cells of all of the cuboids for a given data cube. This, however, is exponential to the number of dimensions.

Iceberg Cube:

In order to save processing time and disk space and for more focused analysis. The cells that cannot pass the threshold are likely to be too trivial to warrant further analysis. Such partially materialized cubes are known as iceberg cubes. "iceberg" is the potential full cube including all cells. An iceberg cube can be specified with an SQL query,

Closed Cube:

A closed cube is a data cube consisting of only closed cells.

Shell Cube:

Another strategy for partial materialization is to precompute only the cuboids involving a small number of dimensions, such as 3 to 5. These cuboids form a cube shell for the corresponding data cube.

General Strategies for Cube Computation

With different kinds of cubes as described above, we can expect that there are a good number of methods for efficient computation. In general, there are two basic data structures used for storing cuboids. Relational tables are used as the basic data structure for the implementation of relational OLAP (ROLAP), while multidimensional arrays are used as the basic data structure in multidimensional OLAP (MOLAP).

Optimization Technique 1: Sorting, hashing, and grouping.

Sorting, hashing, and grouping operations should be applied to the dimension attributes in order to reorder and cluster related tuples. In cube computation, aggregation is performed on the tuples (or cells) that share the same set of dimension values. Thus it is important to explore sorting, hashing, and grouping operations to access and group such data together to facilitate computation of such aggregates.

This technique can also be further extended to perform shared-sorts, i.e., sharing sorting costs cross multiple cuboids when sort-based methods are used, or to perform shared-partitions, i.e., sharing the partitioning cost across multiple cuboids when hash-based algorithms are used.

Optimization Technique 2: Simultaneous aggregation and caching intermediate results.

In cube computation, it is efficient to compute higher-level aggregates from previously computed lower-level aggregates, rather than from the base fact table. Moreover, simultaneous aggregation from cached intermediate computation results may lead to the reduction of expensive disk I/O operations.

Optimization Technique 3: Aggregation from the smallest-child, when there exist multiple child cuboids.

When there exist multiple child cuboids, it is usually more efficient to compute the desired parent (i.e. more generalized) cuboid from the smallest, previously computed child cuboid.

In the following sections, we introduce several popular methods for efficient cube computation that explore some or all of the above optimization strategies.

3. Different Method for Cube Computation

1. General Cube Computation with Optimizing

Techniques: Multi- Dimensional aggregate computation [2]

Author's extended basic sort based and hash based methods to compute multiple group-bys by incorporating optimizations techniques like smallest-parent, cache-results, Amortize-scans, share-sorts and share-partitions.

Smallest-parent: This optimization aims at computing a group by from the smallest previously computed group-by. In this, each group-by can be computed from a number of other group bys.

Cache-results: This optimization aims at caching (in memory) the results of a group-by from which other group bys are computed to reduce disk I/O.

Amortize-scans: This optimization aims at amortizing disk reads by computing as many group-bys as possible, together in memory.

Share-sorts: This optimization is specific to the sort-based Algorithms and aims at sharing sorting cost across multiple group bys.

Share-partitions: This optimization is specific to the hash based algorithms. When the hash table is too large to fit in memory, data is partitioned and aggregation is done for each partition that fits in memory. We can save on partitioning cost by sharing this cost across multiple group bys.

4. Bottom-Up Approach: Bottom-Up Computation (BUC) [4]

BUC is an algorithm for sparse and iceberg cube computation. BUC uses the bottom-up approach that allows pruning unnecessary computation by recurring to A-priori pruning strategy. if a given cell does not satisfy minsup, then no descendant will satisfy minsup either. The Iceberg cube problem is to compute all group-bys that satisfy an iceberg condition. First, BUC partitions dataset on dimension A, producing partitions a1, a2, a3, a4.Then, it recurses on partition a1,the partition a1 is aggregated and BUC produces <a1,*,*,*>. Next, it partitions a1 on dimension B. It produces <a1, b1,*,*> and recurses on partition a1, b1. Similarly, it produces <a1, b1, c1,*> and then <a1, b1, c1, d1>. Now, it returns from recursion and produces <a1, b1, c1, d2> etc. After processing partition a1, BUC processes partition a2 and so on as shown in Figure 2 below.

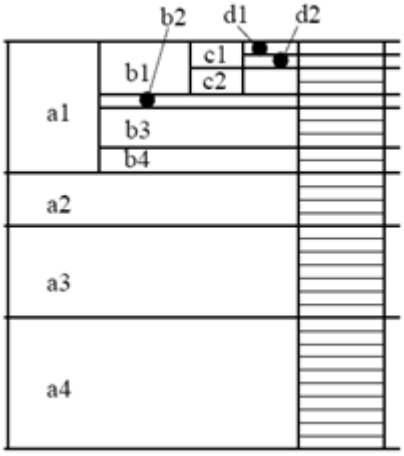

Figure 2: BUC Partitioning

BUC is sensitive to data skew and to the order of the dimensions processing first most discriminating dimensions improves performance. It shares partitioning costs.BUC does not share computation between parent and child cuboids.

5. Top-Down Approach: Multi-Way Array Aggregation [3]

The computation starts from the larger group-bys and proceeds towards the smallest group-bys. As show in below figure;

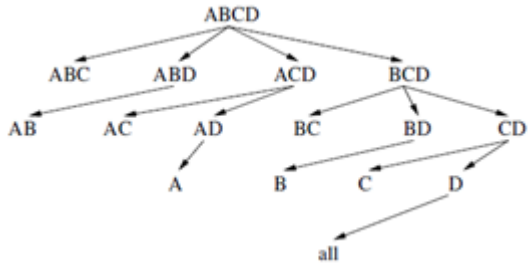

Figure 3: Top-Down Approach

In this, a partition-based loading algorithm designed and implemented to convert a relational table or external load file to a (possibly compressed) chunked array. There are no direct tuple comparisons. It perform Simultaneous aggregation on multiple dimensions. In MultiWay array aggregation Intermediate aggregate values are re-used for computing ancestor cuboids .It cannot do Apriori pruning means it cannot perform iceberg cube optimization.

In Multi-Way array aggregation, it partition arrays into chunks (a small sub cube which fits in memory). It uses compressed sparse array addressing: (chunk_id, offset) and compute aggregates in — "multiway" by visiting cube cells in the order which minimizes the # of times to visit each cell, and reduces memory access and storage cost.

What is the best traversing order to do multi-way Aggregation?

Method: the planes should be sorted and computed according to their size in ascending order

Idea: keep the smallest plane in the main memory, fetch and compute only one chunk at a time for the largest plane.

Limitation of the method: computing well only for a small number of dimensions. If there are a large number of dimensions, top-down computation and iceberg cube computation methods can be explored.

6. Mixed Approach: Star Cubing [8]

Star Cubing integrate the top-down and bottom-up methods. It explores shared dimensions. E.g., dimension A is the shared dimension of ACD and AD. ABD/AB means cuboid ABD has shared dimensions AB. Star cubing allows for shared computations .e.g., cuboid AB is computed simultaneously as ABD. Star Cubing aggregate in a top down manner but with the bottom-up sub-layer underneath which will allow Apriori pruning. Its shared dimensions grow in bottom-up fashion. As shown in Fig 4.

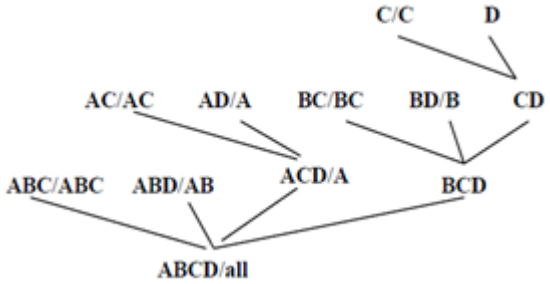

Figure 4: An Integrating Method: Star Cubing

7. Parallel Approaches [7]

Parallel Algorithms are introduced for cube computation over small PC clusters. Algorithm BPP (Breadth-first Writing, Partitioned, Parallel BUC), in which the dataset is not replicated, but is range partitioned on an attribute basis. The output of cuboids is done in a breadth-First fashion, as opposed to the depth-first writing that BUC do. In Depth First writing, cells may belong to different cuboids. For example, the cell a1 belongs to cuboid A, the cell a1b1 to cuboid AB, and the cells a1b1c1 and a1b1c2 belong to ABC. The point is that cuboids is scattered. This clearly incurs a high I/O over-head. It is possible to use buffering to help the scattered writing to the disk. However, this may require a large amount of buffering space, thereby reducing the amount of memory available for the actual computation. Furthermore, many cuboids may need to be maintained in the buffers at the same time, causing extra management overhead. In BPP, this problem is solved by breadth-first writing, implemented by first sorting the input dataset on the "prefix" attributes. Breadth-First I/O is a significant improvement over the scattering I/O used in BUC.

Another Parallel algorithm PT (Partitioned Tree) works with tasks that are created by a recursive binary division of a tree into two sub trees having an equal number of nodes. In PT, there is a parameter that controls when binary division stops. PT tries to exploit a affinity scheduling. During processor assignment, the manager tries to assign to a worker processor a task that can take advantage of prefix affinity based on the root of the subtree.PT is top-down. But interestingly, because

each task is a sub tree, the nodes within the sub tree can be traversed / computed in a bottom up fashion. In fact, PT calls BPP-BUC, which offers breadth-first writing, to complete the processing. Algorithm PT load-balances by using binary partitioning to divide the cube lattice as evenly as possible PT is the algorithm of choice for most situations.

8. Limitations of Existing Methods

There are three main limitations in the existing techniques:

1. They are designed for a single machine or clusters with small number of nodes. It is difficult to process data with a single (or a few) machine(s) at many companies where data storage is huge (e.g., terabytes per day)
2. Many of the techniques use the algebraic measure and use this property to avoid processing groups with a large number of tuples. This allows parallelized aggregation of data subsets whose results are then post processed to derive the final result. Many important analyses over logs, involve computing holistic (i.e., nonalgebraic) measures. Holistic measures pose significant challenges for distribution.
3. Existing techniques failed to detect and avoid extreme data skew. Extension of cube analysis usage can be avoided by these limitations.

There is need of technique to compute cube efficiently in parallel and identification of interesting cube groups on important subset of holistics measures over massive data sets. Hadoop based Mapreduce [8] environment handles large amount of data in clusters with thousands of machines. So MapReduce based technique which supports holistic measures is best option for data analysis. It helps to detect extreme data skew problem.

9. MapReduce Based Approach-MR Cube

MR-Cube, a MapReduce-based algorithm was introduced [13] for efficient cube computation and identification of interesting cube groups on holistic measures. Here each node in the lattice represents one possible grouping/aggregation. We use the term cube region to denote a node in the lattice and the term cube group to denote an actual group belonging to the cube region. First we begin by identifying a subset of holistic measures that are easy to compute in parallel than an arbitrary holistic measure. We call them partially algebraic measures. This notion is inspired by common ad hoc practices for computing a single holistic measure from an extremely large number of data tuples.

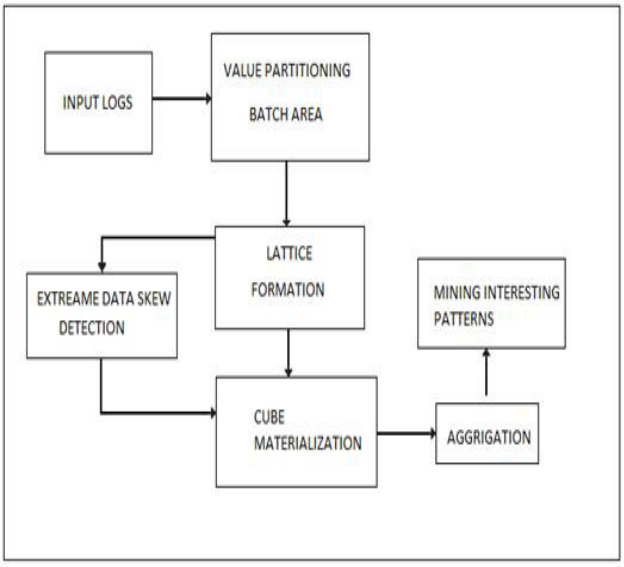

Figure 5: Proposed System Architecture

MR-Cube, a MapReduce-based algorithm was introduced [13] for efficient cube computation and identification of interesting cube groups on holistic measures. Here each node in the lattice represents one possible grouping/aggregation. We use the term cube region to denote a node in the lattice and the term cube group to denote an actual group belonging to the cube region. First we begin by identifying a subset of holistic measures that are easy to compute in parallel than an arbitrary holistic measure. We call them partially algebraic measures. This notion is inspired by common ad hoc practices for computing a single holistic measure from an extremely large number of data tuples.

Then two techniques needed for effectively distribute the data and computation workload. Value Partitioning is used for effectively distribute data for that we are going to run Naïve Algorithm [12].we want to perform value partitioning only on groups that are likely to be reducer unfriendly and dynamically adjust the partition factor. We adopt a sampling approach where we estimate the reducer un friendliness of each cube region based on the number of groups it is estimated to have, and perform partitioning for all groups within the list of cube regions (a small list) that are estimated to be reducer unfriendly.

For effectively distribute computation we use partitioning technique called Batch Area. Each batch area represents a collection of regions that share a common ancestor region.

The combined process of identifying and value partitioning unfriendly regions followed by the partitioning of regions into batches is referred to as ANNOTATE .So lattice formed is annotated lattice.

In MR-Cube algorithm, the MR-CUBE-MAP emits key: value pairs for each batch area. In required, keys are appended with a hash based on value partitioning, the shuffle phase then sorts them by key. The BUC Algorithm is run on each reducer, and the cube aggregates are generated. All value partitioned groups need to be aggregated to compute the final measures.

After materializing the cube (i.e., computing measures for all cube groups satisfying the pruning conditions) we can identify interesting cube groups for that cube mining algorithm is used which takes the partially materialized cube. By using the parent group label as the primary key and the group label as the secondary key, measures are clustered based on the parent group level, while ensuring sort endless on the group label. This allows a one-pass discovery of the most interesting group for each parent

Group-dimension combination, Using above mentioned approach now it is now feasible to perform both large scale cube materialization and mining in the same distributed framework.

10. Conclusion

Efficient Cube computation is important problem in data cube technology. So many techniques are used for computing cube like Multiway array aggregation, BUC, Star Cubing, the computation of shell fragments and parallel algorithms. BUC is sensitive to skew in the data; the performance of BUC degrades as skew increases. However, unlike MultiWay, the result of a parent cuboid does not help compute that of its children in BUC. For the full cube computation, if the dataset is dense, Star Cubing performance is comparable with MultiWay, and is much faster than BUC. If the data set is sparse, Star-Cubing is significantly faster than MultiWay and BUC, in most cases. Parallel algorithm like BPP and PT are designed for small PC clusters and therefore cannot take advantage of the MapReduce infrastructure. Proposed approach effectively distributes data and computation workload .Using important subset of holistic measures we are doing cube materialization and identifying interesting cube groups.

MR-Cube algorithm efficiently distributes the computation workload across the machines and is able to complete cubing tasks at a scale where a previous algorithm fails.

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