Business Intelligence for Evaluating the Intangible Benefits of On-Shelf High Utility Itemset from the Temporal Transaction Database

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Abstract: Utility Mining is the progression of identifying High Utility Itemsets (HUI’s) from enormous transaction data. Utility mining plays a decisive role in the inspection of the data or giving actionable information to help managers, sales executives, and other commercial end-users to generate versed business decisions. In the hypermarkets, the showcase period of every item in display will vary such as new products, seasonal products, and so on. Itemsets with time period are not retrieved by existing utility mining algorithms. Hence, On-Shelf Utility Mining algorithms were proposed to discover HUI’s and a general on-shelf period of all items in temporal databases is considered. Research work aims to propose an algorithm called LOSUM (List On-Shelf Utility Mining) to retrieve on-shelf HUI’s from a temporal transaction database by reducing the data stores scan. The algorithm is enhanced by implementing a list structure to store utility information of every itemset. The candidate itemsets are generated from the list itself. This reduces the supplementary scan of a database. The LOSUM is compared with FOSHU using Chess, Accident, Kosarak, and Mushroom datasets. The experimental results illustrate that the LOSUM is efficient than the existing algorithm FOSHU (Fast On-Shelf High Utility itemset mining) algorithm.

Keywords: Utility Mining, High Utility Itemset, List Structure, Periodic utility, On-shelf utility value.

I. INTRODUCTION

Data mining (DM) is the progression of mining needed patterns or interesting information from repositories and its task includes finding classification, association and clustering rules. Among these DM methods, an Association Rule Mining (ARM) is the most popular task. ARM has two segments, the first segment finds out all the repeated itemsets based on a user-defined minimum threshold value. In the subsequent phase, the ARM is generated from the identified repeated itemset. Frequent Itemset Mining (FIM) considers only the incidence of an item in a database. The significance likely price, weight or profit of an item inside a transaction is not considered. Some items or itemset in a dataset may have low support value that may bring higher earnings due to their high price or high profit of the frequency of an item within transactions. In this case, such valuable and profitable itemset are failed to spot by FIM [1].

In Weighted Frequent Itemset Mining (WFIM), weights (each item has individual weight) of the item is considered for mining needed information. If an item with the highest weight but its occurrence is infrequent, in this situation also, this item is still found in the transaction. This kind of framework ignores the number of incidences of items. Users may also look for itemsets having consistent profit as well as desired quantity, which cannot be satisfied by WFIM [2]. Utility Mining [3] is developed to overcome the limitations of FIM/WFIM and considers the utility of entire item in a transaction which is based on the interestingness of the user’s preference or frequent patterns of interest. Temporal data mining has enchanted a lot of academicians and business peoples due to its nature of practicality [4, 5]. In hypermarkets, newly arrived products are put on the stores front display and taken off multiple times in a day whenever particular items are in need. To recognize such itemsets, On-Shelf Utility Mining algorithms were proposed [6]. In order to acquire the accurate utility value of a itemset, the On-Shelf period (time period) of every product is computed. This algorithm has lined the way for the entrepreneur to make efficient and effective decisions at business.

Most of the researches based on utility mining emphasize suggestions to invent HUI’s from the huge transaction database [7, 8, 9]. Most of the academicians and researchers were proposed an association rule-based technique to dynamically mine the much-needed items [1, 4, 5, 10 and 11]. An example of dynamic itemset mining is finding “the frequent patterns of On-shelf products”. However, a consumable item may be placed on a shelf and taken out of the shelf numerous times in a store. High On-Shelf Utility itemset considers quantity, profit and time period of every item in a transaction as well. For example, consider the following frequent item "In the rainy season, clients habitually purchase sweaters and rain-coats jointly". The itemset [rain-coats, sweaters] may not frequent items all from end to end of the complete database, but maybe a HUI’s in the rainy season. Hence, a three-scanning algorithm called TS-HOUN (Three-Scan Algorithm for Mining On-shelf HUI’s with Negative unit profit) is commenced for proficient mining. TS-HOUN is outperformed by the algorithm FOSHU. The FOSHU is improved by invoking a list structure to store utility information of itemsets. This reduces the extra scan of a database. The candidates are generated from the created list itself. This improved algorithm is called as LOSUM (List-On-Shelf Utility Mining Algorithm). This research work implements the list structure to store the calculated utility data is retrieved from the list for further calculations. Retrieving data from list structure reduce the database scan.

This paper is ordered as follows. section II, elaborately describes the literature review. In section III discusses about the problem definition, preliminary definitions and the proposed solution. Section IV demonstrates illustrative example. Section V compares the resultant value of time and memory of both existing and proposed algorithm. Conclusions are given in Section 6.
II. RELATED WORKS

Lan et al. [13] have designed a two-phase mining algorithm for the effective discovery of On-Shelf HUI’s from the transactional database. In the initial phase, within every time period the possible candidates of On-Shelf HUI’s are found by the way of a level by level approach and the candidate items were generated in the succeeding phase. By a supplementary database scan, the candidates of On-Shelf HUI’s are examined for the definite price of utility item. In the FIM considers only the occurrence of an item in a database. On-Shelf HUI includes weight, profit, and time periods of On-Shelf consumable products.

Lin et al. [14] has proposed a new method that assimilates utility mining’s previous two-phase procedures. Condensed tree structure and downward closure property is expanded using the incorporation of traditional approach called FP-tree. Author’s proposed algorithm evidence the better performance when the algorithm is evaluated against the traditional two-phase algorithm. From the valuation, it’s found that execution time and generation tree node is reduced.

Liang et al. [15] proposed THUI (Temporal HUI’s)-mine approach. The utility value considers the profit of the items. UM aims at recognizing the itemsets which poses high utility rate. Temporal HUI’s are used for retrieval temporal HUI’s from data streams proficiently. The method of identifying all temporal HUI’s beneath entire-time windows of data streams can be accomplished successfully with compact amount of execution time and fewer memory space.

Wong et al. [16] have shown a new approach using an incremental mining algorithm, which is proposed to maintain discovered HUI’s based on effective manner. Itemsets are first segregated into three parts by considering the factors namely have small, pre-large, or large (high) TWU in the original database or not and in inserted transactions. Finally, individual functions are then executed for every single part of the data.

Lan et al. [17] developed an incremental mining algorithm for proficient mining of HUI’s and is based on the model of the Fast-Update (FUP) method. ARM is also accomplished with FUP algorithm. At the beginning itemsets are partitioned in to four parts based on the High Transaction Weighted Utility (TWU) value in the original database. FUP achieves better as well as faster solution than the two-phase batch mining algorithm in the background of irregular data. ARM, which is based on the amount of occurrence values of items. FUP is entirely different from the traditional ARM approach.

Zida et al. [18] have come out with the EFIM approach (Efficient HUI’s). EFIM has on two upper-bounds criterions named the local and sub-tree utility, search space is more efficiently pruned. A novel array-based utility counting method was named as Fast Utility Counting (FUC) which is mainly used to estimate the upper-bound values in direct space and time. Moreover, FUC is to lessen the rate of database scans. EFIM is a proficient database transaction and projection of assimilation techniques. Illustrations in this paper with several dataset’s shows that EFIM is quicker and consumes lesser memory than the algorithms HUI-Miner, d2HUP, FHM, UP-Growth+, and HUP-Miner.

Hong et al. [19] have presented an innovative variety of pattern entitled as On-Shelf HUI’s. An item’s distinct profit, amount of entire item in an operation, and on-shelf time periods in a database are taken in to account of. Thus proposed a 3-scan mining algorithm which is efficient to find out the needed itemsets. The proposed work implements a pruning scheme and an itemset-generation mechanism to prune repeated candidate itemsets. From the transaction of itemset pruning is done to systematically check and eliminate the repeated or duplicate itemsets in a database.

III. PROPOSED ON-SHELF UTILITY MINING ALGORITHM: LOSUM

A. Preliminary definitions

Some of the preliminary explanations for retrieving On-Shelf HUI’s [12].

Definition 1: In the data T = {t1, t2, . . . , tj, . . . ,tn} represents the time periods (tp), where tj represents the jth period in the entire set of periods, T. V = {v1, v2, . . . ,vn} is a set of items shown in a transactions. Temporal transaction database is represented as D = {trans1, trans12, trans13,...,transmn} where transji is the jth transaction in the ith time period. The temporal transaction utility q(i, transji).

Definition 2: The External Utility (EU) value of an item s(i) and i represents the profit and reflects the impact of every individual item in the item. Choosing the profit value as an EU is general practice and are stored in a distinct utility table.

Definition 3: The utility value $u(v, trans_{ji})$ of an transaction $v$ in the temporal transaction is called as

$$ u(v, trans_{ji}) = s(v) * q(v, trans_{ji}) $$

Definition 4: The transaction utility $tu(v, trans_{ji})$ is the total value of all the items within the transaction.

$$ tu(v, trans_{ji}) = \sum_{v \in trans_{ji}} u(v, trans_{ji}, y) $$

Definition 5: The summation of the utility values of W in a itemset is periodical utility $pu(W, t_j)$ of an itemset.

$$ pu(W, t_j) = \sum u(W, trans_{ji}) $$

Definition 6: The sum of the transaction utilities of all transactions within the jth period of $t_j$ is the periodical total transaction utility $ptu(t_j)$.

Definition 7: calculate $ptu$ for every time period (tp) from the created On-ShelfList. $ptu$ calculated by the summing up of same periods of all the items.

$$ ptu(t_j) = tu(trans_{ji}) + \ldots + tu(trans_{im}) $$

Definition 8: On-Shelf utility value of an itemset by summing up the values of $pu$.

$$ ou(v) = pu(u(v, trans_{ji})) $$
Algorithm: Pseudo-code for LOSUM

\[ \text{List-continuation}\]

\[ \text{End for}\]

\[ \text{Step 2: Create a list structure called On-ShelfList with Three columns that stores Time period, Transaction_id and Utility value. The following table contains the On-ShelfList of M.}\]

\[ \text{Step 3: Generate the candidate itemsets with those items. From the generated candidate itemsets, the values namely periodic utility value and the high pu(W, t_j) of an itemset W is calculated from the created list structure (On-ShelfList). The periodical utility ratio pu(W, t_j) of an itemset W is the pu(W, t_i) of W within the jth period. Pu(W) is compared with a minimum threshold value and then a HPUI is retrieved. An itemset is called a high On-Shelf utility itemset when it satisfies the condition if puur(W, t_j) greater than k (minimum_threshold value).}\]

\[ \text{Step 4: A sorted transaction is created using the List Structure, in this step all the void transaction (transaction having zero values) will get confiscated to reduce the calculation time.}\]

\[ \text{Step 5: If HPU > MITU then: //minimum tu value}\]

\[ \text{Step 6: Display High On-Shelf Utility Value}\]

\[ \text{Step 7: Update list}\]

\[ \text{Step 8: End if}\]

\[ \text{Step 9: Display High On-Shelf Utility Value}\]

\[ \text{Step 10: Update list}\]

\[ \text{Step 11: End if}\]

\[ \text{Step 12: Update list}\]

\[ \text{Step 13: Display High On-Shelf Utility Value}\]

\[ \text{Step 14: End if}\]

\[ \text{Step 15: Update list}\]

\[ \text{Step 16: Display High On-Shelf Utility Value}\]

\[ \text{Step 17: Update list}\]

\[ \text{Step 18: Display High On-Shelf Utility Value}\]

\[ \text{Step 19: Update list}\]

\[ \text{Step 20: Display High On-Shelf Utility Value}\]

\[ \text{Step 21: End if}\]

\[ \text{Step 22: End for}\]

\[ \text{Step 23: Display High On-Shelf Utility Value}\]

\[ \text{Step 24: End if}\]
Step 3: With the help of On-ShelfList, intersection of individual itemsets through Transaction_id is accomplished. If the item has common transactions, then create candidate itemsets with those items. From the generated candidate itemsets, periodic utility value and the utility of an item is estimated. Calculate tu value by considering the same transaction id from the On-ShelfList.

Transaction Utility (tu) for T1
\[
\begin{align*}
t_1.1 &= 37 \\
t_1.2 &= 25 \\
t_1.3 &= 31 \\
t_1.4 &= 35 \\
t_2.1 &= 24 \\
t_2.2 &= 31 \\
t_2.3 &= 32 \\
t_3.1 &= 26 \\
t_3.2 &= 10 \\
t_3.3 &= 21 \\
t_3.4 &= 16 
\end{align*}
\]

Step 4: Create itemset On-ShelfList.
Step 5: Total utility values of $W$ is the $pu(W,t_j)$ which is an itemset in every transactions including $W$ contained by the $j^{th}$ period $t$. The periodic utility value computation is done from the itemset generation having the same transaction id.

$MN = 29$  $MO = 72$  $MP = 98$
$MQ = 40$  $MR = 92$  $NO = 64$
$NP = 15$  $NR = 23$  $OP = 64$
$OQ = 18$  $PQ = 43$  $PR = 34$

Step 6: Estimation of the PTTU for every time period from the created On-ShelfList. Pttu is calculated by the summing up of same periods of all the items.

$PTTU_{t1} = 128$  $PTTU_{t2} = 108$  $PTTU_{t3} = 73$

Step 7: The $pur(W,t_j)$ of an itemset $W$ within the $j^{th}$ period $t$ is the summation of the $pu(W,t_j)$ of $W$ over the summation of all the $j^{th}$ period $t_j$.

$pur(W,t_j)$ is compared with a minimum threshold value and then HPUI is retrieved.

V. RESULT AND DISCUSSION

Experimentation is carried out using Java and accomplished in a PC with 3.20 GHz CPU. Performance of LOSUM and FOSHU is compared using the performance metrics namely memory space occupied and execution time.

A. Dataset Description

| Dataset Name | Instances | Attributes |
|--------------|-----------|------------|
| Mushroom     | 8,124     | 22         |
| Accidents    | 40,183    | 39         |
| Kosarak      | 45,678    | 54         |
| Chess        | 28,056    | 6          |

Table 5: Memory Usage for LOSUM and FOSHU algorithm

| Dataset | Threshold | Memory Usage for FOSHU | Memory Usage for LOSUM | Time Consumption for FOSHU | Time Consumption for LOSUM |
|---------|-----------|------------------------|------------------------|---------------------------|---------------------------|
| Mushroom| 0.8       | 16.65                  | 14.45                  | 1735                      | 1564                      |
|         | 0.7       | 18.49                  | 17.22                  | 1922                      | 1752                      |
|         | 0.6       | 15.87                  | 16.61                  | 2641                      | 2499                      |
|         | 0.5       | 31.84                  | 27.81                  | 4578                      | 3921                      |
|         | 0.4       | 19.39                  | 18.23                  | 15704                     | 14891                     |
|         | 0.8       | 24.1                   | 19.56                  | 2981                      | 1954                      |
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|       | 0.7  | 0.6  | 0.5  | 0.4  |
|-------|------|------|------|------|
| Accident | 54.09 | 43.98 | 2671 | 1673 |
|        | 56.68 | 49.77 | 2659 | 1561 |
|        | 39.02 | 28.51 | 2545 | 1397 |
|        | 73.87 | 63.65 | 2661 | 1489 |
| Kosarak | 5.89  | 4.67  | 3145 | 2667 |
|        | 7.69  | 5.56  | 4932 | 3577 |
|        | 8.72  | 6.91  | 5676 | 4311 |
|        | 118.59 | 105.11 | 20282 | 15678 |
|        | 142.36 | 125.38 | 17658 | 12887 |
| Chess  | 15.47 | 5.91  | 656  | 6487 |
|        | 15.81 | 18.2  | 918  | 12984 |
|        | 18.47 | 24.32 | 1063 | 25874 |
|        | 27.15 | 31.25 | 1782 | 51025 |
|        | 24.89 | 41.58 | 5988 | 121865 |

Figure 2: The graphical representation of LOSUM and FOSHU algorithm’s performance. From the result, it is found that LOSUM outperforms FOSHU in terms of memory usage.
VI. CONCLUSION

The display period of every individual item in a hypermarket may vary likely newly arrived product, season based product and so on. Such itemsets are not retrieved by available utility mining algorithms. Thus, On-Shelf utility mining algorithms are proposed to discover such itemsets. On-Shelf HUI mining considers individual profit, the quantity in addition to that it considers On-Shelf periods of all items temporal databases. In this work, a new algorithm was proposed. On-Shelf HUI’s were retrieved from a transaction database. To overcome the repeated database scan, items are stored in the created List-Structure. This reduces the extra database scan of the transaction database. The candidates were generated from the list itself. The LOSUM is compared with the existing algorithm FOSHU using the datasets namely Chess, Accident, Kosarak, and Mushroom. Memory usage and utilization of time is efficient in LOSUM when compared to FOSHU and found through the illustrated experiment’s result. In the future, the negative profit items and data streams can be incorporated for finding On-Shelf HUI’s.

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