Modified Fuzzy Min-Max Neural Network for Pattern Classification

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ABSTRACT
In data mining two important tasks involved are classification and clustering. In general, in classification the classifier assigns a class label from a set of predefined classes to a new input object. In the context of machine learning, classification is supervised learning.There are different approaches used for classification. Originally, Simpson proposed the fuzzy min-max (FMM) neural network [2] for classification, in which the classes are represented as an aggregation of fuzzy set hyperboxes in the n-dimensional pattern space. In the recent past, many variants of original FMM neural network have been proposed for classification and clustering. This paper proposes novel modified FMM (MFMM) neural network training algorithm by suggesting significant modifications in the original FMM neural network learning. Similarly to the original algorithm, the hyperbox fuzzy sets are used for a representation of classes. Unlike other variants, more importantly the proposed modifications resulted in single pass training. Moreover, like other variants, the proposed learning is quick, efficient and capable of constructing nonlinear decision boundaries. All these benefits make it suitable for difficult real world problems involving classification. A detailed description of the MFMM neural network topology, its learning algorithm and comparison with other recent FMM variants by evaluating the efficacy of MFMM using benchmark Fisher Iris Data set is given.

General Terms
Pattern Classification; Data Mining; Neural Networks; Fuzzy Logic

Keywords
Classification; Clustering; Fuzzy Min-Max Neural Network

1. INTRODUCTION
Artificial neural networks have been successfully used in many pattern classification, recognition and clustering problems [1].In supervisedlearning, frequently referred as a pattern classification problem in which class labels are available with input patterns during training and the trained classifier constructs decision boundaries between classes that minimize misclassification.

However,the unsupervised learning is often referred as a clustering problem. The patterns during training are unlabeled and the task is dividing a set of unlabeled patterns into few clusters using some suitable relationship. There are different relationship measures used for creating clusters of unlabeled data set. The most popular is a distance measure. The data samples which are close to each other in the pattern space are assigned to the same cluster, while the data samples whichdiffer considerably are placed in different clusters. Thus theclustering always performs partitioning of patternsin disconnected or overlapped clusters.

The fundamental characteristic of human reasoning is theease in handling uncertain data that appears in the real life. The traditional statistical approaches to patternclassification have been found inadequate in such circumstancesand this deficiency has prompted for the search with alternative solutions that allows representation of ambiguous data and moreflexible labeling in classification problems. The fuzzysets were suggested as a way to remedy this difficulty [2].

The fuzzy neural network (FNN) synergetic combinationof fuzzy sets and artificial neural networks in the pattern classification and clustering has been studiedby many researchers. The gracefulness of fuzzy setsand the computational efficiency of artificial neural networks has caused a greatamount of interest in the combination of these two techniques for solving classification and clustering problems successfully.

Originally, Simpson proposed the FMM classification and clustering neural networks [2], [3], in which the classes are represented as an aggregation of fuzzy set hyperboxes in the n-dimensional pattern space. Subsequently, several researchers [4-27] have proposed variants of the FNNs suggesting different ideas and modifications in their learning algorithms.

Most of the researchers claim that their proposed algorithms can learn nonlinear class boundaries in a single pass through the data and provides the ability to incorporate new and refine existing classes without retraining and therefore supports online adaptation. However, all these learning algorithms need few passes to train the network by adjusting tuning parameter(s) after each pass during training. As an example in most of the training algorithms, the value of Θ is adjusted during training after each pass to decrease the number of misclassifications, where Θ is the maximum size of the fuzzy set hyperbox. This tuning process continues till zero misclassifications occur. The number of passes required for training leading to no misclassification is also unpredictable. Further how to choose initial value of Θ is also uncertain. It means that no approach supports online adaptation in real sense.

The proposed MFMM neural network removes the constraint on maximum size of fuzzy set hyperbox. The learning of MFMM neural network allows creation and expansion of the fuzzy set hyperboxes as per the demand of the data set and hence the problem in hand. The removal of a constraint on maximum size of the fuzzy set hyperbox is madepossible by suitably modifying the learning algorithm leading to single pass training.

The remainder of this paper is organized as follows. The brief review of the related work is given in Section 2. This section gives a short description of the original FMM algorithms followed by a brief account about a general fuzzy min-max

(GFMM) neural network [5] which is a fusion of the original FMM algorithms with a few new ideas. This section also gives brief information about the enhanced fuzzy min–max (EFMM) neural network. Section 3provides a background to understand the MFMM neural network. Section 4 presents a detailed discussion on the proposed MFMM neural network learning algorithm and its architecture. Section 5 gives the account on performance evaluation of the proposed model comparing with only some of the existing approaches. Finally, the conclusions are outlined in Section 6.

2. RELATED WORK

The FMM classification neural network [2] uses hyperbox fuzzy sets.A fuzzy set hyperbox is defined by its min-max points and thehyperbox fuzzy set membership function. Ahyperbox min-max points define a region in the n-dimensional pattern space, and all patternscontained within the hyperbox have a full class membership. The hyperbox fuzzy sets are aggregatedto form a single fuzzy set class during classification.Learning in the FMM classificationneural network consists of creating, expanding and contractinghyperboxes in the pattern space.

The learning begins by inputting an input pattern and finding the nearest hyperbox tothat pattern that can expand (if necessary) to include the pattern.If a hyperbox cannot be found that meets the expansion criteria,a new hyperbox is created and added to the system. Author claims that this augmentationprocess permits existing classes to be refined over a time,and it allows addition of new classes without the need of retraining, ignoring adjustment of the tuning parameter Θ, required after each pass during training till the neural network is trained to deliver zero misclassifications.One of the unwanted effects of hyperbox expansion isthe overlappinghyperboxes belonging to the different classes. This overlapping results inan ambiguity because patterns falling in the overlapping area fully belong totwo or more different classes.

A contraction process isutilized to get rid of any undesired hyperbox overlaps. The overlap is removedemploying the minimum disturbance principleand only forhyperboxes that represent different classes. The trained network consists of three layers; input layer, hyperbox nodes layer and class nodes layer. The input layer nodes do not do any processing. The hyperbox nodes use the fuzzy membership function to deliver its output. Finally the class nodes perform aggregation of outputs of appropriate hyperboxes belonging to that particular class to provide soft decision.

The FMMclustering neural network in [3] also uses the hyperbox fuzzy sets and learning consists of creating, expanding and contractinghyperboxes in the pattern space. The learning begins by inputting an input pattern and finding the nearest hyperbox tothat pattern that can expand (if necessary) to include the pattern.If a hyperbox cannot be found that meets the expansion criteria,a new hyperbox is created and added to the system. This augmentationprocess permits existing clusters to be refined over time,and allows addition of new clusters without the need of retraining.

One of the unwanted effects of the hyperbox expansion is overlappinghyperboxes. This overlapping causes ambiguity because the patterns falling in the overlapping area fully belongs totwo or more different clusters. A contraction removes the overlap byemploying the minimum disturbance principle. This principle removes overlap in only one dimension in which it is minimum.

The trained network consists of only two layers; input layer, hyperbox nodes layer. The input layer nodes do not do any processing. The hyperbox nodes represent clusters and use the fuzzy membership function to deliver its output. The output is soft decision indicating to which cluster the input pattern belongs.

The general FNNs are the algorithms which take care of labeled and unlabeled patterns that are applied during training. These FNNs incorporate fusion of supervised and unsupervised paradigms. Therefore the single algorithm can be used for pure classification, pure clustering or cross of classification and clustering.

TheGFMM neural network is a generalization and extensionof the fuzzy min-max clustering and classification algorithms developedby Simpson [5]. The GFMM algorithm combines the supervisedand unsupervised learning within a single training algorithm.This combination can be used for pure clustering, pure classification,or hybrid clustering/classification. This fusion exhibitsan interesting property of finding decision boundaries between the classes and clusters during training.

Like [2-3], the GFMM algorithm utilizes the hyperbox fuzzy sets for representation of clusters/classes. The learning requires a few passes through thedata set. It also consists of placing and adjusting the hyperboxes in thepattern space which is referred to as an expansion–contractionprocess. It incorporates many new ideas and suitable to handle labeled/unlabeled data samples presented during training. The classification results are fuzzy and if required can be converted to crisp decisions.

The GFMM algorithm preserves few remarkable features of the original algorithms. However, a numberof modifications also have been proposed. These modifications include new definition of the input in order tohave room for the fuzzy input patterns in the form of lower and upperbounds, fusion of the supervised and unsupervised learning, new well behaving membership function, modified hyperbox expansion criterion and incredible learning algorithm to tackle with labeled and unlabeled data patterns emerging during training.

Authors claim that learning allows incorporation of new datawithout the need for retraining ignoring the fact that the training may require few passes by adjusting the value of Θ.

An enhanced fuzzy min–max (EFMM) neural networkis proposed for pattern classification in [25]. The purpose is to beat a number of limitations of the original FMM neural network to get better classification performance. Three heuristic rules to enhancethe learning algorithm of the FMM are introduced. First, a new hyperbox expansionrule is introduced to eliminate the overlapping problem during the hyperboxexpansion process. Second, the existing hyperboxoverlap test rule is extended by discovering other possible overlappingcases. Third, a new hyperbox contraction rule to resolvepossible overlapping cases is provided. The effectiveness of the algorithm isevaluated using benchmark data sets and a real medical diagnosistask. The results are better than various popular existing classifiers.

Most of the FNNs [2-27] offer numerous benefits such as: soft decision, quick learning, and nonlinear separability. Everyone claims that the algorithm supports online adaptation, forgetting that whenever there is a need to accommodate a new data sample, few passes may be required for training by adjusting tuning parameter(s). Therefore, it is clear that retraining with previous data samples is indispensable. In a true sagacity no one supports online adaptation.

On the other hand, the proposed learning approach in the MFMM integrates many modifications to support single pass training through the data set. The MFMM neural networkrequires the complete data set in advance during training. Unlike the existing approaches, the guarantee of single pass training for the offline data set is noteworthy attribute of the MFMM neural network.

The vital uniqueness of the proposed MFMMthat allow single pass training of offline data set leading to no misclassification of samples used during trainingis summarized in the following points.

i) The bound on Θ i.e. maximum size of fuzzy set hyperbox defined in [2][3][25] has been removed allowing uncontrolled growth.

ii) Hyperbox expansion step in [2][3][25] has been modified to allow unbounded free growth of hyperboxes to satisfy the demand of the classes of variable sizes in the data set.

iii) Hyperbox overlap test in [2][3][25] has been modified by utilizing directly available data samples in the offline data set.

iv) The contraction step in [2][3][25] is extremely simplified making all the steps in [2][3][25] redundant.

The algorithm can be suitably modified further to learn in a single pass for online adaptation also. However, the scope of this paper is limited to a single pass training using offline data sets only.

3. BACKGROUND

The MFMM neural network utilizes an aggregation of fuzzy set hyperboxes to represent a class. A hyperbox is a fuzzy set characterized by its mean and max points in a given pattern space. It is also characterized by its associated membership function. Similarly to [2][3][25]. the membership function of the hyperbox fuzzy set assigns graded membership to all points in the pattern space.

The researchers in [2][3][25] have proposed different membership functions for the hyperbox fuzzy set. However, the membership function in [25] is well behaving. Itreturns full membership if the pattern is included in the hyperbox fuzzy set and the membership values decrease steadily with increasing distance from the hyperbox. Therefore, the MFMM neural network utilizes the membership function defined in [25].

For the clarity, the notations used have been kept consistent,as far as possible, with the previous papers introducing and modifying fuzzymin-max neural networks. The details of the input and fuzzy membership function are given below.

The input is specified as the ordered pair

$$\{\boldsymbol{X}_h, d_h\} \in D \quad (1)$$

where $\boldsymbol{X}_h = (x_{h1}, x_{h2}, ..., x_{hn})$ is the hth input pattern contained within a n- dimensional unit cube I^n; $d_h \in \{1, 2, ..., p\}$ is one of the p classes, and D is the labeled data set.

Following [2], let the hth hyperbox fuzzy set, B_j, is defined by the ordered set

$$B_j = \{\boldsymbol{X}_h, \boldsymbol{V}_j, \boldsymbol{W}_j, b_j(\boldsymbol{X}_h, \boldsymbol{V}_j, \boldsymbol{W}_j)\} \quad (2)$$

where $\boldsymbol{V}_j = (v_{j1}, v_{j2}, ...\ ..., v_{jn})$ is the min point of the jth fuzzy set hyperbox, $\boldsymbol{W}_j = (w_{j1}, w_{j2}, ...\ ..., w_{jn})$ is the max point of the jth fuzzy set hyperbox and the membership function of the jth fuzzy set hyperbox is $0 \le b_j(\boldsymbol{X}_h, \boldsymbol{V}_j, \boldsymbol{W}_j) \le 1$. The membership function in [25} is modified for the input defined in the MFMM as

$$b_j(\boldsymbol{X}_h, \boldsymbol{V}_j, \boldsymbol{W}_j) = \min_{i-1..n} \left(\min\left([1 - f(x_{hi} - w_{ji}, \gamma)],\right.\right.$$

$$\left.\left.[1 - f(v_{hi} - x_{ji}, \gamma)]\right)\right) \quad (3)$$

where $f(r,\gamma) = \begin{cases} 1 & \text{if } r\gamma > 1 \\ r\gamma & \text{if } 0 \le r\gamma \le 1 \\ 0 & \text{if } r\gamma < 0 \end{cases}$

is two parameter ramp threshold function and γ is the sensitivity parameter which decides how fast the membership values decrease outside the hyperbox fuzzy set.

4. MFMM NEURAL NETWORK

The MFMM neural network learning assumes that the labeled data set is available in advance during offline training. The learning algorithm is designed to train the network in the single pass. Section 4.1 gives details of MFMM neural network learning algorithm and section 4.2 describes the topology of the network constructed after learning.

4.1 MFMM Learning Algorithm

The proposed supervised learning approach removes the constraint on the maximum size of the hyperbox fuzzy sets during training and allows them to grow as per the need of the varying sizes of the classes that are present in the labeled data set. All the proposed changes lead to single pass training algorithm avoiding any adjustment of tuning parameter(s).

Likeoriginal FMM neural network [2], the learning algorithm consists of three steps; creation/expansion of the hyperboxes; overlap test; and contraction.

Creation/Expansion of the Hyperboxes: The training starts by picking up the labeled patterns from the data set one by one randomly and by making efforts to include it using hyperbox fuzzy set.

To include the input pattern $\{\boldsymbol{X}_h, d_h\}$, the hyperbox, B_j, belonging to the class of input pattern and giving maximum membership is found. The hyperbox min and max points are preserved if required by contraction step as

$$\boldsymbol{V}_j^{temp} = \boldsymbol{V}_j \quad \text{and} \quad (4)$$

$$\boldsymbol{W}_j^{temp} = \boldsymbol{W}_j \quad (5)$$

The hyperbox fuzzy set, B_j, is adjusted if required to include the input pattern as

$$v_{ji}^{new} = \min(x_{hi}, v_{ji}^{old}) \text{ for } i = 1, ..., \ n \quad (6)$$

$$w_{ji}^{new} = \min(x_{hi}, w_{ji}^{old}) \text{ for } i = 1, ..., \ n. \quad (7)$$

If no one from the existing hyperboxes belong to the class of the input pattern then the input pattern is included by creating the new hyperbox, B_k, , as

$$v_{ki}^{new} = w_{ki}^{new} = x_{hi} \quad \text{for} \quad i = 1, ..., \ n \quad \text{and} \quad (8)$$

$$class(B_k) = d_h. \quad (9)$$

Overlap Test: The expansion of the hyperbox fuzzy set in the previous step may result in the inclusion of patterns belonging to other class(s). The expanded hyperbox must contain the patterns belonging to the class of the hyperbox.

Unlike [2][3][25], in spite of checking the overlap amongst the hyperboxes belonging to different classes, a new approach is used to check and avoid the possibility of overlap. The overlap is present, if the hyperbox fuzzy set includes the patterns from other classes after expansion. Let B_j is the hyperbox expanded in the previous step and $\boldsymbol{X_p}$ is the pth pattern, such that, $d_p \neq class(B_j)$. For all patterns, such as $\boldsymbol{X_p}$, in a data set D, which are not belonging to the class of the expanded hyperbox, B_j, if

$$b_j(\boldsymbol{X}_p) \neq 1 \quad (10)$$

then overlap is absent. In such circumstances contraction is not needed. Therefore, the training continues with the next pattern from the data set.

Else the expanded hyperbox B_j has created the overlap and includes the patterns from other class. In the next step, this overlap is removed by contraction.

Contraction: The hyperbox B_j is restored as

$$\boldsymbol{V}_j = \boldsymbol{V}_j^{temp} \quad \text{and} \quad (11)$$

$$\boldsymbol{W}_j = \boldsymbol{W}_j^{temp}. \quad (12)$$

These three steps are used to include all the labeled patterns in the data set.

4.2 MFMM Neural Network Topology

Like original FMM in [2], the trained neural network consists of three layers; input layer, hyperbox nodes layer and class nodes layer. The nodes in the hyperbox nodes layer and the class nodes layer are constructed during training. The topology grows as learning continues.

The nodes in these layers do similar processing as in original FMM [2]. The input layer nodes do not do any processing. They simply forward the input to the output. The connections between input layer nodes and hyperbox nodes layer represent min and max points of the hyperboxes. Two matrices, **V** and **W**, are used to store these weights.

The hyperbox nodes use the fuzzy membership function as defined in equation (3) to deliver its output. The weights between hyperbox nodes layer and class nodes layer are binary as in [2]. The matrix **U** stores these weights.

Finally, the class nodes perform a union of outputs of appropriate hyperboxes belonging to that particular class to provide soft decision.

5 SIMULATION RESULTS

The performance of the MFMM have been tested on IRIS data set which is used in various clustering and classificationstudies. The data set is obtained from the machine learning repository of the Universityof California at Irvine [28]. Thisstorehouse also contains the details of many other the data sets with some information and experimental results.

The Fisher IRIS data set is very popular and there are numerous published results for a broad range of classificationtechniques. The IRIS data consists of 150 four-dimensional patterns and there are three separate classes of patterns, 50 patterns in each class.

In our performance evaluation, the experimental results have been restricted to the direct comparison between original FMM [2] and GFMM [5] algorithms. The algorithms in [2] and [5] have been tested in the identicalsetting for the same training and testing data, and the same orders of the input pattern presentations.

The experiments are performed by dividing the data set into two parts; training and testing set. In the first experiment training set was formed by 25 randomly selected patterns from each class. The remaining 75 patterns formed the testing set. Table 1 shows the comparison of FMM, GFMM with the proposed approach.

Table 1. Evaluation of FMM, GMM with MFMM

	Starting Θ	Number of Hyperboxes	Passes	Number of Misclassifications
FMM	0. 3	48	15	00
GFMM	0. 3	49	12	01
MFMM	-	48	01	01

Table 1 shows arbitrary starting value of Θ chosen for FMM and GFMM algorithms during training when we carried out our experimentation. How to choose initial value of Θ is a question and nobody has given clear guidelines for its adjustment. In FMM it is adjusted manually by trial and error by examining the present number of misclassifications after each training pass and doing further adjustments to reduce the number of misclassifications. This process of adjustment ends after reaching to a situation of zero misclassifications.

The GFMM suggests a way to decrease Θ adaptively after each pass during training. However, how to choose the initial value of Θ is ambiguous.Experiments are performed by varying Θ in complete range and best results obtained are noticed and published. The proposed approach as shown in Table 1 has removed this constraint of adjustment of tuning parameter, Θ, and requires only one pass for training.

In the next experiment all 150 patterns are used for training and testing. Similar results noted down are listed in Table 2. Table 2 demonstrates the strength of the MFMM learning algorithm. It is trained in single a pass and moreover, constructs less number of hyperboxes.

Table 2. Evaluation of FMM, GMM with MFMM

	Starting Θ	Number of Hyperboxes	Passes	Number of Misclassifications
FMM	0. 3	11	18	00
GFMM	0. 3	10	16	00
MFMM	-	09	01	00

6 CONCLUSIONS

This paper explains modified FMM neural network learning algorithm. Like the original FMM and GFMM algorithms, the hyperbox fuzzy sets are used for a representation of classes. The bound on the size of hyperboxes is removed. The learning requires only one pass to train the network. Therefore, in a true sense it allows inclusion of new datawithout the need for retraining and adjustment of tuning parameter(s) after every training pass.

The experimentation carried out reveals that the network is trained in a single pass and hence the proposed approach outperforms as far as training time is concerned. Moreover the trained network yields comparable results with less number of hyperboxes. However, the learning requirescompleteoffline data set in advance. Therefore, for real time classification further research is possibleby adapting the proposed approach by including the use of hyperline segments and so to make it suitable for online adaptation of data arising in real time.

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