Considerations of the Nature of the Relationship Between Generalization and Interpretability in Evolutionary Fuzzy Systems

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ABSTRACT

Performance out of sample is a clear determinant of the usefulness of any prediction model regardless of the application. Fuzzy knowledge base systems are also useful due to interpretability; this factor is often cited as an advantage over "black box" systems which make model verification by expert users more difficult. Here we examine additional advantages of interpretability for promoting general performance out side training data.

Categories and Subject Descriptors

I.5.m [**Computing Methodologies**]: Pattern Recognition-Miscellaneous

General Terms

Experimentation

Keywords

Evolutionary Computation, Fuzzy Systems

1. INTRODUCTION AND BACKGROUND

Genetic Fuzzy Systems (GFS), or Genetics-Based Machine Learning Algorithms, are a category of techniques for learning fuzzy knowledge base systems, or parts of them, using genetic algorithms, evolutionary computation, and natural computing techniques. They are part of recent trends toward hybrids of neueral networks, fuzzy systems and a range of heuristic techniques to form fields of knowledge such as Computational Intelligence and Soft Computing. Recently this fushion has further developed and led to many novel and powerful GFS approaches as novel techniques and improved computation power are applied to learning fuzzy knowledge based systems. Multiobjective evolutionary algorithms have also led in useful new directions in obtaining solutions that balance the, often conflcting, objectives of accuracy and human interpretability. We test a range of multiobjective evolutionary algorithms for learning fuzzy rules, including: NSGAII, a steady state version of NSGAII (SSNSGAII) [?], SPEA2 [?] MOCell [?] FastPGA (Fast Pareto Genetic Algorithm) [?].

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2. DESCRIPTION OF THE PROBLEM AND APPROACH

A classifier is a mapping $D : \Re^n \rightarrow \Omega$ from a vector of observations $\mathbf{x} = x_1, \ldots, x_n \in \Re^n$ to a set of c class labels $\omega_1, \ldots, \omega_c \in \Omega$. To obtain classification, we use fuzzy rules that have an if-then structure involving a series of conjunctions in the consequent if part and a vector in the consequent then part[?]. The output is interpreted as a degree of certainty an observation is a member in each class given the pattern of features specified in the antecedent. A single rule r_k of M has the following form

$$R_k : \text{if } x_1 \text{ is } A_1 \wedge \ldots \wedge x_n \text{ is } A_n; \text{ then } (z_{k,1}, \ldots, z_{k,c})$$

where $x_1 \ldots x_n$ are feature observations that are described by linguistic labels $A_1 \ldots A_n$, these are common in the different rules and specified in the "database" part of the knowledge base. Examples of possible descriptions are low, high, medium etc. A rulebase is a set of rules $r_1, r_2, \ldots, r_k$. The classification is taken to be the *most supported class*. Rulebases provide the mapping using the well known fuzzy classifier designs TSKI, II, II and IV.

For optimization, we consider three objectives relating to solution interpretability and solution accuracy. Accuracy is measured as classification error and interpretability is divided into the number of rules and the number of inputs per rule. Solutions are encoded as integer arrays with problem specific mutation and crossover.

3. EXPERIMENTATION

We apply the fuzzy rulebase learning methods to the iris data from the UCI Machine Learning repository [1]. The table

[1]`http://archive.ics.uci.edu/ml/`

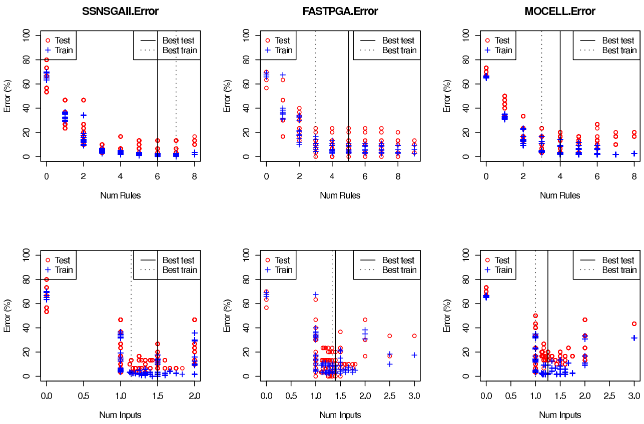

Figure 1: Iris type 1 fuzzy system found by SSNSGA, fastPGA and MoCell algorithms, with best in and out sample results marked.

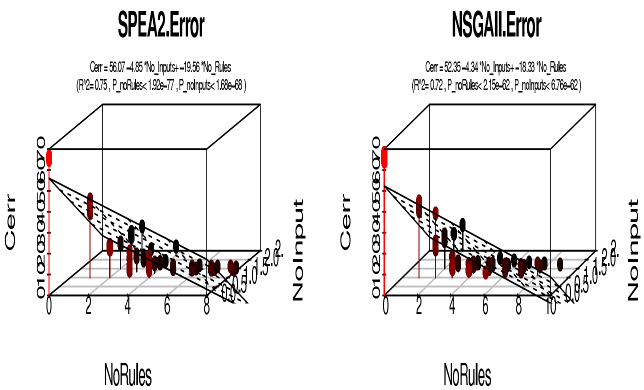

Figure 2: Iris type 1 fuzzy system found by NSGAII and SPEA2.

shows the average best result from 30 runs for the MOEA and fuzzy system evaluation methods that were tested. Best performance was for TSK 2 and NSGAII. There was a clear relationship between the number of rules and inputs, and the classification error. The error was reduced by, on average, 3-5% for each increase in average inputs by 1 and by around 25% for additional rules. Figure **??** shows that the best in sample rulebas was generally simpler than the best out sample rulebase, figure **??** shows the relationship between accuracy and interpretability.

Table 1: Average best results of the methods tested (from 30 runs) in the iris dataset.

Iris Dataset					
	NSGAII	SPEA2	SSNSGA	FastPGA	MOCell
TSK FS 1	1.67	2.29	4.16	3.33	5
TSK FS 2	0.83	2.5	1.67	5	3.33
TSK FS 3	2.08	1.67	1.67	3.33	4.16
TSK FS 4	4.17	3.33	1.67	4.16	1.67

4. CONCLUSION

This paper has provided an overview the application of a genetic fuzzy system for learning classifiers for five distinct datasets. In comparison to other state of the art approaches, a direct genotype encoding approach to learning fuzzy knowledge bases (rather than an a multi-stage approach [**?**]) has performed credibly and sometimes better than good results reported in the literature. We have also found that there is a statistically significant relationship between interpretability (i.e. the number of rules/inputs per rule) and accuracy with the addition of rules and inputs both contributing to improved performance up to a point (with p-value for the effect of number of rules and inputs $<$0.0005 in all cases). In the iris data tested, additional rules provided more than 20% improvement for early rules and the advantages quickly became negligible (e.g. a linear model was $E = 60 - 1.35 * NumInput - 18.81 * NumRules$ for SPEA2).

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6. REFERENCES

[1] O. Cordón, F. Gomide, F. Herrera, F. Hoffmann, and L. Magdalena. Genetic fuzzy systems. new developments. *Fuzzy Sets and Systems*, 141(1):1–3, 2004.

[2] K. Deb, A. Pratap, S. Agarwal, and T. Meyarivan. A fast and elitist multiobjective genetic algorithm: Nsga-ii. *Evolutionary Computation, IEEE Transactions on*, 6(2):182 –197, April 2002.

[3] H. Eskandari, C. Geiger, and G. Lamont. Fastpga: A dynamic population sizing approach for solving expensive multiobjective optimization problems. In Shigeru Obayashi, Kalyanmoy Deb, Carlo Poloni, Tomoyuki Hiroyasu, and Tadahiko Murata, editors, *Evolutionary Multi-Criterion Optimization*, volume 4403 of *Lecture Notes in Computer Science*, pages 141–155. Springer Berlin / Heidelberg, 2007.

[4] H. Ishibuchi and Y. Nojima. Analysis of interpretability-accuracy tradeoff of fuzzy systems by multiobjective fuzzy genetics-based machine learning. *Int. J. Approx. Reasoning*, 44(1):4–31, 2007.

[5] A.J. Nebro, J.J. Durillo, F. Luna, B. Dorronsoro, and E. Alba. Mocell: A cellular genetic algorithm for multiobjective optimization. *Int. J. Intell. Syst.*, 24(7):726–746, 2009.

[6] E. Zitzle, M. Laumanns, and L. Thiele. Spea2: Improving the strength pareto evolutionary algorithm. Technical report, 2001.