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Tim Kovacs Xavier Llorà
Keiki Takadama Pier Luca Lanzi
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# Learning Classifier Systems

International Workshops, IWLCS 2003–2005
Revised Selected Papers

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Springer

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# Preface

The work embodied in this volume was presented across three consecutive editions of the International Workshop on Learning Classifier Systems that took place in Chicago (2003), Seattle (2004), and Washington (2005). The Genetic and Evolutionary Computation Conference, the main ACM SIGEvo conference, hosted these three editions. The topics presented in this volume summarize the wide spectrum of interests of the Learning Classifier Systems (LCS) community. The topics range from theoretical analysis of mechanisms to practical consideration for successful application of such techniques to everyday data-mining tasks.

When we started editing this volume, we faced the choice of organizing the contents in a purely chronological fashion or as a sequence of related topics that help walk the reader across the different areas. In the end we decided to organize the contents by area, breaking the time-line a little. This is not a simple endeavor as we can organize the material using multiple criteria. The taxonomy below is our humble effort to provide a coherent grouping. Needless to say, some works may fall in more than one category. The four areas are as follows:

**Knowledge representation.** These chapters elaborate on the knowledge representations used in LCS. Knowledge representation is a key issue in any learning system and has implications for what it is possible to learn and what mechanisms should be used. Four chapters analyze different knowledge representations and the LCS methods used to manipulate them.

**Mechanisms.** This is by far the largest area of research. Nine chapters relate theoretical and empirical explorations of the mechanisms that define LCS on the following subjects: (1) bloat control for variable-length representations, (2) classifier manipulation techniques: classifier ensembles and post processing (3) error guidance and the exploration/exploitation dilemma, (4) internal-model driven multistep LCS, (5) effects of class imbalance, (6) bounding convergence criteria for reinforcement-based LCS, and (7) techniques for dealing with missing data.

**New directions.** This group of chapters focuses on LCS applied to new and unconventional problems. Two chapters present work on the usage of LCS as learning models for system composition where they are used to create complex strategies based on properly assembling basic capabilities. Two other chapters explore seminal work on LCS as function approximators, exploring different architectures and methods to efficiently achieve this goal. Another chapter describes a new way of using LCS for determining relevant variables for the predictive process, instead of only focusing on classification performance. The last chapter of this group explores formal relations between LCS and ant colony optimization for the traveling salesman problem, illustrating how LCS can also be used to solve such a class of problems.

**Application-oriented research and tools.** The last group of chapters describes applied research, mostly oriented to data-mining applications. Two chapters explore and analyze how to improve the performance and accuracy of LCS for data-mining tasks. Two other chapters explore a more practical path that involves the creations of tools for (1) assisting the process of knowledge discovery and its visualization for medical data, and (2) creating computer-aided design tools that can help designers to identify and explore application areas where LCS methods can provide an efficient solution.

As mentioned earlier, this volume is based on the 6th, 7th, and 8th editions of the International Workshop on Learning Classifier Systems and would not have been possible without all the authors who contributed to it via the workshop.

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## Part III New Directions



## Part IV Application-Oriented Research and Tools

# Analyzing Parameter Sensitivity and Classifier Representations for Real-Valued XCS

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**Abstract.** To evaluate a real-valued XCS classifier system, we present a validation of Wilson's XCSR from two points of view. These are: (1) sensitivity of real-valued XCS specific parameters on performance and (2) the design of classifier representation with classifier operators such as mutation and covering. We also propose model with another classifier representation (LU-Model) to compare it with a model with the original XCSR classifier representation (CS-Model.) We did comprehensive experiments by applying a 6-dimensional real-valued multiplexor problem to both models. This revealed the following: (1) there are critical threshold on covering operation parameter ($r_0$), which must be considered in setting parameters to avoid serious decreases in performance; and (2) the LU-Model has an advantage in smaller classifier population size within the same performance level over the CS-Model, which reveals the superiority of alternative classifier representation for real-valued XCS.

## 1 Introduction

XCS [6] is a learning classifier system which has the potential to evolve accurate, maximally general classifiers to cover the state space for each action [3,7]. XCS takes *bit string* inputs, the same as traditional learning classifier systems [2] (LCS). To facilitate XCS and broaden the range of applicable problem representation while keeping its generalization abilities, XCSR [8] was proposed by Wilson to deal with *real-valued* problems, and he found that XCSR could learn appropriately on the real-valued 6-multiplexor problem.

Although Wilson analyzed the potential of XCSR, its validity was insufficient in two respects. Firstly, the parameter settings used for the experiment seemed to be set ad hoc, especially for the two newly introduced parameters $m_0$ and

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$r_0$ that were used in the real-valued classifier operations of *mutation* and *covering*. Secondly, the reason he adopted proposed classifier representation is not discussed, despite the possibility of other classifier representations.

Therefore, what we focus in this paper are (1) an analysis of the settings of real-valued XCS specific parameters to evaluate the model; and (2) an analysis of classifier representation with classifier operators such as covering and mutation. To achieve the latter, we propose an opponent model that presents another real-valued classifier representation that was inspired by Wilson's other model XCSI to deal with integer-valued input [9]. Although the requirement of extending XCS to integer-valued input is basically similar to that of extending XCS to real-valued input, XCSI adopts a different design concept over classifier representation. This concept can easily be applied to design another real-valued classifier representation, which we propose and adopt in the opponent model. For convenience, we have called this opponent the LU-Model and the original model the CS-Model, names which originate from the attributes used in each classifier condition that will be described later.

The rest of the paper is organized as follows. Section 2 describes both the CS and LU-Models by revealing the part extended from the XCS to achieve real-valued input. Section 3 describes the real-valued 6-multiplexor problem. Section 4 presents some simulation experiments that were done by applying both the CS and LU-Models to the real-valued 6-multiplexor problem. Section 5 has discussions based on the experimental results to validate real-valued XCS. Section 6 is the conclusion.

## 2 Extensions to XCS for Real-Valued Input

Both CS and LU-Models are based on XCS but differ in their classifier representation. This section presents the CS-Model, which adopts XCSR classifier representation and the LU-Model, where classifier representation is inspired by XCSI. It is done by describing their classifier representations in detail, which are the extended parts from XCS[1].

### 2.1 XCSR-Based Classifier Representation (CS-Model)

This section explains the CS-Model regarding its difference from XCS, which is equivalent to describing XCSR classifier representation with classifier operators such as covering, mutation, and crossover. To catch up with recent developments in XCS called the classifier *subsumption* mechanism, the "is-more-general" operator has been additionally defined which checks whether the classifier can subsume the other target classifier.

**Representation of Classifier Conditions:** The representation of the classifier in the CS-Model differs from the original XCSR in the condition part, which

[1] The implementation of the XCS part of the CS and LU-Models is based on Butz and Wilson [1].

replaces the bit string with a set of attributes named *interval predicates* by Wilson. The interval predicate is composed of two real values ($c_i$, $s_i$) where suffix $i$ denotes the position in the condition part. Each interval predicate represents an interval $[c_i - s_i, c_i + s_i]$ on the real number line, and if the corresponding element of the input (which is a real-valued vector) is included in the interval, matching succeeds. If, and only if, all elements match the corresponding interval predicates in the classifier condition, can matching be considered a success. The domain of attributes $c_i$ and $s_i$ are both set between 0 and 1, which inherit the setting of XCSR in the CS-Model, but is not a necessary requirement for this representation.

**Covering Operator:** The covering operator creates a new classifier that matches a specified input. When a real-valued vector is denoted as $(x_1, ..., x_i, ..., x_n)$, where $n$ is the dimension of input, each interval predicate of covered classifier condition $(c_1, s_1)...(c_i, s_i)...(c_n, s_n)$ is set as follows.

$$\begin{cases} c_i = x_i \\ s_i = rand(r_0). \end{cases} \tag{1}$$

Here, $r_0$ is a parameter used to decide the distribution range of the spread of the covering interval, where $rand(x)$ is a function that returns a random value distributed in the interval $0 \leq rand(x) \leq x$. The value of $r_0$ is set below 1 to maintain the $s_i$ within its domain of $[0, 1]$ inherited from XCSR, but is not a necessary requirement for this operation.

**Mutation Operator:** The mutation operator mutates the classifier condition by adding delta values $\Delta c_i$ and $\Delta s_i$ to interval predicate variables $c_i$ and $s_i$ at the constant possibility of mutation parameter $\mu$ at each interval predicate. Each delta value for attributes $c_i$ and $s_i$ are calculated as follows.

$$\begin{cases} \Delta c_i = \pm rand(m_0) \\ \Delta s_i = \pm rand(m_0). \end{cases} \tag{2}$$

Here, $m_0$ is a parameter used to decide the distribution range of both $\Delta c_i$ and $\Delta s_i$, where $\pm rand(x)$ is a function that returns a random value distributed in interval $0 \leq rand(x) \leq x$ with the sign chosen uniform randomly. If the mutated value exceeds the domain of $[0, 1]$, the value is adjusted to 0 or 1. The setting for this domain is inherited from XCSR, but is not a necessary requirement for this operation.

**Crossover Operator:** The crossover operator works the same as the crossover in XCS, except that the crossover point is not set between the condition bits but between the interval predicates.

**Is-More-General Operator:** The is-more-general operator judges whether a classifier condition is more general than another classifier condition. The basic idea of generality is the inclusion of the set of classifier condition's possible matching inputs. If the possible matching inputs of classifier condition $X$ completely include and are larger than the possible matching inputs of classifier condition $Y$, $X$ is more general than $Y$. This idea can be realized for real-valued classifier representation by comparing the inclusion of the interval on the real number line for each corresponding interval predicate. For two classifier conditions $X : (c_1, s_1)...(c_i, s_i)...(c_n, s_n)$ and $Y : (c'_1, s'_1)...(c'_i, s'_i)...(c'_n, s'_n)$, if $(c_i - s_i) \leq (c'_i - s'_i)$ and $(c'_i + s'_i) \leq (c_i + s_i)$ for all $i$ except where all attributes are equal, X is more general than Y.

## 2.2 XCSI-Inspired Classifier Representation (LU-Model)

This subsection proposes the LU-Model with another real-valued classifier representation inspired by XCSI, which is an XCS extended model to deal with integer-valued inputs. XCSI adopts a different design concept over classifier representation, as it specifies the interval by using the value for the lower and upper bounds. This concept can easily be applied to designing real-valued classifier representation that differs from the CS-Model. The details are described below.

**Representation of Classifier Condition:** The representation of classifier condition in the LU-Model seems to be like that in the CS-Model as its interval predicate is composed of two real values $(l_i, u_i)$, where suffix $i$ denotes the position in the condition part. However, the denoting interval on the real number line differs from the CS-Model. The $i$th interval predicate simply denotes an interval $[l_i, u_i]$. If the corresponding element of input is included in the interval, matching between the element and the interval predicate succeeds. If, and only if, all elements match the corresponding interval predicates in the classifier condition, can matching be considered a success. The domain of attributes is restricted to $0 \leq l_i \leq u_i \leq 1$. This setting for domain inherits the concept of XCSI, but is not a necessary requirement for this representation.

**Covering Operator:** The covering operator creates a new classifier that matches a specified input. When a real-valued vector is denoted as $(x_1, ..., x_i, ..., x_n)$, where $n$ is the dimension of the input, each interval predicate of the covered classifier condition $(l_1, u_1)...(l_i, u_i)...(l_n, u_n)$ is set as follows.

$$\begin{cases} l_i = x_i - rand(r_0) \\ u_i = x_i + rand(r_0). \end{cases} \tag{3}$$

Here, $r_0$ is a parameter used to decide the distribution range of the distance from input value $x_i$ to $l_i$ and $u_i$, where $rand(x)$ is a function that returns a random value distributed in the interval $0 \leq rand(x) \leq x$. If the covering value exceeds the domain of $0 \leq l_i \leq u_i \leq 1$, $l_i$ and $u_i$ are set to be kept within their domains as the follows: if $l_i$ is smaller than 0, $l_i$ is set to 0; and if $u_i$ exceeds 1, $u_i$ is set to 1.

**Mutation Operator:** The mutation operator mutates the classifier condition by adding delta values $\Delta l_i$ and $\Delta u_i$ to $l_i$ and $u_i$ at the constant possibility of