Neural Networks - Final Report: Learning Vector Quantization

Ryan Spangler

March 14, 2011

Abstract

This paper explores the Linear Vector Quantization (LVQ) neural network paradigm and its application to a real world problem. Given a set of training data about land use, this experiment proceeds to train the network to optimal performance, then progressively remove features until only the essential features remain. Using this subset of features, the network is able to be trained to high optimality.

Introdution/Background on LVQ

The LVQ is a supervised training algorithm that relies on competition between its PEs to attain a classification of inputs according to a scheme it discovers through training. During training the incoming vectors are compared against the vectors represented by each PE. The closest one is considered the "winner" and its output is transmitted to the next layer to determine which class the input vector belongs to. If it is the correct class, the PE is moved closer to the input vector, and if not it is moved away (this is known as "repulsion"). After the network has been trained, it performs classification according to the same principles, only the vectors for each PE are no longer moved. Each pass through the network at this point represents a classification of the vector to one of a certain number of classes, determined by the number of output elements chosen before training.

The overall effect of the LVQ is "as if" the network is optimized to classify its set of presented data according to the classes associated with them, regardless of the nature of the data and without having to have any specific knowledge about the data outside of what classes each training vector belongs to.

Problem Statement

The problem for this project is, given the training data set of 52 features and using the LVQ neural network paradigm, discover the smallest subset of features that enables the network to correctly classify the data above 90% of the time. It is claimed that 9 features is sufficient for the network to achieve these results, and that even smaller subsets are possible. My task is to find this minimal subset.

Experimental Process

Results

Numbering the 52 features from 0-51 in the order given in the test data, the critical 5 features that attained almost 92% classification accuracy were

- 13
- 44
- 45
- 46
- 49

The other features were more or less irrelevant. The presence of all the other features combined contributed only a 1-2% increase in classification performance.

Conclusion

Ultimately, finding the ideal subset of 5 features that could be used to adequately classify the vectors from the test set was not difficult, as their relative applicability was encoded in the values of the weights from each input to the competitive PEs. The network naturally excluded features that did not contribute to the classification through inhibitory weight modifications. Only the features that actually correlated to the desired classification scheme were encouraged through weight increases, the others were effectively rendered irrelevant.