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A new interestingness measure for maintaining specific attributes in Numerical Association Rule Mining

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***Abstract*—In Numerical Association Rule Mining, some attributes are more inclined to disappear. These attributes are inclined to disappear primarily when rules consist of a small value of support or confidence. These kinds of attributes are mainly discrete. In this paper, the problem of disappearing attributes is tackled by proposing a new interest measure that controls the specific qualities. The series of experiments underpins the rationale of the latest interest measure.**

Keywords—Association Rule Mining, Numerical Association Rule Mining, optimization

I. INTRODUCTION (*HEADING 1*)

Association Rule Mining (ARM) is a Machine Learning (ML) method responsible for searching for associations between attributes in transaction databases [1]. One of the first algorithms for ARM was Apriori, developed by Agrawal et al. [2], that mines the association rules exhaustively. Numerical Association Rule Mining offers an innovative way of mining association rules where continuous and discrete attributes enter the rule mining pipeline. Usually, Numerical Association Rule Mining is modeled as an optimization problem, traditionally solved using population-based metaheuristics. In this case, the quality of the numerical association rule is defined by evaluating the fitness function, which consists of several measures of significance and interest. The most common measures of relevance are support and confidence, while amplitude, coverage, and inclusion are among the most popular [3].

In our recent study [4], the influence of low-quality association rules was explored, and, within the study, an interesting phenomenon was discovered: some attributes are more inclined to disappear. These kinds of attributes are most likely fading away when rules consist of a small value of support or confidence. However, a more significant incline was examined in the study, that features of categorical type are more susceptible to disappearing, since their support metrics are limited by the number of different classes. Although this phenomenon may not be desirable when dealing with some specific datasets or when mining class association rules, in this paper, a new evaluation metric is proposed that prevents the specific attribute from vanishing during the mining process.

The main contributions of the paper are as follows:

- a new interesting metric is defined for maintaining the specific attributes within the evolutionary process,
- the behavior and parameters of the new metric are analyzed,
- a series of experiments are performed involving the new metric.

The structure of the remainder of the paper is as follows: The basic methodologies needed for understanding the subjects that follow are reviewed in Section 2. Section 3 introduces the proposed metric for maintaining specific attributes during the evolutionary search process. The experiments and results are discussed in Section 4. The paper is concluded with Section 5, where the performed work is summarized and directions are outlined for future work.

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II. Materials and Methods

A. Numerical Association Rule Mining

The classical Apriori algorithm on transaction databases consists of categorical attributes only. These attributes need to be discretized if the numerical attributes are to be processed using this algorithm. However, this phase can be avoided when the Numerical Association Rule Mining (NARM) is applied [5]. The algorithms for NARM typically work with the numerical attributes as intervals of values, and support three types of attributes, i.e., categorical, integer, and floating-point.

The NARM is defined formally as follows: Let us assume a set $I = \{i_1^{(a)}, \dots, i_M^{(a)}\}$ of M attributes called items and a set $T = \{t_1, \dots, t_N\}$ of transactions called the database are given, where each attribute $a \in A$ is of specific type $A = \{Cat, Int, Float\}$ denoting categorical, integer, or floating-point attribute type, and each transaction in T has a unique transaction ID and contains a subset of the items in I. Then, the association rule is an implication:

$$X \Rightarrow Y, \tag{1}$$

where it holds that: $X \subseteq I$, $Y \subseteq I$, and $X \cap Y = \emptyset$. Many measures have been devised for assessing the quality of the association rule, such as, for example:

$$\text{supp} = \text{P}(\text{X} \cup \text{Y}) = \frac{(\text{number of transactions containing X and Y})}{(\text{N})}, \tag{2}$$

$$conf(X \Rightarrow Y) = \frac{supp(X \cup Y)}{supp(X)}, \tag{3}$$

$$incl(X \Rightarrow Y) = \frac{|X| + |Y|}{M}, \tag{4}$$

where N denotes the number of transactions, $M = |A^{(Cat)}| + |A^{(Int)}| + |A^{(Float)}|$ the number of attributes in the transaction database, $|X|$ represents the size of the set of objects belonging to the antecedent, and $|Y|$ the size of the set of objects belonging to the consequent.

Indeed, only those association rules satisfying relations $supp(X \Rightarrow Y) \geq S_{min}$ and $conf(X \Rightarrow Y) \geq C_{min}$ are mined during the mining process. Thus, the variable S_{min} denotes the minimum support, and the variable C_{min} the minimum confidence, and determine that only those association rules with support and confidence higher than the corresponding threshold values are taken into consideration, respectively. On the other hand, the third measure estimates how many features belong to the particular association rule among all, and it is expressed as a real number on the interval [0,1]. The closer this value is to one, the higher the inclusion, and vice versa.

B. uARMSolver

Universal Association Rule Mining Solver (uARMSolver) [6] presents an open source framework for NARM written in C++. The framework consists of four parts: a problem definition, preprocessing, rule mining, and visualization. The problem is defined in the format supported by the UCI ML repository (i.e., .csv raw text) [7]. In the preprocessing stage, the uARMSolver transforms the raw text dataset into a transaction database, where more squashing methods are also available, in order to reduce the number of records by preserving the quality of the information. More EAs and SI-based algorithms can be used for NARM. At the moment, the Differential Evolution (DE) [8] and the Particle Swarm Optimization (PSO) [9] can be applied by the framework. The visualization part of the framework is open for including various modules for visualization.

The uARMSolver is founded on a stochastic nature-inspired population-based algorithm paradigm that mimics either the process of Darwinian nature evolution (e.g., Evolutionary Algorithms, EA), or processes directing the behavior of social living animals or insects (e.g., Swarm Intelligence, SI). These algorithms operate on a population of individuals that undergoes actions of variation operators (e.g., crossover and mutation in EAs, or move in SI-based algorithms). In contrast, only the fitter individuals according to the fitness function can survive in the simulated environment.

The definition of the fitness function in nature-inspired algorithms is crucial for obtaining qualitative results. The fitness function in uARMSolver is represented as a linear combination of the aforementioned NARM metrics, in other words:

$$f(X \Rightarrow Y) = \frac{\alpha \cdot supp(X \Rightarrow Y) + \beta \cdot conf(X \Rightarrow Y) + \gamma \cdot incl(X \Rightarrow Y)}{\alpha + \beta + \gamma}, \tag{5}$$

where each individual needs to be mapped from its representation in the solution space (also called the genotype space) to the solution in the problem space (also called the phenotype space). Obviously, the individual is decoded from its vector representation with floating-point elements to the corresponding association rule. Interestingly, the applied metrics in Eq. (5) are weighted by weights α, β, and γ.

III. Proposed Metric

The motivation behind the development of the new metric for maintaining the association rules containing the specific attributes in the evolutionary mining process was four-fold: (1) to make the metric universal for maintaining the specific attribute of all three types, (2) to fix the domain values of the metric within the interval [0,1], (3) to consider the new metric in the fitness function in such a way that this will not corrupt the quality of the association rule estimated with the old fitness function, and (4) finally, to include the metric into the new fitness function $f'(X \Rightarrow Y)$. In line with this, a metric $attr(a, X \Rightarrow Y)$ is proposed as follows:

$$attr(a, X \Rightarrow Y) = \begin{cases} 1, & X \Rightarrow Y : i^{(a)} \in X \vee i^{(a)} \in Y, \\ 0, & otherwise, \end{cases} \tag{6}$$

where the metric returns value 1 when the item $i^{(a)}$ of an attribute a is part of a consequent X or an antecedent Y of the observed association rule $X \Rightarrow Y$. On the contrary, if it is not a part of the association rule, the metric returns 0. Consequently, the metric is universal for all types of specific attributes, and returns values from the interval [0,1] by weighting down by a particular value of parameter, thus satisfying demands (1) and (2).

The proposed metric is considered in the new fitness function as follows:

$$f'(a, X \Rightarrow Y) = \frac{\alpha \cdot supp(X \Rightarrow Y) + \beta \cdot conf(X \Rightarrow Y) + \gamma \cdot incl(X \Rightarrow Y) + \delta \cdot attr(s, X \Rightarrow Y)}{\alpha+\beta+\gamma+\delta}, \quad (7)$$

from which it can be observed that a contribution of the metric is observed only if the specific attribute is found in the association rule; otherwise, the contribution is set to zero. This means that the metric affects the fitness function value only, if the specific attribute has arisen in the association rule, otherwise, the quality of the same rule is estimated proportionally to the original fitness function. In this case, the proposed metric also satisfies the demand (3). The proposed metric is included into the upgraded version of the uARMSolver, more specifically, uARMSolver+.

The association rules with specific attributes that show a tendency of being disappeared from the mining process remain active until their fitness function values are higher than, or equal to the fitness function values of their counterparts with no such attribute. This request can be expressed mathematically as:

$$\underbrace{\frac{\alpha \cdot x_1 + \beta \cdot x_2 + \gamma \cdot x_3 + \delta \cdot x_4}{\alpha+\beta+\gamma+\delta}}_{f'(a, X \Rightarrow Y)} = \underbrace{\frac{\alpha+\beta+\gamma}{\alpha+\beta+\gamma+\delta}}_{K} + \underbrace{\frac{\alpha \cdot x_1 + \beta \cdot x_2 + \gamma \cdot x_3}{\alpha+\beta+\gamma}}_{f(X \Rightarrow Y)} + \underbrace{\frac{\delta \cdot x_4}{\alpha+\beta+\gamma+\delta}}_{\Delta f(X \Rightarrow Y)}, \quad (8)$$

where $x_1 = supp(X \Rightarrow Y)$, $x_2 = conf(X \Rightarrow Y)$, $x_3 = incl(X \Rightarrow Y)$, and $x_4 = attr(X \Rightarrow Y)$. As can be seen from Eq. (8), the equation can be rewritten as:

$$\begin{aligned} f'(X \Rightarrow Y) &= K \cdot f(X \Rightarrow Y) + \Delta f(X \Rightarrow Y), \\ \Delta f(X \Rightarrow Y) &= f'(X \Rightarrow Y) - K \cdot f(X \Rightarrow Y), \end{aligned} \quad (9)$$

where the $f'(X \Rightarrow Y)$ denotes the new fitness function value regarding Eq. (7), the variable $K = \frac{\alpha+\beta+\gamma}{\alpha+\beta+\gamma+\delta}$ the ratio between the old and the new fitness function values, $f(X \Rightarrow Y)$ the old fitness function regarding Eq. (5), and $\Delta f(X \Rightarrow Y)$ is the contribution of the attribute disappearing from the association rule. Theoretically, the association rule with a specific attribute disappears from the evolutionary search process when $\Delta f(X \Rightarrow Y) < 0$.

Interestingly, Eq. (9) illustrates only the relation between the new and old metrics, i.e., nothing is said about where the best association rule with the rare attribute having disappeared has arisen. Obviously, the new metric introduces new conditions and, therefore, the new behavior of the evolutionary search process. As a result, a threshold where the association rule with the attribute disappears needs to be determined by the uARMSolver itself. The threshold can be described mathematically as follows:

$$f^*(X \Rightarrow Y) = \max_{attr(s, X \Rightarrow Y) = true} f(X \Rightarrow Y), \quad (10)$$

where $f^*(X \Rightarrow Y)$ denotes the maximum fitness function value (i.e. threshold) of those association rules that have disappeared.

Example. Let us assume the parameters $\alpha = \beta = \gamma = \delta = 1$, the fitness function of the best quality rule measured by the old metric $f(X \Rightarrow Y) = 0.9682$, and the threshold fitness value of the association rule with categorical attributes being preserved is $f^*(X \Rightarrow X) = 0.7132$. Then, the same association rule $X \Rightarrow Y$ as estimated by the new metric, is expressed as:

$$f'(X \Rightarrow Y) = \frac{3}{4} \cdot f(X \Rightarrow Y) = \frac{3}{4} \cdot 0.9682 = 0.7261 \quad (11)$$

The task of using the new metric is to direct the evolutionary search process towards searching for the best association rules with categorical attributes, and preserve them till the termination of the optimization. In our case, the new metric needs to be capable of preserving the association rule with the categorical attribute being disappeared by the threshold fitness function value $f^*(X \Rightarrow X) = 0.7132$ measured by the old metric.

IV. Experiments and Results

The goal of our experimental work was to show that the attributes disappearing from the mining process can be maintained until the miner terminates. The attributes are preserved by using the proposed new metric that is considered within the proposed fitness function. The introduction of the proposed fitness function caused an upgrade of the existing uARMSolver to the novel uARMSolver+.

Indeed, the two mentioned versions of the uARMSolver were applied during the experimental work (i.e., uARMSolver and uARMSolver+). Both algorithms employed parameter settings as illustrated in Table I, from which it can be observed that Differential Evolution (DE) (Storn and Price 1997) played the role of association rule miner. As a result, the same parameter setting was considered for both miner versions. Due to their stochastic nature, the results of 25 independent runs were considered, and the best among them was taken into consideration during the analysis.

TABLE I. Algorithm's setup of both uARMSolver versions

Parameter	Abreviation	Value
Population size	N_p	100
Fitness function evaluations	FE_s	1000
Scale factor	F	0.9
Crossover Rate	CR	0.5
Mutation strategy	n/a	*DE/rand/1/bin*
Fitness function weights	$\alpha, \beta, \gamma, \delta$	1.0

The experiments were conducted on four datasets from the UCI ML repository (Dua and Graff 2017), whose characteristics are presented in Table II.

TABLE II. Characteristics of the datasets

Dataset	Instances	Feature types			Features total
		Categorical	*Integer*	*Floating point*	
Abalone	4177	1	1	7	9
Forest Fires	519	2	3	8	13
Iris	150	1	0	4	5
Yeast	1484	2	0	8	10

The datasets were selected intentionally with a smaller number of categorical and a higher number of numerical attributes. Consequently, datasets of the mentioned characteristics are more sensitive to losing the small-numbered attributes through the mining process. In our study, we focused on the losing of the categorical attributes. Although all the exposed datasets consist of relatively small numbers of instances, these are appropriate candidates for demonstrating the goals of the study.

The quality of the mined rules was estimated according to the corresponding fitness functions. Only those rules improving the current best ones were maintained within the archive.

A. Experiments

Two experiments were conducted, in order to test the power of the new metric: (1) identifying the threshold where the specific attributes were disappearing, and (2) maintaining the attributes of being disappeared to the end of the mining process. The results of the mentioned experiments are described in detail in the remainder of the paper.

1) Threshold identifying: The purpose of the experiment was to identify the threshold fitness value $f^*(X \Rightarrow Y)$ according to Eq. (10), where the specific attributes that remained are already included in the association rule. After increasing the value, the attribute vanished from the mining process, due to the prevalence of the attributes of the other types, by contributing better fitness values.

The following change of the uARMSolver needs to be applied to identify the threshold: When the new best solution is found in some generation, the miner also needs to report if the association rule includes the specific attribute or not, next to its best fitness function value. Then, the last occurrence of the fitness function value, calculated by the association rule with the specific attribute, determines the threshold value according to Eq. (10).

The results of the uARMSolver are aggregated in Table III, which represents the thresholds, fitness function values, the number of rules, and time complexity for each of the observed datasets.

TABLE III. RESULTS OF THE UARMSOLVER

Dataset	$f(X \Rightarrow Y)$	$f^*(X \Rightarrow Y)$	Rules	Time (s)
Abalone	0.9629	0.7142	364	71.67
Forest Fires	0.9487	0.4964	340	18.13
Iris	0.9333	n/a	231	1.48
Yeast	0.933	0.4524	330	27.31

As evident from Table III, the attributes of categorical types are maintained till the termination of the search process by mining the Iris dataset only. By mining all the other datasets, the categorical attributes were lost because the miner focused on the association rules of better fitness function values, and, thus, the corresponding threshold ones prevailed.

Interestingly, the threshold by mining the Abalone dataset indicates that, when the association rule with a categorical attribute with the value $f^* > 0.5356$ is found, this rule can be maintained during the evolutionary search process. These values were even lower in the case of the Forest Fires and Yeast datasets. The number of discovered association rules was slightly higher than 300 by mining all the observed datasets, except for the Iris dataset, where this number was 231. The higher time complexity was detected by mining the Abalone dataset.

2) Maintaining the disappeared attributes: In this experiment, we wanted to show that the new metric was capable of maintaining the association rules with specific attributes till the termination of the optimization. Additionally, the goal of the experiment was to analyze the influence of the parameter δ on the results of the optimization. Actually, the parameter δ regulates the importance of those association rules that include the attributes being disappeared.

The results of the optimization of the uARMSolver+ using the proposed metric are illustrated in Table IV, which is divided into six columns: (1) the mined dataset, (2) the new fitness function value, (3) the value of parameter δ, (4) the number of mined association rules, (5) the type of the rare attribute being disappeared, and (6) the time needed for the optimization.

TABLE IV. RESULTS OF THE UARMSOLVER+

Dataset	$f'(X \Rightarrow Y)$	δ	Rules	Maintaining	Time (s)
Abalone	0.8414	1.0	401	categorical	71.67
Forest Fires	0.7713	1.0	307	categorical	18.13
Iris	0.9500	1.0	231	categorical	1.48
Yeast	0.8029	1.0	315	categorical	27.31

As can be observed from Table IV, the uARMSolver+ is capable of maintaining the association rules with categorical attributes till the termination of the optimization. Maintaining them is ensured by setting the parameter $\delta = 1.0$. Obviously, the fitness function values are normally lower than in the case of the uARMSolver using the old metric, while the number of mined association rules is comparable for both solvers.

The purpose of the second test was to analyze the influence of the parameter δ on the behavior of the mining process. The results of the test are presented in Table V, which is divided into two parts, i.e., the results obtained by mining the Abalone, and those obtained by mining the Yeast datasets. Thus, the values of the parameter δ are varied in the interval $delta \in [0.0,1.0]$ in steps of 0.1.

As can be indicated from Table V, the uARMSolver+ is capable of maintaining the categorical attributes within the association rules, either with setting the parameter $\delta = 0.6$, and higher by mining the Abalone, or $\delta = 0.8$ and higher by mining the Yeast dataset, respectively. Although the setting of the parameter to $\delta = 1.0$ is general enough for maintaining the categorical attributes within the association rules for all the observed datasets, the proper setting of the parameter might be the subject of huge experiments in practice.

TABLE V. INFLUENCE OF THE PARAMETER δ ON MINING THE ABALONE AND YIEST DATASETS

δ	Abalone				Yeast			
	$f'(X \Rightarrow Y)$	*Gen.*	*Time (s)*	*Maintain?*	$f'(X \Rightarrow Y)$	*Gen.*	*Time (s)*	*Maintain?*
0.0	0.9629	2	36.74	No	0.9333	1	7.96	No
0.1	0.9318	2	36.57	No	0.9032	1	7.97	No
0.2	0.9027	1	31.93	No	0.8750	1	7.96	No
0.3	0.8753	1	32.03	No	0.8485	1	7.97	No
0.4	0.8496	1	31.92	No	0.8235	1	8.01	No
0.5	0.8253	3	63.76	No	0.8000	1	7.91	No
0.6	0.8238	5	70.59	Yes	0.7778	1	7.92	No
0.7	0.8285	4	82.25	Yes	0.7568	1	7.89	No
0.8	0.8330	4	61.18	Yes	0.7603	8	29.44	Yes
0.9	0.8373	6	81.42	Yes	0.7921	4	25.16	Yes
1.0	0.8414	5	74.37	Yes	0.8030	3	25.29	Yes

B. *Discussion*

The results of the experimental work showed that losing the specific attribute from the association rules causes the evolutionary search process to focus on mining the rules with the other attributes. On the other hand, the proposed metric affects the miner to search for those association rules that include all the attributes. Thus, the value of the inclusion metric is increased. This fact is reflected by mining those association rules that decrease the value of the support metric, but increase the value of the other metrics (Table VI).

TABLE VI. CHARACTERISTIC OF THE BEST ASSOCIATION RULE MINED BY UARMSOLVERS

Algorithm	Support	Confidence	Inclusion	Attribute	Fitness
uARMSolver	0.9998	1.0000	0.8889	n/a	0.9629
uARMSolver+	0.3656	1.0000	1.0000	1.0000	0.8414

The results in Table VI compare the characteristics of the best association rules, captured by the three/four metrics included into the fitness function, mined by different uARMSolvers. Although the value of the fitness function mined by the uARMSolver is higher than by the uARMSolver+, the latter achieved better values even by all three metrics (i.e., confidence, inclusion, and attribute) except support. The uARMSolver focuses on maximizing the corresponding fitness function value by increasing the maximum values of the support, but at the expense of losing some other metrics.

This discovery is also mirrored in Tables VII and VIII, which illustrate the best association rules mined by different solvers mining the same Abalone dataset.

TABLE VII. THE BEST ASSOCIATION RULE MINED BY UARMSOLVER

Antecedent	Consequence
'Sex M' & 'Whole weight_0.0020_0.5625' & 'Length_0.0750_0.1620' & 'Shucked weight_1.1055_1.3440' & 'Rings_12_23' & 'Diameter_0.2843_0.3738' & 'Viscera weight_0.0653_0.7356' & 'Shell weight_0.2128_1.0050'	'Height_0.0000_0.1796'

TABLE VIII. THE BEST ASSOCIATION RULE MINED BY UARMSOLVER+

Antecedent	Consequence
'Diameter_0.0550_0.6500' & 'Whole weight_0.5695_1.0073'	'Shucked weight_0.0010_0.7449' & 'Length_0.0750_0.0750' &'Rings 1 29' & 'Viscera weight_0.2448_0.7600' & 'Shell weight_0.4917_0.6409' & 'Height_0.2051_0.3811'

In Table VII, the uARMSolver mines the best association rule including all the nine attributes, while the uARMSolver+ finds the best association rule consisting of only eight attributes, and without the categorical one (in Table VIII). Unfortunately, the attributes of the specific types could be unavoidable for some real-world analysis.

V. CONCLUSION

The attributes of specific types that are rarely represented in transaction databases are usually the subject of elimination due to the nature of the evolutionary mining process. These types of attributes are unavoidable for some analyses in practice. In order to maintain the kind of attributes within the evolutionary process, the new metric was proposed and considered within the fitness function.

The existing uARMSolver served as a basis for implementing the proposed metric. The upgraded version of the existing miner uARMSolver+ was applied to four UCI ML datasets, with the aspiration of the emerging of specific attributes. The results of the uARMSolver+ showed that the proposed metric is capable of maintaining the rare attributes during the evolutionary mining process.

There are several directions for future work as well. Among others, we should mention only a few: The arbitrary databases should be tested for maintaining the specific attribute that has disappeared. Thus, any attribute in a transaction database could play the role of the specific attribute. Finally, the uARMSolver+ features could also be integrated into the current version of the uARMSolver.

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