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Improved FTWeightedHashT Apriori Algorithm on Big Data using Hadoop-MapReduce Model

ABSTRACT

Mining frequent itemset on big datasets is almost being the most important problem on data mining. Apriori is the best-known basic algorithm for frequent itemset mining. Due to the drawbacks of Apriori algorithm, many improvements were done to make Apriori better, efficient and faster. We have reviewed over 100 papers related to this work that include enhancements be done to improve Apriori algorithm. Weighted based Apriori and Hash Tree based Apriori are the most significant improvements. One of the recent papers integrated the weight concept of weighted Apriori and Hash tree construction concept of Hash Tree Apriori to produce a hybrid Apriori algorithm named WeightedHashT. In this study, we aim to propose a new approach to improve WeightedHashT Apriori algorithm on big data using Hadoop-MapReduce model by employing the transaction filtering technique. The experiment of this work using different datasets manifest that the proposed algorithm is efficient and effective in term of execution time.

Keywords: [Big Data, Hadoop, MapReduce, Apriori, Frequent Itemset Mining]

1. INTRODUCTION

We swim in a sea of data and the level of the sea is increasing rapidly. Seemingly, we are actually living in the data age. Terabytes or petabytes of data pours into our computer networks, the World Wide Web (WWW), and various data storage devices every day from business, society, science and engineering, medicine, and almost every other aspect of daily life. This explosive growth of available data volume is a result of the computerization of our society and the fast development of powerful data collection and storage tools. Big data is the science of analyzing high volumes of diverse data in near-real time [1]. The computerization of our society has substantially enhanced our capabilities for both generating and collecting data from diverse sources. A tremendous amount of data has flooded almost every aspect of our lives. This explosive growth in stored or temporary data has generated an urgent need for new techniques and automated tools that can intelligently assist us in transforming the vast amounts of data into useful information and knowledge. This has led to the generation of a promising and brilliant frontier in computer science called data mining. Data Mining is the method to gain new models for data analysis in order to get benefits of business [2]. It is also a process of discovering unknown and useful information from large databases. Data mining methods involve several common classes of data mining techniques according to function and application purpose: outlier detection, association rule mining (ARM), classification, clustering, regression, summarization, and mining time-series data. The need for data mining algorithms is to handle and process the massive data. Big Data algorithms analyze the huge amount of information, reveal the association rules, hidden patterns, trends and the other meaningful information. Among them, association rules is the most popular one. Many business enterprises accumulate large quantities of data from

their day-to-day operations. For example, huge amounts of customer purchase data are collected daily at the checkout counters of grocery stores. Retailers are interested in analyzing the data to learn about the purchasing behavior of their customers. Such valuable information can be used to support a variety of business-related applications such as marketing promotions, inventory management, and customer relationship management. To address the aforementioned issues, association analysis comes in, which is useful for discovering interesting relationship hidden in a large datasets. The uncovered relationships can be represented in the form of association rules or sets of frequent items.

Association Rule Mining (ARM) is the process of finding the co-occurrences between items in a given dataset and describing the association relationship among different items. There are many studies have been proposed for association rule mining on big data. The most used algorithm is Apriori. To address the drawbacks of Apriori, number of methods have proposed such as [3][4][5-15]. The common drawback in these algorithms is a delay in execution time. We have noted that the latest study [4] is efficient to improve the performance of Apriori on MapReduce implementation in term of time execution as well as memory utilization; it was designed by combining the benefits of weighted Apriori algorithm and Hash tree Apriori algorithm to get a hybrid Apriori algorithm called "WeightedHashT" whereas, the result that they have introduced is about 50 Mb of memory utilization and about 9900 ms for execution time. With respect to their study, we consider that there is a delay on execution time especially when the data increasing exponentially. Increasing the volume of data with various types; structured, unstructured, and/or semi-structured needs to be processed in fast way by using different architecture than the existed ones. A distributed architecture is able to serve as an umbrella for many different systems. Hadoop is just one example of a framework that can bring together a broad array of tools and services such HDFS and MapReduce for splitting a given big task into small-tasks and running them in parallel way. Thus, the proposed work aims to improve the algorithm presented in [4] by reducing the complexity of time execution to get the best result in finding the frequent itemset on big data using Hadoop-MapReduce model.

The proposed work is conducted with boundaries such that, we focused only in generating frequent itemset on big datasets, So generating association rules is not considered. Therefore, will not consider the measure confidence that used in Apriori algorithm.

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71 2. RELATED WORKS

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The most famous algorithm in ARM is Apriori which has been proposed in 1993 by Agrawal [16]. A number of Apriori based algorithms have been proposed to minimize the execution time, reduce the memory consumption, and to enhance the scalability [3][4][5-15][17-19].

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Y. Xun et. Al. [17] designed a parallel frequent itemsets mining algorithm called FiDooP using the MapReduce programming model. To achieve compressed storage and avoid building conditional pattern bases, their proposed algorithm, FiDooP, incorporates the frequent items ultrametric tree, rather than conventional FP trees. In FiDooP, three MapReduce jobs are implemented to complete the mining task. In the crucial third MapReduce job, the mappers independently decompose itemsets, the reducers perform combination operations by constructing small ultrametric trees, and the actual mining of these trees separately. They implemented FiDooP on their in-house Hadoop cluster. They also developed a workload balance metric to measure load balancing across the cluster's computing nodes. Their developed metric called FiDooP-HD, an extension of FiDooP, to speed up the mining performance for high-dimensional data analysis. The reason behind their proposed algorithm is to solve the scalability and load balancing challenges in the existing parallel mining algorithms for frequent itemsets.

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91 D. Apiletti et. Al. [18] did a comparative analysis which reviewed Hadoop- and Spark-based
92 scalable algorithms addressing the frequent itemset mining problem in the Big Data domain
93 through both theoretical and experimental comparative analyses. The main contributions of
94 their survey are the following: 1) A theoretical analysis of the algorithmic choices that have
95 been proposed to address the itemset mining problem in the Big Data context by means of
96 MapReduce, with the analysis of their expected impact on main memory usage, load
97 balancing, and communication costs. 2) An extensive evaluation campaign to assess the
98 reliability of our expectations. Precisely, we ran more than 300 experiments on 14 synthetic
99 datasets and 2 real datasets to evaluate the execution time, load balancing, and
100 communication costs of five state-of-the-art parallel itemset mining implementations. 3) The
101 identification of strengths and weaknesses of the algorithms with respect to the input dataset
102 features (e.g., data distribution, average transaction length, number of records), and specific
103 parameter settings. 4) The discussion of promising open research directions for the
104 parallelization of the itemset mining problem.

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106 S. Singh et. Al. [19] introduced six factors which affecting performance of MapReduce based
107 Apriori on Hadoop cluster. They have investigated the factors that significantly affects the
108 execution time of MapReduce based Apriori running on homogenous and heterogeneous
109 Hadoop clusters. Factors are specific to both algorithmic and non-algorithmic improvements.
110 Considered factors specific to algorithmic improvements are filtered transactions and data
111 structures. The non-algorithmic include speculative execution, nodes with poor performance,
112 data locality & distribution of data blocks, and parallelism control with input split size. They
113 claimed that these factors are important that influence the performance.

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115 Singh et. Al. [3] has implemented the Apriori algorithm on MapReduce framework for the
116 central structures hash tree, trie, and hash table trie and evaluated the execution time of
117 Apriori algorithms for these data structures in MapReduce context. This study considers
118 three data structures in Java to be used in MapReduce code. In sequential computing
119 environment, trie outperformed hash tree experimentally as well as theoretically. Hash table
120 trie theoretically accelerates the Apriori algorithm but experimentally could not success. In
121 their experiment on Hadoop cluster, trie outperforms hash tree as usual but hash table trie is
122 outstanding among the three data structures for both real-life and synthetic datasets. Their
123 paper discussed the execution times of three algorithms on dataset T10I4D100K with
124 minimum support of 0.02.

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126 However, Sumithra et. al. [4] have proposed hybrid Apriori association rule algorithm which
127 combined the benefits of both hash tree and weighted Apriori algorithms "its tree-based
128 hybrid approach". In their proposed system, the selected synthetic data sets contain
129 numerous numbers of transaction. From these transactions, it is needed to predict the items
130 in the transactional dataset. For predicting the frequent items and association rules in the
131 transactional dataset, it generally consume lot of memory storage and time. To overcome
132 the problem, their new proposal computes the frequent pattern without the generation of
133 candidate itemsets. Tree based mining approach is used to reduce the consumption of
134 memory usage in the association rule prediction during reducing phase. It uses correlation-
135 based approaches to optimize the process. Their work conclude on implementation of new
136 improved WeightedHashTrie Apriori algorithm which termed as hybrid algorithm in Hadoop-
137 MapReduce environment. In their proposed algorithm, they selected retail and mushroom
138 datasets.

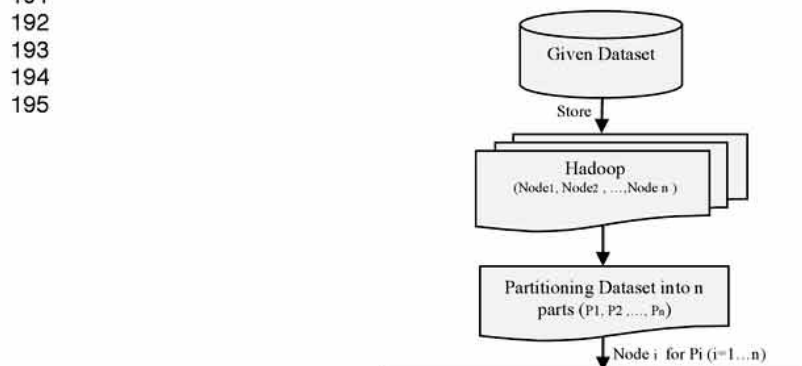
140 3. PROPOSED WORK

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142 Although WeightedHashTrie succeeded in extracting frequent itemsets, it consumes more time
143 to execute because of multi scans of dataset where the scanning process include frequent

and infrequent itemsets. To address this problem, we proposed a novel approach named "FTWeightedHashT" (Filtered Transaction Weighted Hash Tree). The framework (Figures 1-2) of the proposed algorithm works as follows: A given dataset will be processed in parallel way in Hadoop cluster with n nodes. Figure 1 shows the different phases of the proposed algorithm for j th node. At the first step, the entire dataset will be stored in HDFS. JobTracker will partition the dataset into n small parts ($P_1, P_2, \dots, P_n$). TaskTracker will assign each part P_i ($i=1,2,\dots,n$) to j th node. At the second step, each partition P_i ($i=1,2,\dots,n$), will be scanned (i.e. first scan) to compute the frequency of itemsets (denoted by FP_i). The obtained FP_i is used to compute the weight of itemsets (denoted by WPI) for transaction filtering as the third step. The way of calculating WPI is similar to [4]. Transaction filtering was first used in a sequential implementation of Apriori by Christian Borgelt [20]. if T is a transaction of dataset; then, a filtered transaction of T is the itemsets obtained by removing infrequent itemsets from transaction T . Transaction filtering is sufficient to determine all the frequent itemsets [21]. We apply (at the present work) transaction filtering in efficient parallel implementation of Apriori using Hadoop-MapReduce model. The transaction filtering phase is used to scan the partition P_i at the j th node to determine all frequent itemsets. In fourth step, the obtained frequent itemset will be stored in a file called "FT file" to be scanned instead of scanning the whole partition of dataset. This will address the main drawback of the consumed time calculated by the hybrid WeightedHashT algorithm [4] (i.e. wasting time on scanning both frequent and infrequent itemsets). After that, the tree is constructed by getting the frequent itemsets from the FT file and mapping it to a path of fixed order in the tree (i.e. Second scan) as fifth step. These steps will be repeated until all transactions in j th node are covered to get the frequent itemset for the partition P_i and return back the result to the JobTracker. Certainly, Hadoop will process all the above steps for all nodes in a parallel way and combine the discovered frequent itemsets from each node and return the final result back to the application as shown in Figure 2.

3.1 Design of Proposed FTWeightedHashT Apriori Algorithm

FTWeightedHashT Apriori algorithm contains three main phases: Item Prediction phase, Filtration phase, and Tree Construction phase (see Figure 3). In the first phase, the algorithm scans the dataset for counting the frequencies of the itemsets. At the second phase, the algorithm calculates the weight of itemsets by giving a transaction a particular importance/weight where weight is the relevance of the itemset with other itemsets while considering overall unique transactions; then filters the itemsets by removing infrequent itemsets (i.e. itemsets with $wsupport$ less than the minimum $wsupport$ value). The last phase contains two sub-phases namely relevancy computation and reachability verification. These sub-phases depicts for constructing frequent tree with direct and indirect relationship. The relevancy computation (direct relationship) is the process of predicting the relationship between the nodes in the tree which means the itemsets in the frequent itemset tree. The reachability verification (indirect relationship) refers to the ability to reach the end point of the transaction of each itemset in the tree. More explanation of tree generation is in the next subsection.



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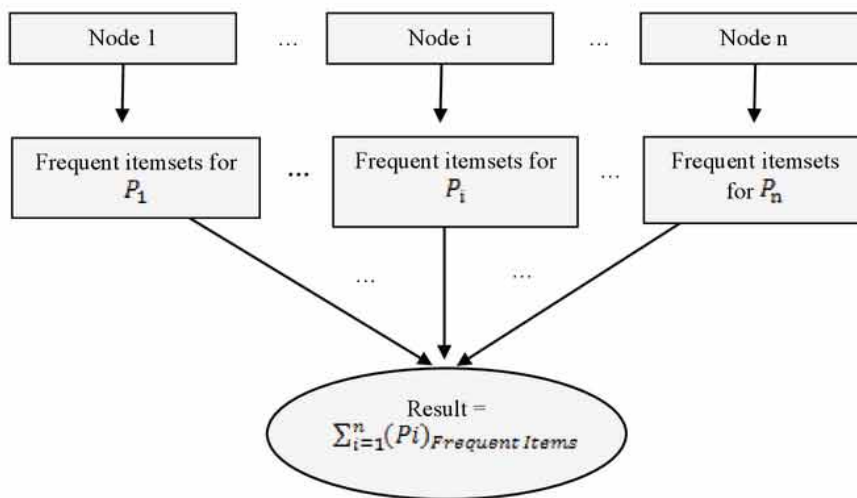
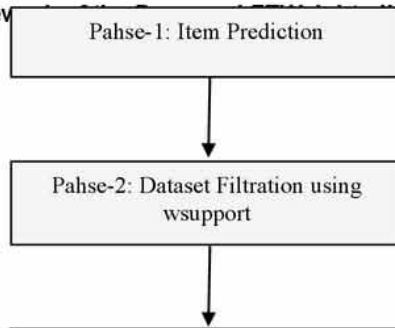


Figure 2: Framework of MashT Algorithm for final result



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The proposed algorithm mines the transactional dataset which is considered to be the data for distribution. The algorithm uses weighted support (wsupport) measure instead of using support count measure. The diagram above depicts the way of representing the logic of the algorithm formation. It iterates for specific number of times till no new frequent itemset is found. The algorithm is defined as map tasks to be executed on the distributed data which is available on various nodes of Hadoop cluster. Then the results are combined using reduce task as shown in Figure 2.

3.2 Pseudo Code of the Proposed FTWeightedHashT Apriori Algorithm

The phases present in the flow diagram of Figure 3 are implemented in Java programming language as given in Figure 4 that is the Pseudo code of the proposed algorithm. The algorithm has a transactional dataset as input and it produces frequent itemsets as output. We illustrate the phases of the algorithm as follows:

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Input:  $D = \{p_1, p_2, \dots, p_i\}$  where  $p_i$  is the partition of transactional dataset
Output: Frequent Itemsets
FTWeightedHashT Apriori Algorithm
BEGIN
(1).....  $TD = \text{Read\_TransactionalDataset}(D);$ 
(2).....  $F_i = \emptyset;$ 
(3).....  $F_I = \emptyset;$  2
      //Phase-I: Compute Frequency for  $F_{p_i}$ 
(4)..... For  $i = 1 \dots n$  Then //  $n = \text{Number of Transactions}$ 
(5).....   For  $i = 1 \dots m$  then
(6).....      $F_I = F_I \cup \text{Indexof}(I_i);$ 
(7).....      $F_{I_i} = F_{I_i} + 1;$ 
(8).....   End For  $i$ 

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340 As aforementioned, the proposed algorithm consists of three phases. in the first phase, the
341 algorithm scans the dataset for counting the frequency of itemsets. Here, we used a function
342 named indexof() to obtain the frequency of each itemset in a particular partition of dataset.
343 Whereas the second phase is to calculate the weight of itemsets by cal_weight() function,
344 and then filters the items by removing the infrequent items. Here all itemsets that satisfy the
345 wsupport measure are decided as frequent itemsets. The last phase is the tree construction.
346 The tree is constructed by generatetree() function. We followed [4] for building the tree. The
347 tree is built by getting the filtered items. The nodes are corresponding to itemsets and having
348 a counter for each node. it reads one transaction at a time and mapping it to a path of fixed
349 order. Paths can overlap when transactions are sharing items with the same prefix, if so;
350 then counters are incremented.

351 4. IMPLEMENTATION AND EXPERIMENTAL DETAILS

352 To take advantage of the parallel processing that the Hadoop provides, we need to submit
353 our query as a MapReduce Job on Hadoop cluster. A job is configured using a Driver class.

354 A driver class is defined with a Mapper class and a Reducer class of MapReduce
355 framework. Also input/output directory in HDFS, and other problem specific parameters are
356 specified in driver class. To implement Apriori algorithm on MapReduce framework we have
357 split it into two independent sub-problems corresponding to map and reduce tasks. Each
358 mapper processes a chunk of input datasets and generates local candidates with local
359 weighted support count. Each reducer receives local candidates and sums up the local count
360 to generate frequent itemsets. All the mappers and reducers execute in parallel across
361 different nodes of cluster but final result cannot be obtained until all reduce tasks are not
362 completed. Apriori is an iterative algorithm so we have to submit job each time a new
363 iteration starts.

364 The proposed FTWeightedHashT Apriori algorithm is implemented over Hadoop distributed
365 data processing platform as MapReduce model that reflects the phases of the approach:
366 Item Prediction phase, Transaction Filtering phase, and Tree Construction phase. The
367 overall results of the implementation is to increase the performance of Apriori in term of
368 execution time. The implementation of the proposed Apriori algorithm using Hadoop-
369 MapReduce involves the following steps:

370 Step1: All data preprocessing is performed on a given dataset using MapReduce paradigm.
371 It is used as text files directories into NameNode then uploaded to HDFS which divides the
372 input text files into data blocks of size 64MB. The HDFS stores the metadata of each block in
373 the NameNode and all the data blocks in the DataNodes.

374 Step2: Running the proposed FTWeightedHashT Apriori algorithm over Hadoop to generate
375 the frequent itemset.. The result is stored in a directory called "output" on HDFS.

377 4.1 Dataset Description

378 The improved algorithm is tested with retail, mushroom datasets which have been taken from
379 UCI data repository. Retail itemset is having 176324 transactions, 16470 items and with a size
380 of 4153 KB. Mushroom data is with 8124 instances, 22 attributes and with a size of 558 KB.

382 4.2 Environment Setup

383 The experiment is carried out in a machine with Intel core i5-G570 with 2.40GHz and RAM of
384 12GB. VirtualBox workstation is installed. Most of Literature works have used 2 VMs, one VM
385 for Hadoop and the other VM for Eclipse. However, the present work has used only 1 VM for
386 both Hadoop and Eclipse. The VM is used for Hadoop 2.6.0 – cdh 5.10.0 setup and Eclipse
387 3.3.2 with the configuration of 167GB SSD hard disk and 8192 MB base memory. RedHat
388 64-bit is installed in it. Virtual machine are created using VirtualBox workstation 7.1.3.
389 Cloudera-quickstart-vm-5.10.0-0 is the platform which the Hadoop and Eclipse work in.

391 4.3 Hadoop Setup

392 This section describes the experimental environment for testing our proposed approach. We
393 implement the proposed FTWeightedHashT Apriori algorithm using Java programming
394 language. The experimental environment is built on a MapReduce cluster with 4 nodes. One
395 of these nodes is configured as Hadoop Master or as the NameNode which controls the data
396 distribution over the Hadoop cluster and the other nodes acting as DataNodes.

397 HDFS splits dataset into 64 MB chunks each presented as a map task and then distribute
398 them among workers with 3 replications by default, the input split includes location
399 information for the next block. HDFS stores replicas of each data block to ensure both
400 reliability, availability, and performance.

401 Split is a logical division of the input data while block is said to be a physical division of data.
402 HDFS default block size is default split size if input split is not specified in the code. Split is

403 said to be user defined and its size can be controlled in the MapReduce program. One split
404 can be mapping to multiple blocks and there may be multiple split of one block. The number
405 of splits specify the number of map tasks (Mapper). Hence the number of mappers depends
406 on file size and the block size. Block size is fixed as 64 MB here, but file size varies as per
407 the input dataset.

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410 5. RESULTS AND DISCUSSION

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412 Here, we summarize and discuss the results of the experiments that are conducted. We use
413 Retail and Mushroom datasets. We evaluate the performance of the improved
414 FTWeightedHashT Apriori algorithm with respect to the execution time of the former work
415 [4]. We notice that only two passes over the dataset to obtain the frequent itemsets are
416 required (one scan for frequency of itemsets and the other scan to build the tree of frequent
417 itemsets) rather than the algorithm in [4] which take three passes (one scan for frequency of
418 itemsets, one scan to build the tree, and one scan to obtain the frequent itemsets).

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420 5.1 Investigation of Execution Time for FTWeightedHashT (Retail dataset)

421 We measure the execution time by execute the improved FTWeightedHashT Apriori
422 algorithm on Retail dataset with wsupport 0.3 and run on 4 nodes. The time consumed in
423 WeightedHashT was 9900 milliseconds while in the proposed algorithm is 2170
424 milliseconds. We get improved results about 60% with comparison to WeightedHashT
425 because of employing transaction filtering technique. Figure 5 depicts the execution time
426 with Retail dataset.

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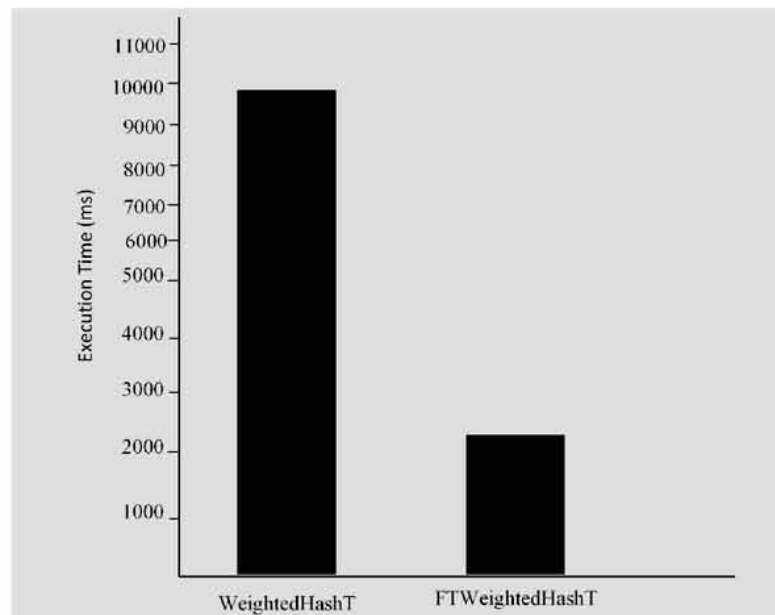
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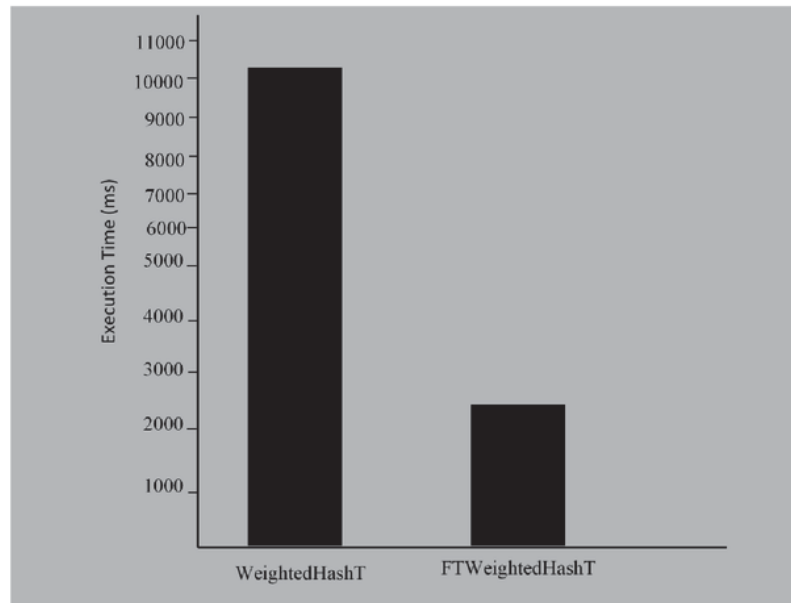
451 5.2 Investigation of Execution Time for FTWeightedHashT (Mushroom dataset)

452 Figure 5: Execution time Comparison with Retail dataset

453 As described in Retail dataset, we also measure the execution time with Mushroom dataset

454 and get improved results about 65% compared to WeightedHashT. The time consumed in

455 WeightedHashT was 10200 ms while in the proposed algorithm is 2458 ms. Figure 6
456 explains the execution time with Mushroom dataset.



478 **Figure 6: Execution time Comparison with Mushroom dataset**

482 6. CONCLUSION

483 **1** Re-designing data mining algorithms on MapReduce paradigm to analyze and mine big data
484 is the new movement in research. So we proposed a novel approach called
485 "FTWeightedHashT" Apriori algorithm for extracting frequent patterns. In our experiment on
486 Hadoop cluster, various comparison charts are given to analyze the performance and it is
487 made sure that the presented work is the best in term of time execution where the proposed
488 algorithm obligates the process to read only the frequent itemsets from FT file instead of
489 reading in each iteration from the dataset which contains both frequent and infrequent ones.
490 Further possible study could be done in order to improve and enhance of the Hadoop-based
491 Apriori. One can apply the existing idea with auto-multi minimum support because for many
492 datasets it is difficult to choose the value of minimum support. Too small values may cause
493 rule explosion, and too large values may cause rare item deadlock. Thus, implement auto-
494 multi minimum support expected to give better result. Another thing is that we can apply the
495 proposed algorithm to be run on Spark instead of MapReduce. Because of main memory
496 caching mechanism that Spark has, it will give better results absolutely.

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514 **COMPETING INTERESTS**

515

516 Declaration of competing interest should be placed here. ⁶ All authors must disclose any
517 financial and personal relationships with other people or organizations that could
518 inappropriately influence (bias) their work. Examples of potential conflicts of interest include
519 employment, consultancies, honoraria, paid expert testimony, patent
520 applications/registrations, and grants or other funding. If no such declaration has been made
521 by the authors, SDI reserves to assume and write this sentence: "Authors have declared that
522 no competing interests exist."

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526 **AUTHORS' CONTRIBUTIONS**

527

528 ⁶ ²³ Author A' designed the study, designed the framework of the study, wrote the pseudo code
529 ⁶ the proposed algorithm, implemented the proposed algorithm on eclipse (java-based) and
530 wrote the first draft of the manuscript. 'Author B' managed the analyses of the study, review
531 the result ⁶ and the all proposed work in general (as a supervisor of author 1 on master's
532 degree). All authors read and approved the final manuscript."

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537 **REFERENCES**

538

- 539 1. A.L.Sayath Saabith, Elankovan Sundararajan, Azuraliza Abubaker, PARELLEL
540 IMPLEMENTATION OF APRIORI ALGORITHMS ON THE HADOOP-MAPREDUCE
541 PLATFORM- AN EVALUATION OF LITERTURE, JATIT, Vol.85(3), (March-2016) pp.321-
542 351.
- 543 2. Jiawei Han, Micheline Kamber, and Jian Pei, Data Mining: Concepts and Techniques,
544 Elsevier, Third Edition (2013)
- 545 3. Sudhakar Singh, Rakhi Garg, P.K.Mishra. Performance Analysis of Apriori Algorithm with
546 Different Data Structures on Hadoop Cluster, **International** Journal of Computer
547 Applications Vol.128(9) (Oct-2015) pp.45-51.
- 548 4. R. Sumithra, Sujni Paul and D. Ponmary Pushpa Latha, A hybrid Algorithm Combining
549 Weighted and Hash T Apriori Algorithm in MapReduce Model Using Eucalyptus Cloud
550 Platform, WSEAS Transactions on COMPUTERS Vol.14 . E-ISSN: 2224-2872, (2015)
551 pp.382-388.
- 552 5. Ezhilvathani, A., & Raja, K. Implementation of parallel apriori algorithm on hadoop cluster.
553 International Journal of Computer Science and Mobile Computing. Vol. 2(4), (2013) pp.
554 513-516.
- 555 6. Hazarika, M., & Rahman, M. Mapreduce Based Eclat Algorithm for Association Rule
556 Mining in Datamining : Mr _ Eclat. International Journal of Computer Science and
557 Engineering, Vol. 3(1), (2014) pp.19-28..

- 558 7. Itkar, S., & Kulkarni, U. Distributed Algorithm for Frequent Pattern Mining using Hadoop-
559 Map Reduce Framework. Proceeding of International Conference on Advances in
560 Computer Science, AETACS, (2013) pp.15-24.
- 561 8. Jyoti, L. D., & Kiran, B. D. A Novel Methodology of Frequent Itemset Mining on Hadoop.
562 International Journal of Emerging Technology and Advanced Engineering, Vol. 4(7),
563 (2014) pp. 851–859.
- 564 9. Kovacs, F., & Illes, J. Frequent itemset mining on hadoop., 2013 IEEE 9th International
565 Conference on Computational Cybernetics, (2013) pp. 241–245.
- 566 10. Modgi, M. P. Mining Distributed Frequent Itemset with Hadoop. International Journal of
567 Computer Science & Information Technologies(IJCSIT), Vol5(3), (2014) pp. 3093–
568 3097.
- 569 11. Moens, S., Aksehirli, E., & Goethals, B. Frequent Itemset Mining for Big Data. Big Data,
570 2013 IEEE International Conference on, (2013). pp. 111–118.
- 571 12. Oruganti, S., Ding, Q., & Tabrizi, N. Exploring HADOOP as a Platform for Distributed
572 Association Rule Mining. In FUTURE COMPUTING 2013, The Fifth International
573 Conference on Future Computational Technologies and Applications (2013). pp. 62–67.
- 574 13. Qureshi, Z., & Bansal, S. Improving Apriori Algorithm to get better performance with
575 Cloud Computing. International Journal of Software & Hardware Research in
576 Engineerin, Vol. 2(2), (2014). pp. 33-37.
- 577 14. Vajk, I. Performance Evaluation of Apriori Algorithm on a Hadoop Cluster. Wseas.Us,
578 (2013). pp.114–121.
- 579 15. Vinodhini, S., & Vinoth, M. Frequent Pattern Identification using Map Reduce Paradigm.
580 International Journal of Engineering Research & Technology, Vol. 3(3), (2014). pp.
581 1763-1768.
- 582 16. Rakesh Agrawal, Tomasz Imieliński, and Arun Swami, "Mining association rules between
583 sets of items in large databases", SIGMOD Rec. 22, 2, 207-216.
584 DOI=10.1145/170036.170072. (June 1993).
- 585 17. Yaling Xun, Jifu Zhang, and Xiao Qin, FiDoo: Parallel Mining of Frequent Itemsets
586 Using MapReduce, IEEE transactions on systems, man, and cybernetics: systems, vol.
587 46, no. 3, march 2016.
- 588 18. D Apiletti et. Al., Frequent Itemsets Mining for Big Data: A Comparative Analysis, Big
589 Data Research (2017), <http://dx.doi.org/10.1016/j.bdr.2017.06.006>
- 590 19. S. Singh, R. Garg and P. K. Mishra, "Observations on factors affecting performance of
591 MapReduce based Apriori on Hadoop cluster," 2016 International Conference on
592 Computing, Communication and Automation (ICCCA), Greater Noida, India, 2016, pp.
593 87-94. doi: 10.1109/CCAA.2016.7813695
- 594 20. Christian Borgelt, Efficient Implementations of Apriori and Eclat, In B. Goethals and M. J.
595 Zaki, editors, Proceedings of the IEEE ICDM Workshop on Frequent Itemset Mining
596 Implementations (FIMI'03), volume 90 of CEUR Workshop Proceedings, Melbourne,
597 Florida, USA, (2003).
- 598 21. Ferenc Bodon, "A trie-based APRIORI implementation for mining frequent item
599 sequences," in Proceedings 1st international workshop on open source data mining:
600 frequent pattern mining implementations, ACM, (2005).

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