

Chapter VI

Fast Learning in Neural Networks

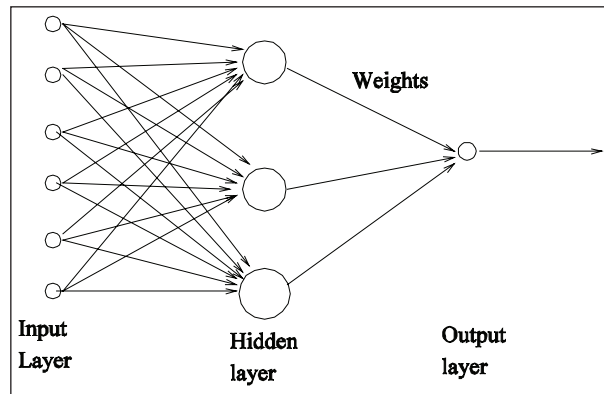
Introduction

We noted in the previous chapters that, while the multilayer perceptron is capable of approximating any continuous function, it can suffer from excessively long training times. In this chapter we will investigate methods of shortening training times for artificial neural networks using **supervised learning**. Haykin's (1999) work is a particularly good reference for **radial basis function** (RBF) networks. In this chapter we outline the theory and implementation of a RBF network before demonstrating how such a network may be used to solve one of the previously visited problems, and compare our solutions.

Radial Basis Functions

Note. Activation is fed forward from the input layer to the hidden layer where a (basis) function of the Euclidean distance between the inputs and the centres of the

Figure 1. A typical radial basis function network



basis functions is calculated. The weighted sum of the basis function outputs is fed forward to the output neuron.

A typical radial basis function (RBF) network is shown in Figure 1. The input layer is simply a receptor for the input data. The crucial feature of the RBF network is the function calculation which is performed in the hidden layer. This function performs a *nonlinear* transformation from the input space to the hidden-layer space. The hidden neurons' functions form a basis for the input vectors and the output neurons merely calculate a linear (weighted) combination of the hidden neurons' outputs.

An often-used set of basis functions is the set of Gaussian functions whose mean and standard deviation may be determined in some way by the input data (see below). Therefore, if $\mathbf{f}(\mathbf{x})$ is the vector of hidden neurons' outputs when the input pattern \mathbf{x} is presented and if there are M hidden neurons, then,

$$\mathbf{f}(\mathbf{x}) = (f_1(\mathbf{x}), f_2(\mathbf{x}), \dots, f_M(\mathbf{x}))^T$$

where $f_i(\mathbf{x}) = \exp(-1_i \|\mathbf{x} - \mathbf{c}_i\|^2)$

where the centres i of the Gaussians will be determined by the input data. Note that the terms i represent the Euclidean distance between the inputs and the centre. For the moment we will only consider basis functions with i . The output of the network is calculated by,

$$y = \mathbf{x} \cdot \mathbf{f}(\mathbf{x}) = \mathbf{w}^T \mathbf{f}(\mathbf{x})$$

where \mathbf{w} is the weight vector from the hidden neurons to the output neuron.

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