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A Dimension Separation Based Hybrid Classifier Ensemble for Locating Faults in Cloud Services

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Abstract: Cloud services provide Internet users with various services featured with data fusion through the dynamic and expandable virtual resources. Because a large amount of data runs in different modules of the cloud service systems, it will inevitably produce all kinds of failures when the data is processed in and transferred between modules. Therefore the job of rapid fault location has an important role in improving the quality of cloud services. Because of the features of large scale and data fusion of data in the cloud service system, it is difficult to use the conventional fault locating method to locate the faults quickly. Taking the requirements on the speed of locating faults into account, we will make a clear division to all possible failure causes according to the business phases, and quickly locate the faults by implementing a cascading structure of the neural network ensemble. At last, we conducted an experiment of locating faults in a cloud service system runned by a telecom operator, comparing the proposed hybird classifier ensemble with neural networks trained by separated data subsets and a conventional neural network ensemble based on bagging algorithm. The experiment proved that the neural network ensemble based on dimension separation is effective for locating faults in cloud services.
Keywords: fault locating, hybird classifier ensemble, dimension separation, cloud service, data fusion, neural network.

1 Introduction

Cloud service is a mode of increasing, applying and delivering service provided through the Internet with dynamic and virtualized resources [1]. Cloud services are easily expandable and delivered in accordance with users' requirements [2]. These services are typically related with the fields of IT, software and Internet.

In the general cloud service systems, the data of account information, user resources, credit status, billing data, order information and other transaction data needing to be fused. In spite of the convenience of business support, data fusion brings problems of oversize of data storage, complexity of data processing and frequent data transferring [3]. These problems will inevitably lead to more failures of cloud service systems [4].

The speed of locating fault is an important measure to maintain and improve the quality of cloud services [5]. However, due to the large data size and complexity of fused data, conventional methods of customer feedback, regular inspection, data audit and other methods delay the progress of locating faults. As for common intelligent classification algorithms, the whole cloud system is taken as a black box, even if the fault can be detected, it would be very hard to locate it.

Taking into account the requirement of rapid locating, we make a clear division to all kinds of possible failure causes according to the business phases, and quickly locate faults by implementing a cascading structure of the classifier ensemble. At last, we conducted an experiment of locating faults in a cloud service system running by a telecom operator in China, comparing the proposed ensemble with neural networks trained with data subsets of dimension separation and a conventional neural network ensemble. The experiment proved that the proposed hybrid classifier ensemble based on dimension separation is effective for the rapid location of cloud service failure.

2 Related works

There are two kinds methods of locating faults in information systems: (1) Regular methods; (2) Pattern recognition methods of artificial intelligence.

2.1 Regular methods

Conventional methods of locating faults include customer feedbacks, regular inspection and data auditing.

Despite the fact that the customer feedbacks are helpful in locating the faults, the fault location based on customer feedback has three drawbacks: (1) time delaying; (2) hurt on user experience; (3) high costs. The negative sides hinder the application of this method in cloud service systems [4].

Regular inspection is another way to find the fault in the cloud service system. For cloud service system operators, regular inspection on the important system module is a must. There are two the problems for regular inspection: (1) the boring work of inspection leads to low efficiency and high error rate; (2) it is hard to find the complex problems.

Data auditing is a method of verifying the failure based on the data generated by the system. This method is generally based on the reports and statistics services. It can only be used to find the faults meeting with two conditions: (1) the faults and the causes are acknowledged; (2) data auditors are experienced with the faults. It is not effective in using the method in locating faults caused by the uncertain problems, despite that facts that this method is simple, accurate and speedy in application.

2.2 Pattern recognition based on artificial intelligence

The problem of locating faults using pattern recognition method is eseentially a problem of classification. There are many classification algorithms, such as artificial neural network, support vector machine and wavelet analysis [6]. In general, for the problem of locating faults in cloud service systems, neural network (shown in Fig.1) is commonly used [7].

In Fig.1, there are following problems existing in the general model of locating faults based on neural network:

- Requiring large number of data samples. In the task, all types of faults are located using the same neural network, so it is necessary to provide a large number of training samples, which hinders the application of the model in practical applications. In order to train a neural network for locating faults in cloud services, the input data should include all kinds of negative samples and the positive samples, without which the appropriate neural network parameters could not be trained during the training process. Therefore, we must obtain a large number of samples to locate the fault types in the system, which leads to a great increase in the operating costs of cloud services.

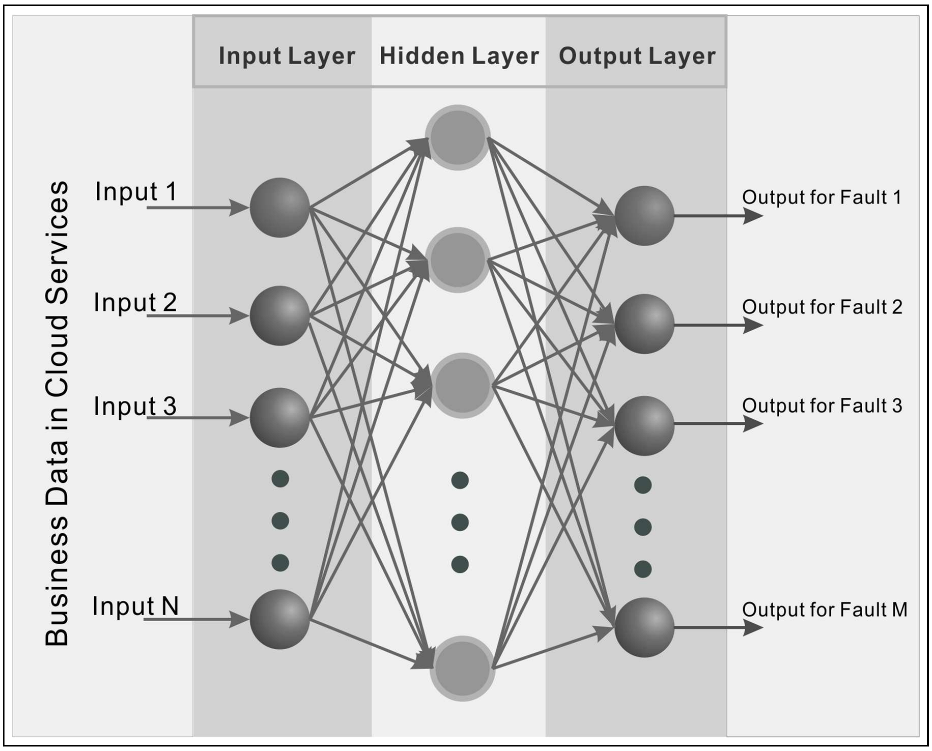

Figure 1: The general model for locating faults based on neural network

- Increasing the complexity of computation. As each cause of system failure is represented by one or serveral data dimension, the application of locating faults based on neural network requires high dimensional data. The neural network trained by the high dimensional data will have a very complex structure, which leads to a substantial increase in the amount of computation, and greatly reduces the accuracy of locating faults. Consequently, it will increase costs of subsequent failure recognition and troubleshooting.

- Lacking of explanation for the causes of system faults. It is hard to establish a clear causal relationship between the failure phenomenon (the output of the neural network) and the cause of the fault (the input of the neural network) through the fault locating neural network. Therefore it is very difficult to accurately locate the system failure because that we can't confirm the relationship between the output data and the input data.

3 Framework

In order to reduce the training sample size, simplify the computational complexity and improve the explanation of locating faults using neural networks, we need to reduce the dimension of data. Dimension reduction is based on the correlation of different data dimensions. When the correlation between the data dimensions is low, simple dimension reduction will lead to the loss of information supported by the data.

The approach used in this research is to divide the original high dimensional data set into several low dimensional data sets according to the business relationship. Then, a neural network is allocated for each of the low dimensional data sets separated dimensionally. And the corresponding neural network is trained and tested with the low dimensional data set. In order to reduce the computational complexity and improve the recognition efficiency, we use the cascading structure to integrate the various neural networks to form the neural network ensemble based on dimension separation as shown in Fig. 2.

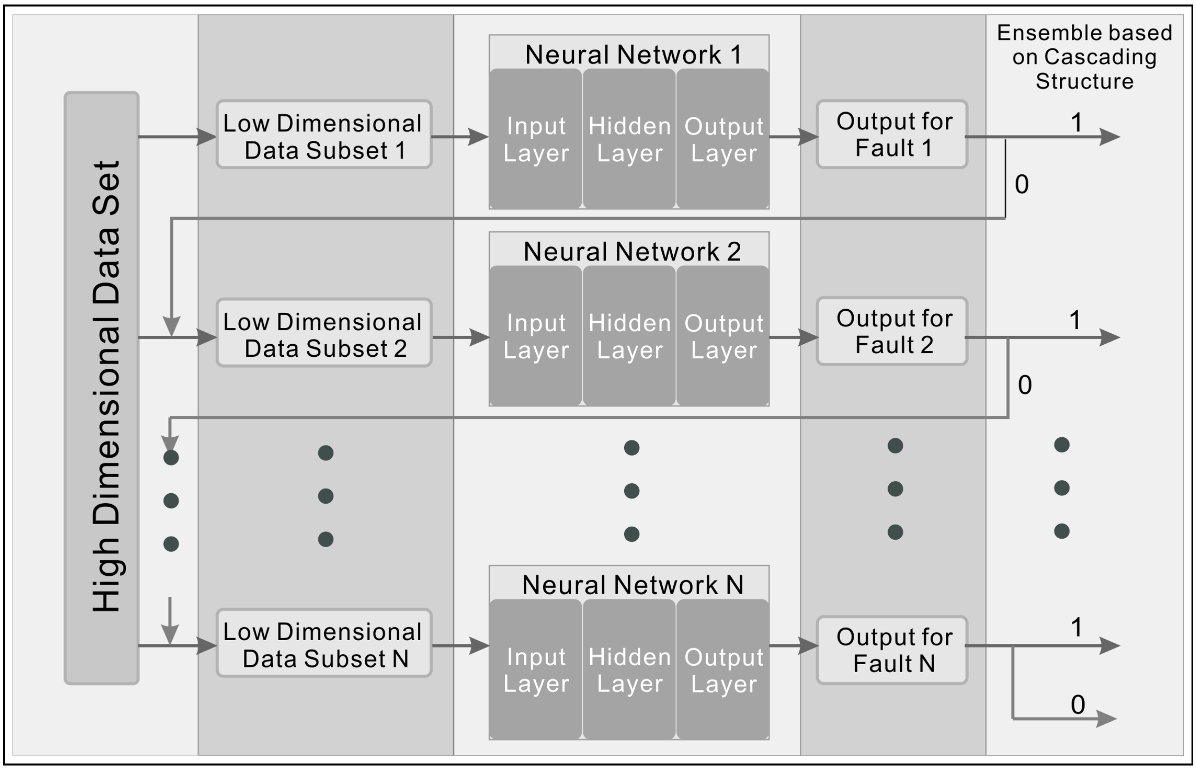

Figure 2: Schematic diagram of fault locating neural network ensemble based on dimension separation

In the cascading ensemble structure, if the output of the current neural network is 1, which indicates that there is an error with the transaction corresponding to the neural network. Therefore, there is no need to carry out the further fault location. Otherwise, the next neural network and the corresponding low dimensional data subset will be set for locating further faults.

Compared with the single neural network, there are three advantages in the proposed ensemble based on dimension separation:

- The work efficiency of the proposed ensemble is higher. Because that the high dimensional data is divided into low dimensional data subsets, each neural network in the ensemble needs only be trained and tested by a data subset, which greatly improves the work efficiency of the classifier based on the ensemble.

- The reason causing the fault is clearer. Because different neural networks in the proposed ensemble are built according to different fault types, the fault reason can be determined according to the neural network corresponding to the output data.

- It is easier for the ensemble than the single neural network to expand. The neural network ensemble could be added with more neural networks without changing the fundamental structure, which means it can be used to locate a new fault when it is needed.

The defect of this study is that we need to determine the fault types and to train the corresponding artificial neural networks in order to setup the proposed neural network ensemble, which requires the application supporters to understand the business logics of the system and corresponding failure reasons.

4 Hybrid classifier ensemble based on dimension separation

The speeding requirement of fault locating requires that we should locating the fault occurring frequently first. The premise of satisfying this requirement is that all kinds of faults can be clearly divided, so we adopt the method of dimension separation, based on the cascading structure, to integrate the neural networks and other classifiers, in which the fault causes and fault phenomena are correlated to achieve the goal of locating faults [8].

The algorithm of hybrid classifier ensemble based on dimension separation involves two steps: dimension separation and neural network ensemble.

4.1 Dimension separation

In this research, various neural networks are integrated in ensemble structure. These different neural networks have their own responsibilities. They only receive data subsets with dimensions related to the corresponding transaction failures. The original high dimensional samples are separated into the low dimensional data. The separated dimensions of the data subsets are determined based on different transaction phases.

The N-dimensional data $A = \{B_1, B_2, B_3, \cdots, B_N\}$ is separated into $A_1, A_2, A_3, \cdots, A_m$ as shown in equation (1).

$$\begin{aligned} A_1 &= \{B_i, B_j, B_k, \cdots, B_l\} \\ A_2 &= \{B_m, B_n, B_o, \cdots, B_p\} \\ &\cdots \\ A_M &= \{B_i, B_k, B_m, \cdots, B_n\} \end{aligned} \tag{1}$$

In equation (1),$\{i, j, k, l, m, n, o, p\} \in \{1, 2, 3, \cdots, N\}$. The data dimension subscripts in the data subsets are not necessarily continuous relative to the original N-dimensional data set. And the dimension subscripts of different subsets allow to be repeated.

In this research, we divided the related transaction process in the cloud service system into five phases: the ordering phase, the using phase, the billing phase, the accounting phase and the grading phase. For transaction data, we can separate the related dimensions of the original business data into corresponding data subsets in accordance with these five phases as shown in Fig. 3.

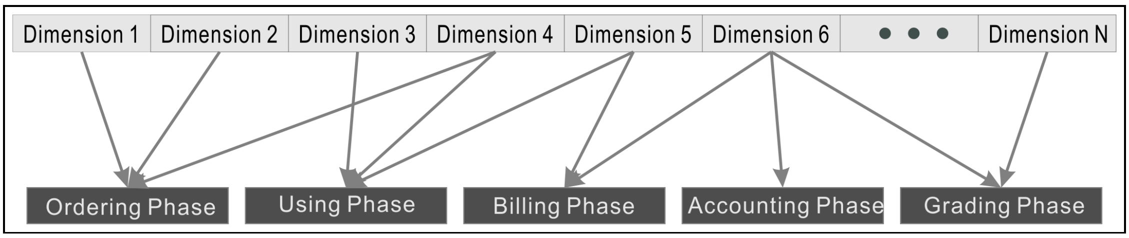

Figure 3: Dimension separation diagram

4.2 Neural network ensemble

The general understanding of the theory of neural network ensemble is: on the premise that the generalization errors of the neural networks in the ensemble are stable, it can effectively enhance the generalization ability of neural networks, and reduce the errors of the neural networks [9].

In general, there are two ways to deversify the neural networks in ensemble: one way is to increase the differences in the structure of neural networks, for example, set different numbers of hidden layers or choose different objective functions; the other way is to provide completely different training data for different neural networks in the ensemble based on the weak learning theory and the boosting techniques.

Neural network ensembles are different with different functions. When the neural network is used to solve the classification problem, the output result of the neural network can be processed by simple average or weighted average. Perrone's research suggests that the weighted average can promote the generalization ability of the neural network ensemble [10], but some studies also show that the adjustment of weights in the process may negatively affect the generalization ability of neural network [11].

In a dynamic weighted ensemble neural network with n neural networks, the training dataset is $A = \{(x_1, y_1), (x_2, y_2), \cdots, (x_n, y_n)\}$. And the output value of one neural network in the ensemble is $y = f_i(x)$. The output of the ensemble is given in equation (2).

$$f_o = \sum_{i=1}^{n} w_i f_i(x) \tag{2}$$

In equation (2), the value of weight w_i could be set to $1/n$ by simple average.

The absolute majority voting method is usually used in the classification of the neural network ensemble, which means the decision of a classification result is determined equally by every neural network in the ensemble. If more than half the neural network classifiers are prone to a result, the result would be used as the classification result of the ensemble. If the probability of voting for the right result for each neural network classifier is $1-p$, and the result of each neural network is not affected by other neural networks, the probability of voting for the right results for the ensemble consisting of N neural networks would be given in equation (3).

$$P_{true} = 1 - \sum_{k>N/2}^{N} \binom{N}{k} p^k (1-p)^{N-k} \tag{3}$$

Obviously, when $p < 1/2$, N and P_{true} are positively correlated with each other, which means the probability of voting for the right result for the ensemble increases with the increase of the number of neural networks.

4.3 Hybrid classifier ensemble

After the separation of dimensions and the training of neural networks, the neural networks can be integrated into an ensemble structure. Considering the computational accuracy and complexity in locating faults, we choose the cascading structure as the ensemble structure. The cascading structure consists of many layers, where each independent neural network can be put. The neural networks can only be trained and tested with the subsets with fewer dimensions separated from the original data. The output of the neural network in the nst layer can be the input parameters of the $n+1$st layer. The independence of the layers in ensemble structure determines the degree of freedom of selecting algorithms put into the layers in the ensemble.

Besides neural networks, other forms of classification algorithm can also be integrated into the ensemble. Here, according to the features of the large transaction volume and simple standard of classification for some faults locating in the cloud services, the algorithm of binary tree is introduced into the ensemble structure, forming a hybrid classifier ensemble of binary trees and neural networks [12].

In the task of locating faults in cloud services, part of the transaction logic is very simple, or can be completed according to the existing disciminant rules. Therefore, there is no need to use the neural networks. For this type of fault locating with simple transaction logic, classification method based on binary tree can be employed [11].

The algorithm of binary tree is very simple. There is no need for complex training process in the binary tree. The application of the tree only needs a discriminant function. For example, for the input data subset $A = \left(x_1, x_2, x_3, \cdots, x_n\right)$, if the computational result of the function satisfies the condition of K, we would be able to locate the fault in the cloud service system as shown in equation (4).

$$y = \begin{cases} 1 & \text{if } f\left(A\right) \text{ satisfies } K \\ 0 & \text{otherwise} \end{cases} \tag{4}$$

For some other nonlinear and complex samples not suitable for neural network or binary tree, we can use other classifiers to integrate the classification results as a layer in the ensemble.

The ensemble integrating binary trees, neural networks and other classifier can locate various faults in cloud service systems [13], as shown in Fig. 4.

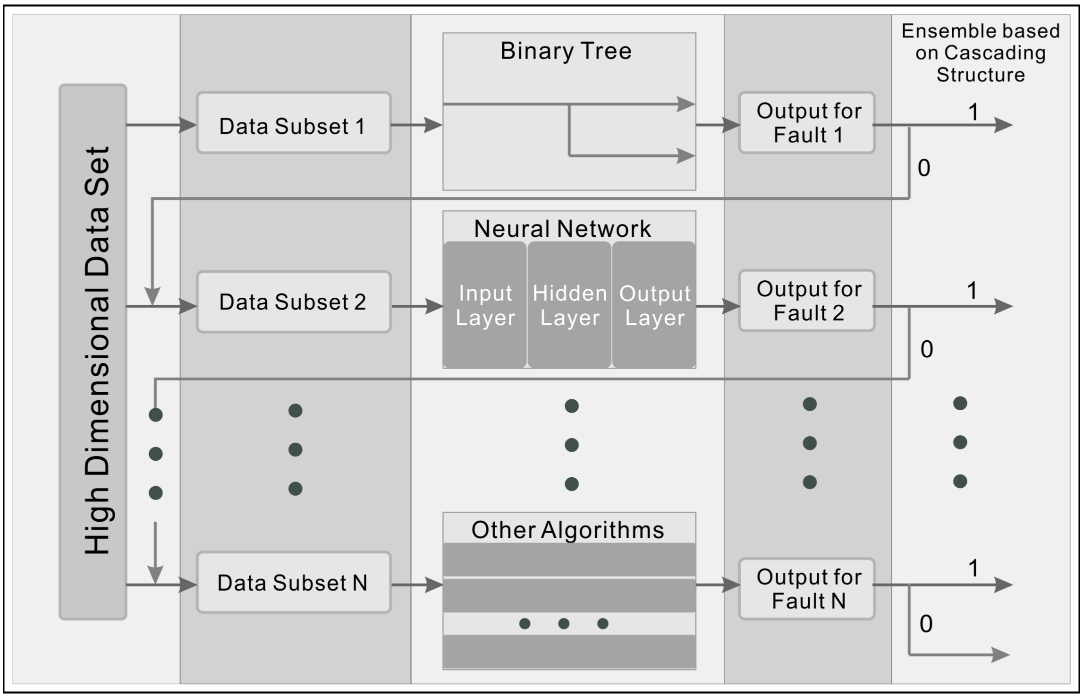

Figure 4: Hybrid Classifier Ensemble

5 Experiment

5.1 Dimension selection

There are a wide variety of transactions in cloud service systems. In this experiment, we monitor and obtain the data from the ordering phase, the using phase, the billing phase, the accounting phase and the grading phase of a transaction for locating the faults.

The basis for selecting what kind of business data is the transactional features. For example, there are many fields involving in the ordering phase of a transaction in a cloud service. These fields involve the process and its details. Therefore, we need to obtain the fields related with locating faults in transaction from the database of the cloud service based on the transactional features for locating faults.

Data values of obtained fields involved in related aspects of the transaction process are listed in Tab. 1. In the table, the letters O, U, B, A and G respectively represent the ordering phase, the using phase, the billing phase, the accounting phase and the grading phase of a transaction.

Table 1: Related fields of five phases of a transaction

Field Name	O	U	B	A	G	Field Name	O	U	B	A	G
Field 1	■					Field 21			■		
Field 2	■	■				Field 22			■		
Field 3		■	■			Field 23			■		
Field 4		■	■			Field 24			■	■	
Field 5		■	■			Field 25			■		
Field 6		■	■			Field 26				■	
Field 7		■	■			Field 27				■	
Field 8		■	■			Field 28				■	
Field 9		■	■			Field 29				■	
Field 10		■	■			Field 30				■	
Field 11		■				Field 31				■	
Field 12		■				Field 32				■	
Field 13		■				Field 33				■	
Field 14		■				Field 34					■
Field 15						Field 35					■
Field 16						Field 36					■
Field 17		■				Field 37					■
Field 18		■				Field 38					■
Field 19		■				Field 39					■
Field 20		■									

In the process of data collection, the user identity is the unique identifier. The related data of the user in every phase are collected with comments and foreign keys excluded.

In this experiment, 39 fields in Tab. 1 are collected. The dimensions corresponding to the fields are separated according to the transaction phases. Then the separated dimensions are used in the training and testing steps.

Some setup values are given in Tab. 2.

5.2 Neural network ensemble with high dimensional data

The common neural network training and testing methods are used in the ensemble for the high dimensional data. And the majority voting method is used to integrate the results of neural networks to get the ensemble results to locate the faults in the cloud service system. 28 neurons are determined to setup in the hidden layers after "trial and error" tests. And four neural networks are created to be layers in the ensemble. Therefore, the four neural networks are trained based on the high dimension samples respectively. And the test data is used to test the validation of the neural networks respectively. The classification results are integrated to obtain fault locating results by the majority voting method.

In order to diversify the four neural networks to be integrated, the 6001 training samples are tripled to 18003 samples. Then 6001 samples were randomly selected to train each neural network. After the completion of the training, 900 test samples were tested on each neural network respectively. And test confusion matrices of the four neural networks are shown in Fig. 5. Correct rates of each phases of the ensemble are 0.278, 0.833, 0.882, 0.955 and 0.962. The overall correct rate of the ensemble is 0.679.

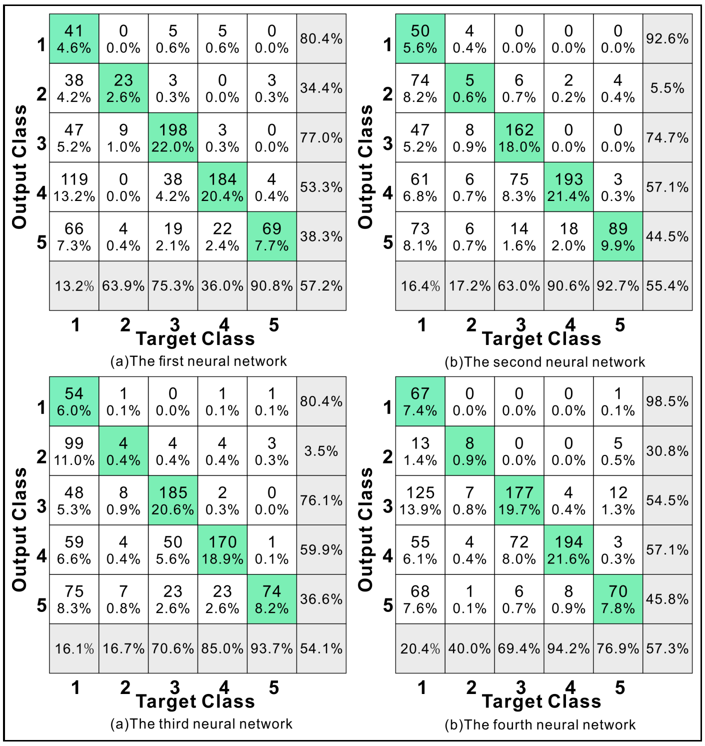

Figure 5: Test confusion matrices of four neural networks for ensemble with high dimensional data

Table 2: Setup values of the experiment

Item	Value
Platform	MatLab 2011a
Neural network tool	patternnet()
trainFcn	‘trainscg’
performFcn	‘crossentropy’

5.3 Neural networks with low dimensional data

As the rule for locating faults in the ordering phase is very simple, a binary tree is used to locate fault by implementing the rule on the data subset related with the ordering phase.

Four classification neural networks are created by using the function "patternnet()" corresponding to the other four data subsets after dimension separation according to the dimension relations in Tab. 5. The dimension numbers of the data subsets corresponding to the four phases are 17, 13, 9 and 6 respectively. After some " trial and error", 10 neurons are determined to be in the hidden layers in the four neural networks, in order to obtain expected training and testing results.

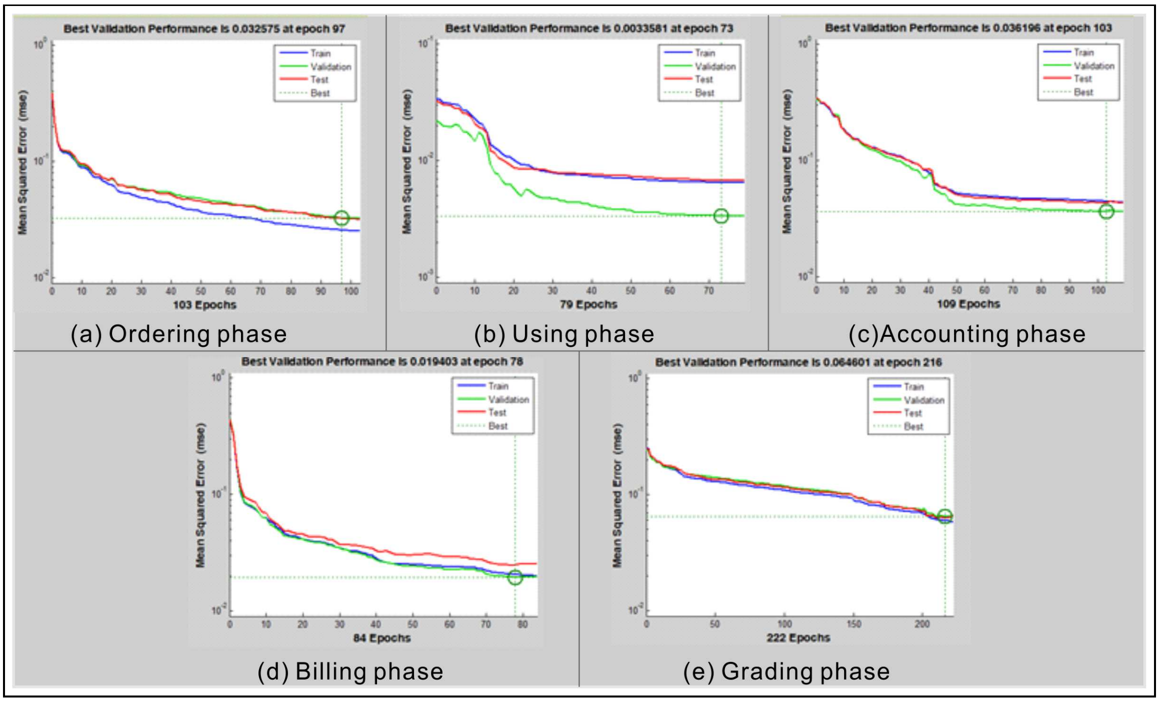

Figure 6: The training processes of neural networks for five business phases

The four created neural networks are respectively trained on the corresponding data subsets separated dimensionally. And the training processes in Fig. 6 are obtained by using the "plotperform()" function.

900 records of the data subsets being dimensionally separated are respectively used to test the binary tree and the four trained neural networks. The test confusion matrices are given in Fig. 7. According to the test results, the accuracy of the grading phase is about 92

5.4 Analysis of experiment results

In this experiment, we compared the common neural network ensemble with the dimension separation based hybrid classifier ensemble in the task of locating faults in a cloud service system. It was found that the dimension separation based hybrid classifier ensemble performances better than the common neural network ensemble, and the experimental results are shown in Tab. 3.

Test confusion matrices in Fig. 5 and Fig.7 give the numbers of true positive (TP), false positive (FP), false negative (FN) and true negative (TN) samples of different classifiers and different layers in a classifier. The sensitivities of TP, FP, FN and TN are respectively true positive rate (TPR), false positive rate (FPR), false negative rate (FNR) and true negative rate

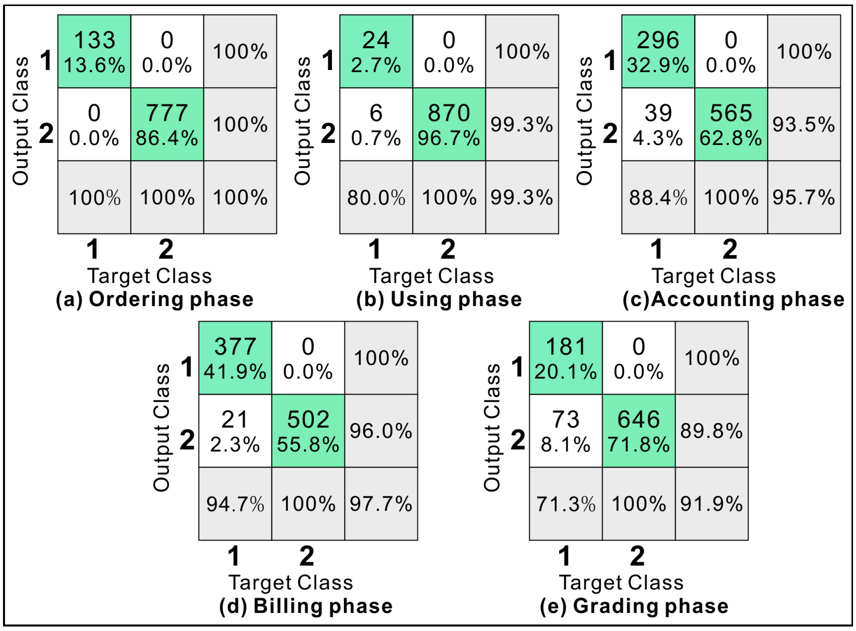

Figure 7: Test confusion matrices of the binary tree and the neural networks trained with low dimensional data subsets

Table 3: Comparison of common neural network ensemble,dimension separation based neural networks and dimension separation based neural network ensemble

	common neural network ensemble	dimension separation based classifiers	dimension separation based hybird classifier ensemble
Accuracy of Ordering Phase	0.278	1.000	
Accuracy of Using Phase	0.833	0.993	
Accuracy of Accounting Phase	0.882	0.957	
Accuracy of Billing Phase	0.955	0.977	
Accuracy of Grading Phase	0.962	0.919	
Overall Accuracy	0.679	0.969	0.979

(TNR). The values of TP and TN of the layers in hybrid classifier ensemble of cascading structure are given in equation (5). In the equation, i is the number of the layer containing the classifier.

$$TP_{i+1} = TPR_{i+1} \cdot (FN_i + TN_i) \tag{5}$$

And the overall accuracy of the proposed ensemble is given in equation (6). In the equation, n is the total number of layers of the propose ensemble.

$$A_{Overall} = \frac{(TN_1 + TP_1) + (TN_2 + TP_2) + ... + (TN_n + TP_n)}{(TN_1 + TP_1 + FN_1 + FP_1) + (TN_1 + FN_1) + ... + (TN_{n-1} + FN_{n-1})} \tag{6}$$

High accuracy of classification is the premise of troubleshooting of cloud services. The experimental results in Tab. 3 prove that the proposed hybrid classifier ensemble based on dimension separation is more suitable for locating faults in cloud service systems than the common neural network ensemble.

5.5 Applications

The application framework for the proposed hybrid classifier ensemble is given in Fig. 8.

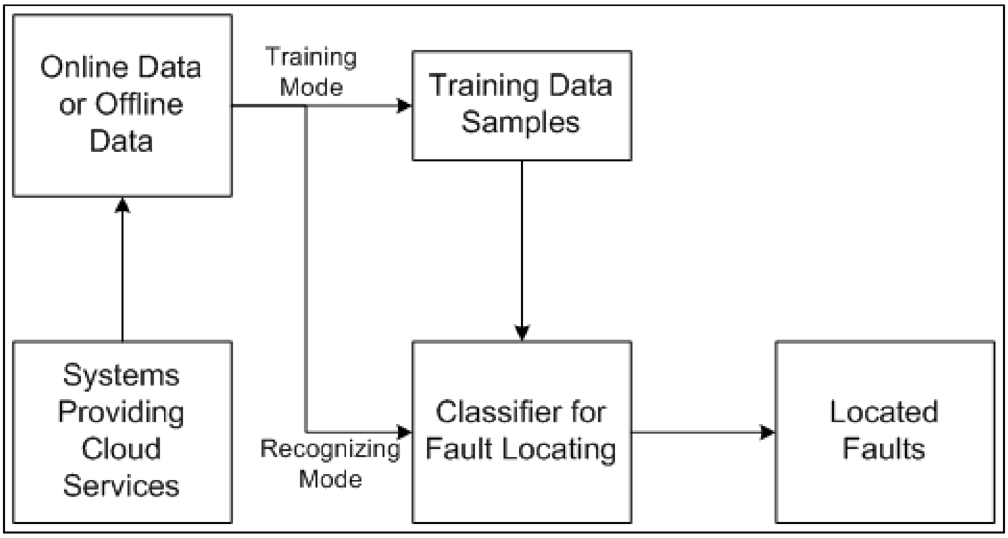

Figure 8: The application framework of the hybrid classifier for locating faults in cloud services

The data are collected from the cloud service systems. These data may be real-time online business data, or be offline business data stored in the data warehouse. In the training mode, data is organized into training sample sets for training the proposed classifier of fault locating. After training, the online and offline data collected from the cloud systems are to be used to locating faults of the cloud services by the proposed classifier.

According to the real-time feature of input data for the proposed classifier, the faults can be divided into two categories: (1) when the input is the real-time data, based on the input real-time data, the running cloud services and supporting systems are real-time monitored to detect the system faults; (2) when the input data are offline, we can audit the businesses through checking the logical relationship between data representing the businesses to find out the problems in business.

Conclusions and future work

Fault locating is an important job for supporting the operations of cloud services because of large data scale and data fusion. The key to fault location is to accurately locate the faults and clearly explain the causes. On the premise that the causes of the faults are complex, the neural network becomes an important method for fault location. Common neural network has two problems: (1) the low accuracy of fault location; (2) unexplainable fault locating results.

Considering that the neural network has higher classification accuracy for the data with the fewer dimensions, we divide business data into data subsets according to the business phases through dimension separation. And then a binary tree and four neural networks corresponding to the business phases are created, trained and integrated into the cascading ensemble structure for locating faults. Experiments show that the proposed hybrid classifier ensemble based on dimension separation is more accurate and explainable in locating faults in cloud service systems than common neural network ensemble.

The problem of this research is the architecture of the proposed ensemble is more dependent on the familiarity level of the business supporters of the cloud service system, because the works of obtaining data obtain and separating dimensions are both dependent on the transaction environments in real world.

Due to the openness of cascading ensemble structure, we could integrate binary trees or other suitable classification algorithms into the proposed ensemble based on dimension separation by replacing existing neural networks with other algorithms, according the real environments of the cloud service system.

The proposed fault location classifier can be used in two aspects: (1) real-time monitoring of the cloud service system for locating faults in the operation; (2) logic matching on the business data for detecting business problems of cloud services.

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