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The selection of the relevant association rules using the ELECTRE method with multiple criteria

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ABSTRACT

The extraction of association rules is a very attractive data mining task and the most widespread in the business world and in modern society, trying to obtain the interesting relationship and connection between collections of articles, products or items in high transactional databases. The immense quantity of association rules obtained expresses the main obstacle that a decision maker can handle. Consequently, in order to establish the most interesting association rules, several interestingness measures have been introduced. Currently, there is no optimal measure that can be chosen to judge the selected association rules. To avoid this problem we suggest to apply ELECTRE method one of the multi-criteria decision making, taking into consideration a formal study of measures of interest according to structural properties, and intending to find a good compromise and select the most interesting association rules without eliminating any measures. Experiments conducted on reference data sets show a significant improvement in the performance of the proposed strategy.

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Nomenclature and abréviations

	Nomenclatures	Abbreviations	
Ai	Alternative i	AR	Association rules
Aij	The performance of Aj against Cj.	CONF	The confidence
*c**	The concordance threshold	COS	The Cosinus
Ci	The criteria i	SUP	The support
Cik	The concordance index for pair of Ai and Ak	CONF	The confidence
*d**	The discordance threshold	DEA	Data Envelopment Analysis
D	Transactional database	DM	Data mining
Dik	The discordance index for pair of Ai and Ak	ECR	Example end counter example rate
I	The set of all items	IG	The information gain
Mj	The interestingness measure j	JRD	The Jacard
Ri	Association rule i	MCDA	Multi-Criteria Decision Analysis
T	The set of transactions	PS	Piatetsky Shapiro
Wj	The weight of criteria j	KDD	Knowledge discovery in databases

1. INTRODUCTION

Knowledge discovery in databases (KDD) is a new discipline with the vocation to extract information hidden in large amounts of data that can be useful to users in decision-making processes, information management, planning, research, process control and management, and query optimization. The KDD is a multi-step process starting from the pre-selection and preparation of data to the interpretation of results, including the central phase of data mining. Data mining is a primary field of computer research, it is generally used in different application areas such as business (insurance, commerce, finance), scientific studies (astronomy, medicine), and government security (discovery of criminals and terrorists). Association rules is one of the most important tasks DM, it aims to identify and discover interesting and useful models and relationships in massive amounts of data. An association rule is an implication representation designed as, where A and B are disjointed elements. The potency of an association rule can be judged according to its support and confidence.

The majority of existing association rule algorithms [1], based on support and confidence, will build a large number of rules. As a result, users and the decision-maker are unable to determine the most impressive and, consequently, they are unable to make decisions. To overcome this problem, several measures have been proposed in the literature to discover the best rules [2-3]. Nevertheless, the abundance of these measures in the literature has created an additional obstacle, which is the choice of measures that adequately satisfy the users.

Many studies aim to assist the operator in the choice of the measure the most appropriate to the scope of the decision. In some studies, the order of the rules provided by the measures of interest for this return by human experts is analyzed and the measure that gives the closest ranking of the experts is kept. Nevertheless, their findings cannot be considered a general conclusion. Furthermore, it is not always possible to obtain the expert's ranking. Another techniques and strategies have been introduced by providing a set of criteria for designing measures of interest [4], or by examining the resemblance and the similarity between measures to rank them [5]. Vaillant *et al*. [6] offered to derive a preorder on set of measures and identifying the clusters and groups of measures. Toloo *et al*. [7] suggested an proposal to evaluate and classify the performance of association rules using several criteria through a non-parametric data development analysis (DEA) procedure. The identical as Toloo, S.Shukla *et al*. [8] proposed a novel model for prioritizing association rules produced from the data mining and taking into account the preference and desirability of the decision maker for different criteria. At the same time, other authors identify useful rules without privileging or rejecting any measure by using the concept of sky model and dominance between the rules [9]. Our preceding work [10] has proposed to discover meaningful and pertinent rules by simultaneously adopting the notion of dominance between rules and algorithm genetics. This paper extends into this context; we introduce a method based on ELECTRE method, which enables to select the association rules without privileging or removing any measure.

The document is organized as following. In the second section, we present the required scientific background and an overview of the association rules, the measures of interest and the ELECTRE method and structural properties. In the third section, we present our approach based on the ELECTRE method. In fourth section, we will examine the experimental results and its analysis; the conclusion and scope of future research are presented in the final section.

2. BACKGROUND

2.1. Association rules mining

The ARM present an effective technique of studying very large binary data sets. Association rules constitute an effective technique of analyzing massive binary data sets. A current use is to uncover the relationships among binary variables in transaction datasets, and this kind of examination is referred to as "market basket analysis".

Let $I = \{i_1, i_2, ..., i_n\}$ be a set of all items, association rules are extracted over a huge set of transactions, denoted by T with $T = \{t_1, t_2, ..., t_m\}$ every transaction t_i is an itemset and meet $t_i \subseteq I$. Given a non-empty set I, an association rule is a statement of the form $X \to Y$, where $X, Y \subset I$ such that $X \cap Y = \varnothing$. The set X is called the antecedent of the rule; the set Y is called the consequent of the rule.

An association rule can be considered interesting if the elements are often at play together and there are suggestions that one set might, in some sense, lead to the presence of the other set. The power of an association rule can be estimated by applying mathematical material concepts called "support" and "confidence".

$$Support(X \to Y) = P(X,Y) = \frac{n(X \cup Y)}{n} \quad Confidence(X \to Y) = \frac{P(X,Y)}{P(X)} = \frac{n(X \cup Y)}{n(X)}$$

Where $n(X \cup Y)$ is the number of transactions that contain items (i.e $X \cup Y$) of the rule $n(X)$ is the number of transactions containing itemset X and n is the total number of transactions. To find significant association rules from the given database, the support and the confidence of the rule should persuade thresholds predefined by the users called minimum support " Minsup" and a confidence threshold named minimum confidence " Minconf ".

2.2. Interestingness measures

ARM can produce a huge number of rules, most of which are not attractive to the decision maker and the user. IM performs a crucial role in DM, they are employed to detect the really interesting rules and to choose and establish items and patterns according to their potential benefit to the user. These measures may be divided broadly into two categories: objective measures (data-driven) based on the statistical strengths or characteristics of the discovered rules, and subjective measures e.g. unexpectedness and action ability [11] (user-driven) which are obtained from the user views, beliefs or expectations of their particular problem domain.

Support, confidence, and lift are the most popularly used objective measures to decide relevant rules. In addition to these measures, there are several additional objective measures offered by Tan *et al*. [12], such as: phi-coefficient, ods ratio measures, kappa measure, mutual information, jmeasure, gini-index, laplace measure, conviction measure, interest measure, and cosine measure. Their research confirms that several measures have different fundamental properties and classifies them from several viewpoints, and compares their characteristics, and identifies their roles in the DM process, and provides procedures for choosing suitable measures for applications and assume that there is no one is better than others in all employment domains.

Liu *et al*. [13] Examine the obtained AR using the users designations to identify those relevant and interesting ones for the user and finds the most relevant if they are unexpected (conflicting user's conviction) or provide strategic information on which the user can influence.

There are other authors [14] who identify interesting rules using a new methodology to merge data-based (objective) and user-oriented (subjective) measures of evaluation. Their design is that objective measures are first used to screen the set of rules, then subjective measures are used to help the user analyze the rules according to their understanding and objectives.

Paul Razan [15] utilized a semantic IM for discovering AR. Semantic IM take into account how data attributes are semantically associated. It uses the construction of the ontology that receives the corresponding items (e.g. specialization, generalization etc.). Due to the great number of IM existing in the literature, how to select the proper one becomes a serious challenge. To defeat this challenge, various techniques and methods were introduced, by offering some formal intuitive criteria that a good measure should check to assess the level of interest of the rule [16]. Tan *et al.* [12] discuss the properties of a set of measures and assumes that there is no one is better than others in all areas of application. Selected objective IM presented in Table 1 and used to assess the performance or value of the rules.

Table 1. Some interestingness measures

Measures	Formula	Measures	Formula
Lift	$Lift(X \to Y) = \frac{P(XY)}{P(X)P(Y)}$	Pearl	$PRL(X \to Y) = P(X)\lvert P(Y/X) - P(Y)\rvert$
Information Gain	$GI(X \to Y) = log_2 \frac{P(XY)}{P(X)P(Y)}$	Loevinger	$LVG(X \to Y) = \frac{P\left(\frac{Y}{X}\right) - P(Y)}{1 - P(Y)}$
Example & Counter Example Rate	$ECR(X \to Y) = 2 - \frac{1}{conf(X \to Y)}$	Conviction	$CNV = \frac{P(X)P(\overline{Y})}{P(XY)}$
Jaccard	$JRD(X \to Y) = \frac{P(XY)}{P(X\overline{Y}) + P(Y)}$	Zhang	$ZHN(X \to Y) = \frac{P(XY) - P(X)P(Y)}{max\{P(XY)P(\overline{Y}), P(Y)P(X\overline{Y})\}}$
Cosinus	$COS(X \to Y) = \frac{P(XY)}{\sqrt{P(X)P(Y)}}$	Piatetsky Shapiro	$PS(X \to Y) = P(XY) - P(X)P(Y)$

2.3. Properties of a measure

The formal study of measures of interest according to formal properties consists in proposing a set of formal properties of measures that have been treated by several works in the literature according to which the most appropriate measures are chosen according to the user's needs. We will now synthesize and formulate a set of measurement properties proposed in the literature, in order to take a general idea on the different existing properties.

Property 1: The value of the measurement must be zero $M(X \to Y) = 0$, when X and Y are independent i.e. $P(xy) = Px.Py.$

Property 2: The measurement $M(X \to Y)$ must be monotonously increased as a function of $P(xy)$ when the size of the premise n_x and the size of the conclusion n_y remain constant.

Property 3: The measurement $M(X \to Y)$ must be reduced according to the size of the premise n_x or according to the size of the conclusion n_y when the other parameters (n_{xy}, n_x, n_y) remain the same.

Property 4: The measurement is antisymmetric under the column or row permutation operation.

Property 5: The measurement $M(X \to Y)$ must verify the following relationship:

For any rule, $X \to Y$ we should have: $M(X \to Y) = -M(\overline{X} \to Y)$

Property 6: The measurement $M(X \to Y)$ must verify the following relationship:

For any rule, $X \to Y$ we should have: $M(X \to Y) = -M(X \to \overline{Y})$

Property 7: Desired relationship between rules $X \to Y$ *and* $\overline{Y} \to \overline{X}$, the measurement M must verify the relationship: $M(X \to Y) = M(\overline{Y} \to \overline{X})$

Property 8: The measurement $M(X \to Y)$ must be invariant when the size n of the learning set T increases and all other numbers $(n_X,\ n_Y \text{ and } n_{XY})$ remain constant.

Property 9: The concrete meaning of the measurement or the understandability of the measurement, i.e., the measurement must be intelligible and easy to interpret by the user to be able to communicate and explain the results obtained.

Property 10: The measure must make it possible to distinguish between, $X \to Y$ and $X \to \overline{Y}$ the examples of one being the counter-examples of the other.

Property 11: A measure must evaluate $X \to Y$ *et* $\overline{Y} \to \overline{X}$ in the same way in the case of logical implication.

Measure with a fixed value in case of logical involvement i.e.

$$\text{if } \exists b \in R\ \forall\ X \to\ Y \text{ we have } P(Y/X) = 1 \Rightarrow m(X \to Y) = b$$

Property 12: Setting a threshold, Easy to set a threshold for acceptance of the rule [15]. It is preferable that the measure lends itself well to the determination of the acceptance threshold of the rule because this allows the interesting rules to be retained without having to classify them.

Property 13: The measurement must have a fixed value in the case of equilibrium i.e. in the case where the number of examples and the number of counter-examples are identical.

Property 14: Measurement must be robust, i.e., the measurement of a rule must be resistant to database disturbances due to a typo during database creation or a value that is missing in the data.

There are several properties in the literature and this translates the problem into a description of many key criteria and properties and the structural conditions that need to be verified by the measures of interest in order to choose the right measure for a given application area. However, these approaches do not guarantee the selection of the appropriate and best measure for the simple reason that this measure does not verify such a property used.

2.4. ELECTRE method

Multi-criteria decision analysis (MCDA) [17] is a common structure for holding difficult decision-making situations with often and several conflicting goals and objectives that organization groups and/or decision-makers value differently. Many MCDA techniques have been perfected over the years and implemented to decision problems in different areas. Among the popular research area within MCDA we find the outranking approach, and in particular ELECTRE methods [18]. MCDA aims to provide decision-makers or data analysts with a set of tools to help them resolve the problem of decision making, among several points of view often considered contradictory.

There are many ways to classify the different existing MCDA methods. The best-known classification is that adopted by Roy [19]. They classify MCDA methods into three main families:

– Value measurement models (aggregation method).
– Purpose, aspiration or reference level models.
– Outranking Models.

Allow a MCDA problem among m criteria and n alternatives. Let $C_1,\ldots,C_m$ and $A_1,\ldots,A_n$ denote the criteria and alternatives, respectively. The value a_{ij} describes the performance of alternative A_j against criterion C_i. We assume that a higher rate value indicates a better achievement for any object of minimization can be clearly converted into an object of maximization. We assign to each criteria C_i a positive weight w_i, it indicates the corresponding effect of criteria Ci.

ELECTRE method derived from the Outranking family, it intends to obtain all the alternatives that dominate other options and they cannot be dominated by any other choice. ELECTRE [18] (Elimination Et Choix Traduisant la Réalité) is one of the MCDA methods and this method permits decision makers to select the best choice with most advantage and least conflict in the function of different criteria. We use the ELECTRE to choose the suitable choice from a set of actions. Among the simplest method of ELECTRE family, we find ELECTRE1.

The next step is to decide on the desirable choice taking into account the advantages of each alternative over each criterion (in the form of a decision matrix m x n) and the corresponding weights of the criteria established by the decision-maker.

For creating the favourite knowledge among each pair of alternatives, such as A_i and A_k $(i,k=1,...,m)$, ELECTRE utilizes the term of outranking relations. The alternative outranks if on a great part of the criteria performs at least as good as (concordance form), while its poor efficiency is still satisfactory on the other criteria (non-discordance condition). After determining for each pair of alternatives whether one alternative overclasses another, these pair upgrading estimates can be combined into a partial or total ranking. The outranking family intends to discover all options that dominate other options and they cannot be dominated by any other alternative. Each criterion is attributed a subjective weight w_k by the decision-maker, where: $\sum_{i=1}^{N} w_i = 1$. The ELECTRE method is based on the quotient of concordance and discordance discordance described as follows. We first check the data from the decision table and verify here that the sum of the weights of all criteria matches 1.

The concordance index c_{ik} for each and every pair of alternatives A_i and A_k, $i,k=1,.....,m$ (remark that an alternative is not compared to itself) is established as the sum of all the weights for those criteria where the execution rate of Ai is least as high as that of Ak, i.e.

$c_{jk} = \sum_{i:a_{ij} \geq a_{ik}} W_i \qquad j,k=1,\ldots,n \quad j \neq k$. The concordance score extends between 0 and 1.

Likewise, The calculation of the discordance index d_{jk} for each criterion where A_k exceeds A_i is described as the ratio between the difference in execution level between A_k and A_i and the maximum difference in level on the criterion attended between any pair of alternatives. The maximum of these scores (which want to endure between 0 and 1) is the discordance index, i.e.: $d_{jk}=0$ if $a_{ij} > a_{ik}, i=1,...,m,$ i.e. the discordance index is zero if A_i execute better than A_k on all criteria. Otherwise,

$$d_{jk} = \max_{i=1,\ldots m} = \frac{a_{ik}-a_{ij}}{\max_{j=1,\ldots n} a_{ij} - \min_{j=1,\ldots n} a_{ij}} \quad , j,k=1,\ldots,n, \ \ j \neq k$$

Then, an overall concordance threshold, c, and an overall discordance threshold, d, are identified to provide the overall concordance and discordance scoring analyses. The higher the threshold values, the more challenging it is to succeed in the examinations (Generally, c = 0.7 and d = 0.3 [20]. For an outranking relationship to be inferred as right, the two aggregate records must not violate their corresponding thresholds. That is $C_{ik} \geq c^* \quad and \quad D_{ik} \leq d^*$. Once the two tests are completed for all pairs of alternatives, the best alternatives are those that outrank more than being outranked. By building such a relation among each and every pair of alternatives, one can then remove the dominated alternatives and achieve the non-dominated solutions.

A partial ranking of an outranking family could not provide the best alternative immediately. A subset of propositions can be defined such that at least one member of the subset outranks any proposition not in the subset. The goal is to make this subset smaller. This subset of propositions can be supposed as a shortlist, inside which a good compromise statement should be obtained by additional methods or considerations.

3. THE PROPOSED APPROACH

Before the immense amount of produced rules through association rules mining method, applying Apriori [1, 21], close, close+ [22] or charm [23], etc...; Therefore it may be hard to select valuable knowledge from them, and we risk to waste information. In this context, we suggest to employ multi-criteria decision analysis (MCDA) ELECTRE method to obtain a good compromise without eliminating or benefiting any measures, which allow choosing the most interesting association rules.

After ARM from a transactional database D, lets R a set of AR extracted by Apriori, and M a set of measures to evaluate the rules. So we take the set of rules as alternatives and a set of measures as criteria to transform decision table.

Let two association rules. A true outranking relation of, implies that is preferred to. We say that an association rule outranks another association rule if only if is at least as good as on a majority of criteria and if it is not significantly worse on any other criteria, (i.e., the distinction between the two are inside a pre-defined threshold).

We calculate the concordance index and discordance index for each and every pair of rules and to build an outranking relation, both global indices should satisfy their correspondent threshold. And the preferred association rules are those that outrank more than being outranked.

The main idea of this contribution is to apply the ELECTRE method to find the best association rules, for this purpose, measures are taken as attributes and association rules as alternatives, which makes it possible to create the decision matrix. The second contribution in this work is to take into consideration the formal study of measures of interest according to structural properties. This is why they are integrated into the ELECTRE method at the weight level. The weight of the measurements is taken as the number of properties verified by the measure of interest. In this point, our work is supported by the advantage of using formal properties to decide which is the right measure [12, 24-25].

4. RESULTS AND DISCUSSION

In this part, we will examine and demonstrate the advantages of the suggested method. Firstly, we generate AR utilizing Apriori [1] from a set of famous datasets acquired from UCI machine learning repository [26] a (mushroom (Mus), flare1 (F1), flare2 (F2), monks1 (M1), monks2 (M2), monks3 (M3), zoo (Z)). The Table 2 abstracts the properties of the related datasets and gives the minimum support used for each dataset chosen and the number of rules obtained from the different datasets applying Apriori algorithm.

Table 2. Characteristics of the used datasets number of AR generated for each dataset

Data set	Items	Transactions	Minsup	Number of rules generated
Mushroom	22	8124	40	2654
Flare1	32	323	20	3468
Flare2	32	1066	20	3342
Monks1	19	432	20	3564
Monks2	19	432	5	2422
Monks3	19	432	5	2516
Zoo	28	101	5	2554

As described in the section (II-B), to judge association rules, we apply a collection of interestingness measures. The measures employed for the executed test are: support (SUP), confidence (CONF), lift, cosinus (COS), information-gain (IG), piatetsky-shapiro (PS), jacard (JRD) and example\& counter example rate (ECR). These measures are calculated utilizing the equations indicated in Table 1, and we take as weigh of each measure the number of properties verified by the selected measure.

Now we apply the ELECTRE1 algorithm to select the most interesting association rules using multi criteria. The Table 3, display the obtained results from the rules produced through Apriori for each dataset (MUS, Z, M1, M2, M3, F1, F2).

Table 3. The obtained results for different datasets

	Mushroom	flare1	flare2	Monks1	Monks2	Monks3	Zoo
A.R	2654	3468	3342	2422	2516	2554	3564
Skyrules	658	13	105	509	252	43	1596
Our approach	730	1808	529	1635	2180	1748	512

We produce the results of the test evaluation, which its purposes are multiple. Primary, we confirm through experiments that our method can significantly decrease the immense number of rules generated from the data sets. To approve our approach we compare it with another method of skyrules. These tests have the power to quantify the decrease of the rules offered by our method. Therefore, we compare the number of non-dominated rules of our method to the number of non-dominated rules of skyrule and to the total number of association rules (denoted AR).

The skyrule strategy aims to identify undominated association rules without favoring or eliminating any interestingness measures using dominance relation. Table 3 compares the size of non-dominated rules of our approach with the rules of skyrules [9] and with all the association rules. Also giving the corresponding histograms for the table to illustrate the results in Figure 1.

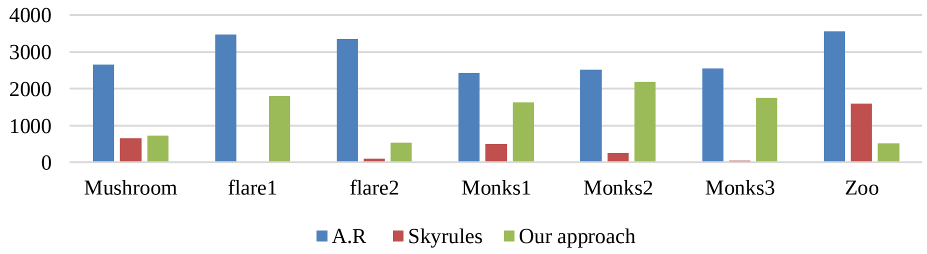

Figure 1. The corresponding histogram of the results

In order to investigate the execution of our recommended method, we have compared the average value of confidence in each dataset of our approach to the skyrule approach [9] and to the all association rules produced utilizing Apriori. The Figure 2 shows the obtained result of values of confidence in the different datasets. When interpreting this figure, it is clear that the rules obtained by our method have good qualities compared to other methods, which ensures the effectiveness of our proposed method.

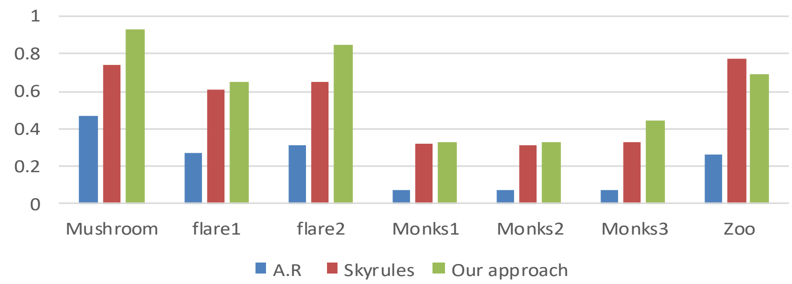

Figure 2. The histogram of the average of confidence

5. CONCLUSION

In this paper, we introduced an approach utilizing MCDA for finding the interesting association rules. The principal benefit of the recommended approach is that it is not limited by the abundance of measures and it judges the association rules adopting a set of criteria, not only one. When the suggested algorithm is practiced to various datasets, we acquire results including desired rules with maximum interestingness. The numbers of rules generated by the recommended algorithm are significantly less as compared to skyrule method. Therefore, we can say our algorithm can overcome the problem of the abundance of AR and optimizes the association rule efficiently and adequately. As future activities, we intend to improve our approach to be capable to classify and rank the association rules.

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