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Learning of RBF network by using Teaching-Learning Based Optimization (TLBO) Algorithm

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Abstract: ***TLBO (Teaching - learning – based optimization) is a nature inspired optimization algorithm. There are many evolutionary algorithms like genetic algorithm, ant colony optimization, particle swarm optimization etc. All these algorithms depend on algorithmic parameters. A small change in these algorithmic parameters may cause a large change in the effectiveness of the algorithm. In this scenario TLBO is coming to picture. TLBO is independent of algorithmic parameters. TLBO follows the Teacher – Student and Student – Student interaction in the class room. TLBO have two phases, Teacher Phase and Learner Phase. The key feature of TLBO is, in the first stage algorithm attains average learning, in the second stage algorithm pick the best solution. In teacher phase, teacher is one of the learners among the population who has best knowledge level. Teacher tries to improve the mean knowledge level of class up to his level. When learners reached teacher's knowledge level, algorithm needs a new teacher with more knowledge. In the learner phase, learners interact with each other to improve their knowledge. This technique will be used in the learning of the parameters of the RBF network***

Keywords: ***ANN(Artificial Neural Network), RBFN(Radial Basis Function Network), TLBO***

1. Introduction

Finding global optimum of a function is the main task of many of the scientific application. In many cases these global optimization problems are non-differentiable. So solution for these problems cannot be finding by gradient based methods. To overcome these problems many modern heuristic algorithm have been developed for searching near optimum solution to the problem.All evolutionary and swarm intelligence based algorithms are probabilistic algorithms and require common controlling parameters, like population size and number of generations. Besides common control parameters, different algorithms require their own algorithm-specific control parameters. The proper tuning of the algorithm specific parameters is very crucial factor, which affect the performance of the above mentioned algorithms. The improper tuning of algorithm-specific parameters either increases the computational effort or yields the local optimal solution.

A new population-based evolutional algorithm named Teaching–Learning-Based Optimization (TLBO) algorithm introduced to overcome above mentioned problem, which is independent of algorithmic specific parameters. TLBO requires only common controlling parameters like population size and number of generations for its working. In this way TLBO can be said as an Algorithm-specific parameter-less algorithm.

A radial basis function (RBF) network is an artificial neural network that uses radial basis functions as activation functions. The output of the network is a linear combination of radial basis functions of the inputs and neuron parameters. A radial basis function (RBF) is a real-valued function whose value depends only on the distance from the origin, so that; or alternatively on the distance from some other point c, called a center, so that any function that satisfies the property is a radial function.

2. Artificial Neural Networks

Artificial Neural Networks are relatively crude electronic models based on the neural structure of the brain. The brain basically learns from experience. ANN is made up of interconnecting artificial neurons which are programmed like to mimic the properties of m biological neurons. These neurons working in unison to solve specific problems. Single feed-forward or acyclic network, Multi layer feed forward network, Recurrent network, Radial basis function network etc are different ANN types. There are many different algorithms that can be used when training artificial neural networks. Supervised learning, Unsupervised learning and Reinforcement learning are the mainly used algorithms for learning process in ANN. These conventional learning techniques are suitable for small dataset and it is not a suitable technique for large dataset in terms of processing time and efficiency. It doesn't provide optimized learning.

A survey on different neural network types, Rehan et al. [18] says RBF can model any nonlinear function using a single hidden layer, which removes some design-decisions about numbers of layers. Mustafa et al. [11] used both MLFF and RBF for prediction of suspended sediment discharge in river, a case study for compare the neural network concluded the RBF network model provided slightly better results than the MLFF network model in predicting suspended sediment discharge**.** Hao Yu et al. [12] did a comparison of different neural network for digital image recognition, it results, from the point of generalization ability, RBF networks perform much better than traditional backpropagation networks. Amrita Biswas et al. [13] in their comparison of different neural network architectures for classification of feature transformed data for face recognition says the training time of RBFN are significantly less than feed forward neural networks.

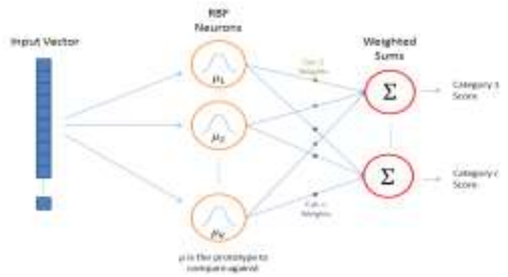

Figure 1: RBF network architecture

Radial basis function (RBF) networks are feed-forward networks trained using a supervised training algorithm. They are typically configured with a single hidden layer of units whose activation function is selected from a class of functions called basis functions. The structure of an RBF networks in its most basic form involves three entirely different layers.

The input vector is the *n*-dimensional vector that you are trying to classify. The entire input vector is shown to each of the RBF neurons.

Each RBF neuron stores a "prototype" vector which is just one of the vectors from the training set. Each RBF neuron compares the input vector to its prototype. The neuron's response value is also called its "activation" value. The prototype vector is also often called the neuron's "center".

The output of the network consists of a set of nodes, one per category that we are trying to classify. Each output node computes a sort of score for the associated category. Typically, a classification decision is made by assigning the input to the category with the highest score.

3. Training the RBFN

The training process for an RBFN consists of selecting three sets of parameters: the prototypes (mu) and beta coefficient for each of the RBF neurons, and the matrix of output weights between the RBF neurons and the output nodes

Selecting The Prototypes: Here we used K means clustering algorithm to select prototype vector for each neuron

Selecting Beta Values: If we use k-means clustering to select your prototypes, then one simple method for specifying the beta coefficients is to set sigma equal to the average distance between all points in the cluster and the cluster center.

$$\sigma = \frac{1}{m}\sum_{i=1}^{m} ||x_i - \mu||$$

Here, mu is the cluster centroid, m is the number of training samples belonging to this cluster, and x_i is the ith training sample in the cluster.

Once we have the sigma value for the cluster, we compute beta as

$$\beta = \frac{1}{2\sigma^2}$$

Output Weights: The final set of parameters to train are the output weights. These can be trained using gradient descent (also known as least mean squares).

Conventional learning techniques not suitable for large and multi dimensional dataset. It is difficult to find the global optima by these techniques, it falls on local minima. Here the nature inspired, population based algorithms like evolutionary and swarm intelligence algorithms are coming into picture. Tuba Kurban et al. [14], observed in their comparison of RBF neural network training algorithm for inertial sensor based terrain classification, conventional algorithms like gradient descent and Kalman filtering (both are derivative based) have some weakness such as converging to a local minima and time-consuming process of finding the optimal gradient. Salman Mohaghehi et al. [15], compared PSO and back propagation algorithm for training RBF neural networks for identification of a power system with statcom, concluded PSO algorithm has shown to have several advantages, both in terms of robustness and the efficiency in finding the optimal weights for the RBFN neuroidentifier. The computational effort is comparable and even less significant than in the case of back propagation. Sultan Noman et al. [20], proposes RBF Network hybrid learning with Particle Swarm Optimization (PSO) for better convergence, error rates and classification results.

4. Teaching–Learning-Based Optimization (TLBO)

The TLBO method is based on the effect of the influence of a teacher on the output of learners in a class. Here, output is considered in terms of results or grades. The teacher is generally considered as a highly learned person who shares his or her knowledge with the learners. The quality of a teacher affects the outcome of the learners. It is obvious that a good teacher trains learners such that they can have better results in terms of their marks or grades.

TLBO is based on traditional teachers learners process in the class room. Assume two different teachers, T1 and T2, teaching a subject with the same content to the same merit level learners in two different classes. Figure 2 shows the distribution of marks obtained by the learners of two different classes evaluated by the teachers. Curves 1 and 2 represent the marks obtained by the learners taught by teacher T1 and T2 respectively.

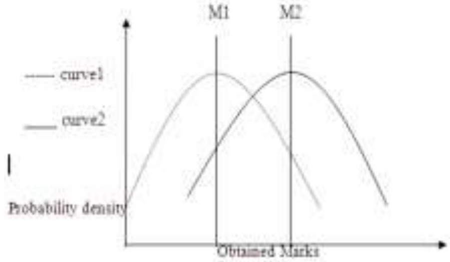

Figure 2: Distribution of marks obtained by learners taught by two different teachers

The normal distribution is defined as

$$f(x|\mu,\sigma) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$$

Where σ^2 is the variance, μ is the mean and x is any value for which the normal distribution function is required.

In the figure Figure 2, curve-2 shows better results than curve-1 and we can say that teacher T2 is better than teacher T1 with respect to teaching. The main difference between both the results is their mean (M2 for Curve-2 and M1 for Curve-1), i.e. a good teacher make a better mean for the results of the learners. Learners also learn from interaction between themselves, which also helps in their results.

Based on the above teaching process, a mathematical model is prepared and implemented for the optimization of a unconstrained non-linear continuous function, thereby developing a novel optimization technique called Teaching–Learning-Based Optimization (TLBO).

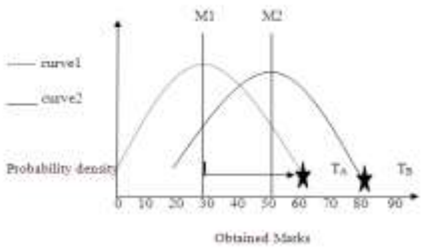

Figure 3: Model for the distribution of marks obtained for a group of learners

In the above figure Figure 3, it shows a model for the marks obtained for learners in a class with curve-A having mean M_A. The teacher is considered as the most knowledgeable person, so the best learner is mimicked as a teacher, here T_A is considered as teacher. The teacher is tries to spread knowledge among learners, which will increase the knowledge level of the whole class. So a teacher increases the mean of the class according to his or her capability. In the figure teacher T_A moves the mean M_A towards his level of knowledge. The new mean will be M_B. Teacher TA will put maximum effort into teaching his or her students, but students will gain knowledge according to the quality of teaching delivered by a teacher and the quality of students present in the class. The quality of the students is judged from the mean value of the population. Teacher TA puts effort in so as to increase the quality of the students from M_A to M_B, at which stage the students require a new teacher, of superior quality than themselves, i.e. in this case the new teacher is TB. Hence, there will be a new curve-B with new teacher TB.

Like other nature-inspired algorithms, TLBO is also a population based method that uses a population of solutions to proceed to the global solution. For TLBO, the population is considered as a group of learners or a class of learners. In optimization algorithms, the population consists of different design variables. In TLBO, different design variables will be analogous to different subjects offered to learners and the learners' result is analogous to the 'fitness', as in other population-based optimization techniques. The teacher is considered as the best solution obtained so far.

The process of TLBO is divided into two parts. The first part consists of the 'Teacher Phase' and the second part consists of the 'Learner Phase'. The 'Teacher Phase' means learning from the teacher and the 'Learner Phase' means learning through the interaction between learners

Teachers Phase

This phase of the algorithm simulates the learning of the students (i.e. learners) through the teacher. During this phase, a teacher propagates knowledge among the learners and makes an effort to increase the mean result of the class. Since a teacher is the most experienced and knowledgeable person on a subject, the best learner in the entire population is considered as teacher. The teacher will put maximum effort into increasing the knowledge level of the whole class, but learners will gain knowledge according to the quality of teaching delivered by a teacher and the quality of learners present in the class.

Let M_i be the mean and T_i be the teacher at any iteration i. T_i will try to move mean M_i towards its own level, so now the new mean will be T_i designated as M_{new}. The solution is updated according to the difference between the existing and the new mean given by

$$\text{Difference\_Mean}_i = r_i\,(M_{new} - TF\,M_i) \qquad (5.2)$$

Where TF is the teaching factor, which decides the value of mean to be changed, and r_i is the random number in the range [0, 1]. The value of TF can be either 1 or 2. The value of TF is decided randomly with equal probability as:

$$TF = \text{round}[1 + \text{rand}(0, 1)\{2 - 1\}] \qquad (5.3)$$

This difference modifies the existing solution according to the following expression

$$X_{new,i} = X_{old,i} + \text{Difference\_Mean}_i. \qquad (5.4)$$

It may be noted that the values of r_i and TF affect the performance of the TLBO algorithm. r_i is the random number in the range [0, 1] and TF is the teaching factor. However, the values of r_i and TF are generated randomly in the algorithm and these parameters are not supplied as input to the algorithm (unlike supplying crossover and mutation probabilities in GA, inertia weight and cognitive and social parameters in PSO, and colony size and limit in ABC, etc.). Thus, tuning of ri and TF is not required in the TLBO algorithm (unlike the tuning of crossover and mutation probabilities in GA, inertia weight and cognitive and social parameters in PSO, and colony size and limit in ABC, etc.). TLBO requires tuning of only the common control parameters, like population size and number of generations, for its working, and these common control parameters are required for the working of all population based optimization algorithms. Thus, TLBO can be called an algorithm-specific parameter-less algorithm.

Learners Phase

Learners increase their knowledge by two different means: one through input from the teacher and the other through interaction between themselves. A learner interacts randomly with other learners with the help of group discussions, presentations, formal communications, etc. A learner learns something new if the other learner has more knowledge than him or her. Learner modification is expressed as

Algorithm for Learners Phase

For i = 1 : P_n

Randomly select two learners X_i and x_j, where i not equal to j

If f (x_i) < f (X_j)

$X_{new,i} = X_{old,i} + r_i(X_i - X_j)$

Else
$X_{new,i} = X_{old,i} + r_i(X_j - X_i)$
End If
End For
Accept $X_{new,i}$ if it gives a better function value.

5. Integrating TLBO in RBFN Learning

There are three learning parameters in RBF, the Center of neuron (one of the training example), the **'β'** values which are derived from the standard deviation **'σ'** and the weights between hidden and output layer. The first parameter find by using K-Means clustering algorithm. And our intention is to implement Teachers Learners based optimization technique (TLBO) in learning process of **'β'** value, which makes good performance improvement in the output prediction.

We used error sum of squares function as cost function for TLBO to find beta values. This is through the standard deviation,' **σ'**.

$$\beta = \frac{1}{2\sigma^2}$$

6. Experiments

The experiments conducted on classification problems obtained from UCI repository to compare the performance of RBF network trained by using TLBO with RBF network trained by gradient descent. The benchmark datasets used to evaluate the performance are Indian Liver Patient dataset, and Blood Transfusion Service Center dataset

Experiment 1- Indian Liver Patient Dataset

This data set contains 416 liver patient records and 167 non liver patient records. This data set has 10 input attributes and one class attribute. The input attributes are Age of the patient, Gender of the patient, Total Bilirubin(TB), Direct Bilirubin (DB), Alkaline Phosphotase (Alkphos), Alamine Aminotransferase (sgpt), Aspartate Aminotransferase (sgot), Total Protiens (TP), Albumin (ALB) and Albumin and Globulin Ratio (A/B Ratio). The class label used in this dataset is 'Selector' which classify the dataset into groups (liver patient or not).

Table 1: Statistical PCCS results of Indian Liver Patient Dataset

Sl No	No of test instances classified correctly with Gradient descent out of 175 test dataset	No of test instances classified correctly with TLBO out of 175 test dataset	Testing Accuracy with Gradient Descent (PCCS)	Testing accuracy with TLBO (PCCS)
1	122	125	69.7	71.4

When applying Gradient Descent as learning technique, RBF network classified 122 test instances correctly out of 175 test instances with a 69.7% testing accuracy. But after applying TLBO as learning technique RBF classify 125 out of 175 test instances correctly with 71.4% test accuracy. Table 1 shows performance of RBF with TLBO is better than that of Gradient descent.

Experiment 2- Blood Transfusion Service Center

Blood Transfusion Service Center dataset contains total 748 records. This data set has 5 attributes. The first four attributes are input attributes, they are Recency - months since last donation (R), Frequency - total number of donation (F), Monetary - total blood donated in c.c (M) and Time - months since first donation (T). The last attribute is class label which classify the dataset into two categories by checking the person donated blood in the particular date.

Table 2: Statistical PCCS results of Blood Transfusion Service Center Dataset

Sl No	No of test instances classified correctly with Gradient descent out of 224 test dataset	No of test instances classified correctly with TLBO out of 224 test dataset	Testing Accuracy with Gradient Descent (PCCS)	Testing accuracy with TLBO (PCCS)
1	174	182	77.7	81.3

RBF network with Gradient Descent learning technique classify 174 instances from 224 test data correctly with a 77.7% PCCS, but TLBO technique classify 182 instances from the same data with an 81.3% PCCS. Table 2 shows performance of RBF with TLBO is better than that of Gradient descent.

7. Conclusion and Future Work

Conclusion

In this paper an attempt made to increase the performance of Radial Basis Function Network for classification problems with a new evolutionary technique - Teachers Learners Based Optimization Technique. Traditional techniques are showing lesser performance in prediction of class variable. Even the other evolutionary techniques lacks the performance due to, these algorithms are dependent on its own specific algorithmic parameters. The TLBO technique is independent of these algorithmic specific parameters and produce good performance for classification problems. This paper proposed implementation of TLBO to find the second learning parameter of RBFN, the beta value.

Future Work

The future work, this paper proposed is to implement TLBO for finding the third parameter, the weight between hidden and output layer. It may again improve the performance of the network.

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