International Journal of Advanced and Applied Sciences, 3(2) 2016, Pages: 40-44

Contents lists available at Science-Gate

International Journal of Advanced and Applied Sciences

Journal homepage: http://www.science-gate.com/IJAAS.html

Ranking bank customers using Neuro-Fuzzy network and optimization algorithms

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A R T I C L E I N F O

Article history:
Received 28 January 2016
Received in revised form
27 March 2016
Accepted 27 March 2016

Keywords:
Genetic algorithm
Particle swarm algorithm
Feature selection
Neural network
Neuro-fuzzy network

A B S T R A C T

Ranking system is considered as one of the most important tools to control and manage risk in banks. Ranking is the separation and classification of customers into various groups. This study is presented a solution for improving the accuracy of ranking customers of banks based on the hybrid neuro-fuzzy networks modeling and optimization algorithms. In this regard, two major parts namely selecting the features and rating were targeted. In features selection, particle swarm algorithm is used in addition to genetic algorithm, which is used frequently in the field of risk management. Also, neuro-fuzzy network technique is used to ranking. The mentioned solution was applied on the data obtained from the customers of one of the German banks with a population of 1,000 people; then, they were evaluated. The results showed that particle swarm algorithm has a better performance to achieve the goal, fewer features and errors in selecting features. Also, in modeling customers' ranking, neuro-fuzzy network technique provides more favorable results than the neural network technique.

1. Introduction

Credit risk analysis is a major issue in risk management and it has a special importance in the banking industry. Today, most banks have a lot of information about customers, which it contains personal information and their performance. Accreditation or customers' credit ranking is considered as one of the main concerns of these institutions. Indeed, ranking means the level of assessing the applicants' ability to repay loans and financial facilities and the probability of failure to repay the credits, which are received by them (Thomas et al., 2002). Finding the patterns and knowledge lies in this information leads to identify the needs of customers, credit risk assessment and understand market's trend of change, and finally it makes a significant contribution for decision makers in the realm of financial management After emerging extremely powerful techniques of information processing and overflowing customers' information, on the one hand and developing credit facilities market, as well as increasing rates of irreversible and outstanding claims, on the other hand, credit institutions decide to accredit their customers (Akkoç, 2012). Thus, data mining technique was considered by the institutions. Data mining refers to analyze massive amounts of data in order to explore meaningful and hidden rules and patterns within them (Witten and Frank, 2005). Classification is considered as one of the data mining techniques. Since, classifying customers into various categories is the purpose of ranking; it is categorized under the classification. Credit level model was introduced for the first time in the 1940s, it was decided to pay loans in 1979 using variable such as loan amount, age, gender, marital status, number of dependents, number of resident years, amount of monthly payment for the house, rental or ownership residential, other monthly earnings, the total payments for debts in a month, type of bank accounts, and amount of annual profit (Ang et al., 1979). Various techniques of data mining are used in accreditation of bank customers. They are classified using regression and classification tree technique on features of gender, age, marital status, education level, employment status, job status, annual income, and housing status. This research is used information of 80,000 customers in a Taiwanese bank for making and evaluating customers' accreditation model. Review of literature revealed that regression method had a better performance than techniques such as rules mining, SVM (He et al., 2014). Moreover, the use of neural networks in this area has been very successful. For example, this technique is used on inputs including loan amount, term of loan repayment, bank branch code, gender, marital status, age, monthly income, housing status (owned or rented house) to accredit the customers of an Egyptian bank. Conventional methods such as discriminant analysis, logit regression and analyze

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based on the minimum deviations from the average are also used that logit regression with 88% correct prediction had better performance than the other two methods; but it had a weak performance compared to the neural network since neural network with 96% accuracy had the best performance. One of the most important issues affecting the quality of classifiers results is the feature, which is used. Feature selection is one of the techniques of data preprocessing, which eliminates the duplicate and redundant features and improves the rate and accuracy of the classifier (Abdou et al., 2008). Neural network technique has been used to accredit bank customers and genetic algorithm along with statistical methods is used for feature selection. Results showed that genetic algorithm has produced better results than statistical methods. Taken together, this study seeks to provide a model based on neuro-fuzzy network classification. It is focused on feature selection to improve the performance. Due to the non-use of population optimization algorithms in this field, particle swarm algorithm has been used in addition to genetic algorithm in the field of feature selection. The proposed solution is applied on 1000 customers of a German bank and the performance of the mentioned optimization algorithms on the accuracy of network or classifier is compared and analyzed. Results show that particle swarm algorithm has done a more efficiently feature selection than genetic algorithm, and in classifier, neuro-fuzzy network technique has better performance than neural network. This article consists of four sections; the second part deals with concepts of ranking and neuro-fuzzy network. Section three introduces and implements the proposed method along with analyzing the results and comparing their performance; finally, section four is dedicated to conclusions (Oreski et al., 2012).

2. Research concepts

2.1. Accreditation

Banks are always looking to maximize their profits. Services such as accreditation and facilities payment and so on not only should not cause loss but also they should be profitable. For this purpose, the bank introduces a process called accreditation, which its goal is evaluation of loan applications' risk according to the previous information. Therefore, this study attempts to analyze the effects of various requests for facilities, features, errors and shortcomings by using statistical techniques (Lee et al., 2006).

2.2. Neuro-fuzzy network (ANFIS)

Adaptive network-based fuzzy inference system is one of the most widely used neuro-fuzzy networks. The technique was first presented in 1993 by Jang. This type of networks provides a powerful tool for analyzing complex processes by using neural network learning abilities and high adaptability of fuzzy systems. ANFIS designs fuzzy inference system by using input-output data sets, which its parameters are regulated by learning algorithms. Adaptive neuro-fuzzy inference system is a method that designs nonlinear mapping between input and output spaces by using a recursive multi-layered network and fuzzy logic and neural network learning algorithms. Fig. 1 shows the structure of a simple ANFIS network with two input variables (X, Y). The network is composed of five layers, which each input variable has two fuzzy subsets. As it can be seen in Fig. 1, A1 and A2 are subsets of X and B1 and B2 are subsets of Y.

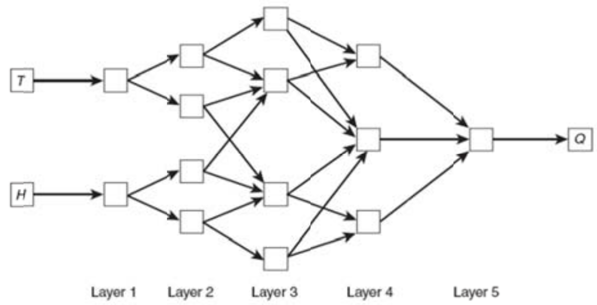

Fig. 1: Neuro-fuzzy network structure

The structure of this network includes directional arcs and nodes to establish communication between nodes. As the network's name suggests a part of or all of nodes have the ability to adopt, i.e. the output node is dependent on the parameters associated with the node. The way and rate of change in parameters is defined by learning rules in order to reduce the error (Jang, 1993).

3. The proposed method

As it is described, this study deals with ranking bank customers or classifying them, and seeks to provide efficient model using neuro-fuzzy network. It is focused on two major sections in order to improve the existing solutions. In ranking or generally classification, feature selection is considered as one of the most important stages. This research is used genetic optimization and particle swarm algorithms to select features. Another focus is on improvement of network ranking. This study is used optimization algorithms for selecting features and neuro-fuzzy network for ranking. So, it is tried to reduce the error rate. Then, the accuracy of implementing models made by neuro-fuzzy network and neural network is compared and results are shown in tables and diagrams.

3.1. Identifying data

Accreditation is done by using the proposed method on 1000 customers of a German bank. Each sample contains 24 variables from each customer. The response variable represents customers' credit in classes with good credit (700 customers) and bad credit (300 customers).

3.2. Data Preprocessing and feature selection

The raw data have usually problems such as noise, extreme changes, etc. And using them in this way will weaken the model. Data preprocessing includes all transformations that takes place on raw inputs and make them more effective for further processing such as using them in classification. There are various methods and tools such as data cleansing, data integration, data mapping and dimension reduction.

This study, first is cleansed the data, including detecting lost and missed data and eliminating them. Then, non-numeric data are coded into numerical values. Since, the abnormal data strongly effect on the neuro-fuzzy network performance. In the next stage, they were normalized and mapped at the interval of (1, -1). Another data preprocessing stages and techniques is feature selection, which it eliminates the extraneous and unrelated features and finds the smallest subset of features with the greatest influence. As it can be inferred by definition, feature selection is an optimization issue, which it seeks for an optimal subset of features. Optimality, which actually is discussed in the form of merit functions, on the one hand, is the short length of subset and on the other hand, is increasing the accuracy of response or classifier (Oreski et al., 2014). This research is accredit namely classified the customers based on their 24 features. It is obvious that some of these 24 features have greater impact on the output; and others have no specific and regularized impact on the output. Thus, it is better to select the features that have the greatest impact on the output. Many solutions have been proposed for feature selection, which this article has done it by using a binary version of particle swarm and genetic algorithms. In order to model the issue, features are marked by numbers 1 to 10; then, a binary array of 24 features is created. The presence of each feature is encoded with the number 1 and removal of each feature is encoded with the number 0. The object is determination of the best array; that is, finding the best combination of features. A population of 20 particles from binary random vectors (0 or 1) of features (in length of feature numbers namely 24) is created for particle swarm algorithm. Inertia coefficients is equal to 0.7298 and learning coefficients is regulated as c1=1.4 and c2=1.4. According to the performance of this algorithm, first, all particles are broadcast in the search space and each particle divulges its velocity on the basis of the best local and global position found in the search space and exposures to the next position. The cycle is repeated 60 times up to the algorithm converges to the optimal response. A population of 20 chromosomes from binary random vectors (0, 1) of features is produced by genetic algorithm to find the feature selection vector; then, next generations are created using genetic operators (mutation, acquisitions and direct select) and this process continues up to 60 generation. The results of these two algorithms are given in Fig. 2.

Regarding the Table 1 and Fig. 2, as it can be seen, particle swarm algorithm has fewer errors than genetic algorithm for feature selection and it has a better performance.

There is significant difference in the number of selected features between particle algorithm (21) and genetic algorithm (23). Taken together, particle swarm algorithm had better met the objectives, i.e. more accuracy and fewer numbers of features than the genetic algorithm.

Table 1: Performance of optimization algorithms in feature selection

Method	Training Error	Test Error	Total Error
Particle Swarm Algorithm	0.86	0.98	0.88
Genetic Algorithm	0.81	1.19	0.89

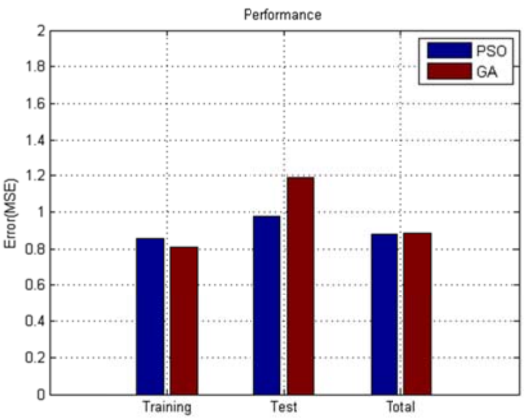

Fig. 2: Diagram of optimization algorithms in feature selection

3.3. Neuro-fuzzy network model

There are various methods for ranking bank customers; so that, the model have had the least errors. This means that the most accurate model of the data to be obtained. This article is used neuro-fuzzy network and neural network techniques and the results show that the neuro-fuzzy network has higher accuracy then neural network technique. Sugeno-type fuzzy inference system is used here, which it has 5 layers. The first hidden layer resembles the input variables relatively to the membership functions. Nodes of this layer are adaptive and the output from this layer is calculated according to the following formula (Eq. 1):

$$O_I^1 = M_{A_I}(x) \tag{1}$$

X is the input of i, Ai is the fuzzy subset related to the input variable of x. O_I^1 is the output of node i from the first layer, and $M_{A_I}(x)$ is the membership function relevant to the fuzzy subset of the input variable of x with the maximum value of 1 and the minimum value of 0. Fixed nodes in the second layer calculate the level of threshold for each rule by multiplying the input values and consider them as the output. Function of each node in this layer is finding the weight (W) for the fuzzy rules by using the membership functions. Achieving these values would be possible through the following formula (Eq. 2):

$$W_I = M_{A_I}(X) \times M_{B_I}(Y) \quad , i = 1,2,\ldots \tag{2}$$

The weights obtained from the second layer are normalized by the third layer nodes along with using the following formula (Eq. 3):

$$\overline{W}_I = \frac{W_I}{W_1 + W_2} \tag{3}$$

The node i in the fourth layer calculate the contribution of the rule i in the final output through the following node function. Wi is the output of the third layer, {pi, qi, ri} are a set of parameters, known as outcome parameters 1. This layer shows the results of the rule in the ANFIS model (Eq. 4).

$$O_I^4 = \overline{W}_I F_I = \overline{W}_I(P_I X + Q_I Y + R_I) \tag{4}$$

Only the node in the fifth layer obtains the final output through calculating the outcome of input signals and by using the following formula (Eq. 5):

$$O_I^4 = \text{overall output} = \sum_I \overline{W}_I F_I = \frac{\sum_I W_I F_I}{\sum_I W_I} \tag{5}$$

The neural network, which is used for ranking the customers, is a progressing network with two hidden layers; the first layer consists of five neurons and sigmoid transfer function and the second layer or the purpose layer includes one neuron and the linear transfer function. In the training stage, part of the data is given to the network. Then, network weights are adjusted by using network learning algorithm, so that the error between the predicted output and purpose be minimized. Now that the network is trained, a series of not-analyzed inputs are applied into the network in the form of test data for evaluating the correctness of training.

After implementing the program in MATLAB and setting relevant to the two models, their output performance are shown in Fig. 2 and 3; and also, the final results are presented in Table 2.

Table 2: Results of models performance

Results	Training error	Test error	Time of process
Neuro-fuzzy network	0.55	0.59	1.67
Neural network	0.68	0.67	5.76

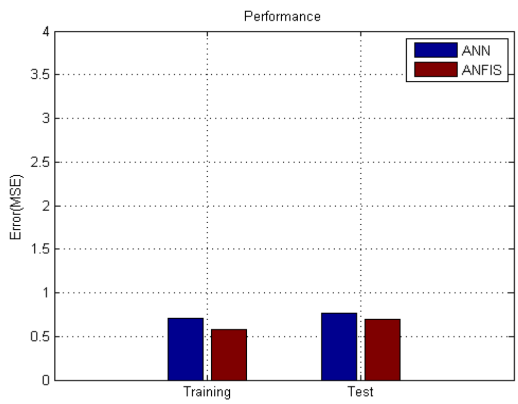

Fig. 3: Comparing the error of neuro-fuzzy network and neural network models

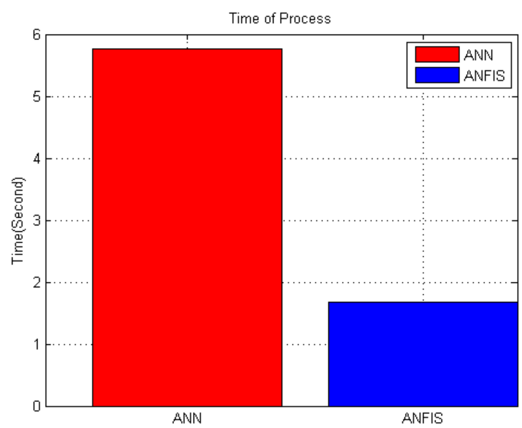

Fig. 4: Comparing the time of process in neuro-fuzzy network and neural network

As it can be seen in Table 2 and Figs. 3 and 4, neuro-fuzzy network model has a better performance than the neural network.

4. Results

This article is proposed a solution based on the neuro-fuzzy network for ranking the customers in a German bank (including 1,000 customers). The proposed solution is used particle swarm and genetic algorithm to select the features of bank's customers. Also, it is used the neuro-fuzzy network and neural network for ranking model. Results indicate that particle swarm algorithm is better for feature selection and the neuro-fuzzy network model provides better outcomes for ranking.

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