Ranking of Bank Customers using Neural Network (Case Study: Babol’s Tejarat Bank, Iran)

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Abstract

In so far as banks always face credit risk due to granting facilities and loads, it is expected that proper evaluation of credit customers of bank could play significant role in decreasing this risk. To evaluate real customers of Tejarat bank using financial and essential information of the companies receiving facilities, in this study, three models of three-layer perceptron neural network (8-6-6), Single-layer feed-forward neural network (21 neuron in hidden layer), three-layer feed-forward neural network (8-6-6) and Nero Solution software have been used. For comparison of the mentioned models, MAE and MSE criteria have been utilized. The study of the results show that single-layer feed-forward neural network is better in evaluation of customer than two other methods on the condition that granting facilities in banks to be done with the least error and least personal opinions.

Keywords: Credit scoring, Credit risk, Ranking, Neural network.
Introduction
Credit institutions, whose main pillar is banks, need some examinations for qualitative and quantitative recognition of applicants to grant facilities to them known as credit scoring. Credit scoring is in fact the comparison of credit risk of an enterprise with other enterprises or evaluation of the capacity of people in receiving facilities including measuring management ability, the issue of using facilities, its proper usage, profiting, the need for resources, return of resources and evaluation of customer risk and etc.

To this end, banks and credit institutions make use of certain criteria that indicate the performance of applicant in the past and estimate his credit capability. Thus, to achieve the determined objectives and strategies, the individuals and companies might face limited financial resources and refer to financial institutions including banks to compensate it. Thus, for logical responding to applicants’ request, banks should respect national and regional policies, examine and estimate the applicants' demand concerning their required resource deficiency to compensate for financial deficiency of economic units in commercial, economic and manufacturing sectors, services, housing and building and event ordinary people and specify manner of granting facilities, manner of returning resources, type of facilities, its duration and etc. In addition, they should carry out some studies concerning its associated risks, i.e. customer risk, since there is the probability of failure to pay and arising demands following any repayment of loans and debts.

The pathology of uncommitted debts of the banking system is very important. People and companies who do not return their received facilities have confiscated public resources belonging to all people given to them for economic development and employment. Thus, commercial banks are interested in studying several factors in allocating credit to each customer, the most important of which include:

- Reliability
- Technical competency and capability
- Financial capacity and credit worthiness
- Guaranty and financing

Statistical methods are the most common and applicable methods for making score cards or ranking models. First, discriminant analysis and regression were the only models used in credit ranking. The first paper published on the use of discriminant analysis in credit ranking is related to AOS, (2011) who showed that this method presents a good prediction on credit repayment. Davis (2007) compared the precision of discriminant analysis and regression in credit ranking. Thomas, (2006) used regression for ranking of the applicants of commercial loans. Lung Huang (2006) used logistic regression in credit ranking for the first time. he compared logistic regression with discriminant analysis and conclude that logistic regression is better than discriminant analysis. Limsombunchai (2005) used discriminant analysis and Probit model for ranking the applicants of a big chain store in America.

The other statistical methods used in credit ranking include non-parametric smoothing. Henley and Hand (1997) compared the precision of four different methods in ranking using data related to a big electronic sale company, they used four methods of linear regression, logistic regression, closest neighboring and decision tree. The results of study was that the method of closest neighboring has better performance compared to three other methods and logistic regression, linear regression and decision tree are in next ranks in terms of precision of classification. From the time when artificial intelligence systems including artificial neural networks, genetic algorithms and expert systems were designed and introduced, their use in
financial studies and credit ranking becomes common and it is rapidly expanding. From the papers that have used expert system in credit ranking, Davis (1987) and Leonard could be mentioned. For example, from the applications of genetic algorithm in credit ranking, Shin & Lee could be mentioned that used the audited financial statements of 528 industrial companies for estimation of probability of bankruptcy. The results showed that in average, the model has proper prediction capability in 80% of cases.

There are various papers concerning the application of neural networks in credit ranking. West (2000) compared the precision of five neural network models of Multi-Layer Perceptron (MLP), Radial Basis Function (RBF), Learning Vector Quantization (LVQ), Fuzzy Adaptive Resonance (FAR), Mixture of Expert (MOE) and five logistic regression statistical method, the closest neighbors, discriminant analysis and kernel density; here, MOE, RBF and MLP were selected as the best models.

The studies of Yegorov et al. (2001) based on logit model) that were implemented based on the ratio, showed proper ranking rate of 87% for bad credit and 86% for good credit and total ranking rate of 86%. While neural networks properly classify 92% of observations that do not indicate the higher efficiency of neural network compared to Logit classic model, the results of De Lurgio and Hays (2002) indicated that the neural network model showed good credit as 83% (30 out of 36 customers) and bad credit as 88% (65 out of 74 customers). On contrary, proper ranking rate of Logit model has been 47% for good customers (17 out of 36 customers) and 85% for bad credit (63 out of 74 customers). The discriminant analysis model has also properly recognized 56% of good customers and 85% of bad customers. Frerichs and Wahrenburg (2003) explains that the use of parametric methods for deduction of probability of default of credit scales might lead to overestimation or underestimation of capital demands compared to the use of default ratings (not repaying the loans) of credit ranking. Malhatra and Malhatra (2003) concluded that the average proper ranking in neural networks related to bad customers has been 64-79% and discriminant analysis model of 56-59%. Moreover, the average proper ranking in neural networks related to good customer has been 47-75% and discriminant analysis model of 39-74% that indicates neural networks has better performance. Kim and Sohn (2004) in their study concluded that after training, it classified good customers by 66-86% and bad customers by 64-83% and its total precision was 71-84%. Finally, the average proper ranking rate has been 78%. The results of Lee, Chiub and Jaeo (2004) show that when data volume and the number of variables is high, the use of Cart method is a simpler and more efficient solution. The results of Commerce Division and Limsombunchai (2005) showed that proper prediction of Logit model has been 85% that compared to probable neural network model has been performance and it has relatively similar performance compared to multi-layer neural network; this is while the cost of first error is more than the cost of second error, i.e. classification of good customer instead of bad customer. In Dinh Thi Huyen & Kleimeier (2006), it was concluded that the effective variables in developing countries are the effective variables in banks of developed countries; although the strength and weakness of the effect of any variable might be different. The interesting conclusion of this study is that in developing countries, due to the economy of these countries that are constantly changing, credit model should be reconsidered and updated once in several years. Lung Huang et al. (2007) explain that artificial intelligence methods have better efficiency than classic statistical methods and use neural networks as benchmark and have obtained the accuracy of prediction about 80% for markets of unitedstates and Thailand. The solutions presented in Thomas (2006) show that the use of a statistical model could effectively help us in credit analysis of customers. Abdou and Pointon (2008) in their study prove that the first
type error in feed-forward neural network is less than other methods; thus, these neural network recognize bad customers better than good customers; this assumption leads to decreased credit risk in banks. The results of ICSP group S.A. (2011) showed that there is considerable difference in rate of failure to pay and meeting obligations between companies with high and low risk.

In Iran, there are various papers concerning the applications of neural networks in various fields including medicine, engineering and economy; however, the application of neural networks in credit ranking is rarely considered. Abdou et al. (2008) predicted the stock price of Khodro Company using neural networks. Other studies include Thomas (2006) who have designed prediction model of stock price of investment companies using artificial neural networks. Thomas (2006) used artificial neural network to study the existence of turmoil process in total yield index of stock price in Tehran exchange market. In addition, Thomas (2006) used neural network models for prediction of total yield index of Tehran stock and showed that neural network model has better performance in prediction of daily and weekly index of Tehran stock yield than some time series models. Lung Huang (2006) used neural network to predict pistachio export of Iran Myers and Forges (2003) studied the application of neural network models in prediction of economic bankruptcy of stock exchange market. AOS, (2011) studied the applicability of stock price prediction through technical analysis indices using neural networks Davis (2007) studied the application of artificial neural network in prediction of occupational income tax in Iran economy. Leonard (2004) claimed that in estimation of credit capacity, neural network models have higher capacity than linear logistic. The results of Frerichs and Wahrenburg (2003), show that it is possible to classify the behavior of customers by creditworthy, non-creditworthy and ordinary by appropriate architectural design for neural network and determination of the number of hidden layers and the number of appropriate neurons in any layer. Henly and Hand (2005) in his study proved that the probable linear model is an efficient and effective model in prediction of weak credit risk, logistic models and multi-layer perceptron neural network. West (2000) explained that neural networks properly realize non-creditworthy customers up to 81-93%, past maturity customers up to 85-87% and creditworthy customers up to 72-76%. The results of Stern (2008) indicated that discriminant analysis and Logit model better recognize creditworthy customer than non-creditworthy; however, neural network better recognizes non-creditworthy customer.

Sarle (2011) presented a neural network model for classification of loan applicant using SOM algorithm. The results of Kim and Sohn (2004) explain that using neural networks of expert system and hybrid models, it is possible to modify and balance the problem of non-payment of facilities granted to customers. Lung Huang C. & et al, (2007), explains that neural network model generally works better than Logit model in reliability level 95%. Meanwhile, the performance of neural network model has similar efficiency with Logit model in classification of creditworthy and non-creditworthy customers. Shin and Lee (2010) presented a model based on compatible neural-fuzzy argument that determines the credit of customers and ranks them based on risk that bank might incurs.

1. **Introduction of data and data collection method**

The studied statistical population in this study includes all people receiving loans over 450,000,000 million IRR in branches of Tejarat bank of Babol as following table. This population has been selected through census and 200 documents have been selected and their
required information has been collected. However, due to confidentiality of the customer information and to maintain trust and integrity, in data collection, some information including surname, family name, phone number and even account number of customers of the bank have not been included.

Table 1. The number of documents in branches of Tejarat bank, Babol branch

<table>
<thead>
<tr>
<th>Name of branch</th>
<th>Number of documents</th>
</tr>
</thead>
<tbody>
<tr>
<td>Central branch</td>
<td>100</td>
</tr>
<tr>
<td>Shariati branch</td>
<td>37</td>
</tr>
<tr>
<td>Nima branch</td>
<td>23</td>
</tr>
<tr>
<td>Bazaz branch</td>
<td>15</td>
</tr>
<tr>
<td>Tandast branch</td>
<td>11</td>
</tr>
<tr>
<td>Taleqani branch</td>
<td>9</td>
</tr>
<tr>
<td>Keshavarz branch</td>
<td>5</td>
</tr>
<tr>
<td>Total</td>
<td>200</td>
</tr>
</tbody>
</table>

The variables used in this study include age of customer, the type of business license, experience in field of activity, type of bargain in sale, extra income (in case of having another source of income), repayment duration, the ratio of average 6-month account of customer to source of facilities, uncommitted debts to banking system, bounced check, year of receiving facilities, credit status (response variable), some variables have been used quantitatively and some categorically. The categorical variables used in this paper and their categories have been presented in table 2.

The variable of credit status has been specified by two level of good and bad. From those receiving loan, individuals with more than three uncommitted debts are classified as non-creditworthy and other as creditworthy. Other variables have been considered as independent variables.

Table 2. Categorical variables

<table>
<thead>
<tr>
<th>Variable</th>
<th>Name of variable</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age</td>
<td>Age of customer</td>
<td>Age is entered in number.</td>
</tr>
<tr>
<td>License</td>
<td>Type of business license</td>
<td>Lacking any business license</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Temporal license less than 5 years</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Temporal license above 5 years</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Permanent or official</td>
</tr>
<tr>
<td>Experience</td>
<td>Amount of experience in field of activity</td>
<td>The number of years is entered in number</td>
</tr>
<tr>
<td>Bargain</td>
<td>Type of bargain in sale</td>
<td>In cash</td>
</tr>
<tr>
<td></td>
<td></td>
<td>On credit</td>
</tr>
<tr>
<td></td>
<td></td>
<td>In cash and on credit</td>
</tr>
<tr>
<td>Other income</td>
<td>Extra income (in case of having another source of income)</td>
<td>The income number is entered</td>
</tr>
<tr>
<td>Duration</td>
<td>Repayment duration</td>
<td>Duration of repayment is entered in number</td>
</tr>
<tr>
<td>Average loan</td>
<td>the ratio of average 6-month</td>
<td>The amount is entered in number</td>
</tr>
</tbody>
</table>
amount | account of customer to source of facilities  
---|---  
Uncommitted debt | Uncommitted debts in banking system  
No | Yes  
Over draft | Bounced check  
1. customer has more than 3 bounced check  
Customer has 2-3 bounced check  
Customer has one bounced check  
Customer has no bounced check  
Year | Year of taking facilities  
Entered in number  

| 2. Selection and development of model  
Considering the subject of this study and independent variables and the use of appropriate software, the Lung Huang model (2006, credit ranking of real customers of business field using neural network model and Logit model. Banking sciences institute, 2009) used in this study is as follow by consideration of meaningfulness of the model:  
\[ M_{GB} = C + b_1 M_{AI} + b_2 M_{LI} + b_3 M_{EI} + b_4 M_{BR} + b_5 M_{OAt} + b_6 M_{DAt} + b_7 M_{Dt} + b_8 M_{Alt} + b_9 M_{UDt} + b_{10} M_{yt} \]  
Where,  
M\(_{GB}\): Creditworthy or non-creditworthy  
C: Constant number  
M\(_{AI}\): Age of customer  
M\(_{LI}\): Type of customer business certificate  
M\(_{EI}\): Customer experience in field of activity  
M\(_{BR}\): Type of bargain in sale  
M\(_{OAt}\): Customer bounced check  
M\(_{DAt}\): Repayment duration  
M\(_{Alt}\): Ratio of average 6-month account of customer to source of facilities  
M\(_{UDt}\): Uncommitted debt in banking system  
M\(_{yt}\): Year of getting facilities  
t: 1, ..., 200  

3. Method used for construction of ranking model  
Since the aim of ranking is to divide the loan applicant to two creditworthy and non-creditworthy groups, the issue of ranking is closely related to issue of classification (Chen and Huang). In fact, classification models are used as an instrument for classification of applicants.  
Since the main aim of this study is to use neural network models in credit ranking of load applicants, three models of three-layer perceptron neural network, three-layer feed-forward neural network and single-layer feed-forward neural network have been used for classification and the results of three models will be compared.  

4. Neural network model  
A neural network model is a collection of neurons collected in the entrance, middle and output layers; however, the middle layer could be located between entrance and output layers. A neural network model uses the input variables in first later. The output of network is usually a solution for a problem. In this study, the output of network could indicate a creditworthy
and non-creditworthy applicant. The network allocates numerical value 1 to a creditworthy applicant and 2 to non-creditworthy applicant.

To calculate the outputs, neural network model uses weight. Weights show the relation between two neurons in form of number and indicate the relative significance of any input variable. In frequent revision of weight, a network would be trained. Learning process in a neural network includes calculation of output and revision of weights. By iteration of learning process, the network identifies the proper values of weights.

Any neuron performs the following tasks:
- Receive signals from other neurons. \((X_0, X_1, X_2)\)
- Signals are multiplied by the corresponding weights. \((W_0X_0, W_1X_1, W_2X_2)\)
- Weighted signals are summed. \((SUM = W_0X_0 + W_1X_1 + W_2X_2)\)
- The obtain sum value is transferred by a transfer function. \([F(Sum)]\)
- The sum value is sent to other neuron (iteration of stages 1 to 4).

![Figure1. A sample of simple neural network [17]](image)

The input of a neuron or node is the weighted sum exited from its connected nodes. Thus, the entrance of a node is as follow:

\[
Net_{input_i} = \sum_j w_{ij} \times output_j + \mu_i. \tag{1}
\]

Where, \(w_{ij}\) is the connected weight of neuron \(j\) to neuron \(i\). A negative weight \(w_{ij}\) usually means that the output of neuron would decrease and a positive weight leads to motivation of neuron. \(Output_j\) is the output of \(j\) and \(\mu_i\) is threshold limit of neuron \(i\). The threshold limit of a neuron at the absence of other inputs is called bias threshold limit. Neural network receives inputs and produces output as vector. \(Net_{input_i}\) is the point multiplication of input and weight vectors. For a certain set of input, error is the difference between real value and output value of network. The error criterion we considered here is the mean square error. Network changes the weight such that the mean square error is minimized. Various neural networks calculate error based on used learning algorithm. Since learning algorithm has the capability of identifying patterns in a wide range of data after error propagation, it could be used in financial affairs and in prediction of function of financial systems, stock performance, credit ranking and examination of loan requests or identification of dishonest customer concerning credit cards (Malhtera, 2003)

If a network has linear transfer function, a multi-layer network could be shown as a single-layer network that is obtained from multiplication of weighted matrices of any layer. Researchers also use many non-linear activation functions. Nonlinear transform function between layers provides the possibility of multiplying layers to create new modeling capabilities (Harrington, 1993) The use of certain activation function is optional; however,
usually it is the selection of a monotonic function. Some ordinary activation functions are as follow (Sarle, 2008).

Linear or identity \( F(x) = x \)

Hyperbolic tangent \( F(x) = \tanh(x) \)

Otherwise threshold \( F(x) = 0 \) of \( x < 0.1 \)

Gaussian \( F(x) = x \exp(-x^2/2) \)

Logistic \( F(x) = (1 + e^{-x})^{-1} \)

The most common activation function is in circular (Sigmoid) or logistic form such as:

\[
F(x) = \frac{1}{1 + e^{-x}}
\]

A recognizable activation function is required. A small weakness of this circular function is that it doesn’t have effective interpolation and extrapolation (Sarle, 2011).

Neural networks have various types. Here, feed-forward neural networks including neural networks have wide application and due to the close relation of these networks with the used network in this paper, in follow, we will briefly introduce them.

These networks are constituted from several layers. Any neuron in any layer is connected to all neurons of previous layer. Such networks are also called fully associated networks. These networks are constituted from two output layer and several middle layers. The outputs of first layer constitute the input of second layer and in this way; the output vector of second layer makes the input vector of third layer. Finally, the outputs of last layer constitute real response of network. Clearly speaking, the signal flow in network is in a feed-forward path (from left to right from one layer to another).

Any layer could have a number of different neurons with various transform functions. A simple sample of feed-forward neural networks is perceptron neural network. These networks are among the most applicable neural networks. These networks are able to approximate a nonlinear mapping with desired precision with selection of appropriate number of layers and neural cells that are not much. Figure 2 is a layout of a multi-layer perceptron neural network. One of the neural networks used in this paper for evaluation of load applicants is a three-layer perceptron neural network with capability of learning after error whose layout is shown in figure 2.

Figure 2. Graph of a multilayer feed-forward neural network

4.1. Learning process and determination of network parameters

In order neural network model to be well trained, it is required to use sample that is representative of the whole population for network learning. As mentioned in previous
section, for network learning, the whole statistical population of 200 subjects including good and bad applicants will be used. Moreover, in order the network to effectively receive training, decision making about the structure of neural network and the number of neurons in output, middle and output layers is required. The number of neurons in input layer is simply equal to the number of variables in the data set constituting the input of network; i.e. just the same 10 mentioned variables. Concerning the aim of study that is classification of applicants to two groups; two neurons are used in output layer. Moreover, perceptron neural network has considered as having three middle layer and feed-forward neural network with one and three layer. Moreover, perceptron neural network has been considered as having three middle layers and feed-forward single and three-layer neural network and the number of neurons in this layer should be decided on. Although there are many experimental laws that could be used for selection of the number of neurons of middle layer, in most cases, test and trial is the best solution to determine the number of neurons (Kim and Seven, 2004). In addition to having proper number of neurons of middle layer, neural network should be trained by optimum number of learning cycles. If the network is trained in a few courses, the problem of underestimation would happen and if it is trained in many courses, it leads to overestimation (Malhtra, 2003)

### 4.2. Analysis of artificial neural network

The neural network used for credit scoring of bank customers include three-layer feed-forward neural network, single-layer feed-forward neural network and three-year perceptron neural network. Feed-forward neural network with three hidden layers have eight elements in the first hidden layer, six elements in second hidden layer and six elements in third hidden layer. Single-layer feed-forward neural network includes 21 elements in the hidden layer and three-layer perceptron neural network with three hidden layers includes eight elements in the first hidden layer, six elements in second hidden layer and six elements in third hidden layer. All layers of this structure includes input layer, hidden layer and output layer in series. In this study, in input layer of network, we used 10 variables or 10 neurons called age of customer, the type of business license of customer, the experience of customer in field of activity, type of bargain in sale, extra income, bounced check, duration of repayment, the ratio of 6-month account of customer to price of facilities, uncommitted debts and finally the year of taking facilities and the transfer function is in sigmoid first layer. Moreover, in three-layer feed-forward neural network and three-layer perceptron neural network, the main processing is done by neurons in the hidden layer and the number of hidden neurons of this layer for any mentioned neural network is in form of (8-6-6). Moreover, sigmoid function is used as actuation function for neurons in hidden layers. The number of neurons in the output layer equals to the number of outputs of neural network, i.e. 2 that is creditworthy and non-creditworthy customers. Moreover, the actuation function used for output is sigmoid function. However, this function was also used in feed-forward neural network and finally their results have been compared. Concerning what was mentioned so far, it is possible to summarize the structure of neural network in following table.

As previously mentioned, the software used in this study is Neuro solution v.5. Using this software, graphs and tables related to training and test of network, the error will be shown and the results will be compared.

**Table 3.** The specification related to architecture of artificial neural networks
5. The results of ranking with three-layer perceptron neural network, single-layer and three-layer feed-forward models

5.1. Single-layer feed-forward neural network

Figures 3 and 4 respectively show the process of credit scoring of creditworthy and non-creditworthy customers to achieve minimum error and relative corresponding error and the comparison of output and predicted one. As seen, error has reached its minimum, i.e. 0.02 in Epoch 1921.

The results of data analysis using single-layer feed-forward network is shown in tables 4 and 5. Table 4 shows that training has been well done and the mean error square in single layer feed-forward network has deceased up to 0.00998 and the graph of testing standard deviation is 0.94.

![MSE versus Epoch](image)

**Figure 3.** Prediction of credit scoring of customers (MSE with Epoch 10000)
Figure 4. Prediction of credit scoring of customers (MSE with Epoch 10000)

Table 4. The results of training of neural network (single-layer feed-forward)

<table>
<thead>
<tr>
<th>Best Network</th>
<th>Training</th>
</tr>
</thead>
<tbody>
<tr>
<td>Epoch #</td>
<td>1930</td>
</tr>
<tr>
<td>Minimum MSE</td>
<td>0.009986382</td>
</tr>
<tr>
<td>Final MSE</td>
<td>0.009986382</td>
</tr>
</tbody>
</table>

Table 5. The results of various values of testing errors of neural network (single-layer feed-forward)

<table>
<thead>
<tr>
<th>Performance</th>
<th>1</th>
</tr>
</thead>
<tbody>
<tr>
<td>MSE</td>
<td>0.048459965</td>
</tr>
<tr>
<td>RMSE</td>
<td>0.230097676</td>
</tr>
<tr>
<td>MAE</td>
<td>0.133624108</td>
</tr>
<tr>
<td>R</td>
<td>0.949737156</td>
</tr>
</tbody>
</table>

5.2. Three-layer feed-forward neural network

Figure 5 and 6 respectively show the credit scoring stages of creditworthy and non-creditworthy to achieve least error and relative corresponding error and the comparison of real and predicted output. As observed, error has reached its minimum, i.e. 0.01 at Epoch 2741.

Figure 5. Prediction of customer credit scoring (MSE with Epoch 20000)
The results of data analysis using three-layer feed-forward network have been presented in tables 6 and 7. Table 6 shows that training has been well done and the mean least error in three-layer feed-forward network has decreased up to 0.00999 and in test graph, standard deviation is considered as 0.048.

Table 6. The results of training neural network (three-layer feed-forward)

<table>
<thead>
<tr>
<th>Best Network</th>
<th>Training</th>
</tr>
</thead>
<tbody>
<tr>
<td>Epoch #</td>
<td>2752</td>
</tr>
<tr>
<td>Minimum MSE</td>
<td>0.009990891</td>
</tr>
<tr>
<td>Final MSE</td>
<td>0.009990891</td>
</tr>
</tbody>
</table>

Table 7. The results of training neural network (three-layer feed-forward)

<table>
<thead>
<tr>
<th>Performance</th>
<th>1</th>
</tr>
</thead>
<tbody>
<tr>
<td>MSE</td>
<td>0.048501879</td>
</tr>
<tr>
<td>RMSE</td>
<td>0.230296691</td>
</tr>
<tr>
<td>MAE</td>
<td>0.134288826</td>
</tr>
<tr>
<td>R</td>
<td>0.950093346</td>
</tr>
</tbody>
</table>

5.3. Three-layer perceptron neural network

Figures 7 and 8 respectively show the credit scoring stages of creditworthy and non-creditworthy customers to achieve minimum corresponding relative error and the comparison of real and predicted outputs. As observed, error has reached its minimum value, i.e. below 1.5 in Epoch 9991.

Figure 7. Prediction of customer credit scoring (MSE with Epoch 10000)
Figure 8. The comparison of real and predicted output (three-layer perceptron neural network)

The results of data analysis using three-layer perceptron network is expressed as follow: mean least error in three-layer perceptron neural network has decreased up to 0.0848 and in graph, standard deviation is 0.217.

Table 8. The results of training neural network (three-layer perceptron)

<table>
<thead>
<tr>
<th>Best Network</th>
<th>Training</th>
</tr>
</thead>
<tbody>
<tr>
<td>Epoch #</td>
<td>10000</td>
</tr>
<tr>
<td>Minimum MSE</td>
<td>0.0848049517605877</td>
</tr>
<tr>
<td>Final MSE</td>
<td>0.0848049517605877</td>
</tr>
</tbody>
</table>

Table 9. The results of various values of test errors of neural network (three-layer perceptron)

<table>
<thead>
<tr>
<th>Performance</th>
<th>I</th>
</tr>
</thead>
<tbody>
<tr>
<td>MSE</td>
<td>0.21745131</td>
</tr>
<tr>
<td>RMSE</td>
<td>1.032502623</td>
</tr>
<tr>
<td>MAE</td>
<td>0.424956524</td>
</tr>
<tr>
<td>R</td>
<td>0.906294457</td>
</tr>
</tbody>
</table>

6. The comparison of analysis and determination of the best method

In this study, two criteria are used: mean square error (MSE), mean absolute error. Moreover, \( R^2 \) is determination coefficient. \( R^2 \) value is between zero and one, 1 indicates full conformity of data; while, zero indicates the performance that could be expected of using real mean output value \( d \) as the basis of predictions.

\[
MSE = \frac{\sum (\hat{y}_t - y_t)^2}{N} \tag{3}
\]

\[
MAE = \frac{\sum |\hat{y}_t - y_t|}{N} \tag{4}
\]

where, \( \hat{y}_t \) is prediction, \( y_t \) is time series value at moment \( t \), \( N \) is the number of predictions or the number of input pattern of network.
Any model with the least error could be considered superior than other model. In table 10, the comparison of errors to compare three used method has been presented.

Table 10. The results of comparison of three proposed models for ranking of bank customers

<table>
<thead>
<tr>
<th>Tejarat bank</th>
<th>MES</th>
<th>MAE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Single-layer feed-forward network</td>
<td>0.04842</td>
<td>0.1336</td>
</tr>
<tr>
<td>Three-layer feed-forward network</td>
<td>0.04850</td>
<td>0.1342</td>
</tr>
<tr>
<td>Three-layer perceptron neural network</td>
<td>0.2174</td>
<td>0.4249</td>
</tr>
</tbody>
</table>

As it is observed, concerning the results presented in above table, MSE and MAE values of feed-forward neural network is less than three-layer perceptron network. Thus, it could be concluded that feed-forward neural network is more efficient than perceptron neural network. Moreover, concerning table 9, if we want to do comparison between single-layer feed-forward neural network and three-layer feed-forward neural network, as it is observed, concerning less errors of single-layer feed-forward neural network compared to three-layer feed-forward neural network, we will conclude that single-layer feed-forward neural network is more appropriate for credit scoring of the customers of Tejarat bank.

7. Results

In this study, for credit scoring of customers and their classification to good and bad customers, single-layer feed-forward neural network, three-layer feed-forward neural network and perceptron neural network have been used and compared in terms of MSE and MAE performance criteria. The results of these analyses show that:

1. In single-layer feed-forward neural network, errors are minimized in Epoch 1930 and the results of network training is minimum MSE= 0.00998 and the results of network testing are MSE=0.04845 and MAE= 0.1336.
2. In three-layer feed-forward neural network, errors are minimized in Epoch 2752 and the results of network training is minimum MSE= 0.0099 and the results of network testing are MSE=0.0485 and MAE= 0.1342.
3. In three-layer perceptron neural network, errors are minimized in Epoch 1000 and the results of network training is minimum MSE= 0.08480 and the results of network testing are MSE=0.2174 and MAE= 0.4249.
4. Comparing feed-forward neural network and three-layer perceptron network, the efficiency of feed-forward neural network is proved due to lower error.
5. Comparing single layer feed-forward neural network and three-layer feed-forward network, single-layer feed-forward neural network is considered more appropriate due to lower error.
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