Empirical Methodology and Innovative Algorithm for Mining High Utility Itemset on Temporal Data

Rachith Raj, Ajay Krishnan, C.V. Prasanna Kumar

Abstract: Ever since the humans found the significance of data we are using different methodologies to extricate data patterns in the most useful way to reach at various conclusions based on our needs. The proper utilization of data will lead to meaningful full results. Here our focus is to expand the concept of "High utility itemset mining" and also introducing the concept of "timestamp" on it. Here we proposed an effective algorithm to find the best possible data patterns that generate maximum profit within the given "time period" and also proposed a new framework to calculate the "utility support". Our analysis can be utilized to improve profitability in business and also make better decisions for improving sales in the organization.

Key Terms: Data mining, Frequent Itemset Mining, High utility Itemset mining, temporal data.

I. INTRODUCTION

The Method of retrieving vital information or facts from colossal amounts of data is known as data mining. The most crucial study of Data Mining is the retrieval of transactional information. Discovering frequently used & significant information from an expansive database exhibits an imperative part in data mining. Frequent Itemset mining is the core method in data mining, detecting fascinating and frequently appearing items from the dataset. Frequent Itemset Mining could be a strategy for market basket analysis that allows retailers to identify relationships between the items that consumers buy from their business. But when we think in terms of business perspective the sole purpose is to find the pattern that generates maximum profit gaining itemsets by overcoming the limitations of FIM by introducing the new concept on “high utility itemset mining”. High utility itemset mining is an adjunct of the issue of frequent itemset mining. The High utility Itemsets allows the merchants to understand consumer’s purchase patterns that generate more profit. A Temporal data is a data related to time instances, time is an important aspect when it comes to a business perspective. Here we introduce the time cube ("TC") which is a new conception for considering time hierarchies in the mining process and we conduct factual experiments on fictitious datasets to analyze the algorithm's efficiency. The structure of our paper is as follows: We discuss some related work in conjunction with our research in “section II”. We elaborate our study based on the experimental evaluation in “section III”. We review our result in section IV. We wind up our paper with a conclusion in “section V”.

II. RELATED WORK

There are lots of studies happened recently in the field of FIM(Frequent Itemset Mining), commonly used traditional algorithm in the area of FIM are A-priori, fp-growth, Lcm etc. Various studies are conducted to optimize and extend FIM algorithm in order to acquire better results. Several works of literature are available on the area of frequent itemset mining and other related fields. Gorbani and abessi have efficiently extended the apriori algorithm by adding the time related information and they also introduced a new value of threshold to resolve the overestimation problem as relates to time, their study was about finding frequent itemset from temporal data[1]; HoudaEssalmi et al. has proposed the “a-priorimin algorithm” that optimized a-priori algorithm to improve the performance by instigating a strategy for calculating the FI and the above approach has lessens the execution time by improving the performance [2]. Conventional research in mining retail information in any case does not take under consideration the product’s cost’s and how such settings can affect potential demand, Yen-Liang Chen et al. proposed the new methodology by proposing a representation strategy to consolidate cost information into historical transaction data[3]. But in business perspective our concern will be regarding the profit this study has taken us to the most emerging area in data mining called high utility itemset mining. Prashant N et al. has proposed the “Tku” & “Tko” that mines from “Tkhuis” without the threshold [4]. YING LIU et al. presented a 2-phase algorithm that prunes out the number of items to acquire the highly profited itemset using a different approach [5]. Alva Erwin et al. proposed an algorithm to undergo parallel projection strategy to utilize disk space when main memory cannot accommodate large dataset [6], this will give an idea about how we can mine efficiently from colossal dataset. Han et al. [7]. Has developed an effective method to mine the “segment wise periodicity” that helps us to understand periodic pattern mining on temporal data. Rakesh Agarwal &RamakrishnanSrikanth [8] has presented two algorithm “apriori and aprioriTID” & also presented “apriorihybrid” algorithm that become basis for

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III. MINING HIGH UTILITY ITEMSET ON TEMPORAL DATA

A. New Framework

Let \( X = \{ x_1, x_2, x_3, \ldots, x_n \} \) be a group of items in the dataset and \( Ds \) be the Dataset containing the transactions. Each transaction has an unique transactional ID called “TID” and also the time in which it occur \( (t) \). When we deal with data related to time we define a new term called Time Cube (TC).

Refer Fig Below

![Fig. 1. The cubic model with 3 time hierarchies](image)

Frequent itemset mining has few limitations, as the quantity purchased is not taken into account, all the items have the same importance and profit is not calculated, to resolve these limitations the problem of “frequent itemset mining on temporal data” is redefined as the problem of “high utility itemset mining on temporal data”.

Let \( X \) be the itemset, and \( x_i \) is the items in the itemset and value of \( I \) can varies from “0 to n”.

\[
U = \sum_{i=0}^{m} (P(x_i) \cdot Q(x_i)) / m
\]

\( P(x) \) = unit profit of an item, \( Q(x) \) = quantity of an item in the transaction and \( m \) = number of items in the itemset. (Refer Table 1 and Table2).

\[
\text{Utility}(X) = \sum_{i=0}^{k} U / k
\]

Where Utility(X) is the utility for the items and \( k \) refers to the number of transactions in which an item is present.

B. Recommended Algorithm for mining high utility itemset on temporal data

The Suggested Algorithm Intended to find itemset \( X \) That generates maximum profit above the utility threshold considering the time cube on temporal data. Candidate having utility threshold above the minimum utility threshold within that time cube is considered as the high profitable itemset. By Implementing below 3 algorithms we able to generate most profitable itemsets along with their purchased date and their respective profit.

Input: [Data (Ds), minth, TC] Output: \( L_k \)

1. \( L_1(Ds, \text{minth}, \text{TC}) \)
2. \( k=2 \)
3. While (\( L_{k-1} \) ! = NULL)
4. \( C_k=\text{CandidateGen} (L_{k-1}) \)
5. For (\( i=0 : n, X=C_k(i) \))
6. \( \text{CalcUtility} (X) \)
7. Endfor
8. For (every \( Y_i \rightarrow M_j \rightarrow D_k \mid Y_i, M_j, D_k \in \text{TC} \))
9. If (Utility (\( C_{TC} \)) > = minth)
10. \( L_{TC}=L_k \cup C_{TC} \)
11. Endfor
12. \( k++ \)
13. End while

Input: [Data (Ds), minth, TC] Output: \( L_1 \)

1. \( L_i=\emptyset \)
2. For(\( X_i, i \rightarrow 0 : n, X_i \in E \))
3. For( \( Y \rightarrow M \rightarrow D_k \mid Y_i, M_j, D_k \in \text{TC} \))
4. IF( \( X_i \) contains)
5. Sum += Utility(\( X_i \))
6. Count Support \( X_i \)
7. Endfor
8. Utility(\( X_i \)) = Sum/Count Support
9. If( Utility(\( X_i \)) > = minth)
10. \( L_i = L_i \cup X \)
11. Endif
12. Endfor

Algorithm 1.3: Candidate generation Algorithm

Input: [\( L_{k-1} \)] Output: \( C_k \)

1. \( C_k=\emptyset \)
2. For all pairs of \( L_{j1}, L_{j2} \in L_{k-1} \)
3. \( C_r = L_{j1} \bowtie L_{j2} \)
4. If (|\( C_r | > K \))
5. Put \( C_r \) into \( C_k \)
6. Endif
7. Endfor

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Algorithm (1.1) is the procedure to mine the high utility itemset within the time cube “TC”. Algorithm (1.2) will get input parameters such as Data, minimal utility threshold, TC which is passed from algorithm 1.1, utility weight of each itemset within the time cube is calculated by our new framework. All the itemset above the minimal utility threshold will be added to L1. L1 is returned to algorithm (1.1). Algorithm (1.3) is a procedure to generate candidate itemset (until Lk-1 not equal to null). The algorithm (1.3) use “joint operator” that generates higher level itemset from the lower level. The result of candidate itemset will return to algorithm (1.1) and algorithm (1.1) will compute the “utility” of each candidate itemset, all the itemset above minimal threshold within the time cube that provides maximum profit is considered as our outcome.

IV. RESULT AND DISCUSSION

We have implemented the proposed algorithm with the real dataset, on our implementation we go through various steps like data loading, Data preprocessing, candidate key generation and calculated the utility support of the “candidate itemset” using our new framework and from that, we able to generate L1 and process goes through until “Lk-1 not equal to null” and we able to find the most profitable “itemsets pattern” in the given “time interval” with at most accuracy. The tabular representation of the result is given below-

| Itemsets   | Items purchased Date | Profit generated by Itemsets |
|------------|----------------------|------------------------------|
| #95123A, #21089 | [10/12/1, 10/12/2] | 82.45                        |
| #95125A, #55366B | [10/12/1, 10/12/2] | 62.15                        |
| #95123A, #95099B | [10/12/1, 10/12/2] | 56.94                        |
| #23752, #22669, #22467 | [10/12/2] | 47                            |
| #21088, #21243 | [10/12/1] | 55.71                        |

(Tabular representation of experimental result.)

V. CONCLUSION

In our study, we have gone through the mining of “high utility Itemsets” together with “Temporal pattern” for that we proposed an algorithm that extracts itemsets generating high profit along with their “time-related information”, that help us to identify the high profit generating purchase pattern on specific “time interval”, and we able to overcome few limitations existed in frequent pattern mining and extended ”the concept of high utility itemset mining” by adding ”time cube (TC)” & also we able to introducing the new framework to calculate the ‘utility support’ by considering the quantity, unit profit, etc. to obtain the result. Our study can be utilized in the business domain to improve profitability as well as sales, and from the manager’s point of view, they able to make better decisions to improve their organization’s business strategy.

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