A Genetic Algorithm as a Learning Method Based on Geometric Representations

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A number of different methods combining the use of neural networks and genetic algorithms have been described [1]. This paper discusses an approach for training neural networks based on the geometric representation of the network. In doing so, the genetic algorithm becomes applicable as a common training method for a number of machine learning algorithms that can be similarly represented. The experiments described here were specifically derived to construct claim regions for Fuzzy ARTMAP Neural Networks [2,3].

The adaptation of several principles to guarantee the success in traditional training of neural networks provided a similar level of success for the GA. Especially exciting is that this method provides the rare case of a GA guaranteeing a perfect solution with an increasing probability with each generation.

One neural network that has demonstrated good success, specifically for classification problems, is Fuzzy Adaptive Resonance Theory-MAP Neural Networks [2]. Fuzzy-ARTMAP Neural Networks (FAM-NN) provide numerous benefits, the most notable being online learning and notification of inputs that cannot be classified with the current learning [2,3]. FAM-NN constructs claim regions which can be viewed as geometric shapes, i.e. rectangles, cubes or hyper-cubes, in n-dimensional space. Each region has an assigned a category. Based simply on the classification rules, points within these regions are classified as being part of that claim region's category. Georgiopoulos provides a more detailed discussion on this point as it applies to the rules within FAM-NN [3].

The genetic algorithm for this application used a variable length representation. Each individual consists of m-pairs of points in n-dimensional space. Each pair constitutes the vertices of a rectangle, cube or hyper-cube, depending on the dimensionality of the representational space. Just as in the claim regions in FAM-NN, each pair is also assigned a category according to the classification categories in the training data.

The operators selected for this work concentrate on achieving success comparable to the traditional FAM-NN training. By adapting operators that emphasize the best traditional performance, the GA performance is improved and new characteristics emerge further improving the training. The genetic algorithm uses single-point crossover with random selection of parents. Mutation consists of several possibilities, the latter of which are novel.

Typical mutation of a randomly selected dimension of a particular vertex occurs at a given probability. Additionally, pairs of points are randomly added, deleted or swapped. Identical pairs of points based on particular input patterns

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are added. By doing this, the new point is guaranteed to correctly classify the particular input pattern. The input pattern is randomly selected from a queue that is filled with patterns that were misclassified in the previous fitness evaluations. To counter the increased number of claim regions and achieve highest possible compression, a mutation operator is utilized which combines vertices of like category regions.

We used three test patterns in this study. They include random points generated within a grid, a circle in a square and two spirals – Fig. 1.

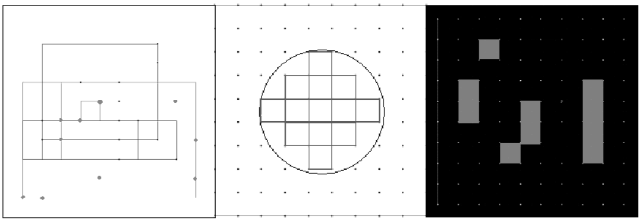

Fig. 1. Final Solution (Left) Random Points. Larger dots and lighter gray indicate category 1. The smaller dots and darker gray represent category 2.(Center) Circle in a Square (Right)Two spirals

The solution for the classification of a data set of random points was optimized with 6 regions for 25 training patterns resulting in a compression rate of 76%. The solution for the circle in a square problem was found at 1700 generations. It is optimized with 4 regions for 100 points resulting in a compression rate of 96%. The solution for the two spirals problem was found around generation 1400 with a compression of 9 regions of 100 or a 91% compression rate.

The combination of the techniques used in traditional FAM-NN provides an excellent springboard for an effective solution to training a good online classifying system. The method leverages the geometric representation allowing for an expansion to other machine learning algorithms on the basis of their geometric representation. The ability of a GA to provide a guarantee of convergence with an increasing probability with each generation provides a novel complement to remaining question of GA convergence. The extension of this work to hybrid algorithms that utilize a wider variety of geometric representation could provide a classification method beyond those currently developed.

References

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