of repayment),
e) x_2 (period of repayment), and x_7 (an existing or potential bank client).

The five logit models containing the independent variable sets (a) – (e) are estimated. Among them we choose the logit model that is the best fit in terms of:

- Wald statistic (5) – all independent variables are statistically significant,
- chi-squared statistic (3), and
- correlation coefficients.

The selected model describes the probability of loan redemption using the set of discriminant variables (b). Parameter estimates of the regression model (3) are as follow:

$$\hat{y}_i = 215 + 0.001x_{1i} - 2.19x_{4i} + 1.43x_{2i} \tag{11}$$

$$L = 24.033;\ cor(y, \hat{y}) = 0.6$$

According to the model (11) specification, neural networks are constructed employing the variable set (b) as input neurons x_i. On the basis of RMS errors (10), obtained for the validation sets, three supervised learned neural nets are chosen for classification. These networks contain three variables: x_1, x_4 and x_2 in the input layer (7) or (9), one output variable y (y = 1 or y = 0) and 4 or 5 hidden neurons[4]:

- MLP 3-4-1 ($RMS_{validation\ set}$ = 0.37);
- MLP 3-5-1 ($RMS_{validation\ set}$ = 0.38);
- RBF 3-5-1 ($RMS_{validation\ set}$ = 0.42);

CLASSIFICATION ACCURACY EVALUATION

Let us assume that there are n objects O_i (i = 1, 2,..., n) which are to be classified. The two different classes A_p (p = 1, 2) containing n_p elements is obtained through the process

[4] MLP 3-4-1 denotes that there are three input neurons, four elements in the hidden layer and one output.

as described in Figure 1. Every borrower from our data base is an object. The content of both classes is known from the information that we have of whether the borrower is in default or not. In our investigation we find the algorithm of the object (borrower) recognition and evaluate the accuracy of classification by comparing the classes that was constructed to the actual ones by checking every object. If we know the pattern of the classified object (borrower), then it is possible to evaluate errors of classification by comparing elements which should belong to the groups A_p with elements of classes $\hat{A}_p$, where $\hat{A}_p$ denotes the classes which are constructed from the results of our classification experiments. The general classification error is then defined as follows:

$$E = \frac{\sum_{p=1}^{2} K_p}{\sum_{p=1}^{2} n_p} \cdot 100\% \tag{12}$$

where: K_p – is the number of misclassified objects of the class A_p, i.e. number of borrowers who should belong to the class A_p but they are recognized as belonging to another class, n_p – is the count of the A_p class.

The general classification error shows the percentage share of misclassified objects. The error can be calculated for the whole set of observation as well as for separate sets: training, validation, and testing. We may also consider the E_p classification error that shows the share of misclassified objects from p-th class in the total count of elements belonging to the class A_p:

$$E_p = \frac{K_p}{n_p} \cdot 100\% \tag{13}$$

This error is especially important when the borrowers classification is considered since K_p calculates the number of defaulted clients that are recognized by the model as credit worthy clients indicating the hypothetical number of loans that will not be redeemed. Thus the error E_p shows the share of misclassified objects in the set of defaulted clients.

RESULTS OF BORROWERS CLASSIFICATION

Applying the logit function (9) and the artificial neural networks (MLP 3-4-1, MLP 3-5-1 and RBF 3-5-1), the borrowers are classified into two classes. To compare the accuracy of the classification of the logit model and ANN, it is necessary to take into consideration the whole set of 100 observations. Table 2 presents the results generated by the models in terms of general classification errors and the comparison of counts of objects belonging to A_p and $\hat{A}_p$ groups. Bold numbers denote the correct classification.

The logit model properly recognized 51 borrowers who did not default on the loan (that is 81% of observation belonging to the class of credit worthy clients) and 20 clients who defaulted on the loan (that is 54% of objects from the group of defaulted clients).

Table 2. Classification of borrowers
Tabela 2. Klasyfikacja kredytobiorców

Actual number of borrowers who:	Predicted number of borrowers who:		General classification error
	Did not default	Defaulted	
	logit	model	29%
Did not default	51	12	
Defaulted	17	20	
	MLP 3-4-1	model	19%
Did not default	53	10	
Defaulted	9	28	
	MLP 3-5-1	model	24%
Did not default	51	12	
Defaulted	12	25	
	RBF 3-5-1	model	22%
Did not default	52	11	
Defaulted	11	26	

Source: Own calculation.
Źródło: Obliczenia własne.

The general classification error shows that 29% of the object is misclassified while 71% of borrowers are correctly classified.

The results obtained from the neural networks model indicate that the general classification errors, calculated for the whole set of observation, are smaller than the one obtained for the logit model. All the models correctly predicted from 51 to 53 (i.e. over 80%) of credit worthy clients. The misclassification of defaulted clients depends on the model construction and it differs from 24% (i.e. 9 misclassified borrowers) to 46% (i.e. 17 incorrectly classified defaulted clients).

The real predictive power of the accuracy of the classification, from applying supervised learned neural networks, can be shown by comparing the general classification errors calculated for the testing set. In Table 3, the comparison of errors (10) in every set is presented.

The best results are obtained for the RBF network. Although the RBF network general classification error for the training set is the biggest among the analysed neural

Table 3. Classification errors for artificial neural networks
Tabela 3. Błędy klasyfikacji dla sztucznych sieci neuronowych

Set of data	Number of observations	MLP 3-4-1	MLP 3-5-1	RBF 3-5-1
Training	50 (number of creditworthy clients: 33)	2%	26%	28%
Validation	25 (number of creditworthy clients: 15)	32%	20%	16%
Testing	25 (number of creditworthy clients: 15)	40%	24%	16%
Number of	misclassified observations in testing set	10	6	4
Share* of	misclassified defaulted clients E_p	(7) 70%	(2) 20%	(2) 20%

*Number in parenthesis denotes number of misclassified objects in the testing sets
Source: Own calculation.
Źródło: Obliczenia własne.

networks, this network can correctly predict 84% of objects from the testing set and only 20% of defaulted clients as credit worthy ones. The network MLP 3-4-1 seems to be "overtrained" since the classification error is very small for the training set and it is rising for two other sets.

CONCLUSIONS

This paper endeavors to employ binary response models to predict the credit worthiness and potential loan default by bank borrowers in a transition country like Poland. Credit and risk management evaluation of loan lending is an essential part of a bank's operations. Banks in transition countries like Poland need to establish a reliable credit policy that may be more applicable to a transitional country by providing bank credit officers with an evaluation tool to determine the credit worthiness of potential borrowers. The results of this paper show that artificial neural networks model have strong predictive power over logit models. The results also indicated that the X_1 (age), X_2 (period of loan repayment (in quarters)), and X_4 (level of education) in model (11) had the best statistical performance and the lowest classification errors. Thus, this set of variables was used in our experiments. Other variables such as X_3 (income), X_5 (place of resident), and X_6 (gender) do not seem to be important as predictive (discriminant) variables.

The classification provided by artificial neural networks seems to be more accurate than the one made by the logit model. Among the analyzed neural networks, the RBF network generates the smallest classification errors.

The appearance of qualitative features is the main obstacle in the application of binary response models to individual borrower classification. Thus, special methods should be applied to correlation investigation and classification. It is worth mentioning that some of features describing objects are not correlated with the grouping variable i.e. the credit repayment. Banks in transitional countries like Poland should revise the credit granting procedure where most loans are small valued loans extended to individual clients by taking into account the supporting instrument offered by artificial neural networks to evaluate credit risk.

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PRZEWIDYWANIE SPŁATY KREDYTU W KRAJU TRANSFORMACJI GOSPODARCZEJ: PORÓWNANIE MODELI LOGITOWYCH I SZTUCZNYCH SIECI NEURONOWYCH

Streszczenie. Banki przekazują środki finansowe od depozytariuszy do kredytobiorców, co jest obarczone ryzykiem kredytowym, kiedy pożyczka nie jest spłacana w terminie (lub nie zastanie w ogóle spłacona). Dlatego możliwość dokonania oceny zdolności kredytowej lub posiadanie metodologii wspomagającej to działanie jest istotne w zarządzaniu ryzykiem bankowym. W krajach takich jak Polska, których gospodarka jest w okresie transformacji, ocena zdolności kredytowych jest szczególnie trudna z powodu przemian zachodzących na rynku finansowym. Artykuł porównuje zastosowanie modeli logitowych i sztucznych sieci neuronowych do oceny ryzyka kredytowego. W szczególności wykażemy, że sztuczne sieci neuronowe są lepszym narzędziem prognostycznym niż modele logitowe.

Słowa kluczowe: spłata kredytu, klasyfikacja, model logitowy sztuczne sieci neuronowe

Accepted for print – Zaakceptowano do druku 30.03.2008