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EDITORIAL

Special issue on advances in Learning Classifier Systems

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Learning Classifier Systems (LCS) belong to the rule-based class of machine learning algorithms which typically combine evolutionary computing with a problem relevant learning strategy. LCS research, since its inception more than three decades ago, continues to inspire and lead research in the emerging discipline of evolutionary machine learning. Recent LCS research has focused on the improvement of system performance, including model accuracy, compactness, and learning speed among others, for large and complex problems. Pattern mining and data classification remain amongst the key problem areas of interest for LCS application. New LCS algorithms are being developed to deal with a variety of different problem domains. However, Stewart Wilson's Michigan-style, accuracy-based XCS and the closely related UCS algorithm, specifically adapted for supervised learning tasks, dominate the focus of the field. This special issue presents revised versions of selected papers presented at the 16th International Workshop on Learning Classifier Systems (IWLCS 2013) and at the Genetic Based Machine Learning (GBML) Track of the 2013 Genetic and Evolutionary Computation Conference (GECCO).

The five papers presented in this issue broadly reflect the current research trends mentioned above. Specifically, the first paper, *Self Organizing Classifiers: First Steps in Structured Evolutionary Machine Learning* by Vargas et al., deals with structural preservation of classifier populations in LCS. In this paper, authors extend their work on a version of LCS that they refer to as Self-Organizing Classifiers (SOC). SOC applies the Self Organizing Maps (SOM) concept to structure classifier populations using an adaptive clustering technique. The authors purport that the introduction of SOM based population structure in SOC allowed defining and keeping explicit and distinct niches in LCS framework, which can be useful to avoid some of the problems, such as forgetting, associated with the implicit and dynamic niching used in LCS. This work extends SOC with an adaptive SOM which does not require tuning a learning rate externally and adapts SOM parameters autonomously. The proposed algorithm is evaluated in some challenging multi-step environments characterised by noisy, dynamically changing and continuous valued input-action mazes. The proposed system shows promising performance in these problems.

The second paper, *Learning complex, overlapping and niche imbalance Boolean problems using XCS-based classifier systems* by Iqbal et al. deals with scaling XCS to the classification problems with overlapping decision boundaries and imbalance niches. The authors introduce XCSCFA, a variant of the XCS algorithm that utilizes a more flexible genetic programming related encoding and explicit state-action mapping through computed, code-fragment actions. The authors investigated the performance of standard XCS and XCSCFA on learning complex Boolean problems with the above mentioned characteristics.

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The authors show that the traditional approach of tunning and adapting standard parameters and learning mechanisms does not scale XCS to deal with such complex problems. The authors then demonstrate that XCSCFA, successfully solves overlapping and niche imbalance problems. The authors attribute this success to the redundancy provided by the GP-like code-fragment actions in XCSCFA and its ability to deal with inconsistent actions.

The third paper, *Adaptive Artificial Datasets Through Learning Classifier Systems for Classification Tasks* by Marzukhi et al., deals with the autonomous evaluation of LCS algorithms. The authors use a competitive co-evolutionary framework to tune the difficulty of automatically generated test classification problems. The idea involves using a search algorithm to generate artificial classification datasets whose fitness are determined by the performance of an LCS run on these data sets. Two artificial test generators are introduced in the framework including a local search heuristic (Tabu search) and a Pittsburgh style LCS test generator. The quality, in terms of complexity and difficulty, of the datasets generated by both algorithms is then evaluated by a receiver LCS. The framework is experimentally tested and is shown to be able to generate datasets with tunable difficulty levels.

The fourth paper, *Performance Analysis of Rough Set Ensemble of Learning Classifier Systems with Differential Evolution based Rule Discovery* by Debie et al., deals with the issue of scaling Michigan-style LCS to higher dimensional problems. The authors propose a rough set based LCS ensemble approach to deal with high dimensional data mining problems. The rough set is a non-statistical mathematically founded data analysis approach that aims at finding the minimum number of features required to approximate concepts in a classification problem. The rough set technique has been used successfully to complement several machine learning algorithms, such as decision trees, but has not been previously integrated and tested with in an LCS framework. A key characteristic of rough set technique, in contrast to other feature selection approaches is that this approach generates a set of representative feature subsets instead of a single optimal subset. The authors utilize this powerful characteristic to train several base LCS in an ensemble setting on separate representative feature subspaces. Each base classifier in the ensemble is a UCS enhanced with a differential evolution rule discovery component instead of the traditional GA rule discovery. The authors present the different performance characteristics of their proposed system on a number of classification tasks and its superiority over the standard LCS.

The fifth paper *A Multi-Core Parallelization Strategy for Statistical Significance Testing in Learning Classifier Systems*, by Rudd et al. deals with speedup issues in LCS through hardware parallelization approaches. The authors emphasize the importance of developing and adopting statistical significance testing strategies for the application of LCS algorithms to real-world problems such as biomedical data mining. This work seeks to make the computationally demanding task of performing permutation-based statistical analysis in LCS more feasible on a single multi-core workstation. The authors' python implementation yielded near linear speedups as long as the number of concurrent processes did not exceed the availability of CPU cores. This simple LCS parallelization code has been made available for download.

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