International Journal of Creative Research Thoughts
Volume 1, Issue.3, March 2013 ISSN:-2320-2882

ORIGINAL ARTICLE

AI based Mining Algorithm for Managing Databases

Dr. Vikash Kumar Singh
Ph. D. (Computer Science and Engineering) &
UGC-NET (Computer Science and Applications)
Assistant Professor
Mr. Sudesh Kumar
M.Sc. (Computer Science)
& M. Tech (Computer Science)
Assistant Professor

ABSTRACT

The Mining Database archives and provides efficient access to all data necessary for the conduct of Survey Operations. Operational Database is the database-of-record, consisting of system-specific reference data and event data belonging to a transaction-update system. It may also contain system control data such as indicators, flags, and counters. The operational database is the source of data for the data warehouse. It contains detailed data used to run the day-to-day operations of the business. The data continually changes as updates are made, and reflect the current value of the last transaction. Data Warehouse Systems make use of storage techniques for efficient end user accessing and query facilities. With the evolution of semantic data representation in the operational database environment, the accomplished analysis in DWS demands new synchronism ways. The proposed algorithm uses the principle of Bernoulli trials to find expected frequent itemsets. This can reduce a number of times to scan an original database. Assuming that the minimum support and confidence do not change, the algorithm can maintain association rules for a dynamic database. We proposing a probability-based new association rule discovery algorithm are to deal with from a different perspective other than similar techniques. The proposed algorithm uses the principle of Bernoulli to find expected frequent itemsets. Hence, there is a growing interest in DWS that can rapidly absorb the operational database updates, without compromising the operational query processes.

KEYWORDS:

Association Rule Discovery, Association frequent Rule Discovery, Data mining in operational databases.

1. INTRODUCTION:

In the last few years, data mining has been considered as new set of techniques and tools for intelligently transforming the processed data into useful information and knowledge. Data mining provides the techniques to analyze and convert mass volume of data and to detect hidden patterns in data into valuable information. Data mining can be applied in an intelligence environment in a number of domains (Guo, Zhao 2008; Thuraisingham, Ceruti 2000; Du et al. 2008; Gong 2008; Juan et al. 2008 anduhr et al. 2005). The technique of data mining is association rules mining (Argrawal-993) which studies the buying behaviors of customers and thus improves the quality of business decisions. It aims to extract interesting correlations, frequent patterns, associations or casual structures among sets of items in the databases. Association rule mining is widely used in several business such as mobile data service environment in (Pawar, Aggarwal 2004), intelligent transportation system in [Juan et al. 2008], market basket analysis in (Brin 1997) and (Liu et al.1999), hospital information system in (Elfangary, Atteya 2008),etc.The rules discovered from a database only reflect the current state of the database. However, in an operational database where new transactions are inserted frequently, association rules discovered in the previous database possibly no longer valid and interesting rules in the updated database. As a result, new business information such as changing customer preferences or new seasonal trends may not be discovered. To create an intelligent environment such that new business information can be discovered in a operational database, association rules algorithms should be capable of mining in operational database frequently . Different research works (Ayan et al. 1999; Chang et al. 2005; Lee et al. 2001; Feldman et al. 1990; Ratchadaporn, Kreesuradej 2007; Sarda et al. 1998 and Veloso et al. 2002) have proposed several algorithms to deal with this problem. Here, we propose a new association rule discovery algorithm, called a New Probability-Based Association Rule Algorithm, for the environment of an operational database.

The algorithm is capable of dynamically discovering new association rules when a number of new records have been added to frequent updated operational database. In our approach, we use the probability to predict infrequent itemsets that have capable of being frequent itemsets after a number of new records have been added to operational database. The infrequent itemsets is called expected frequent itemsets. We designed an algorithm which reduces a number of times to scan an original operational database. As a result, the algorithm has execution time faster than that of previous methods where here it concerns frequent (or) regular business operational databases.

2. PREVIOUS WORK:

In databases, new transactions are appended as time advances. This may introduce new association rules and some existing association rules would become invalid. Thus, the maintenance of association rules for databases is an important problem. Maintaining association rules has been studied popularly in data mining. There are 2 main approaches to mining association rules for databases incrementally. The first approach assumes that association rules to be found are not stable over time, so that use operational databases. Recent patterns that represent new trends to be discovered are more interesting than old patterns. Thus, the first approach treats recent added transactions higher important than old transactions. The association rules obtained from the first approach is just the approximation of those obtained by re-running Apriori algorithm.

As the first approach, Zhang et al. (Zhang et al. 2003) proposed a weighting

technique for discovering association rules in a operational database of more dynamic nature of data. The technique gives recent added transactions higher weight than old transactions. Then, frequent itemsets can be maintained incrementally by using a competitive model to promote infrequent itemsets to frequent itemset and degrade frequent itemset to infrequent itemset.

Similar to Zhang's work, Dudek et al. (Dudek et al. 2005) proposed a method of a time influence function in order to reflect that recent patterns are more interesting than old patterns. The time influence function gives recent added transactions higher weight than old transactions. In addition, this work also proposed using estimated support and confidence to deal with situation that new association rules are discovered only in new transactions but are not discovered only in old transactions. However, this work did not propose the method to estimate the estimated support and confidence.

Unlike the first approach, the second approach assumes that association rules to be found are stable over time. Thus, the second approach treats both old and new transactions as of equal importance. As a result, the association rules obtained from the second approach is the same as those obtained by re-running Apriori algorithm. According to Teng and Chen (Teng, Chen 2005), the second approach is categorized into Partition-based, Pattern growth and Apriori-based techniques.

Partition-based techniques partition a database into n partition and processes each partitions for an on going time variant database. For each frequent itemset must exist at least one of the n partitions. Sliding-window filtering (SWF) (Lee et al. 2001) is a partition algorithm for an association mining. The concept of SWF is partitioning a transaction operational database into n partitions, P_1, P_2, …, P_n and processing one by one. The filtering threshold is employed for selecting frequent itemset in each partition to deal with the candidate itemset generation. The key idea of SWF is to compute candidate 2-itemset as close to frequent 2-itemset as possible. SWF need one scan over the updated database for finding the frequent item set from the candidate ones. Based on SWF, FI_SWF and CI_SWF (Chang, Yang 2003) are proposed to reduce the number of candidate itemsets of SWF.Pattern-Growth techniques are basically based on FP-tree to discover association rules. Since FP-tree cannot be directly applied to the problem of association incremental mining, two alternative forms of FP-tree, i.e., DB-tree (Ezeife, Su 2002) and Potential Frequent Pattern tree (PotFP-tree) (Ezeife, Su 2002), are proposed to solve the problem.

Below, FUP computes frequent itemsets using large itemsets found at previous iteration. The major idea of FUP is re-using frequent itemsets of previous mining to update with frequent itemsets of an increment operational database. At each iteration, the supports of the size-*k* frequent item sets of an original operational database are updated by scanning an increment database. As well as any k-frequent itemset of the increment database are updated by scanning the original operational database to find the new frequent itemsets. As a result, FUP requires multiple-scan for maintaining frequent itemsets.For enhance the efficiency of FUP algorithm, UWEP algorithm is presented by Ayan et al. (Ayan et al. 1999). The major idea of UWEP algorithm is reducing the number of candidate itemset by pruning the supersets of an old frequent itemset in previous mining that no longer remain in an updated operational database with at most once scanning in original database.

To deal with the rescanning problem, negative border approach is presented by Toivonen (Toivonen 1996), Thomas et al. (Thomas et al. 1997) and Feldman et al. (Feldman et al. 1999).This approach maintains both frequent itemsets and border itemsets. The border itemset is not

a frequent itemset but all its proper subsets are frequent itemsets. The approach need to keep a large number of border itemsets in order to reduce scanning times of an original operational database. Basically, the border-based algorithms start by scanning a new database. Then, the border-based algorithms update support counts of all frequent sets and border sets. Most updated frequent itemsets can be found not only from frequent itemsets but also from border itemsets. This can reduce scanning times of an original operational database. However, when new frequent itemsets are introduced as updated frequent itemsets, several database scanning is required to obtain support counts of the new frequent itemsets and their subsets. Adnan et al. (Adnan et al. 2005) shows that the execute time of the border-based algorithms can severely slower than that of Apriori when new frequent itemsets are introduced as updated frequent itemsets.This paper is the extension work of Probability-based Incremental Association Rule Discovery Algorithm, introduced by Amornchewin andKreesuradej[Amornchewin,Kreesuradej2008]. The paper provides more theoretical fundamentals of the algorithm and comprehensive experimental results than that of Amornchewin and Kreesuradej [Amornchewin, Kreesuradej 2008].

3.NEW PROBABILITY-BASED ASSOCIATION RULE DISCOVERY ALGORITHM:

When an operational database is inserted new transactions, not only some existing association rules may be invalidated but also some new association rules may be discovered. This is the case because frequent itemsets can be changed after inserting new transactions into a dynamic database. The problem description is given as section 3.1. Then, we describe our algorithm into 2 subsections. Firstly, probability-based expected frequent itemsets is presented. Secondly, updating frequent and expected frequent itemsets is introduced.

3.1 Problem Description:

Let F be the set of all frequent itemsets in the original database, i.e. DB, σ be the minimum support threshold and |DB| be the number of transactions in DB. Assume that the support count of each frequent itemset in the original operational database is kept. After some updates, an increment database, i.e. db, is added into the original database DB, resulting in an updated database, i.e. UP. The numbers of transactions in db and UP are denoted |db| and |UP|, respectively, and the support counts of itemset X in DB, db and UP are c(X,DB), c(X,db), c(X,UP), respectively. With the same minimum support threshold σ, a frequent itemset X of DB remains a frequent itemset of UP if and only if its support in UP is greater than or equal to σ, i.e. $c(X,UP) \geq (|DB| + |db|) * \sigma$ .According to Tsai et al. (Tsai et al. 1999), an itemset, i.e. X, can be categorized into four cases:

Case 1: X is a frequent itemset in both DB and UP.
Case 2: X is a frequent itemset in DB and an infrequent itemset in UP.
Case 3: X is an infrequent itemset in DB and a frequent itemset UP.
Case 4: X is neither a frequent itemset in DB nor UP.

Obviously, the itemset of case 4 cannot range an association rule because the itemset is an infrequent itemset in both DB and UP. The itemset of case 1 and 2 can easily be discovered because updating support count of the frequent itemset, which is trivial tasks, requires only the frequency of the itemset from db. The task of discovering the itemset of case 3 is the hardest task because it requires rescanning an original database. Thus, how to efficiently discovery the itemset of case 3 is an important problem. In the next subsection, a new algorithm to deal with this problem is proposed.

3.2 Predicting Expected Frequent Item Sets:

The task of an association rule discovery algorithm for a dynamic database can be divided into three tasks. The first task is to update support count of existing frequent itemsets. The second task is to prune existing frequent itemsets that have support count below a minimum support threshold after updating the database. The third task is to discover new frequent itemsets that have support count equal or above a minimum support threshold after updating the database.Updating support count of existing frequent itemsets and pruning existing frequent itemsets are trivial tasks. To perform updating and pruning tasks, the association rule discovery algorithm requires only frequency of itemsets from new transactions. Thus, an association rule discovery algorithm does not need to rescan an original database to perform the tasks.

Unlike the other tasks, the task for discovering new frequent itemsets requires not only frequency of itemsets from new transactions but also that from an original database. An association rule discovery algorithm need to rescan an original database to perform the tasks. Therefore, the discovering new frequent itemsets task is a nontrivial task for maintaining frequent itemsets

For our algorithm, an original database, which is a database before being inserted new transactions, is firstly mined to find all frequent itemsets that satisfy a minimum support count, denoted $k_{original}$. The proposed algorithm also predicts and keeps expected frequent itemsets that may become frequent itemsets if new transactions are inserted into the original database.

The process of inserting m transactions into an original database of n transaction can be considered as (m+n) Bernoulli trials, which are (m+n) sequence of identical trials. Each itemset has its probability of appearing in a transaction, denoted by $p_{itemset}$, i.e. the probability of success. According to the principle of Bernoulli trials, the probability of the number of an itemset to appearing in (n+m) transactions, denoted by $P(x)_{itemset}$, can be found by the following equation:

$$P(x)itemset = (n+m/x).\ p_{itemset}.^{x}\ (1 - p_{itemset})^{n+m-x}$$

Where $p_{itemset}$ is the probability of an itemset appearing in a transaction, m is a number of new transactions, and n is a number of transactions of an original operational database. Figure 1 shows the scheme of predicting expected frequent itemsets based on Bernoulli trials.

If k is a minimum support count after inserting new transactions into an original operational database, the probability of an itemset to be a frequent itemset in an updated operational database can be obtained as the following equation:

$$P\ (x \geq k)_{itemset} = 1P(x < k)_{itemset} \quad (1)$$

According to equation 1, P(x < k) itemset can be found as the following equation:

$$P(x<k)_{itemset} = \sum_{x=0}^{k-1} \binom{n+m}{x} p_{itemset}^{x}(1-p_{itemset})^{n+m-x} \quad (2)$$

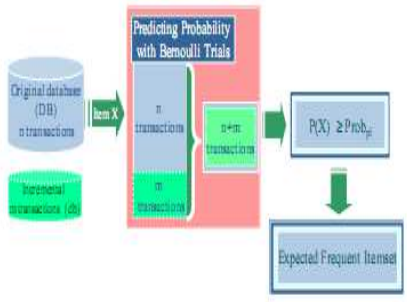


Figure1: The scheme of predicting expected frequent itemsets based on Bernoulli

Here, an expected frequent itemset is an itemset that is not a frequent itemset but has its probability to be a frequent itemset greater than $Prob_{pl}$. $Prob_{pl}$ is a threshold constant specified by users. $Prob_{pl}$ indicates the minimum confidence level that a promising frequent itemset will be a frequent itemset after inserting new transactions into an original database. The higher $Prob_{pl}$ is set, the lesser expected frequent itemsets are kept. As results, the

algorithm may need more number of rescanning times in the original operational database when the algorithm performs the discovering new frequent item task.From equation 2, the probability of success of an itemset, i.e., $p_{itemset}$, can be derived from the following equation:

$$p_{itemset} = \frac{c(itemset, DB) + c(itemset, db)}{|DB| + |db|}. \quad (3$$

where c(itemset, DB) is support counts obtained from an original database, c(itemset, db) is support counts obtained from an increment database, db is the total number of transactions of an increment database, and |DB| is the total number of transactions of an original operational database.

According to the scheme of predicting expected frequent itemsets, an expected frequent itemset need to be obtained from an original database before an increment database is available. Therefore, the probability of success of an itemset has to approximate from an original database. Here, an original operational database, which has n transaction, is considered as a sample data of (n+m) transactions. The approximation of the probability of success of an itemset can be obtained as

$$\hat{p}_{itemset} = \frac{c(itemset, DB)}{|DB|}. \quad (4$$

Where c (itemset, DB) is support counts obtained from an original database, i.e., DB, and $|DB|$ is the total number of transactions of an original operational database. It is important to evaluate the accuracy of the approximation of the probability of success of an itemset. The following theorem gives a lower bound, i.e. ε, and maximum probability, i.e. δ, for an error of the approximation of the probability of success of an itemset.

Theorem 1[Mannila et al. 1994; Toivonen 1996] the probability that

$$error = \left| p_{itemset} - \hat{p}_{itemset} \right| > \varepsilon$$

at most δ. If the size of an original database satisfies the following equation:

$$|DB| \geq \frac{1}{2\varepsilon^2} ln \frac{2|UP|}{\delta}.$$

Where DB is the size of an original database and UP is the size of an updated database. According to the theorem, if size of an original is sufficient large, $\hat{p}_{itemset}$ is a good approximations of $p_{itemset}$,there for equation 2 can be rewritten as follows

$$P(x < k)_{itemset} = \sum_{x=0}^{k-1} \binom{n+m}{x} \hat{p}_{itemset}^{\,x} (1 - \hat{p}_{itemset})^{n+m-x} \quad (5)$$

As an example, an original operational database has 10 transactions, i.e. |DB| =10.Then, five new transactions are inserted into the original database, i.e. |db| =5. Here, minimum support count for mining association rules is set to 4 (40 percent). If we defined probability for a count for mining association rules is set to 4 (40 percent). If we defined probability for a expected itemset is $\text{Prob}_{pl} = 0.10, P(x \geq k)$ is accomplished shown in figure-2

Figure 2: Transaction data and candidate 1-itemsets

TID	List of item
1	A, B, E
2	B, D
3	B,C
4	A, B,D
5	A, C
6	B, C
7	A, C
8	A, B, C, E
9	A, B, E
10	A,C

$$P(x \geq 6)_A = 1 - \sum_{x=0}^{5} \binom{15}{x} \frac{7}{10}^x \frac{3}{10}^{15-x} = 1$$

$$P(x \geq 6)_B = 1 - \sum_{x=0}^{5} \binom{15}{x} \frac{7}{10}^x \frac{3}{10}^{15-x} = 1$$

$$P(x \geq 6)_C = 1 - \sum_{x=0}^{5} \binom{15}{x} \frac{6}{10}^x \frac{4}{10}^{15-x} = 1$$

$$P(x \geq 6)_D = 1 - \sum_{x=0}^{5} \binom{15}{x} \frac{2}{10}^x \frac{8}{10}^{15-x} = 0.06$$

$$P(x \geq 6)_E = 1 - \sum_{x=0}^{5} \binom{15}{x} \frac{3}{10}^x \frac{7}{10}^{15-x} = 0.28$$

From the example, the frequent 1- itemset is {A, B, C}. Item {E} is an expected frequent 1-itemset because its probability, which is equal to 0.28, is greater than Prob_{pl}.The proposed algorithm generates candidate next k-itemsets by using both frequent k-itemsets and expected frequent k-itemsets. Firstly, new itemsets is obtained by union of frequent k-itemsets and expected frequent k-itemsets. Then, the candidate (k+1)-itemsets is obtained by self joining the new itemset together. Both frequent (k+1)-itemsets and expected frequent (k+1)-itemsets can be found similar to that of k-itemsets. The example

of generating candidate next k-itemsets is shown in figure-3

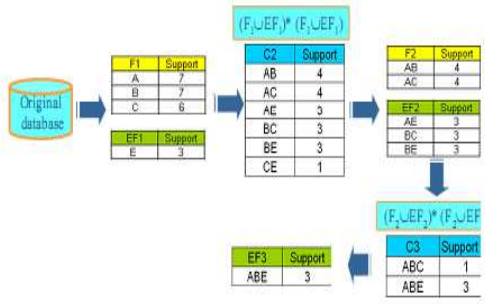


Figure-3.The example of generating candidate next k-itemsets

3.3 Updating frequent and expected frequent item sets

When new transactions are added to an original database, an old frequent k-itemset could become an infrequent k-itemset and an old expected frequent k-itemset could become a frequent k-itemset. This introduces new association rules and some existing association rules would become invalid. To deal with this problem, all k-itemsets must be updated when new transactions are added to an original database. The notation used in this section is given in table1.

DB	Original database
db	Increment database
UP	Updated database
k	Number of itemset
σ	Minimum support
ρ	Minimum expected frequent
C_k	Candidate k-itemset
F_k	Frequent k-itemset
EF_k	Expected frequent k-itemset

Table 1: The notation for updating frequent and expected frequent itemsets algorithm

Here, a new updating algorithm shown in figure 4 is proposed in this paper. The algorithm consists of three phases. The first phase is updating 1- frequent and expected frequent itemsets, i.e. line1-3. The second phase is repeatedly updating the other frequent and expected frequent itemsets by using only an increment database, i.e. line 6-11. The third phase is scanning an original database, i.e. line 13-16.

Figure 5 shows the algorithm for updating 1- frequent and expected frequent itemsets. According to the algorithm, the 1-candidate itemsets of an updated database, i.e C_1^{DB} can be found by combining the 1-candidate itemsets of an original operational database, i.e. C_1^{db} then the support count of C_1^{UP} can be updated by scanning only frequent and expected itemsets of an updated database can be found as shown in line 5 and 6 respectively.

Algorithm1 : Main Algorithm

Input : DB, db, k, σ^{UP}, ρ^{UP}, ρ^{DB}, C_1^{DB}, F_1^{DB}, EF_1^{DB} and their count

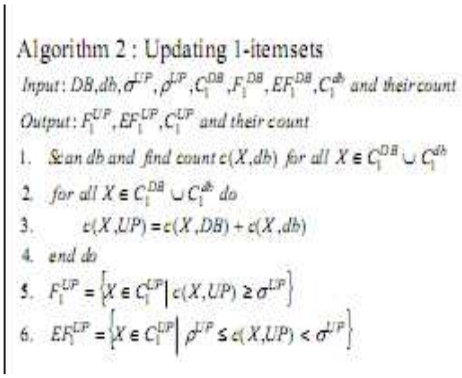
Output: F_k^{UP}, EF_k^{UP}

```
1.  k = 1
2.  if k = 1
3.     Update 1 – itemset
4.     k = k + 1
5.  else
6.     for (k = 2; F_k^UP ≠ φ; k++) do
7.        Generate Candidate Itemset
8.        Update k – itemset (return m, Temp_scanDB)
9.        //m is the maximum itemset of Temp_scanDB
10.       k = k + 1
11.    end do
12. end if
13. k = 2
14. while (Temp_scanDB_k ≠ φ and (k ≤ m)  do
15.       Scan Original Database(Temp_scanDB_k)
16.       k = k + 1
17. end do
18. clear Temp_scanDB
```

Figure 4: Main algorithm

The second phase has 2 major steps which are a generating k-increment candidate itemsets step and an updating support count of k-increment frequent and k-increment expected frequent itemsets step for k greater than or equal to 2. The algorithm for generating k-increment candidate itemsets for k greater than or equal to figure 6. For k = 2, the 2-increment candidate itemsets are easily obtained by joining F_1^{UP} With F_1^{UP}, i.e. line 3. For k > 2, the algorithm is firstly find k-candidate itemsets of an increment database, i.e. C_k^{db} by joining F_{k-1}^{db} with F_{k-1}^{db}, i.e. line 6. Similar to Apriori

algorithm, the k-candidate itemsets of an increment database can be the updated frequent itemsets, i.e. F, only if the subsets of the k-candidate itemsets of an increment database must be in the (k-1)-updated frequent. Thus, the k- increment candidate itemsets, i.e. itemsets, i.e. line 7-9. This can prune the k- candidate itemsets of an increment database that can't be the k- updated frequent itemsets.

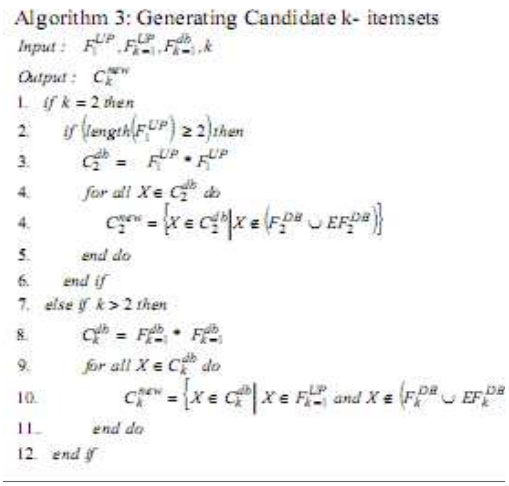

Algorithm 2 : Updating 1-itemsets

Input: $DB, db, \sigma^{UP}, \rho^{UP}, C_1^{DB}, F_1^{DB}, EF_1^{DB}, C_1^{db}$ and their count

Output: $F_1^{UP}, EF_1^{UP}, C_1^{UP}$ and their count

1. Scan db and find count $c(X,db)$ for all $X \in C_1^{DB} \cup C_1^{db}$
2. for all $X \in C_1^{DB} \cup C_1^{db}$ do
3. $c(X,UP) = c(X,DB) + c(X,db)$
4. end do
5. $F_1^{UP} = \{X \in C_1^{UP} \mid c(X,UP) \geq \sigma^{UP}\}$
6. $EF_1^{UP} = \{X \in C_1^{UP} \mid \rho^{UP} \leq c(X,UP) < \sigma^{UP}\}$

: Fig-5 Updating 1-itemsets,


Algorithm 3: Generating Candidate k- itemsets

Input : $F_1^{UP}, F_{k-1}^{UP}, F_{k-1}^{db}, k$

Output : C_k^{new}

1. if $k = 2$ then
2. if $(length(F_1^{UP}) \geq 2)$ then
3. $C_2^{db} = F_1^{UP} * F_1^{UP}$
4. for all $X \in C_2^{db}$ do
4. $C_2^{new} = \{X \in C_2^{db} \mid X \in (F_2^{DB} \cup EF_2^{DB})\}$
5. end do
6. end if
7. else if $k > 2$ then
8. $C_k^{db} = F_{k-1}^{db} * F_{k-1}^{db}$
9. for all $X \in C_k^{db}$ do
10. $C_k^{new} = \{X \in C_k^{db} \mid X \in F_{k-1}^{UP}$ and $X \in (F_k^{DB} \cup EF_k^{DB}$
11. end do
12. end if

Fig-6 Generating candidate k-itemset algorthim.

Figure 7 shows an algorithm for updating support count of k-updated frequent itemsets and k-updated expected frequent itemsets for k greater than or equal to 2. As shown in line 1, the algorithm scans an increment database to find and update support count of the k- updated candidate itemsets, i.e. C^{UP} . When any k-itemsets are not in the union set of the original *k*-frequent and the original *k*- expected frequent itemsets, i.e.

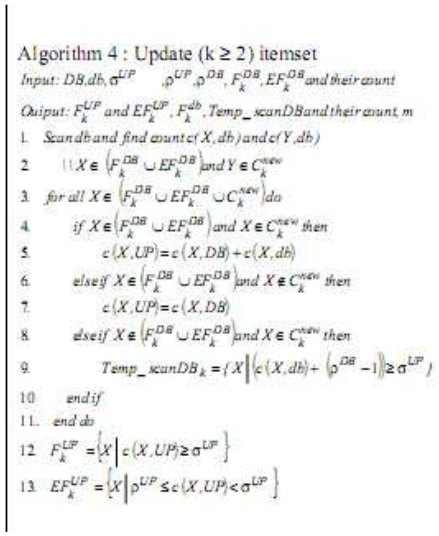
k-itemsets □□*DB*

k

DB

$Fk \cup EF$, but is in the k- increment candidate itemsets, i.e. k-itemsets ∈

k-itemsets $\notin F^{DB} \cup EF^{DB}$, but is in the k- increment candidate itemsets, i.e. k-itemsets ∈ ck their support counts need to be specially updated. This is the case because their support counts obtained from an original database are not available .since these k-itemsets are not in $F^{DB} \cup EF^{DB}$ their support counts are at best equal to ρ^{DB} -1 . Here their support counts are assumed to be equal to the sum of ρ^{DB} - 1 and their support counts obtained from an increment database, i.e $c(X, db) + (\rho^{DB} - 1)$. If any k- itemsets have support counts below updated min support count, i.e. σ^{UP}, the k- itemsets can't be the *k*-updated frequent itemsets. On the other hand, if any k-itemsets have support counts above or equal to an updated min support count; the k-itemsets are likely to be the k- updated frequent itemsets. Thus, the k-itemsets, which have support counts above or equal to an updated min support count, are set aside for finding their true support counts from an original database, i.e. line 9.


Algorithm 4 : Update (k ≥ 2) itemset

Input: $DB, db, \sigma^{UP}, \rho^{UP}, \rho^{DB}, F_k^{DB}, EF_k^{DB}$ and their count

Output: F_k^{UP} and $EF_k^{UP}, F_k^{db}, Temp\_scanDB$ and their count, m

1. Scan db and find count $c(X,db)$ and $c(Y,db)$
2. $\forall X \in (F_k^{DB} \cup EF_k^{DB})$ and $Y \in C_k^{new}$
3. for all $X \in (F_k^{DB} \cup EF_k^{DB} \cup C_k^{new})$ do
4. if $X \in (F_k^{DB} \cup EF_k^{DB})$ and $X \in C_k^{new}$ then
5. $c(X,UP) = c(X,DB) + c(X,db)$
6. else if $X \in (F_k^{DB} \cup EF_k^{DB})$ and $X \in C_k^{new}$ then
7. $c(X,UP) = c(X,DB)$
8. else if $X \in (F_k^{DB} \cup EF_k^{DB})$ and $X \in C_k^{new}$ then
9. $Temp\_scanDB_k = \{X \mid (c(X,db) + (\rho^{DB} - 1)) \geq \sigma^{UP}\}$
10. end if
11. end do
12. $F_k^{UP} = \{X \mid c(X,UP) \geq \sigma^{UP}\}$
13. $EF_k^{UP} = \{X \mid \rho^{UP} \leq c(X,UP) < \sigma^{UP}\}$

Figure 7: Update (k ≥ 2) itemset algorithm

At the third phase, an original database is scanned to find true support counts for the k-itemsets that are likely to be the *k*-updated frequent itemsets. The algorithm is shown in figure 8. The support counts of the likely k-updated frequent itemsets are found and updated by scanning an original database as shown in line 1-6. Then, all k-updated

frequent itemsets and k- updated expected frequent itemsets are found as shown in line 7-8.

The figure 9 shows the increment database and the figure 10 shows the example of three phases of updating frequent and expected frequent itemsets. In the first phase, the 1-frequent and expected frequent itemset can be updated by scanning only an increment database. In the second phase, the 2-updated candidate itemset is generated by joining frequent 1-itemset of updated database together. The new candidate 2-itemset is pruned if it is member of frequent and expected frequent itemset of an original database. In this case, set of {AD, BD, CD} are new candidate 2-itemset in the updated database.

The increment database is scanned for 2-itemset of frequent, expected frequent and new updated candidate. Only new candidate itemset that has support count greater than or equal to minimum support of increment database, it require to scan in the original database. To reduce the number of itemset for scanning original database, if sum of any new candidate's support count and support of $prob_{pl}$ minus 1 is greater than minimum support of updated database, then it will be moved to Temp_scanDB. In this example, only set of BD is moved to Temp_scanDB. The last phase, original database is scanned for finding true support of BD. Finally, the frequent and expected frequent k-itemsets for updated database are found.

4. RESULTS AND DISCUSSIONS:

The purpose of this research is to explore an alternative way to improve the performance of the association rule mining while facing dynamic database environments. To evaluate the performance of probability-based incremental association rules discovery algorithm, the algorithm is implemented and tested on a PC with a 2.8 GHz Pentium 4 processor, and 1 GB main memory. The experiments are conducted on a synthetic dataset, called T10I4D20K. The technique for generating the dataset is proposed by Agrawal (Agrawal 1994).

The synthetic dataset comprises 250,000 transactions over 70 unique items. Each transaction of the synthetic dataset has 10 items on average and the maximal size itemset is 4.

Algorithm 5 : Scanning an original database

Input : $Temp\_scanDB_k, \sigma^{UP}, \mu^{UP}, F_k^{UP}, EF_k^{UP}$ and their count

Output : F_k^{UP}, EF_k^{UP} and their count

1. Scan DB and obtain count $c(X, DB)$ for all $Temp\_scanDB_k$
2. for all $X \in Temp\_scanDB_k$ do
3. $\quad c(X, UP) = c(X, DB) + c(X, db)$
4. end do
5. $F_k^{new} = \{X \mid X \in Temp\_scanDB_k \text{ and } c(X, UP) \geq \sigma^{UP}\}$
6. $EF_k^{new} = \{X \mid X \in Temp\_scanDB_k \text{ and } \mu^{UP} \leq c(X, UP) < \sigma^{UP}\}$
7. $F_k^{UP} = F_k^{UP} \cup F_k^{new}$
8. $EF_k^{UP} = EF_k^{UP} \cup EF_k^{new}$

Figure 8: Algorithm for scanning an original database

Firstly, we show the performance of our algorithm with minimum support 3% and 4%. The proposed algorithm with $Prob_{pl}$ = 0.06 is used to find frequent itemsets, expected frequent itemsets and association rules from an original database of 20,000 transactions. Then, several sizes of increment databases, i.e. 25%, 50%, 75% and 100% of the original database, are added to the original database. Then, the proposed algorithm is used to maintain frequent itemsets, expected frequent itemsets and association rules of the updated database. For comparison purpose, FUP, Borders and Pre-large algorithm are also used to find frequent itemsets, expected frequent itemsets and association rules from the same original database and the same increment databases.

Increment Database	
TID	List of item
11	A, B, D, E
12	B, C, D
13	B, D, E
14	A, B, C, D
15	A, C

Figure 9: Increment database

The experimental results with various minimum support thresholds are shown in

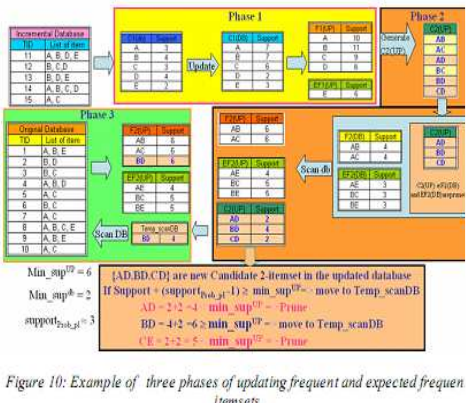
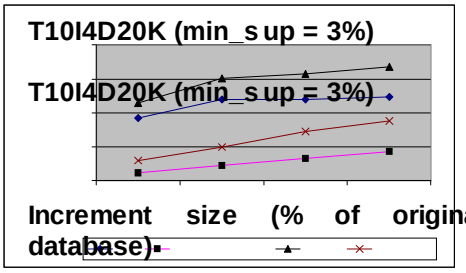


Figure 10: Example of three phases of updating frequent and expected frequen

Figure 11, table 2 and table 3. Table 2 and table 3 shows the number of frequent k-itemsets and k-expected itemsets in an original database for FUP, Borders, Pre-large algorithm and the proposed algorithm. Since these algorithms are in the second approach which is assumed that association rules to be found are stable over time, the association rules or frequent itemsets should be the same as those obtained from re-runing Apriori algorithm. Thus, each frequent itemset obtained from these algorithms is compared with that obtained from re-runing Apriori algorithm. The experiments show that all frequent itemset obtained from FUP, Borders, Pre-large algorithm and the proposed algorithm are the same as those obtained from re-runing Apriori algorithm.



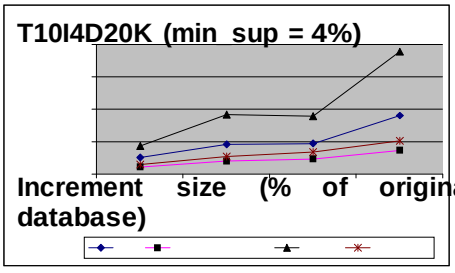


Figure 11: Execution time in FUP, Borders and Probability-based when(a)min_sup =3% and (b) min_sup =4%

Original Database : Min_sup = 3%										
k-item	Apriori		FUP		Borders		Pre-Large		Probability-based	
	Number of Frequent itemset	Number of kept Infrequent itemset	Number of Frequent itemset	Number of kept Infrequent itemset	Number of Frequent itemset	Number of kept Infrequent itemset	Number of Frequent itemset	Number of kept Infrequent itemset	Number of Frequent itemset	Number of kept Infrequent itemset
k=1	68	0	68	0	68	1	68	1	68	0
k=2	700	0	700	0	700	1578	700	418	700	14
k=3	158	0	158	0	158	5003	158	399	158	15
k=4	39	0	39	0	39	44	39	80	39	1
k=5	21	0	21	0	21	0	21	10	21	0
k=6	7	0	7	0	7	0	7	1	7	0
k=7	1	0	1	0	1	0	1	0	1	0

Table 2: Number of itemset of an original database for each algorithm with min_sup=3%

Original Database : Min_sup = 4%										
k-item	Apriori		FUP		Borders		Pre-Large		Probability-based	
	Number of Frequent itemset	Number of kept Infrequent itemset	Number of Frequent itemset	Number of kept Infrequent itemset	Number of Frequent itemset	Number of kept Infrequent itemset	Number of Frequent itemset	Number of kept Infrequent itemset	Number of Frequent itemset	Number of kept Infrequent itemset
k=1	65	0	65	0	65	4	65	3	65	1
k=2	442	0	442	0	442	1638	442	258	442	25
k=3	24	0	24	0	24	2160	24	134	24	3

Table 3:Number of itemset of an original database for each Algorithm with min_sup = 4%

From both table 2 and table 3, the results also show that the proposed technique requires slightly more space to keep the k-expected itemsets than that of FUP. This is the case because FUP does not need to keep some infrequent itemsets to maintain updated frequent itemsets but FUP requires multiple-scan an original database to maintain updated frequent itemsets. Thus, FUP requires more times for scanning an original database than that of the proposed algorithm. As a result, the proposed algorithm has better running time than that of FUP. As shown in figure 11, the proposed requires lesser memory space to keep the k- expected itemsets than that of Borders algorithm and Pre-large algorithm. However, the algorithm still has better running time than that of Borders algorithm and Pre-large algorithm. This is the case because the proposed algorithm, which is based on the principle of Bernoulli trials, has more efficient to predict expected frequent itemsets than Borders algorithm and Pre-large algorithm. Thus, the proposed algorithm requires less times for scanning an original database than Borders algorithm and Pre-large algorithm. As a

result, the proposed algorithm has better running time than that of Borders algorithm and Pre-large algorithm.

	Average of Execution time for 100 trials (sec)			
min_su	**FUP**	**Bord**	**Pre-**	**Probability-**
4%	5900.722	7588.617	4207.582	2661.803

Table 4: The average execution time for FUP, Borders and Probability-based

Minimum support 4%

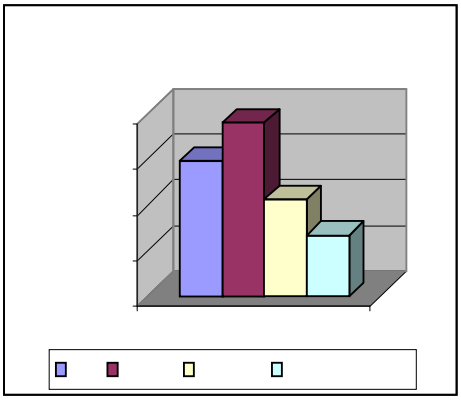


Figure 12: The Average of execution time in FUP, Borders and Probability-based when min_sup =4%

Secondly, the proposed algorithm with $Prob_{pl}$ = 0.06 used to find frequent itemsets, expected frequent itemsets and association rules from an original database of20,000 transactions. Then, the same sizes of increment databases, i.e. 10% of the original database, are added to the original database for 100 trials. For comparison. Purpose, FUP, Borders and Pre-large algorithm are also used to find association rules from the same original database and the same increment databases. Table 4 and figure 12 show the average execution time of FUP, Borders, Pre-large and the proposed algorithm. The results show that the proposed algorithm has much better running time than that of the other algorithms.

CONCLUSION:

To create an intelligent environment such that new information can be discovered in a dynamic database, this paper proposes mining a dynamic database using probability- based incremental association rule discovery algorithm. The proposed algorithm uses the principle of Bernoulli trials to find expected frequent itemsets. This can reduce a number of times to scan an original database. Assuming that the minimum support and confidence do not change, the algorithm can maintain association rules for a dynamic database. The experiments show that our algorithm has better running time than that of FUP, Borders and Prelarge algorithm.

REFERENCES:

1. [Adnan et al. 2005] Adnan, M., Alhajj, R., and Barker, K.: "Performance Analysis of Incremental Update of Association Rules Mining Approaches"; In Proceeding of 9th IEEE International Conference on Intellgent Engineering System 2005, September 16-19, 2005, 129-134

2.[Agrawal et al. 1993] Agrawal, R., Imielinski, T., and Swami, A.: Mining association rules between sets of items in large databases , In Proceeding of the ACM SIGMOD Int'l Conf. on Management of Data (ACM SIGMOD '93), Washington, USA, May 1993, 207-216.

3.[Agrawal, Srikant 1994] Agrawal, R. and Srikant, R.: "Fast algorithms for mining association rules , In Proceedings of 20 th Intl Conf. on Very Large Databases (VLDB'94) "; Santiago, Chile (1994), 478-499.

4. [Alon et al. 1992] Alon, N. and Spencer, J. H., 1992, "The probabilistic method"; Wiley Interscience, New York.

[Amornchewin, Kreesuradej 2007] Amornchewin, R., and Kreesuradej, W.: "Incremental association rule mining using promising frequent itemset algorithm "; In Proceeding

6th International Conference on Information, Communications and Signal Processing, Singapore, 2007.

5. [Amornchewin, Kreesuradej 2008] Amornchewin, R., and Kreesuradej, W.: "Probability-based incremental association rule discovery algorithm"; The 2008 International Symposium on Computer Science and its Applications (CSA-08), Australia, 2008. [Ayan et al. 1999] Ayan, N.F., Tansel, A.U., and Arun, E.: "An efficient algorithm to update large itemsets with early pruning"; Proceedings of the Fifth ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, San Diego, August 1999, 287-291.

6. [Brin et al. 1997] Brin, S., Motwani, R., and Silverstein, C.: "Beyond Market Baskets: GeneralizingAssociation Rules to Correlations"; Proceedings of the ACM SIGMOD Conference, 1997, 265-276.

7. [Chang, Yang 2003] Chang, C.-H. and Yang, S.-H.: "Enhancing SWF for Incremental Assocaition Mining by Itemset Maintenance"; Proceedings of 7th Pacific-Asia Conference on Knowledge Discovery and Data Mining, April 2003.

8. [Chang et al. 2005] Chang, C.C., Li Y.C., and Lee, J.S.: "An efficient algorithm for incremental mining of association rules "; Proceedings of the 15th international workshop on research issues in data engineering: stream data mining and applications (RIDE-SDMA'05), IEEE, 2005.

9. [Cheung et al. 1996] Cheung, D., Han, J., Ng, V., and Wong, C. Y.: "Maintenance of discovered association rules in large databases: An incremental updating technique"; In 12th IEEE International Conference on Data Engineering, February 1996, 106-114.

10.[Cheung et al. 1997] Cheung, D. W., Lee, S.D., and Kao, B.: "A General incremental technique for maintaining discovered association rules";In Proceedings of the 5 th Intl. Conf. on Database Systems for Advanced Applications (DASFAA'97), Melbourne, Australia, April 1997, 185-194.

11. [Du et al. 2008] Du, Y. Zhao, M., Fan G.: "Research on Application of Improved Association rules Algorithm in intelligent QA system"; Second International Conference on Genetic and Evolutionary Computing, 2008.

12. [Dudek, Zgrzywa 2005] Dudek, D., Zgrzywa, A.:"The Incremental Method for Discovery of Association Rules"; Springer Berlin / Heidelberg, volume 30, 2005, 153-160.

13. [Elfangary, Atteya 2008] Elfangary, L.,Atteya, W.A.: "Mining Medical Database using Proposed Incremental Association rule Algorithm (PIA)"; Second International Conference on the Digital Society, IEEE (2008).
[Ezeife, Su 2002] Ezeife, E. I. and Su, Y.: "Mining Incremental Association Rules with Generalized FP-Tree"; Proceedings of the 15th Conference of the Canadian Society for Computational Studies of Intelligence on Advances in Argificial Intelligence, May 2002, 147-160

14. [Gong 2008] Gong M. :"Personalized E-learning System by Using Intelligent Algorithm"; 2008.
15. [Guo, Zhao 2008]Guo, M., Zhao Y.: "An Extensible Architecture for Personalized InformationServices in An Ambient Intelligence Environment"; IEEE 2008.
16. [Han et al. 2000] Han, J.,Pei, J. and Yin, Y.: "Mining Frequent Pattern without Candidate Generation";Proceedings of the 2000 ACM-SIGMOD International Conference on Management of Data, May 2000, 355-359.