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A hybrid model of fuzzy ARTMAP and genetic algorithm for data classification and rule extraction

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ABSTRACT

A two-stage hybrid model for data classification and rule extraction is proposed. The first stage uses a Fuzzy ARTMAP (FAM) classifier with Q-learning (known as QFAM) for incremental learning of data samples, while the second stage uses a Genetic Algorithm (GA) for rule extraction from QFAM. Given a new data sample, the resulting hybrid model, known as QFAM-GA, is able to provide prediction pertaining to the target class of the data sample as well as to give a fuzzy if-then rule to explain the prediction. To reduce the network complexity, a pruning scheme using Q-values is applied to reduce the number of prototypes generated by QFAM. A 'don't care' technique is employed to minimize the number of input features using the GA. A number of benchmark problems are used to evaluate the effectiveness of QFAM-GA in terms of test accuracy, noise tolerance, model complexity (number of rules and total rule length). The results are comparable, if not better, than many other models reported in the literature. The main significance of this research is a usable and useful intelligent model (i.e., QFAM-GA) for data classification in noisy conditions with the capability of yielding a set of explanatory rules with minimum antecedents. In addition, QFAM-GA is able to maximize accuracy and minimize model complexity simultaneously. The empirical outcome positively demonstrate the potential impact of QFAM-GA in the practical environment, i.e., providing an accurate prediction with a concise justification pertaining to the prediction to the domain users, therefore allowing domain users to adopt QFAM-GA as a useful decision support tool in assisting their decision-making processes.

1. Introduction

Artificial neural networks (ANNs) have been applied successfully to many fields, e.g. marketing (Guresen, Kayakutlu, & Daim, 2011), healthcare (Huang, 2010), industry (Nemeth, 2014), and robotic (Duka, 2014). Among them, data classification is one of the popular application domains of ANNs (Zhang, 2000; Ngwangwa, Heyns, Breytenbach, & Els, 2014). Many ANNs have been proposed to undertake data classification problems, e.g. from the conventional Radial Basis Function (RBF) (Moody & Darken, 1989) and Multi-Layer Perceptron (MLP) (Rumelhart, Hinton, & Williams, 1986) networks as well as recent hybrid models, e.g. Adaptive Resonance Theory (ART-2) and RBF (Bielecki, Barszcz, Wójcik, & Bielecka, 2014) and MLP with a recurrent architecture (Gnana Jothi & Meena Rani, 2015).

In ANN-based learning models, catastrophic forgetting (Mccloskey & Cohen, 1989; Ratcliff, 1990) is one of the crucial problems, whereby ANNs are not able to remember previously learned information when new information is absorbed. This problem has also been addressed as the stability-plasticity dilemma (Carpenter & Grossberg, 1987). On the other hand, maximizing accuracy and minimizing network complexity constitute another challenge of ANN-based data classification models. As a result, we propose a new hybrid intelligent model that is able to solve the aforementioned problems in this study.

To overcome the problem of stability-plasticity dilemma, a number of ANNs with the capability of incremental learning have been developed, e.g., Adaptive Resonance Theory (ART) (Carpenter & Grossberg, 1987) networks and Fuzzy Min–Max networks (Simpson, 1992). In this study, we focus on a supervised ART network, namely Fuzzy ARTMAP (FAM) (Carpenter, Grossberg, Markuzon, Reynolds, & Rosen, 1992), owing to its online learning capability that is able to increase the number of network nodes (prototypes of input samples) incrementally and stably. This is achieved by measuring the similarity level between the prototype nodes and a new input sample against a threshold, i.e., the vigilance test (Carpenter et al., 1992). If the vigilance test is not satisfied, a new prototype node can be added into FAM to encode the new input sample. This incremental learning

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methodology is able to solve the stability–plasticity dilemma, i.e., absorbing new information incrementally (plastic) without corrupting or erasing previously learned information (stable) in the network.

In data classification, one of the key issues is how to accurately classify input samples that are spread along the decision boundary of two (or more) different classes. This is particularly challenging when the data samples are noisy. In terms of FAM, this issue translates into how to select the best winning prototype to give a prediction of the target class. Many hybrid models have been proposed to improve the performance of FAM, e.g. FAM with Gaussian models (Williamson, 1996), FAM with Fuzzy C-means clustering (Lim, Leong, & Kuan, 2005), and FAM with a Genetic Algorithm (GA) (Daraiseh, Georgiopoulos, Anagnostopoulos, Wu, & Mollaghasemi, 2006).

In this paper, Reinforcement Learning (RL) (Barto & Sutton, 1998) is used to help select the best winning nodes in FAM. RL is a semi-supervised learning algorithm that deploys an evaluative feedback to solve prediction and control (Barto & Sutton, 1998) as well as classification problems (Likas, 2001; Likas & Blekas, 1996; Quah, Quek, & Leedham, 2005). As such, we employ RL to improve the FAM performance, especially for undertaking noisy data problems. On the other hand, rule extraction is another important property of a data classification model in revealing its prediction to domain users. This property is particularly important in safety critical applications, e.g. medical diagnosis or fault detection and classification.

In the literature, many rule extraction (Taylor & Darrah, 2005) techniques have been proposed for ANN models. In Carpenter and Tan (1995), a technique for extracting *if-then* rules from FAM was introduced. The proposed technique consists of two stages. In the first stage, the network is pruned by removing prototype nodes that are less informative, while in the second stage, the prototype weights are quantized and converted into a set of rules. In Ishibuchi, Murata, and Türkşen (1997), rule extraction based on a Genetic Algorithm (GA) was introduced. Another rule extraction technique similar to that of Ishibuchi et al. (1997) was used in Quteishat, Lim, and Kay (2010).

Based on the above account, a two-stage hybrid model is proposed to tackle data classification and rule extraction problems. The first stage equips FAM with a reinforcement learning technique, i.e., Q-learning, to produce an incremental learning classifier known as QFAM. The second stage uses a GA to extract a set of *if-then* rules from QFAM, in order to provide useful explanation of the prediction from QFAM to domain users. The resulting hybrid model is known as QFAM-GA. In QFAM-GA, network pruning and feature selection are conducted to improve its usefulness in tackling practical problems. Each prototype node in QFAM is assigned with a Q-value. Pruning is accomplished based on the Q-value, in order to reduce the network complexity by removing less informative prototype nodes. To extract a concise rule set containing only the important features in each rule, the concept of an “open prototype” is adopted for the GA to retain the most discriminative data features while maximizing classification accuracy. A number of benchmark problems are examined to demonstrate the effectiveness of QFAM-GA.

This paper is organized as follows. In Section 2, a review on FAM, RL, feature selection, and rule extraction is presented. The dynamics of FAM are presented in Section 3. In Section 4, the proposed QFAM-GA model is explained in detail. To evaluate the effectiveness and usefulness of QFAM-GA, a series of experiments is conducted, and the result and analysis are presented in Section 5. Finally, conclusions and suggestions for further research are presented in Section 6.

2. Background

2.1. Fuzzy ARTMAP

FAM is a supervised neural network with the capability of incremental learning. Since its inception in 1992 (Carpenter et al., 1992), it has been one of the most popular ART-based models to solve data classification problems. Over the years, many researches have been carried out to enhance the performance of FAM, and to apply it to a variety of applications. Some examples of FAM variants are discussed, as follows.

An FAM-based model to approximate continuous mapping function was introduced in Marriott and Harrison (1995). The model performed better than FAM in undertaking mapping tasks with noisy data. A combination of a Gaussian model and FAM was proposed in Williamson (1996). While the Gaussian ARTMAP was complex in terms of learning, it was resilient to noise. In Mokhtar and Howe (2013), the performance of Gaussian ARTMAP was compared with FAM in building an Energy Management System (EMS). The results showed Gaussian ARTMAP was able to overcome the weakness of FAM and to provide better EMS controls. In Chralampidis, Kasparis, and Georgiopoulos (2001), the testing phase of FAM was modified to handle noisy data samples. The proposed model outperformed FAM. An FAM-based model was proposed to automatically classify targets based on radar range profiles. The proposed model was able to perform better than the k-nearest neighbor in memory saving. In Tan, Rao, and Lim (2008), a hybrid neural network comprising FAM and Dynamic Decay Adjustment (DDA), known as FAMDDA, was proposed. FAMDDA was able to solve the overlapping problem among prototype nodes from different classes. The experimental results showed that FAMDDA performed better than FAM. In Zhang, Ji, and Zhang (2014), an FAM-based neural network known as TTPFAM was proposed to undertake the category proliferation problem. TTP-FAM used a filtering technique during the FAM training phase to avoid the problem of category proliferation. It then employed the Q-max value and posterior probability during the FAM testing phase to give better predictions of the target classes. The results showed that TTP-FAM outperformed FAM, ARTMAP-IC and other models in terms of accuracy and number of prototypes.

A number of models have been developed to solve the problem of category proliferation of FAM. In Dagher, Georgiopoulos, Heileman, and Bebis (1999), an ordering algorithm based the min-max clustering model that identified a fixed order of training patterns for FAM was formulated. The model performed better than or at least as good as FAM. In Emilio, Eduardo, and Dimitriadis (2003), distributed learning was used to reduce the effects of category proliferation of FAM. In Castro, Georgiopoulos, Demara, and Gonzalez (2005), to speed up the training phase of FAM and to avoid the problem of category proliferation especially in high-dimensional data sets, the Hilbert space-filling curves (HSFC) were formed to divide the data samples into several partitions. Each partition was used to train a different FAM model. The TPPFAM (Threshold and Posterior Probability for category reduction in Fuzzy ARTMAP) model (Zhang et al., 2014) used a filter during the learning phase of FAM. In the prediction phase, a combination of the Q-max value and a posterior probability estimator was used to predict the target class.

2.2. Reinforcement learning

RL (Barto & Sutton, 1998) is a machine learning technique that receives inputs from the environment and selects the best action and applies it. It then obtains a reinforcement signal that penalizes or rewards the chosen action. Trial-and-error and delayed rewards are two important properties of RL. RL can learn from its received awards when interacting with an unknown environment. It has been used to solve many problems related to control (Lin & Lin, 1996) and planning (Kareem, Mohammad, & Quadan, 2011). Unlike unsupervised learning techniques, the target is known for RL, which helps decide how to choose an action to maximize the reward signal. In Monteserin and Amandi (2013), an RL-based technique was proposed to improve the selection of argument-based negotiation. The proposed technique was evaluated successfully in stationary and dynamic environment. In Dorça, Lima, Fernandes, and Lopes (2013), an RL method for