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Rule Base Simplification and Constrained Learning for Interpretability in TSK Neuro-Fuzzy Modelling

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ABSTRACT

Neuro-fuzzy systems based on a fuzzy model proposed by Takagi, Sugeno and Kang known as the TSK fuzzy model provide a powerful method for modelling uncertain and highly complex non-linear systems. The initial fuzzy rule base in TSK neuro-fuzzy systems is usually obtained using data driven approaches. This process induces redundancy into the system by adding redundant fuzzy rules and fuzzy sets. This increases complexity which adversely affects generalization capability and transparency of the fuzzy model being designed. In this article, the authors explore the potential of TSK fuzzy modelling in developing comparatively interpretable neuro-fuzzy systems with better generalization capability in terms of higher approximation accuracy. The approach is based on three phases, the first phase deals with automatic data driven rule base induction followed by rule base simplification phase. Rule base simplification uses similarity analysis to remove similar fuzzy sets and resulting redundant fuzzy rules from the rule base, thereby simplifying the neuro-fuzzy model. During the third phase, the parameters of membership functions are fine-tuned using a constrained hybrid learning technique. The learning process is constrained which prevents unchecked updates to the parameters so that a highly complex rule base does not emerge at the end of model optimization phase. An empirical investigation of this methodology is done by application of this approach to two well-known non-linear benchmark forecasting problems and a real-world stock price forecasting problem. The results indicate that rule base simplification using a similarity analysis effectively removes redundancy from the system which improves interpretability. The removal of redundancy also increased the generalization capability of the system measured in terms of increased forecasting accuracy. For all the three forecasting problems the proposed neuro-fuzzy system demonstrated better accuracy-interpretability tradeoff as compared to two well-known TSK neuro-fuzzy models for function approximation.

KEYWORDS

Approximation, Fuzzy Modelling, Interpretability, Learning, Neuro-Fuzzy Systems

1. INTRODUCTION

System modelling is the act of approaching a real system in order to fabricate a theoretical design that eases the understanding of the real system. The goal is the design of comprehensible and reliable models that enable to explain, simulate, control, predict or improve the real system. In this regard, fuzzy modelling is a well-known approach to model a real system using descriptive language based on fuzzy logic (Casillas and Cordon, 2003). Fuzzy models offer unique benefits in system modelling. These systems have the advantage of explicitly representing expert knowledge in the form of fuzzy if-then rules. This enables to model various aspects of human knowledge and reasoning process

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without using precise qualitative analysis (Jang, 1993). These systems are therefore useful in modelling uncertain and ill-defined systems. Also, fuzzy if-then rules result in better transparency as it is easier to interpret the system information allowing an in-depth understanding of its functionality. Like multi-layer perceptron (MLP), fuzzy models are also capable of universal approximation (Castro, 1995) but standalone fuzzy systems lack learning ability. As a result, neuro-fuzzy systems which combine the advantages of fuzzy models in terms of interpretability and learning capability of artificial neural networks (ANN) were proposed. In case expert knowledge is used to build a fuzzy model it is easier to ensure that the system remains interpretable. On the other hand if automated data driven approaches are used to construct fuzzy rules, the interpretability aspect is not necessarily guaranteed as it usually results in a fuzzy model with poor transparency. In fact there are two main but contradictory goals of designing fuzzy systems which are also used to access the quality of fuzzy models: (1) accuracy which is the ability of the system to faithfully represent the real system; (2) interpretability which is the ability to express the behavior of the system in a comprehensible manner (Casillas and Cordon, 2003). In practical data driven fuzzy modelling one of these two properties prevails over the other, increasing one usually decreases the other. During 1990' significant proliferation in the research on fuzzy modelling happened but the focus was on improving accuracy as much as possible with no attention paid towards the main motivation of using fuzzy systems which is their descriptive power (Ishibuchi and Nojima, 2007). Various techniques were proposed that increased accuracy of these systems which usually increased model complexity also. Nonetheless, lately there is a shift in the fuzzy modelling research towards achieving a tradeoff between accuracy and interpretability (Yen and Wang, 1999).

The neuro-fuzzy systems based on TSK fuzzy modelling technique (Sugeno et al., 1988) are one of the major areas in theoretical and practical fuzzy system literature. These have found significant practical applications in prediction, control and inference. Widely used neuro-fuzzy models like the one proposed by Takagi and Hayashi (1991) and adaptive neuro-fuzzy inference system (ANFIS) (Jang, 1993) are based on TSK model. But TSK based neuro-fuzzy models have been used in practical applications mainly to replace other non-linear models with focus on how accurately the model approximates a real system, ignoring the interpretability aspect which is the core motivation for using fuzzy systems. This is mainly due to the assumption that a fuzzy model is implicitly interpretable in the form of fuzzy if-then rules which is not essentially true. Therefore, these systems have been used in much the same way as other black box techniques like ANNs with approximation accuracy as the main goal which is questionable as indicated in Nauck and Kruse (1999). However, lately the research trend in fuzzy system modelling has shifted towards obtaining models with high accuracy using various approaches such that interpretability is not compromised. This paper investigates the potential of TSK based neuro-fuzzy systems in developing interpretable models of complex real systems. The methodology is based on employing techniques that ensure interpretability during the two main stages of fuzzy modelling viz. structure learning and parameter learning.

Structure learning of a TSK system is typically a data-driven process in which the initial fuzzy rule base is generated automatically from experimental input-output patterns using methods like data clustering. This process usually introduces redundancy in the model for example in the form of similar fuzzy sets of variables and redundant fuzzy rules. This leads to unnecessary complexity that affects the model interpretability. For simplifying the rule base and therefore improving interpretability, structure learning is followed by a second phase in which we use similarity analysis based on a set theoretic similarity measure to identify similar fuzzy sets and which are then merged. In case rule base redundancy is high, merging of the fuzzy sets results in redundant fuzzy rules in the rule base. To handle this problem, rule merging is subsequently done to further simplify the model.

Parameter learning involves the use of a learning algorithm to fine-tune the fuzzy model parameters for maximizing approximation precision. Parameter learning of fuzzy systems is usually performed in an unconstrained manner during which highly complex fuzzy rule bases may evolve leading to decreased interpretability of the system. Therefore, a constrained hybrid learning algorithm

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