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CONTENTS

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   RESULTS & DISCUSSION

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CONTRIBUTIONS TO BOOKS

- Sharma T., Kwatra, G. (2008) Effectiveness of Social Advertising: A Study of Selected Campaigns, Corporate Social Responsibility, Edited by David Crowther & Nicholas Capaldi, Ashgate Research Companion to Corporate Social Responsibility, Chapter 15, pp 287-303.

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- Schemenner, R.W., Huber, J.C. and Cook, R.L. (1987), "Geographic Differences and the Location of New Manufacturing Facilities," Journal of Urban Economics, Vol. 21, No. 1, pp. 83-104.

CONFERENCE PAPERS

- Garg, Sambhav (2011): "Business Ethics" Paper presented at the Annual International Conference for the All India Management Association, New Delhi, India, 19–22 June.

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- Kumar S. (2011): "Customer Value: A Comparative Study of Rural and Urban Customers," Thesis, Kurukshetra University, Kurukshetra.

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A I R E P: A NOVEL SCALED MULTIDIMENSIONAL QUANTITATIVE RULES GENERATION APPROACH

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ABSTRACT
This paper is aimed to propose an AIREP algorithm which uses association rule mining (ARM) discovery technique which is widely used in various data mining applications. The task of discovering scalable rules from the multidimensional database with reduced support is an area for exploration for research . In this paper we have proposed an algorithm AIREP to generate scaled rules using the pruning technique. The algorithm also prunes the database at each step in order to reduce the search space and to reduce the unnecessary frequent subset generation at each step. IREP induces a set of rules in disjunctive form growing and pruning phases and help in generating the scaled and efficient association rule. Experimental on real world datasets show that the proposed approach improves performance over existing approaches by minimizing the explosion of number of rules involving frequent items and without missing the frequent itemsets involving rare items.

KEYWORDS
Association rules, Data Mining algorithms, Frequent itemsets, Pre-pruning and Post-pruning.

INTRODUCTION
Due to increase in the amount of information available for analysis is increasing, scalability of data mining applications is becoming a critical factor. The scalability of data mining techniques is very important due to the rapid growth in the size of databases. Scalability in data mining can be done in large datasets by using scalable input /output architecture, minimizing transaction time. We can scale the data mining algorithms by using data reduction techniques such as aggregation, dimensional reduction, compression, and discretization. We can use reduce algorithm complexity by using parallelization methods (M.S.Danessh 2010, Jyothi Pillai 2010).

Data mining represents techniques for discovering knowledge patterns hidden in large databases (R Uday Kiran 2009). Data mining tasks can be classified into two categories, Descriptive Mining and Predictive Mining. The Descriptive Mining techniques such as Clustering, Association Rule Discovery, Sequential Pattern Discovery, is used to find human-interpretable patterns that describe the data. The Predictive Mining techniques like Classification, Regression, Deviation Detection, use some variables to predict unknown or future values of other variables (Jyoti Pillai 2010).

The discovery of association rules in transaction databases is an important data-mining problem because of its wide application in many areas, such as market basket analysis, decision support, financial forecast, collaborative recommendation, and prediction. For data mining approach, the association rule set is usually used for prediction. However, traditional association rule algorithms typically generate a large number of rules, most of which are unnecessary when used for prediction (Anurag Choubey 2011). The problem of mining association rules is to generate a set of potentially interesting association rules in a data set of sessions that have support higher than the specified minimum support threshold and assign an interestingness value to all rules based on an interestingness measure (Maja Dimitrij 2011) .

Association rules are an commonly used representation to describe the effective discovery of correlations among the underlying data in large databases. ..In this model, the set I = {il, i2 , . . . , im} is a collection of items or attributes. The database DB consists of a set of transactions, where each transaction is a subset of items in I. An association rule is an implication of the form $X \rightarrow Y$ with $X, Y \subset I$ and $X \cap Y = 0$. The meaning of the rule is that a transaction containing items in X will likely contain items in Y.(Neelu Khare 2009, Tarek F. Gharib 2010). To determine whether an association rule is interesting, two measures are used: support and confidence. An association rule, $X \rightarrow Y$, has support s% in DB if s% of transactions in DB contains items in X U Y (C.S.Kanimozhi 2009). The same association rule is said to have confidence c% if among the transactions containing items in X, there are c% of them containing also items in Y. So, the problem is to find all association rules which satisfy predefined minimum support and minimum confidence constraints (S. Lofti 2009).

Many interesting and efficient algorithms have been proposed for mining association rules for these Boolean attributes, for examples, Apriori (R. Agrawal 1994), DHP (J S. Park 1995), and partition algorithms (A Savasere 1995). However, in a real database, attributes can be quantitative and the corresponding domains can have multiple values or a continuous range of values, for examples, age, and salary. A common approach to the QAR mining problem is to transform it into a problem of conventional BAR mining (R. Agrawal 1995 , Agrawal R 1993). Existing algorithms involve discretizing the domains of quantitative attributes into intervals so as to discover quantitative association rules. For each distinct value of a quantitative or categorical attribute, the pair <attribute, value> is mapped to a Boolean attribute and then algorithms for mining BARs are applied.

In many cases, the number of intervals associated with an attribute is large hence when we join the attributes in the mining process, the number of itemsets (i.e., a set of <attribute, interval> pairs) can become prohibitively large. As a result, effective techniques to prune the large search space of QAR mining and avoid the costly generation of a large number of candidate sets are necessary in order to develop an efficient algorithm for the problem. Also these intervals may not be meaningful enough for human experts to easily obtain nontrivial knowledge (Suraj Srivastava 2010).

We may be able to build a decision tree which perfectly reflects the data but the tree may not be generally applicable. Pruning is a technique for simplifying and hence generalising a decision tree. Error-Based Pruning replace sub-trees with leaves .It uses decision class is the majority. The pruning is based on predicted error rates. It prunes sub trees which result in lower predicted error rate (Fadi Thabtah 2006). The two common techniques are:

1) Cost Complexity Pruning: The predicted error rate modelled as weighted sum of complexity and error on training set and the test cases used to determine weighting .

2) Reduced Error Pruning: In this approach we use test set to assess error rate directly.

Pruning mechanisms are an important component of practical learning algorithms for decision trees and lists and are essential for learning comprehensible and accurate classifers in the presence of noise (Tzung-Pei Hong 2008).

This research work is the extension of the previous work where we have proposed algorithm for Aprori-UB which uses multidimensional access method UB-tree to generate better association rules with high support and confidence. The Aprori-Ub approach reduces not only the number of item sets generated but also the overall execution time of the algorithm. In this paper we have used the incremental reduced error pruning method to minimize the error during the generation of the scaled multidimensional association rule (Przemyslaw Kazienko 2009).

The rest of the paper is organized as follows. Section 2 gives the overview of the previous work done in the same field. Section 3 explains the concepts used in this paper. Section 4 gives the proposed work. Section 5 gives the experimentation details. Section 6 and Section 7 discusses the conclusion and future scope.

RELATED WORK

In the previous section we have introduced the basic concept of scalable Data Mining, Association Rule mining, Pruning. A brief overview of various algorithms, concepts and techniques defined in different research papers have been given in this section.

The popular approaches like Apriori discover association rules based on frequent itemsets which are extracted by fixing the same (or single) minimum support for all items (J.Shahrabi 2009). Let's start by defining association rule mining that finds correlation between the items in the data sets (] Michael Hahsler 2009, Laszlo Szathmary 2010). ARM is two step process i.e. first finds all frequent itemsets having minimum support and then generate strong association rules having minimum confidence, from the frequent itemsets. i.e. ARM finds out association rules which satisfy the predefined minimum support and confidence from a given database. Let J = {i1, i2…im} be a set of items, D be a set of database transactions and T is transaction contains set of items such that (. Mart´inez-Ballesterosa 2011). Let A, B be set of items and T is said to contain A, iff A⊂T. An association rule is an implication of the form A⇒B holds, where A⊂ J also B⊂J and A∩B is NULL. The rule holds in transactions set D with support s, where s is the percentage of both A and B. The A⇒B rule has confidence c in the transaction set D if c is the percentage of transactions in D containing A that also contains B (Rakhi Garg 2011).

Association analysis is an important data mining technique, widely used in commercial, financial, telecommunications, medical fields and so on, but rarely applied in the bibliometric analysis [12]. Our research shows that association rules can discover information hidden in the keywords, publications, authors, research institutions and other materials. In particular, it can instruct researchers to find research fields and techniques related to its research direction. At the same time, it helps them broaden research ideas and even discover new research fields by providing relevant publications, authors and research institutions. This has significant instructive value to research works.

CONCEPT USED

Associative algorithms normally derive a large set of rules since (R. Uday kiran 2009) classification data sets are typically highly correlated and (Anurag Choubey 2011) association rule mining approaches that consider all attribute values combinations in the database are used for rules discovery. As a result, there have been many attempts to reduce the size of their classifiers, mainly focused on preventing rules that are either redundant or misleading from taking any role in the prediction process of test data objects. The removal of such rules can make the classification process more effective and accurate (Fadi Thabtah 2006).

Several pruning methods have been used effectively to reduce the size of the classifiers, some of which have been adopted from decision trees, like pessimistic estimation, others from statistics such as chi-square testing (x^2). These pruning techniques are utilised during either rule discovery or the construction of the classifier. For instance, a very early pruning step, which eliminates rule items that do not pass the support threshold, may occur in the process of finding frequent rule items[3,2]. Another pruning such as chi-square testing may take place when generating the rules, and a late pruning method like database coverage may be used after discovering all potential rules.

There are various pruning methods used and each method is cast in the framework of the search in the state space (Floriana Esposito 1999) .Some of the pruning methods are :-

REDUCED ERROR PRUNING (REP)

This method uses the pruning set in order to evaluate the goodness of a sub tree of tree T_{ax}. Search is accomplished in the any-depth branch pruning state pace, Ẏp(T),{πT }) according to the first-better search strategy and a post-order traversal. The evaluation function f is defined as follows:

$$f(T) = -\sum_{t€r} e(T)$$

where e(t) is the number of errors made by node t during the classification of the examples in the pruning set. The search in the space moves from a state ¹ to a state T^1 € T\`t($Ẏ_r$) if the inequality

f(T\`) >= f(T) holds or equivalently if

$$\sum_{t€r} e(T) <= \sum e(T)$$

The states to be explored are generated according to the order defined by bottom-up methods, hence there is no choice of the best state to be reached, starting from another state (Kahayan Lal 2010).

PESSIMISTIC ERROR PRUNING

This pruning method, proposed in (Quinlan J.R 1987) as well, is characterized by the fact that it avoids using an independent pruning set. Search is accomplished in the any-depth branch pruning state space, ({Ẏp(T),{πT }), according to thefirst-better search strategy and a pre-order traversal. The evaluation function f is defined as follows:

f (t) = -∑n\`t

t€ Ẏp where n\`(t) = [e(t) + ½]and e(t) is the number of errors made by node t during the classification of the examples in the training set. Indeed, let T\` be the arrival state of an edge out coming from T such that it is obtained by pruning a node t€T. Then it can be proved that f(T\`) – f(T) = n(T_t) – n1(t)

where n(T_t) = -∑ e(s) +| ẎT_t | . Pruning is accomplished also when the following condition holds: -SE(n\`-$T_t$)) <= f(T\`) – f(T).

where SE is the standard error. This is equivalent to prune when

as stated in Quinlan's original formulation. Therefore, there is no evaluation of the best pruning to perform among the possible ones, and the first pruning operation that turns out to be good is performed. It follows that the search strategy adopted is the first-better with a pre-order traversal (M. Mart´inez-Ballesterosa 2010, Maja Dimitrijevic 2011).

It should also be noted that the top-down approach to tree pruning used in PEP is not justified when there is no guarantee that all subtrees of a pruned branch T_t have to be pruned. Indeed, it may happen that by pruning a node t other nodes that should not be pruned according to the same criterion are actually discarded. However, this top-down approach gives the pruning method a high run-speed, with a computational complexity being linear in the number of nodes (Fang Li 2009, Preetham Kumar 2008).

MINIMUM ERROR PRUNING (MEP)

This method was proposed as a bottom-up approach for searching a single tree that minimizes the expected error rate. For a k-class problem, the expected probability that an observation reaching a node t belongs to the ith class is the following:

$$pi(t) = \frac{n_i(t) + p_{aim}}{N(t) + m}$$

where n_i (t) is the number of training examples in t classified into the ith class, p_{ai} is the apriori probability of the ith class, m is a parameter of the estimate method, N(t) is the number of training examples reaching t. When a new observation reaching t is classified, the expected error rate is given by

$$EER = \min(i)\ \{1 - p_i - (t)\}$$

In the MEP method, the choice of m is critical. We have to decide to choose the value m using an independent pruning set. More precisely, given a set of possible values for m, we select that returning the smallest tree with the lowest empirical error rate on an independent pruning set. Therefore, this is an example of two-phased pruning method (Pratima Gautam 2010).

CRITICAL VALUE PRUNING (CVP)

It is a pruning method that searches in the one-depth branch pruning state space, (ŸP(T),π). The evaluation function associated with this reduced space is given by the sum of the values taken by the selection measure in each internal node of the tree (f (T = 0) [17]. Therefore, if GR(t) is the gain ratio at node t, the evaluation function can be defined as $f(T) = \sum GR(T)/T_t$.A tree T` will be generated from a tree [1] if it happens that f(T`) = min $f(T`)/t\pi_r$.

The search goes on according to a hill-climbing strategy until the minimum tree $T^1$is reached (Jianying Hu 2007).

At the end of the search, the number of the explored states will be $|\dot{Y}T_{max}|$, denoted as $T_{max}...T_{max-1}$. This method is two-phased as the previous one. However, in this case not all states traversed are considered in the second phase. A traversed state Ti, i<=1 <= $\dot{Y}_x$is considered to be transient if it happens that

$f(Tj)-f(T_{j-1}) >= f(Tj)-f(T_{j-1})$, j<=1.

For the second phase, we have to choose the best tree among the sequence of the pruned trees by measuring both the significance of the tree as a whole and its predictive ability. The significance of the tree is estimated by means of the G statistics, which evaluates the degree of interdependence between the leaves of a tree and the classes of the problem: It will be higher for fully expanded trees that correctly classify the whole set of examples. The weakness of this measure is that a test on this statistics is only able to establish whether the predictive ability of a tree is meaningful, but it cannot be used to choose among trees that pass the test (Maja Dimitrijevic 2011).

COST –COMPLEXITY PRUNING

This pruning method is characterized by two phases:

(1) Selection of a family of sub trees of T_{max} according to some heuristics.

(2) Choice of the best tree in the family according to an accurate estimate of the actual error rate.

For what concerns the first phase, search is performed in the any depth branch pruning state space according to a hill-climbing strategy and a post-order traversal. The evaluation function can be defined as follows: $f(T) = -\sum_{t \in \dot{Y}_r} e(T)$

where e(t) is the number of errors made by node t on the training, growing set. It is possible to move from T to T` =πr(t) if it happens that

$$\frac{f(T) - F(T`)}{|\dot{Y}_T| - |\dot{Y}_{T-1}|} = f(T) - F(T`)$$

For each reached state, the next state that gives the lowest value of the ratio and apparent error rate increase on and number of leaves decrease is detected. The search goes on until the smallest tree $T_{1\ is}$ reached(E. Chandra 2010, Przemyslaw Kazienko 2009).

The second phase of the method aims at selecting the best among the trees traversed in the first phase. Once again, not all states are considered, and a transient state can be defined as follows: let

$T_{max} = T^{m,}-T^{m-1}$,....T_0...T_1...T_m be the states followed by the search process and let ^{T}the complexity parameter of a state T^i,T^m then it is transient if бi = бi-1 Jyothi Pillai 2010, Fan Lilin 2010).

PROPOSED WORK

We define ,C_k as a candidate itemset of size k ,Z_k as a frequent itemset of size k, An AIREP algorithm is

1. Find frequent set L_{k-1}
2. Join step: C_k is generated by joining L_{k-1} with itself (cartesian product L_{k-1} x L_{k-1})
3. Prune step : Use theIncremental Reduced Error pruning to generate scalable single rule.
4. Frequent set L_k has been achieved.

The proposed AIREP (Aprori Incremental Reduced Error Pruning) pseudo code:

```
AIREP (T, ụ)
Z1 ← large multidimensional itemsets that appear in more than
Of large item set ụ transactions
K ← 2
While ( Zk-1 ≠ 0 )
Ck ← Generate (Zk-1 ) // join and prune step
// using IREP
procedure I-REP (Examples, SplitRatio)
Theory = Ө ;
While Positive (Examples) ≠ Ө;
Clause = Ө;
Split Examples (Split Ratio, Examples, Growing Set, Pruning Set)
Cover = Growing Set
While Negative (Cover) ≠ Ө ;
Clause = Clause ᴜ Find Literal (Clause; Cover)
Cover = Cover (Clause, Cover)
loop
NewClause = BestSimplification (Clause, PruningSet)
if Accuracy(NewClause,PruningSet) < Accuracy(Clause,PruningSet)
exit loop
Clause = NewClause
if Accuracy(Clause,PruningSet)<=Accuracy(fail,PruningSet)
exit while
Theory = Theory ᴜ Clause
Examples = Examples -Cover
return (Theory)
```

```
// end of IREP
//frequent set generation
        for transaction t € Z
        Ck ← Subset(Ck,t)
        for candidates c € Ct
                count[c] =count[c + 1]
        Zk ← { c € Ck| count[c] >= e}
k ← k+1
return Zk
```

FIGURE 1: PSEUDOCODE OF PROPOSED AIREP ALGORITHM

The basic idea of Incremental Reduced Error Pruning (IREP) is that instead of first growing a complete concept description and pruning it thereafter, each individual clause will be pruned right after it has been generated. This ensures that the algorithm can remove the training examples that are covered by the pruned clause before subsequent clauses are learned thereby preventing these examples from influencing the learning of subsequent clauses.

Figure 1 shows pseudo-code for this algorithm. As usual, the current set of training examples is split into a growing (usually 2/3) and a pruning set (usually 1/3). However, not an entire theory, but only one clause is learned from the growing set. Then, literals are deleted from this clause in a greedy fashion until any further deletion would decrease the accuracy of this clause on the pruning set. Single pruning steps can be performed by submitting a one-clause theory to the same BestSimplification subroutine used in REP or, as in our implementation, one can use a more complex pruning operator that considers every literal in a clause for pruning. The best rule found by repeatedly pruning the original clause is added to the concept description and all covered positive and negative examples are removed from the training growing *and* pruning set. The remaining training instances are then redistributed into a new growing and a new pruning set to ensure that each of the two sets contains the predefined percentage of the remaining examples. From these sets the next clause is learned. When the predictive accuracy of the pruned clause is below the predictive accuracy of the empty clause (i.e., the clause with the body fail), the clause is not added to the concept description and I-REP returns the learned clauses. Thus,
the accuracy of the pruned clauses on the pruning set also serves as a stopping criterion. Post-pruning methods are used as pre-pruning heuristics.

In figure 2 the attributes of the dataset are divided into instances and converted into divided attributes. In order to build a rule, IREP uses the following strategy. First the uncovered examples are randomly partitioned into two subsets, a growing set and a pruning set. Next, a rule is grown. It begins with an empty conjunction of conditions, and considers adding to this any condition of the form $Z_n = U_i$, $Z_n <= \Theta$ or $Z >= \Theta$ where Z_n is a nominal attribute and u is a legal value for Z_n, or Z_c is a continuous variable and Θ is some value for Z_c that occurs in the
training data. After growing a rule, the rule is immediately pruned. After growing a rule, the rule is immediately pruned To prune a rule, our implementation considers deleting any final sequence of conditions from the rule and chooses the deletion that maximizes the function

$$u(Rule,PrunePos,PruneNeg) = \frac{X + (N - n)}{X + N}$$

where X (respectively N), is the total number of examples in PrunePos ,PruneNeg and p ,n, is the number of examples in PrunePos ,PruneNeg covered by Rule.This process is repeated until no deletion improves the value of u.

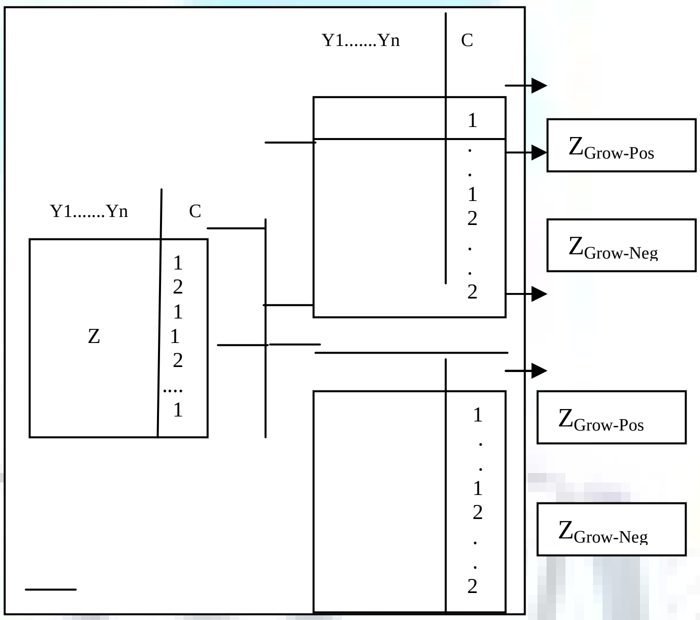
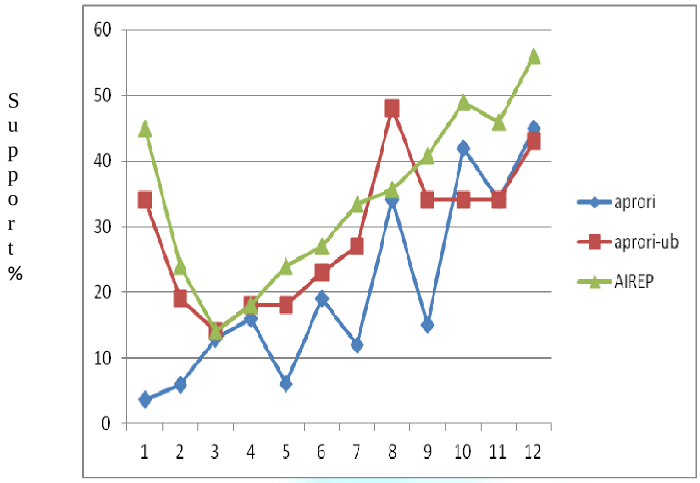


FIGURE 2: PARTITIONING OF ORIGINAL DATA SET OF LABELLED INSTANCES

EXPERIMENTATION

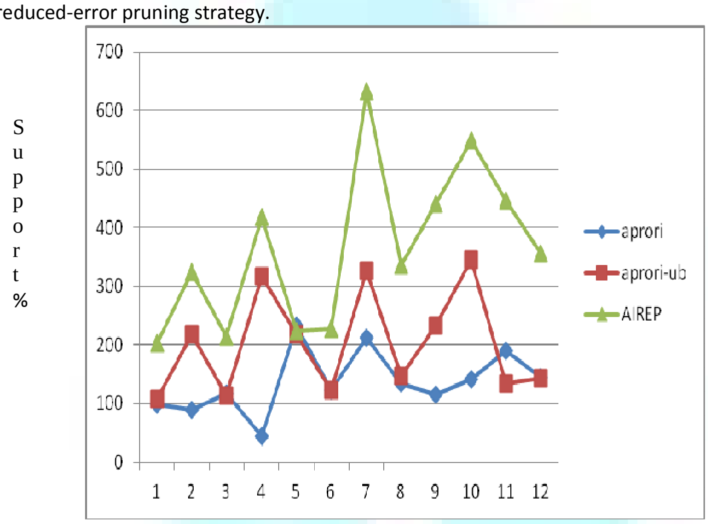
The experiments with proposed AIREP showed that the rules generated were fast and efficient. We used java programming language to implement the AIREP algorithm. We used the synthetic and real world dataset to test the efficiency of the algorithm. The experiment were conducted on breast-cancer real life dataset and other synthetic dataset .The dataset is belongs to UCI Machine repository datasets.The features of the dataset is computed from a digitized image of a fine needle aspirate (FNA) of a breast mass. The attributes of the dataset includes ID number, Diagnosis, radius, texture, area, smoothness.



Items sorted based on support.

FIGURE 3: SUPPORT% OF REAL WORLD DATASET USING AIREP

AIREP learns the clauses in the order in which they will be used by a PROLOG interpreter. Before subsequent rules are learned, each clause is completed (learned *and* pruned) and all covered examples are removed. Therefore, the AIREP approach eliminates the problem of incompatibility between the separate-and conquer learning strategy and the reduced-error pruning strategy.



Item sorted based on support

FIGURE 4: SUPPORT% OF SYNTHETIC WORLD DATASET USING AIREP

The experiment show that AIREP's asymptotic complexity is *O*(*n* log2 *n*), *n* being the size of the training set. The cost of growing one clause in REP is*O*(*n* log *n*), because for selecting each of the £(log *n*) literals. Thus, a constant number of conditions is tested against *O*(*n*) examples. AIREP considers *every* literal in the clause for pruning. Therefore, each of the £(log *n*) literals has to be evaluated on the £(*n*) examples in the pruning set until the final clause has been found, i.e., at most *O*(log *n*) times. Thus, the cost of pruning one clause is *O*(*n* log2 *n*). Assuming that AIREP stops when the correct theory of constant size has been found, the overall cost is also *O*(*n* log2 *n*). This is significantly lower than the cost of growing an over fitting theory which has been shown to be -(*n*2 log *n*) under the same assumptions .

No.	Label	Count
1	10-19	0
2	20-29	1
3	30-39	36
4	40-49	90
5	50-59	96
6	60-69	57
7	70-79	6
8	80-89	0
9	90-99	0

TABLE 5: SUPPORT COUNT OF THE ATTRIBUTES OF DATASET

We tested our proposed method that contained a wide range of item numbers (more than 900 items) in a transaction, to find only multi dimensional quantitative association rules. To use data, we appended the two attribute fields namely tumor size and age using data generating programs based on randomization functions, in order to ensure that the final test data remained unbiased. The data contained 49,100 transactions. The number of rules obtained under different values of constraints, such as minimum support and minimum size of item-sets generated scaled association rules.

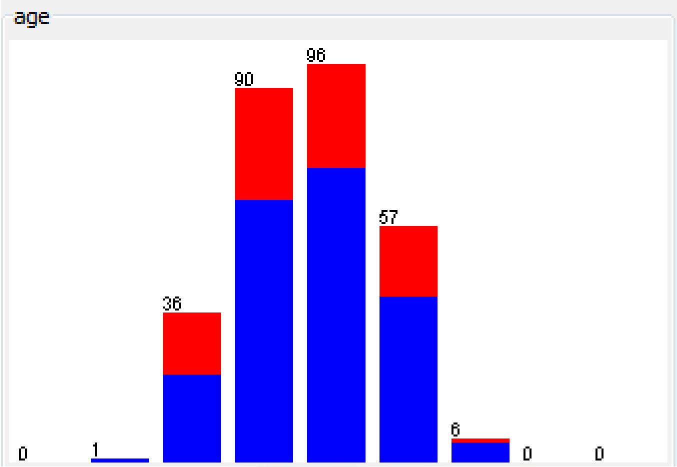


FIGURE 6: AGE ATTRIBUTE RULE GENERATION OF BREAST-CANCER DATASET

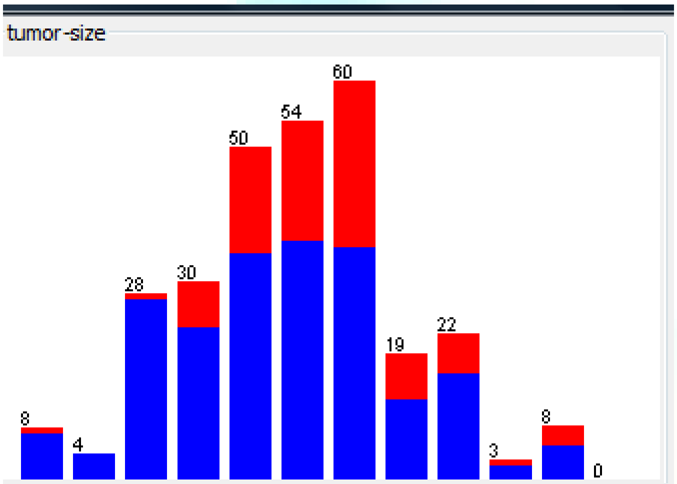
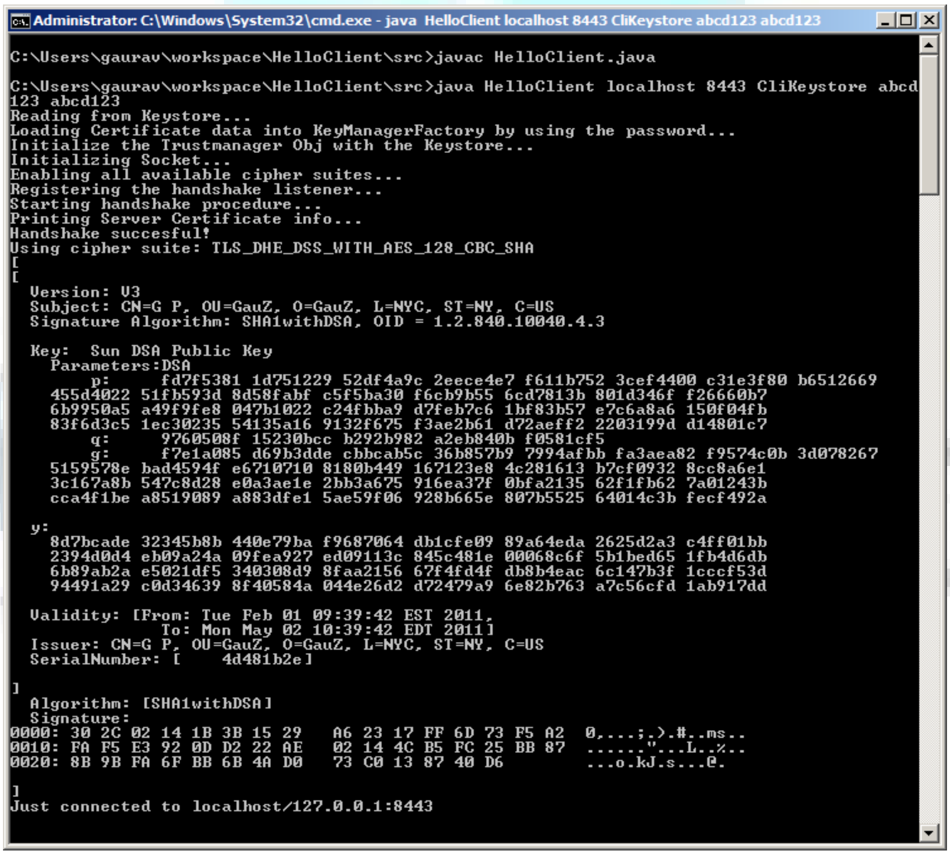


FIGURE 7: TUMOR-SIZE ATTRIBUTE RULE GENERATION OF BREAST-CANCER DATASET



```
Administrator: C:\Windows\System32\cmd.exe - java  HelloClient localhost 8443 CliKeystore abcd123 abcd123

C:\Users\gaurav\workspace\HelloClient\src>javac HelloClient.java

C:\Users\gaurav\workspace\HelloClient\src>java HelloClient localhost 8443 CliKeystore abcd
123 abcd123
Reading from Keystore...
Loading Certificate data into KeyManagerFactory by using the password...
Initialize the Trustmanager Obj with the Keystore...
Initializing Socket...
Enabling all available cipher suites...
Registering the handshake listener...
Starting handshake procedure...
Printing Server Certificate info...
Handshake succesful!
Using cipher suite: TLS_DHE_DSS_WITH_AES_128_CBC_SHA
[
[
  Version: V3
  Subject: CN=G P, OU=GauZ, O=GauZ, L=NYC, ST=NY, C=US
  Signature Algorithm: SHA1withDSA, OID = 1.2.840.10040.4.3

  Key:  Sun DSA Public Key
    Parameters:DSA
        p:     fd7f5381 1d751229 52df4a9c 2eece4e7 f611b752 3cef4400 c31e3f80 b6512669
    455d4022 51fb593d 8d58fabf c5f5ba30 f6cb9b55 6cd7813b 801d346f f26660b7
    6b9950a5 a49f9fe8 047b1022 c24fbba9 d7feb7c6 1bf83b57 e7c6a8a6 150f04fb
    83f6d3c5 1ec30235 54135a16 9132f675 f3ae2b61 d72aeff2 2203199d d14801c7
        q:     9760508f 15230bcc b292b982 a2eb840b f0581cf5
        g:     f7e1a085 d69b3dde cbbcab5c 36b857b9 7994afbb fa3aea82 f9574c0b 3d078267
    5159578e bad4594f e6710710 8180b449 167123e8 4c281613 b7cf0932 8cc8a6e1
    3c167a8b 547c8d28 e0a3ae1e 2bb3a675 916ea37f 0bfa2135 62f1fb62 7a01243b
    cca4f1be a8519089 a883dfe1 5ae59f06 928b665e 807b5525 64014c3b fecf492a

  y:
    8d7bcade 32345b8b 440e79ba f9687064 db1cfe09 89a64eda 2625d2a3 c4ff01bb
    2394d0d4 eb09a24a 09fea927 ed09113c 845c481e 00068c6f 5b1bed65 1fb4d6db
    6b89ab2a e5021df5 340308d9 8faa2156 67f4fd4f db8b4eac 6c147b3f 1cccf53d
    94491a29 c0d34639 8f40584a 044e26d2 d72479a9 6e82b763 a7c56cfd 1ab917dd

  Validity: [From: Tue Feb 01 09:39:42 EST 2011,
               To: Mon May 02 10:39:42 EDT 2011]
  Issuer: CN=G P, OU=GauZ, O=GauZ, L=NYC, ST=NY, C=US
  SerialNumber: [    4d481b2e]

]
  Algorithm: [SHA1withDSA]
  Signature:
0000: 30 2C 02 14 1B 3B 15 29   A6 23 17 FF 6D 73 F5 A2  0,....;.).#..ms..
0010: FA F5 E3 92 0D D2 22 AE   02 14 4C B5 FC 25 BB 87  ......"...L..%..
0020: 8B 9B FA 6F BB 6B 4A D0   73 C0 13 87 40 D6        ...o.kJ.s...@.

]
Just connected to localhost/127.0.0.1:8443
```

FIGURE 8: RULE GENERATION AFTER PRUNING

The efficiency increases with an increase in minsupport because an itemset now needs to be present in a larger number of transactions to eventually make it to the large set. The candidate set contains itemsets expected to be large as well as those expected to be small.

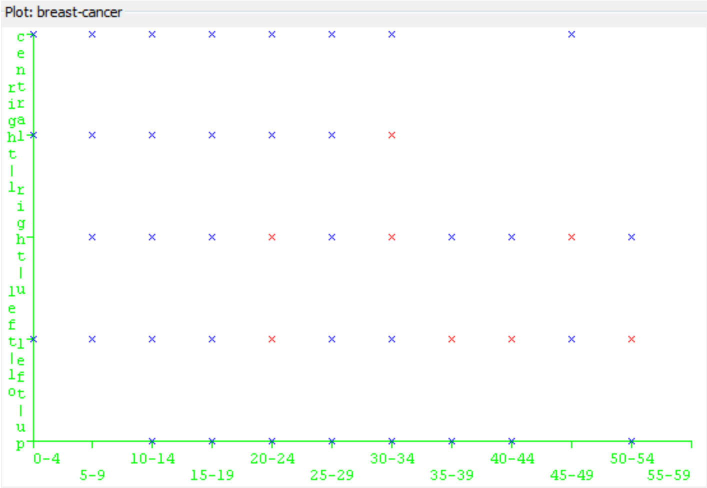


FIGURE 9: COMPARISON OF BREAST-CANCER DATASET ATTRIBUTES

Scaled Figure 8 bears out that most of the candidate itemsets expected to be large indeed turn out to be large. Initially, there is a large increase in the fraction of itemsets expected to be small in the candidate set as minsupport increases. Candidate itemsets as minsupport increases. Figure 7,8 shows efficiency of the pruning function optimization, with the remaining tuple optimization turned . It plots the fraction of new itemsets pruned due to this optimization .Figure 9 shows the results of the rule generated after pruning. The effectiveness of the optimization increases with an increase in minsupport as we can use a smaller value for. We also measured the pruning of new and old item sets when both the remaining tuple and pruning function optimizations were turned on. The curves for combined pruning tracked closely the two curves for the remaining tuple optimization. The pruning function optimization does not prune old candidate itemsets. The scaled rules obtained were classified on the basis of the attributes such as and generated with high confidence and support.

CONCLUSION

The goal of mining association rules is to discover important associations among items in a database of transactions such that the presence of some items will imply the presence of other items. The problem of mining association rules has been decomposed into two sub-problems: discovering the large Item-sets, and then generate rules based on these large Item-sets. The attention has been placed on the first sub-problem since the second sub-problem is quite straightforward up to some extent. Thus, there have been several algorithms proposed to solve the first sub-problem. These researches in algorithms of mining association rules are basically motivated by the fact that the amount of the processed data in mining association rules is huge; thus it is crucial to devise efficient algorithms to conduct mining on such data. The rules that we discover have one item in the consequent and a union of any number of items in the antecedent. We tested the effectiveness of our algorithm by applying it to sales data obtained from a large retailing company. For this data set, the algorithm exhibited excellent performance. The estimation procedure exhibited high accuracy and the pruning techniques were able to prune out a very large fraction of itemsets without measuring them.

FUTURE WORK

As a part of future work, we are going to investigate appropriate methodology for assigning confidence values in a dynamic manner to generate rare association rules in an efficient manner.

The existing approaches extract frequent item sets involving rare items by assigning minimum support to each item and employing an iterative process to discover frequent item sets. We are going to investigate how popular noniterative approaches like frequent-pattern growth approaches can be extended to assign minimum support to each item to extract frequent itemsets involving rare items. In future we discuss and propose a method to generate conditional hybrid dimension association rules using fuzzy logic, whereas hybrid dimension association rule is hybridization between inter-dimension and intra-dimension scaled association rules.

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