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Efficacy of utilizing a hybrid algorithmic method in enhancing the functionality of multi-instance multi-label radial basis function neural networks

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A B S T R A C T

The facts show that multi-instance multi-label (MIML) learning plays a pivotal role in Artificial Intelligence studies. Evidently, the MIML learning introduces a framework in which data is described by a bag of instances associated with a set of labels. In this framework, the modeling of the connection is the challenging problem for MIML. The RBF neural network can explain the complex relations between the instances and labels in the MIMLRBF. The parameters estimation of the RBF network is a difficult task. In this paper, the computational convergence and the modeling accuracy of the RBF network has been improved. The present study aimed to investigate the impact of a novel hybrid algorithm consisting of Gases Brownian Motion Optimization (GBMO) algorithm and the gradient based fast converging parameter estimation method on multi-instance multi-label learning. In the current study, a hybrid algorithm was developed to estimate the RBF neural network parameters (the weights, widths and centers of the hidden units) simultaneously. The algorithm uses the robustness of the GBMO to search the parameter space and the efficiency of the gradient. For this purpose, two real-world MIML tasks and a Corel dataset were utilized within a two-step experimental design. In the first step, the GBMO algorithm was used to determine the widths and centers of the network nodes. In the second step, for each molecule with fixed inputs and number of hidden nodes, the parameters were optimized by a structured nonlinear parameter optimization method (SNPOM). The findings demonstrated the superior performance of the hybrid algorithmic method. Additionally, the results for training and testing the dataset revealed that the hybrid method enhances RBF network learning more efficiently in comparison with other conventional RBF approaches. The results obtain better modeling accuracy than some other algorithms.

1. Introduction

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Data classification methods play a key role in the analysis and interpretation of images. Generally speaking; the traditional data classification approaches assign a specific class to an image based on its global features. As frequently has been demonstrated, these approaches are functionally inadequate because they fail to cope with real-world problems. As a consequence, multi-instance multi-label framework develops a new and flexible learning model to handle this problem. This section aims to compare the overall features of MIML with other rival frameworks:

Multi-instance learning (MIL): This framework is a weakly supervised learning [1]. The input is represented by sets of bags and each bag is identified by a specific label. Characteristically, a bag will be considered to be positive if it contains at least one positive instance. It is claimed that MIL can handle the ambiguities existing in the input space. In fact, in the past decade, numerous algorithms have been proposed for training classifiers capable of handling problems like boosting algorithm [2], support vector machine (SVM) and neural networks. Additionally, the MIL framework has a wide spread application in computer vision such as object detection [2], tracking and classification [3].

Multi label learning (single-instance multi-label learning): The operational basis in multi-label learning consists of a set of labels assigned to a specific instance. In fact, each image is defined by an instance [4].

Traditional supervised learning (single-instance single-label learning): In this approach, an object is represented by an instance. The instance is a feature vector associated with a particular class label [5]. This framework has a limited scope and it cannot formulize many real-world problems. The reason is that objects consist of complex features may be assigned to multiple labels

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simultaneously. For this framework, algorithms such as decision trees, neural networks, *k*-nearest neighbor classifiers and support vector machines are used. As an illustration, an image may belong to several classes at the same time and such cross-classification prevents it from being represented by a single label.

Multi-instance multi-label learning (MIML): This is a learning framework which describes the training data by a bag of instances associated with a set of labels. This framework can satisfy a wider range of applications compared with other existing frameworks mentioned above. In facts, it can deal with many real-world learning problems. Here, a training image contains multiple patches or segments and each patch can be described by a feature vector; and the related image may belong to multiple classes. Apparently, the traditional supervised learning approach is a degenerated version of MIML; since each instance can only be described and represented by a single label. MIML has a few algorithms including RBF neural network [6]. Fig. 1 illustrates the algorithms.

MIMLBoost and **MIMLSVM** reduce the MIML problem to MISL and SIML problem respectively [7]. MIMLBoost uses MIBoosting [8] to solve MIL problem. These algorithms lose information during the reduction. MIMLSVM employs a cluster to map a bag of instances into a single instance. The clustered medoid solves the ML learning by utilizing MLSVM [9]. The **MIML-KNN** algorithm uses *k*-nearest neighbor method to make predictions which are based on the neighboring and citing examples [10]. The algorithm considers the correlation between instances and labels of MIML example and it is superior to MIMLSVM and MIMLBoost algorithms.

D-MIMLSVM transforms a single instance or single-label example into MIML learning [11]. The method is very useful when we cannot extract sufficient information of the real problems. The algorithm defines an objective function to balance the loss between the labels and predictions. This algorithm can achieve better performance in comparison with MIMLBoost and MIMLSVM algorithms. The **M^{3}MIML** algorithm can exploit the relation between the instances and labels using *a maximum margin method* [12]. The algorithm is faster than the MIMLBoost algorithm. The M^{3}MIML algorithm obtains superior performance compared with MIMLSVM and MIMLBoost.

Markov-MIML learning presents an efficient algorithm to reduce the computational cost for MIML learning [13]. The algorithm is a nearest neighbor approach to learn correct labels based on neighbor information as well as the affinities in a Markov chain. The MIML-KNN method determines *k* nearest neighbors of the unseen object and maximum posterior is used to calculate the label of object. The Markov chain enjoys the class probability of each object. It can spread through the neighbor during iterations to represent the importance of a set of labels to an object. The performance of Markov-MIML is better than M^{3}MIML for some evaluation metrics. Moreover, it is faster than M^{3}MIML and MIMLBoost.

The **MIMLNN** algorithm uses two layers of multilayer Perceptrons (MLPs) [14]. The back-propagation limits the performance of the algorithm. The gradient descent has several drawbacks such as the dependency of the error surface, the starting point and the tuning parameters. The **MIMLRBF** method uses radial basis function (RBF) neural networks to estimate the relationship between instances and labels [6]. The algorithm utilizes a *k*-medoids clustering for the examples of each class. In the first step, the clustering algorithm uses Hausdorff metric to measure the distance bags and the classes can be coded to the medoids. In the second step, the weights of second layer are optimized by a sum of square error function. The MIMLRBF method achieves poor performance when an imbalance problem appears in the number of samples in class. The M^{3}MIML only assumed linear models to solve the MIML learning problem while other nonlinear models such as RBF can handle the limitation.

The improved MIMLRBF (**IMIMLRBF**) neural network improves the MIMLRBF to handle this problem. The algorithm applies an improved k-medoids clustering on the dataset [15]. The cluster number can be calculated by the data density for each class. The IMIMLRBF take much more time than MIMLRBF, while the performance of algorithm is better than that of MIMLRBF for unbalanced samples. **EnMIMLNN** replaces the back-propagation neural network in MIMLNN with RBF [14]. The EnMIMLNN algorithm combines different distance metrics to determine the distance between the proteins. The algorithm achieves better performance than MIMLNN, MIMLBOOST and MIMLKNN.

MIML problem can be solved using a **Gaussian process**. The algorithm considers a likelihood function and covariance matrix to represent, simultaneously, the connection between the instances and each label as well as the correlation among labels [16]. The performance of the algorithm is better than MIMLRBF. The efficiency of the algorithm is weaker than MIMLRBF and MIMLSVM because the Gaussian process spends more time.

The MIML framework has been used successfully in a variety of applications including audio analysis, text categorization, bioinformatics [17] and computer vision. The video annotation task is inherently a MIML learning problem. As a matter of fact, the En-MIMLSVM is a new approach for the **video annotation** task [18]. The MIML learning is used for automatic tag recommendation and each **Web page** is divided into a bag of instances [19]. For automatic **object detection** tasks, a large number of training images are labeled by a multi-task multi-label multi-instance learning (MTML-MIL) [20].

The performance of RBF neural network depends on the center and the width of radical basis function and the weight values. The RBF neural network learning has significant drawbacks. It uses the results of the optimal solution to determine the structure parameters. In this section, a new hybrid search method is proposed to achieve better results for RBF model in the MIMLRBF. Our proposed algorithm is developed by the GBMO algorithm and the SNPOM method (GBM-SNPOM). In the search strategy, the search capability of GBMO and efficiency of the gradient search are exerted. The proposed algorithm applies the global search of GBMO and the fast convergence of SNPOM. In the same vein, the algorithm combines the fast convergence rate and strong global search capability which can improve speed of convergence, stability, and modeling accuracy of RBF. Therefore, in this paper, the GBM-SNPOM algorithm was used to optimize the RBF learning strategy. The purpose of training in the proposed algorithm is to determine the spread and centers of the nodes of hidden layer and the weights of the output layer. The spread and centers are nonlinear parameters and weights are linear parameters. Proper values are set for these training parameters of RBF with the GBMO algorithm. The parameters can be estimated by a fast convergence optimization. The nonlinear parameters are estimated by LMM; the LSM is used for linear optimization using SVD for weights estimation. The findings demonstrated the superior performance of the hybrid algorithmic method. Additionally, the results for training and testing the dataset revealed that the hybrid method enhances RBF network learning more effectively in comparison with conventional RBF approaches. In the same vein, better modeling accuracy was obtained considering the other algorithms.

The rest of this paper is organized as follows. Section 2 includes MIMLRBF structure and evolutionary algorithms. Section 3 introduces the architecture and the training phase of the proposed algorithm. In Section 4, the result of the scene and text datasets are reported. The last section includes the conclusions and suggestions for future research. The goals of the paper are listed as follows:

(1) Proposing a new hybrid algorithm by introducing a new training algorithm based on the GBMO and the SNPOM method.

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