Reduction of Frequent Itemsets Mining in Big Data with the Help of FP Algorithm and Msegt-Tree

Srinivasa Rao Divvela, V Sucharita

Abstract: Frequent itemset mining is very crucial to minimize the cost and time of executions but when considering multiple distributed data streams in big data the frequent itemset mining has been a little cost consuming and taking more space and time complexity. In this paper we reduce the load and minimize the cost while minimizing the space and time complexities of the process by using reduction mechanism and indexing structures for preserving complexities. A 2-level architecture modal which will be helpful in handling the distributed data streams where the root node will be in level-0 and local nodes at level-1 is proposed. Each local node will evaluate the patterns in their specific data stream using the algorithm ‘FP’ which will help in lessening the burden on the root node and will be sent to root. With help of the patterns received from local nodes the root will generate a global pattern set.

Key Words: Frequent Itemset Mining, Distributed Data Streams, Indexing Structures, Space and Time Complexity.

I. INTRODUCTION

With technology upgrading day to day field that is used to analyze and extract information from too large or complex datasets by using data processing application software called big data is vastly used. Big data is characterized by 3V’s: Volume, Variety and Velocity of data must be processed. By analyzing the past and the real time data can be used to improve their marketing strategies to satisfy the customer needs. Different branches of information found in the big data include: Comparative analysis which means compare the one company products with those of its competition. The uncertain data in an organization is accounted before it is used in big data analytics. Information technology also needs to ensure that they have enough accurate data available to produce correct results. Big data brings new and existing opportunities to companies who utilize the platforms available. Processing large datasets when coupled with hadoop distributed file systems can be used to handle big data is the programming methodology of the map reduction in big data. It has the capability to handle structured as well as unstructured data. Knowledge identification through data mining technique is a kind of technique for learning from databases. At the end of the day Data Mining is extraction of fascinating examples or learning’s from enormous quantity of information. Fundamentally, it manages information recovery from vast databases relying upon the particular goal shown by every customer in a conceivable situation. Information Mining is to find learning in huge social database that finds coordinating outcomes in enormous number of datasets.

II. RELATED WORK

| S.No | Algorithm Name                          | Author Name                  | Year | Disadvantage                                |
|------|----------------------------------------|------------------------------|------|---------------------------------------------|
| 1.   | A-CLOSE                                | Nicolas Pasquier             | 1999 | Costly when mining long patterns or with low minimum support thresholds in large databases |
| 2.   | CHARM (Closed Association Rule Mining) | Mohammed Jawed Zaki, Chung-Ju Hsiao | 1999 | It does not work well in higher support of order of magnitude. |
| 3.   | CLOSET                                 | Jian Pei, Jawei Han, Runying Mao | 2000 | It does not work well in lower support of order of magnitude. |
| 4.   | CLOSET+                                | Wang J, Han J, Pei J         | 2003 | Work well for datasets with small average row length. |
| 5.   | CARPENTER (Combining Columns and Row)  | Pan F, Cong G, Tung AKH, Yang J, Zaki M | 2003 | Encounters problem for datasets that have large number of rows and features |
| 6.   | COBBLER (Combining Columns and Row)    | Pan F, Cong G, Xu X          | 2004 | It cannot make full use of the minimum support threshold to prune search space. As a result, experiments |

III. PROBLEM & PROCEDURE

When we look upon a distributed system it has N number of data streams in it which are over looked by their corresponding local nodes and the overall performance is looked up by the root node. Let L1,L2,……Ln are the local nodes for D1,D2,……Dn data streams. The calculation of the frequent items is done at the root node which is the union of all the sets from the local nodes which is D1 U D2 U…..Dn. Let F = {f1,f2,……,fn} are the obtained sets of items from their respective nodes. The below figure depicts a 2-level architecture modal which will be helpful in handling the distributed data streams where the root node will be in level-0 and local nodes at level-1. Each local node will evaluate the patterns in their specific data stream using the algorithm ‘FP’ which will help in lessening the burden on the root node and will be sent to the root node. The root node with help of the patterns received from local nodes will generate a global pattern set. If a change happens in any of the local node then immediately the updated set will be sent to the root node for updating. This will significantly reduce the load on root node and minimize the communication cost along with maintaining the root node updated all the times.

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IV. ALGORITHMS & IMPLEMENTATION

Processing at local node:
Each local node will evaluate the patterns in their specific data stream using the algorithm ‘FP’ which will help in lessening the burden on the root node and will be sent to the root node. If a change happens in any of the local node then immediately the updated set will be sent to the root node for updating.

Algorithm ‘FP’
1. START ‘FP’
2. In descending order arrange all the itemsets FIS (frequent itemsets) with respect to their sizes.
3. If FIS of size n then
   4. RFIS ← FISn
   5. Where n is the largest FIS &RFIS is the reduced set to forward to root
   6. End if
   7. If remaining FISi , i<n-1 then
      8. If FISi not in Subset (RFIS) then
         9. RFIS ← FISi
      10. End if
     11. End if
     12. Return RFIS
     13. END ‘FP’

The root node with help of the patterns received from local nodes will generate a global pattern set. We implement the indexing algorithms for obtaining the global set of frequent items. Let’s see two indexing algorithms best suited for the extraction. They are as follows:

I-List Algorithm:
This algorithm stores data in the form a linked list where the index value and frequent item value will be stored in the list.
1. procedure L_list (new local itemset pi)
2. H=H-list(pj)
3. mpre0 ← φ
4. for n:=H do
   5. mprep = mprep + n_i; count = 1; n_i = n_p;
   6. while count < p_i.length do
      7. flag=false; count++;
      8. for n_i : N_c do
         9. if n_i == H.next() then
            10. mprep = mprep + n_c; n_i = n_c
            11. flag=true;
            12. break;
         13. end if
      14. end for
      15. if flag=false then
         16. break;
      17. end if
      18. end while
   19. if mprep < mprep.size then
      20. mprep = mprep
   21. end if
22. end for
23. return MsegT after p_i being inserted.
24. end procedure

Seg-Tree Modified Algorithm:
There are 3 steps for the calculation of the patterns required at the root node which are
1. Prefix matching – to identify local node itemsets sent to root.
2. Attribute value updation – for every new set inserted the value has to be updated for processing.
3. Final global frequent itemset extraction – this again has 2 stages
   i. Global sets extraction
   ii. Global frequent sets extraction
1. procedure MsegT-GFI(H) → where H is pointer to H-list
2. gfi ← φ, GFI ← φ → where gfi and GFI are the sets of global frequent items and itemsets respectively
3. for each item i in H-list do
   4. Traverse the list by ref
   5. ζ_totali ← φ
   6. for each node in ref list of i do
      7. if |ζ_totali| ≥ θ then
         8. break;
      9. else
         10. ζ_totali = ζ_totali ∪ ζ
      11. end if
     12. end for
    13. if ζ_totali ≥ θ then
       14. gfi ∪ [i]
    15. end if
   16. end for
17. SubSeq ← SUBSEQUENCE(gfi)
18. Sort the SubSeq in decreasing order of size of their itemset.
V. EVALUATIONS

The evaluation is done on the basis of the performance exhibited by the proposed methodology and some of the existing models. The evaluation shows that the FP algorithm gives us relatively high compression ratio and minimizes the communication cost. The both space and time complexity is greatly minimized with the help of Seg-Tree modified algorithm.

VI. CONCLUSION

In real-time distributed relational data streams data summarization is very crucial and impractical situation. So that for an outstanding data summarization on uncertain data streams an efficient system is needed to helps in continuously growing data environment. The proposed model solved the problem of global frequent itemset extraction when a union of data streams are involved. FP algorithm maximizes process speed as the load on root node is cut off and also it minimizes the communication cost for the nodes. Seg-Tree reduces the space and time complexities for the calculation of the itemsets. Further implications can be brought by using these approached in Utility mining and increasing the security factors.

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