

Incremental Neural Network Training for Medical Diagnosis

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INTRODUCTION

Artificial intelligence has attracted many researchers in recent years for its usefulness in the medical field. With the increase in research interest, artificial intelligence systems have found widespread usage in the medical domain (Remzi & Djavan, 2004; Tsakonas, Dounias & Jantzen, 2004). These applications arise as medical datasets usually contain a high volume of data, and it is very costly for human manual analysis and handling. The intelligent systems possess the ability to process datasets, extract useful information from them, and interpret the data at a much lower cost (Raymer, Doom, Kuhn & Punch, 2003) as compared to the manual handling. Intelligent systems like evolutionary computing, fuzzy logic, and neural networks are just some that many researchers have recently looked into.

Neural network has been used in the medical field to a great extent (Hayashi & Setiono, 2002) and more noticeably for classification problems (Abbass, 2002), since more frequently the outcome of the medical diagnosis is to categorize the patient into the different classes. The conventional method of neural network training for medical diagnosis is to present all the input attributes together as a batch at the same time to the neural network. However, some input attributes are more important and contain a higher consideration factor than others, and the criteria that each attribute uses for classification is also different. If all inputs are presented as a batch at the same time, trouble arises easily if there is interference among them. Thus, if all the input attributes are trained together in a batch,

each attribute will interfere in the decision-making of others.

The input feature space and architecture of the output layer has proved to be a factor affecting the performance of neural network (Guan & Li, 2002a; Guan & Li, 2002b; Guan & Li, 2004; Guan, Li, & Qi, 2004). Input data space clustering techniques were applied in neural networks studies (Plikynas, 2004; Sun & Peterson, 1999). Sun and Peterson (1999) partitioned the input space into different regions and applied differential weighting for different regions so they have different agents that specialize in local regions. However, to date, little work has been reported to investigate the interference of the input attributes and, inferring from the information, to devise a carefully designed feature-partitioning algorithm.

This chapter proposes a novel method of incremental interference-free neural network training (IIFNNT) for medical datasets, which takes into consideration the interference each attribute has on the others. A specially designed network is used to determine if two attributes interfere with each other, after which the attributes are partitioned using some partitioning algorithms. These algorithms make sure that attributes beneficial to each other are trained in the same batch, thus sharing the same subnetwork while interfering attributes are separated to reduce interference. There are several incremental neural networks available in literature (Guan & Li, 2001; Su, Guan & Yeo, 2001). The architecture of IIFNNT employed some incremental algorithm: the ILIA1 and ILIA2 (incremental learning with respect to new incoming attributes) (Guan & Li, 2001).

This chapter is divided into five sections. The next section describes the incremental neural networks used in the IIFNNT. In Section 3, the method to evaluate interference between two attributes and the interference-free attribute partitioning algorithm is presented. The results of experiments on a diabetes medical dataset are given and analyzed in Section 4, together with a comparison to other related work in literature. The conclusion of our research, together with suggestions for future work, is given in Section 5.

Incremental Neural Networks Used

As mentioned earlier, the architecture of IIFNNT is based on the incremental algorithm ILIA (Guan & Li, 2001). When additional input attributes are considered, the ILIA expands its input space to accommodate these new attributes. The architecture of the ILIA algorithms from Guan and Li (2001) is described here.

ILIA1

The existing available attributes are first presented to the network, as shown in Figure 1. Network consists of direct connections from all the input units to all the output units. All input units are connected to all the hidden units. All the hidden units are also connected to all output units. The ILIA used the Constructive Backpropagation Learning algorithm (Lehtokangas, 1999) to train the weights and to determine the number of hidden neurons needed for its network. After the

weights of the network have been trained, they are fixed and no longer changed.

When there are new attributes to be considered, increase the input dimension to accommodate the new attributes and a new subnetwork (in terms of new direct connections and new hidden units) is added to the existing network. The newly formed neural network architecture is shown in Figure 2. The process of adjusting the weights and installing new hidden units is done only for the new subnetwork.

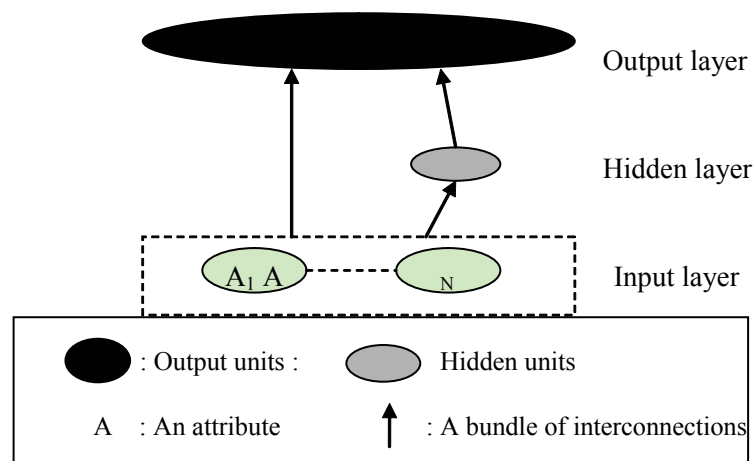
ILIA2

An extension to ILIA1 is also given in Guan and Li (2001). In ILIA2 (Figure 3), new output units are added to the neural network obtained in ILIA1. The number of new output units is equal to the number of output units in ILIA1. Thus, with new output units being added to the neural network obtained in ILIA1, the output units in ILIA1 are being collapsed and have effectively become a new hidden layer.

INTERFERENCE-FREE NEURAL NETWORK

There are several steps needed to form the interference-free neural network. The steps will be broken down and the major ones presented in the following subsections. An example using the diabetes dataset will also be used along the way to illustrate the method.

Figure 1. Initial network



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