Apriori-based Frequent Itemset Mining Algorithms on MapReduce

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ABSTRACT
Many parallelization techniques have been proposed to enhance the performance of the Apriori-like frequent itemset mining algorithms. Characterized by both map and reduce functions, MapReduce has emerged and excels in the mining of datasets of terabyte scale or larger in either homogeneous or heterogeneous clusters. Minimizing the scheduling overhead of each map-reduce phase and maximizing the utilization of nodes in each phase are keys to successful MapReduce implementations. In this paper, we propose three algorithms, named SPC, FPC, and DPC, to investigate effective implementations of the Apriori algorithm in the MapReduce framework. DPC features in dynamically combining candidates of various lengths and outperforms both the straight-forward algorithm SPC and the fixed passes combined counting algorithm FPC. Extensive experimental results also show that all the three algorithms scale up linearly with respect to dataset sizes and cluster sizes.

Categories and Subject Descriptors
H.2.8 [**Database Management**]: Database Application-Data mining

General Terms
Algorithms, Performance

Keywords
Association Rule Mining, MapReduce, and Hadoop

1. INTRODUCTION
The Apriori algorithm [2] is one of most well-known methods for mining frequent itemsets in a transactional database. The algorithm works within a multiple-pass generation-and-test framework, comprising the joining and the pruning phases to reduce the number of candidates before scanning the database for support counting. Many algorithms such as the FP-growth algorithm [7] and so on have been proposed to overcome the weakness of the Apriori algorithm: level-wise candidate generations and multiple-pass database scans. Researchers also endeavor to parallelize these frequent itemset mining algorithms to speed up the mining of the ever-increasing sized databases [21].

Parallelized mining attempts to divide the mining problem into smaller ones and solve the sub-problems using homogeneous nodes such that each node may work independently and simultaneously. Although the parallelization may improve the mining performance, it also raises several issues including the partitioning of the input data, the balancing of the workloads, the formation of global information from local nodes, and the minimization of the communication costs. Deploying the mining methods into a grid computing environment by decomposing the task into smaller pieces and dispatching the sub-tasks to grid nodes may also improve the performance. The assumption of all grid nodes are fail-safe and all tasks can be correctly completed might be too strong in real grid environments. In general, the potential errors due to failure nodes increase as the number of grid nodes increases. The failure of nodes cannot be ignored since erroneous or incomplete data are introduced. Even worse, the failure may cause an endless re-execution of all the jobs. Additionally, the scalability of the grid is limited because running on hundreds of nodes is prone to error.

To overcome the above problem, the MapReduce framework [5] has been introduced. MapReduce enables the distributed processing of huge data on large clusters, with good scalability and robust fault tolerance. A scale-up of hundreds or even thousands of nodes can be smoothly established. Algorithms running in the framework are described by two major functions, *map* and *reduce*. The input data are partitioned (and possibly replicated) and stored in a number of nodes. A master node initiates and schedules the two functions for executions in the nodes. The *map function* takes (from its node) the input data as a <key, value> pair and outputs a list of <key, value> pairs in a different domain. The *reduce function* takes the sorted output of the map function as <key, list-of-values> and outputs a collection of values. Both functions (i.e. a map task and a reduce task) can be performed in parallel. Thus, MapReduce can be an efficient platform for frequent itemset mining in huge datasets of terabyte or larger scale. Using the MapReduce framework to parallelize the mining task on a cluster of cheap servers might outperform some serial mining algorithms on a powerful server.

Converting a serial Apriori-like mining algorithm into a distributed algorithm on the MapReduce framework might not be difficult, but the mining performance might be unsatisfactory. The multiple-pass feature of the Apriori algorithm necessitates multiple map-reduce phases. The master must schedule jobs to initialize each map-reduce phase. The map function of a map-reduce phase cannot start until all the reduce functions of its

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previous phase have finished. Nodes that finishes their reduce functions have to wait for all the unfinished nodes to complete. The scheduling and the waiting are pure overheads to the core mining task. In addition, each map function receives only a portion of the input data since the input data are partitioned into many nodes. The partitioned input inhibits effective local information exchanges among map tasks. Global information can be obtained only by the reduce function. Thus, the map function is unaware of the results of other map tasks and must output all the local information without pruning in a phase. To efficiently implementing the level-wise mining algorithms using the MapReduce framework, we need to minimize the number of scheduling invocations, maximize the utilization of each node during each map-reduce phase, and balance the workloads of all nodes in the MapReduce cluster.

Therefore, we propose three algorithms in this paper, named *Single Pass Counting* (abbreviated as SPC), *Fixed Passes Combined-counting* (abbreviated as FPC), and *Dynamic Passes Combined-counting* (abbreviated as DPC), to investigate the performance of the Apriori-like algorithms in a MapReduce framework. SPC is a straight-forward conversion of the Apriori algorithm into a MapReduce version. At each pass of database scanning, the map task generates the candidates and outputs <χ, 1> for each candidate χ contained in a transaction. The reduce task collects the support counts of a candidate and outputs candidates having enough counts as frequent itemsets for the map tasks of the next pass. Aiming at reducing the number of scheduling invocations, FPC performs the generation-and-test tasks of consecutive three passes in a map-reduce phase. Such a technique is similar to the *pass bundling* technique in [14]. A trade-off exists, however, between the number of saved database passes and the number of false-positive candidates in the counting. DPC further balances the workloads between combined passes by dynamically merging candidates of several passes to maximize the utilization of each node during each map-reduce phase. Our experiments using both synthetic and real datasets show that DPC can be eight times faster than SPC. The experiments of increasing database sizes also indicate that the proposed algorithms scale up linearly.

The rest of the paper is organized as follows. Some related works are briefly reviewed in Section 2. Section 3 describes the preliminaries in the following context. Section 4 presents the three proposed algorithms. Comprehensive experimental results are given in Section 5. Section 6 concludes the paper.

2. RELATED WORKS

Extensive algorithms on frequent itemset mining have been proposed for the past decades [2, 7]. As the size of the database increases to terabyte or petabyte scale, even a powerful computing server may handle the mining well. Thus, parallel mining algorithms [3, 4, 14, 16, 20, 21] are proposed. However, parallel mining comes out new problems to be solved, such as workload balancing, data distribution, jobs assignment, and parameters passing between nodes…etc., many challenges need to be handled in parallel mining. To run a mining task on a cluster, the database should be split into many sub-databases and be distributed to nodes. And the job for each node should also be decided. If the workload for each node is not balance, the total execution time will be delayed by stragglers. With a missing setting for parallel mining, many nodes may be idled and total execution time may be increased.

With the rise of cloud computing, MapReduce [5] becomes one of most important technique for cloud computing, it hiding the problems like data distribution, fault tolerance, and workload balance and users just focus on algorithms. MapReduce has been widely researched in many areas, such as database [1, 10], text similarity search [12, 19], and data mining [8, 11]. Moreover, the performance of MapReduce is also discussed and many enhancing techniques have been proposed [6, 9, 13, 15, 18]. In this paper, we also proposed three mining algorithms to analyze the impact on performance of different implementations, and summarize a technique for enhancing the performance of mining algorithms using MapReduce.

3. PRELIMINARIES

3.1 The Apriori Algorithm

Three algorithms are proposed to investigate the Apriori-like algorithms in the MapReduce paradigm. The Apriori algorithm mines all the frequent itemsets in a transactional database, where each transaction t_i contains a set of items called *itemset*. An itemset having k items is called a k-itemset and its *length* is k. An itemset X is frequent if its support, which is the fraction of transactions containing X in the database, is at least certain user-specified minimum support *min_sup*. Let L_k denote the frequent itemsets of length k and C_k denote the candidate itemsets of length k. The Apriori algorithm joins L_{k-1} to generate C_k, counts the supports of C_k, and determine the L_k in k-*th* database scanning. The algorithm terminates when no C_k or L_k is generated. Note that usually the discovery of frequent 1-itemsets is accomplished by a simple counting of items in the first pass of database scanning (pass-1). Starting from pass-2, the hash-trees are used for arranging C_k to facilitate fast support counting. The pruning of candidates using the downward closure property is effective for candidates of length larger than two, starting from pass-3.

3.2 The MapReduce Paradigm

MapReduce [5] is proposed to support distributed computing, i.e. a share nothing architecture, on huge data and Hadoop [23] is one of the implementations of the MapReduce frameworks. The features of MapReduce include the following. First, MapReduce partitions data into equal sized blocks with some replicas and distributes blocks evenly to the distributed file systems (such as HDFS [16]) automatically so that users are free from the locations and the distributions of data. Second, MapReduce re-executes a crashed task without re-executions of the other tasks and achieves good fault-tolerances. Third, MapReduce increases total throughputs by re-assigning un-finished tasks of slower or busy nodes to idle nodes (which have accomplished their tasks) in a heterogeneous cluster.

In a MapReduce cluster, one node is designated as the *master*, who schedules tasks for execution among nodes, and other nodes are the *workers*. The master and the workers can be located at the same node. Computations in the MapReduce framework are distributed among nodes and are described by the map function and the reduce function. Programmers address the required computations to be executed in parallel by designing map tasks and reduce tasks. The map tasks (also the reduce tasks) will be executed concurrently by the configured workers. The input data file is evenly divided into disjoint chunks and stored in the nodes in the distributed file system like GFS or HDFS. Usually, workers having input chunks are assigned with map tasks to reduce the required data transmissions for input. Map tasks and reduce tasks can be assigned to the same worker.

The master schedules the map tasks and the reduce tasks to the configured cluster nodes when a job is initialized. Each map task then reads one block from the file system, and outputs the <key, value> pairs specified by the map function. Each reduce task receives the sorted <key, value-list> pairs of the associated keys. All the pairs of the same key are sent to one assigned worker responsible for that key. The reduce task performs the operations specified in the reduce function and finally outputs the results to a file. Additionally, the *combine* function is specified, usually at the end of the map task, to collect local <key, value> pairs at a map worker to reduce communications between map tasks and reduce tasks. The combine function merges the <key, value> pairs of the same key in the map worker into one <key, value> pair and finally outputs the pair.

Algorithms in the MapReduce framework may comprise several map-reduce phases. The master can collect the results from a map-reduce phase in a file, then schedule workers for the next map-reduce phase. The *DistributedCache* is used when the entire content of a file is to be read by all the map workers or reduce workers. Moreover, outputs of both a map and a reduce task are written to files so that the failure of a map-reduce phase can be recovered from such checkpoints without having to re-execute the job from the beginning when an error occurs.

4. PROPOSED ALGORITHMS

The fundamentals of parallelizing the Apriori algorithm in the MapReduce framework is to design the map and the reduce functions for candidate generations and support counting. The first proposed algorithm, Single Pass Counting (**SPC**), finds out frequent *k*-itemsets at *k*-th pass of database scanning in a map-reduce phase. The second proposed algorithm, Fixed Passes Combined-counting (**FPC**), finds out frequent *k*-, (*k+1*)-, …, and (*k+m*)-itemsets in a map-reduce phase. In this paper, FPC discovers frequent *k*-, (*k+1*)-, and (*k+2*)-itemsets. The third proposed algorithm, Dynamic Passes Combined-counting (**DPC**), considers the workloads of nodes and finds out as many frequent itemsets of various lengths as possible in a map-reduce phase. For convenience, a map task is called a *mapper*, and a reduce task is called a *reducer* in the following context.

In general, the number of mappers is larger than the number of reducers in MapReduce. With the size of cluster increasing, the more mappers can be used for processing data, and the problem can be divided into smaller granularity. In all of our algorithms, each mapper calculates counts of each candidate from its own partition, and then each candidate and corresponding count are output. After map phase, candidates and its counts are collected and summed in reduce phase to obtain partial frequent itemsets. By using count distribution between map phase and reduce phase, the communication cost can be decreased as much as possible. Since frequent 1-itemsets are found in pass-1 by simple counting of items. Phase-1 of all the three algorithms is the same, as shown in Figure 1. The mapper outputs <item, 1> pairs for each item contained in the transaction. The reducer collects all the support counts of an item and outputs the <*item*, *count*> pairs as a frequent 1-itemset to the file L_1 when the *count* is no less than the minimum support count.

At first, different map-reduce functions are designed to characterize the features of the three algorithms, starting from pass-2. The huge number of C_2 in common executions, however, may overload nodes of map functions if candidates of length larger than two are combined for support counting. Thus, the same phase-2 is applied to all the three algorithms. Figure 2 shows phase-2 of the proposed algorithms. The apriori-gen() function, subset() function, and the hash-trees in Figure 2 are the same as those in Apriori [2]. In fact, the reduce function in phase-2 is the same for all subsequent phases in all the three algorithms.

```
Map(key, value = itemset in transaction $t_i$) :
Input: database a database partition $D_i$
1. foreach transaction $t_i \in D_i$ do
2.    foreach item $i \in t_i$ do
3.       output <$i$, 1> ;
4.    end
5. end
Reduce (key=item, value=count) :
1. foreach key $y$ do /* Initial $y$.count = 0 */
2.    foreach value $v$ in $y$'s value list do
3.       $y$.count += $v$ ;
4.    end
5.    if y.count ≥ minimum support count
6.       output <$y$, $y$.count> ; /* collected in $L_1$ */
7.    end
8. end
```

Figure 1. Phase-1 of SPC, FPC, and DPC algorithms.

In phase-2, each mapper first reads frequent itemsets L_1 to generate C_2 in a hash tree. The L_1 is located at the *DistributedCache* in Hadoop [23]. The mapper then reads a transaction t_i, uses the subset function to identify all the candidates in t_i, and outputs <c, 1> for all such candidates c. The reducer collects all the support counts of a candidate itemset and outputs the <*itemset*, *count*> pairs as a frequent 2-itemset to the file L_2 when the *count* is no less than the minimum support count.

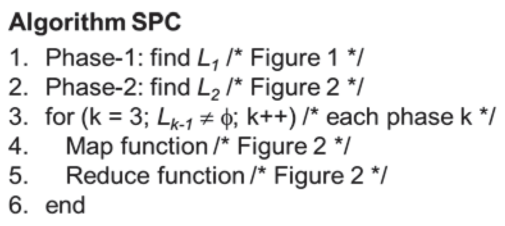
```
Map(key, value = itemset in transaction $t_i$) :
Input: a database partition $D_i$ and $L_{k-1}$ (k ≥ 2)
1.read $L_{k-1}$ from DistributedCache;
2.construct a hash-tree for $C_k$ = apriori-gen($L_{k-1}$) ;
3.foreach transaction $t_i \in D_i$ do
4.   $C_t$ = subset($C_k$, $t_i$) ;
5.   foreach candidate $c \in C_t$ do
6.      output <$c$, 1> ;
7.   end
8.end
Reduce (key=itemset, value=count) :
1.foreach key $y$ do /* Initial $y$.count = 0 */
2.   foreach value $v$ in $y$'s value list do
3.      $y$.count += $v$ ;
4.   end
5.   if y.count ≥ minimum support count
6.      output <$y$, $y$.count>; /* collected in $L_k$ */
7.   end
8.end
```

Figure 2. Phase-2 of SPC, FPC, and DPC algorithms.

Starting from phase-3, the three algorithms use different counting strategies and have diverse designs of the map-reduce functions, as described in the following.

4.1 Single Pass Counting (SPC)

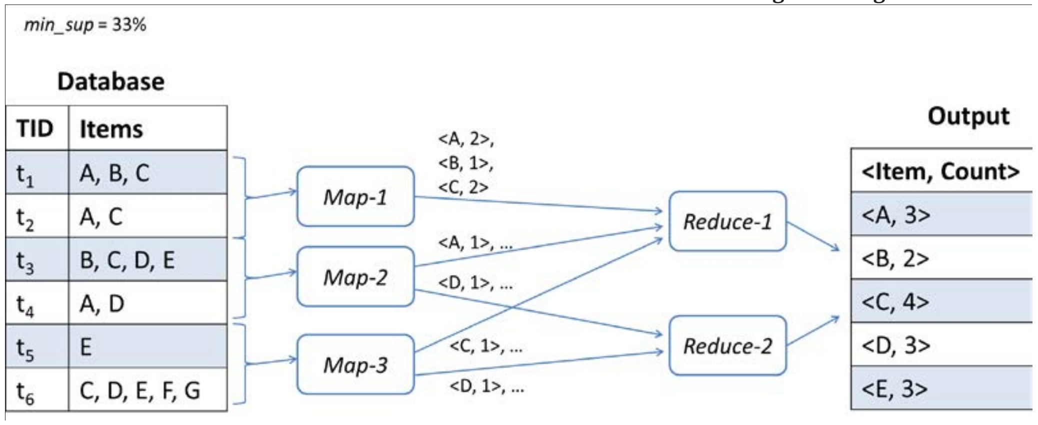
Figure 3 outlines the SPC algorithm. SPC discovers L_k in phase-*k* iteratively and it terminates when L_k is empty. Phase-1 of the SPC algorithm discovers L_1 using the map-reduce functions in Figure 1. Phase-2 of the algorithm discovers L_2 using the map-reduce functions in Figure 2. SPC is a straight-forward conversion of Apriori so that phase-3 and all the subsequent phases are the same as phase-2.



Algorithm SPC

```
1. Phase-1: find $L_1$ /* Figure 1 */
2. Phase-2: find $L_2$ /* Figure 2 */
3. for (k = 3; $L_{k-1} \neq \phi$; k++) /* each phase k */
4.     Map function /* Figure 2 */
5.     Reduce function /* Figure 2 */
6. end
```

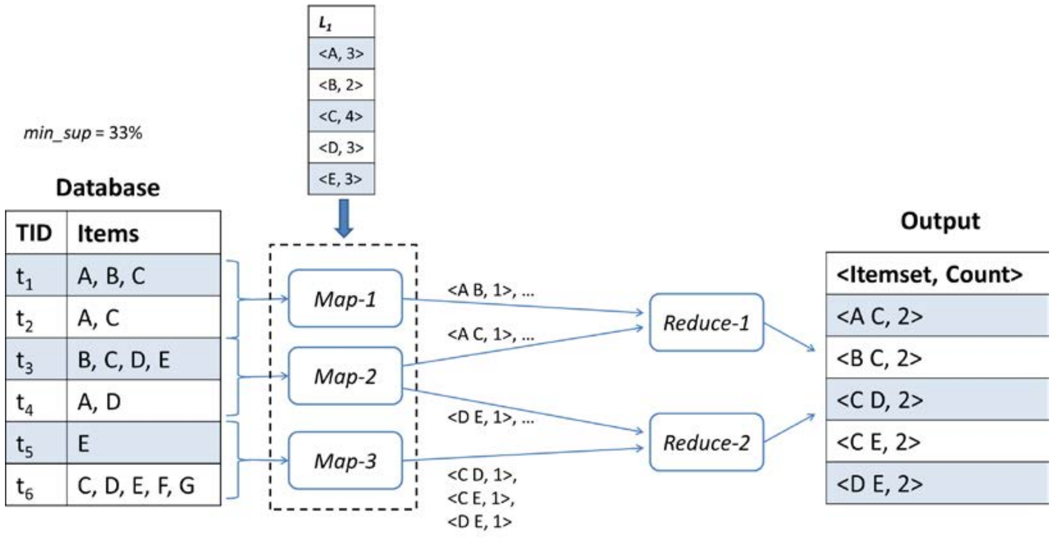
Figure 3. Algorithm SPC.



TID	Items
t_1	A, B, C
t_2	A, C
t_3	B, C, D, E
t_4	A, D
t_5	E
t_6	C, D, E, F, G

<Item, Count>
<A, 3>
<B, 2>
<C, 4>
<D, 3>
<E, 3>

Figure 4. An execution example of Phase-1.



L_1
<A, 3>
<B, 2>
<C, 4>
<D, 3>
<E, 3>

TID	Items
t_1	A, B, C
t_2	A, C
t_3	B, C, D, E
t_4	A, D
t_5	E
t_6	C, D, E, F, G

<Itemset, Count>
<A C, 2>
<B C, 2>
<C D, 2>
<C E, 2>
<D E, 2>

Figure 5. An execution example of Phase-2

In phase-*k* ($k \geq 2$) of SPC, each mapper first reads L_{k-1} from the *DistributedCache* to generate C_k in a hash tree. It then performs the support counting and outputs the <*itemset*, *count*> pairs as a frequent *k*-itemset to the file L_k if the *count* passes the minimum threshold. Note that the combine function in Hadoop MapReduce framework is invoked for all the mappers in all the proposed algorithms to reduce the communications between mappers and reducers. Recall that the input data is evenly divided into disjoint chunks in Hadoop so that each mapper can reads only part of the whole database.

We use an example to illustrate the executions of SPC as follows. A database of six transactions, *min_sup* = 33%, three mappers, and two reducers are shown in Figure 4. In phase-1, the mapper handles transaction t_1 by outputting <A, 1>, <B, 1>, and <C, 1> pairs, and handles transaction t_2 by outputting <A, 1> and <C, 1> pairs. The *combine* function then is invoked to sum up the counts, and outputs <A, 2>, <B, 1>, and <C, 2> finally. The reducer sums up the counts associated with each key (i.e. item-id) and outputs items having counts at least 2 into L_1.

In phase-2, as shown in Figure 5, each mapper reads L_1 and generates C_2 in a hash tree. The mapper *Map-3*, for example, reads t_5 but outputs nothing, then reads t_6 and outputs <C D,1>, <C E, 1>, and <D E, 1> for the reducers. The reducer sums up the counts and outputs frequent 2-itemsets into L_2. Similarly, phase-3 of SPC is invoked, <C D E, 2> is outputted, and then SPC terminates.

4.2 Fixed Passes Combined-counting (FPC)

Being a level-wised algorithm, SPC iterates k times of the map-reduce phase when the maximum length of the frequent itemsets is k. The number of candidates often is small so that the utilization of the workers is low in the last few phases. The scheduling of mappers and reducers becomes an overhead in comparison to the workload of a worker for these phases. Moreover, the number of database scans required is the number of map-reduce phases performed in SPC. Thus, the cost of database loading in the beginning of each phase is relatively high if only few candidates are counted in a phase. Therefore, FPC combines candidates from several phases in SPC and performs the support counting in a single map-reduce phase.

The FPC algorithm is shown in Figure 7 and the map-reduce phase in the FPC algorithm is shown in Figure 6. Phase-1 and phase-2 of FPC are the same as that of SPC. Starting from phase-3, FPC combines candidates from a fixed number of database passes for support counting in a map-reduce phase. In this paper, the fixed number is three so that candidates of every three consecutive lengths are counted in one phase. Thus, FPC counts the supports of C_3, C_4, and C_5 in phase-3, that of C_6, C_7, and C_8 in phase-4, and so on. As shown in Figure 6, the mapper reads L_{k-1} from *DistributedCache* to generate C_k. C_{k+1} and C_{k+2} are generated using C_k and C_{k+1}, respectively. These candidates are then placed in a prefix-tree for support counting. The reduce function in fact is the same as that in SPC. Therefore, in comparison to SPC, FPC reduces the number of map-reduce phases required and has better utilizations of the workers in the last few database passes. The number of database scans consequently is reduced.

Nevertheless, the number of candidates from combined passes may overload the workers, especially when the number of passes to be combined is fixed. The number of candidates generated at earlier passes, such as C_3, can be too large to be combined with candidates of longer length. The reduction in database passes turns out to increase the number of false-positive candidates that overloads the mapper. The resulting performance of FPC would be worse than that of SPC. An example is shown in the experimental result in Figure 11(b). The weakness of FPC thus is the inability to prune candidates due to fixed combined counting without flexibility. Therefore, algorithm DPC is proposed to dynamically determine the candidates to be merged in a map-reduce phase.

4.3 Dynamic Passes Counting (DPC)

FPC might suffer from overloading candidates for a mapper if the number of candidates after merging is too large. Therefore, DPC is proposed to strike a balance between reducing the number of map-reduce phases and increasing the number of pruned candidates. DPC dynamically combines candidates of consecutive passes by considering the workload of workers. The aim is to combine as many passes as possible without generating too many false-positive candidates. In addition, the Hadoop cluster environment needs to be considered because the nodes might have different computing power.

The DPC algorithm is shown in Figure 9 and the map-reduce phase in the DPC algorithm is shown in Figure 8. Starting from phase-3, DPC differs from FPC in that DPC dynamically combines candidates in several passes while FPC statically combines candidates in a fixed numbered passes. In Figure 8, DPC first calculates the *candidate threshold ct*, which number indicates the maximum number of candidates for counting in a mapper for the map-reduce phase. Next, DPC continuously generates and collects candidates of longer length until the total number of candidates is larger than the threshold. A prefix-tree then is constructed for these candidates for support counting. The reduce function is similar to the one in SPC.

```
Map(key, value = itemset in transaction t_i) :
Input: a database partition D_i and L_{k-1} (k > 2)
1.  read L_{k-1} from DistributedCache;
2.  C_k = apriori-gen(L_{k-1}) ;
3.  C_{k+1} = apriori-gen(C_k) ;
4.  C_{k+2} = apriori-gen(C_{k+1}) ;
5.  construct a prefix-tree for C_k ∪ C_{k+1} ∪ C_{k+2} ;
6.  foreach transaction t_i ∈ D_i do
7.      C_t = subset(C_k ∪ C_{k+1} ∪ C_{k+2}, t_i) ;
8.      foreach candidate c ∈ C_t do
9.          output <c, 1> ;
10.     end
11. end
Reduce (key=itemset, value=count) :
1. foreach key y do /* Initial y.count = 0 */
2.     foreach value v in y's value list do
3.         y.count += v ;
4.     end
5.     if y.count ≥ minimum support count
6.         output <y, y.count>; /* collected in L_k, L_{k+1},
and L_{k+2} respectively */
7.     end
8. end
```

Figure 6. Phase-k (k>2) of FPC algorithms.

```
Algorithm FPC
1. Phase-1: find L_1 /* Figure 1 */
2. Phase-2: find L_2 /* Figure 2 */
3. for (k = 3; L_{k-1} ≠ ϕ; k += 3) /* each phase k */
4.     Map function /* Figure 6 */
5.     Reduce function /* Figure 6 */
6. end
```

Figure 7. Algorithm FPC.

DPC uses the execution time of previous phase to adaptively adjust the candidate threshold. Although the configuration of workers can be used as a reference, using the number of mappers and reducers for estimation might be error-prone since the cluster may have workers of various computing power. Thus, the candidate threshold is set to be in proportion to the number of the longest frequent itemsets in the last phase, $ct = \alpha \times |L_{k-1}|$. If the execution time of the previous map-reduce phase is too long, such as longer than $\beta = 60$ seconds, α is set to 1. Otherwise, α is set to 1.2 in the paper. The values of α and β can be adjusted according to the MapReduce configuration.

DPC takes the advantages of SPC and FPC, and balances well between reducing the number of map-reduce phases and the number of candidates. DPC reduces the number of candidates as many as possible for earlier database passes (the number of candidates of shorter length usually is huge), and combines passes of light workloads. The experimental results confirm that DPC outperforms both SPC and FPC for different minimum supports and various sizes of databases.

```
Map(key, value = itemset in transaction $t_i$) :
Input: a database partition $D_i$ and $L_{k-1}$ (k > 2)
1.  read $L_{k-1}$ from DistributedCache ;
2.  Candidate threshold $ct = \alpha * |L_{k-1}|$ ;
3.  $C_{set} = C_k$ = apriori-gen($L_{k-1}$) ;
4.  for (counter = 0; $|C_{set}| \le ct$; counter++)
5.      $C_{k+1+counter}$ = apriori-gen($C_{k+counter}$) ;
6.      $C_{set} = C_{set} \cup$ apriori-gen($C_{k+1+counter}$) ;
7.  end
8.  construct a prefix-tree for $C_{set}$ ;
9.  foreach transaction $t_i \in D_i$ do
10.     $C_t$ = subset($C_{set}$, $t_i$) ;
11.     foreach candidate $c \in C_t$ do
12.         output <c, 1> ;
13.     end
14. end
Reduce (key=itemset, value=count) :
1. foreach key y do /* Initial y.count = 0 */
2.     foreach value v in y's value list do
3.         y.count += v ;
4.     end
5.     if y.count ≥ minimum support count
6.         output <y, y.count>; /* collected in $L_k \ldots L_{k+counter}$ */
7.     end
8. end
```

Figure 8. Phase-k (k>2) of DPC algorithms.

```
Algorithm DPC
1.  Phase-1: find $L_1$ /* Figure 1 */
2.  Phase-2: find $L_2$ /* Figure 2 */
3.  for (k = 3; $L_{k-1} \neq \phi$;) /* each phase k */
4.      Map function /* Figure 8 */
5.      Reduce function /* Figure 8 */
6.      k += (counter+1) ;
7.  end
```

Figure 9. Algorithm DPC.

5. PERFORMANCE EVALUATION

Extensive experiments were conducted to assess the performance of the proposed algorithms. All the experiments were performed in a Hadoop 0.21.0 cluster of four nodes, where each node contains an Intel Pentium Dual Core E6500 2.93GHz CPU, 4GB RAM, and a 500GB hard disk running Ubuntu 10.10. All of the experiments were configured with 7 map tasks and 1 reduce task. All of the three algorithms are implemented in Java and the JDK version is 1.6.0_23.

Both real and synthetic datasets were used in the experiments. Real datasets BMS-POS and BMS-WebView-1 from FIMI were used [22]. The synthetic datasets were generated by the IBM dataset generator. The number of distinct items (|N|) is 10,000 and the average length of transactions (|T|) is 10. We report the result of T10I4D1000k here. The results of experiments using different settings of |T|, |N|, and |I| are consistent.

The result of varying minimum supports on mining synthetic dataset T10I4D1000k is shown in Figure 10. The execution times of the three algorithms are the same for minimum support larger than 0.2 because the mining finished after phase-2. Recall that phase-1 and phase-2 of the three algorithms are the same. As the minimum support becomes smaller than 0.2, both FPC and DPC outperform SPC. The reduction in execution is resulted from the combined counting of three different length candidates in each map-reduce phase in FPC. Fewer map-reduce phase initializations and fewer database scans reduce the total execution time for both FPC and DPC. DPC consistently outperforms FPC because FPC might be overloaded with too many false-positive candidates, as shown in Figure 11.

On mining real dataset BMS-WebView-1, FPC exhibited a potential weakness of the fixed-passes combined counting strategy. Figure 11(a) shows that DPC is about two times faster than SPC, and at least 4.5 times faster than FPC for low supports. Both DPC and FPC outperform SPC when *min_sup* $\geq$ 0.125%. Surprisingly, FPC is slower than SPC for *min_sup* $\leq$ 0.1%. When *min_sup* = 0.1%, FPC conducted support counting for a total 431883 candidates (of length 3 to 5) while SPC did that for a total 20066 candidates (17137+2688+241). The frequent 2-itemsets generated 17137 candidates of length 3, these 17137 candidates generated 85375, and the 85375 candidates generated 329371 candidates in FPC. The large number of false-positive candidates generated from the combined support counting in fact can be pruned in the level-wise counting. FPC thus might perform badly due to the overloaded candidates. DPC never has such an overloaded problem because it dynamically combines variable sized candidates for counting, by considering the total number of candidates to be counted in a map-reduce phase. Note that in Figure 11(b), FPC failed to complete the mining on BMS-POS with *min_sup* < 0.225% because it ran out of memory due to the huge candidate sets.

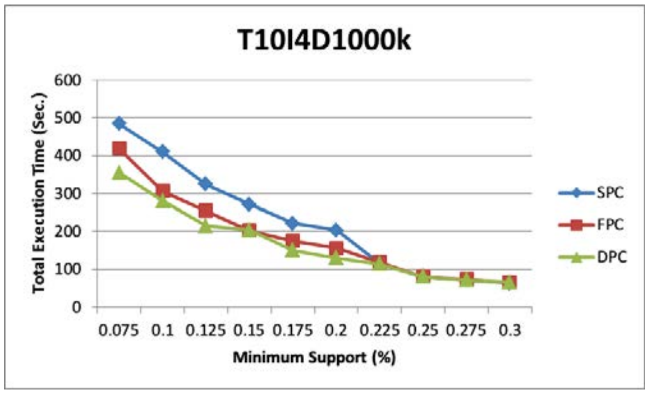


Figure 10. Total execution time of mining synthetic dataset T10I4D1000k.

Table 1 lists the breakdown of the execution time for the three algorithms on mining BMS-Web-View-1, *min_sup* = 0.1%. In SPC spends a total 156 seconds by using one each map-reduce phase for each database scan. FPC combines pass-3 to pass-5 in one phase and pass-6 to pass-7 in another phase. Candidates of lengths 4 and 5 are generated using C_3 so that no pruning can be done. It results into the longest processing time for FPC. Although the total number of map-reduce phases in DPC is the same as that in FPC, DPC prevents the generation of many false-positive candidates and outperforms the other two algorithms.

Figure 13 shows the speedup of three algorithms, and the line marked with cross is ideal speedup. Speedup means the rate of performance enhanced when adding an extra node. The old time divided by the new time and the speedup is obtained. The old time means the total execution time with only one node used, and the new time means the total execution time when adding an extra node or more nodes. As the result, both FPC and DPC have good speedup. When DPC is running on three nodes, the speedup is approximately 2 and the speedup is approximately 3 when DPC is running on four nodes.

6. CONCLUSION

We have proposed three algorithms, namely SPC, FPC, and DPC, to investigate the performance of the Apriori-like algorithms in a MapReduce framework in this paper. SPC is a simple conversion of the serial Apriori algorithm into the distributed MapReduce version. SPC finds the frequent *k*-itemsets in *k*-th database scan (map-reduce phase), using mappers to generate candidates' supports and reducers to collect global supports. FPC improves SPC by using a mapper to count the candidate *k*-, (*k+1*)-, and (*k+2*)-itemsets altogether in a map-reduce phase. Consequently, FPC effectively reduces the number of map-reduce phases. Nevertheless, the performance of FPC might be worse when too many false-positive candidates are collected for counting by mappers. DPC is proposed to strike a balance between reducing the number of map-reduce phases (by combining variable-length candidates) and increasing the number of pruned candidates. DPC dynamically collects candidates of variable lengths for counting by mappers according to the number of candidates and the execution time of previous map-reduce phases. As shown in the experimental results, DPC outperforms both FPC and SPC and has good scalability.

Acknowledgements

This research is supported partly by the National Science Council under grant NSC-100-2410-H-324-004, Taiwan.

Table 1. The execution time of each map-reduce phase in BMS-WebView-1 (*min_sup* = 0.1%).

	Pass-1	Pass-2	Pass-3	Pass-4	Pass-5	Pass-6	Pass-7	Total (Sec.)
SPC	20	26	24	23	20	23	20	**156**
FPC	22	26	371			20		**439**
DPC	20	25	22	22				**89**

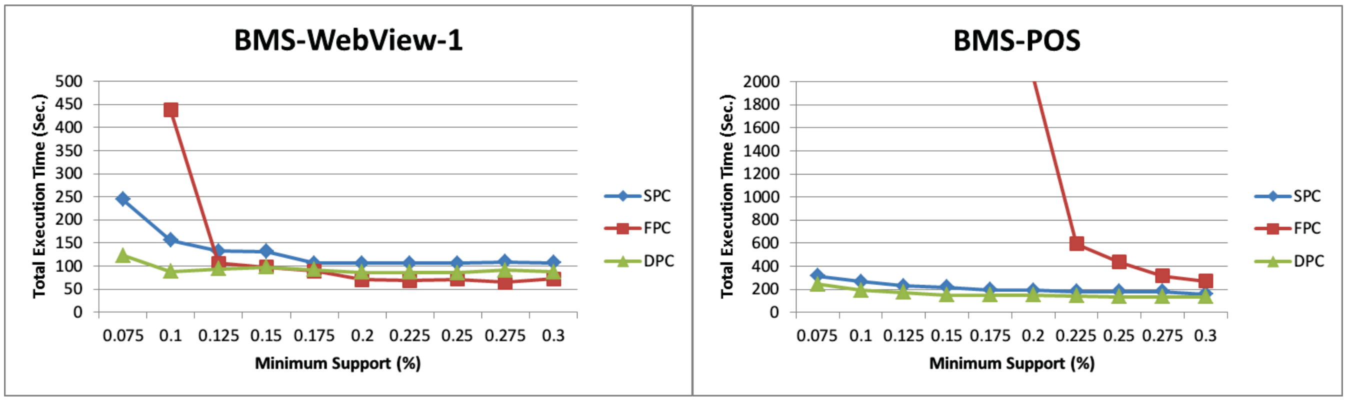


Figure 11. (a) BMS-WebView-1 (b) BMS-POS

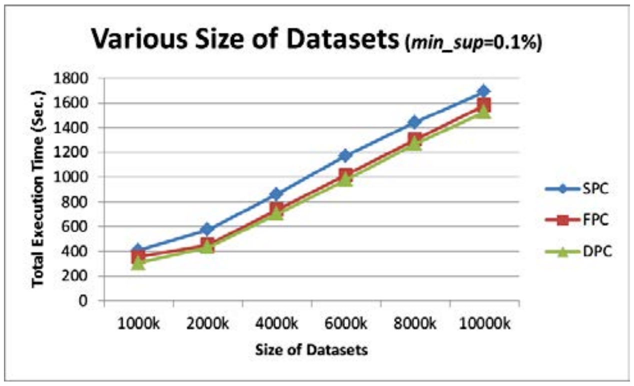


Figure 12. Scalability in different size of datasets

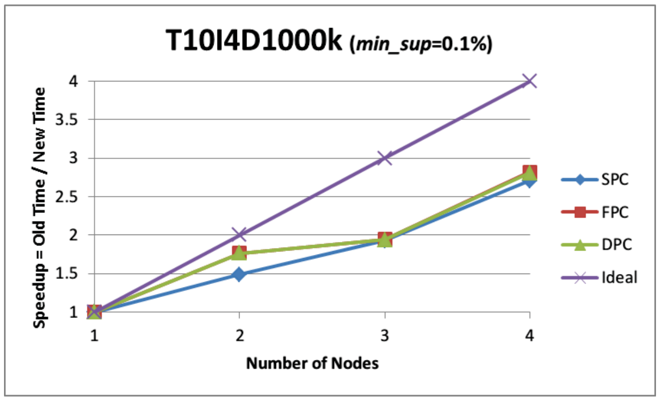


Figure 13. Speedup

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