MODULE COMBINATION BASED ON DECISION TREE IN MIN-MAX MODULAR NETWORK

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Abstract: The Min-Max Modular (M^3) Network is the convention solution method to large-scale and complex classification problems. We propose a new module combination strategy using a decision tree for the min-max modular network. Compared with min-max module combination method and its component classifier selection algorithms, the decision tree method has lower time complexity in prediction and better generalizing performance. Analysis of parallel subproblem learning and prediction of these different module combination methods of M^3 network show that the decision tree method is easy in parallel.

1 INTRODUCTION

With the rapid growth of online information, we have faced large-scale real-world problems in data mining, information retrieval, and especially text categorization. For large-scale text categorization problems, one common solution is to divide the problem into smaller and simpler subproblems, assign a component classifier, which is called module in this paper, to learn each of the subproblems, and then combine the modules into a solution to the original problem.

Lu and Ito (Lu and Ito, 1999) proposed a min-max modular (M^3) network for solving large-scale and complex multi-class problem with good generalization ability. And it has been applied to solving real world problems such as patent categorization (Chu et al.,) and classification of high-dimensional, single-trial electroencephalogram signals (Lu et al., 2004). Lu and his colleagues have also proposed several efficient task decomposition methods, based on class relations, or using geometric relation (Wang et al., 2005) and prior knowledge (Chu et al.,). In existing work the min and max principles are generally used to combine the modules.

In this paper, we apply the decision tree idea into M^3 network, to make module combination work better. The decision tree method only uses part of the sub-modules in prediction, to reduce the time used in predicting testing data, and ease the parallel subproblem learning.

This paper is structured as follows. In Section 2, M^3 network and its two classifier selection algorithms are introduced briefly. Section 3 is an analysis of applying a new module combination method based on decision tree to the modular network. In Section 4, we designed a group of experiments on different data sets, in order to compare the performances and time complexities of different module combination methods. In Section 5, conclusions are outlined.

2 MIN-MAX MODULAR NETWORK

The min-max modular (M^3) network model is designed to divide a complex classification problem into many small independent two-class classification problems and then integrate these small parts according to two module combination rules, namely the minimization principle and the maximization principle (Lu and Ito, 1999). The learning procedure of M^3 has three major steps: *Task Decomposition, Sub-module Learning,* and *Min-max Modular Network assemble*.

In task decomposition, a large binary-class problem is divided into a series of small sub-problems, based on the class correlation. Let T denote the training set of a *binary* class problem.

$$\begin{aligned}\mathcal{T} &= \{(X_l, Y_l)\}_{l=1}^{L} \\ &= \mathcal{T}^{+1} \bigcup \mathcal{T}^{-1} \\ &= \{(X_l, +1)\}_{l=1}^{L^+} \bigcup \{(X_l, -1)\}_{l=1}^{L^-}\end{aligned} \quad (1)$$

where $X_l \in R^d$ is the input field in the form of feature vectors, $Y_l \in \{+1, -1\}$ is the corresponding desired output field, and L is the total number of training samples.

After partitioning $\mathcal{T}^{+1}$ into N^{+1} subsets and $\mathcal{T}^{-1}$ into N^{-1} subsets.

$$\begin{aligned}\mathcal{T}^{+1} &= \bigcup_{u=1}^{N^{+1}} \{(X_l, +1)\}_{l=1}^{L_u} \\ \mathcal{T}^{-1} &= \bigcup_{v=1}^{N^{-1}} \{(X_l, -1)\}_{l=1}^{L_v}\end{aligned} \quad (2)$$

Then the original problem $M_{+1,-1}$ is divided into $N^+ \times N^-$ small and balanced two-class problems $M_{+1,-1}^{(u,v)}$. We call each of those a module:

$$M_{+1,-1}^{(u,v)} = \{(X_l, +1)\}_{l=1}^{L_u} \bigcup \{(X_l, -1)\}_{l=1}^{L_v} \quad (3)$$

In the learning step, we can use any suitable learning algorithm on every sub-problem module. After that, we integrate them using the minimization and maximization principles to form a composite classifier for the original problem.

$$M_{+1,-1} = \max_{1 \le u \le N_{+1}} \min_{1 \le v \le N_{-1}} M_{+1,-1}^{u,v} \quad (4)$$

For a K-class problem, We apply an one-versus-one multi-class decomposition method to the training set. So there are $\binom{K}{2}$ outputs of these two-class sub-problems. We need to further recombine them into a multi-class output. There are many rules to do this work in the case of one vs. one decomposition, such as most-win and DDAG.

The min-max process described above is illustrated in Figure 1.

Task decomposition make data get much redundant, but it also ease the parallel learning. Assume the time complexity of a N-size problem is $O(N^K), K > 1$. If the problem is learned in parallel, the time complexity of each subproblem will be reduced to $O(\frac{N}{(N^{+1} \times N^{-1})^{K-1}})$

3 MODULE COMBINATION BASED ON DECISION TREE

To accelerate the assembling process, two classifier selection algorithms has been propose, named as asymmetric classifier selection (ACS) (Zhao and Lu, 2005) and symmetric classifier selection (SCS)(Ye and Lu, 2007). They are illustrated in Figure 2, $N_i \times N_j$ module $M_{i,j}^{(u,v)}$ form the matrix.

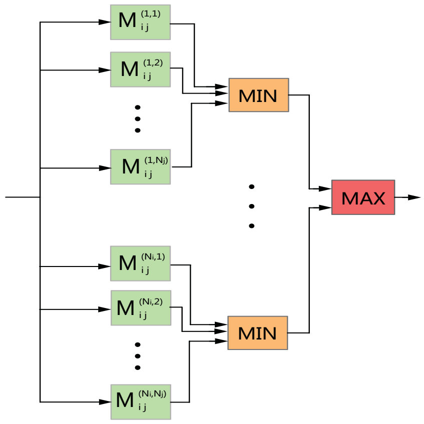


Figure 1: Min-max modular network for sub-modules in $T_{i,j}$.

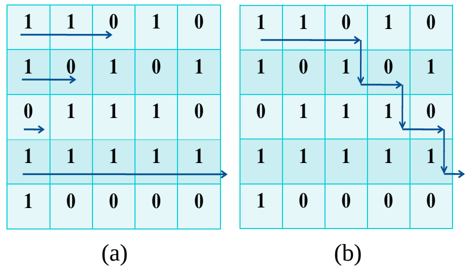


Figure 2: Classifier selection algorithms: (a) ACS, Assign "1" to $M_{i,j}$ if a full row of "1" exists in the matrix, otherwise, assign "0" to $M_{i,j}$. (b) SCS, Assign "0" to $M_{i,j}$ if none full row of "1" exists in the matrix, otherwise, assign "1" to $M_{i,j}$.

Let's consider SCS again. It aims to find a route from the upper-left of the $N_i \times N_j$ matrix and go right or down to exit the matrix at the bottom or right side. It also looks like a route from the root to a leaf in a binary tree. It is evident that nodes (sub-classifiers) on the upper layer are more important than those on the lower layer.

Zhao and Lu (Zhao and Lu, 2006) also put forward a modular reduction method concluding characteristic of SCS. But the modular reduction method can only move a whole row or column in the matrix, restricted by the min-max principle. In SCS, when we get to the (i, j) sub-classifier, all those sub-classifiers above it and left to it in the matrix are discarded, even if some of them are more important than the rest.

According to Meta-Learning (Vilalta and Drissi, 2002), we introduce decision tree algorithm to break up the min-max principle restriction to move the most useful sub-classifier to the upper-left position freely (Ye, 2009). We learn a decision tree for classifier se-

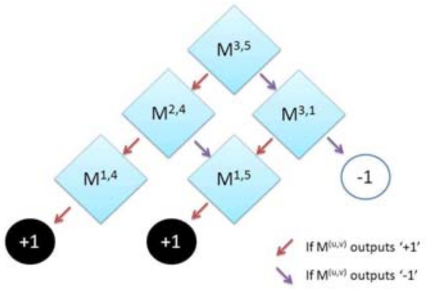


Figure 3: An example of DTCS

lection in the training period as shown in Figure 3.

Accessible decision tree tools, for example C4.5 Release 8 (Quinlan, 1993), are used to ease the decision tree classifier selection process (DTCS).

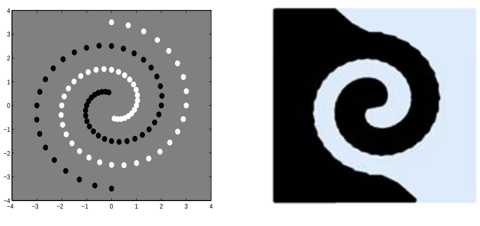
4 EXPERIMENTS

Two experiments are designed to analyze the performance of DTCS algorithm

4.1 Two-spiral Problem

The two-spiral problem is an extremely hard two-class problem for plain multilayer perceptrons (MLP), and the input-output mapping formed by each of the individual trained modules is visible. The aim of this example is to compare M^3 network and DTCS network visibly.

We choose multilayer quadratic perceptrons (MLQP)(Lu et al., 1993) with one hidden layer and five hidden units as the low-layer classifiers in the module. The 96 training inputs of the original two-spiral problem are shown in Figure 4.



(a) (b)

Figure 4: The 96 training inputs of two-spiral problem

In the first simulation the original training inputs belonging to class *BLACK* were divided randomly into 3 training subsets. And class *WHITE* were divided randomly into 3 training subsets, too. The training inputs of the 3×3 = 9 subproblems were constructed from the combinations of the above six training subsets.

Nine MLQP were selected as the network modules to learn the nine subproblems. Each of the network modules has 5 hidden units. The responses of the individual trained modules are shown in Figure 5.

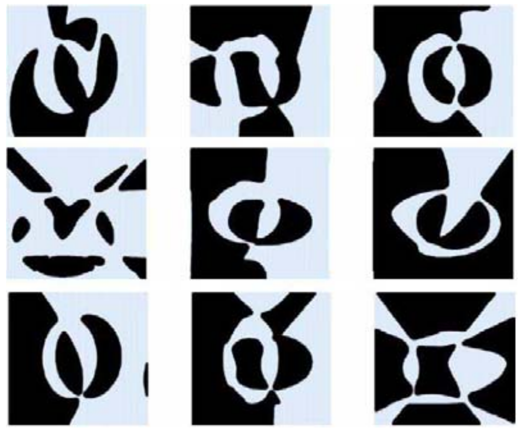


Figure 5: The responses of 3×3 modules

(a) (b)

Figure 6: The responses of (a) min-max approach and (b) decision tree classifier selection

Figure 6 shows the responses of min-max and DTCS after module combination. Through Figure 5, we can see that the MLQP with 1 hidden layer and 5 hidden units cannot learn each $M_{i,j}$ problem well, and the min-max principle just stiffly combines them into a rough output. But DTCS method can combine the discrete low-layer classifiers outputs into a consecutive solution. So DTCS can adapt to weak low-layer sub-classifier better than the min-max approach.

4.2 Patent Categorization

Patent classification is a large-scale, hierarchical, imbalanced and multi-label problem.

Every year, there are over 300,000 Japanese patent data. Ten years worth of Japanese patent categorization using M^3-SVMs has been done by Lu and his colleagues (Chu et al.,). Now we will choose a subset of these Japanese patents to compare the performance of M^3 and DTCS. The experiment setup is as follows:

- *Experiment data collecting.* We collected 8000 documents from Japanese patents from the year 1999 for training and 4000 documents from the year 2000 for testing.
- *Feature selection.* We used the *CHI_avg* feature selection method to convert each document into a 5000 dimensional vector.
- *Base classifier selection.* Because of its effectiveness and wide usage in text categorization. SVM^{light} was employed as the base classifier in each module. Each SVM^{light}s had a linear kernel function, and c (the trade-off between training error and margin) is set to be 1.

For evaluating the effectiveness of category assignments by classifiers to documents, we use the standard recall, precision and F_1 measurement.

The results comparison is shown in Table 1. In the table, four methods (min-max, scs, acs, and DTCS) are listed in the first column, and the DTCS using pruned C4.5 is also listed as DTCS(p). In the last column, #module denotes the average number of modules used to predict a sample in the modular network.

Table 1: Results comparison of patent categorization.

Method	P(%)	R(%)	F_1(%)	#module
Min-max	71.51	71.48	71.49	700
ACS	71.51	71.48	71.49	350
SCS	71.51	71.48	71.49	250
DTM	71.10	71.05	71.08	200
DTM(p)	71.86	71.83	71.84	140

From Table 1, we can see that the DTCS with a pruned C4.5 has the best performance and lowest time complexity. We also notice that DTCS with an unpruned C4.5 performed worse than min-max, because of the over-fitting problem of unpruned C4.5 algorithm.

For selecting less modules than min-max method, DTCS highly increases the parallel learning efficiency.

5 CONCLUSIONS

We apply the decision tree to module combination step in min-max modular network. Compared with the min-max approach, the advantages of the new method are its lower time complexity in prediction, especially in parallel prediction, and better adaptive ability to weak low-layer sub-classifier.

Our future work is to adjust traditional decision tree algorithm to adapt to M^3 network, and continue to analyze and test DTCS generalizing performance through a series experiments; with a focus on large-scale patent categorization.

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