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Research Article

Design and Explanation of the Credit Ratings of Customers Model Using Neural Networks

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Abstract: The aim of this study formed with purpose of providing a suitable model to investigate the credit behavior of consumer of speculation loan using neural networks for credit ratings. Nowadays, intelligent systems found many applications in different fields of banking and financing. One of main application of neural networks is review and approval of credits. Thus, at first factors affecting credit behavior of consumer was identified and then, consumers divided in three categories: on-time payer (good payer), bad payer and overdue (belated) payer. In the next step, neural network models designed using the training data was instructed and then tested with these experimental data. The results show that the credit behavior of the customers could be predicted using neural networks ranking models.

Keywords: Credit ranking, facilities, neural network

INTRODUCTION

In issuing credits which is one of the main tasks in the financial services of banks and credit institutions, correct decision making require determining credit rating and ability of recipient to repay loan principal and interest, in effort to reduce the probability of overdue return of facility's principal and profit or the risk of credit rating. One way to reduce this risk is determining the credit rank of facility recipients and the center of this system model is a credit rating or credit evaluation and assessment (Shayan, 2001). Using such a model, rank or grade of the applicant will be specified and on the basis of this ranking, the decision is taken about granting facility or not. Currently, using intelligent systems in order to optimize and predict operations as an advanced tools that are frequently used in various fields of science; are very common (António and Ricardo, 2012). Neural networks apply in different areas of finance including credit approval, as an intelligent system. When approving credits, customer credit evaluation is a very complex process in the financial activities (Gaganis, 2007).

Granting banking facilities is economically very important because the increased quantity of capital lead to economic development (Hedaiati *et al*., 1990). But in granting loans, banks are facing a large risk which called the credit risk. This is the cause of banks' exposure to financial crisis. Credit risk can be the risk of non- repayment of loans taken by the applicant (Sinkey *et al*., 1992). Credit risk management can be done using different methods. One of these methods is designing a credit ranking system for financial facility recipients.

The purpose of this study was designing and implementing client's credit rating system in the credit markets, in an effort to identify customer behavior patterns and finally providing a possibility for forecasting consumer's behavior.

Credit rating systems can be classified in three categories (Fensterstock, 2003):

- Judgmental systems
- Ranking based on statistical techniques
- Intelligent systems

Judgment systems are very time-consuming and expensive. Generally, when the numbers of demands are high and limited number of experts available, these systems is not efficient enough. In statistical method, every techniques of this method require specific assumptions. Obviously, with the absence or weakness of assumptions, excess's accuracy and correctness is questionable (Pter, 2011). When the decision rules are clear and information are reliable, expert systems are a great help to solve problems. But in most institutions whom grant loans, there are not any transparent data and there is no information at all or part of the information is not correct; in this situation, neural networks are a good option. A good credit ranking system is indispensable if contain a suitable criteria for consumer evaluation before granting any facility, so that the bank loan allocated to optimal customers using this system (Behr and Andre, 2008). The banking system viewed desirable consumers as the clients who spent the accommodations he received in different economic sectors, in order to facilitate timely paying back of loan into the banking system. Failure to repay the loan on time suggests that facility recipient has not had much success in exploiting the granted credit (Morsman, 1997). Credit rating is basically a way to detect group differences in a population. The idea of differentiating groups within a population in statistics was introduced by Fisher (1963) and Thomas (2002).

Denham (1983) developed the first credit evaluation system for demand letters of consumers, using the following five criteria (Altman, 2000).

Position, earnings, financial situation, guarantee, vouch or collateral, bank loan repayment information.

The objectives of current research can be stated as follows:

- Identify the basic characteristics of clients in determining their rankings effectively.
- Designing suitable model for assessment of customer rating using neural networks.
- Reduce credit risk in the bank and thus the optimal use of banking resources and facilities.

Neural networks devised a suitable learning algorithm by making artificial neurons, putting them together in a parallel form and introduce learning ability; in order to process information quickly and accurately; in this manner and unlike other statistical methods, they will able to act smart and learn processes, so that have optimized results in new and undefined or unpredicted situation (Jafry, 2004). The first practical application of neural networks was introduced in the late 50 decade of 20^{th} century, when Rosenblatt and his colleagues built a network which able to identify the patterns and at same time in 1960, the Bernard Vidoro proposed Adalian adaptive neural network with a new learning rule (Duff and Einig, 2009). Development of neural networks continued until the 70 decade of twentieth century; during the 80th century the growth of microprocessor technology increased tremendously and research and new ideas were raised on neural networks (Jensen, 1996).

In this study, the independent variables include occupation, education, income, value of collateral, credit history.

They were identified using 5C system (the first credit analysis method is 5C, most common way also. In this method the credit applicant analyzed in 5 dimension: Character, capacity, capital, collateral and conditions) and the above variables are used as input variables of the artificial neural network model.

Dependent variables are the same as the output of neural network models and estimated using independent variables. These variables are as follows: good credit clients, overdue customers, bad credit customers.

MATERIALS AND METHODS

Considering that the aim of the study was customer's credit rating, the study population included 450 speculation loan applicant of Saman bank in Tehran. All of the 450 clients of Tehran province was used as a criterion for researching trends and customer behavior.

The population consists of reliable clients (with less credit risk), past due customers (with moderate credit risk), moderate and bad customer (higher credit risk) at Saman Bank in Tehran. According to the statistical literature and neural network which used for designing this models, in this study we had to consider a number of clients with special traits from past bank's customers. Based on statistical population of study and statistical formula, a sample of 350 customers were selected:

95% confidence level, Percent error of 1%

The standard deviation was 9% based on the prototype (pilot study):

$$n = \left(\frac{Z_{\frac{\alpha}{2}} \delta_X}{d} \right)^2, \quad n = \left(\frac{1/96 \times 0/09}{0/01} \right)^2 = 311$$

After identifying the critical features affecting credit rating of bank customers, the output should be designed. This model is actually a function with some input variables and three output variables. This function is considered customer characteristics as input variables of function. The intended function should receive the input variables and transform them to the output variables.

After reviewing the records, it was observed that 50% of the cases related to the credit facility with low risk, 43.33% of cases related to the moderate credit risk and 16.57% of cases was facilities with high credit risk. Because the number of available files on the all branches were 450, according to the table, 350 records are required for sampling. According to the above mentioned percentage, we need 175 good credit customers (a sample of 117 record for training and 58 record for testing), 117 customer with moderate credit risk (a sample of 78 record for training and 39 record for testing) and 58 customer with high credit risk (a sample of 39 records for training and 19 records for testing). The listed numbers were selected randomly for two groups.

Information collected will be analyzed and evaluated in several stages.

First phase: In this phase, data collected from the branches manually examined and steps will be taken to correct it.

Second phase: In this phase, research data is coded and classified using EXCEL software and transformed to information worksheet.

Step three: Collected data assessed by Neurosolution software and data preparation process is done.

Step four: Using NEUROSOLUTION software, the study variables are categorized and then, using sophisticated calculations that performed by this software, among independent variables those that had a significant relationship with dependent variables was identified; using relevant variables, a neural network model is designed by NEUROSOLUTION software package.

Summary of mathematical calculations are listed below.

Input vector with five input converted to vectors that activate the top layer distributed toward upper layer, which is the result of multiplication of the coefficients by the values of the activation. A U-shaped Sigmoid function is used as follow to determines the activate results of one unit, Aj, in the upper layer:

$$Aj^{(l)} = \frac{1}{1 + \exp\left[\sum_{i=0}^{n} WxAi^{(L-1)(L)} - Oj\right]}$$

If the upper layer isn't an output layer, then the vector will spread forward again. Signs L-1, L represents the upper and lower layers. If the upper layer is an output layer, the activation of each output unit is compared with its optimal value and the error is measured by the following equation:

$$E = \frac{1}{2}\sum_{j=0}^{n}(Di - Aj)^2$$

RESULTS

This section is explaining the modeling and ranking of facility customers using the feedback poll neural network.

The required data prepared by extracting suitable data from facilities applicant records and the variables obtained. It is noteworthy that the choice of variables is based on literature studies performed on this topic. Clients selection and extraction of required data from their files were done randomly, which cause equality in each layer and an attempt was made to select a file that contains more complete records. In this study, the amount of R^2, MSE for ranking surveys using neural networks, has been calculated. The variables that selected based on expert opinion and according to the investigation are include: the value of the collateral, education, income, credit history and job.

For network training, generalized forward neural network, with four layers of 5 elements in the first layer and 3 element in the final layer, two hidden layers with different elements in the middle (in models A and B) are used. According to prior researches, 4-layer is considered for network. The number of neurons in the last layer is equal with number of network output, which in this study includes three output. The number of neurons in the first layer compromise the number of inputs which is 5 and the number of neurons in the middle layer determined based on the network effectiveness.

Table 1: Model A

Performance	Output (1)	Output (2)	Output (3)
MSE	0.050905325	0.054243446	0.032658400
NMSE	0.203621298	0.244095508	0.235140478
MAE	0.120618186	0.133064573	0.095359186
Min Abs error	0.000803790	1.17722E-O5	0.000134769
Max Abs error	0.882390503	0.667410742	0.753558877
R	0.892427956	0.869730550	0.875873612
Percent correct	94.871794870	93.589743590	74.35897436

Table 2: Model A

Best network	Training
Epoch #	25000
Minimum MSE	0.085888677
Final MSE	0.131171759

Table 3: Model A

Performance	Output (1)	Output (2)	Output (3)
MSE	0.059648720	0.062085918	0.037877917
NMSE	0.238594880	0.279386633	0.272720961
MAE	0.140680756	0.154224109	0.105212329
Min Abs error	0.000608107	0.001592124	0.000177976
Max Abs error	0.910641516	0.755785332	0.948448497
R	0.872857560	0.851551454	0.852973159
Percent correct	94.017094020	92.307692310	74.35897436

Table 4: Model B

Best network	Training
Epoch #	30000
Minimum MSE	0.072960933
Final MSE	0.075751159

Another important factor in the network architecture is the training number. The used Software support up to 50000 training, but the software offer 1000 training, which in the current study, the training of network had been done 25000 and 30000 time.

Results of training number 30000 were done with fewer errors (Table 1). Then it was concluded that the multi-layer perceptron networks, generalized feedback, with two hidden layers, hidden layer elements 3-10-10-5 3-15-15-5 Model A and 3-15-5-15 Model B, the tangent function, train number of 25000 times was used for model A and 30,000 times for model B.

The neural network with 234 sample of training data were taught; containing 117 examples of low risk, 78 example of medium risk and 39 example with high risk. In the final model, the following variables used as input. Collateral values, education, income, credit history, job.

As you can see, the network in model A trained wit Error rate (MSE), 0.085 (Table 2). And then ranked the customers with standard deviation of 0.85 for bad credit, 0.85 for medium credit and 0.87 for good credit customers (Table 3).

In Model B, the network was able to train with error rate of 0.072 (Table 4), then ranked customers with standard deviation of 0.87 for bad credit customer accounts, 0.89 for overdue customers accounts and 0.89 for good credit customer accounts.

The tables and figures relating to the training and testing of the network demonstrated.

The results of implementing model A show that the model is able to accurately forecast bad credit accounts

Table 5: Comparison of results

Model	High credit accounts	Medium credit accounts	Low credit accounts
A	74.35	92.30	94.01
B	74.35	93.58	94.87

Table 6: Result of implementing model A

Output/desired	Output (1)	Output (2)	Output (3)
Output (1)	110	5	3
Output (2)	6	72	7
Output (3)	1	1	29

Table 7: Result of implementing model B

Output/desired	Output (1)	Output (2)	Output (3)
Output (1)	111	5	3
Output (2)	5	73	7
Output (3)	1	0	29

with accuracy of 74.35%, past due clients with the accuracy of 92.30 and good credit clients with 94.01% precision (Table 5).

Number of customers who have mistakenly predicted from each category can be seen in the following table.

The result of running model B (Table 6) show that the model is able to forecast bad credit clients with the accuracy of 74.35%, past due customers with 93.58% of precision and good credit clients with the accuracy of 94.87%.

Customers who wrongly predicted in each category are shown in Table 7 is obtained.

As shown in Table 5, we can observe that model B has the highest differentiation ability. Because ranked facilities applicants with higher percentage.

Here we have the answer to research questions, because the credit rating of customers implemented using customer’s credit characteristics; and the number of loans that are deferred or past due was specified. With this system, managers can avoid paying the loans which are deferred or write off and if they have to pay the loans, adopt more guarantees or voucher.

CONCLUSION

Grant credit to qualified customers is accounted for one of the most important and complex tasks of banks. Banks collect their funds in the country in various ways and allocate them to individual customers and corporate clients. How to allocate these resources as a credit facilities affect the profitability and job creation in the country; if and if it’s granted to qualified and competent customers. Proper allocation of financial resources in addition to the country's economic results and benefits, may provide necessary background for the survival of banks. Thus, banks must consider criteria and indicators of risk effectiveness and also the credit rank of customers, before granting any loans and facility to them. Using multi-layer perceptron neural networks, we can rate the facility and credit customer of the bank. This hypothesis which considered as study’s innovation, seeking the effectiveness of neural network models in the search for a practical model for estimating the three variables. The results showed that the multi-layer perceptron neural network model is effective in achieving the goal of efficiency. Therefore, after observing a significant relationship between the characteristics of customers and their credit ranking as key elements of efficient allocation of credits; NEUROSOLUTION software was used for designing the coordinates of the basic elements of effectiveness of neural networks model. The main characteristics that identified using the NEUROSOLUTION software was used as input layer (input vector) and introduced into the multi-layer perceptron neural network model and then corresponding neural network model was fitted. The results of the fitting and data analysis showed that this model could be applied as a model for determining credit ratings of credit applicants.

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