

Can Evolution Strategies Improve Learning Guidance in XCS? Design and Comparison with GA-based XCS

Sergio Morales-Ortigosa

Albert Orriols-Puig

Ester Bernadó-Mansilla

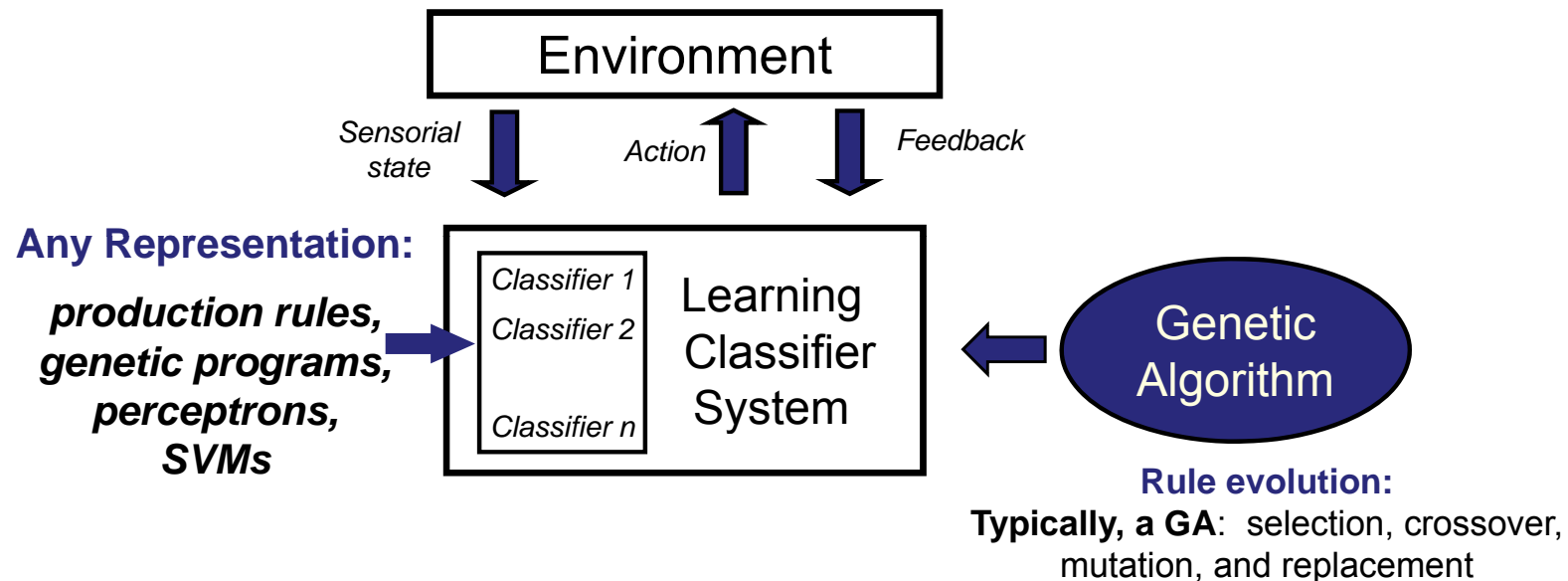
Enginyeria i Arquitectura La Salle

Universitat Ramon Llull

{s09767,aorriols,esterb}@salle.url.edu

Framework

- Michigan-style LCSs (Holland, 1976) have reached maturity

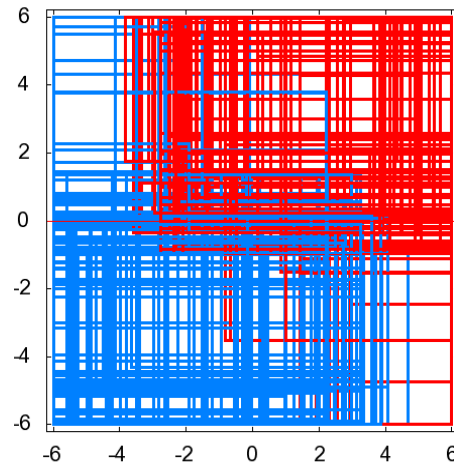
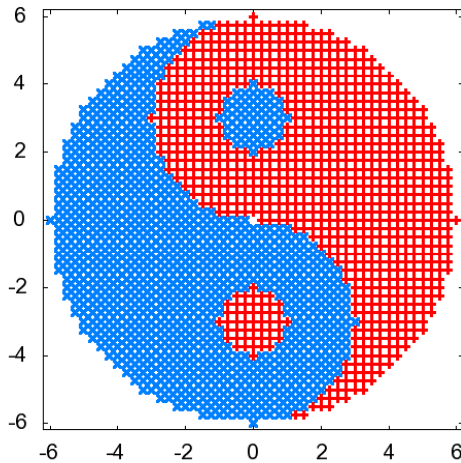


- Extended Classifier System - XCS (Wilson, 1995, 1998)
 - By far, the most influential LCS

Motivation

□ Problems with continuous attributes

- Interval-based representation (Wilson, 2001)
- **IF** $v_1 \in [l_1, u_1]$ *and* $v_2 \in [l_2, u_2]$ *and* ... *and* $v_n \in [l_n, u_n]$ **THEN** class_i



□ They yield competitive results, but we have little understanding of how they work!

• **2-point crossover**

➤ Too disruptive?

• **Mutation:** add a random uniform value

➤ Could we use more information?

□ Could we design better genetic operators?

- Not exactly clear the impact of crossover and mutation
- Systematic analysis
- Creative analysis: propose new operators

Purpose of the Work

- **Looking at the continuous optimization realm**
 - Evolution strategies
 - Real-coded GAs

- **The purpose of this work is to**
 - Design an XCS based on evolution strategies (ES)
 - **Adapt classifier representation**
 - **Design ES mutation and crossover alike for XCS**

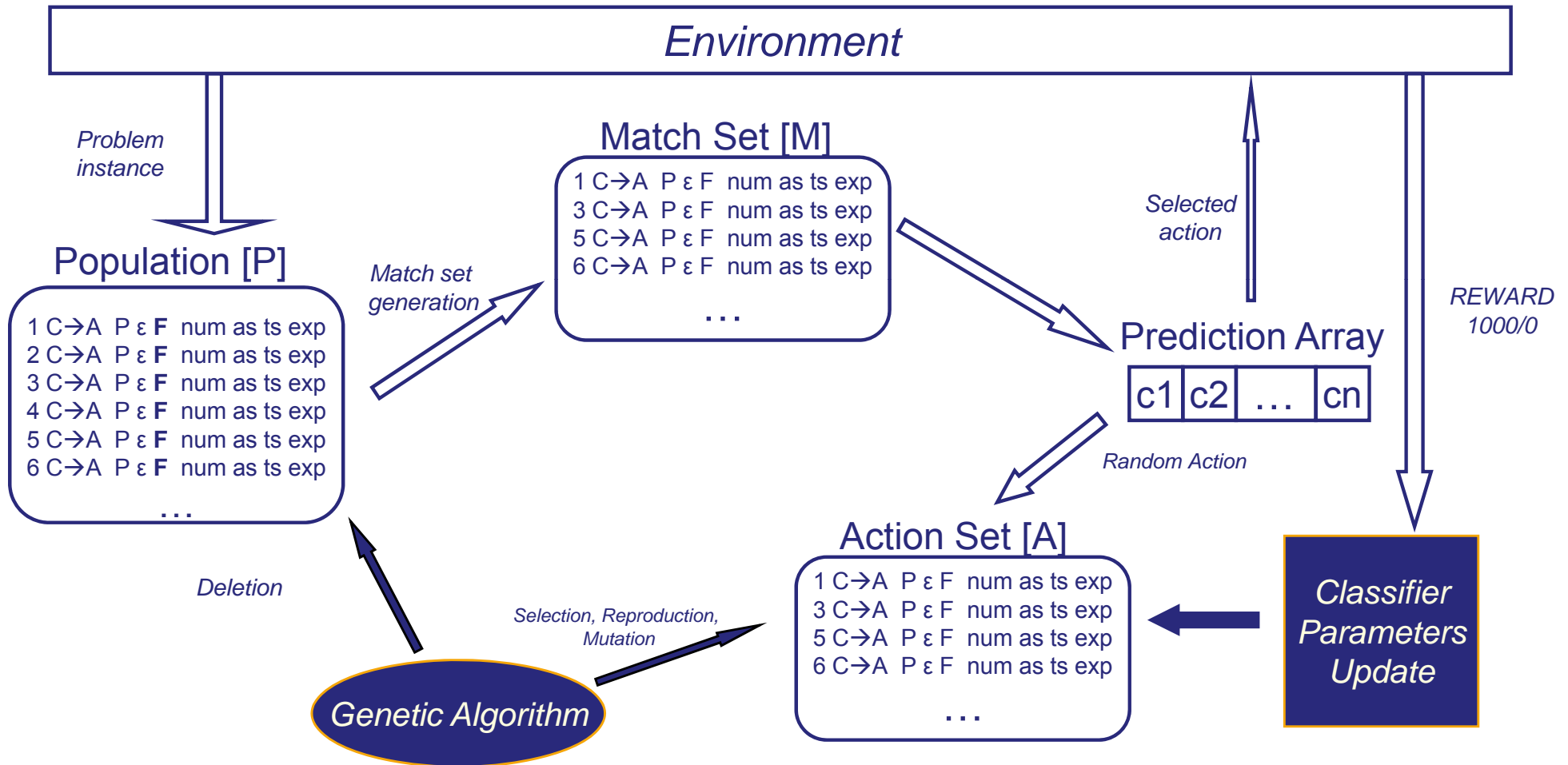
 - Analyze the role of Gaussian mutation

 - Compare whether ES-based XCS outperforms GA-based XCS

Outline

- 1. Description of XCS**
- 2. Evolution Strategies in XCS**
- 3. Experimental Methodology**
- 4. Results**
- 5. Conclusions and Further Work**

Description of XCS



Genetic Operators

□ Selection

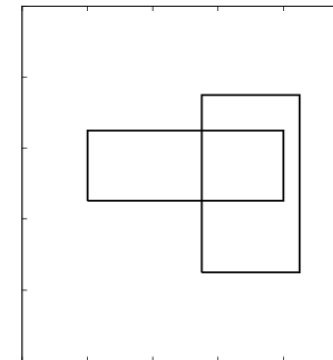
- Proportionate selection
- Tournament selection

□ Crossover:

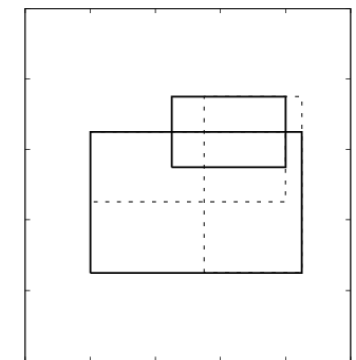
- Two-point crossover

$$\begin{array}{l} \langle [0.20, 0.80], [0.45, 0.55] \rangle \\ \langle [0.60, 0.85], [0.25, 0.75] \rangle \end{array} \Rightarrow \begin{array}{l} \langle [0.20, 0.85], [0.25, 0.55] \rangle \\ \langle [0.60, 0.80], [0.45, 0.75] \rangle \end{array}$$

Parents

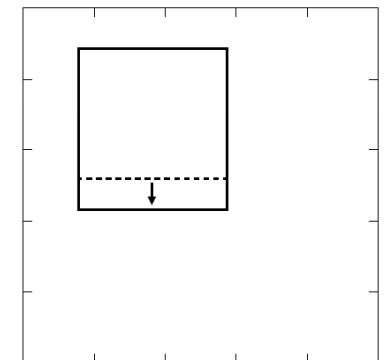


Offspring



□ Mutation:

- GA-based XCS: Add a uniform random value



Outline

1. Description of XCS

2. Evolution Strategies in XCS

3. Experimental Methodology

4. Results

5. Conclusions and Further Work

GAs vs ESs Head to Head

□ Genetic Algorithms

- Initially used with binary representation
- Key aspects:
 - **GAs process (mix & ensemble) building blocks**
 - **Crossover** as primary search operator
 - **Mutation** as local search operator

□ Evolution Strategies

- Initially designed for problems with continuous attributes
- Key aspects:
 - **Search focuses little improvement/selection**
 - **Gaussian mutation** is the search operator
 - **Crossover** included afterwards to resemble GAs

ES-based XCS

- Representation extended with a vector of strategy parameters

IF $v_1 \in [l_1, u_1]$ and $v_2 \in [l_2, u_2]$ and ... and $v_n \in [l_n, u_n]$ THEN class_{*i*}

$(\sigma_1, \sigma_2, \dots, \sigma_n)$

- The strategy parameters (SP) evolve with the representation
- Genetic operators modified to deal with the new rep.

- **Mutation**

- Intervals *i* mutated as:

$$l_i = l_i + \sigma_i N(0,1) \quad u_i = u_i + \sigma_i N(0,1)$$

- Strategy parameter vector mutated as:

$$\sigma_i' = e^{\tau_0 N_0(0,1)} e^{\tau N_i(0,1)}$$

where

$$\tau_0 = 1/(2n)^{0.5} \text{ and } \tau = 1/(2n^{0.5})^{0.5}$$

ES-based XCS

□ Crossover

- Discrete/dominant recombination for *object parameters*
 - **Each variable and SP are randomly selected from one parent**
- Intermediate recombination for *strategy parameters*
 - **Calculates the center of mass of the parents**
 - **Pushes to the average value**

□ Selection

- Fitness proportionate selection
- Tournament selection
- Truncation selection

Outline

1. Description of XCS

2. Evolution Strategies in XCS

3. Experimental Methodology

4. Results

5. Conclusions and Further Work

Experimental Methodology

- Analyze the effects of
 - Selection + mutation (local search)
 - Selection + mutation + crossover (innovation)
- Experiments run on 12 real-world data sets (UCI rep.)
 - 10-fold cross-validation

Id.	dataset	#Inst	#Fea	#Re	#In	#No	#Cl	%MisInst
<i>bal</i>	Balance	625	4	4	0	0	3	0
<i>bpa</i>	Bupa	345	6	6	0	0	2	0
<i>gls</i>	Glass	214	9	9	0	0	6	0
<i>h-s</i>	Heart-s	270	13	13	0	0	2	0
<i>irs</i>	Iris	150	4	4	0	0	3	0
<i>pim</i>	Pima	768	8	8	0	0	2	0
<i>tao</i>	Tao	1888	2	2	0	0	2	0
<i>thy</i>	Thyroid	215	5	5	0	0	3	0
<i>veh</i>	Vehicle	846	18	18	0	0	4	0
<i>wbcd</i>	Wisc. breast-cancer	699	9	0	9	0	2	2.3
<i>wdbc</i>	Wisc. diagnose breast-cancer	569	30	30	0	0	2	0
<i>wne</i>	Wine	178	13	13	0	0	3	0

Experimental Methodology

- **Results statistically compared by means of**
 - The multicomparison Friedman test
 - The post-hoc Bonferroni-Dunn test for multiple comparisons
 - The Wilcoxon signed-ranks test for pairwise comparisons

- **XCS configured as:**
 - #iter=100000, $N = 6400$, $\theta_{GA} = 50$, $P_{cross} = 0.8$, $P_{mut} = 0.04$,
 $r_0 = 0.6$, $m_0 = 0.1$

Outline

- 1. Description of XCS**
- 2. Evolution Strategies in XCS**
- 3. Experimental Methodology**
- 4. Results**
- 5. Conclusions and Further Work**

Analysis of Selection + Mutation

□ Test Accuracy

	XCS-GA with proportionate	XCS-ES with proportionate	XCS-GA with tournament	XCS-ES with tournament	XCS-ES with truncation	XCS-ES weighted mutation
Dataset	XCS_{GA-ps}	XCS_{ES-ps}	XCS_{GA-ts}	XCS_{ES-ts}	XCS_{ES-tr}	weig. XCS_{ES}

According to a post-hoc Bonferroni-Dunn test:

- XCS-ES tourn. significantly outperformed XCS-GA with both selection schemes
- XCS-ES proportionate significantly outperformed XCS-GA proportionate

<i>pim</i>	70.83 (4)	71.05 (2)	69.99 (6)	72.87 (1)	70.88 (3)	70.53 (5)
<i>tao</i>	89.32 (6)	92.90 (3)	89.79 (5)	93.80 (1)	93.01 (2)	89.90 (4)
<i>thy</i>	94.73 (6)	95.50 (4)	95.66 (2.5)	96.28 (1)	94.88 (5)	95.66 (2.5)
<i>veh</i>	65.52 (3)	66.00 (2)	64.50 (4)	67.26 (1)	63.83 (6)	64.34 (5)
<i>wbcd</i>	80.88 (6)	85.84 (1)	81.26 (5)	85.65 (2)	82.50 (4)	82.93 (3)
<i>wdbc</i>	78.68 (2)	75.28 (3)	80.20 (1)	74.93 (4)	67.60 (6)	69.13 (5)
<i>wne</i>	80.71 (5)	86.70 (1)	82.21 (2)	82.02 (3)	78.09 (6)	81.65 (4)
rnk.	4.38	2.67	3.54	2.00	4.50	3.92
pos.	5	2	3	1	6	4

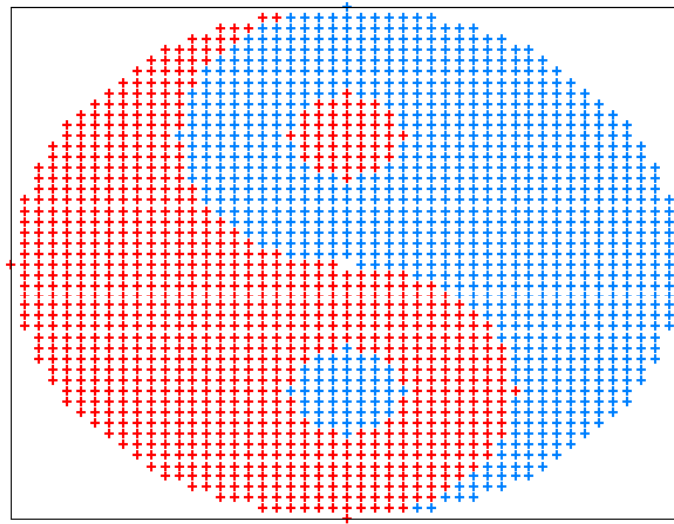
Selection + Crossover + Mutation

	XCS-GA with proportionate	XCS-ES with proportionate	XCS-GA with tournament	XCS-ES with tournament	XCS-ES with truncation
Dataset	XCS_{GA-ps}	XCS_{ES-ps}	XCS_{GA-ts}	XCS_{ES-ts}	XCS_{ES-tr}
<i>bal</i>	83.20 (1)	82.77 (2.5)	82.72 (4)	82.77 (2.5)	82.13 (5)

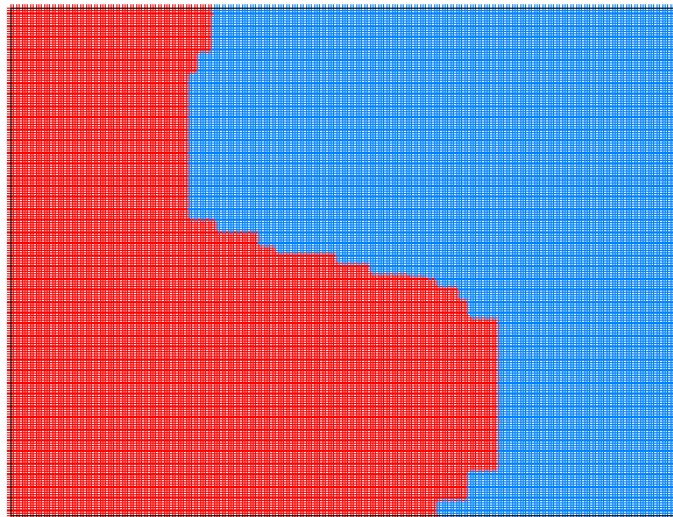
- XCS-ES still is the best method
- But now, no significant differences

<i>pim</i>	72.53 (5)	74.43 (2)	73.39 (4)	73.83 (3)	74.74 (1)
<i>tao</i>	91.22 (4)	93.52 (3)	91.19 (5)	94.35 (1)	94.17 (2)
<i>thy</i>	95.81 (2)	95.50 (5)	96.43 (1)	95.66 (3.5)	95.66 (3.5)
<i>veh</i>	71.79 (2)	71.75 (3)	71.20 (4.5)	72.89 (1)	71.20 (4.5)
<i>wbcd</i>	94.85 (3)	95.47 (1.5)	93.51 (4)	95.47 (1.5)	92.61 (5)
<i>wdbc</i>	91.09 (4)	91.80 (3)	92.44 (2)	92.85 (1)	89.51 (5)
<i>wne</i>	95.50 (4)	96.25 (1.5)	95.69 (3)	96.25 (1.5)	91.38 (5)
rnk.	2.79	2.5	3.33	2.17	4.21
pos.	4	2	3	1	5

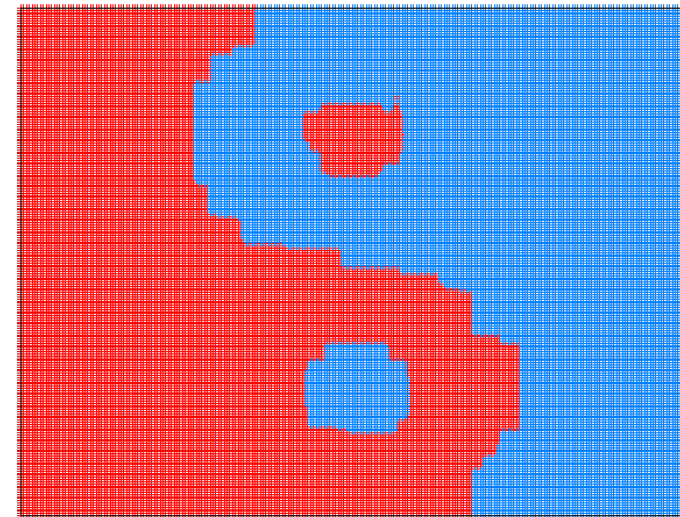
A Cool Example



Domain



XCS-GA with proportionate selection



XCS-ES with proportionate selection

Outline

- 1. Description of XCS**
- 2. Evolution Strategies in XCS**
- 3. Experimental Methodology**
- 4. Results**
- 5. Conclusions and Further Work**

Conclusions

- **The analysis performed in this paper permitted**
 - To study the discovery component of XCS, especially focusing on the role of mutation.
 - Improve XCS to deal with problems with complex boundaries described by continuous attributes.

- **Two important observations:**
 - Gaussian mutation performs innovation tasks.
 - When crossover is included XCS-GA does not significantly outperform XCS-ES. But still, it wins.

- **The overall work clearly shows the importance of further researching on GA operators.**

Further Work

- **XCS-ES is good! But, always?**
 - On average, yes!
 - Specific problems may not benefit from ES operators

- **May evolution tell me when to use one type of search or another?**
 - Existing studies on self-adaptation mutation for ternary rules
 - Search for evolution signals
 - Combine different operators
 - Let classifiers decide which operator to use
 - Characterize learning domains

Can Evolution Strategies Improve Learning Guidance in XCS? Design and Comparison with GA-based XCS

Sergio Morales-Ortigosa

Albert Orriols-Puig

Ester Bernadó-Mansilla

Enginyeria i Arquitectura La Salle

Universitat Ramon Llull

{s09767,aorriols,esterb}@salle.url.edu