IDEA GROUP PUBLISHING
701 E. Chocolate Avenue, Hershey PA 17033-1240, USA
Tel: 717/533-8845; Fax 717/533-8661; URL-http://www.idea-group.com
ITB8616

Chapter I

Designing Neural Network Ensembles by Minimising Mutual Information

Yong Liu
The University of Aizu, Japan

Xin Yao
The University of Birmingham, UK

Tetsuya Higuchi
National Institute of Advanced Industrial Science and Technology, Japan

ABSTRACT

This chapter describes negative correlation learning for designing neural network ensembles. Negative correlation learning has been firstly analysed in terms of minimising mutual information on a regression task. By minimising the mutual information between variables extracted by two neural networks, they are forced to convey different information about some features of their input. Based on the decision boundaries and correct response sets, negative correlation learning has been further studied on two pattern classification problems. The purpose of examining the decision boundaries and the correct response sets is not only to illustrate the learning behavior of negative correlation learning, but also to cast light on how to design more effective neural network ensembles. The experimental results showed the decision boundary of the trained neural network ensemble by negative correlation learning is almost as good as the optimum decision boundary.

INTRODUCTION

In single neural network methods, the neural network learning problem is often formulated as an optimisation problem, i.e., minimising certain criteria, e.g., minimum error, fastest learning, lowest complexity, etc., about architectures. Learning algorithms, such as backpropagation (BP) (Rumelhart, Hinton & Williams, 1986), are used as optimisation algorithms to minimise an error function. Despite the different error functions used, these learning algorithms reduce a learning problem to the same kind of optimisation problem.

Learning is different from optimisation because we want the learned system to have best generalisation, which is different from minimising an error function. The neural network with the minimum error on the training set does not necessarily have the best generalisation unless there is an equivalence between generalisation and the error function. Unfortunately, measuring generalisation exactly and accurately is almost impossible in practice (Wolpert, 1990), although there are many theories and criteria on generalisation, such as the minimum description length (Rissanen, 1978), Akaike's information criteria (Akaike, 1974) and minimum message length (Wallace & Patrick, 1991). In practice, these criteria are often used to define better error functions in the hope that minimising the functions will maximise generalisation. While better error functions often lead to better generalisation of learned systems, there is no guarantee. Regardless of the error functions used, single network methods are still used as optimisation algorithms. They just optimise different error functions. The nature of the problem is unchanged.

While there is little we can do in single neural network methods, there are opportunities in neural network ensemble methods. Neural network ensembles adopt the divide-and-conquer strategy. Instead of using a single network to solve a task, a neural network ensemble combines a set of neural networks which learn to subdivide the task and thereby solve it more efficiently and elegantly. A neural network ensemble offers several advantages over a monolithic neural network. First, it can perform more complex tasks than any of its components (i.e., individual neural networks in the ensemble). Secondly, it can make an overall system easier to understand and modify. Finally, it is more robust than a monolithic neural network and can show graceful performance degradation in situations where only a subset of neural networks in the ensemble are performing correctly. Given the advantages of neural network ensembles and the complexity of the problems that are beginning to be investigated, it is clear that the neural network ensemble method will be an important and pervasive problem-solving technique.

The idea of designing an ensemble learning system consisting of many subsystems can be traced back to as early as 1958 (Selfridge, 1958; Nilsson, 1965). Since the early 1990s, algorithms based on similar ideas have been developed in many different but related forms, such as neural network ensembles

Related Content