EFFICIENT DECISION MAKING IN SMART SYSTEMS USING WEIGHTED FREQUENT ITEMSET MINING

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Abstract: Making good selections is that the key technology of this generation systems. We use downward closure property for the weighted frequent itemsets and therefore the existence property of weighted frequent subsets are introduced and proved initial. Based on these two properties, the Weight judgement Downward closure property primarily based Frequent Itemset Mining (WD-FIM) algorithm is planned to slender the looking house of weighted frequent itemsets and improve the time potency. Moreover, the completeness and time potency of WD-FIM algorithmic program square measure analyzed theoretically. Finally, the performance of the planned WD-FIM algorithmic program should be proved on each artificial and real-life datasets

INTRODUCTION

Intelligent decision - making is the key technology for smart system. In decision - making activities, data mining technology has played an increasingly important role. As one of the hottest research topics in data mining, FIM (Frequent Itemset Mining) is an important approach to discovering association rules in datasets, widely used in precision marketing, custom recommendations, network optimization, medical diagnosis, and so on. However, with the rapid development of data acquisition and data processing technologies, different forms of complex data have emerged, such as uncertain data. Uncertain data means that a probability or probability measure is used to describe an item in a transaction.

The primary disadvantage is that the dataset size would be a lot bigger because of the likelihood of presence being stored. Another drawback is that there will be more complicated and time consuming mining algorithms for dubious databases. Consequently, as of late, the improvement of successful mining algorithms for uncertain databases has turned into a hotly debated issue of research. Numerous algorithms were created in dubious databases to mine frequent itemsets. Most existing investigations accept a similar significance is joined to all items in dubious databases. As a general rule, however, the values and imports of different items are usually different from users. For instance, it is difficult to specify the benefits of expensive luxury goods and modest living products at the same moment. Therefore, mining is inadequate to recognize useful and meaningful patterns based on only occurrence frequencies or probabilities of existence without taking into account imports or values of items.

Prominent solution to address this issue is to allow users to allocate different weights to items to indicate their relative imports or values. Users can set the weight of items to indicate profits, risks, costs and so on based on their professional domain knowledge or specific application requirements. In this context, user-friendly itemsets will be discovered. In addition, weight introduction of items can significantly reduce the number of frequent itemsets. However, as items are assigned different weights, the downward closure property used for mining frequent itemsets in uncertain databases would no longer hold. This means that there may be a frequent superset of an infrequent itemset. As a result, according to the downward closure property, the search space can no longer be narrowed, resulting in low time efficiency of FIM algorithms. In this paper, the Weight judgment Downward closure property based on Frequent Itemset Mining (WD-FIM) algorithm depends on the weight judgment downward closure property to limit the search space for weighted frequency itemsets and improve the time effectiveness. In this way, it is conceivable to find more useful and meaningful weighted frequent itemsets in dubious databases. It presents and demonstrates the weight judgment downward closure property and the existence property of weighted frequency subsets for unsure databases. The downward closure property weight judgment can be utilized to limit the search space for weighted frequency itemsets. Weighted frequent subsets existence property can guarantee that all weighted frequent itemsets are found. The WD-FIM algorithm utilized to restrict the search space of weighted frequent itemsets and improve the time proficiency dependent on weight judgment downward closure property.

LITERATURE SURVEY

Weighted support and significance framework [1] does not satisfy “downward closure property”. These can be improved by a property called “weighted downward closure property”. Based upon this improved model an algorithm called Weighted Association Rule Mining (WARM) is developed.

Frequent Itemset Mining algorithms reflect importance of items. weighted frequent itemset mining (WFIM) [2] focused on satisfying the downward closure property. In this model, a weight range and a minimum weight are considered. Different weights are given items within the weight range. For reducing the search space, consider weight and support for each item separately.

Weighted Itemset represents Correlations among multiple highly relevant terms that are neglected by previous approaches. The MWI-SUM [3] makes minimal use of language-dependent analyses. It can also be applicable to the collection of documents belongs to different languages.

There exists the problem of mining frequent itemset from uncertain data under probabilistic model. To avoid this problem, Decrimental Pruning (DP) technique [4] is used. Through this, we can achieve significant computational cost savings comparing with other existing approaches.

We find the problem of mining frequent itemsets from uncertain data under a probabilistic framework. A data trimming framework [5] improves mining efficiency. It saves CPU cost & I/O cost.

The well known algorithms for handling uncertanity data are UF-growth and UFP-growth. The trees used by these algorithms are large and thus degrade the mining performance. A more compact tree structure is to capture uncertain data and an algorithm for mining all frequent patterns from the tree. PUF Tree [6] is more compact than the UF-tree or UFP-tree, and as compact as the FP-tree and also finds frequent patterns efficiently.

The issue of finding itemsets from uncertain data streams are considered in UDS-FIM [7]. The present computations can't pack trade itemsets to a tree as limited as the built up FP Tree, since they exhaust extra time and memory space. To comprehend this issue, an estimation UDS-FIM and a tree structure UDS-tree. UDS-FIM has achieved a tolerable go about to the extent runtime and memory usage.

A novel Tree-based calculations are used to mine successive item sets from uncertain data [8]. It demonstrates the adequacy of our calculations in mining continuous itemsets from dubious information.

There are many real-life situations with the finding of patterns from traditional transactions databases. To avoid such situations, a tree-based mining algorithm [9].

Another method MAFIA [10] calculates maximal successive itemsets from a transactional database. The search methodology of calculation incorporates a profundity first traversal of the itemsets with successful pruning components. The inquiry methodology usage joins a vertical bitmap portrayal of the database.

Due to the rapid generation of data items in a data streams, the database become very larger and as a result current frequent pattern mining methods are unable to produce dynamic patterns. An efficient method to discover the set of latest frequent patterns from dynamic data stream using Compact Sliding Window (CSW) & sliding window model (CSW-SWM) [11]. CSW-SWM has an excellent performance in terms of runtime, memory usage.

By considering probabilistic models as incompleteness models, a Probabilistic-tables [12] model is introduced, that is shown to be complete and closed under the relational algebra. It uses existential probability property.

It become more costly affair to generate the candidate set, especially when there exist a large number of patterns. Frequent - Pattern tree (FP - tree) [13] is an extended prefix - tree structure for the storage of compressed, crucial information on frequent patterns and the development of an effective FP - tree - based mining method.

In this paper [14] two efficient algorithms for mining erasable patterns are used. The first algorithm, erasable closed pattern mining (ECPat) is the best method for sparse data sets. The second algorithm dNC-ECPM algorithm is best for all remaining data sets in terms of the mining time and memory usage.

Extracting the frequent itemsets by using greedy strategy [15] is a new method through which the Apriori estimation can be advanced. The balanced figuring presents components time expended in trades separating for candidate itemsets and the amounts of rule delivered are moreover decreased.

Dhanashree Shirke and Deepti Varshney[16] developed a parallel frequent itemsets mining algorithm called FiDoop using the MapReduce programming model to achieve compressed storage and avoid constrction of conditional pattern bases using ultrametric tree, rather than conventional FP trees. FiDoop algorithm enables automatic parallelization, load balancing, data distribution, and fault tolerance on large clusters while mining frequent itemsets.

In the Association Rule mining (ARM) approach, break even with weight is allocated to all itemsets in the dataset. Weight ought to be relegated dependent on the essentialness of each itemset. Fluffy based WARM fulfils the descending conclusion property and prunes the irrelevant standards by allocating the weight to itemset and furthermore lessens the calculation time and execution time. Enhanced Fuzzy-based Weighted Association Rule Mining (E-FWARM) [17] gives calculation for productive mining of the successive itemsets. Prefiltering technique is connected to the information dataset to expel the thing having low fluctuation. The E-FWARM calculation yields most extreme incessant things, affiliation tenets, precision and least execution time than the current calculations.

Mining Quantitative Association Rules in Large Relational Tables [18] presents the issue of mining affiliation governs in vast social tables containing both quantitative and straight out traits. The issue is handled by utilizing a "more important than-foreseen regard" interest measure to distinguish the fascinating principles with regards to the yield. It depicts the after effects of utilizing this methodology on a real-life dataset.

Frequent Pattern Mining (FPM) [19] has been an engaged topic in deciding. A short review of the flow status of FPM and talk about a couple of promising exploration headings are discussed. It is trusted that FPM examine has widened the extent of information investigation and will have profound effect on Data Mining philosophies and applications.

Finding concealed data from web log information is called web use mining. The point of finding successive examples in web log information is to get data about the navigational conduct of the clients. In Frequent Pattern Mining in Web Log Data [20], three example mining approaches are explored from the web log mining. They are page sets, page sequences and page graphs.

Algorithm for Mining Frequent Itemsets (AMFI) [21] depends on a packed vertical parallel portrayal of the information and on a very quick help tally. AMFI plays out a BFS (Breadth First Search) through identicalness classes.

A canonical directed acyclic graph namely Zero Suppressed Binary Decision Diagram (ZBDD)[22] has been shown to be very effective in other computer science fields such as Boolean SAT solvers. Mine Frequent Itemsets with ZBDDs.

A three-strategy adaptive algorithm, called BISC [23], solves the efficiency problem when a large number of Frequent Itemsets are involved. BISC1 is used in the recurrence's innermost steps. BISC2 divides an itemset into prefix and suffix & improves the performance by pruning all the itemsets with infrequent prefixes.

The principle issue in the majority of the arrangement mining calculations is that despite everything they create an exponentially substantial number of consecutive examples when a base help is brought down and they don't give elective approaches to alter the quantity of successive examples other than expanding the base help. In this paper a weighted consecutive example mining algorithm called WSpan [24] is utilized. The principle approach is to drive the weight imperatives into the successive example development approach while keeping up descending conclusion property.

Constraint-Based sequential pattern Mining: A pattern Growth Algorithm Incorporating compactness, Length and Monetary [25] used a new framework based on a sequential pattern growth methodology to deeply push constraints effectively and efficiently to mine sequential pattern . This framework can also be extended to mine constraint-based structured patterns.

The principle disadvantages of existing methodologies are the failure of LSA to consider the connection between mixes of different report terms and the fundamental ideas, the characteristic excess of regular itemsets in light of the fact that comparative itemsets might be identified with a similar idea, and the powerlessness of itemset-based summarizers to correspond itemsets with the hidden archive ideas. The, ELSA [26] methodology performed essentially superior to both itemset-based and LSA-based summarizers, and superior to anything the vast majority of the other best in class approaches.

The nonstop, unbounded, and asked for course of action of data things delivered at a quick rate in a data stream so the database end up being greater and visit configuration mining methodologies have been defined issue that don't fittingly respond to the unbounded data. Frequent Pattern Mining Over Data Stream Using Compact Sliding Window Tree & Sliding Window Model [27], a capable system to discover the game plan of latest persistent precedents from dynamic data stream using sliding window model and CSW (decreased sliding window) tree.

A parallel mining guess calculation dependent on the Map Reduce structure by consolidating an exceptionally effective calculation for static information [28]. One of the hot research points on the continuous example mining over questionable information is the spatiotemporal productivity improvement of mining calculations. Frequent Pattern mining issues over powerful questionable information streams, in light of the current calculations. Spatiotemporal productivity of the calculation in this paper is greatly improved than those of alternate calculations.

Mining Patterns by Pattern-Growth: Methodology and Implications [29], presents a methodology diagram and analyzes its procedures and executions. We show that the development of visit design is proficient in the mining of substantial databases and can lead to versatile mining.

ALGORITHM

The WD-FIM algorithm uses the candidate generate-and-test paradigm to undermine the weighted frequent itemsets from an uncertain database. Repeated iteration such as the U-Apriori algorithm discovers the weighted frequency itemsets. There are obviously significant differences between the algorithm WD-FIM and the algorithm U-Apriori. First, the WD-FIM algorithm for weighted frequent items in mining. First, the WD-FIM algorithm is suggested in uncertain datasets for mining weighted frequent itemsets. U-Apriori, however, can only be used in uncertain datasets to identify frequent itemsets. Second, the basis of the WD-FIM algorithm uses weight judgment downward closure property and existence property of weighted frequent subsets, but the downward closure property is used directly to decrease the search space in the U-Apriori algorithm for frequent itemsets. The pseudo code of the WD-FIM algorithm is given below based on the above definitions and theorems.

Algorithm : WD-FIM algorithm
Input:
DS, an uncertain transactional dataset;
wtable, a weight table;
ε, a user-specified minimum expected weighted support threshold.
Output:
The set of weighted frequent itemsets WFIS.
/* initialization */
1. initialize the variables and parameters
/* scan the dataset and get weighted frequent 1-itemset */
2. for each item I_j in DS do
3. scan DS and calculate expwSup(I_j)
4. if expwSup(I_j) $\geq$ |DS| $\times$ $\boldsymbol{\varepsilon}$ then
5. $WFIS_1 = WFIS_1 \cup \{I_j\}$
6. end if
7. end for
8. $WFIS = WFIS \cup WFIS_1$
/* scan the dataset and get weighted frequent k-itemsets */
9. $CWFIS_1 = I$
10. let $SCWFIS_1$ be sorted $CWFIS_1$ by weight in descending order
11. set k =2
12. while $WFIS_{k-1} \neq$ null do
13. $CWFIS_k$ = Connection($WFIS_{k-1}$,$CWFIS_1$)
14. $NCWFIS_k$ = wConnection(($CWFIS_{k-1} - WFIS_{k-1}$),$SCWFIS_1$)
15. $RCWFIS_k = CWFIS_k - NCWFIS_k$
16. for each candidate K itemset X in $RCWFIS_k$ do
17. scan DS and calculate expwSup(X)
18. if expwSup(X) $\geq$ |DS| $\times$ $\boldsymbol{\varepsilon}$ then
19. $WFIS_k = WFIS_k \cup \{X\}$
20. end if

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    end for
    WFIS = WFIS ∪ WFISk
end while
return WFIS
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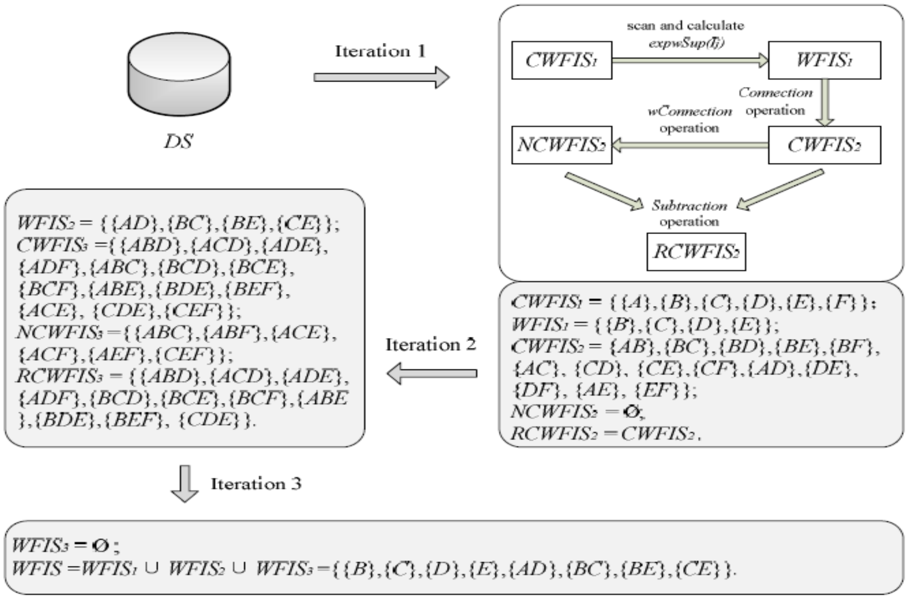

Fig.1 Architecture of WD-FIM algorithm

EXPERIMENTAL ANALYSIS

In this segment, the execution of the WD-FIM algorithm are confirmed and analyzed on both synthetic and real-life datasets are used. The current U-apriori algorithm is the most well known FIM algorithm for mining expected support frequent itemsets in dubious datasets. The existing HEWI - Uapriori is the only candidate to generate a weighted frequent articles algorithm based on FIM in uncertain datasets for mining. The Uapriori algorithm and HEWI - Uapriori algorithm are along these lines utilized as benchmark algorithms for examination with the WD-FIM algorithm.

The WD-FIM algorithm and other comparable algorithms are implemented in Python. Experiments are performed on a computer running the 64-bit Microsoft Windows 7 operating system with Intel Core i7-4510U 2.6GHz processor and 8GB RAM (Random Access Memory). The characteristics of real-life and synthetic data sets used in the experiments are shown in Table 1. There are two real-life data sets (mushroom and foodmart) and one synthetic dataset (T10I4D100K). |DS| is the total number of transactions on a dataset. |*I*| is the number of different items in the dataset. AvgLen means the average number of items in a transaction. In addition, the weights of items in a dataset and the existential probabilities of items in transactions are generated randomly in the interval (0,1].

Three groups of experiments have been conducted in order to test the effectiveness and efficiency of the algorithm to show the performance of the WD - FIM algorithm with respect to runtime, number of patterns and memory consumption.

A. Performance of runtime

In that subparagraph, the runtime and algorithms are first analyzed of the WD - FIM algorithm. The sizes of the datasets are determined in this group of experiments. But, to analyze corresponding change in operating times, the minimum weighted support threshold is changed. The Uapriori algorithm can be regarded as a FIM algorithm for weighted uncertain data sets with a set weight of 1. In addition, both the calculation time and the time for the data set is included in the runtime.

It can be seen in the Fig. 2, Fig. 3 and Fig. 4 that U-Apriori, HEWI-Uapriori, and WD-FIM algorithms all gradually decrease with an increase in the expected minimum weighted support threshold. The reason is that, with the increase of the lowest expected weighted support threshold, the number of candidates weighted the frequent items to be verified. Therefore, all the three algorithms need no longer scan the dataset for a great deal of time.

Dataset	$\|DS\|$	$\|I\|$	$AvgLen$
mushroom	8124	119	23
retail	88162	16470	10.3
T10I4D100K	100000	870	10.1

Table 1 dataset characteristics

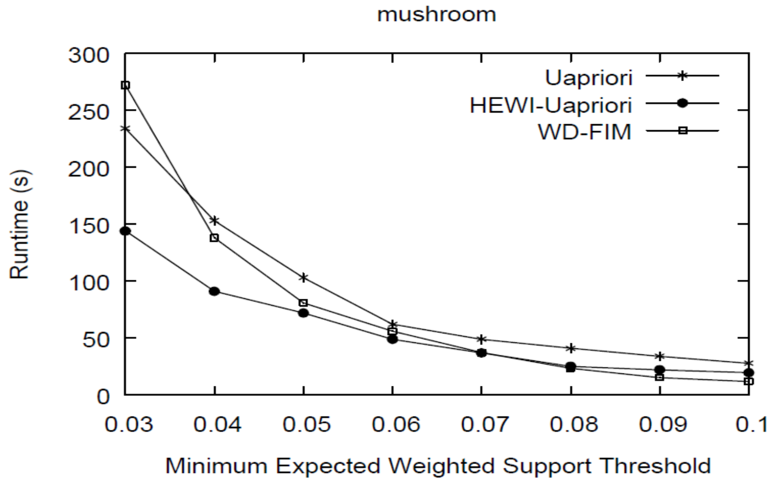

Fig.2 runtime analysis for the mushroom dataset

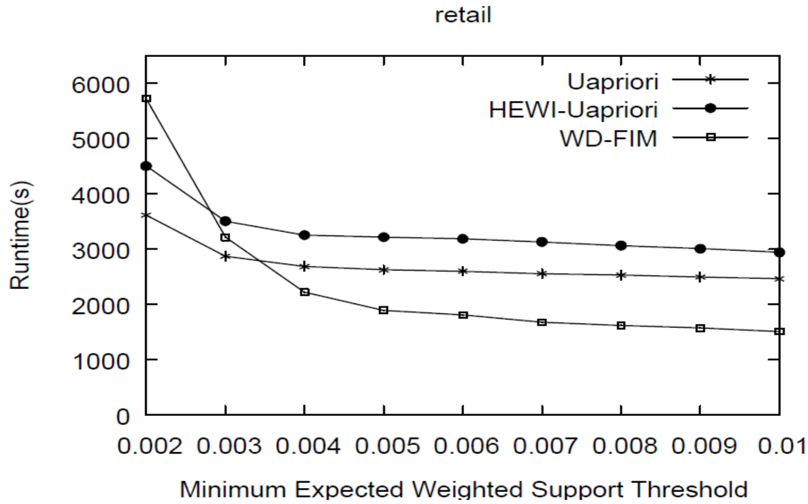

Fig.3 runtime analysis for retail dataset

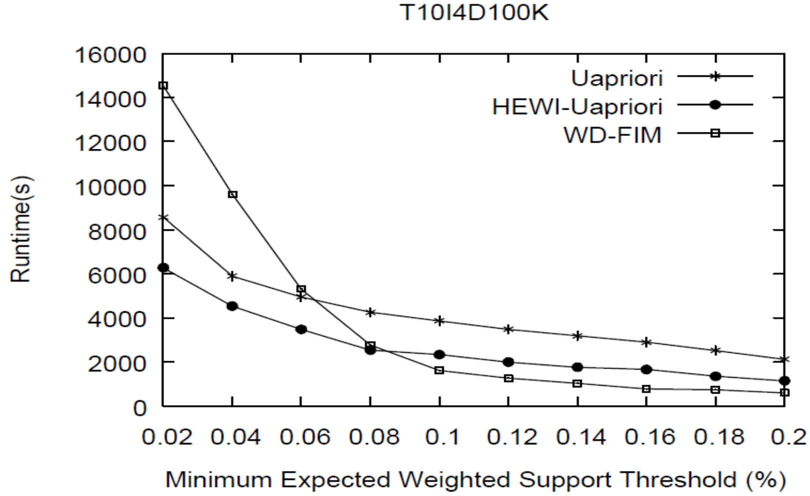

Fig.4 runtime analysis for the T10l4D100K dataset

From Fig. 2, Fig. 3 and Fig. 4, it may also appear that when the minimum expected weighted support level is relative, the WD-FIM algorithm is faster than Uapriori and HEWI-Uapriori. This is because the weight assessment downwards closure property can effectively reduce the number of candidates. However, if the weighted minimum support threshold is reduced, $CWFIS_K$ will include more candidates. Therefore, $CWFIS_K$ can be a very time-consuming process of wConnection and the removal of itemsets that are definitely not weighted often k-itemsets. The runtime of the WD-FIM algorithm is thus significantly increasing. For an instance fig. 3 shows that when the minimum expected weighted support threshold ranges from 0.004 to 0.01 the WD-FIM algorithm runtime is far shorter. However, if the minimum weighted aid threshold of expected value is 0.002 it is much less than the Uapriori and HEWI-Uapriori algorithms that the WD-FIM algorithms run.

As for Uapriori algorithm's performance and HEWI - Uapriori, it is visible as Fig.2 and Fig.4 Uapriori's algorithm for mushroom data set and T10I4D100K datasets is slower than HEWI - upriori. This is because all item weights in mushrooms can be viewed as 1. For Uapriori algorithms. Therefore, if the minimum supply threshold expected is fixed, it is likely that there will be many more applicants than the HEWI - Uapriori algorithm for an Uapriori algorithm which uses the downward closure property to prune promising candidates. But Fig.3 shows that the algorithm Uapriori is faster for retail datasets than the algorithm HEWI - Uapriori. It is also reasonable, since the retail dataset contains too many items. The property in the Uapriori algorithm for the downward closure plays a more efficient role in narrowing the search area of the weighted frequency articles.

B. Patterns analysis

In this paragraph, various low expected weighted support threshold values are evaluated first for the numbers of designs found in Uapriori algorithm, the HEWI - Uapriori algorithm and the WD - FIM algorithm. The patterns found in the Uapriori algorithm can be considered as supporting frequent objectsets (EFIs), HEWI - Uapriori algorithm patterns are highly anticipated as weighted objects (HEWIs), and WD-FIM algorithm patterns are weighted as frequent arrays (WFIs). Weighting frequent arrays (WFIs). As shown in the figure, the results for the mushroom dataset, retail and T10I4D100K are shown in Fig.5, Fig.6 and Fig.7 respectively.

From Fig.5, Fig.6 and Fig.7, it can be seen that with the increase of the minimum expected weighted support level the number of patterns discovered through all three algorithms gradually declines. At first, but late stage, the downward trend is significant. When the minimum weighted support threshold is set, it is clear to know that the algorithm of Uapriori can always find more designs than the HEWI - Uapriori algorithm and the WD - FIM algorithm it is proposing. The reason is that the weight of all items can be viewed as 1 in the Uapriori algorithm. So, when the minimum weighted supporting threshold is fixed, an item set is more likely to be the EFI. In addition, an important fact is that the number of patterns found with HEWI - Uapriori and WD - FIM are the same. The HEWI-Uapriori algorithm as well as the suggested WD-FIM algorithm are accurate methods to detect all possible weighted frequent articles in the dataset.

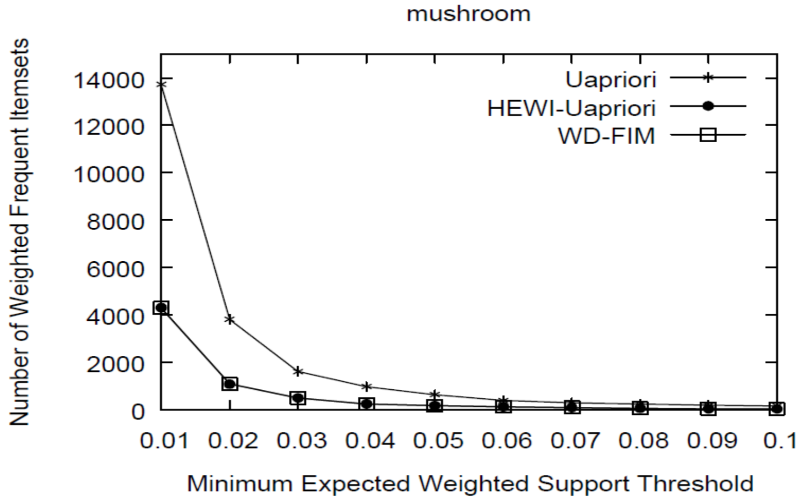

Fig.5 Patterns analysis for the mushroom dataset

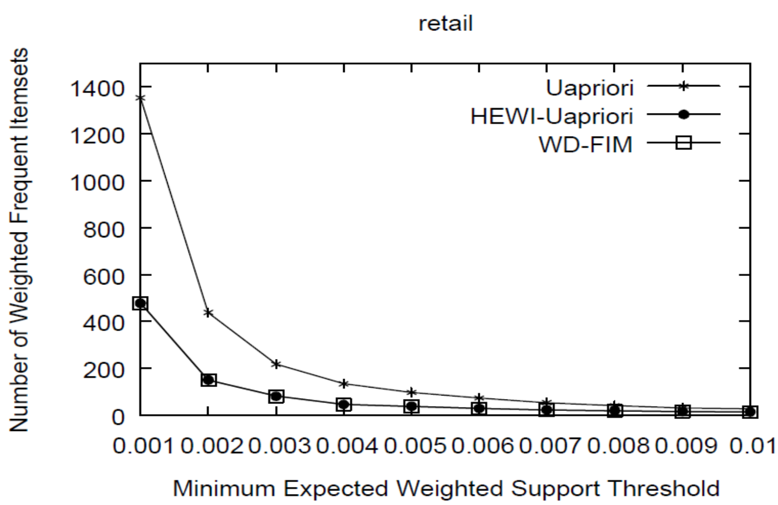

Fig.6 Patterns analysis for the retail dataset

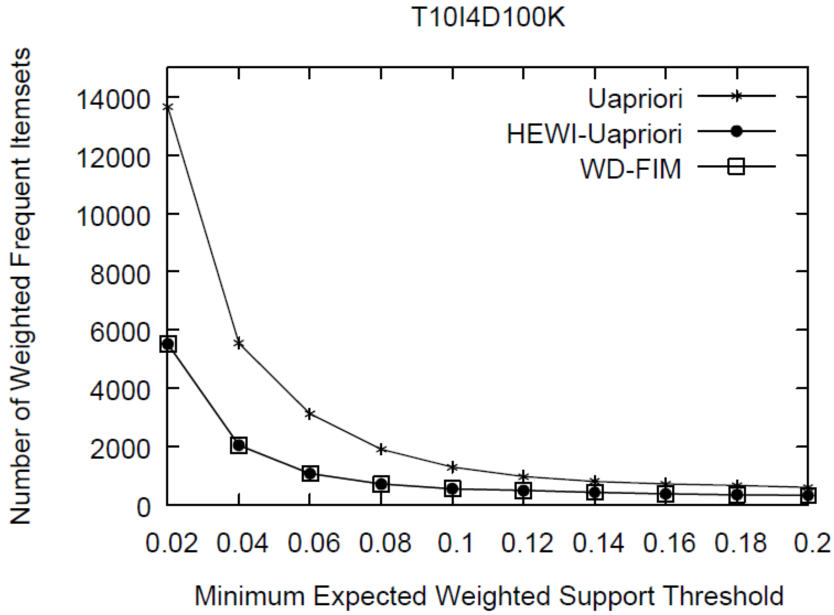

Fig.7 Patterns analysis for the T10lD100K dataset

The number of k-itemsets detected by the Uapriori algorithm, HEWI - Uapriori algorithm and the WD-FIM algorithm are also discussed in the next experimental group. Results for different datasets are shown in Fig.8, Fig.9 and Fig.10 respectively.

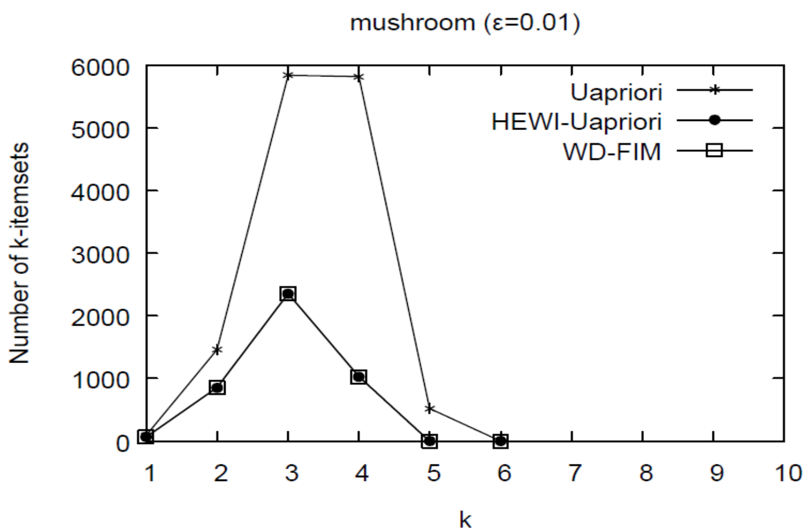

Fig.8 number of K-itemsets analysis for the mushroom dataset

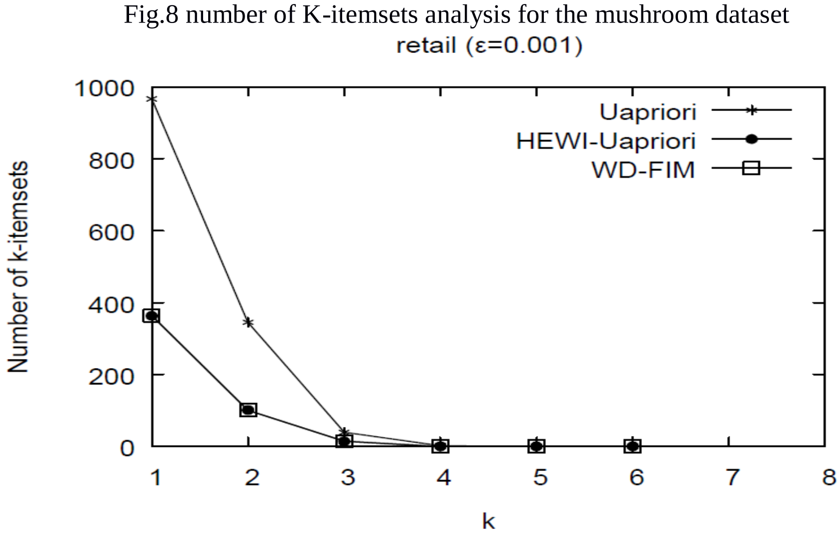

Fig.9 number of K-itemsets analysis for the retail dataset

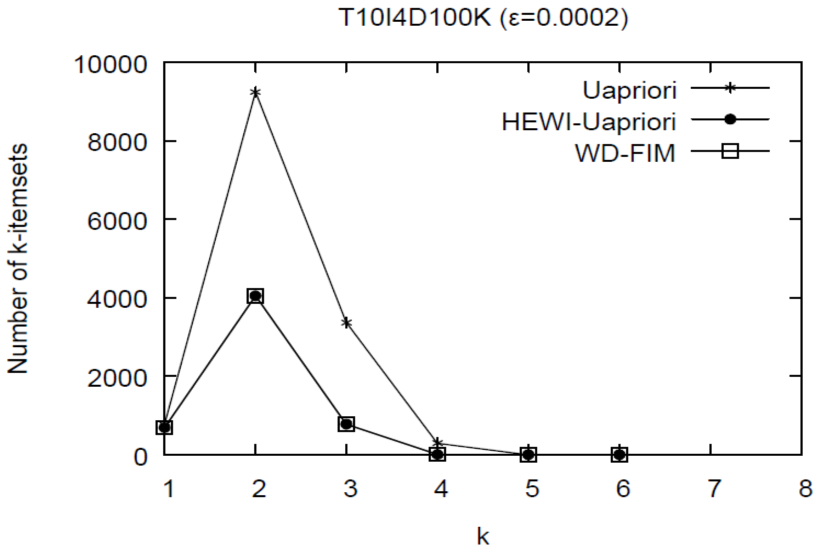

Fig.10 number of K-itemsets analysis for the T10l4D100K dataset

From Fig.8, Fig.9 and Fig.10, the WD - FIM algorithm can produce the same quantity of)-itemsets on all of the three datasets as the HEWI - Uapriori algorithm. The number of k-itemsets produced by HEWI - Uapriori and the WD - FIM algorithm are, however, smaller than those identified by the Uapriori algorithm. This is because the HEWI - Uapriori algorithm and the WD - FIM algorithm take into account both the weight and the probability properties. So, compared with the Uapriori algorithm, fewer and more meaningful items are produced. In addition, the k-itemsets of the three algorithms compared have the same distribution trend for the same dataset.

C. Performance of memory consumption

Additional experiments have also been conducted in this subparagraph to evaluate the memory consumption of Uapriori algorithm, HEWI-Uapriori and the WD-FIM algorithm. Memory usage for different datasets are shown in Fig.11, Fig.12 and Fig.13 respectively.

From Fig.11, Fig.12 and Fig.13 it can be seen that the algorithm Uapriori needs more memory than the algorithm HEWI - Uapriori and the WD - FIM suggested. For this, there are many reasons. The Uapriori algorithm first uses the property to close down to directly prune numerous unpromising EFI candidates. Thus, less candidates are generated. Second, the HUBEW downward closing property is used by the HEWI - Uapriori algorithm for coping with candidates. The candidates are still stored in the main memory after the first dataset scan. The WD-FIM algorithm used to reduce the search area of weighted frequent items to the weight assessment downward closure property. The $NCWFIS_K$ should therefore be calculated and maintained in the main memory.

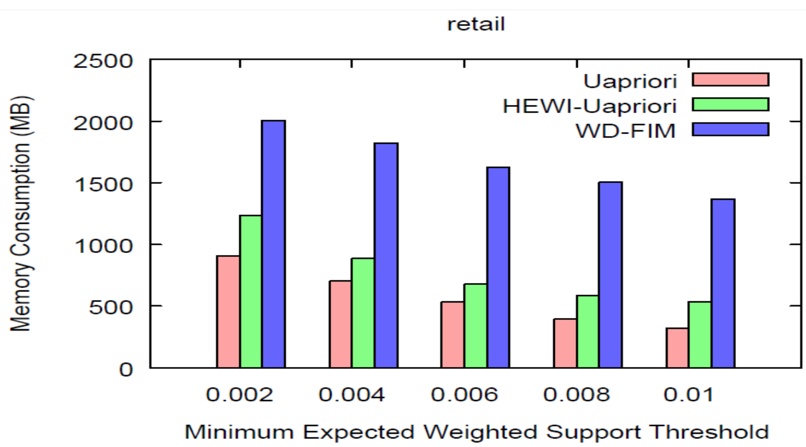

Fig.11 memory consumption analysis for the retail dataset

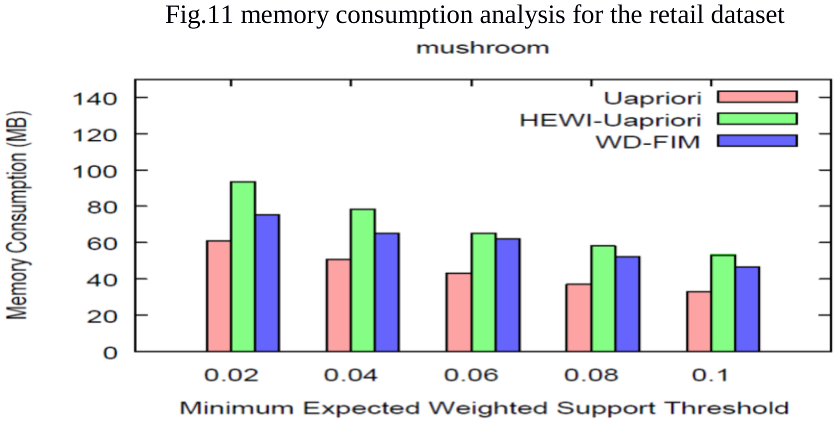

Fig.12 memory consumption analysis for the mushroom dataset

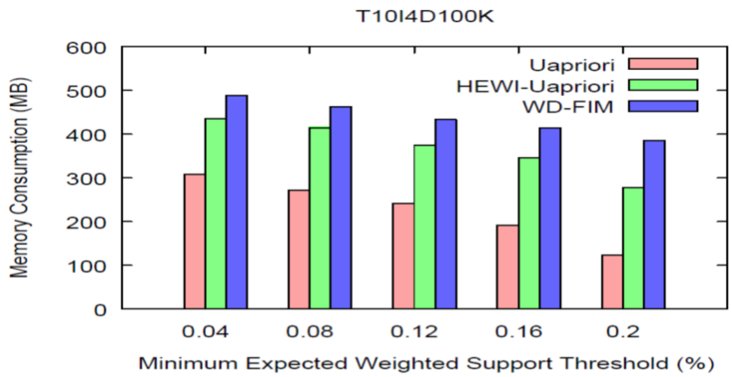

Fig.13 memory consumption analysis for the T10l4D100K dataset

CONCLUSION

To achieve intelligent decision making on intelligent systems, we used a weight assessment downwards based on frequent itemset mining algorithm, which aims to narrow the search space and enhance the time efficiency of the weighted frequent itemsets. The downward weight assessment property and the existence of weighted frequency subsets are first demonstrated. The weight assessment for the weighted frequency subsets The WD - FIM algorithm is described in detail based on these two characteristics. The WD-FIM algorithm is also theoretically analyzed for its completeness and efficiency over time. Finally, on both synthetic and real-life datasets, the performance of the WD-FIM algorithm is checked.

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