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Multi-objective local search for mining Pittsburgh classification rules

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1 Context

Classification rule mining aims to extract, from known data, rules predicting a chosen fact – called *class*, which can be for example *cardiovascular risk* in a medical context. The following rule is an example of what can be extracted:

diabetes and age > 70 → cardiovascular risk

Training data is composed of observations (sales, credit approvals, patients. . .), each of them having some attributes (e.g.: items sold, salary, diagnosis. . .). The obtained prediction rules are understandable, in contrast to models found by *neural networks* or *support vector machines*. *Decision trees* (C4.5, Oblique-DT, DT-GA) are another popular method but have a drawback when multiple contexts can explain a same class, since they are not able to find overlapping rules. This can happen in medical data, e.g. *cardiovascular risk* is higher when both *high blood pressure* and *diabetes* are found than when only *diabetes* or *high blood pressure* is found.

2 Multi-objective local search for classification rule mining

A large number of available rules can be generated from a small number of attributes; exploring all of them to extract only the interesting ones is a costly task, even impossible when a lot of attributes are available. Therefore combinatorial optimization methods are candidate methods to deal with rule mining; they are able to deal with large search spaces. Two major rule encodings are available; *Michigan* is the common one, where each solution is a single rule. In *Pittsburgh* encoding each solution is a set of rules. This encoding increases the search space and adds complexity for mutation and cross-over operators but allows finding complementary rules, like in medical data. *Accuracy* is often used as a fitness function. *Accuracy* measure counts good classifications provided by a rule: *true positives* and *false negatives*, over all classifications given by this rule. A rule with an *accuracy* of 1 makes no wrong classification, while a rule with an *accuracy* of 0.7 is wrong for 30% of observations. Another popular criterion is *Minimum description length* (MDL) principle [4], an application of Occam’s razor: given two equivalent rules, the simplest rule (the shortest) must be preferred.

Multi-objective approach can handle mining rules on multiple criteria, obtaining rules having both good performance and simplicity. Many multi-objective methods were proposed for rule mining and most of them are detailed in Srinivasan and Ramkrishnan’s review [5]. Methods using an aggregation of objectives can give interesting results, like *learning classifier systems* (*LCS*), including GAssist [1] and XCS [6]. Most of them are based on *genetic algorithms*, especially NSGA-II. But one of them uses GRASP which is a greedy algorithm.

We propose a multi-objective model, based on 2 criteria: maximizing *accuracy* and minimizing the number of terms (MDL principle). We implemented a *Dominance-based multi-objective local search* (DMLS), which is a population-based local search algorithm dedicated to multi-objective and has proven to give at least as good results as NSGA-II on several problems [3]. Moreover, DMLS is easier to parameter than a GA and does not need any cross-over operator. Our solution encoding is Pittsburgh. Each of our rules-sets contains only partial classification rules (e.g.: only rules predicting *cardiovascular risk*), avoiding rule inconsistency.

3 Results

3.1 Experimentations

Fernández et al compared 22 state-of-the-art classification rule mining algorithms on 30 datasets, providing their obtained *accuracy* on each dataset [2]. We compared our method to the results they obtained. In the proposed datasets, we selected 5 of them with less continuous attributes since our model was designed to handle discrete attributes. When continuous attributes were available (*crx*, *hea* and *hep* datasets), we discretized each attribute in 10 bins. According to Fernández et al protocol, our algorithm was run 25 times for each dataset. Datasets are split into 5-fold cross-validation: 20% of observations in each fold. Then 4 folds are used for training, 1 for evaluation. For each available partition, the algorithm was run 5 times. After each run, obtained rule sets are merged into one rule set, on which we can compute *accuracy*.

Results are available in Table 3.1. We selected among the 22 available, the 10 algorithms giving the best results. For each dataset (*bre*, *crx*, *hea*, *hep*, *tic*) we selected the best obtained *accuracy* by these algorithms. Then we computed the relative error to the best for each algorithm. A value of 0 indicates the algorithm that obtained the best *accuracy*. Our results are available in the first column.

	MOCA	XCS	SIA	Oblique-DT	CORE	Gassist	OCEC	DT-GA	HIDER	C4.5
bre	0.0000	0.0074	0.0795	0.1672	0.0325	0.0200	0.1333	0.0278	0.0000	0.0144
crx	0.0008	0.0067	0.2404	0.0727	0.0411	0.0060	0.0000	0.0043	0.0625	0.0124
hea	0.0686	0.0194	0.1563	0.0759	0.0675	0.0000	0.0259	0.0352	0.0962	0.0056
hep	0.0500	0.0000	0.0667	0.0750	0.1111	0.0472	0.1222	0.0944	0.0639	0.1250
tic	0.2650	0.1448	0.0000	0.0971	0.2965	0.0467	0.1860	0.1716	0.2991	0.1400

Table 1. Relative error to the best for some state-of-the-art classification rule mining algorithms

MOCA: Multi-Objective Classifier Algorithm, SIA: Supervised Inductive Algorithm, Oblique-DT: Oblique Decision Tree, CORE: CO-Evolutionary Rule Extractor, GAssist: Genetic Algorithms based claSSifier sySTem, OCEC: Organizational Co-Evolutionary algorithm for Classification, DT-GA: Hybrid Decision Tree - Genetic Algorithm, HIDER: Hierarchical DEcision Rules

3.2 Discussion

Table 3.1 shows that our method obtained the best solutions on *bre* dataset. When outperformed, it is each time by different algorithms, moreover on *crx* the obtained *accuracy* is very close to the best. Furthermore, these results are obtained with a local search, which is easier to configure than most of evaluated algorithms that are GA. Bad results on *tic* and *hea* datasets suggest neighborhood operators may be weak regarding those used by GA: GAssist with a similar model but more operators obtained better results. A future work could focus on improving our operators.

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