Multi-class Contour Preserving Classification

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Abstract. The original contour preserving classification technique was proposed to improve the robustness and weight fault tolerance of a neural network applied with a two-class linearly separable problem. It was recently found to be improving the level of accuracy of two-class classification. This paper presents an augmentation of the original technique to improve the level of accuracy of multi-class classification by better preservation of the shape or distribution model of a multi-class problem. The test results on six real world multi-class datasets from UCI machine learning repository present that the proposed technique supports multi-class data and can improve the level of accuracy of multi-class classification more effectively.

Keywords: contour preserving classification, data preprocessor, neural network, outpost vector, pattern classification.

1 Introduction

A multi-layer perceptron (MLP) [1–3] is a feed-forward neural network (FFNN) model that maps sets of input data onto a set of output. It comprises multiple layers of nodes in a directed graph. Each layer is fully connected to the next one. Each node is a neuron with a nonlinear activation function except for the input nodes. An MLP uses a supervised learning technique called back-propagation for training the network. It is a modification of the standard linear perceptron (single-layer perceptron), which can distinguish data that is not linearly separable.

When an MLP is used to solve multi-class problem, the placement of classifying hyper-planes significantly affects the level of accuracy of classification. Considering a problem in Fig. 1a, a two-dimension three-class problem comprising three classes of input vectors that is separable by a two-neuron non-linear classifier is presented. When a two-layer feed-forward neural network having two hidden neurons is applied, it possibly learns to classify the three classes of input vectors as shown in Fig. 1b. Line 1 and 2 are the classifying hyper-plane that represents the two hidden neurons. When a two-layer feed-forward neural network having four hidden neurons is applied, a possible solution may be as shown in Fig. 1c. Line 3, 4, 5 and 6 are the classifying hyper-plane that represents the four hidden neurons. Applying a typical variation of back-propagation learning

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