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High Transaction Weighted Rare Utility Itemset Mining Over Data Streams Using Sliding Window Algorithm

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Abstract: *A standout amongst the bestrecent data mining area is Utility Miningthat highlighting on a broad range of utility elements and alsointegrates utility ideas in data mining process. Rare utility mining that goes for finding itemsets that infrequently occur but has higher utilities in the database. The Existing research on high utilityrareitemsets mining concentrate on the static transaction database, where all transactions are treated with the same significance and the database are scanned more than once. Data mining high utility rare items from the evolving data streams is a significant challenge, because of the high arrival rate, enormous in size and so forth. In numerous applications, clients are concerned with recent happenings. Among the different data stream models, sliding window model attracted high interest. This paper proposed a novel strategy, to be precise HTWRUI (High Transaction Weighted Rare Utility Itemset Mining based on Sliding Window model), for proficiently and successfully mine high utility rare itemsets. The model permits the user to decidethe windowsize, window counts and different weights for every window. The novel commitment of HTWRUI is that it can viably extricate those itemsets that show up occasionally in the current time window in one pass.*

I. Introduction

In business, things having low offering frequencies (uncommon thing) may have high benefits. These unusual data can help in diverse choice making areas. At the point when contrasted with milk and bread, a few things like a gold ring and a chain[1]are rarely acquired, nonetheless, may pass on exceptionalbenefits to theseller.These phenomenal affiliations that one as often as possible in databases might not expect however would be critical for a seller. These uncommon or rare finding illustrationsdevelop a novel research problem;that candiscover the rare elementsof high utility value. Many applications of rare utility mining are there[2], for example, inventory planning, enhancing business development, page associationapplications, etc.Not at all like data mining using association rule mining, rare utility mining helps to discover productive elements that might not show up as often as possible in databases.

II. Literature Review

Different data mining algorithmswere proposed for mining of high utility items from transactional databases [1], [3]. They extract utility itemsets from static databases. However, they cannot be proficiently utilized as a part of applications that are real-time in nature, for example, health care systems, online business trades, banking applications, insurance policies,etc.Mining high utility itemsets over fast, ceaseless and unbounded data streams is aninterestingproblem because of varyingbehavior of data and constrained processing speed and memory of computing systems[4]. In data streams, data are continually added, and their sizes are ceaselessly expandedaccording to the accumulation of transaction data. In this way, patterns created over data streams additionally turn out to be substantial, which means investing much time mining the patterns, and consequently, it can damage one of the requirements for mining data streams. Data mining over data streams[5]must fulfill the necessities in which every information component required for data stream analysis must be scanned just once, and the majority of the entered data must be handled as quickly as time permits and results of data stream mining ought to be accessible in a flash and also their quality ought to be adequate at whatever point user need the outcomes.By the advantages said above, this proposal pushes rare utility itemsetmining into data stream mining. In the process of adding datainto the data streams constantly, thesignificance of certain information entered quite a while prior can decay, or they may not be anymore required while as of late included data significance can be moderately high. To apply these qualities in the mining process, a mixture of window model-based mining methodologies havebeen proposed. The different data stream mining models[6]are the landmark model [7], the tilted-time window model [8]and the sliding window model [9]. Different from the other two models, the sliding window model aimsatlatestinformation and user can decidethe window size for a fixed period or a given number of transactions[3], [10]. Similar to conventional sliding window model[11], at a particular pointin time, weconsider only the data in one window. Thisresearchapplied weighted sliding window model for mining data stream dataand is implemented according to the requirements of data streams[12]. Especially since the sliding, window-based mining methods perform mining operations with just the latest information among huge accumulated data streams; this proposal can generate high-quality surprising results by utilizing them. The model permits the user to determine the how many windows are needed, window size, and the weight for each and every window. In this proposal, HTWRUI, we generate high transaction weighted rare utility itemsets over data streams.

Because of high speed and huge information, utility,itemset mining calculation must possess a less storage and be as quick as could reasonably be expected. The proposed approach utilizes the sliding window model that can perform mining operations concentrating on recent parts of data streams and discover that high utilityrare patterns. The old frequent pattern mining systems do not fulfill these necessities since they need to go through two or more database scans to mine. In this way, to resolve these issues, proposed approach apply mining methodologies with only one scan and data stream mining can be done efficiently. In real applications many mining algorithms have been developed to discover frequent patterns over data stream[7], [13], [14]. Lots of research has already done to extractlatestmost frequentdata from data streams using sliding window [15], [16]. Be that as it may, these algorithms are not relevant for mining rare utility elements. Unlike association mining, rare utility data mining can discover productive elements that might not show up regularly in databases.
Chu and Tseng initially proposed a utility mining strategy on the data stream, the THUI-Mine algorithm, which parts the database into several sections and scans the database more than once. Li, Yeh, & Chang [17] proposed another two algorithms given utility mining on the data stream using sliding window. However, the sliding window data be should be scanned twice, which cannot satisfy the data stream mining requirements. Also, those researches on applying utility mining on data stream cannot discover the rare utility itemsetsthat might not happenregularly in the database.The proposed approach utilizes the sliding window model that can perform mining operations concentrating on recent parts of data streams and can discover the high utility value raredata in the data stream environment.

III. Problem Definition

Definition 3.1

Utility Mining is defined as a process of discoveringthose elements with utility values greater than the user specified minimum utility thresholdfrom the transaction database [1], [18].Let theset of all itemsetsbe defined as I= {i1, i2, i3…} and T be a transaction set{T1,T2…Tn}, where each item i ε I. All transaction items in set T is given an identifier (T_ID) called transaction identifier. The utility setis defined as U= {u1, u2…}[19].Consider an example, in transaction T1 in TABLE 1, the count of items a, d, e are 1, 2, 1respectively.

Definition 3.2

An itemset X utility value is defined as u(X), is the summation of all utility values of itemset X in everytransaction that contains the itemsetX[20].

Definition 3.3

An itemset X is defined as a high utility itemset if u(X) >= minimum utility threshold (min_utility)[21], [22], [23].

Definition 3.4

The internal utility defines the amount of itemsetX in T.The internal utility of an itemsetmirrorshow oftenanitemsetoccurs in a transaction database. ConsiderTABLE 1, the internal utility of itemset a in transaction T1 is 1[24], [25], [26], [27].

Definition 3.5

The external utility of an itemsetis defined as the profit of an itemset. ConsiderTABLE 2, the external utility of itemset a is u(a) = 1[28], [29].

Definition 3.6

Theitemsets that occasionally happen in the transaction data setis defined as rare itemsets.The rare itemset with high utilities gives precious bits of knowledge to the user.

Definition 3.7

The Transaction weighted utility value of an itemset X is the sum of the transaction utility values of all the transactions containing X[1].

Definition 3.8

An itemset X is called a high-transaction weighted utility (HTWU) itemset if the transaction weighted utility value of an itemset X is not less than the minimum utility threshold value[1],[30].

Definition 3.9

The high transaction weighted rare utility (HTWRU) itemsets are itemsetsthat have support count below the minimum threshold of support specified by the user.

IV. Proposed Approach

Illustration of how the weighted sliding window model can be used effectively in data stream environment for finding out high utility value rare elements.The high utility rare elements in a weighted sliding window model data stream environment is defined asthose elementsthat have support countgreater than thesupposedminimum threshold value in the recentwindow.Extracting thesehigh utility rare itemsetsis a significant procedure in a data stream environment. Thewindow size is characterized by time and never by the transactionsize.The user canassign the window countsforthe mining process[10]. They can also assigndissimilar weights to each and everywindowdepending on the significance of data. For example, the weight of each window$wij(1 \leq \varphi \leq 4)$ ισ ασ φολλοωσ: $\alpha 1 = 0.4$, $\alpha 2 = 0.3$, $\alpha 3 = 0.2$, $\alpha 4 = 0.1$, $\sum_{j=1}^{4} \alpha j = 1$

Assigning a higher weight to a nearer window is helpful to get the result after mining nearer to client's necessities. From the TABLE 1, Transaction data at different times are illustrated. Window Wij means j varies from 1 to 4, and irepresent time.For instance, W14means Sliding windowfour at time T1.

Table1 Transaction Data at Different Times

Sliding Window At interval PT3	Sliding Window At interval PT2	Sliding Window At interval PT1	Transaction Data
		W14	T1{(a,1),(d,2),(e,1)} T2{(a,3),(b,5)} T3{(a,1),(b,2)}
	W24	W13	T4{(a,2),(b,5)} T5(c,1),(d,1)} T6{(d,3),(e,2)} T7{(b,3),(c,1)}
W34	W23	W12	T8{(a,2),(b,3), (c,2)} T9{(c,1),(d,2)}
W33	W22	W11	T10{(d,1),(e,2)} T11{(a,1),(b,1),(d,5)} T12{(c,2),(d,1),(e,5)}
W32	W21		
W31			

Table2 Utility TABLE

ITEM	UTILITY(per unit)
a	1
b	5
c	9
d	5
e	3

Table 3 Transaction TABLE with Utility Values

Transaction ID	Transaction Set	Utility
T1	T1{(a,1),(d,2),(e,1)}	14
T2	T2{(a,3),(b,5)}	28
T3	T3{(a,1),(b,2)}	11
T4	T4{(a,2),(b,5)}	64
T5	T5(c,1),(d,1)}	41
T6	T6{(d,3),(e,2)}	21
T7	T7{(b,3),(c,1)}	24
T8	T8{(a,2),(b,3)(c,2)}	35
T9	T9{(c,1),(d,2)}	19
T10	T10{(d,1),(e,2)}	11
T11	T11{(a,1),(b,1),(d,5)}	31
T12	T12{(c,2),(d,1),(e,5)}	38

Using the above TABLES, consider two cases that show the effects of weight on sliding windows in utility mining.Firstly; consider the case with sliding windows without concerning weight.Let us assume that the minimum utility threshold value is 90. The utility values of each itemsetbased on the above TABLEsare evaluated as follows.

u({a})= u({a},w11)+u({a},w12)+u({a},w13)+u({a},w14)=1×1+2×1+2×1+5×1=10
Similarly, u({b})=1×5+3×5+8×5+7×5=95
u({d})=7×5+2×5+6×5+2×5=85
u({e})= 6×3+2×3+1×3=27
From the above calculations, the high utility itemset isb.Secondly; consider the case with sliding windows concerning weight. In this case the minimum weighted utility threshold valueis characterised as the fractional value of minimum utility threshold value and number of sliding windows. Thus, minimum weighted utility threshold =90/4=22.5. The weighted utilities of itemsets based on the above TABLEsare evaluated as follows.
wu({a})=wu({a},w11)+wu({a},w12)+wu({a},w13)+wu({a},w14)=1×1×0.4+2×1×0.3+2×1×0.2+5×1×0.1=1.9
Similarly, wu({b})=1×5×0.4+3×5×0.3+8×5×0.2+7×5×0.1=18
wu({d})=7×5×0.4+2×5×0.3+6×5×0.2+2×5×0.1=24
wu({e})= 6×3×0.4+2×3×0.2+1×3×0.2=9

From the above calculations, d becomes the high weighted utility itemset.The above two calculationsimply that the window weights can influence the determination of high weighted utility itemsets. Regardless of the fact that if an itemset utilityin thehigh weighted window is low and, thetotal utility value of thatitemset is large, it may not turn into a high weighted utility itemset. Accordingly, for getting the mining result closer to user's necessities, we need to assign out a higher weight to a closer window.Thus a weighted sliding window based high weighted utility itemsets mining algorithm is proposed.An algorithm is described as follows:

Algorithm
Description: Mining high utility rare itemset in data streams based on weighted Sliding window algorithm
Min_utility threshold min_u
Size of window=t
Weight of window Wij at timeTi=αj 1≤j≤n
Compute the support count of each itemset
Step 1:Assume current time is Ti
Scan window Wij(i≤j≤n)
Suppose n=4, so scan window w1j 1≤j≤4
Evaluate 1. The transaction utility (TU) for each transaction
2. the transaction weighted utility for each item.
Step 2: Minimum weighted utility threshold min_wu=min_u/n
Step 3: Find HTWU-1 itemsets(HT1)(i.e., those itemsets whose TWU is ≥ min-wu
Step 4: By applying the weight of the sliding windows calculate the weighted utilities of each itemset from step 3.
Step 5: Find HWU 1-itemsets (H1)(i.e., those itemsets whose TWU≥min_utility)
Step 6: For each item HWU 1-itemsets (H1) if(support[H1]<min_support)and if H1 is a rare itemset then
Then H1 is a rare high utilityitemset
Step 7: For (k=2; │HTk-1│>1; k++)
Generate the set of HTWU_K itemset from HTk-1
For each HTWU_K itemsets find the transaction weighted utility itemsets TWU(X)≥min-u
For each item HWU K-itemsets (HK) if(support[HK]<min_support)
Then HK is a rare item.
Step 8: i=i+1, $PT_i=PT_{i-1}$ + t
For(j=1; j≤n-1; j++)
T i (j+1){x}= T i-1 j{x}
End
Step 9: Scan Wi1, evaluate TU for each transaction in Wi1 and TWU for each item
Step 10: Go to step 3.

V. Explanation Of The Proposed Algorithm With Examples

Let us considerthe weighted utility minimum threshold valuebe 20. We illustrated the weighted sliding window based mining process of extracting high weighted utility rare itemsets in the next sections. It consists of 2 stages.
Stage 1: Generate High Transaction Weighted Utility Itemsets.
In this step, at time PT1 every window that has transaction data are examined once as shown in TABLE 4.Then each transaction’s utility valueis generated as shown below in TABLE 5.

Table 4 Weighted Sliding Window at Time Pt1

Items	W11 α=0.1	W12 α=0.2	W13 α=0.3	W14 α=0.4
A	(1,1),(2,3), (3,1)	(5,2)	(8,2)	(11,1)
B	(2,5),(3,2)	(5,5),(7,3)	(8,3)	(11,1)
C	--------------	(4,6),(5,1),(7,1)	(8,2),(9,1)	(12,2)
D	(1,2)	(4,2),(5,1),(6,3)	(9,2)	(10,1),(11,5)
E	(1,1)	(6,2)	-------------	(12,5),(10,2)

Table5 Utility Value of each Transaction

Transaction ID	Utility
T1	14
T2	28
T3	11
T4	64
T5	41
T6	21
T7	24
T8	35
T9	19
T10	11
T11	31
T12	38

Next step is to evaluate the transaction weighted utility for each item in each window. Forexample j=4 (I.e., fourth window)transaction weighted utility value for itemset, a is calculated as the summation of utility values of T1, T2, and T3 as defined in the definition 3.8.Transaction weighted utility (a)= Transaction Utility (T1)+ Transaction Utility (T2)+ Transaction Utility (T3)=14+28+11=53
Similarly, for itemsetb is 39;for itemset c is 0, for itemsetd is14anditemsete is14.Correspondingly, transaction weighted utility for each item in all four windows is illustrated in TABLE 6.From TABLE 6, it is strong that the set ofHigh Transaction Weighted Utility Itemsets (HTWU_1-itemsets) are $\{c\}$ and$\{d\}$.
Stage2: Generate High Transaction Weighted Rare Utility (HTWRU) itemsets from HTWU itemsets. The itemsets that come under the support threshold value are called rare itemsets. Based on the rate of occurrence of high transaction weighted utility itemsets, we have to determine the rare itemsets. Let us consider the minimum threshold support value be 0.8. i.e., min_sup=0.8. Examine all the high transaction weighted utility itemsets that are mined during Phase 1 to identify those that have support value below the minimum threshold support value. Thus, the support count of all itemsetsis tabulated below.

Table 6 Transaction Weighted Utility for each item

Items	J=4	J=3	J=2	J=1	TWU
{a}	53	41	35	31	36.4
{b}	39	65	35	31	39.4
{c}	0	129	54	38	57.2
{d}	14	126	19	80	54.3
{e}	14	21	0	49	25.2

Table 7 Support Count

Item	{a}	{b}	{c}	{d}	{e}
Support count	1.0	1.0	0.6	1.0	0.6

The TABLE 7 shows that {c}, {e} are the rare items at time t1. However,since {e} is not an HTWUitemset[4],itis not mined after phase 1. Thus, from the HTWU_1-itemsets, the HTWRUitemset is {c}, as it has support value below the min_sup provided.Similarly, this approachcan discoverall rare utility valueitemsets from each sliding windows at different times.

VI. Experimental Evaluation

To extract the high utility weighted rare transaction itemsetsfrom a datastream environment, we conducted a number of experiments in various user defined parameters. Likewise, the proficiency of the proposed calculation is assessed by differing different parameters**.** The model is executed in J2SDK 1.5.0. The proposed algorithm is conductedon a machine with 3.0 GHz CPU and 8 GB memory. The experimental data used for evaluation is obtained from autility itemset mining implementations repository, FoodMart2000, Microsoft Developer Network (MSDN), NU-MineBench version 2.0 dataset and technical report.

VII. Conclusions

In this paper, HTWURI mining algorithm is proposed, for mining high utility rareitemsetusing the weighted slidingwindow model. The algorithm can perform mining operations concentrating on recent parts of data streams and can extract the rare pattern that provides outstanding profit to the user.Another exciting feature of this approach is that it can reuse the stored information efficiently toidentify all the high weighted rare utility elements.Experimental evaluations demonstrated that the proposed algorithm of mining high transaction weighted rare utility itemsets (HTWURI) based on data streamscan efficiently extract high utility weighted rare transaction itemsets.

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