Using Taxonomies to Facilitate the Analysis of the Association Rules

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Abstract. The Data Mining process enables the end users to analyse, understand and use the extracted knowledge in an intelligent system or to support in the decision-making processes. However, many algorithms used in the process encounter large quantities of patterns, complicating the analysis of the patterns. This fact occurs with association rules, a Data Mining technique that tries to identify intrinsic patterns in large data sets. A method that can help the analysis of the association rules is the use of taxonomies in the step of post-processing knowledge. In this paper, the \textit{GART} algorithm is proposed, which uses taxonomies to generalize association rules, and the \textit{RulEE-GAR} computational module, that enables the analysis of the generalized rules.

1 Introduction

The development of the data storing technologies has increased the data storage capacity of companies. Nowadays the companies have technology to store detailed information about each performed transaction, generating large databases. This stored information may help the companies to improve themselves and because of this the companies have sponsored researches and the development of tools to analyse the databases and generate useful information.

During years, manual methods had been used to convert data in knowledge. However, the use of these methods has become expensive, time consuming, subjective and non-viable when applied at large databases.

The problems with the manual methods stimulated the development of processes of automatic analysis, like the process of Knowledge Discovery in Databases or Data Mining. This process is defined as a process of identifying valid, novel, potentially useful, and ultimately understandable patterns in data [6].

In the Data Mining process, the use of the association rules technique may generate large quantities of patterns. This technique has caught the attention of companies and research centers [3]. Several researches have been developed with this technique and the results are used by the companies to improve their
businesses (insurance policy, health policy, geo-processing, molecular biology) [8, 4, 9].

A way to solve the problem of the large quantities of patterns extracted by the association rules technique is the use of taxonomies in the step of post-processing knowledge [1, 8, 10]. The taxonomies may be used to prune uninteresting and/or redundant rules (patterns) [1].

In this paper the $\text{GART}$ algorithm and the $\text{RuleE-GAR}$ computational module is proposed. The $\text{GART}$ algorithm ($\text{Generalization of Association Rules using Taxonomies}$) uses taxonomies to generalize association rules. The $\text{RuleE-GAR}$ computational module uses the $\text{GART}$ algorithm, to generalize association rules, and provides several means to analyze the generalized rules.

This paper is organized as following: first by presenting the association rules technique and some general features about the use of taxonomies, second by describing the $\text{GART}$ algorithm and the $\text{RuleE-GAR}$ computational module. Finally the results of some experiments performed with the $\text{GART}$ algorithm along with our conclusion are presented.

2 Association Rules and Taxonomies

An association rule $\text{LHS} \Rightarrow \text{RHS}$ represents a relationship between the sets of items $\text{LHS}$ and $\text{RHS}$ [2]. Each item $I$ is an atom representing the presence of a particular object. The relation is characterized by two measures: support and confidence. The support of a rule $R$ within a dataset $D$, where $D$ itself is a collection of sets of items (or itemsets), is the number of transactions in $D$ that contain all the elements in $\text{LHS} \cup \text{RHS}$. The confidence of the rule is the proportion of transactions that contain $\text{LHS} \cup \text{RHS}$ with respect to the number of transactions that contain $\text{LHS}$. The problem of mining association rules is to generate all association rules that have support and confidence greater than the minimum support and minimum confidence defined by the user to mine association rules. High values of minimum support and minimum confidence just generate trivial rules. Low values of minimum support and minimum confidence generate large quantities of rules (patterns), complicating the user’s analysis.

A way of overcoming the difficulties in the analysis of large quantities of association rules is the use of taxonomies in the step of post-processing knowledge. The use of taxonomies may help the user to identify interesting and useful knowledge in the extracted rules set. The taxonomies represent a collective or individual characterization of how the items can be classified hierarchically [1]. In Fig. 1 an example of a taxonomy is presented where it can be observed that: $t-shirts$ are $light$ $clothes$, $shorts$ are $light$ $clothes$, $light$ $clothes$ are a kind of $sport$ $clothes$, $sandals$ are a kind of $shoes$.

In the literature there are several algorithms to generate association rules using taxonomies (generalized association rules). Algorithms like $\text{Cumulate}$ and $\text{Stratify}$ [10] generate rules sets larger than rules sets generated without taxonomies (because they generate association rules with and without taxonomies). To try decrease the quantity of generated rules, a subjective measure is used to
prune the uninteresting rules [10]. The subjective measure does not guarantee that the quantity of rules will decrease. Our method proposes an algorithm and a module of post-processing [5]. Using the module, the user looks to a small set of rules without taxonomies, builds some taxonomies and then uses the algorithm to generalize the association rules, pruning the original rules that are generalized. Thus our algorithm always decreases or keeps the volume of the rules sets. The proposed algorithm and module are presented in Section 3 and 4.

Fig. 1. An example of taxonomy for clothes.

3 The Algorithm \textit{GART}

We analysed the structure of the association rules generated by algorithms that do not use taxonomies. The results of the analysis show us that it is possible to generalize association rules using taxonomies. In Fig. 2 we show how the association rules can be generalized.

First we changed the items \textit{t-shirt} and \textit{short} of the rules \textit{short $\&$ slipper $\Rightarrow$ cap}, \textit{sandal $\&$ short $\Rightarrow$ cap}, \textit{sandal $\&$ t-shirt $\Rightarrow$ cap} and \textit{slipper $\&$ t-shirt $\Rightarrow$ cap} by the item \textit{light clothes} (which represents a generalization). This change generated two rules \textit{light clothes $\&$ slipper $\Rightarrow$ cap} and two rules \textit{light clothes $\&$ sandal $\Rightarrow$ cap}. Next, we pruned the repeated generalized rules, maintaining only the two rules: \textit{light clothes $\&$ slipper $\Rightarrow$ cap} and \textit{light clothes $\&$ sandal $\Rightarrow$ cap}.

The two rules generated by the Step 1 (Fig. 2) were generalized again. We changed the items \textit{slipper} and \textit{sandal} by the item \textit{light shoes} (which represented another generalization) generating two rules \textit{light clothes $\&$ light shoes $\Rightarrow$ cap}. Then we pruned the repeated generalized rules again, maintaining only one generalized association rule: \textit{light clothes $\&$ light shoes $\Rightarrow$ cap}.

Due to the possibility of generalization of the association rules (Fig. 2), we propose an algorithm to generalize association rules. The proposed algorithm is illustrated in Fig. 3. We called the proposed algorithm of \textit{GART} (Generalization of Association Rules using Taxonomies).
The proposed algorithm just generalizes one side of the association rules - *LHS* or *RHS* (after to look to a small set of rules without taxonomies, the user decides which side will be generalized). First, we grouped the rules in subsets that present equal antecedents or consequents. If the algorithm were used to generalize the left hand side of the rules (*LHS*), the subsets would be generated using the equals consequents (*RHS*). If the algorithm were used to generalize the right hand side of the rules (*RHS*), the subsets would be generated using the equal antecedents (*LHS*). Next, we used the taxonomies to generalize each subset (as illustrated in Fig. 2). In the final algorithm we stored the rules in a set of generalized association rules.
In the final algorithm, we also calculated the Contingency Table for each generalized association rules to get more information about the rules. The Contingency Table of a rule represents the coverage of the rule with respect to the database used in its mining [7]. With the calculation of the Contingency Table we finished the algorithm.

4 The Computational Module RulEE-GAR

In this section we present the RulEE-GAR computational module that provides means to generalize association rules and also to analyze the generalized rules [5]. The generalization of the association rules is performed by the GART algorithm, described in the previous section. Next we describe the means to analyze the generalized association rules. In Fig. 4 we showed the screen of the interface that enables the user to analyze and to explore the generalized rules sets.

Fig. 4. Screen of the analysis interface of generalized association rules.

On the screen of the analysis interface of generalized rules (Fig. 4) there are some spaces where the user puts data to make a query and select a set of generalized rules, accompanied or not of several evaluation measures [7], to be analyzed. Besides allowing the user to select a set of rules, the interface provides four links in the section Downloads to look for and/or download the files. The files contain, respectively, the set of transactional data (Data Set), the set of
source rules (Rule Set), the set of generalized rules (Generalized Rule Set) and the set of taxonomies used to generalize the rules (Taxonomy Set).

Besides links for visualization and/or download of the files, each generalized association rule presents others links that enable the user to explorer information about the generalization of the rule. The links are positioned at the left side of the rules (Fig. 4). The links are described as following:

**Expanded Rule** It is represented in the interface by the letter “E”. This link enables the user to see the generalized rule in expanded way. The generalized items of a rule are changed by the respective specific items.

**Source Rules** It is represented in the interface by the letter “S”. This link enables the user to see the source rules that were generalized.

**Measures** It is represented in the interface by the letter “M”. This link is available only if the user selects the support (Sup) and/or confidence (Cov) measures in its query and these measures present values lower than the minimum support and/or minimum confidence values defined to the mining process of the rules set not generalized. With this link it is possible to see which generalized rules have support and/or confidence values lower than the minimum support and/or minimum confidence values.

In Fig. 4 we also see that the generalized items in a rule (items between parentheses) are presented as links. These links enable the user to see the source items that were generalized. In the analysis interface, the user can also store the information, selected by the query, in a text file.

5 Experiments

We performed some experiments using the GART algorithm to demonstrate that the use of taxonomies, to generalize large rules sets, reduces large quantities of association rules and makes easy the analysis of the rules.

The experiments were performed using a sale database of a Brazilian supermarket. The database contained sales data of the recent 3 month. We made 4 partitions of the database to perform the experiments. The partitions were made using the sale data along of 1 day, 7 days, 14 days and 1 month.

To generate the association rules, we used the implementation of the Apriori algorithm performed by Chistian Borgelt with minimum support value equal 0.5, minimum confidence value equal 0.5 and a maximum number of 5 items by rule. The generated rules sets are described as following:

- RuleSet_1day - 32668 rules generated using the partition of 1 day;
- RuleSet_7days - 19166 rules generated using the partition of 7 days;
- RuleSet_14days - 16053 rules generated using the partition of 14 days;
- RuleSet_1month - 21505 rules generated using the partition of 1 month;

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3 Available for downloading at the web site http://fuzzy.cs.uni-magdeburg.de/~borgelt/software.html.
– RuleSet_3months - 19936 rules generated using the whole database (3 months of sale data).

To perform the experiments, we looked to the database and to the 5 sets of association rules generated to make 18 sets of taxonomies. Then we ran the \textit{GART} algorithm combining each set of taxonomies with each set of rules. In Fig. 5 a chart is presented that shows the reduction rates of the 5 rules sets after running \textit{GART} algorithm using the 18 sets of taxonomies to generalize each rules set. In Fig. 5 the sets of taxonomies are called “T” followed by an identification number, as for example: T01.

As it can be observed in Fig. 5, the experiments show reduction rates of the sets of association rules varying from 14.61% to 50.11%.

![Reduction Rates Chart](image)

\textbf{Fig. 5.} Reduction rates got using taxonomies to generalize association rules.

\section{6 Conclusion}

A problem found in the Data Mining process is the fact that several of the used algorithms generate large quantities of patterns, complicating the analysis of the patterns. This problem occurs with the association rules, a Data Mining technique that tries to identify all the patterns in a database.

The use of taxonomies, in the step of knowledge post-processing, to generalize and to prune uninteresting and/or redundant rules may help the user to analyze the generated association rules.
In this paper we proposed the $\mathcal{GART}$ algorithm that uses taxonomies to generalize association rules. We also proposed the $\mathcal{RulEE-GAR}$ computational module that uses the $\mathcal{GART}$ algorithm to generalize association rules and provides several means to analyse the generalized association rules. Then we presented the results of some experiments performed to demonstrate that the $\mathcal{GART}$ algorithm may reduce the volume of the sets of association rules. As the sets of taxonomies were made by the user, others sets of taxonomies may generate reduction rates higher than the rates presented in our experiments, mainly whether the sets were made by experts in the application domain.

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References

1. J. M. Adamo. *Data Mining for Association Rules and Sequential Patterns*. Springer-Verlag, New York, NY, 2001.
2. R. Agrawal and R. Srikant. Fast algorithms for mining association rules. In Jorge B. Bocca, Matthias Jarke, and Carlo Zaniolo, editors, *Proceedings of Twentieth International Conference on Very Large Data Bases, VLDB*, pages 487–499, 1994.
3. B. Baesens, S. Viaene, and J. Vanthienen. Post-processing of association rules. In *Proceedings of the Special Workshop on Post-Processing. The Sixth ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, pages 2–8, 2000.
4. E. Clementini, P. Di Felice, and K. Koperski. Mining multiple-level spatial association rules for objects with a broad boundary. *Data & Knowledge Engineering*, 34(3):251–270, 2000.
5. M. A. Domingues. Generalização de regras de associação, 2004. Masters Thesis, Instituto de Ciências Matemáticas e de Computação - Universidade de São Paulo, São Carlos, SP - Brazil.
6. U. M. Fayyad, G. Piatetsky-Shapiro, and P. Smyth. The KDD process for extracting useful knowledge from volumes of data. *Communications of the ACM*, 39(11):27–34, 1996.
7. N. Lavrac, P. Flach, and R. Zupan. Rule evaluation measures: A unifying view. In S. Dzeroski and P. Flach, editors, *Proceedings of the Ninth International Workshop on Inductive Logic Programming (ILP-99)*, volume 1634, pages 174–185. Springer-Verlag, 1999. LNAI.
8. B. Liu, W. Hsu, S. Chen, and Y. Ma. Analyzing the subjective interestingness of association rules. *IEEE Intelligent Systems & their Applications*, 15(5):47–55, 2000.
9. T. Semenova, M. Hegland, W. Graco, and G. Williams. Effectiveness of mining association rules for identifying trends in large health databases. In *Workshop on Integrating Data Mining and Knowledge Management. ICDM’01: The 2001 IEEE International Conference on Data Mining*, 2001. Available in [http://cui.unige.ch/~hilario/icdm-01/DM-KM-Final/Semenova.pdf](http://cui.unige.ch/~hilario/icdm-01/DM-KM-Final/Semenova.pdf). Access in 11/01/2005.
10. R. Srikant and R. Agrawal. Mining generalized association rules. *Future Generation Computer Systems*, 13(2–3):161–180, 1997.