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OPTIMIZING FUZZY SYSTEMS USING EVOLUTIONARY ALGORITHMS

Computer Science

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ABSTRACT

Fuzzy rule-based systems (FRBSs) are a well-known method family within soft computing.They are based on fuzzy concepts to address complex real-world problems. We present the R package frbs which implements the most widely used FRBS models, namely,Mamdani and Takagi Sugeno Kang (TSK) ones, as well as some common variants. In addition a host of learning methods for FRBSs, where the models are constructed from data,are implemented. In this way, accurate and interpretable systems can be built for data analysis and modeling tasks. In this paper, we also provide some examples on the usage of the common classification and regression methods available in R .

KEYWORDS

fuzzy inference systems, soft computing, fuzzy sets, genetic fuzzy systems, evolutionary fuzzy system.

I. INTRODUCTION

Fuzzy rule-based systems (FRBSs) are well known methods within soft computing, based on fuzzy concepts to address complex real-world problems. They have become a powerful method to tackle various problems such as uncertainty, imprecision, and non-linearity. They are commonly used for identification, classification, and regression tasks. FRBSs have been deployed in a number of engineering and science areas, e.g. in bioinformatics. FRBSs are also known as fuzzy inference systems or simply fuzzy systems. When applied to specific tasks, they also may receive specific names such as fuzzy associative memories or fuzzy controllers. They are based on the fuzzy set theory, proposed by Zadeh (1965), which aims at representing the knowledge of human experts in a set of fuzzy IF-THEN rules. Instead of using crisp sets as in classical rules, fuzzy rules use fuzzy sets. Rules were initially derived from human experts through knowledge engineering processes.

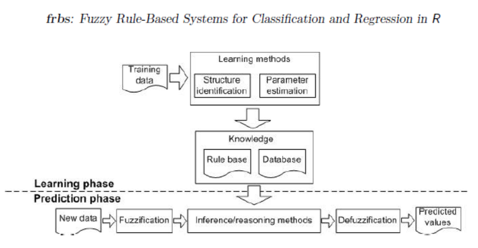

Fig-1:Learning and prediction phase of an FRBS

Designing fuzzy rule-based systems with genetic programming:

Genetic programming (GP) is concerned with the automatic generation of computer programs. Different proposals can be found when using GP to evolve fuzzy rule sets, internally represented as type-constrained syntactic trees . In these kind of systems, fuzzy rules are represented by binary trees.Fuzzy GP,combines a simple GA that operates on a context-free language with a context-free fuzzy rule language. Nowadays, it is possible to distinguish among GPs that utilise a grammar to learn linguistic rules and approaches that use domain-specific knowledge to define the function and terminal set which constitute the building blocks for the fuzzy rules to be learned.Approaches where GAs or simulated annealing and GP are hybridised have also been proposed .

Genetic selection of fuzzy rule sets:

In high-dimensional problems, the number of rules in the RB grows exponentially as more inputs are added. Rule reduction methods have been formulated using neural networks, clustering techniques, orthogonal transformation methods, and algorithms based on similarity measures among others. In recent years, genetic techniques have been considered to address the problem of high-dimensional spaces in FRBS design with a great success.

A genetic multi-selection process,that at the same time eliminates unnecessary rules from the set of candidate rules and refines KBs for classification problems by means of a linguistic hedge learning process (with a double coding scheme, the first chromosome part for rule reduction and the second chromosome part for linguistic hedge learning evolution) proposes a genetic integration process of multiple knowledge bases that can be also considered as a particular case of genetic selection.

Genetic-based machine learning approaches:

GFSs with specific combination of evolution and bio-inspired models have been developed. For instance, genetic schemes inspired on the virus theory of evolution have been derived to learn TSK fuzzy rule sets , including genetic recombination in bacterial genetics and DNA coding schemes .

Soft Computing Systems:

The term Soft Computing indicates a number of methodologies used to find approximate solutions for real-world problems which contain various kinds of inaccuracies and uncertainties. The guiding principle of Soft Computing is to develop a tolerance for imprecision, uncertainty, partial truth, and approximation to achieve tractability, robustness and low solution cost.

The underlying paradigms of Soft Computing are Neural Computing,Fuzzy Logic Computing and Evolutionary Computing. Systems based on such paradigms are Artificial Neural Networks (ANN's), Fuzzy Systems (FS's), and Evolutionary Algorithms (EA's).Rather than a collection of different paradigms, Soft Computing is better regarded as a partnership in which each of the partners provides a methodology for addressing problems in a different manner. From this perspective, the Soft Computing methodologies are complementary rather than competitive.

This relationship enables the creation of hybrid computing schemes which use neural networks, fuzzy systems and evolutionary algorithms in combination.**Fig-2** shows their use in a Soft Computing investigation.In the following, after a description of the three basic Soft Computing.

paradigms, some hybrid soft computing systems are overviewed. These show the rapid growth in the number and variety of combinations using ANN's, FS's and EA's.

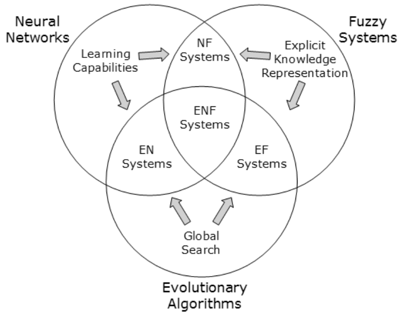

Fig-2. Integration possibilities in Soft Computing.

Principle of Genetic Algorithm:

Although there are many possible variants of the basic GA, the fundamental underlying mechanism consists of three operations: evaluation of individual fitness, formation of a gene pool (intermediate population) through selection mechanism, and recombination through crossover and mutation operators.The specific characteristics of the evaluation method are quite dependent on the application.

Genetic learning processes cover different levels of complexity, from parameter optimization to learning the rule set of a rule based system. Genetic learning processes designed for parameter optimization usually fit to the description given in previous paragraphs, but when considering the task of learning rules in a rule based system, a wider range of possibilities is open.

Main Characteristics of Genetic Algorithms (Gas):

Genetic Algorithms may deal successfully with a wide range of problem areas. The main reasons for this success are: 1) GAs can solve hard problems quickly and reliably, 2) GAs are easy to interface to existing simulations and models, 3) GAs are extendible and 4) GAs are easy to hybridize. All these reasons may be summed up in only one: GAs are robust. GAs are more powerful in difficult environments where the space is usually large, discontinuous, complex and poorly understood. They are not guaranteed to find the global optimum solution to a problem, but they are generally good at finding acceptably good solutions to problems acceptably quickly. The basic principles of GAs are first laid down rigorously by Holland[4]. It is generally accepted that the application of a GA to solve a problem must take into account the following five components:

1. A genetic representation of solutions to the problem.
2. A way to create an initial population of solutions.
3. An evaluation function which gives the fitness of each chromosome.
4. Genetic operators that alter the genetic composition of offspring during reproduction.
5. Values for the parameters that the GA uses (population size, probabilities of applying genetic operators etc).

II. REVIEW OF LITERATURE

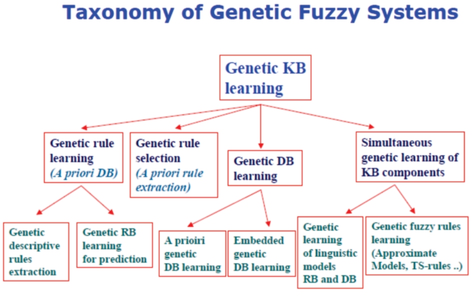

Fig-3 Genetic Fuzzy Rule Based System:

Brief Introduction An FRBS (regardless it is a fuzzy model, a fuzzy logic controller or a fuzzy classifier), is comprised by two main components:

- The **Knowledge Base (KB),** storing the available problem knowledge in the form of fuzzy rules.
- The **Inference System**, applying a fuzzy reasoning method on the inputs and the KB rules to give a system output .
- Both must be designed to build an FRBS for a specific application:
- The KB is obtained from expert knowledge or by machine learning methods.
- The Inference System is set up by choosing the fuzzy operator for each component (conjunction implication defuzzifier,etc).
- a data base (DB), containing the definitions of the scaling functions of the variables and the membership functions of the fuzzy sets associated with the linguistic labels, and
- a rule base (RB), constituted by the collection of fuzzy rules. Sometimes, the latter operators are also parametric and can be tuned using automatic methods.

Genetic Tuning:

Tuning of the scaling functions and fuzzy membership functions is an important task in FRBS design.Parameterized scaling functions and membership functions are adapted by the GA according to a fitness function that specifies the design criteria in a quantitative manner.

As previously said, tuning processes assume a predefined RB and have the objective of finding a set of optimal parameters for the membership and/or the scaling functions . It is also Possible to perform the tuning process a priori, i.e., considering that a subsequent process will derive the RB once the DB has been obtained, that is a priori genetic DB learning.

Tuning scaling functions:

Scaling functions applied to the input and output variables of FRBSs normalize the universes of discourse in which the fuzzy membership functions are defined. Usually, the scaling functions are parameterized by a single scaling factor or a lower and upper bound in case of linear scaling, and one or several contraction/dilation parameters in case of non-linear scaling. These parameters are adapted such that the scaled universe of discourse better matches the underlying variable range.

Genetic learning of rule bases:

Genetic learning of RBs assumes a predefined set of fuzzy membership functions in the DB to which the rules refer to by means of linguistic labels (Fig-8). It only applies to descriptive FRBSs, as in the approximate approach adapting rules is equivalent to modify the membership functions.

The three learning approaches described in previous section can be considered to learn **RBs:** Michigan approach, Pittsburgh approach, and iterative rule learning approach. The RB can be represented by a relational matrix, a decision table ,or a list of rules .

II. PROBLEM RECOGNITION AND STATEMENT

Fuzzy Systems are highly applicable for modeling real world problems, like control ,classification, robotics etc. The ultimate target of the fuzzy systems is to deal with the uncertainty inherent in the real world problems, more specifically linguistic computation based control. But these fuzzy systems may be more accurate in their functioning if we design them using evolutionary approaches, specifically Genetic Algorithms.In this proposal the major focus would be on the following issues:

1.Effective Interpretable Encoding Scheme for the Fuzzy systems in Evolutionary Environment.

2. Consideration of Interpretability enhancement maintaining competitive accuracy.

Fuzzy reasoning builds this understanding into the process rather than tacking it onto the end. Fuzzy logic can model nonlinear functions of arbitrary complexity. You can create a fuzzy system to match any set of input-output data. Fuzzy logic can be blended with conventional control techniques.

III. CONCLUSION

This work presents a new methodology (HILK) for building knowledge bases with a good balance between accuracy and interpretability. It sets a general framework where a KB may include knowledge extracted from different sources. Two kinds of knowledge, expert knowledge and knowledge extracted from data are considered. They convey complementary information, and their fusion can lead to compact and robust knowledge bases. The fuzzy logic formalism allows the expression of both types of knowledge using the same linguistic variables.

It should be noted that HILK has been implemented as open source software in a tool named KBCT. It has been successfully applied in robotics for diagnosis of motion problems, telemedicine application. In consequence, KBCT is an important contribution derived from this dissertation. Notice that all results presented in this document were reached using that tool.

Obtained results are compared with those achieved by other well known techniques, Naïve Bayes and C4.5. The comparison shows that both results are comparable in terms of accuracy, but HILK ones are usually much better in terms of interpretability. This methodology is thought for solving problems where both expert knowledge and experimental data are available, and KB interpretability is of prime importance.

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