Constructive Neural Network Learning Algorithms

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Introduction

Constructive Algorithms offer an approach for incremental construction of potentially minimal neural network architectures for pattern classification tasks. These algorithms obviate the need for an ad-hoc a-priori choice of the network topology. The constructive algorithm design involves alternately augmenting the existing network topology by adding one or more *threshold logic units* and training the newly added threshold neuron(s) using a stable variant of the *perceptron learning algorithm* (e.g., *pocket algorithm*, *thermal perceptron*, and *barycentric correction procedure*). Several constructive algorithms including *tower*, *pyramid*, *tiling*, *upstart*, and *perceptron cascade* have been proposed for 2-category pattern classification. These algorithms differ in terms of their topological and connectivity constraints as well as the training strategies used for individual neurons.

Multi-Category Pattern Classification

Several applications involve assigning patterns to one of M ($M > 2$) classes. The above constructive algorithms are known to converge to zero classification errors on a finite, non-contradictory, 2-category classification task. We have developed provably convergent multi-category extensions of the above constructive algorithms. Simulations on artificial and real world datasets have resulted in fairly compact networks. More recently, we have developed fast constructive algorithms that exhibit superior generalization.

Real world data sets often have continuous valued attributes. *Quantization* can be used to transform continuous valued patterns to an equivalent set of binary/bipolar valued patterns. Our experiments with quantization show that relatively difficult classification tasks can be transformed into simpler ones by effective quantization of the input space (albeit with the added expense of increased dimensionality in the pattern space).

Pruning Strategies

Network pruning involves elimination of redundant neurons and connections. With appropriate pruning strategies for constructive algorithms, it is possible to obtain smaller networks in terms of number of neurons and the number of connection weights. Smaller networks are known to possess better generalization ability. Pruning can be interleaved with the network construction phase or can take place once the entire network has been constructed. Some promising ideas on pruning include, removal of auxiliary neurons not contributing to the faithful representation of a layer in the tiling network; elimination of redundant daughter neurons in the upstart and cascade networks; retraining newly added output neurons in the tower and pyramid algorithms to improve classification accuracy at each successive layer. A systematic analysis of pruning strategies is a topic of ongoing research.

Current Research

Each constructive learning algorithm has a set of inductive and representational biases implicit in the design choices that determine where a new neuron is added and how it is trained. Our goal is to systematically characterize these biases and design constructive learning algorithms that can dynamically add, train, and prune neurons in a manner that is best suited to the needs of each individual classification task.

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References

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