Separating Rule Discovery and Global Solution Composition in a Learning Classifier System

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ABSTRACT

The utilization of digital agents to support crucial decision making is increasing in many industrial scenarios. However, trust in suggestions made by these agents is hard to achieve, though essential for profiting from their application, resulting in a need for explanations for both the decision making process as well as the model itself. For many systems, such as common deep learning black-box models, achieving at least some explainability requires complex post-processing, while other systems profit from being, to a reasonable extent, inherently interpretable. In this paper we propose an easily interpretable rule-based learning system specifically designed and thus especially suited for these scenarios and compare it on a set of regression problems against XCSF, a prominent rule-based learning system with a long research history. One key advantage of our system is that the rules' conditions and which rules compose a solution to the problem are evolved separately. We utilise independent rule fitnesses which allows users to specifically tailor their model structure to fit the given requirements for explainability. We find that the results of SupRB2's evaluation are comparable to XCSF's while allowing easier control of model structure and showing a substantially smaller sensitivity to random seeds and data splits. This increased control aids in subsequently providing explanations for both the training and the final structure of the model.

CCS CONCEPTS

Computing methodologies → Supervised learning by regression; Rule learning.

KEYWORDS

rule-based learning, learning classifier systems, evolutionary machine learning

1 INTRODUCTION

With increasing automation and digitisation, interaction between humans and trained digital agents becomes more widespread. Such socio-technical systems are for example encountered in smart factory settings. Here, human stakeholders are dependent on recommendations made or decisions taken by an agent, e.g. for (re-) configuring a machine. However, at the moment complex learning tasks can rarely be solved perfectly—often because the available data for

training is rather limited, e.g. small sample, large imbalances. This creates a distrust in the entire model among stakeholders, supposedly even if only edge cases were affected. Hard to understand models even exacerbate this issue. The cases of poor performance are rarely easily identifiable and even for good performance on test data, stakeholders often doubt the ability of models with a low transparency.

A common approach to increase stakeholder trust in predictions is explaining the training and prediction processes themselves or the model in its entirety. With increasing model complexity, which is needed for difficult learning tasks, explaining the model or its predictions is less straightforward, leading to some types of models, e.g. rule-based learners, being favoured for these situations, sometimes over better performing ones. Learning Classifier Systems (LCSs) are a family of rule-based learning algorithms that inherently allow application in the aforedescribed settings. [13]

LCS models are composed of a finite set of if-then rules for which the conditions are optimized using a—typically evolutionary metaheuristic [34]. Rules contain submodels of the problem that apply to certain areas of the feature space. These submodels are comparatively simpler than models for the full problem, thus, increasing their comprehensibility by humans. Most LCSs follow the Michigan-style (a single set whose rules are adapted over time), featuring strong online learning capabilities and being employed to solve all major machine learning tasks. However, these types of systems typically construct (and keep in their population) many more, sometimes suboptimal, rules than would be required to solve the problem at hand. A common approach is, therefore, the reduction of the population to the essential rules after training has concluded, using so called *compaction* techniques [24, 29]. The main other style LCSs follow is the Pittsburgh-style. Here, a population of sets of rules is evolved over time to solve supervised learning tasks. As a set of rules is assigned a combined fitness, rather than individual fitnesses for rules, optimal positioning/selection of rules is more difficult to achieve for the optimizer, especially as usually multiple changes to the set are performed per optimization step. Suboptimal positioning does not necessarily substantially harm system performance. However, the importance of improving it increases when explanations for rule conditions or the training process are requested. In general, the learning process is envisioned to create an "accurate and maximally general" [32], "maximally accurate and maximally general" [7] or "maximally general as well as accurate" [16] set of rules. Existing LCS rarely specifically target explanations or transparency beyond the non formally specified requirement of generality, although they are still building interpretable models.

In this paper we present a new LCS algorithm that is specifically designed to evolve both individual rules as well as the global problem solution (rule set), with performance as well as explainability considered during optimization. To facilitate this we separate the optimization of rule conditions (find partitions of the feature space for which a submodel of the given type can be fit well) from optimizing a problem solution using these rules (cf. Section 3). The system employs some of the same goals as the Supervised Rulebased Learning System (SupRB) [14, 15] and—despite not following the Pittsburgh-style—improves some key features in controlling rule positioning and solution composition. Thus, we refer to the new system as SupRB2.

We evaluate SupRB2 against XCSF [38], one of the most developed and advanced LCSs [27], on a variety of different regression datasets (cf. Section 4). We find that, as intended, SupRB2 performs competitively based on hypothesis testing on error distributions as well as Bayesian comparison [4] across datasets.

2 RELATED WORK

The most well known LCSs are XCS and its derivatives [34]. While XCS was originally designed for reinforcement learning tasks, it has (with some extensions) been applied in all of the three major learning settings [34]. One of these extensions is the usage of interval-based matching functions rather than binary ones to operate in real-valued environments [36]. To solve supervised function approximation tasks, XCS' constant predicted payoff was replaced with a linear function forming the original XCSF [38]. The linear model and the interval-based matching functions have later on been substituted with various more complex options [6, 20]. These are, however, sacrificing transparency for a stronger predictive performance.

Two approaches to reach explainability and its related and relevant concepts of interpretability and transparancy and thus, ultimately, understandability (in this paper we refer to those concepts under a broader umbrella of explainability in the spirit of explainable artificial intelligence as a whole), must be distinguished [3]: By intentionally designing transparent models, the model structure itself can be used for its comprehension and the interpretation of the decisions made. For other models, post-hoc methods that operate through visualisation, transformation of complex black-box models into transparent models and other, often model-specific, techniques, need to be utilised. Like other rule-based learning systems, LCSs can, in general, be seen as transparent/interpretable by design. They also relate to human behaviour naturally [3]. There are, however, some limitations that arise primarily through the encoding of variables, the size of the rule set and the complexity of individual rules.

In LCSs these limitations are typically controlled by design. The variables themselves are problem dependent, so overall influence is limited, but using easy to understand matching functions that allow to follow the implications for decision boundaries in the feature space improves model transparency. However, if the variable/feature itself is highly complex, human interpretation is always

limited. Rule complexity is likewise chosen by using a fitting submodel to balance users' transparency requirements with predictive power. Additionally, human understanding can be improved posthoc by employing a variety of different visualisation techniques for classifiers [23, 25, 33].

In contrast to these generally applicable solutions, handling rule set size is approached differently depending on the LCS(-style). Pittsburgh-style LCSs can control set size directly via their fitness function. For example, GAssist [2] can use the minimum description length in combination with accuracy to form a single objective fitness and additionally apply a penalty on individuals' fitnesses when the rule set size falls below a predefined threshold. In Michiganstyle systems, where fitness refers to a rule rather than a rule set and training benefits from larger than necessary populations, similar mechanisms are not available. Instead, compaction mechanisms have been designed [10, 39]. After training is completed, they remove redundant or incorrect rules from the population. Ideally, the rule set size decreases without a negative effect on predictive power. This has first been demonstrated on the Wisconsin Breast Cancer dataset [37] and further advanced until the issue was considered solved by Tan et al. [29]. Recently, Liu et al. [24] have proposed new compaction techniques and demonstrated their improvements over existing methods on a variety of boolean benchmarking and three real world problems.

There are some hybrid rule-based learning systems which combine explicit Michigan- and Pittsburgh-style phases for improving explainability by reducing the number of rules [8, 12, 17, 18]. Most utilise the same evolutionary algorithm for both phases, often some multi-objective evolutionary algorithm to find a proper balance between the number of rules and the accuracy. Furthermore, the two phases can be applied subsequently [8], nested [18] or cyclic, where both phases are executed several times [12].

3 THE SUPERVISED RULE-BASED LEARNING SYSTEM 2

The main idea of SupRB2 is to optimize rule conditions independently of other rules, discovering a diverse pool of well proportioned rules and then use another optimization process to select a good subset of all available rules to find good solutions to the learning problem. By separating these optimization processes both can include multiple objectives to improve explainability of the LCS model, while still targeting overall performance, e.g. rules should encompass large feature spaces but be positioned to allow a well fitted submodel and solutions should be composed of only few rules while still minimizing prediction error. For unknown problems, it is hard to estimate how many rules will likely need to be discovered before a good subset can be selected. Therefore, we alternate between phases of discovering new rules and combining rules from the pool of discovered and fitted rules. The expectation is that we can find a good solution with fewer submodel fittings than with conservative estimates of needed rules, while still being able to find such a solution if the number of rules was underestimated. Note that rules added to the pool remain unchanged and will not be removed throughout the training process. Another advantage of alternating between phases is that we can use information from the solution composition phase to steer subsequent rule discoveries

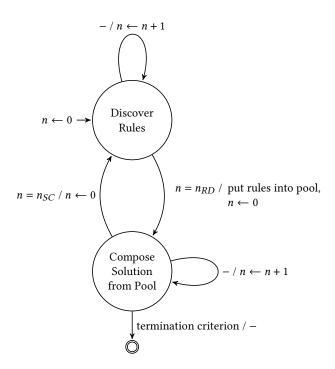


Figure 1: Rule discovery and solution composition phases in SupRB2. n_{SC} denotes the number of steps the solution creating/composing optimizer should undertake, while n_{RD} references the number of steps performed within rule discovery.

towards exploring regions where no or ill-placed rules are found. The overall process is illustrated in the form of a statemachine in Figure 1. The number of optimization steps performed within each phase can be varied, which can impact overall convergence time but does not affect solution strength.

As deriving insights into decisions (cf. Section 2) is a central aspect of SupRB2, its rules are deliberately kept as simple as possible. Thus, conditions use an interval based matching: A rule k applies for example x iff $x_i \in [l_{k,i}, u_{k,i}] \forall i$ with l being the lower and u the upper bounds. Rules' submodels $f_k(x)$ are linear. They are fit using linear least squares with a l2-norm regularization (Ridge Regression) on the subsample matched by the respective rule. When mixing multiple rules to make a prediction, a rule's experience (the number of examples matched during training and therefore included in fitting the submodel) and error are used in a weighted sum.

To discover a new rule for the pool we use an evolution strategy (ES). Note that, in contrast to the hybrid systems described at the end of Section 2, this rule discovery approach can not be considered a Michigan-style phase, especially as new rules are evolved one at a time. Its initial individual is placed around a randomly selected training example, prioritizing examples that have a high in-sample error in the current (intermediate) solution. Then we use a mutation operator without adaptation that samples a halfnormal distribution twice and moves the upper and lower bound further from the center, according to the respective values, to create λ children. From these, we replace the parent with the individual that has the highest fitness based on its in-sample error and the matched feature space volume.

Specifically, the fitness is calculated as

$$F(o_1, o_2) = \frac{(1 + \alpha^2) \cdot o_1 \cdot o_2}{\alpha^2 \cdot o_1 + o_2}, \tag{1}$$

with

$$o_1 = PACC = \exp(-MSE \cdot \beta),$$
 (2)

and

$$o_2 = V = \prod_i \frac{u_i - l_i}{\min_{x \in \mathcal{X}} x_i - \max_{x \in \mathcal{X}} x_i}.$$
 (3)

Its base form (cf. eq. (1)) was adapted from [40], where it was used in a feature selection context, similarly combining two objectives. The Pseudo-Accuracy (PACC) squashes the Mean Squared Error (MSE) of a rule's prediction into a [0, 1] range, while the volume share $V \in [0, 1]$ of its bounds is used as a generality measure. The parameter $\beta = 2$ controls the slope of the PACC and α weighs the importance of o_1 against o_2 . Maximizing both objectives hence corresponds to generating rules that have minimal error and are maximally general. A special form of plus-selection is used in the ES, which simultaneously controls the number of iterations: for every iteration, the best of λ children is saved as an elitist and compared with all elitists from previous iterations. If the elitist from δ iterations before is better than all subsequent elitists, the optimization process is stopped and this specific elitist is added to the pool. This process is performed multiple times before this rule discovery phase ends. As this optimizer is not meant to find a globally optimal rule but rather fill a multitude of niches with optimally placed rules, independent evolution is advantageous.

After new rules have been discovered, a genetic algorithm (GA) selects rules from the pool to form a new solution candidate (a set of rules). Solution candidates are represented as bit strings, signalling whether a rule from the pool is part of the candidate (cf. Figure 2). The GA is configured to use tournament selection and combine two candidate solutions using *n*-point crossover with 90% crossover probability by default. Afterwards, each bit of the children is flipped with a probability given by the mutation rate. The candidate fitness is similarly based on eq. (1), using the candidate's in-sample mean squared error and complexity, i.e. the number of rules selected, as first and second objective, respectively. A certain number of elitist solutions from the previous population is additionally copied to the new population without modification. Note that all individuals in the GA always form a subset of the pool. Rules that are not part of the pool can not be part of a solution candidate and rules remain unchanged by the GA's operations.

4 EVALUATION

For our evaluation of the proposed system, we compare SupRB2 to an XCSF [27]¹ with hyperrectangular conditions (center-spread notation) and linear submodels (with recursive least squares updates [21]), as they closely correspond to the conditions and submodels used in SupRB2.

¹https://github.com/rpreen/xcsf



Figure 2: Example global problem solution for a pool of size n. Selected rules are highlighted. In binary notation (on which the optimizer operates) this individual corresponds to 01010...011.

4.1 Experiment Design

SupRB2 is implemented in Python 3.9^2 , adhering to scikit-learn [26] conventions. Input features are transformed into the range [-1,1], while the target is standardized. Both transformations are reversible but improve SupRB2's training process as they help preventing rules to be placed in regions where no sample could be matched and remove the need to tune error coefficients in fitness calculations, respectively. After a hyperparameter search (cf. Section 4.2), the final evaluation uses 8-split cross-validation, each with 25 % of samples reserved as a validation set. Each learning algorithm is evaluated with eight different random seeds for each 8-split cross-validation, resulting in a total of 64 runs.

Table 1: Overview of the datasets SupRB2 and XCSF are compared on

Name (Abbreviation)	$n_{ m dim}$	n _{examples}
Combined Cycle Power Plant (CCPP) [19, 31]	4	9568
Airfoil Self-Noise (ASN) [5]	5	1503
Concrete Strength (CS) [41]	8	1030
Energy Efficiency Cooling (EEC) [30]	8	768

We evaluate on four datasets part of the UCI Machine Learning Repository [11]. An overview of number of sample size and dimensionality is given in Table 1. The Combined Cycle Power Plant (CCPP)⁴ dataset is very linear and can be accurately predicted using a single rule. Airfoil Self-Noise (ASN)⁵ and Concrete Strength (CS)⁶ are both highly non-linear and will likely need more rules to predict the target sufficiently. The CS dataset has more input features than ASN but is easier to predict overall. Energy Efficiency Cooling (EEC)⁷ is another rather linear dataset, but has a much

higher input features to samples ratio compared to CCPP. It should similarly be possible to model it using only few rules.

4.2 Hyperparameters

Based on our assumptions about the number of rules needed, SupRB2 performs 32 cycles of alternating rule discovery and solution composition, generating four rules in each cycle for a total of 128 rules. The ES runs for ten generations with a λ of 20 in each cycle, thus a total of 32 · 200 = 6400 rules are discovered and fitted. The GA is configured to perform 32 iterations with a population size of 32, evaluating 32 · 32 = 1024 individuals per cycle. The parameters of the optimizers are tuned on every dataset independently. Similarly, for XCSF we select typical default values ⁸ and tune the remaining parameters independently on the four datasets. Table 2 presents the ranges hyperparameters are tuned from and the optimal parameters found. All hyperparameter tuning is done using a Tree-structured Parzen Estimator implemented in the Optuna framework [1], calling the objective function consisting of 4-fold cross validation 256 times per tuning process.

4.3 Results

In our experiments we find that XCSF and SupRB2 achieve comparable results. Table 3 presents the dataset-specific performance in detail. All entries are calculated on 64 runs per dataset (cf. Section 4.1). As both systems were trained for standardised targets, we denote the results for the mean (across runs) mean squared errors (MSE) and their standard deviation (STD) as MSE $_{\sigma}$ and STD $_{\sigma}$, respectively. Standardised targets allow better comparison between the datasets as results are on a more similar scale. Note that predictions of both models can always be retransformed into the original domain. Subsequently, MSE_{orig} references the mean MSE in units of the original dataset-specific target domain. Although this column is less helpful for cross dataset performance interpretations, it allows comparison to other works on the same data. We found that on two datasets (CCPP and ASN) XCSF shows a better performance, albeit only slightly for CCPP, that can be confirmed through hypothesis testing (Wilcoxon signed-rank test using a confidence level of 5%). Contrastingly, for the CS dataset, the hypothesis could not be rejected. Thus, although SupRB2 shows a slightly lower mean MSE, this is not statistically significant. For the EEC dataset SupRB2 outperformed XCSF.

We found that SupRB2's runs had a similar (to each other) performance much more consistently than XCSF's. This is shown by STD_σ (cf. Table 3) and specifically illustrated in Figure 3, which shows the distribution of test errors across all 64 runs. For three of the four datasets XCSF shows some strong outliers that go against its remaining performances. Additionally, the majority of runs is also further distributed around the mean and median values. For the CCPP dataset (Figure 3a) no outliers were produced by XCSF and overall performance is quite similar across runs. This is especially noticeable when comparing the distribution to those on the other datasets. In fact, the runs are so similar (even across models) that it is hard to make any analysis on this scale. Figure 4 shows the

²https://zenodo.org/record/5961223

³https://scikit-learn.org

⁴https://archive.ics.uci.edu/ml/datasets/Combined+Cycle+Power+Plant

⁵https://archive.ics.uci.edu/ml/datasets/Airfoil+Self-Noise

⁶https://archive.ics.uci.edu/ml/datasets/Concrete+Compressive+Strength

⁷https://archive.ics.uci.edu/ml/datasets/Energy+Efficiency

 $^{^8} https://github.com/rpreen/xcsf/wiki/Python-Library-Usage$

⁹ optuna. samplers. TPESampler

 $^{^{10}} https://optuna.readthedocs.io/$

Table 2: Hyperparameters and Tuning Ranges. The table presents SupRB2's and XCSF's (hyper-)parameters that were optimized and the found values for each dataset. The tuning process decides on both optimal parameters and components on a dataset basis, which means that the best performing operator for every component type is chosen, along with their tuned (nested) parameters.

	Component	Operator	Parameter	Range	ССРР	ASN	CS	EEC
SupRB2								
ES	Mutation		σ	$[0, \sqrt{n_{dim}}]$	0.58	2.01	2.62	1.22
	Fitness		α	[0.05, 1]	0.05	0.05	0.07	0.05
	Replacement		δ	[1, 200]	84	146	124	69
GA	General		$n_{ m elitists}$	[06]	5	5	5	6
		Mutation	mutation rate	[0, 0.1]	0.026	0.001	0.024	0.014
	Selection	Roulette Wheel	_	_				
		Tournament (T)	k	[310]	$T(l_{c}=6)$	LR	T(k=5)	T(k=9)
		Linear Rank (LR)	_	_	T(k=6)			
		Random	_	_				
	Crossover	N-Point	n	[110]	5 maint	2	U	U
		Uniform (U)	_	_	5-point	3-point	U	U
XCSF	General		MAX_TRIALS	[50 000, 500 000]	472,201	374,418	121,346	373,259
			POP_SIZE	[250, 2500]	2,495	1,044	622	1,136
	Classifier		ν	[1, 5]	5	1	3	1
	EA		$p_{ m crossover}$	[0.5, 1]	0.54	0.93	0.88	0.75
			θ	[25, 50]	50	41	39	29
			Subsumption	True/False	True	False	True	False
	Selection	Roulette	-	_	Т	Т	Daulast.	Т
		Tournament	_	_	Tournament	Tournament	Roulette	Tournament

Table 3: Overview of the experimental test data results of 64 runs per dataset rounded to four decimals. MSE_{orig} gives the mean of the mean squared error (MSE) of all runs of the models in the dataset's original target space, whereas MSE_{σ} gives the mean MSE in a standardised target space. This makes comparison between datasets easier and has no impact on predictive abilities. Similarly, STD_{σ} displays the standard deviation of MSEs in standardised space. Highlighted in bold are the models where a 5% significance Wilcoxon signed-rank test rejected the null hypothesis of equivalent distributions and the mean was better.

	ССРР		ASN		CS			EEC				
	MSE _{orig}	MSE_{σ}	STD_{σ}	MSE _{orig}	MSE_{σ}	STD_{σ}	MSE _{orig}	${ m MSE}_{\sigma}$	STD_σ	MSE _{orig}	MSE_σ	STD_{σ}
XCSF	0.8745	0.0512	0.0028	0.7930	0.1150	0.1195	2.8291	0.1694	0.1043	0.3660	0.0385	0.1032
SupRB2	1.1433	0.0669	0.0027	1.3079	0.1896	0.0199	2.3779	0.1424	0.0199	0.2776	0.0292	0.0107

results on CCPP zoomed in as far as possible. Even here, the variance is clearly low (STD_{XCSF}: 0.0028; STD_{SupRB2}: 0.0027), but XCSF outperformed SupRB2 on average. From a graphical perspective (cf. Figure 3c), SupRB2 seems to produce more desirable models on CS, even if the hypothesis testing remained ambiguous. On EEC XCSF achieves a slightly better median MSE performance (Median_{XCSF}: 0.014; Median_{SupRB2}: 0.026), however, its mean MSE is poorer due to badly performing runs. Regardless, the overall performance can be viewed as rather close, although both sets of runs are clearly not following the same distribution. As SupRB2's and XCSF's models were trained on the same random seeds and cross-validation splits, we can conclude that SupRB2 is overall more reliable even if not necessarily better.

For SupRB2 we directly control the size (number of rules; *complexity*) of the global solution via the corresponding fitness function used in the GA. Table 4 shows the complexities of the 64 runs per

Table 4: Overview of the solution complexities (number of rules in the solution proposed by SupRB2) across 64 runs per dataset.

	ССРР	ASN	CS	EEC
mean	2.65	26.42	22.31	12.81
standard deviation	0.62	2.47	2.60	1.71
median	3	27	22	13
min	2	19	17	9
max	4	30	30	17

dataset. The maximal complexity is 128, as we did only add 128 rules to the pool. We find that, although theoretically a single rule is able to predict CCPP well, the optimizer prefers to use at least two but at most four rules, achieving slightly better errors than

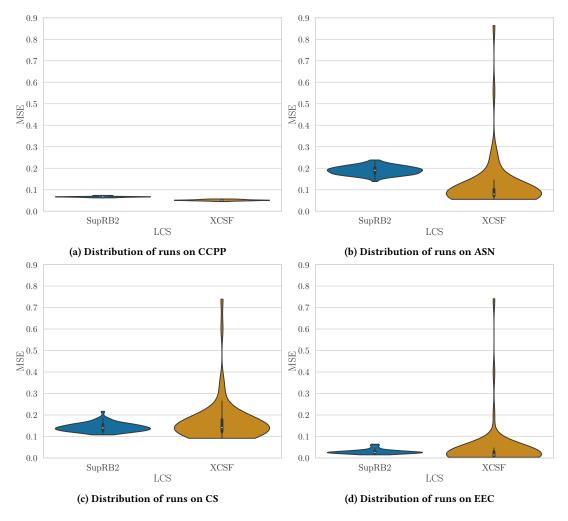


Figure 3: Distribution of runs' errors on the datasets on an equal scale (a-d). Note that XCSF has a few runs that perform much worse than the majority. This leads to a sharp increase in the maximum displayed errors. While equal scales are kept for comparing performance across runs, this renders (a), that shows a much more compact distribution, hard to read. A zoomed in version of (a) is found in Figure 4.

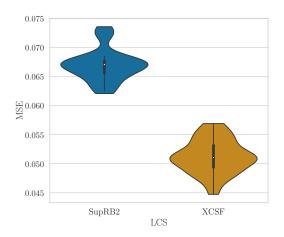


Figure 4: Zoomed in version of Figure 3a

with a singular linear model. As expected, the solutions to the two highly non-linear datasets (ASN and CS) do feature considerably more rules. EEC again was solved with fewer rules, speaking to its more linear nature, although with more than CCPP, for which a linear solution exists. Standard deviations of complexities increase as the mean increases and the median stays close to the mean. Note that, while we did not perform compaction on XCSF, which would make a direct comparison unfair as XCSF relies on this post-hoc technique to produce low complexity rule sets, XCSF's hyperparameter tuning opted for much larger populations than the typical rule of thumb of using ten times as many rules as would be expected (from domain knowledge or prior modelling experience) for a good problem solution [32]. It is reasonably possible that SupRB2's performance would improve in some cases if the pressure to evolve smaller rule sets was lower. However, as explainability suffers with large rule sets, we think that the presented solutions strike an acceptable balance.

Beyond dataset specific performances, we would like to find a more general answer to the question whether the newly proposed SupRB2 does perform similarly to the well established XCSF. To find an initial answer based on the performed experiments we use a Bayesian model comparison approach 11 [4] using a hierarchical model [9] that jointly analyses the cross-validation results across multiple random seeds and all four datasets. We assume a region of practical equivalence of $0.01 \cdot \sigma_{\rm dataset}$.

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p(\text{SupRB2} \ll \text{XCSF}) \approx 63.4 \%

p(\text{SupRB2} \equiv \text{XCSF}) \approx 8.5 \%

p(\text{SupRB2} \gg \text{XCSF}) \approx 28.1 \%
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where

- *p*(SupRB2 ≪ XCSF) denotes the probability that SupRB2 performs worse (achieving a higher MSE on test data),
- p(SupRB2 ≡ XCSF) denotes the probability that both systems achieve practically equivalent results and
- *p*(SupRB2 ≫ XCSF) denotes the probability that SupRB2 performs better (achieving a lower MSE on test data).

From these results we clearly can not make definitive assessments that XCSF is stronger than SupRB2. While it might outperform SupRB2 in less than two thirds of cases, it also will be outperformed in almost a third of cases. Benavoli et al. [4] suggest thresholds of 0.95, 0.9 or 0.8 for probabilities to make automatic decisions. The specific value needs to be chosen according to the given context. We can thus conclude that no clear decision can be made and that the newly developed (and to be improved in the future, cf. Section 5) SupRB2 should be considered equal to the well established XCSF.

5 FUTURE WORK

The experiments have shown that SupRB2 is able to find good solutions consisting of only few rules. Nevertheless, there is still room for improvement concerning the overall prediction error and model complexity, especially when aiming to solve larger and more complex problems. To this end, immediate future work is to determine the necessary changes, focusing on the processes of rule discovery and solution composition and the related optimization tasks:

The rule discovery phase aims at filling many different niches with optimal rules, a process currently guided by the rule's fitness and utilizing an evolution strategy with $\mu=1$. But even though examples matched by fewer rules are prioritized, it is still possible that the pool of rules does contain too many similar rules. Therefore, the utilization of novelty-based objective functions, e.g. novelty search [22], to diversify rule discovery will be explored. Furthermore, the use of other algorithms for fitness- and novelty-based optimization objectives could be examined, including techniques well suited for multimodal optimization, i.e. niching methods such as fitness sharing [28].

In the solution composition phase, an accurate solution is constructed from as few rules as possible by utilizing a genetic algorithm. Potential improvements to this process include the investigation of other (metaheuristic) optimization approaches applied to this task, e.g. ant colony optimization and particle swarm optimization. Furthermore, deterministic operators [35] suited for the binary representation of solutions will be investigated.

Additionally, a more detailed study of the model structure in SupRB2 compared to other LCS, e.g. XCSF, or rule-based learner, e.g. Decision Trees, regarding number of rules as well as their positioning is warranted. For a comparison to XCSF the results of various compaction techniques should be investigated. This would allow a direct comparison of rule set sizes and the impact on performance imposed by size reduction techniques. A combination with detailed rule inspection and visualisation methods would then open up the ability to compare the systems based on their value as transparent systems rather than focussing on their performances.

Finally, an important next step is the application of SupRB2 in a real world digital assistance system where its predictions and explanations are used by human workers with little or no understanding of machine learning or stochastic optimization.

6 CONCLUSION

We presented a new Learning Classifier System (LCS) that separates the process of rule discovery from the composition of rules to form problem solutions. This system performs supervised batch-learning and is called the Supervised Rule-based Learning System 2 (SupRB2). It utilizes a population-based optimizer (genetic algorithm) whose individuals transcribe which rules from the pool of discovered and locally optimized rules are part of a solution. In contrast to many Pittsburgh-style approaches, which also evolve populations of rulesets, the rules from the pool are always and automatically available to all individuals. Optimization of individuals combines a fitness pressure for low errors and low complexities (number of rules). To fill the pool with rules, we utilized a simplistic ES ($\mu = 1$) that optimizes towards low in-sample errors and high volumes of matched feature space. Note that in contrast to other similar systems, the rule discovery is not done in a "Michigan-style phase". Rules are added sequentially in separated evolutionary processes and fitnesses are independent from each other. The primary motivation for our new approach at creating LCS models was to achieve a greater and more direct control over rule set sizes and matching functions, and thus the overall model structure. Finding a good model structure is also known as the model selection problem. Ultimately, this leads to more interpretable models that make providing explanations for both the model itself, as well as its predictions, easier.

To evaluate the system we compared it to XCSF, a well known LCS with a long research history on four real world regression datasets with different dimensionalities and problem complexities. As we wanted to keep explanability high, we limited our study to the use of hyperrectangular conditions and linear models for both systems. After hyperparameter searches for the more sensitive parameters (256 evaluations with 4-fold cross validation), we performed a total of 64 (8 random seeds and 8-fold cross validation with 25% test data) runs of each system on every dataset. We found that, in general, performance is relatively similar. While XCSF showed

 $^{^{11}} https://github.com/janezd/baycomp\\$

a statistically (Wilcoxon signed-rank with 5% significance value) better mean performance on two datasets, it was outperformed on one and no statistically significant decision could be made on the fourth dataset. We then performed a Bayesian model comparison approach using a hierarchical model and found that, again, no clearly better model can be determined. Thus, we conclude that, for now with future research pending, both systems produce similarly performing models.

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