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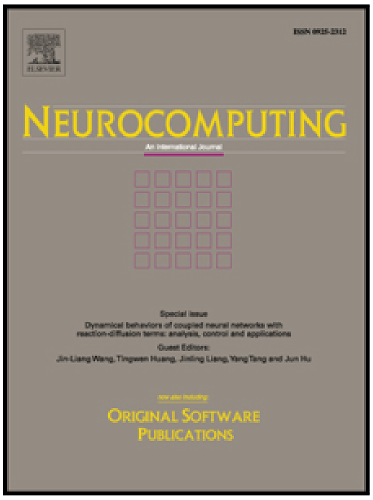

Co-evolutionary multi-task learning with predictive recurrence for multi-step chaotic time series prediction

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Co-evolutionary multi-task learning with predictive recurrence for multi-step chaotic time series prediction

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Abstract

Multi-task learning employs a shared representation of knowledge for learning several instances of the same problem. Multi-step time series problem is one of the most challenging problems for machine learning methods. The performance of a prediction model face challenges for higher prediction horizons due to the accumulation of errors. Cooperative coevolution employs in a divide and conquer approach for training neural networks and has been very promising for single step ahead time series prediction. Recently, co-evolutionary multi-task learning has been proposed for dynamic time series prediction. In this paper, we adapt co-evolutionary multi-task learning for multi-step prediction where predictive recurrence is developed to feature knowledge from previous states for future prediction horizon. The major goal of the paper is to present a network architecture with predictive recurrence which is capable of multi-step prediction through features of multi-task learning. We employ cooperative neuro-evolution and an evolutionary algorithm as baselines for comparison. The results show that the proposed method provides the best generalisation performance in most cases. Comparison of results with the literature has shown to be promising which motivates further application of the approach for related real-world problems.

Keywords:
Cooperative coevolution; neuro-evolution; feedforward networks; multi-task learning; multi-step time series prediction.

1. Introduction

Multi-step-ahead prediction refers to the forecasting or prediction of a sequence of future values from an observed trend in a time series [1, 2]. The prediction horizon defines the extent of future prediction. The chaotic nature and noise in real-world time series makes it challenging to develop models that produce low prediction error as the prediction horizon increases [3, 4, 5]. Multi-step-ahead prediction has been approached mostly with the *recursive* and *direct* strategies. In the recursive strategy, the prediction from a one-step-ahead prediction model is used as input for future prediction horizon [6, 7]. In this approach, any uncertainty or error in the prediction for the next horizon is accumulated in future horizons. The direct strategy considers the multi-step-ahead problem as a multi-output prediction problem [8, 9] which can also be explored through multi-task learning.

Multi-task learning considers an appropriate sharing mechanism of common knowledge across tasks in order to enable knowledge from one task to benefit other(s) [10]. Multi-task learning is considered as a type of inductive transfer that employs the domain information contained in the training signals of related tasks as an inductive bias [11, 12, 13, 14]. This is typically achieved by learning tasks in parallel through a shared knowledge representation. In real-world applications [15, 16, 17, 18, 19, 20], the appropriate way to exploit structures among multiple learning tasks can be challenging as learning tasks consist of several disjoint or partially overlapped task groups with some outlier tasks. Negative transfer of knowledge refers to the case when related and unrelated tasks are combined and treated the same that leads to the decrease the learning performance [21].

Neuro-evolution refers to the use of evolutionary algorithms for training neural networks [22]. Cooperative coevolution (CC) [23] employs divide and conquer approach to decompose the problem into subcomponents. It has been very promising method for neuro-evolution [24, 25, 26] and referred as *cooperative neuro-evolution* [27]. Coevolution has shown features more diverse solutions through the sub-populations when compared to conventional evolutionary algorithms [24] and also ensures modularity. It has also been very promising for time series prediction [28, 29]. Modular neural networks are motivated from repeating structures in nature [30] and were introduced for visual recognition tasks that were trained by genetic algorithms [30]. More recently, a modular neural network was presented where the performance and connection costs were optimised through neuro-evolution which achieved better performance when compared to fully connected neural network [31] and to learn new tasks without forgetting old ones [32].

Multi-tasking evolutionary algorithms have been proposed for optimisation problems by enabling transfer of knowledge between tasks that consist of different types or instances of optimisation problems with some overlapping features taken from same domain [33, 34]. Recently, evolutionary multi-tasking has been used for training feedforward neural networks for n-bit parity problem [35]. The different tasks were implemented as