Article

Introducing a new genetic operator based on Differential Evolution for effective training of neural networks

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Abstract: Artificial neural networks are widely established models used in a variety of real - world problems derived from physics, chemistry etc. These machine learning models contain a series of parameters that must be appropriately tuned by various optimization techniques in order to be effective in the problems they face. Genetic algorithms have been used in many cases in the recent literature to train artificial neural networks and various modifications have been introduced to enhance this procedure. In this article, the incorporation of a novel genetic operator in genetic algorithms is proposed in order to effectively train artificial neural networks. The new operator is based on the differential evolution technique and it is periodically applied to randomly selected chromosomes from the genetic population. The modified genetic algorithm was used to train neural networks for classification and regression datasets and the results are reported and compared against other methods that train neural networks.

Keywords: Neural networks; Genetic algorithms; Grammatical Evolution

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3. Experiments

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4. Conclusions

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