Evolution of adaptive discretization intervals for rule-based genetic learning system

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Abstract

The traditional classifier rules evolved in genetic based machine learning (GBML) systems need a discretization process to handle problems with real-valued attributes. A good discretization procedure is needed to generate a solution with good accuracy because the alternative of a high number of simple uniform-width intervals is bad due to the big search space being hardly explorable in a reasonable time. There exist some good discretization algorithms, like the Fayyad & Irani method [Fayyad and Irani, 1993], but they fail in some problems.

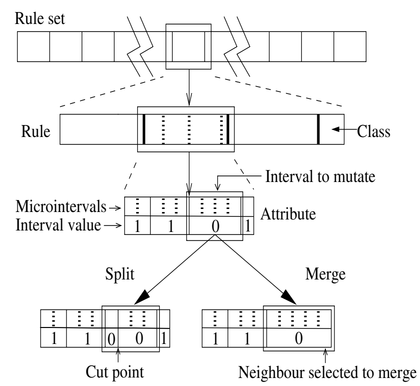
The work being summarized here deals with a rule representation with adaptive discrete intervals which split or merge through the evolution process, finding a robust and correct discretization intervals as the learning process is done with a reasonable computational cost.

Summary

This representation is used inside a Pittsburgh approach genetic classifier system derived from GABIL [DeJong et al., 1993], and the rule structure is taken directly from GABIL, using Conjunctive Normal Form (CNF) predicates.

In order to get a reasonable computational cost and also to bound the growth of the search space, some constrains have been introduced: (1) We define a fixed number of "low level" intervals which we call *micro-intervals*. (2) The adaptive intervals are built merging *micro-intervals*. When we split an interval, we select a random point in its *micro-intervals* to do the process. (3) When we merge two intervals, the value of the resulting interval is taken from the one which has more *micro-intervals*. (4) Finally, if both have the same number, the value is chosen randomly. The representations and split and merge operations are represented in figure 1

Figure 1: Adaptive intervals manipulated by merge and split operators.



We have integrated the split and merge operators inside the mutation operator, as it is the easiest part of the GA cycle to modify. Thus, we redefine the mutation operator adding p_{split} and p_{merge} as the probabilities of splitting or merging an interval which has been selected to mutate, instead of the classic bit-inversion operator.

The method presents a good performance and robustness.

References

[DeJong et al., 1993] DeJong, K. A., Spears, W. M., and Gordon, D. F. (1993). Using genetic algorithms for concept learning. *Machine Learning*, 13(2/3):161–188.

[Fayyad and Irani, 1993] Fayyad, U. M. and Irani, K. B. (1993). Multi-interval discretization of continuous-valued attributes for classification learning. In *IJCAI*, pages 1022–1029.