Fast Algorithms for Mining Interesting Frequent Itemsets

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ABSTRACT

Certifiable datasets are inadequate, dirty and contain hundreds of things. In such situations, discovering interesting standards (comes about) using traditional frequent itemset mining approach by specifying a client defined input bolster edge is not fitting. Since with no domain knowledge, setting bolster edge little or substantial can yield nothing or a huge number of redundant uninteresting outcomes. Recently a novel approach of mining only N-most/Top-K interesting frequent itemsets has been proposed, which finds the top N interesting outcomes without specifying any client defined help edge. Be that as it may, mining interesting frequent itemsets without minimum help limit are all the more exorbitant as far as itemset look space exploration and processing cost. In this way, the efficiency of their mining profoundly depends upon three main components (1) Database representation approach utilized for itemset frequency counting, (2) Projection of relevant transactions to bring down level nodes of inquiry space and (3) Algorithm implementation technique. Thusly, to enhance the efficiency of mining process, in this paper we present two novel algorithms called (N-MostMiner and Top-K-Miner) using the bit-vector representation approach which is extremely efficient as far as itemset frequency counting and transactions projection. In addition to this, few efficient implementation techniques of N-MostMiner and Top-K-Miner are additionally present which we experienced in our implementation. Our experimental

outcomes on benchmark datasets propose that the N-MostMiner and Top-K-Miner are extremely efficient as far as processing time when contrasted with current best algorithms BOMO and TFP.

Keywords:- Datasets, Itemsets, N-MostMiner and Top-K-Miner

INTRODUCTION

Since the introduction of association rules mining by Agrawal et al., it has now turned out to be one of the main mainstays of information mining and knowledge revelation tasks and has been effectively connected in many interesting association rules mining issues, for example, sequential pattern mining, emerging pattern mining , classification, maximal and shut itemset mining. Using the help confidence framework presented in, the issue of mining the entire association rules from transactional dataset is isolated into two sections – (a) finding complete frequent itemsets with help (an itemset's occurrence in the dataset) more prominent than minimum help edge, (b) generating association rules from frequent itemsets with confidence more noteworthy than minimum confidence limit. By and by, the primary stage is the most tedious task, which requires the heaviest frequency counting operation for every candidate itemset.

Give TDS a chance to be our transactional dataset and I be an arrangement of distinct things in the TDS. Every individual transaction t in TDS consists a subset of single things, for example, tI ⊆ I. We call X an itemset, on the off chance that it contains X ⊆ I. Give min-a chance to sup be our minimum help edge, we call an itemset X frequent if its help (support(X)) is more prominent than min-sup; generally infrequent. By following the Apriori property [1] an itemset X cannot be a frequent itemset, on the off chance that one of its subset is infrequent. We denote the arrangement of all frequent itemset by FI. In the event that X is frequent and no superset of X is frequent, we say that X is a maximal frequent itemset, the arrangement of all maximal frequent itemsets is denoted by MFI. On the off chance that X is frequent and no superset of X is as frequent as X, we say that X is a shut frequent itemset; likewise the arrangement of all shut frequent itemset is denoted by FCI. In this way the following condition is straight-forward holds: MFI ⊆ FCI ⊆ FI.

The frequent itemsets mining algorithms take a transactional dataset (TDS) and min-sup as an input and yield every one of those itemsets which show up in any event min-sup number of transactions in TDS. Notwithstanding, the genuine datasets are meager, dirty and contain hundreds of things. In such situations, clients confront troubles in setting this min-sup edge to obtain their coveted outcomes. On the off chance that min-sup is set too huge, then there might be few frequent itemsets, which does not give any attractive outcome. On the off chance that the min-sup is set too little, then there might be a huge number of redundant short uninteresting itemsets, which not only takes a vast processing time for mining.

Han et al. in [18], proposed an another variation of mining Top-K frequent shut itemsets with length more prominent than a minimum client indicated limit min_l, where K is a client wanted number of frequent shut itemsets to be mined. Their work is different from [9] in this sense, if an itemset X is found infrequent at any node n, then all the supersets of X, or the subtree of n can be securely pruned away, which diminishes the general processing time.

MOTIVATION BEHIND OUR WORK

As clear from the Definition 2 depicted over, the Apriori property presented by Agrawal et al. in [1] can not be connected in mining N-most interesting frequent itemset algorithm for pruning un-interesting itemsets. Since the superset of any uninteresting k-itemset might be the N-most interesting itemset of any level h with the end goal that 1≤ h≤ kmax. In this manner, a huge territory of itemset seek space is investigated when contrasted with traditional

frequent itemset mining approach. In our different computational experiments on a few inadequate and dense benchmark datasets, we found that the efficiency of mining interesting frequent itemsets without minimum help limit exceedingly depends upon three main elements. (1) Dataset representation approach utilized for frequency counting [10]. (2) Projection of relevant transactions to bring down level nodes of pursuit space, and (3).

Algorithm implementation technique. The projection of relevant transactions at any node n, are those transactions of dataset which contain the node n's itemset as subset [11]. In this manner, to increase the efficiency of mining interesting frequent itemsets (N-Most or Top-K), in this paper we present novel efficient algorithms (N-MostMiner and Top-K-Miner) using Bit-vector dataset representation approach. The real advantage of using Bit-vector dataset representation approach in our algorithms is that, it advances the itemset frequency counting cost with a factor of 1/32, in the event that we represent 32 lines for every single vertical piece vector region [17].

TDS	The given transactional dataset
$k_{\max}$	Upper bound on the size of interesting itemsets to be found
ξ	Current support threshold for all the itemsets
ξ_k	Current support threshold for the k-itemsets

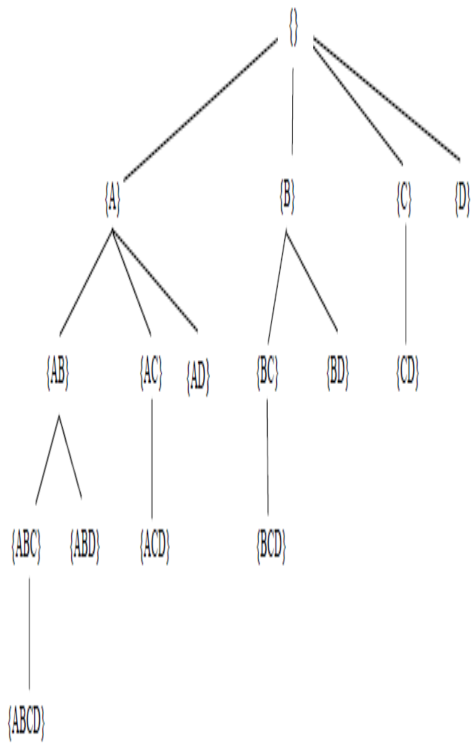
Prior to our work, Bit-vector dataset representation approach has been effectively connected in many complex association rules issues, for example, maximal frequent

itemsets mining [6], sequential patterns mining [4] and blame tolerant frequent itemsets mining [12]. In addition to dataset representation approach, this paper likewise presents a novel piece vector projection technique which we named as anticipated piece regions (PBR).

The main advantage of using PBR in N-MostMiner and Top-K-Miner is that, it consumes a little processing expense and memory space for projection. In section 5 we additionally present some efficient implementation techniques of N-MostMiner and Top-K-Miner, which we experienced in our implementation. Our different experiments on benchmark datasets recommend that mining interesting frequent itemsets without minimum help edge using our algorithms are quick and efficient than the currently best algorithms BOMO [7] and TFP [18].

ALGORITHMIC DESCRIPTION

In this section, we depict our N-most interesting itemset mining algorithm (N-MostMiner) with its few techniques utilized for quick itemset frequency counting and projection. For k-itemset representation at any node, the N-MostMiner utilizes the



transaction of dataset. In the event that thing I shows up in transaction j, then the bit j of bit-vector I is set to one; generally the bit is set to zero. In Figure1 (an) a dataset is shown along with its vertical piece vector representation in Figure1 (b). vertical piece vector representation approach [6]. In a vertical piece vector representation, there is one piece for every To count the frequency

of a k-itemset e.g. {AB} we need to play out a bitwise-AND operation on bit-vector {A} and bit-vector {B}, and resulting ones in bit-vector {AB} denotes the frequency of k-itemset {AB}.

ITEMSET GENERATION

Give < a chance to be some lexicographical request of things in Transactional Dataset (TDS) with the end goal that for each two things an and b, a ≠ b: a < b or a > b. The inquiry space of mining N-most interesting itemset mining can be considered as a lexicographical request [16], where root node contains an exhaust itemset, and each lower level k contains all the k-itemsets. Every node of pursuit space is made out of head and tail elements. Head denotes the itemset of node, and things of tail are the conceivable extensions of new youngster itemsets. For instance with four things {A, B, C, D}, in Figure 2 root's head is unfilled ⟨()⟩ and tail is made with hard and fast of things ⟨(A, B, C, D)⟩, which generates four conceivable youngster nodes {head ⟨(A)⟩: tail ⟨(BCD)⟩}, {head ⟨(B)⟩: tail ⟨(CD)⟩},{head ⟨(C)⟩: tail ⟨(D)⟩}, {head ⟨(D)⟩: tail ⟨{}⟩}. At any node n, the candidate N-most k-itemset or tyke nodes of n are generated by performing join operation on n's head itemset with every thing of n's tail, and checked for frequency or bolster counting. This itemset seek space can be navigated either by profundity initially request or expansiveness initially look. At every node, infrequent things from tail are evacuated by dynamic reordering heuristic [5] by comparing their help with all the itemsets bolster (ξ) and k-itemsets bolster (ξk) edges [7]. In addition to this, our algorithm additionally arrange the tail things by decreasing space is more beneficial and helpful.

k-ITEMSETFREQUENCY CALCUATION

To check, regardless of whether any tail thing X of node n at level k is N-most interesting k-itemset or not, we should check its frequency (bolster) in TDS. Calculating itemset frequency in bit-vector representation requires applying bitwise-∧ operation on n.head and X bit-vectors, which can be implemented by a circle; which we

call straightforward circle, where every iteration of basic circle apply bitwise-∧ operation on some region of n.head with X bit-vectors. Since 32-bit CPU bolsters 32-bit ∧ per operation, hence every region of X bit-vector is made out of 32-bits (represents 32 transactions). In this manner calculating frequency of each itemset by using basic circle requires applying bitwise-∧ on all regions of n.head with X bit-vectors. Be that as it may, when the dataset is meager, and every thing is present in couple of transactions, then
counting itemset frequency by using basic circle and applying bitwise-∧ on those regions of bit-vectors which contain zero involves many unnecessary counting operations. Since the regions which contain zero, will contribute nothing to the frequency of any itemset, which will be superset of k-itemset. Hence, removing these regions from head bit-vectors (using projection) in prior phases of inquiryspace is more beneficial and helpful.

BIT-VECTOR PROJECTION USING PROJECTED-BIT-REGIONS (PBR)

For efficient projection of bit-vectors, the objective of projection ought to be, for example, to bitwise-∧ only those regions of head bit-vector ⟨bitmap(head)⟩ with tail thing X bit-vector ⟨bitmap(X)⟩ that contain an esteem more noteworthy than zero and skip all others. Clearly to do this, our counting strategy must be so effective and have some information which guides it, that which regions are important and which ones it can skip. To accomplish this objective, we propose a novel piece vector projection technique PBR (Projected-Bit-Regions). With projection using PBR, every node Y of pursuit space contains a variety of legitimate region indexes PBR⟨Y⟩ which controls the frequency counting system to navigate only those regions which contain an index in cluster and skip all others.

Figure 3 demonstrates the code of itemset frequency calculation using PBR technique. In Figure 3, the line 1 is retrieving a substantial region index ℓ in ⟨bitmap (head)⟩, while the line 2 is applying a bitwise-∧ on ⟨bitmap (head)⟩ with ⟨bitmap (X)⟩ on region ℓ. One main advantage of bit-vector projection using PBR is that, it consumes a little processing cost for its creation, and hence can be effectively connected on all nodes of hunt space. The projection of tyke nodes at any node n can be made either at the season of frequency calculation if unadulterated profundity initially seek is utilized, or at the season of creating head bit-vector if dynamic reordering is utilized. The system of creating PBR⟨X⟩ at node n for tail thing X is as; when the PBR of ⟨bitmap(n)⟩ are bitwise-∧ with ⟨bitmap(X)⟩ a basic check is perform on each bitwise-∧ result. On the off chance that the estimation of result is more prominent than zero, then an index is assigned in PBR⟨n.head ∪ X⟩. The arrangement of all indexes which contain an esteem more prominent than zero makes the projection of {n.head ∪ X} node.

MEMORY REQUIREMENT

Some different advantages of projection using PBR are that, it is an extremely versatile approach and consumes little amount of memory during projection and can be material on huge inadequate datasets. Versatility is accomplished as; we know that by traversing seek space top to bottom initially arrange; a single tree way is investigated whenever. In this way a single PBR exhibit for each level of way needs to remain in memory. As a preprocessing step a PBR cluster for each level of greatest way is made and stored in memory. At k-itemset generation time different ways of inquiry space (tree) can share this most extreme way memory and don't need to make any additional projection memory during itemset mining.but also increases the complexity of filtering un-interesting itemsets. In both situations, the ultimate goal of mining interesting frequent itemsets is undermined. We refer the readers [7] for further reading about the problem of setting this user defined *min-sup* threshold without any previous domain knowledge about the dataset. For handling such situations, Fu et al. in [9] presents a novel technique of mining only N-most interesting frequent itemsets without specifying any *min-sup* threshold. The problem of mining N-most interesting frequent itemsets of size k at each level of $1 \leq k \leq k_{max}$, given N and k_{max} can be considered from the following definitions.

MINING TOP-K FRQUENT CLOSED ITEMSET

In mining Top-K frequent shut itemsets, we incorporate a similar system for itemset generation, frequency counting and projection, as we have portrayed for N-Most all frequent itemset mining in above sections. The only one major difference is that, a frequent shut itemset is considered to be Top-K only when none of its superset found to be Top-K frequent shut itemset. This shut frequent itemset superset checking can be implementation using a clear sequential searching technique, and could take vast processing time if the K estimate is given to be substantial. In mining Top-K frequent shut itemset there is no concept of k-itemset bolster edge at each level, consequently only the minimum help limit of all the itemset ξ is set to zero. With ξ = 0 we would blindly include any itemsets in our current arrangement of Top-k frequent itemset with minimum length more prominent than min_l. Once the algorithm encountered any k-th itemset, we can securely set the minimum help edge of ξ by assigning to it the minimum incentive among the help of the Top-k frequent itemsets found up until now. Next only that itemset will be included the Top-k frequent itemsets result, which will contain the help and minimum length more prominent than ξ

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and min_l. Figure 6 demonstrates the pseudo-code of mining Top-K-Miner

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Top-k-ClosedMiner (Node n)

(1)     for each item X in n.tail
(2)     for each region index ℓ in PBR⟨n⟩
(3)     AND-result = bit-vector[ℓ] ∧ head_bit_vector of n [ℓ]
(4)     Support[X] = Support[X] + number_of_ones(AND-result)
(5)     Remove infrequent items from n.tail, if support less than ξ
(6)     Reorder them by decreasing support
(7)     for each item X in n.tail
(8)     m.head = n.head ∪ X
(9)     m.tail = n.tail – X
(10)    for each region index ℓ in PBR⟨n⟩
(11)    AND-result = bit-vector[ℓ] ∧ head-bit-vector[ℓ]
(12)If AND-result > 0
(13)  Insert ℓ in PBR⟨m⟩
(14)  head bit-vector of m [ℓ] = AND- result
(15)    Top-k-ClosedMiner (m)
(16)    if none of (n.head) superset itemset is frequent closed Top-K itemset
(18)    Top_k_List = Top_k_List ∪ n.head

(19)    if Top_k_List == kth itemset
increase the support ξ by assigning minimum value support of Top_k_Lis
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EFFICIENT IMPLENATION TECHNIQUES

In this section, we give some efficient implementations thoughts, which we experienced in our N-MostMiner and Top-K-Miner implementations. ELIMINATION REDUNDANT FREQUENT COUNTING OPERATIONS (ERFCO) The codes which we depict in Figure 5 and Figure 6 performs precisely two frequency counting operations for each frequent tail thing X at any node n of pursuit space. To begin with, at the season of performing dynamic reordering, and second, to create {X∪ n.head} bit-vector. The itemset frequency calculation process which is considered to be the most expensive task (penalty) in general itemset mining [10], the bit-vector representation approach languishes this penalty twice over each frequent k-itemset. The second counting operation which we can state is redundant, happens because of gain efficiency in 32-bit CPU and can be eliminated with some efficient implementation, which we portray beneath.

In N-MostMiner, toward the begin of algorithm two vast piles, one for head bit-vectors and one for PBR are made (with 32-bit per stack space estimate). Next, at the season of calculating frequency of k-itemset X a straightforward check is performed to ensure that is there sufficient space left in the two stores. On the off chance that the response is "yes" then the head bit-vector of X and PBR⟨X⟩ are made in the meantime when dynamic reordering is performed, generally normal technique is taken after. The main difference is that, with the efficient implementation bitwise-∧ results and regions indexes are written in piles instead of tree way levels recollections. The span of piles ought to be enough to the point that it can store any frequent thing subtree. From our implementation point of view, we propose that stack measure twofold the aggregate number of transactions is enough for expansive inadequate datasets. In our N-MostMiner and Top-K-Miner implementations we found that it totally eliminates the second frequency counting operation while requiring almost no amount of memory.

INCREASING PROJECTED BIT-REGIONS DENISTY (IPBRD)

The bit-vector projection technique which we depicted in section 3.3 does not give any compaction or compression mechanism for increasing the density in things bit-vector regions. Accordingly, on the inadequate dataset only one or two bits in every region of thing bit-vector are set to one, which not only increases the projection length yet in addition with this, it is not conceivable to accomplish genuine 32-bit CPU performance. In this way, to increase the density in bit-vector regions the N-MostMiner and Top-K-Miner begins with a cluster list [15]. Next at root node, a bit-vector representation for each frequent thing is made which gives sufficient compression and compaction in bit-vectors regions. Sufficient improvements are obtained in our algorithms by using this approach.

2-ITEMSET PAIR

There are two techniques to check whether current candidate k-itemset is frequent or infrequent. To begin with, to straightforwardly register its frequency from TDS. Second one, which is more efficient, is known as 2-Itemset combine. On the off chance that any 2-Itemset match of any candidate k-itemset is found infrequent, then by following Apriori property [1], the candidate k-itemset will be additionally infrequent. We know any k-itemset which contains a length more than two, is the superset of its entire 2-Itemset sets. In this way, before counting its frequency from transactional dataset, our algorithms check its 2-Itemset sets. On the off chance that any match is found infrequent (bolster not exactly ξk or ξ), then that k-itemset is naturally considered to be infrequent without checking its frequency in TDS.

PERFORMANCE EVALUATION

In this section we report our performance aftereffects of N-MostMiner and Top-K-Miner on a number of benchmark datasets. For experimental reason we utilized the original source code of BOMO, which is unreservedly accessible at http://www.cse.cuhk.edu.hk/~kdd/program.html. Unfortunately, there is no freely accessible implementation of TFP, so in experiments we utilized our own implementation which is written in C language. All the source codes of N-MostMiner and Top-K-Miner are written in C language. The experiments are performed on 3.2 GHz processor with main memory of size 512 MB, running windows XP 2005 professional. For experiments, we utilized the benchmark datasets accessible at http://fimi.hi.cs.datasets. These datasets are frequently utilized as a part of many frequent itemset mining algorithms. For definite performance evaluation we ordered the datasets into four different gatherings and select one or two datasets from each gathering. Our first gathering is made out of BMS-WebView1, BMS-WebView2 and Retail datasets. These datasets have a huge number of things yet modest number of transactions and are inadequate. We pick BMS-WebView2 for performance comparison. Our second gathering is made out of BMS-POS and Kosarak datasets. These datasets have many things and additionally substantial number of transactions. In the event that the minimum help is given to be little, these datasets generates immense number of frequent itemsets. We picked BMS-POS for performance comparison. Our third gathering is made out of Chess, Connect, Pumsb, Pumsb-star, accidents and Mushroom datasets. These datasets are exceptionally dense and right around 90% of time is spend on writing frequent itemsets to yield record, if the minimum help is given to be little. We pick Mushroom and Chess for performance comparison. Our last gathering is made out of T10I4D100K and T40I10D100K. These datasets are exceptionally scanty and have vast number of things. We select both datasets for performance comparison. Table 1 demonstrates the description of datasets that we utilized as a part of our experiments.

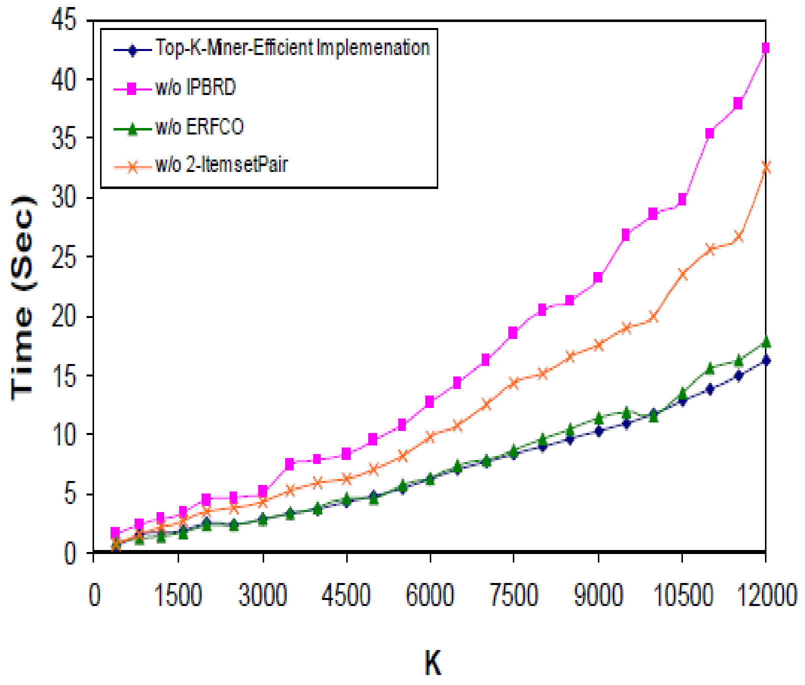

Figure 7: Efficient Implementation Components Performance Results T1014D100K dataset

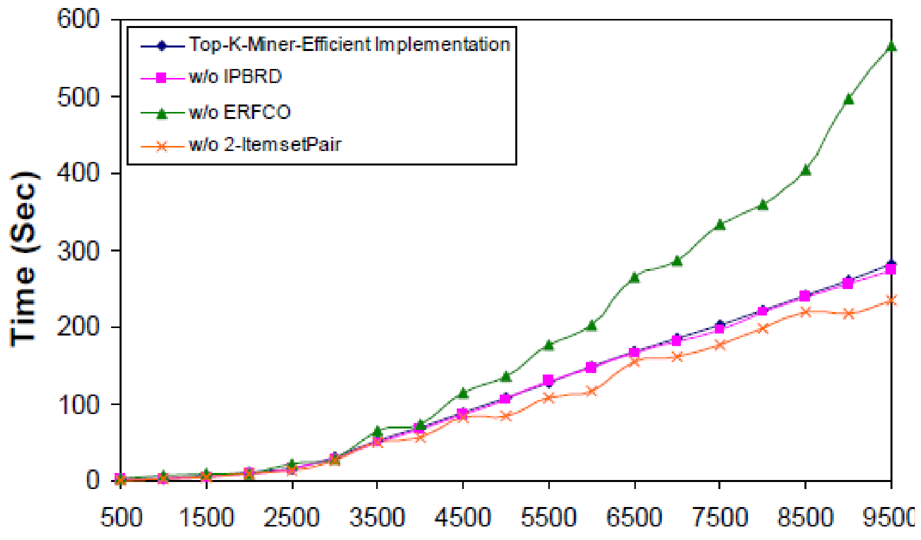

Figure 8: Efficient Implementation ComponentsPerformance Results Of On Chess Dataset

Dataset	Items	Average Transaction Length	Records
T10I4D100K	1000	10	100,000
T40I10D100K	1000	40	100,000
Chess	75	35	3196
Mushroom	119	23	8124
BMS-POS	1658	7.5	515,597
BMS-WebView2	3341	5.6	77,512

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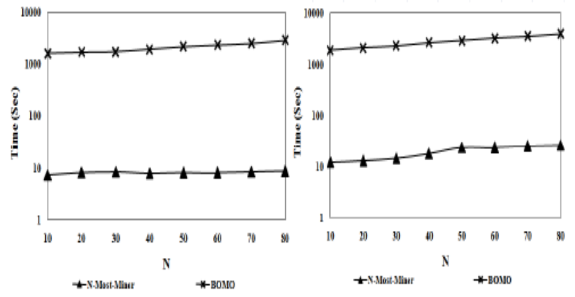
Table 1: Computational Experiments in .

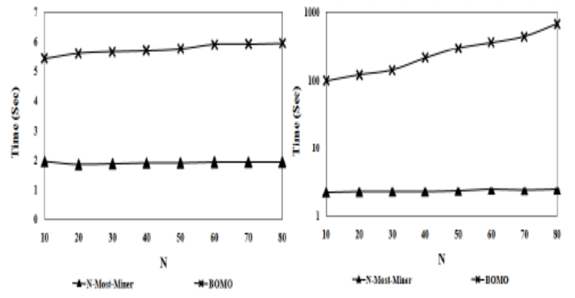
(a) $k_{max} = 5$ (b) $k_{max} = 10$

Figure 11: Performance results on T1014D100K dataset



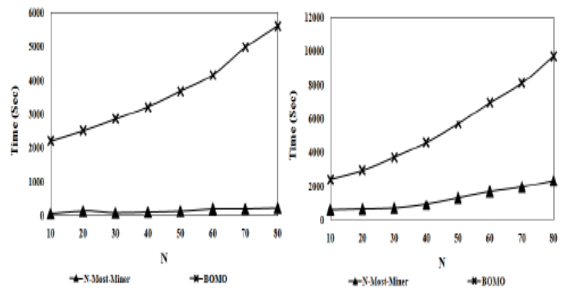
(a) $k_{max} = 5$ (b) $k_{max} = 10$

Figure 12: Performance results on T40I10D100K dataset



(a) $k_{max} = 5$ (b) $k_{max} = 10$

Figure 13: Performance results on BMS-WebView2 dataset



(a) $k_{max} = 5$ (b) $k_{max} = 10$

Figure 14: Results of performance on BMS-POS dataset

PERFORMANCE EVALUATION OF N-Most-Miner

We play out our computational experiments using the different N-most esteems 10, 20, 30, 40, 50, 60, 70 and 80 under two kmax limits esteems, kmax = 5 ((1≤ k≤ 5) and kmax = 10 ((1≤ k≤ 10). The performance measure is the execution time of the algorithms under different N and kmax edge esteems. Figures 9-14 comes about demonstrate that the N-MostMiner beats the BOMO on both all and shut frequent itemsets mining issues, on all levels of mining edges on a wide range of meager and dense datasets. This is expected to its quick frequency counting of k-itemset, projection and efficient implementation techniques. While the BOMO requires a few indirect memory gets to during every k-itemset frequency counting, which moderates down the entire mining process. Figure 9 and 10 demonstrate the performance consequences of two algorithms on dense sort datasets (chess and mushroom). These datasets contain a couple of numbers of things however a maximal transactional length which is same in all transactions. Because of the modest number of transactions, the performance consequence of kitemset frequency counting using bit-vector representation approach is more efficient when contrasted with pattern-development approach. In spite of the fact that in these datasets a substantial number of transactions share a common way in FP-tree. Figure 11 to 14 demonstrate the performance aftereffects of two algorithms on four meager sort datasets both genuine and synthesized. Again the N-MostMiner outflanks the BOMO algorithms on all kind of mining edges on all sort of scanty datasets. On experiments with meager sort datasets we note that BOMO takes a substantially bigger time for its initial FP-tree construction, when ξk (1≤ k≤ kmax) and ξ are both equivalent to zero. Actually, on meager sort datasets N-MostMiner (in the vast majority of the cases) finishes its execution, when BOMO occupied in its initial FP-tree construction. The reason is that, on meager datasets with substantial number of things and little normal transaction length, the greater part of the transactions can't share a common prefix way in FP-Tree that outcomes in a substantial initial FP-Tree construction, which backs off the itemset frequency counting. The performance consequences of our efficient implementation techniques of N-MostMiner particularly 2-Itemset Pair and IPBRD are all the more encouraging on inadequate sort datasets when contrasted with dense sort datasets.

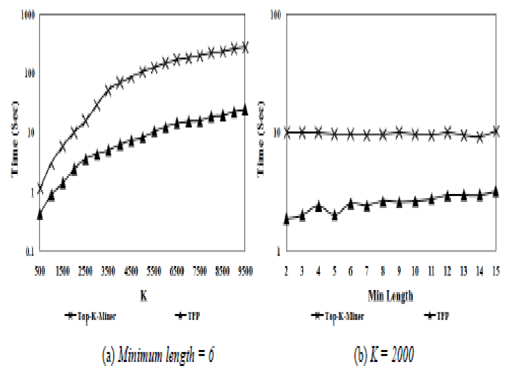


Figure 15: Performance results of Top-K-Miner on Chess dataset

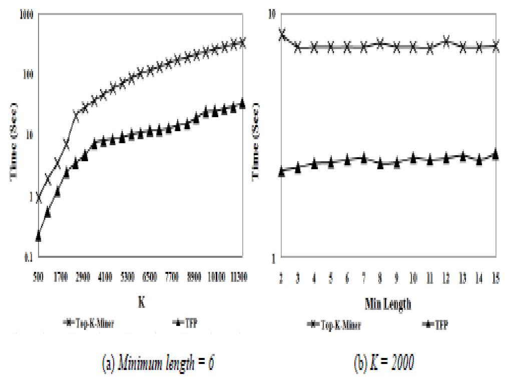


Figure 16: Performance results of Top-K-Miner on Mushroom dataset

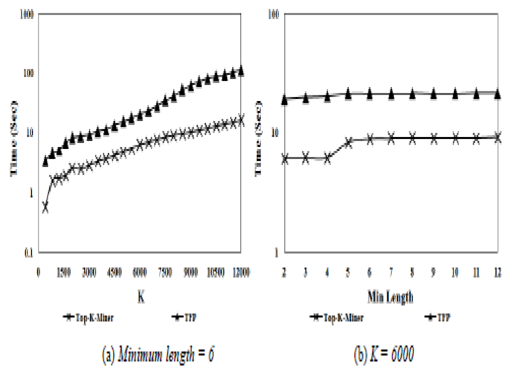


Figure 17: Performance results of Top-K-Miner on T1014D100K dataset

PERFORMANCE EVLATUATION OF TOP-K-MINER

Our second arrangement of experiments were on mining Top-K shut frequent itemsets mining with minimum length more noteworthy than min_l edge. The experiments were performed on each dataset using two different scenarios. In to start with, we settled the minimum length and fluctuated the K esteem. While in second, the K esteem was kept settled and minimum length was changed. Figure 15 and 16 demonstrate the performance aftereffect of TFP and Top-K-Miner on two dense sort datasets (Chess and Mushroom). Because of modest number of things and extensive normal transactional length, TFP makes a minimal initial FP-Tree, in which parcel of transactions shares a common prefix way, which helps in quick itemset frequency counting. On dense sort datasets, we note that the efficient implementation techniques of Top-K-Miner particularly 2-Itemset Pair and IPBRD does not make any significant performance impact, only frequency counting dominates the entire algorithm execution result. Figure 17 to 20 demonstrate the performance comes about on two algorithms on scanty sort datasets. As clear from the figure comes about the Top-K-Miner outflank the TFP on all levels of mining limit esteems, due to its efficient piece vector projection and implementation techniques particularly 2-Itemset Pair and IPBRD. On save datasets with huge number of things and transactions, TFP faces an indistinguishable issue from BOMO of ts initial FP-Tree construction, when ξ equivalent to zero, which backs off the entire algorithm execution.

CONCLUSION

Mining interesting frequent itemsets without minimum help limit are all the more exorbitant regarding processing time because of huge range of itemset look space exploration when contrasted with traditional frequent itemset approach. Because of huge number of candidate itemsets generation, the efficiency of mining interesting (N-Most or Top-K) frequent itemsets algorithm very depends upon the two main elements – (a) Dataset representation approach for quick frequency counting – (b) Projection of relevant transactions to bring down level nodes of pursuit space. In this paper we present two novel algorithms for mining interesting frequent itemset (N-MostMiner and Top-K-Miner) using bit-vector representation approach, which is exceptionally efficient regarding candidate itemset frequency counting. For projection we present a novel piece vector projection technique PBR (anticipated piece regions), which is exceptionally efficient regarding processing time and memory requirement. A few efficient implementation techniques of N-MostMiner and Top-K-Miner are likewise presented, which we experienced in our implementation. Our experimental outcomes on benchmark datasets propose that mining interesting frequent itemsets without minimum help edge using N-MostMiner or Top-K-Miner is very efficient as far as processing time when contrasted with currently best algorithms BOMO and TFP. This demonstrates the effectiveness of our algorithm.

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