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Attribute Relational Analysis (ARA) For Coherent Association Rules: A Post Mining Process For Parallel Edge Projection And Pruning (PEPP) Based Sequence Graph Protrude Approach For Closed Itemset

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I. Introduction

In general, association rules tend to deliver an efficient method of analysing binary or discretized data sets that are large in volume. One common practice is to determine relationships between binary variables in transaction databases, which is known as 'market basket analyses. In the case of non-binary data, initially data being coded as binary and then association rules will be used to analyse. Association rules having their impact on analysing large binary datasets and considered as versatile approach for modern applications such as detection of bio-terrorist attacks [1] and the analysis of gene expression data [2], to the analysis of Irish third level education applications [4].

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The steps involved in a typical association rule analysis are "Coding of data as binary if data is not binary" -> "Rule generation" -> "Post-mining". This survey focused on post mining. It was a century after the introduction of association rules (associations initially discussed in 1902), it is still continuing that the absence of items from transactions is often ignored in analyses.

a) Association rule mining

Given a set I that is non-empty, a rule of association is a statement of the form $X \Rightarrow Y$, where $X, Y \subset I$ such that $X \neq \emptyset$, $Y \neq \emptyset$, and $X \cap Y = \emptyset$. The dataset X is called the antecedent of the rule, the set Y is called the consequent of the rule, and we shall call I the master itemset. Association rules are generated over a large set of transactions, denoted by T. Xn association rule can be deemed interesting if the items involved occur together often and there are suggestions that one of the sets might in some cases lead to the presence of the other set. Xn association rules are characterised as interesting, or not, based on mathematical notions called 'support', 'confidence' and 'lift'. Although there are now a multitude of measures of interestingness available to the analyst, many of them are still based on these three functions.

In many applications, it is not only the presence of items in the antecedent and the consequent parts of an association rule that may be of interest. Consideration, in many cases, should be given to the relationship between the absence of items from the antecedent part and the presence or absence of items from the consequent part. Further, the presence of items in the antecedent part can be related to the absence of items from the consequent part; for example, a rule such as {margarine} ⇒ {not butter}, which might be referred to as a 'replacement rule'. One way to incorporate the absence of items into the association rule mining paradigm is to consider rules of the form X⇒/ Y [20]. Another is to think in terms of negations. Suppose $X \subset I$, then write $\neg X$ to denote the absence or negation of the item, or items, in X from a transaction. Considering X as a binary {0, 1} variable, the presence

of the items in X is equivalent to X = 1, while the negation ¬X is equivalent to XX`€=X`€0. The concept of considering association rules involving negations, or "negative implications", is due to Silverstein et al [20].

b) Post Mining

Pruning rules and detection of rule interestingness are employed in the post-mining stage of the association rule mining paradigm. However, there are a host of other techniques used in the post-mining stage that do not naturally fall under either of these headings. Some such techniques are in the area of redundancy- removal. There are often a huge number of association rules to contend with in the post-mining stage and it can be very difficult for the user to identify which ones are interesting. Therefore, it is important to remove insignificant rules, prune redundancy and do further post-mining on the discovered rules [18, 11]. Liu et al [11] proposed a technique for pruning and summarising discovered association rules by first removing those insignificant associations and then forming direction-setting rules, which provide a sort of summary of the discovered association rules. Lent et al.[19] proposed clustering the discovered association rules.

c) Influences of Input formats

The input formats that influence the post mining methodologies are binary data, text data and streaming data. In association rule mining, much of recent research work has focused on the difficult problem of mining data streams such as click stream analysis, intrusion detection, and web-purchase recommendation systems. In the case of streaming data, it is not possible to perform mining on cached and fixed data records. The attempt of caching data leads to memory usage issues, and the attempt of mining static data leads to worst time complexity since continuous dataset update leads to continuous passes through dataset. From the data mining point of view, texts are complex data giving raise to interesting challenges. First, texts may be considered as weakly structured, compared with databases that rely on a predefined schema. Moreover, texts are written in natural language, carrying out implicit knowledge, and ambiguities. Hence, the representation of the content of a text is often only partial and possibly noisy. One solution for handling a text or a collection of texts in a satisfying way is to take advantage of a knowledge model of the domain of the texts, for guiding the extraction of knowledge units from the texts. One of the obvious hot topics of data mining research in the last few years has been rule discovery from binary data. It concerns the discovery of set of attributes from large binary records such that these attributes are true within a same line often enough. It is then easy to derive rules that describe the data, the popular association rules though the interest of frequent sets goes further.

Based on the proposals [14, 12, 10, 3] recently cited in literature and their motivations, it is observable that the process of rule pruning will opt to one of the two models.

1) Rule pruning under post mining process that demands domain experts observation
2) Rule pruning under post mining process that aims to avoid domain experts role in pruning process.

As in the first case rule pruning accuracy depends on domain expert's awareness on attribute relations. In this case it is always obvious to prune the rules under reliable domain expert's observation. In second case the models prune the rules based on dynamically determined attribute relations. This limits the solution to specific data models. Hence it is not adaptable for all contexts.

The Rest of the paper organized as; in section II we discussed the most frequently cited post mining models to improve rule accuracy. Section III briefs the post mining process [] that we opted. Section IV briefs the approach of closed itemset mining, and inference approach for itemset pruning. Section V explores the process of Attribute Relational weights analysis for rule pruning. Results discussion and comparative study will be in Section VI that fallowed by conclusion and references.

II. Related Work

Huawen Liu, et al[14] proposed post processing approach for rule reduction using closed set to filter superfluous rules from knowledge base in a post-processing manner that can be well discovered by a closed set mining technique. Most of these methods are based on the rule structure analysis where the relations between the rules have been analysed using corresponding problem. This procedure claims to eliminate noise and redundant rules in order to provide users with compact and precise knowledge derived from databases by data mining method. Further, a fast rule reduction algorithm using closed set is introduced. Other endeavours have been attempted to prune the rule bases directly. The typical cases have been elaborated and illustrated by eminent people from all over.

Modest number of proposals is addressed on pre-pruning and post-pruning. In a line, the pruning operation occurs at the phase of generation of significant rules. To add to this, the post pruning technique mainly concerns primarily emphasises that pruning operation occurs after the rule generation, among which the rule cover is a representative case. To extract interesting rules, approri knowledge has also been taken into account in literatures and a template denotes which attributes should occur in the antecedent or the consequent part of the rule.

An association rule is an implication expression illustrates a kind of association relation. A rule is said to be interesting or valid if its support and confidence are user specified minimum support and confidence thresholds respectively. The association rule primarily comprises two phases based on the identification of frequent item sets from the given data mining contexts. However, the problem of massive real world data transactions can be rounded off by adopting other alternatives, which in turn benefits in lossless representation of data. Theoretically, transaction database and relation database are two different inter-transformable representations of data.

The production of association mining is a rule base with hundreds to millions of rules. In order to highlight the important and key ones, certain other rules are proposed which are Second –order rule which states that if the cover of the item set is known, then the corresponding relation can be easily derived. All the technical definitions given hence forth deal with the transaction of the data through item-sets in association mining. The equivalent property significantly states that rules and classes of the same hierarchical database support the power in the content. Traditional data mining techniques are implemented in order to justify the property and its corresponding definition in the specified context. The thus identified second order rules can be used to filter out useless rules out of the priority rule-set.

The effectiveness and efficiency of the classical methods in plating the rules is thoroughly verified under the 2.8 GHZ Pentium PC. Two group experiments were conducted to prune the insignificant association rules and to remove useless association classification rules. Removal of non-predictive rules by virtue of information gain metric is much similar to CHARM and CBA which also work on the same track. To generate association and classification rules by pruning method of Apriori software, some external tools are essentially required. The effectiveness of the pruning algorithm can be inversely related to the number of rules. This along with the computational time consumed, determine an efficient criterion of pruning.

Efficient post processing methods are hence proposed to remove pointless rules from rule-ways by eliminating redundancy among rules. The dependent relation, exploitation, makes this method a self manageable knowledge. The pruning procedure has been sliced into three stages starting from derivation to pruning operation on rule-set by the use of close rule-sets. It is cost-effective and consumes very little time for the transaction. Hence forth, it can be applied to exploit sampling techniques and data structures, thereby increasing the efficiency.

Huawen Liu, et al[14] presented a technique on post-processing for rule reduction using closed set that was targeting to filter the otiose rules in a post-processing of rule mining. The empirical study proved that the discovery of dependent relations from closed set helps to eliminate redundant rules. Hetal Thakkar et al [12]. In the case of stream data, the post-mining of association is more challenging and continuous post mining of association rules is an unavoidable requirement, which is discussed by this author. He presented a technique for continuous post-mining of association rules in a data stream management system. He described the architecture and techniques used to achieve this advanced functionality in the Stream Mill Miner (SMM) prototype, an SQL-based DSMS designed to support continuous mining queries, which is impressive. Hacene Cherfi et al, [10] discussed a post association rule mining approach for text mining that combines data mining, semantic techniques for post-mining and selection of association rules. To focus on the result analysis and to find new knowledge units, classification of association rules according to qualitative criteria using domain model as background knowledge has been introduced. The authors carried out an empirical study on molecular biology dataset that proved the benefits of taking into account a knowledge domain model of the data. Ronaldo Cristiano Prati [3]. The Receiver Operating Characteristics (ROC) graph is a popular way of assessing the performance of classification rules, but they are inappropriate to evaluate the quality of association rules, as there is no class in association rule mining and the consequent part of different association rules might not have any correlation at all. Chapter VIII presents a novel technique of QROC, a variation of ROC space to analyze itemset costs/benefits in association rules. It can be used to help analysts to evaluate the relative interestingness among different association rules in different cost scenarios.

III. Attribute Relational Analysis (ARA) Framework for Coherent association Rules

The approach Attribute Relational Analysis in short can refer as ARA is post mining process to prune the rules based on attribute relational relevancy. The process of ARA Framework can be classified as

- Closed itemset mining
- Describing item class descriptor

The input for ARA Framework is

1. A set of rules
2. An XML descriptor describes attributes, classes, class properties and class relations.

Here in this proposal we considered our earlier work [] to find closed itemsets.

The process steps involved in ARA framework are

1. Initially ARA measures the property support degree for each attribute involved in given rule.
2. By using the property support degree of the attributes, Attribute Relation support of attribute pairs of the given rule will be measured.
3. With the help of Attribute Relation supports of all attribute pairs of an itemset that belongs to a given rule, Attribute relation support degree of that itemset will be measured.
4. Using these Attribute relation support degrees of Left Hand Side and Right Hand Side itemsets of the given rule, relation confidence of the rule will be determined.
5. Prunes the rules based on their attribute relation support degree.

Detailed explanation of each step can be found in Section V.

IV. Closed Itemset Mining Using PEPP [34] and Inference Relations [35]

a) *Dataset adoption and formulation*

Item Sets I : A set of diverse elements by which the sequences generate.

$$I=\bigcup_{k=1}^{n} i_k$$

Note: 'I' is set of diverse elements

Sequence set 'S': A set of sequences, where each sequence contains elements each element 'e' belongs to 'I' and true for a function p(e). Sequence set can formulate as

$$s=\bigcup_{i=1}^{m} <e_i|(p(e_i),e_i\in I)>$$

Represents a sequence's' of items those belongs to set of distinct items 'I'.

'm': total ordered items.

$P(e_i)$: a transaction, where e_i usage is true for that transaction.

$$S=\bigcup_{j=1}^{t} s_j$$

S: represents set of sequences

't': represents total number of sequences and its value is volatile

s_j: is a sequence that belongs to S

Subsequence : a sequence s_p of sequence set 'S' is considered as subsequence of another sequence s_q of Sequence Set 'S' if all items in sequence S_p is belongs to s_q as an ordered list. This can be formulated as

If $(\bigcup_{i=1}^{n} s_{pi}\in s_q)\Rightarrow(s_p\subseteq s_q)$

Then $\bigcup_{i=1}^{n} s_{pi} <: \bigcup_{j=1}^{m} s_{qj}$ where $s_p\in S \text{ and } s_q\in S$

Total Support 'ts' : occurrence count of a sequence as an ordered list in all sequences in sequence set 'S' can adopt as total support 'ts' of that sequence. Total support 'ts' of a sequence can determine by fallowing formulation.

$$f_{ts}(s_t)=|s_t<:s_p \ (\text{for each } p=1..|DB_S|)|$$

DB_S Is set of sequences

$f_{ts}(s_t)$: Represents the total support 'ts' of sequence s_t is the number of super sequences of s_t

Qualified support 'q_s': The resultant coefficient of total support divides by size of sequence database adopt as qualified support 'qs'. Qualified support can be found by using fallowing formulation.

$$f_{qs}(s_t)=\frac{f_{ts}(s_t)}{|DB_S|}$$

Sub-sequence and Super-sequence: A sequence is sub sequence for its next projected sequence if both sequences having same total support.

Super-sequence: A sequence is a super sequence for a sequence from which that projected, if both having same total support.

Sub-sequence and super-sequence can be formulated as

If $f_{ts}(s_t) \geq$ rs where 'rs' is required support threshold given by user

And $s_t<:s_p$ *for any p value* where $f_{ts}(s_t)\cong f_{ts}(s_p)$

b) *Closed Itemset discovery using PEPP: Parallel Edge Projection and Pruning Based Sequence Graph protrude[34]*

As a first stage of the proposal we perform dataset pre-processing and itemsets Database initialization. We find itemsets with single element, in parallel prunes itemsets with single element those contains total support less than required support.

Forward Edge Projection

In this phase, we select all itemsets from given itemset database as input in parallel. Then we start projecting edges from each selected itemset to all possible elements. The first iteration includes the pruning process in parallel, from second iteration onwards this pruning is not required, which we claimed as an efficient process compared to other similar techniques like BIDE. In first iteration, we project an itemset s_p that spawned from selected itemset s_i from

DB_S and an element e_i considered from 'I'. If the $f_{ts}(s_p)$ is greater or equal to rs, then an edge will be defined between s_i and e_i. If $f_{ts}(s_i) \cong f_{ts}(s_p)$ then we prune s_i from DB_S. This pruning process required and limited to first iteration only.

From second iteration onwards project the itemset s_p that spawned from $S_{p'}$ to each element e_i of 'I'. An edge can be defined between $S_{p'}$ and e_i if $f_{ts}(s_p)$ is greater or equal to rs. In this description $S_{p'}$ is a projected itemset in previous iteration and eligible as a sequence. Then apply the fallowing validation to find closed sequence.

Edge pruning

If any of $f_{ts}(s_{p'}) \cong f_{ts}(s_p)$ that edge will be pruned and all disjoint graphs except s_p will be considered as closed sequence and moves it into DB_S and remove all disjoint graphs from memory.

The above process continues till the elements available in memory those are connected through direct or transitive edges and projecting itemsets i.e., till graph become empty

c) Inference Analysis [35]

Inferences:

Pattern positive score is sum of no of transactions in which all items in the pattern exist, no of transactions in which all items in the pattern does not exist

Pattern negative score is no of transactions in which only few items of the pattern exist

Pattern actual coverage is pattern positive score-pattern negative score

Interest gain: Actual coverage of the pattern involved in association rule

Coherent rule Actual coverage of the rule's left side pattern must be greater than or equal to actual coverage of the right side pattern

Inference Support ia_s: refers actual coverage of the pattern

$f_{ia}(s_t)$: Represents the inference support of the sequence s_t

Approach:

For each pattern s_p of the pattern dataset, If $f_{ia}(s_t) < ia_s$ then we prune that pattern

Detailed explanation of the PEPP Algorithm can find at []:

d) Description of Inference Analysis

Set I = {i1, i2… im} be the universe of items composed of m different attributes, ik(k=1,2,...,m) is item. Transaction database D is a collection of transaction T, A transaction t = (tid, X) is a tuple where tid is a unique transaction ID and X is an itemset. The count of an itemset X in D, denoted by count(X), is the number of transactions in D containing X. The support of an itemset X in D, denoted by supp(X), is the proportion of transactions in D that contain X. The negative rule $X \Rightarrow \neg Y$ holds in the transaction set D with confidence conf $(X \Rightarrow \neg Y)$ = supp $(X \cup \neg Y)$ /supp (X).

In Transaction database, each transaction is a collection of items involved sequences. The issue of mining association rules is to get all association rules that its support and confidence is respectively greater than the minimum threshold given by the user.

The issues of mining association rules can be divide into two sub-issues as follows:

· Find frequent itemsets, Generate all itemsets that support is greater than the minimum support;

· Generate association rules from frequent itemsets.

In logical analysis, the direct calculation of support logical analysis is not convenient, To calculate the support and confidence of negative associations using the support and confidence of positive association that is known: set A, $B \subset I$, $A \cap B = \Phi$, then:

$$\sup(\neg A) = 1 - \sup(A);$$
$$\sup(A \cup \neg B) = \sup(A) - Sup(A \cup B);$$
$$\sup(\neg A \cup B) = \sup(B) - \sup(A \cup B)$$
$$\sup(\neg A \cup \neg B) = 1 - \sup(A) - \sup(B) + \sup(A \cup B);$$

Based on the above formulas we perform the logical analysis to derive the actual support of the patterns that improves the rule coherency.

Inference analysis by example:

Let A, $B \in I$ where I is itemset generated with the association of A,B are individual items or subsets.

Under logical analysis we determine $f_{ts}(\neg A \cup \neg B)$, $f_{ts}(A \cup \neg B)$ and $f_{ts}(\neg A \cup B)$.

The support $f_{ts}(I)$, $f_{ts}(\neg A \cup \neg B)$ we consider as positive support and $f_{ts}(A \cup \neg B)$, $f_{ts}(\neg A \cup B)$ we consider as negative support.

Finally we determine $f_{ia}(I) = f_{ts}(I) + f_{ts}(\neg A \cup \neg B) - f_{ts}(A \cup \neg B) - f_{ts}(\neg A \cup B)$;

V. Attribute Relation Analysis Framework

The proposed post mining process Attribute Relation Analysis described in detailed here. Table 1 represents the notations used in ARA framework.

Class Descriptor: The domain expert classifies the attributes involved in transactions will be classified in to different categories. The process of classification as follow

1. Initially classes will be derived based on the properties; hence each class contains set of properties. These classes can be recursive i.e., a class may refer one or more other classes as sub classes.
2. Based on attribute properties, attributes will be categorized into a class.
   a) Ex: if most of the attribute 'a' properties matched to class 'c' then $a \in c$
3. The domain expert also initiates to derive the relation between classes. The relation can be between any two classes, such as
   b) Relation between class and sub-class of other class
   c) Relation between two direct classes
   d) Relation between two sub classes

Note : All related classes of a sub class also related to it's parent class

An xml based attribute class descriptor will be prepared. Fig1 shows an example descriptor. Notations description equations can found in table 1 that fallows.

```
<class-descriptor>
        <properties>
                <property id=1>
                        <name>prop1</name>
                </property>
                <property id=2>
                        <name>prop2</name>
                </property>
                <property id=3>
                        <name>prop3</name>
                </property>
        </properties>
        <attributes>
                <attribute name="item-1" id="1"
properties="{list of property ids}" />
                <attribute name="item-2" id="2"
properties="{list of property ids}" />
                <attribute name="item-3" id="3"
properties="{list of property ids}" />
                .
                .
                <attribute name="item-n" id="n"
properties="{list of property ids}" />
        </attributes>
        <classes>
                <class name="class-1" id="1"
properties="{list of property ids}" />
                <class name="class-2" id="2"
properties="{list of property ids}" />
                <class name="class-3" id="3"
properties="{list of property ids}" />
                .
                .
                <class name="class-n" id="n"
properties="{list of property ids}" />
        </classes>
        <child-classes>
                <!--parent value must be unique -->
                <child-class parent="class-id"
child="{list of class ids}"/>
                .
                .
                <child-class parent="class-id"
child="{list of class ids}"/>
        </child-classes>
        <relations>
                <!--lhs value must be unique -->
                <!--
                classes that related to a child-class
also related to it's parent class
                -->
                <relation lhs="class-id" rhs="{list of
class ids}" />
                .
                .
                <relation lhs="class-id" rhs="{list of
class ids}" />
        </relations>
</class-descriptor>
```

Fig 1 : Class-descriptor

Table1 : Notations used in Attribute Relational Analysis

1	r_{lhs}	Left side itemset of the Rule r
2	r_{rhs}	Right side itemset of the rule r
3	RS	Rule set
4	cpc_c	Class properties count of class c
5	apc_a	Attribute property count of attribute a
6	psd	Property support degree
7	tp_c	Total properties of class c
8	ps_a $ps_a = \frac{apc_a}{cpc_c}$	Property support of attribute a of class c
9	$psd_a = \frac{ps_a}{tp_c}$	where $a \in c$
10	rs_c	Relation support of class c is max threshold value 1.
11	ARS	Attribute Relation support
12	$ARSD_i$	Attribute Relation support Degree of itemset i.
13	If attributes a_i and a_j belongs to same class c	$ARS(a_i, a_j) \cong 1$, $where\ \{a_i, a_j\} \in c$
14	If attribute a_i belongs to class c_i and attribute a_j belongs to class c_j , c_i and c_j relation is true then	$ARS(a_i, a_j) = \frac{psd_{a_i} + psd_{a_j}}{rs_{c_i} + rs_{c_j}}$
15	If c_i and c_j relation is false	$ARS(a_i, a_j) = 0$,
16	$ARS(a_i, a_j) \cong ARS(a_j, a_i)$	Applicable in all cases such as both belongs to same class, both belongs to different classes that are not having relation and both belongs to different classes that are having relation
17	No of attribute pairs in an itemset	pc
18	$pc = 0;$ $\sum_{i=1}^{n-1} pc + i \quad (or) \quad pc = \frac{n-1}{2} \times n$	pc : is total number of pairs in a given itemset. n : is total number of attributes in the given itemset
19	$pc_{r_{lhs}}$	Pair-count of itemset, which is lhs of rule r .
20	$pc_{r_{rhs}}$	Pair-count of itemset, which is rhs of rule r .
21	$pc_{r_{lhs} \cup r_{rhs}}$	Pair-count of itemset that generated from $r_{lhs} \cup r_{rhs}$
22	$PS_i = \{p_1, p_2, ..., p_m\}$	Pair set that generated from itemset i

23	$ARS(p_i)$	Attribute relation support of pair p_i.
24	$ARSD_i = \frac{\sum_{k=1}^{\lvert ps_i \rvert} ARS(p_k)}{\lvert ps_i \rvert}$	Attribute relation support degree of itemset i And $p_k \in ps_i$, here p_k is k[th] pair of pair-set ps of itemset i
25	RC_r	Relation confidence of rule r.
26	$ARSD_{r_{lhs}} = \frac{\sum_{k=1}^{\lvert PS_{r_{lhs}} \rvert} p_k}{\lvert PS_{r_{lhs}} \rvert}$	Attribute relation support degree of itemset, which is lhs of rule r And $p_k \in ps_{r_{lhs}}$, here p_k is k[th] pair of pair-set ps of itemset lhs of rule r
27	$ARSD_{r_{rhs}} = \frac{\sum_{k=1}^{\lvert PS_{r_{rhs}} \rvert} p_k}{\lvert PS_{r_{rhs}} \rvert}$	Attribute relation support degree of itemset, which is rhs of rule r And $p_k \in ps_{r_{rhs}}$, here p_k is k[th] pair of pair-set ps of itemset rhs of rule r
28	$ARSD_{r_{lhs} \cup r_{rhs}} = \frac{\sum_{k=1}^{\lvert PS_{r_{lhs} \cup r_{rhs}} \rvert} p_k}{\lvert PS_{r_{lhs} \cup r_{rhs}} \rvert}$	Attribute relation support degree of itemset that generated from $lhs \bigcup rhs$ of rule r And $p_k \in PS_{r_{lhs} \cup r_{rhs}}$, here p_k is k[th] pair of pair-set ps of itemset that generated from $lhs \bigcup rhs$ of rule r
29	$rc_r = \frac{ARSD_{r_{lhs} \cup r_{rhs}}}{ARSD_{r_{lhs}}}$	Relation confidence of r is the coefficient emerged as result when 30attribute support degree of all attribute involved in rule r is divided by attribute support degree of rule r's lhs

Property Support : No of attribute properties are matched to number class properties to which that attribute belongs to [Table 1 row: 8].

Property Support degree : indicates the ratio of properties matched to class level properties [table 1 row: 9].

Ex: $psd_a = \frac{ps_a}{cpc_c}$; here a is an attribute of class c $[a \in c]$

Attribute Relation support : Indicates the strength of the relation between two attributes of an itemset that are considered as pair for equation [see table 1 row: 11, 13].

Pair Count : Total number of two attributes sets; here these attribute sets must be unique [see table 1, row 17, 18]

Attribute Relation support degree : is an itemset level measurement representing average relation strength of the attributes those belongs to an itemset [see table 1 row: 24]

Relation confidence : is a rule level measurement concludes the relation strength between left hand side itemset and right hand side itemset of a given rule[see table 1 row: 29]

ARA algorithm :

Input: Rule set RS , Class Descriptor CD and relation confidence threshold rct

Output: Significant Rule set $RS^{'}$ which is subset of RS $RS^{'} \subseteq RS$

Begin:

While RS is not empty

Begin:

Read a rule r from RS

Find property support ps_a and property support degree psd_a of each attribute a of r_{lhs} [Table 1 row: 8, 9]

Find property support ps_a and property support degree psd_a of each attribute a of r_{rhs} [Table 1 row: 8, 9]

Find unique two attribute pair set $PS_{\eta lhs}$ from r_{lhs} [Table 1 row: 22]

Find Attribute relation support ARS_p for each pair p , where $p \in PS_{r_{lhs}}$ [Table 1; row: 13, 15, 15 and 16]

Find Attribute relation support degree $ARSD_{\eta lhs}$ of ηlhs [Table 1; row: 24, 26].

Find unique two attribute pair set $PS_{\eta lhs}$ from r_{lhs} [Table 1 row: 22]

Find Attribute relation support ARS_p for each pair p , where $p \in PS_{r_{rhs}}$ [Table 1; row: 13, 15, 15 and 16]

Find Attribute relation support degree $ARSD_{r_{rhs}}$ of ηlhs [Table 1; row: 24, 27].

Find unique two attribute pair set $PS_{\eta lhs \cup r_{rhs}}$ from $r_{lhs} \bigcup r_{rhs}$ [Table 1 row: 22]

Find Attribute relation support ARS_p for each pair p , where $p \in PS_{r_{lhs} \cup r_{rhs}}$ [Table 1; row: 13, 15, 15 and 16]

Find Attribute relation support degree $ARSD_{\eta lhs \cup r_{rhs}}$ of $r_{lhs} \cup r_{rhs}$ [Table 1; row: 24, 28].

Find unique two attribute pair set $PS_{\eta lhs \cup r_{rhs}}$ from $r_{lhs} \bigcup r_{rhs}$ [Table 1 row: 22]

Find Attribute relation support ARS_p for each pair p , where $p \in PS_{r_{rhs} \cup \eta lhs}$ [Table 1; row: 13, 15, 15 and 16]

Find Attribute relation support degree $ARSD_{r_{rhs} \cup \eta lhs}$ of $r_{lhs} \cup r_{rhs}$ [Table 1; row: 24, 28].

Find Relation confidence rc_r of rule r

If $rc_r \geq rct$ then add rule r to resultant rule set $RS^{'}$

End

End

Fig 2 : Attribute Relation Analysis algorithm

This segment focuses mainly on providing evidence on asserting the claimed assumptions that 1) The post mining framework ARA is competent enough to momentously surpass results when evaluated against other post mining techniques [14, 10, 12. 2) Utilization of memory and computational complexity is less when compared to other post mining techniques. 3) There is the involvement of an enhanced occurrence and a probability reduction in the memory exploitation rate with the aid of the trait equivalent prognosis and also rim snipping of the PEPP with inference analysis and ARA. This is on the basis of the surveillance done which concludes that ARA implementation is far more noteworthy and important in contrast with the likes of other notable models [10, 12, 14].

JAVA 1.6_ 20th build was employed for accomplishment of the ARA along with PEPP under inference analysis. A workstation equipped with core2duo processor, 2GB RAM and Windows XP installation was made use of for investigation of the algorithms. The parallel replica was deployed to attain the thread concept in JAVA.

Dataset Characteristics [34, 35]:

We used same experiments platform described in our earlier work [34, 35].Hence the dataset that we opted is Pi and it's characteristics as described in our earlier work [34, 35]:

Pi is supposedly found to be a very opaque dataset, which assists in excavating enormous quantity of recurring clogged series with a profitably high threshold somewhere close to 90%. It also has a distinct element of being enclosed with 190 protein series and 21 divergent objects. Reviewing of serviceable legacy's consistency has been made use of by this dataset. Fig. 3 portrays an image depicting dataset series extent status.

In assessment with all the other regularly quoted forms like [14,12,10], Post-Processing for Rule Reduction Using Closed Set[14] has made its mark as a most preferable, superior and sealed example of post mining copy, taking in view the detailed study of the factors mainly, experts involvement, memory consumption and runtime.

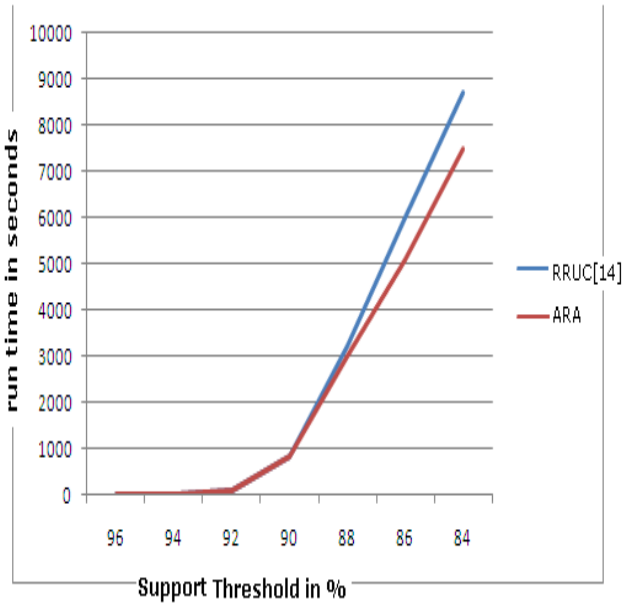

Fig 3 : A comparison report for Runtime[34, 35]

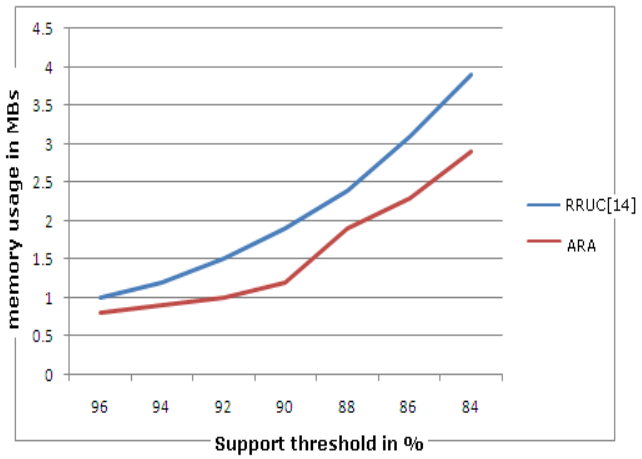

Fig: 4 : A comparison report for memory usage [34, 35]

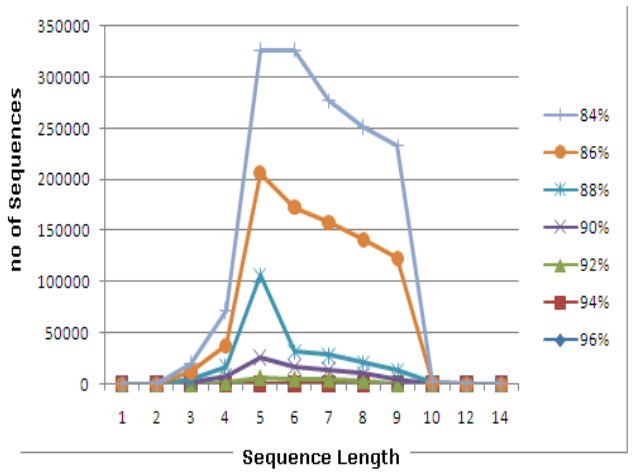

Fig 5 : Sequence length and number of sequences at different thresholds in Pi dataset[34, 35]

In contrast to ARA and RRUC [14], a very intense dataset Pi is used which has petite recurrent closed series whose end to end distance is less than 10, even in the instance of high support amounting to around 90%. The diagrammatic representation displayed in Fig 3 explains that the above mentioned two algorithms execute in a similar fashion in case of rules that are generated at support 90% and above. But in situations when the support case is 88% and less, then the act of ARA surpasses RRUC [14]'s routine. The disparity in memory exploitation of ARA and RRUC [14] can be clearly observed because of the consumption level of ARA being low than that of RRUC. Fig 5 indicates that rules that are contextually irrelevant have been pruned by ARA in high probable rate and stable. Apart from the benefits observed, the rules identified by ARA are more relevant to transaction consequences. It becomes possible since there is no task of experts evaluation in post mining process. Due to the concept of attribute class relation descriptor, the relation between attributes involved in rule is stable.

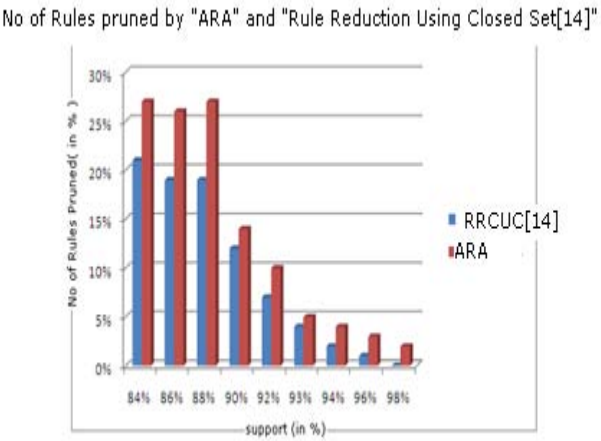

Fig 6 : Rules pruned in % by ARA and RRUC [14]

VI. Conclusion

We proposed a post mining process called Attribute relation analysis framework (ARA) for pruning association rules that are contextually irrelevant. In earlier works [10, 12, 14] the contextual irrelevancy was identified in various ways such as (1) rule evaluation by domain expert, (2) rule evaluation by itemset closeness. We argued that none of these two models is significant in all contexts. In second case adaptability to various data contexts is missing. In the first case, rule selection highly influenced by the experts view, that is when expert changes then rule significance might be rated differently. To defend these limits here we proposed a post mining process as an extension to our earlier proposed closed itemset mining algorithm PEPP with inference analysis [34, 35]. Here in this proposed post mining process ARA, the experts view is not defending

one to other, rather it extends or refines. This become possible in ARA because of the proposed concept called attribute class relation descriptor. In this work we consider relation confidence as bench mark for rule pruning; in future this work can be extended to prune the rules by opting relation confidence threshold under inference analysis.

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