GA-based Normalization Approach in Back-propagation Neural Network for Bankruptcy Prediction Modeling

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The back-propagation neural network (BPN) has long been successfully applied in bankruptcy prediction problems. Despite its wide application, some major issues must be considered before its use, such as the network topology, learning parameters and normalization methods for the input and output vectors. Previous studies on bankruptcy prediction with BPN have shown that many researchers are interested in how to optimize the network topology and learning parameters to improve the prediction performance. In many cases, however, the benefits of data normalization are often overlooked. In this study, a genetic algorithm (GA)-based normalization transform, which is defined as a linearly weighted combination of several different normalization transforms, will be proposed. GA is used to extract the optimal weight for the generalization. From the results of an experiment, the proposed method was evaluated and compared with other methods to demonstrate the advantage of the proposed method.

Received : September 02, 2010 Revision : September 08, 2010 Accepted : September 19, 2010 Corresponding author : Kyung-shik Shin

1. Introduction

Neural networks have long been successfully applied in bankruptcy prediction problems. The BPN model, however, is the most popular neural network for bankruptcy predictions because it outperforms other models in prediction accuracy (Barniv et al., 1997; Chen and Du, 2009; Liu and Marukawa, 2004; Salchenberger et al., 1992; Swicegood and Clark, 2001; Tsai and Wu, 2008; Wilson and Shandra, 1994). Some major issues must be considered, however, before using the BPN algorithm: the network topology, learning parameters and data normalization methods for the input and output vectors.

Various data normalization methods have been applied to machine learning algorithms, such as min-max (A1 Shalabi and Shaaban, 2006; Doherty et al., 2004; Doherty et al., 2007; Jain et al., 2005; Kim, 1999; Kim et al., 2005; Olden and Jackson, 2002; Shanker et al., 1996), Z-score (Chia et al., 2009; Jain et al., 2005; Jolai and Ghanbari, 2010; Schaffer and Green, 1996; Shanker et al., 1996), mean (Wang and Zhang, 2009), median (Jain et al., 2005), range (Mazzatorta and Benfenati, 2002), decimal (A1 Shalabi and Shaaban, 2006; Berry and Linoff, 1997; Davis, 1991; Jain et al., 2005). Different normalization methods can bring about different results (Crone et al, 2006; Kim, 1999). Shanker et al. (1996) found in their study that Z-score normalization was dominant over min-max normalization. On the other hand, A1 Shalabi and Shaaban (2006), from the results of their study, suggested that in all experiments, the min-max normalization data set should always be given the highest priority. Jain et al. (2005) revealed from their study, however, that both min-max and Z-score normalization were sensitive to outliers, and the tangent normalization method was both robust and efficient. Wang and Zhang (2009) discovered from their study that the maximum value and mean methods are more reasonable than the Z-score and min-max methods. Through these previous researches, it can be found that there is no single normalization method that always dominate the others, and that it is important to select a specific normalization procedure according to the nature of the data sets (Visalakshi and Thagavel, 2009).

Thus, in this study, a GA-based normalization transform, which is defined as a linearly weighted combination of several different normalization transforms, is proposed. GA is used to extract the optimal weight for the combination. Of particular interest is how to optimize the normalization methods with GA and how the proposed method affects the performance of BPN for the prediction of the bankruptcy prediction.

2. Related Studies

In developing a bankruptcy prediction model with BPN, the preprocessing procedure plays a very important role. If the preprocessing method is well done, the performance of the model will be improved. Typically, the preprocessing of bankruptcy data includes noise elimination, variable selection, and data normalization. In this study, the effect of normalization on BPN for bankruptcy prediction will be discussed. To understand the proposed method, the related basic concept and individual technology will be briefly reviewed.

2.1 Data Normalization

Data preprocessing is beneficial in many ways, but it is often neglected in the data mining process. Data preprocessing consists of all the actions taken before the actual data analysis process starts. It is essentially a transformation T that transforms the raw real world data vectors to a set of new data vectors (Famili et al., 1997). Data preprocessing includes data cleansing, integration, transformation and reduction. Data cleansing can be used to remove data noise and correct data inconsistencies. Data integration merges data from multiple sources into a coherent data storage area, such as a data warehouse. Data transformation converts data from a source data format into destination data, for which normalization may be applied. Data reduction can reduce the data size by aggregating, and eliminating redundant features, or by clustering (Han and Kamber, 2001). In data transformation, the data are transformed or consolidated into forms appropriate for mining (Han, and Kamber, 2001). Data transformation can involve the following : smoothing, aggregation, generalization, normalization, and attribute construction.

In this paper emphasis will be given to normalization. Normalization is a “scaling down” transformation of features. Within a feature, there is often a marked difference between the maximum and minimum values, as, e.g., 0.01 and 1,000. When normalization is performed the value magnitudes are scaled to appreciably low values (Kotsiantis et al., 2006). Normalization is particularly useful for classification algorithms that involve neural networks (Akdemir and Yu, 2009; Kim, 1999; Mazzatorta and Benfenati, 2002; Shanker et al., 1996), or for distance measurements such as nearest neighbor classification and clustering (de Souto et al., 2008; Doherty et al., 2004; Doherty, 2007; Visalakshi and Thagavel, 2009; Wang and Zhang, 2009). Previous studies on normalization with machine learning algorithms revealed that in most of the studies, normalization improved the performance of the machine learning algorithms (Doherty et al., 2004; Jolai and Ghanbari, 2010; Kim et al., 2005), and there was no single normalization method that always dominate the others (A1 Shalabi and Shaaban, 2006; de Souto et al., 2008; Jain et al., 2005; Shanker et al., 1996; Wang and Zhang, 2009). Thus, it is very important to select specific normalization procedures according to the domain.

2.2 Back-propagation Neural Network

Neural networks, which constitute an area of machine learning, are mathematical models of brain activity. In the area of bankruptcy prediction, neural networks have been used in place of the statistical method for a long time because neural networks need no priori assumption of models and can infer underlying complex, and non linear relationships.

The network model trained by BPN is particularly the most popular tool used for bankruptcy prediction problems because its prediction accuracy outperforms other models. BPN has long been one of the most efficient learning procedures for multi-layer networks. The learning method for BPN is supervised learning. Within the BPN, the layers are connected by weights. The connection weights between the neurons are the links between the inputs and the outputs, and therefore, are the links between the problem and solution. BPN's activation function has two parts. The first part is the combination function that merges all the inputs into a single value. The most common combination function is the weighted sum. The second part of the activation function is the transfer function, which transfers the value of the combination function to the output of the units. Three typical transfer functions for BPN are sigmoid, linear, and hyperbolic tangent. Among these, the sigmoid and hyperbolic tangents are the most widely used functions and they result nonlinear behavior. Their major difference is in the ranges of their outputs, which are [0, 1] for the sigmoid functions and [-1, 1] for the hyperbolic tangent functions (Berry and Linoff, 1997).

Previous studies on BPN for bankruptcy prediction revealed that to prove that BPN is an effective method of bankruptcy prediction problems, most researchers compared BPN with other learning methods such as logistic regression, liner discriminant analysis, multiple discriminant analysis, k-nearest neighbor, decision trees (Barniv et al., 1997; Chen and Du, 2009; Fletcher and Goss, 1993; Javanmard and Saleh 2009; Sharda and Wilson, 1993; Tsukuda and Baba, 1994; Wilson and Shandra, 1994; Yim and Mitchell, 2002). To improve the performance of BPN, most researchers are interested in optimizing the network architecture and learning parameters (Khashman, 2010; Leshno, 1996, Moody and Utans, 1995; Rahimian et al., 1993; Sen et al., 2004; Surkan and Singleton, 1990; Utans and Moody, 1994), and the effects of the normalization on the performance of network are almost neglected.

2.3 Genetic Algorithms

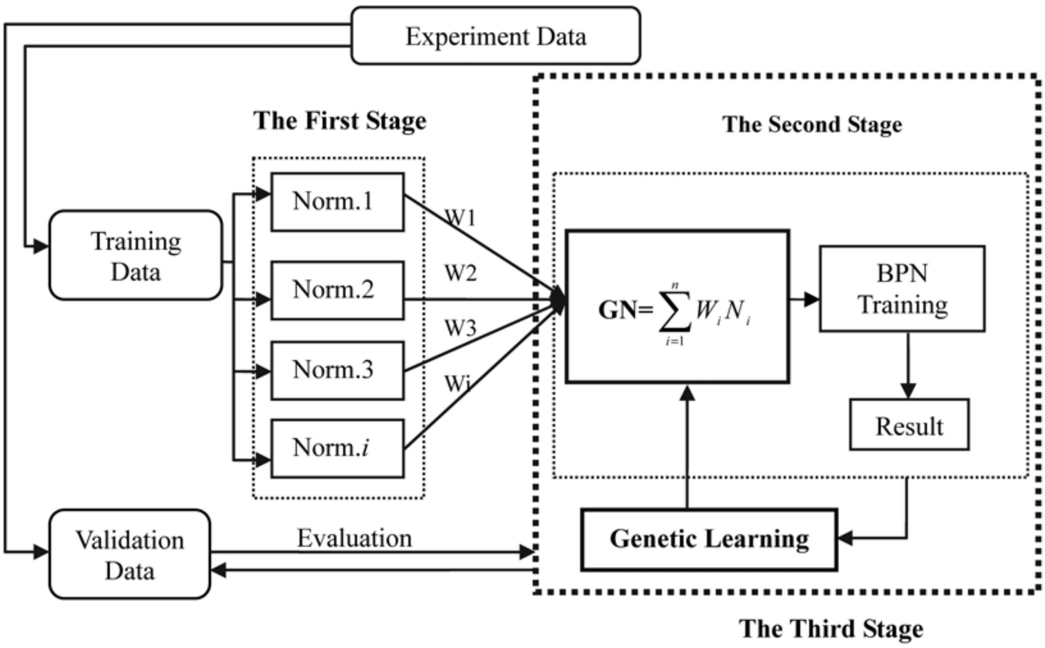
GA is an adaptive search procedure that can search for large and complicated spaces, given certain conditions on the problem domain. GA tend to converge on solutions that are globally nearly so (Deboeck, 1994). GA performs the search process in four stages: initialization, selection, crossover, and mutation (Davis, 1991).

In the initialization stage, a population of genetic structures (called chromosomes) are randomly distributed in the solution space is selected as the starting point of the search. The selection is similar to natural selection, wherein only the fittest individuals in the population survive to pass their genetic material to the next generation. Selection methods can have an important influence on the evolutionary process. The purpose of selection is to choose appropriate individuals from the current generation to create offspring and to propagate the fitter individuals (Mitchel, 1996). The next operator that is applied to the surviving genomes is the crossover. The purpose of the crossover is to split the parent chromosomes and exchange the corresponding components to create offspring, with the expectation that the recombination of genes may introduce new features to the individuals. Mutation rarely occurs in nature and is the result of the passing of a miscoded genetic material from a parent to a child. The resulting change in the gene may represent a significant improvement in the fitness of the existing population (Berry and Linoff, 1997).

GA is particularly suitable for multi-parameter optimization problems with an objective function that is subject to numerous hard and soft constraints. They can also be used as data mining and knowledge discovery to discover previously unknown patterns. Many researchers are becoming interested in bankruptcy prediction problems with GA to optimize the model performance (Jiang et al., 2007; Kim and Han, 2000; Kim and Han 2003; Min et al., 2006; Shin and Han, 1996; Shin and Lee, 2002; Wu et al., 2007).

3. Experiment Design

Each normalization method has its own strengths and weaknesses, and no single normalization method always dominates the others in all domains and algorithms. Thus, it is difficult to determine the optimal normalization method for the input data. Therefore, in this study, a GA-based normalization transform, which is a linearly weighted combination of several different normalization transforms, is proposed. A set of parameters, that include weighting coefficients are determined. To determine the optimal set of parameters in the entire solution space, GA is employed. The proposed GA-based normalization is shown in <Figure 1>.



<Figure 1> A GA based Normalization Approach for BPN

The proposed approach is divided into three main stages: Normalization, Generalized normalization (GN) for BPN, and GA based normalization.

3.1 Normalization Stage

In the normalization stage, each input normalization method is determined. In this study, four types of data normalization methods were used.

Min-max normalization :

$$Norm.1 = \frac{(Vi - \min)}{(\max - \min)} \tag{1}$$

Mean valued normalization :

$$Norm.2 = \frac{(Vi)}{mean} \tag{2}$$

Median normalization :

$$Norm.3 = \frac{Vi}{median} \tag{3}$$

Z-score normalization :

$$Norm.4 = \frac{(Vi - mean)}{\delta} \tag{4}$$

Where in δ is the Standard Deviation.

Excluding the min-max normalization, the input value normalized with the mean, median, and z-score did not fall into [0, 1] rage, so in this study logistic function transformed normalized value was applied to the value of [0, 1].

3.2 Generalized Normalization for BPN

Each normalized input value differs from others according to the normalization method used. To generalize those individually normalized input values, a linearly weighted combination of four normalization transform GN is proposed. In this stage the same weight was assigned to each normalization method, after which it was used to train the BPN.

$$\begin{aligned} \mathrm{GN} = {} & \mathrm{W1} \times \mathrm{N.1} + \mathrm{W2} \times \mathrm{N.2} + \mathrm{W3} \times \mathrm{N.3} \\ & + \mathrm{W4} \times \mathrm{N.4} = \sum_{i=1}^{4} W_i N_i \end{aligned} \tag{5}$$

Here, w1, w2, w3, and w4, are real numbers within the range [0, 1], with w1+w2+w3+w4=1.

To train the BPN with generally normalized input data, PASW Statistics 18.00's Multi-layer Perceptrons were used. Here, the network architecture and learning parameters were determined as follows: for the network architecture, one hidden layer, four hidden units were set, and the sigmoid functions were applied to the hidden units and output's activation functions. For the network training, the batch learning method and 0.3 were used for the initial learning rate, 0.7 for the momentum, and 0.5 for the interval center. To assign an optimal or nearly optimal weight to each normalization method used, the BPN model was represented on Microsoft Excel 2010 sheet.

3.3 GA-based Normalization

In the third stage, GA was used to determine the optimal weight for each normalization method. The weight was then used to transform the input data into the corresponding normalized input value. When GA is applied, the task of defining a fitness function is always application specific. In this study, the objective of the system was to improve the performance of BPN. Thus in this study, the classification rate of the validation set was applied to the fitness function. Mathematically, the fitness function is expressed as :

$$MaximizeHit = \frac{1}{n}\sum_{i=1}^{n} VA_i \tag{6}$$

Wherein is the classification accuracy of the case of the validation set denoted by 1 and 0 ('correct' = 1, 'incorrect' = 0). The parameters i.e., the population size, crossover rate, mutation rate, and stopping condition had to be defined first in the development of the GA-based system. There has been a debate regarding the optimal controlling parameters that should be specified for experimentation. For this study, 500 organizations in the population were used, 0.5 in the crossover rate, and 0.06 in the mutation rate. For the stopping condition, 4,000 trials was used.

4. Experiment and Results

4.1 Research Data and Experiment

The research data consisted of 106 financial ratios of Korean non-audit construction companies. The total sample available included 2020 companies whose commercial papers have been rated during 2003 to 2008. The bankruptcy conditions were defined as outputs and classified as two groups (bankruptcy = 1, healthy = 0) according to the financial status. The data set was arbitrarily split in to three subsets: about 60 percent of the data was used for a training set, 20 percent for a test set and the remain 20 percent for a validation set. The training and test data were used to construct model and the validation data was used to test the validation of the model .

We applied two stage of input variable selection process. At the first stage, we selected 24 variables by 1-way ANOVA. In the second stage, we selected 9 variables using a MDA stepwise method to reduce dimensionality. The aim of input variable se-

<Table1> Definition of Variables

Variables	Definitions	Data Type
X1	Net income before taxes to total assets	Numeric
X2	Net income to sales	Numeric
X3	Retained earning vs. total assets	Numeric
X4	Operating profit of managerial capital	Numeric
X5	Interest expenses to sales	Numeric
X6	Net interest expenses to sales	Numeric
X7	Taxes and dues	Numeric
X8	GrossValue added to total assets or productivity of capital	Numeric
X9	Operating flow vs. total liabilities	Numeric

lection approach is to select the input variables satisfying the univariate test first, and then select significant variables by stepwise method for refinement. The selected variables for this study are shown in <Table 1>.

4.2 Results and Analysis

As mentioned previously, the proposed model has three steps. In the first normalization stage, data were normalized with four different normalization methods (min-max, mean, median, and Z-score). To investigate the effectiveness of GA based normalization, individually normalized data were applied to the BPN. In the second stage, four individually normalized input values were combined with equally assigned weights. These data were also applied to the BPN. In the third stage, GA was applied to search for the optimal weight for each normalization method, then GA based normalization was used to transform the input data into the corresponding normalized input values. <Table 2> shows the effect of different normalization methods on the BPN performance.

<Table 2> Performance of BPN with Differently Normalized Data Sets

Data Sets	Min-max	Mean	Median	Z-score	GAopt
Training & Test	71.03%	69.33%	70.77%	69.64%	72.89%
Validation	68.81%	70.54%	71.29%	66.09%	75.00%

* GAopt = GA-based Normalization.

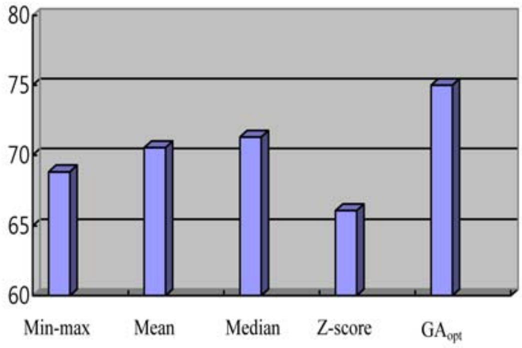
The McNemar test was used to examine whether or not the predictive performance of the proposed approach was significantly better than that of the other methods. Since this study is interested in the impact of normalization methods on the performance of BPN, the test measure for testing was the classification accuracy rate (the number of correct classification from the number of whole validation samples). <Table 3> shows the results of the McNemar

<Table 3> Mcnemar Value for Comparison of Performance between the Normalization Methods

Significant level

	Min-max	Mean	Median	Z-Score	GAopt
Min-max	-	0.483	0.261	0.100*	0.002***
Mean	-	-	0.799	0.039**	0.016**
Median	-	-	-	0.008***	0.037**
Z-Score	-	-	-	-	0.000***
GAopt	-	-	-	-	-

***Significant at 1%, **Significant at 5%, *Significant at 10%



<Figure 2> Classification Accuracy of the Validation Set

test. The results indicate that BPN using input data normalized via the GA approach has significantly higher classification accuracy than other methods..

5. Conclusions

In this study, a GA based normalization approach was proposed. GA was used to find the optimal or nearly optimal weight for the combination. The preliminary results showed that the proposed method significantly increased the BPN performance, which means it is a stable method for BPN in bankruptcy prediction problem. The results of this study also showed that the genetic algorithm is an effective method of knowledge extraction, since nearly optimal or optimal weight can be obtained using GA.

This study had the following limitations that point to the need for further research. The first limitation is that the data used in our study came from a non-audit construction company. In future studies, we need to apply the proposed method to external audit industry companies to examine the method's validity and reliability. The second, limitation is that in setting up the GA optimization problem, several parameters such as the stopping conditions, population size, crossover rate, and mutation rate must be selected. The third, limitation is only four normalization methods (min-max, mean, median, Z-score) were used, even though other normalization methods also have considerable.

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Abstract

유전자알고리즘을 기반으로 하는 정규화 기법에 관한 연구 : 역전파 알고리즘을 이용한 부도예측 모형을 중심으로

태추월* · 신경식**

역전파 알고리즘은 오랫동안 부도예측모형 관련한 연구에 많이 적용되어왔다. 역전파 알고리즘을 사용하기전에 필히 고려해야 할 중요한 요소들로는 네트워크 구조, 학습요소, 정규화 방법 등이다. 하지만 신경망 성과를 향상시키기 위한 네트워크 구조 및 학습요소 최적화 관련한 연구는 기존의 연구들에서 많이 이루어 졌지만 데이터 정규화와 관련한 연구는 아직 많이 이루어지지 않았다. 따라서 본 연구에서는 유전자 알고리즘을 기반으로 하는 정규화 기법을 제시하였다. 최적의 입력데이터 정규화를 위하여 본 연구에서는 우선 각각의 서로 다른 정규화 기법들을 동일 가중치를 두어 일반화 시켰으며 유전자 알고리즘을 이용하여 최적의 가중치를 찾음으로써 최적화된 입력변수 정규화가 이루어지도록 하였다. 제안한 방법론을 검증하기 위하여 부도예측 데이터를 이용하여 실험을 하였으며 제안하는 방법과 기존 다른 방법들간의 비교를 통하여 그 타당성을 검증하였다..

Key words : 정규화 기법, 역전파 알고리즘, 유전자알고리즘, 부도예측모형

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중국 하얼빈조선족사범대학 영어학과를 졸업한 후 중국 연변과학기술대학교에서 근무하였다. 이화여자대학교 경영대학에서 석사학위를 취득하였고, 현재 경영학과 박사과정 재학 중이다. 주요 연구분야는 지능형 의사결정지원 시스템, 인공지능과 데이터 마이닝, 지식기반 시스템 등이다.

신경식

신경식 교수는 이화여자대학교 경영대학 부교수 겸 지식시스템 연구센터장으로 재직 중이다. 연세대학교에서 경영학사, George Washington University 에서 MBA, 한국과학기술원에서 경영정보학으로 박사학위를 취득하였다. 주요 연구분야는 지능형 의사결정지원시스템, 인공지능과 데이터 마이닝, 지식기반 시스템 등이며 이와 관련한 다수의 연구논문 및 산학연구를 수행하였다. 최근에는 가상화에 따른 인간, 조직 및 사회 변화연구, 사회관계망 분석 등에 관련된 연구를 수행하고 있다.