Evolutionary Multi-objective Optimization for Simultaneous Generation of Signal-Type and Symbol-Type Representations

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Abstract. It has been a controversial issue in the research of cognitive science and artificial intelligence whether signal-type representations (typically connectionist networks) or symbol-type representations (e.g., semantic networks, production systems) should be used. Meanwhile, it has also been recognized that both types of information representations might exist in the human brain. In addition, symbol-type representations are often very helpful in gaining insights into unknown systems. For these reasons, comprehensible symbolic rules need to be extracted from trained neural networks. In this paper, an evolutionary multi-objective algorithm is employed to generate multiple models that facilitate the generation of signal-type and symbol-type representations simultaneously. It is argued that one main difference between signal-type and symbol-type representations lies in the fact that the signal-type representations are models of a higher complexity (fine representation), whereas symbol-type representations are models of a lower complexity (coarse representation). Thus, by generating models with a spectrum of model complexity, we are able to obtain a population of models of both signal-type and symbol-type quality, although certain post-processing is needed to get a fully symbol-type representation. An illustrative example is given on generating neural networks for the breast cancer diagnosis benchmark problem.

1 Introduction

Artificial neural networks are one of the most well known signal-type representations in cognitive and vision research. Neural networks are linear or nonlinear systems that encode information with connections and units in a distributed manner, which are more or less of biological plausibility. In contrast, symbol-type representations use meaningful symbols, and information is encoded by defining the relationship among various symbols. Several symbolic representation models have been developed, such as semantic networks, production systems (symbolic rules) and finite-state automata.

Symbolic representations and symbolic processing are believed to have several desirable features that are closely related to mental representations and cognition [12], namely, productivity, systematicity, compositionality and inferential

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coherence. Besides, increasing evidence has been found in cognitive neuroscience that the human brain does have mechanisms that are responsible for symbolic processing [13, 21, 4]. It is widely believed that symbolic systems are more transparent to human users than connectionist networks, which plays an important role when neural networks are employed in critical engineering applications.

For the above reasons, it is often necessary to extract symbolic or fuzzy rules from trained neural networks [3, 20, 11]. A common drawback of most existing rule extraction method is that the rules are extracted after a neural network has been trained, which incurs additional computational costs.

This paper attempts to generate signal-type and symbol-type models simultaneously using the multi-objective optimization approach. Multiple neural networks of various model complexities, instead of either a single signal-type or symbol-type model, will be generated using a multi-objective evolutionary algorithm combined with a local search, where accuracy and complexity serve as two conflicting objectives. It has been shown that evolutionary multi-objective algorithms are well suited and very powerful in obtaining a set of Pareto-optimal solutions in one single run of optimization [8, 7].

Training neural networks using evolutionary multi-objective optimization is not new in itself [30, 1, 2, 19]. However, the existing work focuses on improving the accuracy of a single network or an ensemble of networks. Generating an ensemble of fuzzy classifiers using evolutionary algorithms has also been studied in [16]. Objectives in training neural networks include accuracy on training data, accuracy on test data, number of hidden neurons, and number of connections. Note that a trade-off between the accuracy on the training data and the accuracy on test data does not necessarily mean a trade-off between accuracy and complexity.

Section 2 discusses very briefly the existing methods for controlling model complexity in the context of model selections in machine learning. Methods for converting signal-type neural networks to symbol-type rules in the area of neural networks will also be introduced. Section 3 shows that any formal neural network regularization methods can be treated as multi-objective optimization problems. The details of the evolutionary multi-objective algorithm, together with the local search method will be provided in Section 4. An illustrative example is given in Section 5, where a population of Pareto-optimal neural networks are generated for the breast diagnosis problem. It will be shown that among the models generated by the multi-objective evolutionary algorithm, those with a higher complexity are of more signal quality and those of a lower complexity are of more symbol quality.

2 Complexity Control and Rule Extraction

2.1 Model Selection and Complexity Control

The task of model selection is to choose the best model for a set of given data, assuming that a number of models is available. Several criteria have been proposed based on the Kullback-Leibler Information Criterion [6]. The most popular