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A Survey on Study of Various Machine Learning Methods for Classification

S. Padma[1] and R. Pugazendi[2]

[1]Research Scholar
[1]Research & Development Centre, Bharathiar University, Coimbatore-641 046, Tamilnadu
[2]PG & Research Dept of Computer Science
Govt. Arts College (Autonomous,) Salem-7
[1]padmacde@gmail.com

Abstract

This article comprises a review of various sequential algorithms. The review represents the working nature of the learning methods. It also includes the methods such as Minimal Resource Allocation Network (MRAN), Extreme Learning Machine (ELM), Self-regulated Resource Allocation Network (SRAN) and Meta-Cognitive Neural Network (MCNN) for real –valued neural network. Projection Based Learning with Meta-Cognitive Radial Basis Function Network (PBL-McRBFN) for complex valued neural network. Finally about Meta-Cognitive Fuzzy Inference System (MCFIS) using the Neuro - Fuzzy inference system for learning. The previously said SRAN works on the basis of self – regulatory mechanism in order to reduce the huge loss error and to maximize the class – wise significance. The methods such as MCNN, PBL-McRBFN and MCFIS execute on the human learning strategies such as what – to-learn, when –to-learn and how –to – learn. This review helps to select the learning methods suitable for the data that is to be classified.

Keywords: *Neural Network, learning, neural network, cognitive, sequential*

1. Introduction

Neural networks are important for data classification. Data classification is an essential need in all the fields. The classification through neural network can be done either by sequential learning or batch learning. In batch learning the entire training data set divided into batches and allowed for learning, the batch learning methods require the entire training data must be executed more number of times in order to reduce the approximation errors. This type of learning requires more memory and time as the entire training data is required for execution.

Single Layer Feed forward Network (SLFNs) randomly chooses input weights and hidden layer biases. The hidden nodes in SLFN can be called random hidden nodes. All the parameters with regards to SLFN need to be tuned. To overcome this various sequential algorithms were defined.

Sequential learning algorithms can also be employed for classifying the data. The sample enters the network architecture one – by –one and the samples are discarded after the learning process. The sequential learning algorithms do not need the network architecture to be fixed apriori. The network is build during the training process by adding and pruning the neurons. The updating of the network parameters can be done using the Extended Kalman Filter (EKF). Sequential learning algorithm requires less memory and computation time compared to batch learning algorithms. Error minimization is possible

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as the training data are entered into the architecture sequentially. Streams of data can be used in the architecture of effective classification.

The sequential algorithm in the neural network retrieves knowledge about the information contained in the stream of data by using all the samples in the training data set. The existing sequential algorithm operates on distributing uniformly the sample in the input space. By learning all the samples in the training data set may result in over – training of the sample in the densely populated region of the input space. The sequential learning algorithm strategies can be combined with human information processing abilities such as perception, learning, remembering, judging and problem – solving which are cognitive in nature. The learning process can be made effective when the learners do self – regulation in the learning using Meta – cognition.

Meta –cognition means cognition about cognition. In the meta – cognitive frame work the leagues think about the cognitive component and improve it by developing new strategies using the input data. Extending the principles of self – regulation in a meta – cognitive frame work is an important aspect to develop efficient machine learning algorithms.

A group of sequential learning algorithm has been developed based on human meta-cognition modeled by Nelson. This algorithm addresses what –to-do –learn, when –to – learn and how –to –learn in a Meta –cognitive frame work. It has been show in the iterative manner that these algorithms perform better than other sequential learning algorithms with better generalization ability.

Various sequential learning algorithms are available for better classification for real – valued neural network, complex – valued neural network and neuro – fuzzy inference system.

2. Methods

2.1. MRAN

The first sequential learning algorithm using the framework of radial basis function network was the resource allocation network (RAN). The disadvantages of RAN have been overcome by Minimal Resource Allocation Network (MRAN). The network is initiated with zero hidden units. When the training samples enter the network some of them are added as hidden neurons. Pruning strategy is followed to remove the inactive hidden neurons from the network so as to improve the classification performance. Normalized hidden values are sent to the output layer for classification. Pruning of data helps to avoid over fitting.

2.2. ELM

ELM was originally proposed (Huang) for standard single hidden layer feed forward neural networks (with random hidden nodes (random features)). ELM can be used for both batch as well as sequential learning methods. This can also be used for multi classification as well as regression. The architecture comprises of three layers namely the input layer, hidden layer and the output layer. The numbers of hidden nodes are less than the training samples. The parameters of the hidden nodes are assigned randomly. Different activation functions are used in the hidden layer for better approximation. The weights required for the activation functions are tuned automatically. This method provides better classification in unexpected time.

2.3. SRAN

A sequential learning algorithm has control parameters that are self-regulated. This helps to avoid the over-training of the input data. To approximate the decision function in an effective way the algorithm uses to explicit misclassification error and hinge loss function in growing/learning criteria. The network structure is efficient as it is built upon fewer neurons that are self-regulated with the control parameters.

In the sequential algorithm the data enters one-by-one and the network structure is controlled by the growing criteria, the classified neurons are removed by the deletion criteria, using the Extended Kalman Filter (EKF) the network parameters are updated to learn the neurons.

2.4. MCNN

MCNN is a classifier that is capable of deciding what-to-learn, when-to-learn and how-to-learn the decision functions from the training data. It has two components namely the cognitive component and the meta-cognitive component. The cognitive component has three layers, the input layer maps all features to the hidden layer without doing any transformation. Gaussian activation function is employed in the hidden layer whereas linear activation function is used in the output layer for approximating the decision function.

The meta -cognitive component uses the following measures to retrieve knowledge from the training samples. The measures are class label estimation, maximum hinge error, confidence of classifier and class-wise significance. Using these measures together with the principles of self-regulated human learning the training samples are learnt. The learning strategies are sample delete strategy, neuron growth strategy, parameter update strategy and sample reserve strategy.

2.5. PBL –McRBFN

Projection based learning (PBL) using the Meta –cognitive principles perform well for classification. The working starts with zero hidden neurons and adds neurons for learning to obtain a best network structure. The cognitive component is a radial basis function network which employs Gaussian activation function in the hidden layer. The basic principle of PBL is to minimize the error by hinge loss and (to) define an optimal network structure.

The Meta – cognitive component monitors the cognitive component. The measures of knowledge such as predicted class label, maximum hinge loss, confidence of classifier and class–wise significance is derived using the new training samples. It also has four learning strategies namely sample delete strategy, neuron growth strategy, parameters update strategy and sample reserve strategy. With the self- regulated measures, learning strategies combined with the basic principle of learning what – to –learn, how – to- learn and when –to-learn the classifier performs well.

2.6. McFIS

McFIS is a sequential learning classifier which consists of two basic components. Normally Meta–cognitive neural network contains cognitive component and Meta – cognitive component. In McFIS the neuro- fuzzy inference system acts as the cognitive component. The neuro – fuzzy inference system is employed using the following layers such as input layer, Gaussian layer, normalization layer and output layer.

The role of the meta – cognitive component is to determine the rules and its corresponding parameters by controlling what–to-learn, when –to-learn and how –to – learn in a neuro – fuzzy inference system. The algorithm is controlled by the strategies namely sample deletion, sample learning and sample reserve.

3. Data Sets and Applications

The dataset used for classification can be balanced dataset or imbalanced dataset. Balanced dataset will have samples of equal number for all classes whereas imbalanced dataset will contain samples with unequal numbers for the classes. While training a dataset the balanced dataset provides better result when compared to the imbalanced dataset. It has been proved by all the above said sequential algorithms.

3.1. Applications of Sequential Algorithms

The various sequential algorithms discussed above have been applied in different fields to represent its efficiency. Being unique from its working nature the algorithms proved its betterment. Theses algorithms were applied in various benchmark datasets with different evaluation methods of classifier to prove it.

3.2. Applications of MRAN

Using the pruning strategy the network is built with minimal number of neurons. This helps to avoid the growth of the network with unused neurons. Being a foremost sequential algorithm it has been applied in numerous fields. Congestion control in the ATM networks is well handled by this algorithm. [3] Simulator for a chemical industry using MRAN is also proved. [1] Controlling of aircraft using neurons also applied using MRAN. [2] Besides this it also applied for signal processing [4].

3.3. Applications of ELM

A fast sequential learning algorithm proved its efficiency in various fields. Medical field includes data with high dimensional features. More or less all the existing machine algorithms have been executed in this field. The improved classified efficiency is proved in [5-9].It also proves its betterment in the field of image processing by generating high resolution images from low resolution input [3,10-11].ELM also entered in the field of system modeling and prediction [12-13].

3.4. Applications of SRAN

A sequential algorithm with concepts of pruning, avoiding over fitting, reduction of error rate is applied to produce effective classification in various fields. It has been applied in the medical datasets where data are with huge dimension. It has been applied in various fields such as flight controller for an Aircraft *etc.* [14-15].

3.5. Applications of MCNN

A meta – cognitive neural network which makes the machine to learn about the samples well and classify the data based on the learnt features. It has been applied in various fields such as developing a simulator for medical diagnostics, image processing *etc.*

3.6. Applications of PBLMcRBFN

Projection based learning with the concept of meta cognitive performs well. It has been applied in various fields such as for medical diagnostics, image processing *etc.* [18].

3.7. Applications of McFIS

Meta cognitive learning with the fuzzy inference system hopes to provide better result when compared to other sequential algorithms. It has been applied in various fields such as developing a simulator for medical diagnostics, image processing *etc.* [16-17, 19].

4. Summary

Table 1. Merits and Demerits of Algorithms

S.No	Method	Merits	Demerits
1	MRAN	• Pruning of samples to build a network with minimal number of neurons	• Time taken for learning is more • Learning efficiency is low
2	ELM	• Fast learning algorithm • Input parameters are chosen randomly	• Randomness causes uncertainty problems • Generalization Degradation
3	SRAN	• Self regulated control parameters • Pruning of samples to avoid overtraining	• Knowledge gained from past samples are not used for further learning • Usage of EKF for parameter updation
4	MCNN	• Learning based on what-to-learn, when-to-learn and how-to-learn.	• Usage of EKF for parameter update
5	PBL-McRBFN	• Generalization of self-regulatory learning using meta-cognitive components	• Time taken for learning is moderate
6	McFIS	• Uses self- organized rule generation	• Time taken for learning is moderate

The above Table 1 summarizes the merits and demerits of the machine learning algorithms taken for discussion.

5. Conclusion

This article describes the working nature of different machine learning algorithms such as Minimal Resource Allocation Network (MRAN), Extreme Learning Machine (ELM), Self-regulated Resource Allocation Network (SRAN), Meta-Cognitive Neural Network (MCNN), Projection Based Learning with Meta-Cognitive Radial Basis Function Network (PBL-McRBFN) and Meta-Cognitive Fuzzy Inference System (MCFIS) with its applications in various fields. It also explicates the merits and demerits of the algorithms. Every algorithm has its novelty which distinguishes one from the other. Some algorithms utilize the pruning strategy which removes the samples from overtraining. Random selection of parameters is done in ELM to improve the execution time. Self – regulatory learning is applied to improve the classification efficiency with reduction of error rate. Human learning methods are employed in MCNN, PBL-McRBFN and McFIS. Projection based learning is integrated with meta-cognitive learning to generalize the learning. Fuzzy Inference system has been incorporated with meta-cognition for better learning.

6. Research Direction

The existing algorithms have proved its efficiency on specified datasets. It has been observed that there is no concrete method for effective classification. To improve the efficiency of classification, meta-cognitive components shall be combined with any of the existing algorithms. Also the above said algorithms are applied to limited fields which can be extended to various areas especially in feature extraction, feature selection, big data *etc*.

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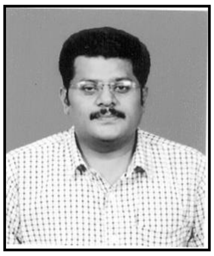
Authors

Ms. S. Padma, MCA., M. Phil., M. E., is a research scholar of Bharathiar University, Coimbatore under part time category-B. She has published 3 papers in International Journals. She has presented 7 papers in International conferences and 10 papers in national conferences. Her areas of interest are Data Mining and Machine Learning.



Dr. R. Pugazendi, M.Sc., M.Phil., M.E., PhD is currently working as Asst Prof in the Department of Computer Science(PG) in Govt Arts College, Salem.-7. He is having 21 years of teaching experience. He is guiding 4 PhD students. He has guided 5 M.Phils in the area of Computer Science in addition to guiding 5 Students for M.Phil. He has also guided more than 100 MCA/MSc students in the area of Computer Science and Applications. He has published 24 papers in International Journals and 3 books. He has presented research papers in 5 International Conferences and 9 National Conferences. His areas of interest are Software Engineering, Network Monitoring, Analysis of Algorithms and Data Mining.