불량 데이타를 포함한 신경망 신용 평가 시스템의 개발

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요 약

지금껏 발표된 많은 연구 결과에 의하면 신경망 시스템의 일반화 정도(정확도)는 통계적 모델과의 비교 평가에서 그 일반화 정도가 그들과 버금가거나 우수하다는 평가를 받고 있다. 그러나, 이러한 신경망 시스템의 우수한 예측 결과는 불량 데이타(noisy data) 가 거의 없는 건전한 데이타, 혹은 일정량의 불량 데이타를 제어할 수 있을 만큼의 충분한 양의 데이타로 신경망을 학습시켰을 경우에만 얻을 수가 있었다. 실제 문제 -특히, 경제, 경영상의 문제- 를 풀기 위하여 모아진 실 데이타는 신경망 시스템이 만족할 만한 예측 결과를 보일 수 있을 정도의 건전한 데이타가 못되는 것이 현실이다. 따라서, 본 연구에서는 일정량의 불량 데이타를 포함하고 있는 훈련 데이타를 통해 신경망을 훈련시킬 경우 신경망 시스템의 일반화 정도를 높일 수 있는 방법에 대하여 논하였다. 본 연구의 관찰된 실험 결과에 의하면 신경망 시스템의 일반화 정도를 높이기 위해 훈련 데이타에서 같은 입력값을 갖는데도 불구하고 서로 상반되는 출력값을 갖는 불량 데이타들을 골라내어 신경망 시스템을 훈련시키는 방법을 제안하였다. 아울러, 두개의 서로 상반된 결과값을 갖는 불량 데이타로 신경망을 훈련 시켰을 경우 두 결과값의 평균값에 의해 신경망의 가중치(weight) 조정이 된다는 이전의 연구 결과[25]도 입증되었다. 또한, 본고에서는 현재 진행중에 있는 신경망을 이용한 신용 평가 시스템 개발에 관한 중간 결과도 기술되어 있다.

Developing a Neural-Based Credit Evaluation System with Noisy Data

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ABSTRACT

Many research results conducted by neural network researchers claimed that the degree of generalization of the neural network system is higher or at least equal to that of statistical methods. However, those successful results could be brought only if the neural network was trained by appropriately sound data, having a little of noisy data and being large enough to control noisy data. Real data used in a lot of fields, especially business fields, were not so sound that the network have frequently failed to obtain satisfactory prediction accuracy, the degree of generalization. Enhancing the degree of generalization with noisy data is discussed in this study. The suggestion, which was obtained through a series of experiments, to enhance the degree of generalization is to remove inconsistent data by checking overlapping and inconsistencies. Furthermore, the previous conclusion by other reports is also confirmed that the learning mechanism of neural network takes average value of two inconsistent data included in training set[2]. The interim results of on-going research project are reported in this paper. These are an architecture of the neural network adopted in this project and the whole idea of

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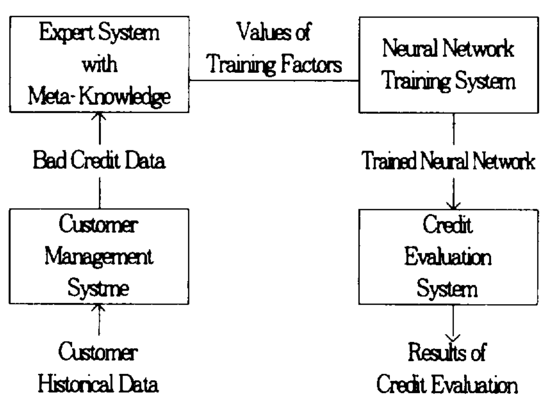
developing on-line credit evaluation system, being integration of the expert(reasoning) system and the neural network(learning) system. Another definite result is corroborated through this study that quickprop, being adopted as a learning algorithm, also has more speedy learning process than does back propagation even in very noisy environment.

1. Introduction

Credit evaluation is one of the most important and difficult tasks usually assigned to experienced officers in credit card companies, mortgage companies, banks, consumer goods companies and other financial institutes.

Traditionally, credit scoring has been the most widely used method in which applicant's credit is evaluated by picking up appropriate score corresponding to categories of evaluation value, then by summing up into total credit for thresholding. Recently, various methods have been introduced to replace the credit scoring system and to provide more objective and convenient tools : statistical method [1, 2, 3, 4, 8, 18, 20], Induction trees(ID3, C3) [5], expert system approach [6, 7, 14, 17, 19, 22] and the neural network researchers have shown that the prediction accuracies of the neural network system, that is, the degrees of generalization, are better than or at least equal to those of the statistical methods [15, 21, 24]. Therefore, many researchers have devoted their research efforts to enhance the degree of generalization to achieve higher level of prediction accuracy. In determining the degree of generalization, involved are many internal and external factors : the network architecture(number of hidden nodes, input nodes, hidden layers, initial weights, learning rate, momentum, etc.), training algorithm (back propagation, self-organization map, quickprop algorithm, activation function, etc.) and composition of training data set and test data set. Researchers experimented with various architectures by modifying factor values and learning agorithm.

There are some experimental reports on the relationship between training data set and the degree of generalization, with recommendation of the ways to achieve higher generalization capability. Whitley and Karunanithi [29] proposed a partitional learning strategy in which the training space is divided into a set of subspace according to the data characteristics and then each subspace is trained using a separate network. In the data selection step, emphasized is decision boundaries and the central tendencies of decision regions. In the test of 'two-spiral' problems [9], they found the performance of partitioned learning strategy.



(Fig. 1) On-Line Credit Evaluation System

Wann, Heidger and Greenbaun [28] recommended the partitioned learning strategy, particularly based on border patterns which constitutes a critical training set for perfect generalization. The space yet belongs to different classes. In training 'two spiral patterns' [9], they achieved almost 100 percent correctness ratio, using the border patterns. Fu and Chen [10] investigated the sensitivity of input vectors on generalization capability, and found that the norm of Jacobian matrix measures the sensitivity of the network performance with respect to its vector and that good generalization must imply insensitivity to changes in the input vectors.

Literature reviews on the generalization capability of the neural network show that almost 100 percent correct answers can be easily obtained, when an efficient neural network architecture with a smart algorithm is employed for training data. However, in the tests on a set of noisy data obtained from a fashion company, it was found that the degree of generalization strongly depends on the characteristics of data set used for training, also on the characteristics of test data set, and therefore a perfect correctness (100%) may not be achieved in noisy data set.

In this paper, interim results of on-going research projects are reported. The Research design and the neural network architecture are described in the following section and the performance results of back propagation algorithm and quickprop algorithm are comparatively analyzed in this section. The research project we are working on is also described in section two to introduce whole idea of developing on-line credit evaluation system through integration of the expert (reasoning) systems and the neural network (learning) systems. In section three, experiment results focused on relationship between inconsistent data and degree of generalization. Section four is reserved for final conclusion and future research.

2. Developing On-Line Credit Evaluation

2.1 An Integrated On-Line Credit Evaluation System

This research was initiated to develop an integrated on-line credit evaluation system which would monitor system performance and enhance prediction accuracy through constantly feedbacking customer's credit data. Especially the neural network mechanism was adopted as a credit evaluating processor in this research. Since the neural network could predict the output values by inlinear mapping through the hidden layer, even though it didn't know the direct relations between the input values and the output values. An expert subsystem with meta-knowledge determines appropriate training factor value : composition of training data set, momentum value, learning rate, number of hidden nodes, and so on. As shown in Figure -1. the integrated on-line system consists of four parts : a customer's credit management, an expert system with meta-knowledge, a neural network training system, and a credit evaluation system. The customer management system receives customer's data from a host computer, scans them to elicit a set of customer data which are evaluated as 'bad customer'. Those bad customers will be sent to meta-knowledge subsystem for analysis and for determining training factor in the neural network training system : appropriate composition of training data, momentum value, learning rate, number of hidden nodes.

The expert system with meta-knowledge possesses a comprehensive knowledge of, in addition to the relationship between neural net's behaviour and characteristics of data the set, the ways to enhance the degree of generalization in credit evaluation neural systems. Based on the knowledge, the expert subsystem with meta-knowledge determines values of trainig factors such as learning rate, momentum, activation function, composition of tarining data set, etc. The neural network training system retrieves training factor values and training data set, and then conducts back propagation training. When the neural network training subsystem finishes its training process, it will pass its determined network to customer's credit evaluation system to make decision whether the applicant should have credit or not.

In developing the on-line system, the most important function the integrated system performs is to understand learning mechanism of neural network system and to determine appropriate values of learning factors which affect convergence speed and the degree of generalization. As the literature review on generalization issue has shown, most research concentrated on the relationship between generalization capability and number of hidden nodes and frequently on convergence speed and neural network architecture such as learning rate, momentum, the number of hidden layer and nodes and learning rate, momentum, the number of hidden layer and nodes and learning algorithm.

A very few research addressed the issue of characteristics of data set and generalization capability. After a number of experiments, the conclusion was reached that characteristics of training data set play very important role in enhancing the degree of generalization. It might be also true that selection of test data set palys importatnt role in determining prediction accuracy.

2.2 Automated Credit Evaluation

With the rapid increase of sales volume and credit market in Korea, many business companies have not imposed any restriction on credit card applicants. This is because, different from American companies with hundreds of years of experiences in financial market, Korean Companies pursue the goal of market penetration and market expansion through granting credit cards to any applicant without any scanning effort.

Esquire LTD. is one of the leading companies in the Korea fashion business. A credit card system of this company is adopted to achieve 'Big Share' in fashion market. Recently, the number of card holders of this company has reached 180,000 and every month the number of overdue or delinquent credits reached 3,500 cases. Such delinquent customers inflict a serious loss to the company and thus the company had to devise a measure to solve the financial problem caused by continuously accumulated bad debts. One of the ideas popped up was to develop an automated credit evaluation system which continuously monitors evaluation system's performance and then can enhance the prediction accuracy through learning from customer's credit data. The automated credit evaluation system will benefit various professional service industries (gas stations, department stores, restaurants, entertainment places, sport comaplexes, ski resorts), household appliances compnies (refregirators, washers and cleaners, room cleaners, air conditioning system, audio distributors), automobile sales compnies, etc.

When the research project initiated and data set was collected, it was recognized that the data set includes too much noise. In the initial stage of the research, collected data were about 2,000 records kept in the customer department of the company from July to August in 1993. Even though the number of collected data was believed to be large enough to train the back propagation network, we found that collected the data form the applicant form did not include all the factors from that are believed to be important in determining customer's creditability. For the reason, the collected data were filtered and only 160 data were selected for training. Another data set of 40 customer records was reserved for testing generalization capability.

2.3 Architecture and Algorithm of Neural Network Training System

The neural network training system, as usual of the back propagation systems, consists of three layers : input layer, hidden layer and output layer. From the customer's records, the eight variables which were believed to have a strong relationship with customer's credit were derived as 'credit factors' : age, sex, marital status, occupation, organization, job position, residential condition, residential area. Selection of input variables for the system's training, that is, selection of critical factors siginificantly influencing on customer's creditability should be determined by consideration of customer's behaviour, social custom, and statisitics. In this sense, the factors included in the current system reflect many features of Korean customers and social practices, and thus factors included in the current system might be much different from factors included in the system developed in other countries. For example, in the study of American loan application, occupation, length of employment, marital status, race and income level are important considerations[4], but work place dose not have a significant impact on credit evaluation. In contrast, work place might be the most important factor in determining an individual's credit status. Also, residential area might be very important factor, which was proved to be unimportant at all.

According to the number of overdue payment, 'credit status' was devided into two plstatus such as 'good' and 'bad'. When the customer's payment is not overdue or the number of overdue payment is less than 3 months, he or she was classified into 'good' credit status. When the number of overdue payment exceeded 3 months, the customer was classified into 'bad' credit status.

(Table 1) Comparison between back propagation and quickprop

Data Set	Back propagation		Quickprop	
	# of Epoch	Degree of generalization	# of Epoch	Degree of generalization
20 / 20	22,644	19/40(47.5%)	28	23/40(42.5%)
30 / 30	42,212	22/40(55%)	49	24/40(60%)
40 / 40	238,802	26/40(65%)	168	24/40(60%)
50 / 50			267	27/40(67.5%)
60 / 60			338	23/40(57.5%)
70 / 70			467	23/40(57.5%)
80 / 80			488	28/40(70%)

2.4 The Quickprop Algorithm

In the initial stage of this research, back propagation algorithm was employed and tested for training sample data. Many experiments with the back propagation algorithm showed that the system with more than 40 training data would not have convergence state within a reasonable time and thus another efficient algorithm should be devised. Later, employed was the quickprop algorithm, an advanced form of back propagation, as a learning mechanism. 'Quickprop' algorithm suggested by Fahlman [9] is important and well-known for speeding up convergence by jumping out directly the parabolic error space to the minimum point of the parabola. In this algorithm, the error derivated defined as $\partial E/\partial\omega(t-1)$ is kept and then, for each weight, the weight change measured by the difference between current weight slope and previous weight slope is used for determinig a parabola.

$$\Delta\omega(t) = \frac{s(t)}{s(t-1)-s(t)}\,\Delta\omega(t-1)$$

where $s(t)$ and $s(t-1)$ are the current and previous values of $\partial E/\partial\omega(t)$

Using the update formula, if the current slope is somewhat smaller than the previous one but in the same direction, the weight will change in the same direction. The step may be large or small, depending on how much the slope was reduced by the previous step. If the current slope is in the opposite direction from the previous one, that means that the system crossed over the minimum point and that the system is on the opposite side of valley.

As predicted and assured by researchers [9], the quickprop algorithm effectively and quickly reduced total error, and thereby enabled the system to reach convergence in a reasonable time limit. As shown in⟨Table-1⟩, ordinary back propagation algorithm required more than 230,000 epochs to reach convergence state in which the degree of generalization was 65%. In contrast, the quickprop algorithm needed only 160 epochs to reach the convergence state in which the degree of generalization was measured around 60%, a slightly lower value that of ordinary back propagation algorithm. When the number of training data set increased to 100(50 bad creditors and another 50 good creditors), the back propagation system did not stop running. That was why the research, in back propagation learning system, could not extend testing the generalization capability beyond 80 cases. To the contrary, the quickprop algorithm with 100 training data easily reached the convergence state at the epoch of 267 and showed a little enhanced prediction capability, 67%.

3. Experiments with Noisy Data

3.1 System Implementation

Quickprop algorithm in this study was implemented in 'C', running on 486 PC with the operating system of LINUX, a PC-level UNIX. The initial values of learning rate and momentum were set by 0.5 and 0.9, respectively. The original program used in the experiments is that Scott Fahlman's quickprop program translated from Common Lisp into C by Terry Regier at the University of California, Berkeley.

3.2 Noisy Data

While working on learning system with customers's data, we found that the data is too much noisy, that is, we could not find any meaningful statistics on customer behaviour. Many examples of unexpected associations between input values and output values were identified. For example, customers with longer job experiece, eventually leading to more income and higher position, than fresh college graduates with only one or two years of work experience were expected to be in good credit standing. However, reality is not so straightforward. Many of the credit cases show that income level and business position do not go along with credit standing, which was unexpected result. The Customers with low income, frequently and unexpectedly, showed good standing in credit transactions, but not all of them. A careful investigation revealed that work place(organization) is more accurate predictor than work experience and job position. In addition to these confusing statisitcs, a few inconsistent cases were found, that is, multiple cases with the same input values (occupation, work experience, job position, age, marital status, residential location, etc) showed different output values

〈Table 2〉 Test Results of Inconsistent Data

ND Noisy Data
Phase-1 training data set without any noisy data
Phase-2 training data set including an inconsistent data as 'bad'
Phase-3 training data set including an inconsistent data as 'good'

	60 / 60				80 / 80							
Phase-1	ND 1	good	ND 2	bad	ND 1	good	ND 2	bad	ND 3	inde-cisive	ND 4	inde-cisive
Phase-2	ND 1	good	ND 2	good	ND 1	good	ND 2	good	ND 3	good	ND 4	good
Phase-3	ND 1	bad	ND 2	bad	ND 1	bad	ND 2	bad	ND 3	bad	ND 4	bad

(e.g. bad credit for one case, and good credit for the other case).

3.3 Experiment of Clustering Algorighm

In a series of the experiments conducted on back propagarion and quickprop algorithm, found was that any reasonable performance level, say 70-80 percent prediction accuracy, cannot be expected. To identify reasonable associations between input values (customer variables) and credit standing, a clustering algorithm was employed for testing existence of any meaningful relationship. In the implementation of GLVQ algorithm of Hathaway and Bezdek[11] on the same training data set, Kang[13] found that some of training data whose output values were 'good' credit standing fell into a clustering boundary, while most of the other training data whose output values were 'bad' credit were scattered around and therefore indicated no direct relations between input values and output values. His conclusion was that no meaningful relationship was found between input values and output values in the cases of 'bad credit customers'. Even though the results of clustering experiments were disappointing, it indicated that a reasonable explanation could be found between input values and output values of 'good credit customers'.

3.4 Handling Inconsistent Data

When the number of training data was increased to achieve higher degree of generalization (prediction accuracy), a serious problem was oberved, the system showed endless oscillation in error space and thus convergence itself was doubtful besides measuring the performance level. In addition, whenever the size of training data became larger than 120, the error curve began to erratically fluctuate. A careful investigation of data set in the experiment showed that the inconsistent data happened to be included in the training set and might be mainly responsible for the oscillation. Accordingly, inconsistent data were removed from the training set and the system easily settled down into convergence and showed 67% prediction accuracy, degree of generalization, on untrained data. Then, a couple of experiments on the inconsistent data set were conducted and analyzed.

On 120 training data and 160 training data were conducted three different experiments. In the phase-1, two pairs of inconsistent data(the same input values but the opposite output values) were removed from the training data set, but included in the test data set. As shown in Table-2, the system showed very interesting responese. In the case of 120 training data set, the system showed 'good' evaluation for one pair and 'bad' evaluation for the other pair, which indicated that the system set up its territory borderline at the middle of both sides, and thus a slight sloping in the input values pushes its conclusion to extreme point. In the case of 160 training data set, the system predicted one 'good' credit, one 'bad', and two 'neutral' credit in response to four pairs of inconsistent input data. In the phase-2, only one data of the inconsistent data pair was included in the training data set, indicating 'good credit' as output value When the same input data in the pair was included in the test data set, the response was slanted into 'good credit' in case of 120 training data set and 160 training data set. In contrast, when only one data in the inconsistent data pair was included in the training data set as 'bad credit', the system response to the same input values was 'bad credit'.

As a conclusion, the result was that trained network strongly reflects data values included in training. When inconsistent data was trained as 'good', the system predicted a new case as 'good', while the system's output was 'bad', when the systen was trained with inconsistent data as 'bad'. When inconsistent data were removed from the training data, the system's output was settled down into the average value of two extreme values. A simple conclusion which has been already observed by researchers [25], based on the experiment results, was that "given two 'right' outputs for same input, the network has learned to produce an output that is the average of the two." [p.114]

3.5 Enhancing Degree of Generalization with Inconsistent Data

As discussed in previous sections, inconsistent data can cause a critical problem by fitting its learning weight to average value of two extreme values and thus by blocking convergence. In terms of the degree of generalization, the inconsistent data tend to bias mapping curve into the direction where the inconsistent data leads. The test results show that generalization capability in Phase-1 with removal of inconsistent data is a little higher than results of Phase-2 and Phase-3. Based on these findings, our recommendation is that the better way to achieve a reasonable degree of generalization is to remove inconsistent data by checking overlapping and inconsistencies.

4. Conclusion and Future Research

In this research, conducted were a series of experiments on couples of inconsistent data included in noisy data set. The experimental results did not bring in any new theory, but only confirmed a simple conclusion that the learning mechanim of neural network takes average value of two inconsistent data included in the training set[25]. However, we believe that the current experimental result might be of a significant importance to those who is are to build an automated real-time learning system. Understanding network's behaviour is required in order to build such a system which possesses a comprehensive meta-knowledge of the network behaviour for automatically determining network's training variables(learning rate, momentum, nodes of input layer, nodes of hidden layer, activation function, learning algorithm, composition of training data set, etc.) for the purpose of achieving higher degree of generalization. Thus, the research to identify relationship between characteristics of training data set and network's response will be continued, and a number of experiments on enhancing the degree of generalization through modifying network's training factors will be conducted. In the next step of this research, an effort will be exerted on whether achieving reasonable degree of generalization, with very noisy data set, is possible or not. As shown the above, the data set we have are so noisy that any reasonable explanation on the data characteristics might not be possible. However, the reality in Korea, as we are in the moving stage from cash society to credit society, is that the credit data collected in various fields are so noisy that any prediction technique such as statistical method, induction trees, expert system approach, or neural network approach cannot provide perfectly exact prediction value. Research should be done with these noisy data.

As shown in Figure-1, current effort to identify neural network's behaviour in response to specific data set is an initial part of research which attempts to build a practically useful system in service companies, integrating meta-knowledge-based system for determining network's training variables and neural training system for credit evaluation. The approach to build an automated real-time credit evaluation system through continuous monitoring customers' credit records and evaluation system's performance will be of great help to other applications : service industries (bank loan, mortgage companies, insurance companies, hotels, sport complexes, luxurious restaurants, department stores, gas franchise etc.), and consumer product distributors (automobile dealers, consumer electronic device distributors, etc.).

Our recommendation obtained from the experiments is that the inconsistent data should be removed from training set, whenever they are identified in the process of training the network, to prevent possible oscillation and possible biases towards the specific data set. The strategy of continuous monitoring and removing inconsistent data set might be important in developing neural net learning system which will be of reasonable help to practioners in the field. In fact, as shown the above, in the real world situation, inconsistent data can be included very often in training data set and then should the carefully handled. We hope that the interim report with very noisy data set can help some researchers who attempts to develop neural network system of practical use in the field.

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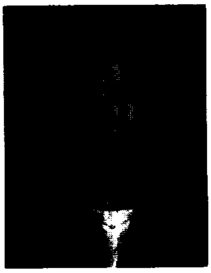

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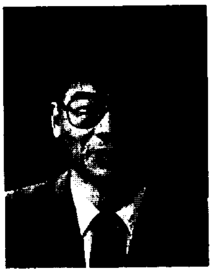

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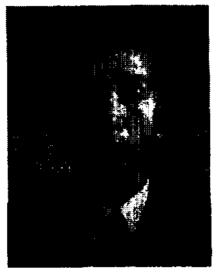

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