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Weakness of Association Rules: A Mechanism for Clustering

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ABSTRACT

We introduce the notion of *weakness* of an AR. After providing the intuition, we develop a *weakness-based* distance-function for clustering ARs. We cluster ARs obtained from a small artificial data set through the average-linkage method. The clusters are compared with those obtained by applying a commonly used method to the same data-set.

1. INTRODUCTION

Rule immensity is an important issue in Association Rule (AR) mining. This problem concerns the multitude of discovered rules that hinder easy comprehension. We define *Weakness* as the extent to which an AR is unable to explain the presence of its constituent items. Weakness is then used as a heuristic to group ARs. Rules with similar *weakness* are placed in the same cluster, thus facilitating easy exploration of connections among them. A user needs to examine only those rules in 'relevant' clusters.

Lent, Swami and Widom [6] introduced the notion of 'clustered' ARs. Adomavicius and Tuzhilin [1] adopted an expert-driven, attribute hierarchy-based similar rule-grouping approach. The distance measure proposed by Toivonen, et al. [8] and Gupta and others [3] clustered rules that 'cover' the same set of transactions. One limitation of [8,3] is the arbitrariness of distance measures [1].

Dong and Li [2] introduced a distance metric for detecting unexpected rules. Sahar's d_{SC} [7] utilized both syntactic matching of item-sets and rule coverage of data. Jorge [5] studied clustering in the context of thematic browsing and summarization of large sets of ARs. Current research has concentrated either on syntactic (item–matching based) comparison [1,2,5] or on transaction-set coverage [3,7,8]. These approaches do not utilize certain intrinsic properties of ARs. We propose *weakness* (an intrinsic property)–based identification of specificity/generality of the AR in describing the presence of its constituents in the database.

2. WEAKNESS OF AN ASSOCIATION RULE

Consider an AR, R: $a_1a_2..a_m \rightarrow a_{m+1}a_{m+2}\ldots a_n$, having support S_R and confidence C_R. If all items of R are present in that transaction (t), then R covers t. Let the support of an individual item $a_i \in R$ with respect to database D be Sa_i. R accounts for only S_R% of transactions in the database and does not explain the portion (of D) containing $1 \quad \frac{S_R}{S_{a_i}}$ % of transactions containing a_i. This fraction may be viewed as *weakness* of R with respect to its constituent a_i: $w_{a_i} \quad 1 \quad \frac{S_R}{S_{a_i}}$ (1)

Weakness of an AR with respect to all its constituents is given by:

$$w_R \quad \frac{1}{n} \quad {}_{a_i} \quad 1 \quad \frac{S_R}{S_{a_i}} \; ; a_i \quad \{a_1, a_2, ..., a_n\} \qquad (2)$$

'w-value' brings out the strength of relationship between an AR and its constituents. A low w-value indicates strong characterization of its constituent items, since most of the transactions containing R's constituent items exhibit the behaviour captured by R. In addition, a low w-value signifies generality (wider coverage in D) of the relationship described by R. In contrast, a high w-value indicates specificity of the relationships revealed by the rule.

3. A WEAKNESS-BASED DISTANCE MEASURE (d_w)

Low generality of a high w-value rule suggests that relationships between the rule's items and items present in other rules may be worth exploring. Actions taken only on the basis of a high w-value (high-specificity) rule could be skewed as the rule brings out only one aspect of the items' behaviour in the database. Since *weakness* reflects the presence of relationships among constituents, action based on rules with equal or near-equal values could yield similar results.

We define *weakness*-based distance as:

$$d_w(R_1, R_2) \quad \frac{|w_1 \quad w_2|}{w_1 \quad w_2}, \; 0 \le w_1, w_2 \le 1. \qquad (3)$$

Any difference Δw results in a larger distance for low w-values and smaller distance for high w-values. *If* $(|w_1\text{-}w_2|=|w_3\text{-}w_4|)$ *and* $(w_1+w_2 \le w_3+w_4)$, *then* $d_w(R_1,R_2) > d_w(R_3,R_4)$. Let w_1=0.4, w_2=0.2, w_3=0.8 and w_4=0.6. Then, $d_w(R_1,R_2)=0.3333$ while $d_w(R_3,R_4)=0.14285$. This may seem counter intuitive. However it has a rationale. R_1 and R_2 are unable to explain 40% and 20% respectively of their constituent items' presence. Thus, they are more *general* than R_3 and R_4 whose w-values are 0.8 and 0.6 respectively. R_3 and R_4 have poorer explanatory power than R_1 and R_2, with respect to their constituent items.

This rationale has an analogical intuitive support. Consider four individuals $A(R_1)$, $B(R_2)$, $C(R_3)$ and $D(R_4)$. Assume A and B possess deeper knowledge (of a topic) than C and D. Let the absolute difference in the knowledge-levels between the individuals in each of $\{A,B\}$ and $\{C,D\}$ be the same. Since A and B are quite knowledgeable, the difference would seem to be larger because it would require more effort to move from A's knowledge-level to B's knowledge-level. This greater effort may be due to the subtle and conceptually deeper knowledge required. However, it may be relatively easier to bridge the gap between C and D. Fewer facts and straightforward knowledge acquisition may suffice. Similarly, R_1 and R_2 may have good explanatory power and hence they may be separated by a larger distance than the more specific pair $\{R_3,R_4\}$.

Table 1. An artificial transaction dataset

Transaction	Nos.	Transaction	Nos.
{Bread,Butter}	6	{Bread,Jam}	5
{Bread,Milk}	4	{Bread,Butter,Milk}	10
{Milk,Chocolate}	6	{Chocolate,Biscuit}	8
{Milk,Chocolate,Biscuit}	11	{Butter,Milk}	3
{Pen,Pencil,Eraser}	13	{Pencil,Eraser}	7
{Chocolate,Pencil,Eraser}	3	{Pen,Eraser}	3
{Chocolate,Biscuit,Pencil}	5	{Bread,Butter,Milk,Jam}	4
{Bread,Jam,Milk}	12	--	--

Table 2. Association Rules extracted from transaction set of Table 1

No	Rule	Support	Confidence	Weakness
R_1	Butter→Bread	0.20	0.86957	0.321315
R_2	Jam→Bread	0.21	1.00	0.243902
R_3	Bread→Milk	0.30	0.7317	0.334146
R_4	Butter→Milk	0.17	0.73913	0.460435
R_5	Butter,Milk→Bread	0.14	0.82353	0.589947
R_6	Chocolate→ Biscuit	0.24	0.72727	0.136364
R_7	Milk,Biscuit→Chocolate	0.11	1.00	0.662778
R_8	Pen→Pencil,Eraser	0.13	0.8125	0.407738
R_9	Pen→Pencil	0.13	0.8125	0.361607
R_{10}	Pencil→Eraser	0.23	0.82143	0.146978
R_{11}	Pen→Eraser	0.16	1.00	0.192308
R_{12}	Jam,Milk→ Bread	0.16	1.00	0.509284
R_{13}	Jam→Milk	0.16	0.76190	0.459048
R_{14}	Chocolate→ Milk	0.17	0.51515	0.572424

Table 3. d_w –based clustering

Step_No	Clusters	
1	**{R_{13},R_4}**	[0.002]
2	**{R_{14},R_5}**;{R_{13},R_4}	[0.015]
3	**{R_3,R_1}**;{R_{14},R_5};{R_{13},R_4}	[0.020]
4	**{R_{10},R_6}**;{R_3,R_1};{R_{14},R_5};{R_{13},R_4}	[0.037]
5	**{R_3,R_1,R_9}**;{R_{10},R_6};{R_{14},R_5};{R_{13},R_4}	[0.049]
6	**{R_{13},R_4,R_{12}}**;{R_3,R_1,R_9};{R_{10},R_6};{R_{14},R_5}	[0.051]
7	**{R_{14},R_5,R_7}**;{R_{13},R_4,R_{12}};{R_3,R_1,R_9};{R_{10},R_6}	[0.066]
8	**{R_8,R_{13},R_4,R_{12}}**;{R_{14},R_5,R_7};{R_3,R_1,R_9};{R_{10},R_6}	[0.077]
9	**{R_{11},R_2}**;{R_8,R_{13},R_4,R_{12}};{R_{14},R_5,R_7};{R_3,R_1,R_9};{R_{10},R_6}	[0.118]
10	**{R_8,R_{13},R_4,R_{12},R_{14},R_5,R_7}**;{R_{11},R_2};{R_3,R_1,R_9};{R_{10},R_6}	[0.140]
11	**{R_8,R_{13},R_4,R_{12},R_{14},R_5,R_7,R_3,R_1,R_9}**;{R_{11},R_2};{R_{10},R_6}	[0.207]
12	**{R_{11},R_2,R_{10},R_6}**;{R_8,R_{13},R_4,R_{12},R_{14},R_5,R_7,R_3,R_1,R_9}	[0.209]
13	**{R_{11},R_2,R_{10},R_6,R_8,R_{13},R_4,R_{12},R_{14},R_5,R_7,R_3,R_1,R_9}**	[0.435]

Note: Values in the brackets represent merging distance

It is easy to establish the metric properties of $d_w(R_i,R_j)$. The intuitive justification of $d_w(R_i,R_j)$ and its being a metric enable d_w-based clustering of ARs.

4. d_w-BASED CLUSTERING OF ARs

Table 1 represents an artificial transaction database consisting of 100 transactions; the complete item-set being {*Bread*,*Butter*,*Jam*,*Milk*, *Chocolate*,*Biscuit*,*Pen*,*Pencil*, *Eraser*}. It contains fifteen unique market-baskets. Support and confidence having respective thresholds of 0.1 and 0.5 yielded fourteen ARs listed in Table 2.

R_6 and R_7 have two common items namely, *Chocolate* and *Biscuit*. R_7 has a higher *w*-value. Support of R_7 (0.11) is much lower than that of R_6 (0.24). Hence R_7 is not able to account for the presence of {*Chocolate*,*Biscuit*} as much as R_6. Secondly, presence of *Milk* in R_7 further increases its *weakness*-value because R_7 is able to explain the presence of *Milk* in only 11 of the 50 transactions (22.0%) that contain *Milk*. However, a high support value does not guarantee a low *weakness*-value. R_3's *weakness*-value (Support=0.30,*w*=0.334146) demonstrates this. R_3's support though high is not sufficient to cover the presence of *Bread* and *Milk*.

Table 3 lists the clusters obtained through the average-linkage method [4]. Despite the difference (0.017523) in the *weakness*-values between R_{14} and R_5 being greater than the difference (0.010614) between R_{10} and R_6, the former pair merges earlier. R_{14} and R_5 being *weaker* rules leads to lesser inter-rule distance as compared to R_{10} and R_6.

A rule and its sub-rules being in different clusters may be due to the difference in support between a rule and its sub-rules. If the support values of a rule's items have wide variation, then different sub-rules may explain their constituents' presence to different extents. This difference in their *weakness*-values may place them in different clusters. Cluster configuration after Step 9 results in clusters C_{w1}:{R_{14},R_5,R_7} and C_{w2}:{R_{10},R_6} whose elements have an average *w*-values of 0.608383 and 0.141671 respectively. R_7 is a member of high-*weakness* C_{w1} while its sub-rules R_{14} and R_6 are members of clusters C_{w1} and low-weakness C_{w2} respectively. Support values of constituents *Milk* (0.50), *Chocolate* (0.33) and *Biscuit* (0.24) also show some variation. Thus, low-support coupled with high variation in the support values of its constituents might result in a *weak* rule.

Surprisingly, rules describing *Milk* (the most frequent item) belong to high-*weakness* clusters. None of the rules that contain *Milk* covers its presence to a substantial extent. High support of *Milk* also increases the *weakness* of low-support rules that contain it. Thus, a frequently occurring item may be present in many high-*weakness* rules if the item is purchased in many non-overlapping low-support market-baskets.

Another observation is with respect to rules in clusters that have relatively lower average *weakness*-values. Low-*weakness* clusters may not contain high-support rules. Consider C_{w2}:{R_{10},R_6}. Note that support of R_{10} (0.23) is quite close to support of its items *Pencil* (0.28) and *Eraser* (0.26). High explanatory power of such a rule is derived from its support value being close to the support values of its constituent items.

5. COMPARATIVE ANALYSIS AND DISCUSSION

Sahar [7] defines d_{SC}-distance on the basis of difference in rule's itemsets and overlap in the set of transactions that each rule covers. d_{SC} considers itemsets in antecedent/consequent in their entirety while d_w considers each item of a rule separately. Table 4 displays d_{SC}–based cluster configurations.

R_9 is a sub-rule of R_8 both having support 0.13. Their antecedents match completely. Hence contribution due to antecedent dissimilarity towards $d_{SC}(R_8,R_9)$ is 0. Also, R_9's consequent ({*Pencil*}) is a subset R_8's consequent ({*Pencil*,*Eraser*}). R_9 covers all transactions covered by R_8 thus increas-

Table 4. d_{SC} –based clustering

Step_No	Clusters	
1	**{R_9,R_8}**	[0.429]
2	**{R_{12},R_2}**;{R_9,R_8}	[0.437]
3	**{R_5,R_1}**;{R_{12},R_2};{R_9,R_8}	[0.442]
4	**{R_{11},R_9,R_8};{**R_5,R_1};{R_2,R_{12}}	[1.098]
5	**{R_4,R_5,R_1}**;{R_{11},R_9,R_8};{R_2,R_{12}}	[1.892]
6	**{R_{13},R_{12},R_2}**;{R_4,R_5,R_1};{R_{11},R_9,R_8}	[1.958]
7	**{R_{10},R_{11},R_9,R_8}**;{R_{13},R_{12},R_2};{R_4,R_5,R_1}	[2.244]
8	**{R_{14},R_6}**;{R_{10},R_{11},R_9,R_8};{R_{13},R_{12},R_2};{R_4,R_5,R_1}	[2.313]
9	**{R_{13},R_{12},R_3,R_2}**;{R_{14},R_6};{R_{10},R_{11},R_9,R_8};{R_4,R_5,R_1}	[2.734]
10	**{R_{13},R_{12},R_3,R_2,R_4,R_5,R_1}**;{R_{14},R_6};{R_{10},R_{11},R_9,R_8}	[2.773]
11	**{R_7,R_{14},R_6}**;{R_{13},R_{12},R_3,R_2,R_4,R_5,R_1};{R_{10},R_{11},R_9,R_8}	[2.875]
12	**{R_7,R_{14},R_6,R_{13},R_{12},R_3,R_2,R_4,R_5,R_1}**,{R_{10},R_{11},R_9,R_8}	[3.980]
13	**{R_7,R_{14},R_6,R_{13},R_{12},R_3,R_2,R_4,R_5,R_1,R_{10},R_{11},R_9,R_8}**	[4.437]

Note: Values in the brackets represent merging distance ing their similarity. Hence their low d_{SC}-value (0.429167). Hence R_8 and R_9 merge at Step 1.

d_{SC}-based clustering is useful in bringing together rules originating from the same portion of a database [7]. Here each cluster consists of rules whose items are members of the same or close domains. However, a rule and its sub-rules may vary a great deal on parameters like explanatory power, etc. Hence, a user may have to examine different clusters to find rules having the same specificity/generality.

Our scheme namely, groups rules having ‘similar’ values of *weakness* (similar explanatory power) irrespective of their domain. Characteristics like average-*weakness* may be used to define low-*weakness* clusters leading to appropriate clusters for further examination. Rules in other clusters need not be examined thus mitigating the rule immensity problem to some extent.

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