A NEW VISUALIZATION METAPHOR FOR ASSOCIATION RULES

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Abstract: In order to discover knowledge from large amount of results generated by the association rules extraction algorithms, visual representations of association rules can be very beneficial to the user. Those representations support the user in finding and validating interesting knowledge. All techniques proposed for association rule visualization have been developed to represent association rule as a hole without paying attention to the relations between attributes and the contribution of each one. In this article, we propose a new visualization metaphor for association rules. This new metaphor represents attributes which make up the antecedent and the consequent, the contribution of each one to the rule, and the correlations between each pair of antecedent and consequent.

1 INTRODUCTION

Association rule extraction (Agrawal et al., 1993) is the task of finding correlations between items in a dataset. Initial research was largely motivated by the analysis of market basket data, the results of which allowed companies to more fully understand purchasing behavior and, as a result, better target market audiences. An association rule is an implication of the form $X \rightarrow Y$, where X (antecedent) and Y (consequent) are non-intersecting sets of items. For example, *milk, eggs* ➜ *bread* is an association rule says that when milk and eggs are purchased, bread is likely to be purchased as well. At the output of the association rules extraction process, the user (decision- maker) must evaluate and select the interesting part of the results (known as rule post-processing). To select interesting rules from the set of all possible rules, constraints on interestingness measures can be used. The best known constraints are the minimum thresh- olds on support and confidence.

- The support:supp(X ➜ Y) = Nb of transactions which contain X and Y / Nb of transactions in the database,
- The confidence:conf(X ➜ Y) = Nb of transactions which contain X and Y / Nb of transactions which contain X.

The main drawback of the association rule extraction process is the volume of generated rules which often greatly exceed the size of the underlying database. Cognitive processing of thousands of rules takes much more time than generating them even by a less efficient tool. To reduce the cognitive load, visual representations of association rules are used to facilitate and speed up comprehension and make easier the rules comparison. All techniques proposed for rule visualization have been developed to represent an association rule as a hole without paying attention to the relations between attributes which make up the antecedent and the consequent and the contribution of each one of them to the rule. Attributes component of an association rule may be more informative than the rule itself (Freitas, 1998). Two rules with the same value of interestingness measures can have very different degrees of interestingness for the user, depending on which attributes occur in the antecedent and in the consequent. In the same way, the information found in form of relations between the attributes (correlation) provides the analyst with a better and clearer image than analysis a rule (Imielinski and Virmani, 1998). Exploring an association rule attributes enable deeper insight into the data. Analysts can be interested by those relationships, rather than static rule. In this paper we propose a new

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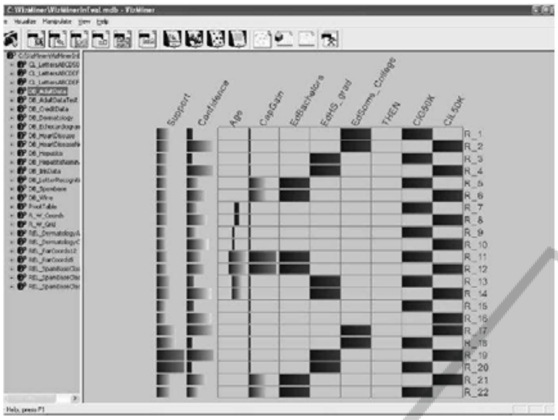
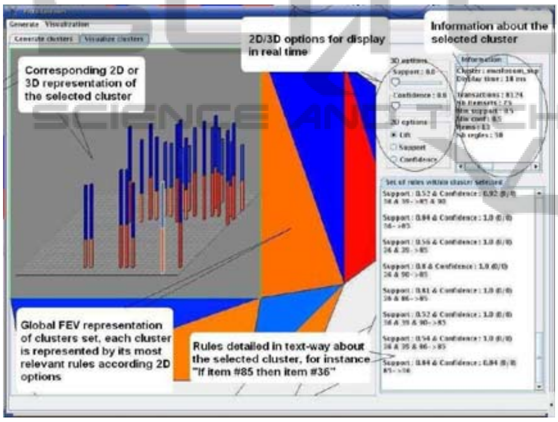
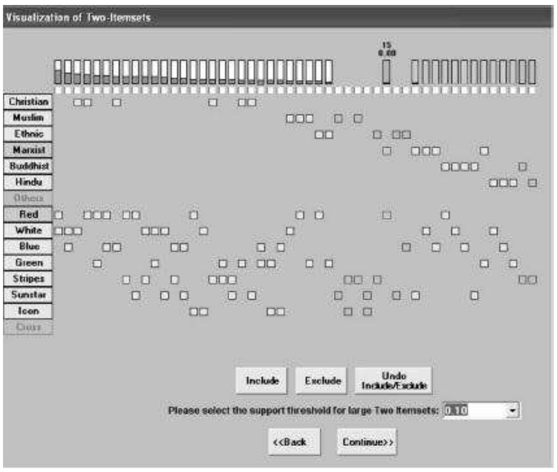
association rule metaphor which represents relations between at- tributes and the contribution of each one to the association rule.



(a): (Kopanakis and Theodoulidis, 2003)



(b): (Couturier et al., 2007)

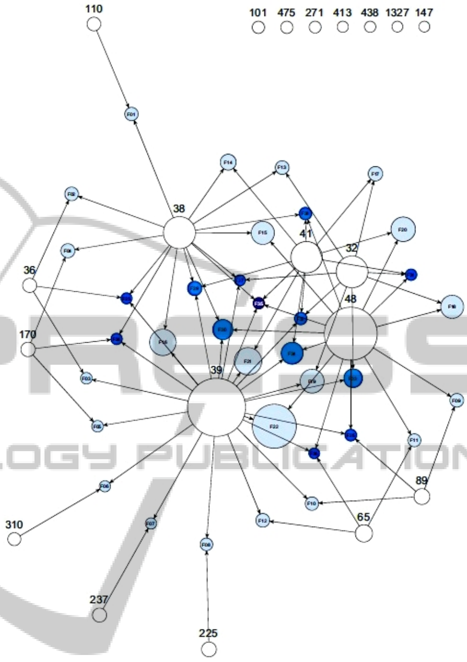


(c): (Liu and Salvendy, 2006)

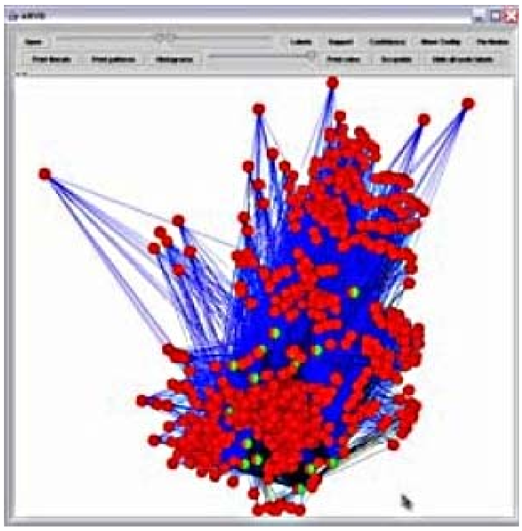
Figure 1: Illustrations of association rule visualization tools based on grid structures and bar charts.

2 ASSOCIATION RULE VISUALIZATION

Visualization can be very beneficial to association rule mining (Simoff et al., 2008). In fact, visualization techniques are an effective means to



(d): (Gordal and Demiriz, 2006)



(e): (Bruzzese and Buono, 2004)

Figure 2: Illustrations of association rule visualization tools based on graph representations.

provide user with meaningful visual representations instead of poorly intelligible textual lists. To display association rules mining results, typical visual representations are grid-like structures and bar charts (Figure.1). The grid view consists of a 2D or 3D matrix of cells where each cell represents a rule (Kopanakis and Theodoulidis, 2003; Couturier et al., 2007; Liu and Salvendy, 2006). One matrix dimension represents rules antecedents and the other one represents rules consequent. Each cell is filled with colored bars indicating rule support and confidence values. However, this representation often suffers from occlusion. Moreover, it is difficult to represent rules if there are too many different attributes in the data or if the rules have many items.

Other visualization techniques are based on graph visualization (Bruzzese and Buono, 2004; ?), the nodes and the edges respectively representing the items and the rules (Figures 2). The interestingness measures are symbolized by colors and sizes. Other work uses 3D objects to represent association rule. In (Blanchard et al., 2007), each rule is represented by a sphere, whose radius maps its support, and by a cone, whose base width maps its confidence (Figure 3). Additionally, the colors of the sphere and cone redundantly represent a weighted average of the measures. the rule position in the arena represents the implication intensity. It's must be noticed that the presented methods and techniques are generally supplied with few interestingness measures and none of these methods represents the relations between attributes in the rule and the contribution of each one of them.

3 IMPORTANCE OF RULE'S INDIVIDUAL ATTRIBUTES

3.1 Attribute Interaction

Two attributes are correlated if they are not independent. Two attributes are independent if changing the value of one does not affect the value of the other. The lift measure calculates the correlation between two attributes from the antecedent or the con- sequent. The correlation between two attributes rep- resents the amount of information shared among the two attributes. The lift measure determines whether attribute1 and attribute2 have a positive (lift >1) or a negative (lift <1) correlation. The correlation is considered positive (negative) if the observed frequency of example satisfying both attribute1 and attribute2 is greater (smaller) than the expected frequency assuming statistical independence between attribute1 and at- tribute2. The (Freitas, 2001) study showed that the concept of attributes interaction can be beneficial to the association rule extraction process and proposed to introduce attribute interaction in the design of association rule mining systems. Attributes interaction allows detection surprising knowledge which can't be discovered analyzing the whole rule. The relationships expressed in a rule totality is quite different from the relationships expressed in separate rule parts (antecedent and consequent).

On the other hand, to discover useful association rules, the user needs to get insight into the data and understand the relationships between the attributes and their statistical properties (Chanda et al., 2010). Exploring attributes relation enables deeper insight into the data and learn about the data model. In many case (biological or genetic context for example) antecedent items has weak associations with consequent. However, they interact together in a complicated way to control the consequent (Chanda et al., 2010).

3.2 Attribute Importance

An attribute can be important for the user if regularities are observed in a smaller dataset, while being unobservable in the entire data. A rule can be considered as disjunction of rules. The size of a disjunct (rule) is the number of items composed the rule's antecedent and the rule's consequent. For example: r : X1 X2 X3 ➜ Y1 Y2 is a rule. A disjunction of rules is r1 : X1➜ Y1 Y2, r2 : X2➜ Y1 Y2, r3 : X3 ➜ Y1 Y2, r4 : Y1 ➜ X1 X2 X3 and r5 : Y2 ➜ X1 X2 X3. At first sight, it seems that this small rules has no importance, since they can be considered as a redundant rules. Based on this view, all most extraction algorithms do not keep this rules in the results. However, small rules have the potential to show unexpected relationships in the data (Freitas, 1998). (Provost and Aronis, 1996) proved that small rules were considered interesting in their field application. Accordingly, it would beneficial that the user can see automatically this small rules.

In order to evaluate the contribution of each item to rule (Freitas, 1998) has proposed the Information Gain measure which can be positive or negative. Item with high positive *Information Gain* is considered as a good one. Item with high negative *Information Gain* is considered as a bad one and should be removed from the association rule. From a rule interesting perspective, the user knows already the most important attributes for its field, and rules containing these items may not be much interesting. At the same time, a rule includes attributes with low or

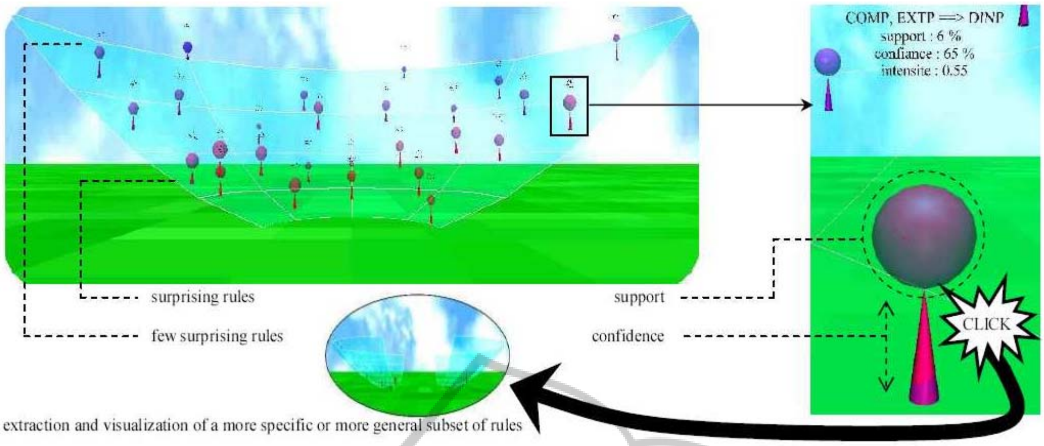


Figure 3: Illustrations of Arvis (Blanchard et al., 2007).

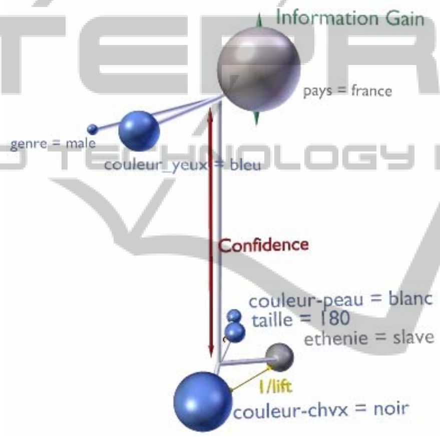


Figure 4: The visual association rule metaphor.

negative information gain (logically irrelevant) can surprise the user in cases where attributes correlation can make irrelevant item into a relevant one. This phenomenon can be interesting to the user.

4 ASSOCIATION RULE METAPHOR

A major default of association rule visualization methods presented in Section 2 is the inability to show the attributes that make up the association rule while they are may be interesting to the user. Another limit, some of those methods do not enhance rules interestingness measures values. For instance, association rules visualization methods based on graph or matrix use color to represent some interestingness measures. This graphic encoding choice for quantitative variables is known to be wrong in information visualization (Bertin, 1984). For our association rule metaphor we refer to Bertin's semiology (Bertin, 1984) to encode rule interestingness measures. As advocated by (Bertin, 1984), we choose a graphic en- coding based on positions and sizes to enhance the most important interestingness measures which is: *Information Gain* and correlation between attributes. To have the greatest degree of freedom we choose to use a 3D representation. Our metaphor (Figure 4) shows two types of interestingness measures.

The first one matches rule attributes description which are categorical variables from the graphic semiology point of view. Each attribute has an associated continuous variable corresponding to the informative gain of each attribute. In the 3D space, each attribute is represented by a sphere and his size is an effective representation of this metric. We note here that the user must know if an item belongs to the antecedent or the consequent. Therefor, we should separate the items of the antecedent to the items of the consequent. in the representation space.

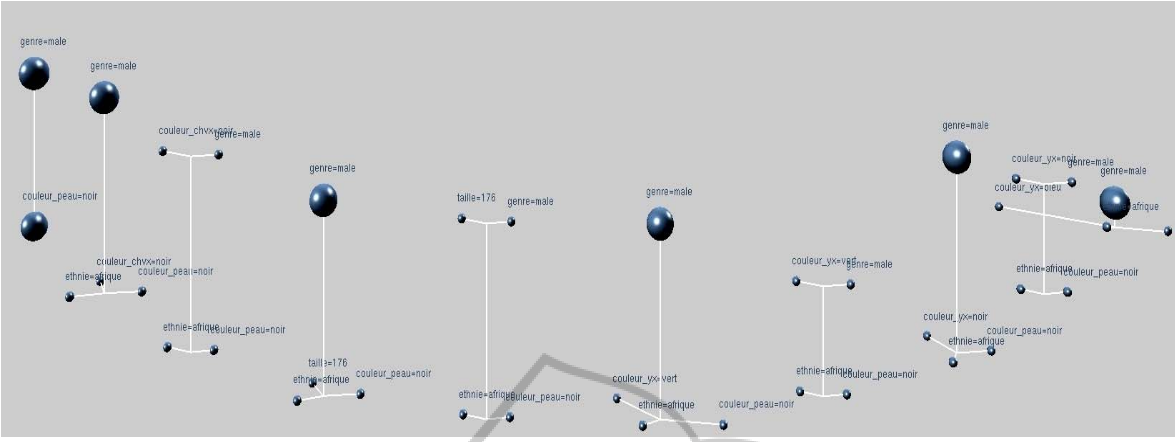


Figure 5: Illustration of a set of association rules.

The lift is a positive measure which used to indication how much two items are correlate. A distance between each two items of the same group is an effective representation of this metric. More the items are correlate more the spheres are close. To generate items coordinates in 3D space we use dynamic graph (Hendley et al., 1999). The dynamic graph algorithm enables the spheres self-organization in the visualization area by the use of a force system in order to find a steady state and determine the sphere positions. Using the hyper system allows correlated items to be near each other, and independent items to be far away. This visualization consists of spheres and links whose properties are given by the association rule parameters. Each sphere represents an item and his size and the color represent his contribution to the rule. The sphere size represents the *Information Gain* (Freitas, 1998) of the item and color shows if the gain is positive (blue) or negative (gray). Graphical encoding should highlight items with high positive contribution and those with high negative contribution (both are interesting to the user).

The second type of interestingness measures correspond to the metric associated with the rule (support, confidence, etc.). This meta information that describe the properties of the rule are quantitative variables according to Bertin’s semiology (Bertin, 1984). Theoretically, it is possible to represent a large number of metrics using visual variables appropriate to the area of interest of each user. For example, we can represent the confidence or the support by a distance between the antecedent and the consequence. The visual metaphor stresses the rules with hight confidence or support (Figure 5). Furthermore, complementary text labels appear above each objects to give the name of the corresponding item.

5 CONCLUSIONS

In this study, we propose a new association rule metaphor allowing the visualization of attributes com- posing the association rule. Also, it shows attributes relationships and contribution of each one of them. but merely developing only novel visual metaphor id rarely sufficient to make new discovery. In association rule extraction process, the decision-maker is overwhelmed by the association rule algorithms results. Representing these results as static images limits the visualization usefulness. This explains why the user need to be able to interact with the association rules representation in order to find relevant knowledge. Interaction allows also the user integration in the association rule extraction process. The user should be able to manipulate the extraction rules algorithms and not only the graphical representations. This allows to focus on interesting knowledge from the user point of view, in order to make the association rule methods be more generically useful to users. Our future works will mainly concern the development of a human-centered tool for rules extraction and manipulation and the implementing a new operators of interesting association rule extraction.

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