MOLeCS: A MultiObjective Learning Classifier System

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The system we propose (MOLeCS) is a Genetic Algorithm (GA) which evolves sets of rules in order to perform classification tasks. Each individual of the GA codifies one rule and the system has to return a complete set of rules which solves the problem.

In this framework, two major points are considered: the fitness evaluation of each classifier and the covering problem (how to cover all the examples).

The fitness evaluation method must promote the formation of accurate and general rules. Previous Classifier Systems base the classifier fitness on the payoff prediction or more recently, on the accuracy of payoff prediction, not in the prediction itself (Wilson, 1995). Horn et al. (1994) also considered the classifier accuracy, but using the hypothesis that all classifiers had the same generality. In this sense, our approach is more related to Horn's study, but taking account of the classifier generality too. So we clearly have two objectives to maximize: accuracy and generality. The classifier accuracy is the rate of correctly classified examples over the number of covered examples. The classifier generality is computed as the rate of covered examples.

The multiobjective maximization is implemented using different MultiObjective (MO) methods: Pareto Ranking and Weighted Sum (WS). The Pareto Ranking Algorithm ranks the population into non-dominated solution sets, and the fitness is assigned according to this rank. In the WS algorithm all the objectives are weighted and summed together to obtain an scalar value (fitness).

The covering goal is promoted with niching mechanisms. We first tested a variant of the De Jong's Crowding. It is based on a steady-state cycle, where each new individual replaces a "low fitness and similar individual". This mechanism favours the diversity but it is not sufficient for maintaining all the necessary niches, resulting in genetic drift. Thus, the final population contained some well-fitted classifiers with high number of copies, while other well-fitted classifiers did not appear. For this reason, we introduced an explicit sharing, dividing up the fitness of each classifier among all the copies of that classifier (sharing with niche radius $\sigma_{sh} = 1$).

MOLeCS was tested in the 6-multiplexer and the 11-multiplexer problems. We compared the results using three different MO algorithms and two niching methods. Figure 1 shows an example of our results in the 11-multiplexer, obtained with the WS algorithm combined with Crowding and with Sharing (population size is 800). The system performance, which is measured as the fraction of correctly classified examples, is better with sharing, reaching the optimum of 100%.

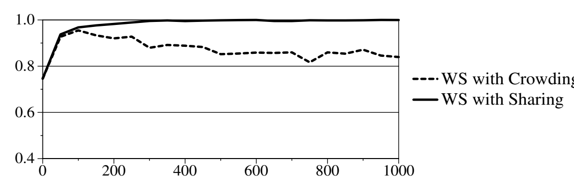

Figure 1: System performance vs generations.

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