EVALUATING GENERALIZED ASSOCIATION RULES COMBINING OBJECTIVE AND SUBJECTIVE MEASURES AND VISUALIZATION

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Abstract: Considering the user view, many problems can be found during the post-processing of association rules, since a large number of patterns can be obtained, which complicates the comprehension and identification of interesting knowledge. Thereby, this paper proposes an approach to improve the knowledge comprehensibility and to facilitate the identification of interesting generalized association rules during evaluation. This aid is realized combining objective and subjective measures with information visualization techniques, implemented on a system called *RulEE-GARVis*.

1 INTRODUCTION

One of the data mining problems is that many algorithms generate a large number of patterns, especially when the association mining technique is used. To overcome this problem, in relation to the association rules, a specialized knowledge can be transformed into a more general concept. This can be realized if an application domain knowledge exists. The knowledge can be represented in different manners, for example, by taxonomies. Thus, the generalized association rules, composed by items contained in any level of a given taxonomy, introduced in (Srikant and Agrawal, 1995), can be obtained in the different steps of the data mining process, given a general view of the domain.

There are many other post-processing techniques that are used to facilitate the pattern comprehension and the identification of interesting knowledge as query evaluation, evaluation measures and information visualization. The knowledge evaluation measures are usually classified as objective or subjective. The objective measures depend exclusively on the pattern structure and the data used in the process of knowledge extraction, while the subjective measures depend fundamentally on the final user's interest and/or needs. Therefore, the objective measures are more general and independent of the domain in which the data mining process is carried out. These measures can be insufficient to identify interesting rules, because the objectives and the specialists' knowledge are not considered. Thereby, the combined use of objective and subjective measures exploits the advantages of each type, improving the identification of interesting knowledge (Sinoara and Rezende, 2006).

As well as the knowledge evaluation measures, the information visualization techniques can also aid the rules evaluation. The visualization techniques usually use the human capability of visual interpretation and assist in knowledge comprehension. According to (Card et al., 1999), the information visualization is the use of visual representation, interactive and computer supported, of abstract data to broader cognition.

There are many works found in literature, related to association rules visualization, as (Hofmann et al., 2000), (Ong et al., 2002), (Yang, 2005), (Bruzzese and Buono, 2004), (Techapichetvanich and Datta, 2005), (Chakravarthy and Zhang, 2003), (Ertek and Demiriz, 2006), (Blanchard et al., 2003). However, these works do not visualize generalized association rules (with exception to (Yang, 2005)) and only use the support and confidence objective measures values. (Melanda and Rezende, 2003) work does not visualize generalized association rules either, but uses other objective measures, while other works utilize subjective measures, as (Liu et al., 2000). (Sinoara and Rezende, 2006) present an approach that combines the (Melanda and Rezende, 2003) objective measures approach with the (Liu et al., 2000) subjective measures approach, verifying that the combined use of objective and subjective measures can be interesting to the user.

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Despite the fact that the generalized association rules enable the knowledge exploration in different levels of abstraction, there still is the need to find a way to explore the potential of this kind of rules. Thus, the main objective of this work is to aid the user in the comprehension and identification of interesting generalized association rules. Therefore an approach is proposed to improve the advantages of combining objective and subjective measures with information visualization techniques.

2 *GARVis*: AN APPROACH TO EVALUATE GENERALIZED ASSOCIATION RULES

The *GARVis* approach allows the user to analyze, through objective measures, a generalized association rule set using SQL queries and graphic analysis, selecting a subset of rules to be explored by a domain expert. From the selected rules, subjective measures can be computed and a subjective measure exploration can be done. That way, the user can analyze a set of rules observing different aspects. The approach is divided in four steps, described as follows.

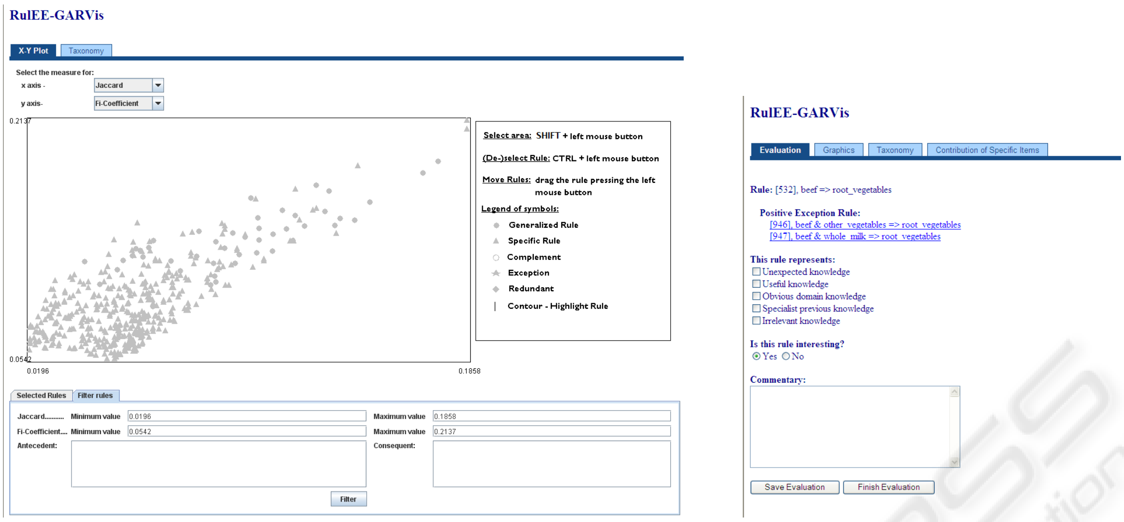
Objective Analysis (1): it is considered, in this step, that the user already has a generalized association rule set obtained by the approach proposed by (Carvalho et al., 2007). Initially, SQL queries are carried out aiming to select some features and/or objective measure values that are of application interest in order to obtain a focus set (the objective measures considered are the ones described in (Tan et al., 2004)). If the user is not interested in specific items, the focus set is formed by the whole rule set. Applying graphic analysis on the focus set using objective measures, the focus set is filtered, conducing to the identification of a subset of potentially interesting rules (PIR). The graphic analysis of this step is realized in an interactive way in a X-Y graphic, enabling the user to directly interact with the graphic, facilitating his/her comprehension and usability.

PIR Subset Evaluation (2): has as input the PIR subset obtained from Step 1 and has as objective the evaluation of these rules by a domain expert. The knowledge expressed in each one of the rules is classified as irrelevant, obvious, previous, unexpected or useful (one or more classification can be selected). During evaluation, the rules considered as irrelevant, by a domain expert, are eliminated from the focus set, as all the other similar rules (rules that contain irrelevant items in the same position (same side) of the rule classified as irrelevant). In cases where there is a rule with the same items, but in different positions, the user is asked to check if the rule has also to be considered irrelevant. During this process, the user can, in parallel, visualize the rules in a textual form and make a graphic analysis. In this step, X-Y graphics and bar charts are available for rule visualization. The user can also visualize redundant, complements and exceptions rules, which can be added in the PIR subset in order to be evaluated. The definitions of redundancy and exception described in the (Zaki, 2004) and (Gonalves et al., 2005) works, are considered respectively. The complement definition is proposed in this work as follows. Consider $R = \{r_1, ..., r_l\}$ a set of rules and $X = \{x_1, ..., x_k\}$ a taxonomy set. Given that $r_i, r_j \in R$, r_i is a complement of r_j if $((r_i.LHS = r_j.LHS \wedge r_i.RHS \setminus r_j.RHS = w \wedge r_j.RHS \setminus r_i.RHS = w') \vee (r_i.RHS = r_j.RHS \wedge r_i.LHS \setminus r_j.LHS = w \wedge r_j.LHS \setminus r_i.LHS = w'))$ and w, w' have the same ancestral in taxonomy x_h. The complement is symmetric, so r_i is a complement of r_j and r_j is a complement of r_i.

Subjective Processing (3): in this step, for each of the rules that are not eliminated from the focus set, the subjective measures conforming, unexpected antecedent, unexpected consequent, and both-side unexpected, defined by (Liu et al., 2000), are computed. To compute these measures, the classifications made in Step 2, for the rules contained in the PIR subset, are used as domain knowledge. That way, it is possible to carry out an analysis with the subjective measures to aid the identification of possible interesting rules not previously found only by the objective measures analysis.

Subjective Measures Analysis (4): during the exploration of the rules contained in the resultant focus set, using the subjective measures computed in Step 3, the user has the support of graphic analysis using X-Y graphics and bar charts. The aim, with these visualizations, is to increase the rule comprehensibility and to facilitate the identification of interesting knowledge, since the user has a visual and interactive exploration option. It is important to mention that the exploration in the resultant focus set should be carried out according to the goals of the user during the analysis. For example, if the user wishes to confirm his/her previous knowledge, he/she can use the conforming measure and list the rules that conform to the rules that had been evaluated as obvious or previous knowledge in Step 2. During this evaluation the user can find some rules, not previously found, that are also interesting for him/her.

After applying the four steps, the approach gener-



(a) PIR subset selection. (b) PIR subset evaluation.

Figure 1: Examples of PIR subset selection and evaluation process.

ates as output a subset containing the interesting rules identified during the process, subset composed by the rules found in the PIR subset plus the rules found in the focus set that were considered interesting according to the subjective analysis.

3 EXPERIMENT AND SCREEN SNAPSHOTS

Experiments were carried out in order to demonstrate the viability and usefulness of the *GARVis* approach, using a system, called *RulEE-GARVis*, that implements the proposed approach. This section presents one of the experiments realized with the *groceries* data set (available for download at http://www.r-project.org/) that contains one month of real-world point-of-sale from a typical grocery outlet. A set composed by 1680 generalized association rules, used in this experiment, was obtained by the approach proposed by (Carvalho et al., 2007).

In the objective analysis (Step 1) a focus set was selected composed by 459 rules with *Interest Factor* values greater than 2. Analyzing these rules (Figure 1(a)) with the *IS/Cosine*, *Jaccard*, *ϕ-coefficient*, *Piatetsky-Shapiro's* and *Kappa* objective measures (according to (Carvalho et al., 2007), the more appropriate measures to be used in the evaluation of rules containing generalized items in the antecedent) 12 rules were selected to compose the subset of potentially interesting rules (PIR).

Analyzing the PIR subset (Step 2), the domain expert classified the knowledge expressed in each one of the 12 rules as unexpected, useful, obvious, previous and/or irrelevant (Figure 1(b)). During this evaluation, the user could visualize the positive and negative exceptions, complements and redundancies, in cases of existence. Using X-Y graphics, similar to Figure 1(a), and bar charts combined with some objective measures, of the 12 PIR, 9 were evaluated as interesting and 3 as not interesting since they presented a previous knowledge.

After the step referring to the subjective measures computation (Step 3), the subjective analysis was made (Step 4). In this step, the user could list in a textual form the evaluated rules, separated according to its classification made in Step 2. The user could also visualize in a X-Y graphic the evaluated rules using different colors, where each color indicated its classification made in Step 2. After selecting one of the rules in the graphic, the user chose some subjective measures, defining its minimum and maximal values, in order to search in the resultant focus set the rules that corresponded to the knowledge expressed by the selected rule (defined in Step 2). From the obtained set, the user visualized the rules in a textual form and defined some of them as interesting. Thus, after the selection and analysis of some rules, 3 interesting rules were selected in this step.

In the end, the user visualized the rules considered interesting in a textual form and through bar and pie charts. In this experiment, 12 interesting rules were found. It is important to mention that 9 of these rules were found using objective measures and 3 using subjective measures, demonstrating the importance of combining both measures supported by visualization.

It could be observed, through this experiment, that the approach is viable, since it aids the user in the comprehension and identification of interesting generalized association rules, allowing the user to explore and evaluate the rules using many resources. Besides, the interactive graphic analysis facilitates the rule set exploration, since this analysis is made with different measures and filters.

4 CONCLUSIONS

This paper presented an approach that aids the post-processing of generalized association rules and facilitates the comprehension and the identification of the interesting ones using objective and subjective measures combined with information visualization techniques, features that distinguish the approach with the ones cited in Section 1. This combination provides the user with different evaluation mechanisms, facilitating his/her participation in the discovery process of interesting knowledge.

The experiment presented in Section 3 shows that the application of the proposed approach using the *RulEE-GARVis* system is viable and useful. As future work, other experiments using the *GARVis* approach with different real data sets and specialists in other domains will be carried out.

REFERENCES

Blanchard, J., Guillet, F., and Briand, H. (2003). Exploratory visualization for association rule rummaging. In *Proceedings of the KDD'03 Workshop on Multimedia Data Mining (MDM)*, pages 107–114.

Bruzzese, D. and Buono, P. (2004). Combining visual techniques for association rules exploration. In *Proceedings of the Working Conference on Advanced Visual Interfaces (AVI)*, pages 381–384. ACM Press.

Card, S. K., Mackinlay, J. D., and Shneiderman, B. (1999). *Readings in information visualization: Using vision to think*. Morgan Kaufmann Publishers Inc.

Carvalho, V. O., Rezende, S. O., and Castro, M. (2007). Obtaining and evaluating generalized association rules. In *Proceedings of the International Conference on Enterprise Information Systems (ICEIS)*, volume 2, pages 310–315.

Chakravarthy, S. and Zhang, H. (2003). Visualization of association rules over relational DBMSs. In *Proceedings of the 2003 ACM Symposium on Applied Computing (SAC)*, pages 922–926.

Ertek, G. and Demiriz, A. (2006). A framework for visualizing association mining results. *Computer and Information Sciences*, 4263/2006:593–602.

Gonalves, E. C., Mendes, I. M. B., and Plastino, A. (2005). Mining exceptions in databases. In *Advances in Artificial Intelligence*, pages 1076–1081. Springer-Verlag.

Hofmann, H., Siebes, A. P. J. M., and Wilhelm, A. F. X. (2000). Visualizing association rules with interactive mosaic plots. In *Proceedings of the 6th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*.

Liu, B., Hsu, W., Chen, S., and Ma, Y. (2000). Analyzing the subjective interestingness of association rules. *Intelligent Systems and Their Applications, IEEE*, 15(5):47–55.

Melanda, E. A. and Rezende, S. O. (2003). Uso combinado de medidas objetivas como filtro de regras de associao. In *Proceedings of the 4th Congress of Logic Applied to Technology Conference (LAPTEC)*, volume 2, pages 170–178.

Ong, K.-H., Ong, K.-L., Ng, W.-K., and Lim, E.-P. (2002). CrystalClear: Active visualization of association rules. In *ICDM'02 International Workshop on Active Mining (AM)*. Press.

Sinoara, R. A. and Rezende, S. O. (2006). A methodology for identifying interesting association rules by combining objective and subjective measures. *Inteligncia Artificial, Revista Iberoamericana de IA*, 10(32):19–27.

Srikant, R. and Agrawal, R. (1995). Mining generalized association rules. In *Proceedings of the 21th International Conference on Very Large Data Bases (VLDB)*, pages 407–419.

Tan, P.-N., Kumar, V., and Srivastava, J. (2004). Selecting the right objective measure for association analysis. *Information Systems*, 29(4):293–313.

Techapichetvanich, K. and Datta, A. (2005). Visar: A new technique for visualizing mined association rules. In *Advanced Data Mining and Applications*, pages 88–95. Springer-Verlag.

Yang, L. (2005). Pruning and visualizing generalized association rules in parallel coordinates. *IEEE Transactions on Knowledge and Data Engineering*, 17(1):60–70.

Zaki, M. J. (2004). Mining non-redundant association rules. *Data Mining and Knowledge Discovery*, 9(3):223–248.