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Abstract

Along with the development of hardware and software, more and more data is generated at a rate much faster than ever. Processing large volume of data is becoming a challenge for data analysis software. Additionally, short response time requirement is demanded by interactive operational data analysis tools. For addressing these issues, people look for solutions based on parallel computing. Traditional approaches rely on expensive high-performance hardware, like supercomputers. Another approach using commodity hardware has been less investigated. In this thesis, we are aiming to utilize commodity hardware to resolve these issues. We propose to utilize a parallel programming model issued from cloud computing, MapReduce, to parallelize multidimensional analytical query processing for benefit its good scalability and fault-tolerance mechanisms. In this work, we first revisit the existing techniques for optimizing multidimensional data analysis query, including pre-computing, indexing, data partitioning, and query processing parallelism. Then, we study the MapReduce model in detail. The basic idea of MapReduce and the extended MapCombineReduce model are presented. Especially, we analyse the communication cost of a MapReduce procedure. After presenting the data storage works with MapReduce, we discuss the features of data management applications suitable for cloud computing, and the utilization of MapReduce for data analysis applications in existing work. Next, we focus on the MapReduce-based parallelization for *Multiple Group-by* query, a typical query used in multidimensional data exploration. We present the MapReduce-based initial implementation and a MapCombineReduce-based optimization. According to the experimental results, our optimized version shows a better speed-up and a better scalability than the other versions. We also give formal execution time estimation for both the initial implementation and the optimized one. In order to further optimize the processing of *Multiple Group-by* query processing, a data restructure phase is proposed to optimize individual job execution. We redesign the organization of data storage. We apply, data partitioning, inverted index and data compressing techniques, during data restructure phase. We redefine the MapReduce job's calculations, and job scheduling relying on the new data structure. Based on a measurement of execution time we give a formal estimation. We find performance impacting factors, including query selectivity, concurrently running mapper number on one node, hitting data distribution, intermediate output size, adopted serialization algorithms, network status, whether using combiner or not as well as the data partitioning methods. We give an estimation model for the query processing's execution time, and specifically estimated the values of various parameters for data horizontal partitioning-based query processing. In order to support more flexible distinct-value-wise job-scheduling, we design a new compressed data structure, which works with vertical partition. It allows the aggregations over one certain distinct value to be performed within one continuous process.

Keywords: MapReduce, multidimensional data analysis, Multiple Group by query, cost estimation, performance optimization, commodity hardware

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Contents

List of Figures **ix**

List of Tables **xiii**

Glossary **xv**

1 Introduction **1**

1.1 BI, OLAP, Data Warehouse 1

1.2 Issues with Data Warehouse 2

1.3 Objectives and Contributions 3

1.4 Organisation of Dissertation 5

2 Multidimensional Data Analyzing over Distributed Architectures **7**

2.1 Pre-computing 9

2.1.1 Data Cube Construction 9

2.1.2 Issue of Sparse Cube 10

2.1.3 Reuse of Previous Query Results 10

2.1.4 Data Compressing Issues 11

2.2 Data Indexing 12

2.2.1 B-tree and B^+-tree Indexes 13

2.2.2 Bitmap Index 15

2.2.3 Bit-Sliced Index 16

2.2.4 Inverted Index 17

2.2.5 Other Index Techniques 19

2.2.6 Data Indexing in Distributed Architecture 20

2.3 Data Partitioning 21

2.3.1 Data Partitioning Methods 22
2.3.1.1 Horizontal Partitioning 22
2.3.1.2 Vertical Partitioning 23
2.3.2 Data Replication 24
2.3.3 Horizontally Partitioning Multidimensional Data Set 24
2.3.3.1 Partitioning Multidimensional Array Data 25
2.3.3.2 Partitioning Star-schema Data 26
2.3.4 Vertically Partitioning Multidimensional Data set 28
2.3.4.1 Reducing Dimensionality by Vertical Partitioning . . . 29
2.3.4.2 Facilitating Index and Compression by Vertical Partitioning 29
2.4 Query Processing Parallelism 30
2.4.1 Various Parallelism Forms 31
2.4.2 Exchange Operator 32
2.4.3 SQL Operator Parallelization 32
2.4.3.1 Parallel Scan 33
2.4.3.2 Merge and Split 33
2.4.3.3 Parallel Selection and Update 34
2.4.3.4 Parallel Sorting 34
2.4.3.5 Parallel Aggregation and Duplicate Removal 36
2.4.3.6 Parallel Join 37
2.4.3.7 Issues of Query Parallelism 40
2.5 New Development in Multidimensional Data Analysis 40
2.6 Summary 41

3 Data Intensive Applications with MapReduce **43**
3.1 MapReduce: a New Parallel Computing Model in Cloud Computing . . 44
3.1.1 MapReduce Model Description 45
3.1.1.1 Fundamentals of MapReduce Model 46
3.1.1.2 Extended MapCombineReduce Model 48
3.1.2 Two MapReduce Frameworks: GridGain vs Hadoop 48
3.1.3 Communication Cost Analysis of MapReduce 50
3.1.4 MapReduce Applications 52

3.1.5 Scheduling in MapReduce 53
3.1.6 Efficiency Issues of MapReduce 56
3.1.7 MapReduce on Different Hardware 57
3.2 Distributed Data Storage Underlying MapReduce 57
3.2.1 Google File System 57
3.2.2 Distributed Cache Memory 59
3.2.3 Manual Support of MapReduce Data Accessing 60
3.3 Data Management in Cloud 62
3.3.1 Transactional Data Management 62
3.3.2 Analytical Data Management 63
3.3.3 BigTable: Structured Data Storage in Cloud 63
3.4 Large-scale Data Analysis Based on MapReduce 63
3.4.1 MapReduce-based Data Query Languages 64
3.4.2 Data Analysis Applications Based on MapReduce 64
3.4.3 Shared-Nothing Parallel Databases vs MapReduce 65
3.4.3.1 Comparison 66
3.4.3.2 Hybrid Solution 68
3.5 Related Parallel Computing Frameworks 69
3.6 Summary 70

4 Multidimensional Data Aggregation Using MapReduce 71
4.1 Background of This Work 71
4.2 Data Organization 72
4.3 Computations Involved in Data Explorations 76
4.4 Multiple Group-by Query 79
4.5 Challenges 79
4.6 Choosing a Right MapReduce Framework 80
4.6.1 GridGain Wins by Low-latency 80
4.6.2 Terminology 81
4.6.3 Combiner Support in Hadoop and GridGain 81
4.6.4 Realizing MapReduce Applications with GridGain 82
4.6.5 Workflow Analysis of GridGain MapReduce Procedure 83
4.7 Paralleling Single Group-by Query with MapReduce 84

4.8 Parallelizing Multiple Group-by Query with MapReduce 85
4.8.1 Data Partitioning and Data Placement 86
4.8.2 Determining the Optimal Job Grain Size 87
4.8.3 Initial MapReduce Model-based Implementation 87
4.8.4 MapCombineReduce Model-based Optimization 91
4.8.5 Performance Measurements 92
4.8.5.1 Experiment Platform: Grid'5000 92
4.8.5.2 Speed-up 93
4.8.5.3 Scalability 95
4.9 Execution Time Analysis 96
4.9.1 Cost Analysis for Initial Implementation 97
4.9.2 Cost Analysis for Optimized Implementation 100
4.9.3 Comparison 102
4.10 Summary 102

5 Performance Improvement 105
5.1 Individual Job Optimization: Data Restructure 106
5.1.1 Data Partitioning 106
5.1.1.1 With Horizontal Partitioning 106
5.1.1.2 With Vertical Partitioning 107
5.1.1.3 Data Partition Placement 107
5.1.2 Data Restructure Design 108
5.1.2.1 Using Inverted Index 108
5.1.2.2 Data Compressing 110
5.2 Mapper and Reducer Definitions 112
5.2.1 Under Horizontal Partitioning 112
5.2.2 Under Vertical Partitioning 115
5.3 Data-locating Based Job-scheduling 117
5.3.1 Job-scheduling Implementation 118
5.3.2 Discussion on Two-level Scheduling 119
5.3.3 Alternative Job-scheduling Scheme 119
5.4 Speed-up Measurements 120
5.4.1 Under Horizontal Partitioning 120

5.4.2 Under Vertical Partitioning 123
5.5 Performance Affecting Factors 126
5.5.1 Query Selectivity 126
5.5.2 Side Effect of Running Multiple Mappers on One Node 127
5.5.3 Hitting Data Distribution 128
5.5.4 Intermediate Output Size 130
5.5.5 Serialization Algorithms 131
5.5.6 Other Factors 132
5.6 Cost Estimation Model 133
5.6.1 Cost Estimation of Implementation over Horizontal Partitions . . 135
5.6.2 Cost Estimation of Implementation over Vertical Partitions . . . 138
5.6.3 Comparison 139
5.7 Alternative Compressed Data Structure 140
5.7.1 Data Structure Description 140
5.7.2 Data Structures for Storing RecordID-list 141
5.7.3 Compressed Data Structures for Different Dimensions 142
5.7.4 Measurements 145
5.7.5 Bitmap Sparcity and Compressing 145
5.8 Summary 146

6 Conclusions and Future Directions 149
6.1 Summary 149
6.2 Future Directions 151

Appendices 153

A Applying Bitmap Compression 155
A.1 Experiments and Measurements 155

References 159

List of Figures

2.1 B-tree index (a) vs. B^+-tree index(b) 14

2.2 Example of Bit-sliced index 17

2.3 A parallel query execution plan with *exchange* operators. 33

3.1 Logical view of MapReduce model. 47

3.2 Logical view of MapCombineReduce model. 49

3.3 Big-top-small-bottom processing structure of MapReduce suitable applications 54

3.4 Manual data locating based on GridGain: circles represent mappers to be scheduled. The capital letter contained in each circle represents the data block to be processed by a specific mapper. Each worker has a user-defined property reflecting the *contained data*, which is visible for master node. By identifying the values of this property, the master node can locate data blocks needed by each mapper. 61

4.1 Storage of original data set and the pre-computed materialized views for the identified frequently demanded queries: sub-figure (a) shows original data set under star-schema; sub-figure (b) shows several materialized views created based on the original data set represented in (a). 74

4.2 Overall materialized view—*ROWSET* 75

4.3 Create the task of MapCombineReduce model by combining two GridGain MapReduce tasks. 82

4.4 Work flow diagram of MapReduce-based application in GridGain. 85

4.5 Single Group-by query's MapReduce implementation design. This design corresponds to the SQL query `SELECT Orderkey SUM(Quantity) FROM LINEITEM WHERE Suppkey = 4633 GROUP BY Orderkey`. 86
4.6 The initial *Multiple Group-by* query implementation based on MapReduce model. 88
4.7 Aggregate table structure 88
4.8 The optimized *Multiple Group-by* query implementation based on MapCombineReduce model. 92
4.9 Speed-up versus the number of machines and the block size (1000, 2000, 4000, 8000, 16000). 94
4.10 Comparison of the execution time upon the size of the data set and the query selectivity. 96

5.1 Data placement for the vertical partitions. 109
5.2 (a) Compressed data files for one horizontal partition. (b) Compressed data files for one vertical partition of dimension x. (DV means Distinct Value) 111
5.3 Speed-up of MapReduce *Multiple Group-by* query over horizontal partitions. 121
5.4 Speed-up of MapCombineReduce *Multiple Group-by* query over horizontal partitions. 122
5.5 Speed-up of MapReduce *Multiple Group-by* aggregation over vertical partitions, MapReduce-based implementation is on the left side. MapCombineReduce-based implementation is on the right side. 125
5.6 Hitting data distribution: (a) Hitting data distribution of qurey with WHERE condition "Color='Pink' "(selectivity=1.06%) in the first 2000 records of ROWSET; (b) Hitting data distribution of query with WHERE condition "Product Family='Accessories' "(selectivity=43.1%) in the first 2000 records of ROWSET. 129
5.7 Measured speedup curve vs. Modeled speedup curve for MapReduce based query on horizontal partitioned data, where the each work node runs one mapper. 138

5.8 Compressed data files suitable for distinct value level job scheduling with measures for each distinct value are stored together. 141
5.9 Compressed data structure storing recordID list as Integer Array for dimension with a large number of distinct values 143
5.10 Compressed data structure storing recordID list as Bitmap for dimension with a small number of distinct values (In Java, Bitmap is implemented as Bitset) 144

List of Tables

2.1 Example of Bitmaps for a column **X**: B_0, B_1, B_2 and B_3 respectively represents the Bitmaps for **X**'s distinct values 0, 1, 2 and 3. 15

3.1 Differences between parallel database and MapReduce 68

4.1 Notations used for describing the cost analysis 98

5.1 Average execution time of multiple mappers jobs on 1 node. 127
5.2 Parameters and their estimated values (in ms) 137
5.3 Execution Times in ms of Group-by queries with different selectivities (S) using new compressed data structures. The numbers shown in italic represents that the corresponding aggregations run over the dimensions correlated to the WHERE condition involved dimension. For example, Product Family and Product Category are correlated dimensions. 146

A.1 Execution Times in ms of Group-by queries with different selectivities (S) using three compressed data structures. The numbers shown in italic represents that the corresponding aggregations run over the dimensions correlated to the WHERE condition involved dimension. For example, Product Family and Product Category are correlated dimensions. 157

Listings

4.1 SQL statements used to create materialized view—ROWSET 73
4.2 SQL statements used for displaying the first page of exploration panel. . 76
4.3 SQL statements used for displaying the second page of exploration panel. 77

1

Introduction

Business Intelligence (BI) end-user tools often require rapid query processing in order to serve the interactive interfaces. The typically required queries are usually complex, with the concerning data from various categories, at different the semantic levels. The typically require queries access a large volume of historical data, which is progressively generated every day. BI software needed to be scalable in order to address this increasing data volume. Short response time requirement and scalability requirement are the two important aspects concerning the performance of BI software. They are also the main objectives for which we start this work. In this chapter, we first review the relevant technologies of BI. Then we illustrate the main problems need to be addressed. After that, we describe the main contributions of this work. Finally, we specify the organization of this dissertation.

1.1 BI, OLAP, Data Warehouse

In present enterprise competitions, business and organizations are faced with changing circumstances and challenges. In order to adapt to changes, business and organizations need to be continually making decisions to adjust their actions so as to grow profitably. BI is a broad category of software applications or technologies for gathering, storing, analysing and providing data access to help users to make sound business decision. BI has increased the need for analytical capabilities. In earlier stage before BI, such as in decision support systems, users' queries are relatively straightforward reports, but now their queries often require on-line analytical capabilities, such as forecasting, predictive modeling, and clustering.

On-Line Analytical Processing (OLAP) provides many functions which make BI happens. It transforms data into multidimensional cubes, provides summarized, pre-aggregated and derived data, manages queries, offers various calculation and modeling functions. In the BI architecture, OLAP is a layer between Data Warehouse and BI end-user tools. The results calculated by OLAP are feed to end-user BI tools, which in turn realize functions like, business modeling, data exploration, performance reporting and data mining etc. During the data transformation, the raw data is transformed into multidimensional data cube, over which OLAP processes queries. Thus, answering multidimensional analytical queries is one of the main functions of OLAP. Codd E.F. put the concept of OLAP forward in (41), where Codd and his colleagues devised twelve rules covering key functionality of OLAP tools.

Data Warehouse is an enterprise level data repository, designed for easily reporting and analysis. It does not provide on-line information; instead, data are extracted from operational data source, and then cleansed, transformed and catalogued. After such a set of processing, manager and business professionals can directly use this data for on-line analytical processing, data mining, market research and decision support. This set of processing is also considered as the typical actions performed in Data Warehouse. Specifically, actions for retrieving and analysing data, actions for extracting, transforming and loading data, and actions for managing data dictionary make up the principal components of Data Warehouse.

1.2 Issues with Data Warehouse

As data is getting generated from various operational data source, the volume of data stored in Data Warehouse is ever-increasing. While today's data integration technologies make it possible to rapidly collect large volume of data, fast analysis over a large data set still needs the scalability performance of Data Warehouse to be further improved. Scaling up or scaling out with increasing volume of data is the common sense of scalability. Another aspect of scalability is scaling with increasing number of concurrent running queries. Comparing with data volume scalability, query number scalability is relatively well resolved in present Data Warehouse.

With BI end-user tools, the queries are becoming much more complex than before. Users used to accept simple reporting function, which involves small volume of aggregated data stored in Data Warehouse. But today's business professionals demand to access data from the top aggregate level to the most detailed level. They play more frequently with Data Warehouse with the ad hoc queries, interactive exploration and reporting. Interactive interface of BI strictly requires the response time should not be above 5 seconds, ideally within hundred of milliseconds. Such a short response time (interactive processing) requirement is another issue with Data Warehouse.

1.3 Objectives and Contributions

In this work, we are going to address data scalability and interactive processing issues arose in Data Warehouse, and propose a feasible, cheap solution. Our work is aiming to utilize commodity hardware. Different from those solutions relying on high-end hardware, like SMP server, our work is realized on commodity computers connecting in a shared-nothing mode. However, regarding to performance and stability of commodity hardware and those of high-end hardware are not comparable. The failure rate of commodity computers is much higher than high-end hardware.

Google proposed MapReduce is the de facto the Cloud computing model. After the MapReduce article (47) publication in 2004, MapReduce attracts more and more attentions. For our work, the most attractiveness of MapReduce is its automatical scalability and fault-tolerance. Therefore, we adopted MapReduce in our work to parallelize the query processing. MapReduce is also a flexible programming paradigm. It can be used to support all of data management processes performed in Data Warehouse, from Extract, Transform and Load to data cleansing and data analysis.

The major contributions of this work are the following:

- **A survey of existing work for accelerating multidimensional analytical query processing**. Three approaches are involved, including pre-computing, data indexing and data partitioning. These approaches are valuable experience, from which we can benefit in new data processing scenario. We summarize a wide range of commonly used operators' parallelizations.

- **Latency comparison between Hadoop and GridGain**. Those are two open-source MapReduce frameworks. Our comparison shows Hadoop has long latency and is suitable to for batch processing, while GridGain has low latency, and is capable of processing interactive query. We chose GridGain because of its advantage of low latency in the subsequent work.

- **Communication cost analysis in MapReduce procedure**. MapReduce hides the communication detail in order to provide an abstract programming model for developer. In spite of this, we are still curious of the underlying communication. We analysed the communication cost in the MapReduce procedure, and discussed the main factors affecting the communication cost.

- **Proposition and use of manual supporting MapReduce data accessing**. Distributed File System, such as Google File System and Hadoop Distributed File System and the file system based on cache are two main data storage approaches used by MapReduce. We propose the third MapReduce data accessing support , i.e. manual support. In our work, we use this approach to works with GridGain MapReduce framework. Although this approach requires developers to take care of data locating issue, it provides chances for restructuring data, and allows to improve data access efficiency.

- **Making GridGain to support *Combiner***. Combiner is not provided in GridGain. For enabling Combiner in GridGain, we propose to combine two GridGain's MapReduce tasks to create one MapCombineReduce task.

- **Multiple Group-by query implementation basing on MapReduce** We implement MapReduce model and MapCombineReduce based Multiple Group-by query. A detailed workflow analysis over the GridGain MapReduce procedure has been done. Speed-up and scalability performance measurement was performed. Basing on this measurement, we formally estimated the execution time.

- **Utilize data restructure improves data access efficiency** In order to accelerate *Multiple Group-by* query processing, we first separately partition data with horizontal partitioning and vertical partitioning. Then, we create index and compressed data over data partitions to improve data access efficiency. These measures result in significant accelerating effects. Similarly, we measure the speed-up performance of *Multiple Group-by* query over restructured data.

- **Performance affecting factors analysis** We summarize the factors affecting execution time and discuss how they affect the performance. These factors are query selectivity, number of mappers on one node, hitting data distribution, intermediate output size, serialization algorithms, network status, use or not combiner, data partitioning methods.

- **Execution time modelling and parameters' values estimation** Taking into account the performance affecting factors, we model the execution time for different stage of MapReduce procedure in GridGain. We also estimate the parameters' value for horizontal partitioning-based query execution.

- **Compressed data structure supporting distinct-value-wise job-scheduling** Data location-based job-scheduling is not flexible enough. A more flexible job-scheduling in our context is distinct-value-wise job-scheduling, i.e. one mapper works to compute aggregates for only several distinct values of one Group-by dimension. We propose a new structure of compressed data, which facilitate this type of job-scheduling.

1.4 Organisation of Dissertation

The rest of this dissertation is organized as follows.

Chapter 2 focuses on traditional technologies for optimizing distributed parallel multidimensional data analysis processing. Three approaches for accelerating multidimensional data analysis query's processing are pre-computing, indexing techniques and data partitioning. They are still very useful for our work. We will talk about these three approaches for accelerating query processing as well as their utilizations in distributed environment. The parallelism of various operators, which are widely used in parallel query processing, is also addressed.

Chapter 3 addresses data intensive applications based on MapReduce. Firstly, we will describe the logic composition of MapReduce model as well as its extended model. The relative issues about this model, such as MapReduce's implementation frameworks, cost analysis will also be described. Secondly, we will talk about the distributed file system underlying MapReduce. A general presentation on data management applications in the cloud is given before the discussion about large-scale data analysis based on MapReduce.

Chapter 4 describes MapReduce-based Multiple Group query processing, one of our main contributions. We will introduce *Multiple Group-by* query, which is the calculation that we will parallelize relying on MapReduce. We will give two implementation of *Multiple Group-by* query, one is based on MapReduce, and the other is based on MapCombineReduce. We also will present the performance measurement and analysis work.

Chapter 5 talks about performance improvement, one of our main contributions. We will first present the data restructure phase we adopted for improving performance of individual job. Several optimizations were performed over raw data set within data restructuring, including data partitioning, indexing and data compressing. We will present the performance measurement and the proposed execution time estimation model. We will identify the performance affecting factors during this procedure. A proposed alternative compressed data structure will be described at the end of this work. It enables to realize more flexible job scheduling.

2

Multidimensional Data Analyzing over Distributed Architectures

Multidimensional data analysis applications are largely used in BI systems. Enterprises generate massive amount of data everyday. These data are coming from various aspects of their products, for instance, the sale statistics of a series of products in each store. The raw data is extracted, transformed, cleansed and then stored under multidimensional data models, such as star-schema[1]. Users ask queries on this data to help making business decisions. Those queries are usually complex and involve large-scale data access. Here are some features we summarized for multidimensional data analysis queries as below:

- queries accesses large data set performing read-intensive operations;
- queries are often quite complex and require different views of data;
- query processing involves many aggregations;
- updates can occur but infrequently, and can be planned by administrator to happen at an expected time.

Data Warehouse is the type of software designed for multidimensional data analysis. However, facing to larger and larger volume of data, the capacity of a centralized Data Warehouse seems too limited. The amount of data is increasing; the number of concurrent queries is also increasing. The scalability issue became a big challenge for

[1]A star schema consists of a single fact table and a set of dimension tables

centralized Data Warehouse software. In addition, short response time is also challenging for centralized Data Warehouse to process large-scale of data. The solution addressing this challenge is to decompose and distribute the large-scaled data set, and calculate the queries in parallel.

Three basic distributed hardware architectures exist, including shared-memory, shared-disk, and shared-nothing. Shared-memory and shared-disk architectures cannot well scale with the increasing data set scale. The main reason is that these two distributed architectures all require a large amount of data exchange over the interconnection network. However, interconnection network cannot be infinitely expanded, which becomes the main shortage of these two architectures. On the contrary, shared-nothing architecture minimizes resource sharing. Therefore, it minimizes the resource contentions. It fully exploits local disk and memory provided by a commodity computer. It does not need a high-performance interconnection network, because it only exchanges small-sized messages over network. Such an approach minimizing network traffic allows more scalable design. Nowadays, the popular distributed systems almost adopted the shared-nothing architectures, including, peer-to-peer, cluster, Grid, Cloud. The research work related to data over shared-nothing distributed architectures is also very rich. For instance, parallel database like Gamma (54), DataGrid project (6), BigTable (37) etc. are all based on shared-nothing architecture.

In the distributed architecture, data is replicated on different nodes, and query is processing in parallel. For accelerating multidimensional data analysis query's processing, people proposed many optimizing approaches. The traditional optimizing approaches, used in centralized Data Warehouse, mainly include pre-computing, indexing techniques and data partitioning. These approaches are still very useful in the distributed environment. In addition, a great deal of work is also done for paralleling the query processing. In this chapter, we will talk about three approaches for accelerating query processing as well as their utilizations in distributed environment. We will present parallelism of various operators, which are widely used in parallel query processing.

2.1 Pre-computing

Pre-computing approach resembles the materialized views optimizing mechanism used in database system. In multidimensional data context, the materialized views become **data cubes**[1]. Data cube stores the aggregates for all possible combination of dimensions. These aggregates are used for answering the forthcoming queries.

For a cube with d attributes, the number of sub-cubes is 2^d. With the augment of the number of cube's dimensions, the total volume of data cube will exponentially increase. Thus, such an approach produces data of volume much larger than the original data set, which might not have a good scalability facing to the requirement of processing larger and larger data set. Despite this, the pre-computing is still an efficient approach for accelerating query processing in a distributed environment.

2.1.1 Data Cube Construction

Constructing data cube in a distributed environment is one of the research topics. The reference (93) proposed some methods for construction of data cubes on distributed-memory parallel computers. In their work, the data cube construction consists of six steps:

- Data partitioning among processors.
- Load data into memory as a multidimensional array.
- Generate a schedule for the group-by aggregations.
- Perform the aggregation calculations.
- Redistribute the sub-cubes to processors for query processing.
- Define local and distributed hierarchies on all dimensions.

In the data loading step (step 2), the size of the multidimensional array in each dimension equals the number of distinct values in each attribute; each record is represented as a cell indexed by the values[2] of each attribute. This step adopted two different

[1]Data Cube is proposed in (67), it is described as an operator, it is also called for short as **cube**. Cube generalizes the histogram, cross-tabulations, roll-up, drill-down, and sub-total constructs, which are mostly calculated by data aggregation.

[2]The value of each attribute is a member of the distinct values of this attribute.

methods for data loading: hash-based method and sort-based one. For small data sets, both methods work well, but for large data sets, the hash-based method works better than the sort-based method, because of its inefficient memory usage[1]. The cost for aggregating the measure values stored in each cell is varying. The reason is that the whole data cube is partitioned over one or more dimensions, and thus some aggregating calculations involve the data located on other processors. For example, for a data cube consisting of three dimensions A, B and C, being partitioned over dimension A, then aggregations for the series of sub-cubes ABC$\rightarrow$AB$\rightarrow$A involve only local calculations on each node. However, the aggregations of sub-cube BC need the data from the other processors.

2.1.2 Issue of Sparse Cube

The sparsity is an issue of data cube storage. In reality, the sparsity is a common case. Take an example of a data cube consisting of three dimensions (*product, store, customer*). If each store sells all products, then the aggregation over (product, store) produces $|product| \times |store|$ records. When the number of distinct values for each dimension increases, the product of above formula will greatly exceed the number of records coming from the input relation table. When a customer enters a store, he/she is not possible to cannot buy 5% of all the products. Thus, many records related to this customer will be a cell "empty". In the work of (58), the authors addressed the problem of sparsity in multidimensional array. In this work, data cube are divided into chunks, each chunk is a small equal-sized cube. All cells of a chunk are stored contiguously in memory. Some chunks only contain sparse data, which are called *sparse chunks*. For compressing the sparse chunks, they proposed a Bit-Encoded Sparse Storage (BESS) coding method. In this coding method, for a cell presents in a sparse chunk, a dimension index is encoded in $\lceil \log |d_i| \rceil$ bits for each dimension d_i. They demonstrated that data compressed in this coding method could be used for efficient aggregation calculations.

2.1.3 Reuse of Previous Query Results

Apart from utilizing pre-computed sub-cubes to accelerate query processing, people also tried to reuse the previous aggregate query results. With previous query results

[1]Sort-based method is excepted to work efficiently as in external memory algorithms it reduces the disk I/O over the hash-based method.

being cached in memory, if the next query, say Q_n, is evaluated to be contained within one of the previous queries, say Q_p, thus Q_n can be answered using the cached results calculated for Q_p. The case where Q_p and Q_n have entire containment relationship is just a special case. In a more general case, the relationship between Q_p and Q_n is only overlapping, which means only part of the cached results of Q_p can be used for Q_p. For addressing this partial-matching issue, the reference (51) proposed a chunk-based caching method to support fine granularity caching, allowing queries to partially reuse the results of previous queries which they overlap; another work (75) proposed a hybrid view caching method which gets the partial-matched result from the cache, and calculates the rest of result from the component database, and then it combines the cached data with calculated data to form the final result.

2.1.4 Data Compressing Issues

As the size of data cube's growth is exponential with the number of dimensions, when the number of dimensions increase to a certain extent, the corresponding data cube will explode. In order to address this issue, some data cube compressing methods are proposed. For instance, Dwarf (97) is a method of constructing compressed data cube. Dwarf considers eliminating prefix redundancy and suffix redundancy over cube computation and storage. The prefix redundancy commonly appears in dense area, while the suffix redundancy appears in the sparse area. For a cube with dimensions (a, b, c), there are several group-bys, including a: (a, ab, ac, abc). Assuming that the dimension a has 2 distinct values a_1, a_2, dimension b has b_1, b_2 and dimension c has c_1, c_2, in the cells identified by (a_1, b_1, c_1), (a_1, b_1, c_2), (a_1, b_1), (a_1, b_2), (a_1, c_1), (a_1, c_2) and (a_1), the distinct value a_1 appears 7 times, which causes a prefix redundancy. Dwarf can identify this kind of redundancy and store each unique prefix only once. For example, for aggregate values of three cells (a_1, b_1, c_1), (a_1, b_1, c_2), and (a_1, b_1), the prefix (a_1, b_1) is associated with one pointer pointing to a record with 3 elements (agg(a_1, b_1, c_1), agg(a_1, b_1, c_2), agg(a_1, b_1)). Thus the storage for cube cells' identifiers, i.e. (a_1, b_1, c_1), (a_1, b_1, c_2), and (a_1, b_1), is reduced to storage of one prefix(a_1, b_1) and one pointer. The suffix redundancy occurs when two or more group-bys share a common suffix (like, (a, b, c) and (b, c)). If a and b are two correlated dimensions, some value of dimension a, say a_i, only appears together with another value b_j of dimension b. Then the cells (a_i, b_j, x) and (b_j, x) always have the same aggregate values. Such a suffix redundancy can be identified and eliminated by Dwarf during the construction of cube. Thus, for a cube of 25 dimensions of one petabyte, Dwarf reduces the space to 2.3 GB within 20 minutes.

The condensed cube (104) is also a work for reducing the size of data cube. Condensed cube reduces the size of data cube and the time required for computing the data cube. However, it does not adopt the approach of data compression. No data decompression is required to answer queries. No on-line aggregation is required when processing queries. Thus, there is no additional cost is caused during the query processing. The cube condensing scheme is based on the Base Single Tuple (**BST**) concept. Assume a base relation R (A, B, C,...) , and the data cube $Cube(A, B, C)$ is constructed from R. Assume that attribute A has a sequence of distinct values a_1, $a_2 ... a_n$. Considering a certain distinct value a_k, where $1 \leq k \leq n$, if among all the records of R, there is only one record, say r, containing the distinct value a_k, then r is a BST over dimension A. To be noted, one record can be a BTS on more than one dimension. For example, continuing the previous description, if the record r contains distinct value c_j on attribute C, and no else record contains c_j on attribute C, then record r is the BST on C. The author gave a lemma saying that if record r is a BST for a set of dimensions, say SD, then r is also the BTS of the superset of SD. For example, consider record r, a BST on dimension A, then r is also the BST on (A, B), (A, C), (A, B, C). The set contains all these dimensions is called $SDSET$. The aggregates over the $SDSET$ of a same BST r concern always the same record r, which means that any the aggregate function $aggr()$ only apply on record r. Thus, all these aggregate values will have equal value $aggr(r)$. Thus, only one unit of storage is required for the aggregates of the dimensions and combination of dimension from $SDSET$.

2.2 Data Indexing

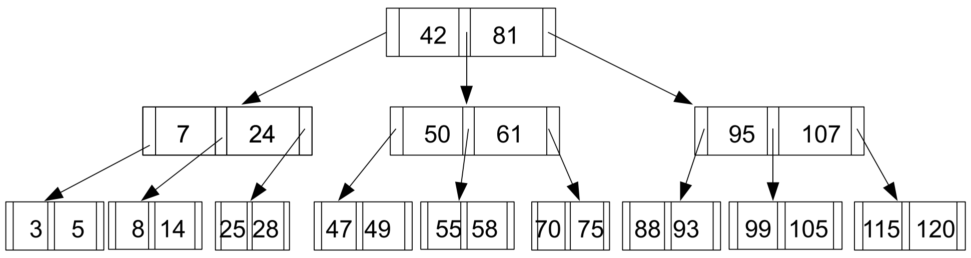
Data indexing is an important technology of database system, especially when good performance of read-intensive query is critical. The index is composed of a set of particular data structure specially designed for optimizing the data access. When performing read operations over the raw data set, within which the values of column are randomly stored, only full table scan can achieve data item lookup. In contrast, when performing read operations over index, where data items are specially organized, and the auxiliary data structures are added, the read operations can be performed much more efficiently. For queries of characteristics of read-intensive, like multidimensional data analysis query, index technology is an indispensable aid to accelerate query processing. Compared with other operations happening within the memory, the operations for reading data from the disk might be the most costly operations. One real example cited from (80) can demonstrate this: "we assume 25 instructions needed to retrieve the proper records from each buffer resident page. Each disk page I/O requires several thousand instructions to perform". It is clear that data accessing operations are very expensive. Especially, it becomes the most common operation in the read-intensive multidimensional data analysis application. Indexing data improves the data accessing efficiency by providing the particular data structures. The performance of index structures depends on different parameters, such as the number of stored records, the cardinality of the data set, disk page size of the system, bandwidth of disks and latency time etc. The index techniques used in Data Warehouse is coming from the index of database. Many useful indexing technologies are proposed, such as, B-tree/B^+-tree index (55), projection index(80), Bitmap index (80), Bit-Sliced index (80), join index (103), inverted index (42) etc. We will review these interesting index technologies in this section.

2.2.1 B-tree and B^+-tree Indexes

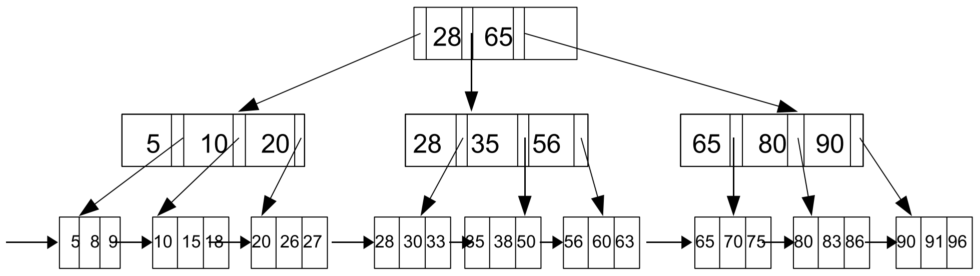
B^+-tree indexes(55) are one of the commonly supported index types in relational database systems. A B^+-tree is a variant of B-tree. To this end, we will briefly review B-tree. The Figure 2.1 illustrates these two types of index. In a B-tree with order of d, each node has at most $2d$ keys, and $2d + 1$ pointers, but at least d keys and $d + 1$ pointers. Each node is stored in form of one record in the B-tree index file. Such a record has a fixed length, and is capable of accommodating $2d$ keys and $2d+1$ pointers as well as the auxiliary information, specifying how many keys are really contained in this node. In a B-tree of order d, accommodating n keys, a lookup for a given key never uses more than $1 + \lceil \log_d n \rceil$ visits, where 1 represents the visit of root, $\lceil \log_d n \rceil$ is the height of tree, which is also the longest path from root to any leaf. As an example, the B-tree shown in Figure 2.1 (a) has order $d = 2$, because each node holds keys of number between d and $2d$, i.e. between 2 and 4. In total, 26 keys reside inside the

B-tree index. Then, a lookup over this B-tree involves no more than $1 + \lceil \log_2 26 \rceil = 3$ operations.

B^+-tree is an extension of B-tree. In a B^+-tree, all keys reside in the leaves, but the branch part (upper level above the leaves) is actually a B-tree index, except that the separator keys held by the upper-level nodes still appear in one of their lower-level nodes. The nodes in the upper-level have different structure from the leaf nodes. The leaves in a B^+-tree are linked together by pointers from left to right. The linked leaves form a sequence key set. Thus, a B^+-tree is composed of one independent index for search and a sequence set. As all keys are stored in leaves, any lookup in B^+-tree spends visits from the root to a leaf, i.e. $1 + \lceil \log_d n \rceil$ visits. An example of B^+-tree is shown in Figure 2.1 (b).



(a)B-tree of order $d = 2$



(b)B^+-tree of order $d = 3$

Figure 2.1: B-tree index (a) vs. B^+-tree index(b)

B^+-tree indexes are commonly used in database systems for retrieving records which contain the given values in specified columns. A B^+-tree over one column takes the distinct values as the keys. In practice, only the prefix of each distinct value is stored in the branch part nodes, for saving space. On the contrary, the keys stored in the leaves accommodate distinct values. Each record of a table with a B^+-tree index on one column is referenced once. Records are partitioned by distinct values of the indexed column, and the list of RecordIDs indicating those records having the same distinct value are associated to a same key.

B^+-tree indexes are considered to be very efficient for lookup, insertion, and deletion. However, in the reference (80), the author pointed out the limitation of B^+-tree index: it is inconvenient when the cardinality of the distinct values is small. The reason is that, when the number of distinct values (i.e. keys in B^+-tree index) is small compared with the record number, each distinct value is associated with a large number of RecordIDs. Thus, a long RecordID-list needs to be stored for every key (distinct value). Assume that one RecordID is stored as an integer, thus it takes 4 bytes for storing one RecordID. Even after compressing, the space required for storing these RecordIDs can take up to 4 times space required for stocking all RecordIDs. Therefore, in case of small number of distinct values, B^+-tree indexes are not space-efficient.

2.2.2 Bitmap Index

Another type of index structures, the Bitmap index is proposed to address the issue of small number of distinct values. Bitmap indexes do not store RecordID-list; instead, they store a bit structure representing the RecordID-list for records containing specific distinct values of the indexed column. This bit structure for representing the RecordID-list is called Bitmap. A Bitmap for a key (distinct value) is composed of a sequence of bits; the length of the bit sequence equals the record number of table; if one certain record, say the r-th record, contains the key in question, then the r-th bit is set to 1, and the other bits are set to 0. Refer to an example of Bitmap shown by Table 2.1.

RecordID	**X**	B_0	B_1	B_2	B_3
0	2	0	0	1	0
1	1	0	1	0	0
2	3	0	0	0	1
3	0	1	0	0	0
4	3	0	0	0	1
5	1	0	1	0	0
6	0	1	0	0	0
7	0	1	0	0	0

Table 2.1: Example of Bitmaps for a column **X**: B_0, B_1, B_2 and B_3 respectively represents the Bitmaps for **X**'s distinct values 0, 1, 2 and 3.

A Bitmap index for a column C containing distinct values v_0,v_1,...,v_n, is composed of a B-tree, in which keys are distinct values of C, and each key is associated with a Bitmap tagging the RecordIDs of records having the current key in its C field. Bitmap indexes are more space-efficient than storing RecordID-list when the number of keys (distinct values) is small (80). In addition, as the Boolean operations (AND, OR, Not) are very fast for bit sequence operands, then operations for applying multiple predicates are efficient with Bitmap indexes. Similarly, this also requires the indexed column has a small number of distinct values.

To be noted, storing Bitmaps and storing RecordID-list (used in B-tree and B^+-tree) are two interchangeable approaches. Both of them are aiming to store information of corresponding RecordIDs for a given distinct value When the number of distinct values of indexed column is small, each distinct value corresponds to a large number of records. In this case, the Bitmap is dense i.e. it contains a lot of 1-bits. Therefore, using Bitmap is more space-efficient. On the contrary, when the number of distinct values is large, then each distinct value corresponds to a small number of records. In such a case, directly storing RecordID-list is more space-efficient.

2.2.3 Bit-Sliced Index

Bit-sliced indexes (80) a type of index structure aiming to efficiently access values in numeric columns. Different from values of "text" type, numeric values can be extremely variable, then the number of distinct values can be extremely large too. For indexing a numeric column, the technologies for indexing text column are not practical. A useful feature of numeric values is that they can be represented using binary number. In order to create a bit-sliced index over a numeric column, one need to represent each numeric value with binary number. Through representing in binary number, one numeric value is expressed by a sequence of 0 and 1 codes with a fixed length, say N, where the bits in this sequence are numbered from 0 to $N-1$. A sequence of Bitmaps, B_0, B_1 ..., B_{N-1}, is created, each Bitmap recording the bit values at i-th position ($i = 1..N-1$) for all the column values. Refer to an example of bit-sliced index from Figure 2.2. In this example, a bit-sliced index is generated for a *sale_qty* column, which stores four data items of quantity of sold products. These four integer values of sale_qty are represented with binary numbers, each of them having 7 bits. Then these binary numbers are sliced into 7 Bitmaps, $B_0 ... B_6$. Bit-sliced indexes can index a large range of data, for instance, 20 Bitmaps are capable of indexing $2^{20} - 1 = 1048575$ numeric values.

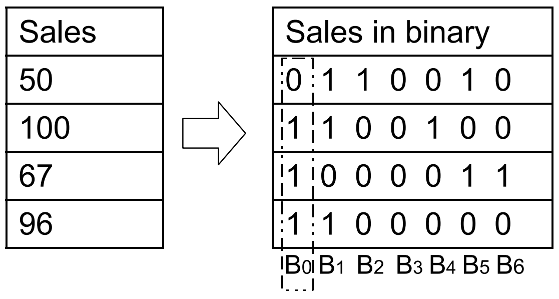


Figure 2.2: Example of Bit-sliced index

2.2.4 Inverted Index

Inverted index(42) is a data structure which stores a mapping from a word, or atomic search item to the set of documents, or sets of indexed units containing that word. Inverted indexes are coming from the information retrieval systems, and widely used in most full-text search. Search engines also adopted the inverted indexes. After web pages are crawled, an inverted index of all terms and all pages is generated. Then the searcher uses the inverted index and other auxiliary data to answer queries. Inverted index is a reversal of the original text in the documents. We can consider the documents to be indexed as a list of documents, each document is pointing to a term list. On the contrary, an inverted index maps terms to documents. Instead of scanning a text and then seeing its content (i.e. a sequence of terms), an inverted index allows an inverted search of a term to find its accommodating documents. Each term appears only once in inverted indexes, but it appears many times in the original documents. The identifier of document appears many times in inverted indexes, but only once in the original document list.

An inverted index is composed of two parts, an index for terms and for each term a posting list (i.e. a list of documents that contain the term). If the index part is sufficiently small to fit into memory, then it can be realized with a hash table; on the contrary, if the index part cannot fit into memory, then the index part can be realized with a B-tree index. Most commonly, B-tree index is used as the index part.

The reference (42) proposed some optimization for B-tree based inverted index. The optimization involves reducing disk I/Os and storage space. As disk I/Os are the most costly operations compared with other operations, reducing disk accesses and reducing storage space also mean accelerating the processing of index creation and index searching. Two approaches for fully utilizing memories[1], i.e. page cache and buffer, were proposed to create inverted index. With page cache approach, the upper level part of B-tree is cached in memory, then sequentially read into each word from documents and write them to the B-tree. In order to update the nodes beyond the cached part of B-tree, an extra disk access is required. With buffer approach, the postings reside in a buffer (in memory) instead of the upper level part of B-tree. When the buffer is full, the postings will be merged with B-tree. During the period of merge, B-tree's each sub-tree is iteratively loaded into memory in order to be merged. The buffer approach is demonstrated to run faster than the page cache approach. Storing the associated posting list of each term in a heap file on disk can reduce both disk I/Os and storage space. For reducing the storage space for posting list, a simple delta encoding is very useful. Instead of storing the locations of all postings as a sequence of integers, delta encoding just records the distance between two successive locations, which a smaller integer occupying less space.

In a multidimensional data set, the columns including only pure "text" type values are very common. For example, the columns storing information about, city name, person name, etc. These columns have a limited number of distinct values[2]. Thus, it is possible to index values of these "text" type column with inverted index. To this end, we consider the column values contained in each record as terms, and the RecordIDs as a document (i.e. posting in the terminology of full-text search). Instead of storing the document-ids as the postings, the RecordIDs are stored as postings in inverted index. Using inverted index allows quickly finding the given term's locations. Similarly, using inverted index can quickly retrieve records meeting a query's condition. The reference (73) proposed a method of calculating high-dimensional OLAP queries with the help of inverted indexes. The issue being addressed in this work is the particularly large number of dimensions in high-dimensional data set. As the number of dimensions are

[1]Assume that the B-tree index is too large to fit into memory, only a part of nodes of B-tree can reside in memory.

[2]In contrast, the columns including only numeric type values can have very large number of distinct values.

too large, the data cube is not possible to pre-calculate because of the data cube's exponential growth with the number of dimensions. In their work, they vertically partitioned the original data set into fragments, each fragment containing a small number of dimensions. The local data cube is pre-calculated over each fragment instead of over the original high-dimensional data set. Along with the calculation of local data cubes, the inverted index for each cuboid[1] is also built. The inverted index for a individual dimension is directly created; the inverted index for non-individual-dimension-cuboid is calculated by intersecting record-lists of two or more concerned values stored in the inverted indexes of concerned individual-dimension-cuboids. Here, these inverted indexes are served to efficiently retrieve concerned RecordIDs for computing cells of a given cuboid.

Lucene(16) is an open-source implementation of inverted index. It is originally created by Doug Cutting, one author of the reference (42). It is now under the Apache Software License. It is adopted in the implementation of Internet search engines. Lucene offers a set of APIs for creating inverted index and search on it. Lucene allows user to reconfigure the parameters to obtain higher performance.

2.2.5 Other Index Techniques

Projection Index

Taking into account that most queries retrieve only a part of columns, accessing the whole table for reading only part of them is considered to be inefficient. For solving this problem, projection index is proposed in (80). A projection index over one column extracts the values of this column from the raw data table, keeping the order of values as in the ordinal data table. In case of processing query concerning a small number of columns being concerned, data access over projection indexes is very efficient.

Join Index

Join index (103) is proposed to optimize the join operations. A join index concerns two relations to be joined. Assuming A and B are two relations to join, and A joins B

[1]A cuboid is an element composing data cube, and it is also a group-by over the original data set. For example, for a data set with 3 dimensions (A_1, A_2, A_3), the cuboids composing the cube (A_1, A_2, A_3) are: $\{A_1, A_2, A_3, (A_1, A_2), (A_1, A_3), (A_2, A_3), (A_1, A_2, A_3)\}$. The cuboid on all dimensions is called base cuboid.

will produce a new relation T. Then a join index for two joining relations A and B—join operation concerns the column a from A and the column b from B—is composed of columns a and b, each qualified record will appear in the produced relation T. Join index can be used together with other indexing technologies, such as Bitmap index, Projection index, Bit-Sliced index. Choosing appropriate combination according to the characteristics of queries will produce high efficiency (80). For instance, a combination between Join index and Bitmap index can avoid creating and storing many Join indexes for all joins probably appear before processing a query, because the join index can be rapidly created in the runtime with the aid of Bitmap index.

R-tree Index

R-tree index is an index structure similar to B-tree, but is used to access cells of a multidimensional space. Each node of an R-tree has a variable number of entries (up to some pre-defined maximal value). Each entry within a non-leaf node stores two pieces of data: a way of identifying a child node, and the bounding box of all entries within this child node. Some research work has exploited R-tree index to build index over data cube, such as Cubetree (92), Master-Client R-Tree (94), and RCUBE index (48). Cubetree is a storage abstraction of the data cube, which is realized with a collection of well organized packed R-trees that achieve a high degree of data clustering with acceptable space overhead. A Master-client tree index is composed of the non-leaf nodes stored on master and leaf nodes stored on clients; each client builds a complete R-tree for the portion of data assigned to it. RCUBE index is similar to Master-Client tree index, except that there is no a global R-tree on a dedicated node (Master), instead, and the queries are passed in form of messages directly to each processor.

2.2.6 Data Indexing in Distributed Architecture

Using indexing technology in a distributed architecture for efficient query processing is still an open issue. The challenge is concerning with data partitioning and data ordering so as to satisfy the requirements of load balancing and minimal disk accesses over each node. More specifically, load balancing requires reasonably partitioning data set and placing each data partitions over nodes so that the amount of data retrieved from each node as evenly as possible[1]; minimal disk accesses requires good data structure to augment the efficiency of data accessing over the disk of each node.

In the reference (44), the author proposed an index method similar to projection indexing and join index to process queries. Differently, they use these indexes in a distributed environment (shared-nothing). This work is based on a star-schema data set, which is composed of several dimension tables and one fact table. In this work, the data index is called *Basic Data Index* (*BDI*). *BDI* is a vertical partition of the fact table, which includes more than one column. The *BDI* is separated out and be stored respectively, having the same number of records as in the fact table. After separating out one *BDI*, the fact table does not keep the same columns. Assuming the star-schema data set has d dimensions, the fact table is vertically partitioned into $d+1$ *BDI*s, which d *BDI*s storing columns related to d dimensions, and 1 *BDI* storing the remaining columns of the fact table. The *Join Data Index* (*JDI*) is designed to efficiently process join operations between fact table and dimension table. Thus, it concerns one of *BDI*s separated from the fact table and one dimension table. A *JDI* add to the *BDI* the corresponding record's RecordIDs, which identify the record in the dimension table. In this way, the join operation between fact table and dimension table can be accomplished with only one scan over *JDI*.

2.3 Data Partitioning

In order to reduce the resource contention [2], a distributed parallel system often uses affinity scheduling mechanism; giving each processor an affinity process to execute. Thus, in a shared-nothing architecture, this affinity mechanism tends to be realized by data partitioning; each processor processes only a certain fragment of the data set. This forms the preliminary idea of data partitioning.

Data partitioning can be logical or physical. Physical data partitioning means reorganizing data into different partitions, while logical data partitioning will greatly affect physical partitioning. For example, a design used in Data Warehouse, namely data mart, is a subject-oriented logical data partitioning. In a Data Warehouse built in an enterprise, each department is interested only in a part of data. Then, the data

[1]Data partitioning will also be referred to later in this chapter.
[2]Resource contention includes disk bandwidth, memory, network bandwidth, etc.

partitioned and extracted from Data Warehouse for this department is referred as a data mart. As we are more interested in the physical data access issue, we will focus on the physical data partitioning techniques.

2.3.1 Data Partitioning Methods

Data partitioning allows exploiting the I/O bandwidth of multiple disks by reading and writing in parallel. That increases the I/O efficiency of disks without needing any specialized hardware (52). Horizontal partitioning and vertical partitioning are two main methods of data partitioning.

2.3.1.1 Horizontal Partitioning

Horizontal partitioning conserves the record's integrality. It divides tables, indexes and materialized views into disjoint sets of records that are stored and accessed separately. The previous studies show that horizontal partitioning is more suitable in the context of relational Data Warehouses(33). There mainly are three types of horizontal partitioning, *round-robin partitioning*, *range partitioning* and *hash partitioning.*

Round-robin partitioning is the simplest strategy to dispatch records among partitions. Records are assigned to each partition in a round-robin fashion. Round-robin partitioning works well if the applications access all records in a sequential scan. Round-robin does not use a partitioning key, and then records are randomly dispatched to partitions. Another advantage of round-robin is that it gives good load balancing.

Range partitioning uses a certain attribute as the partitioning attribute, and records are distributed among partitions according to their values of the partitioning attribute. Each partition contains a certain range of values on an indicated attribute. For example, table CUSTOMER_INFO stores information about all customers. We define column ZIP-CODE as the partition key. We can range-partition this table by giving a rule as zip-code between 75000 and 75019. The advantages of range partitioning is that it works well when applications sequentially or associatively access data[1], since records are clustered after being partitioned. Data clustering puts related data together in physical storage, i.e. the same disk pages. When applications read the related data, the disk I/Os are limited. Each time one disk page is read, not only the targeted data

[1]Associative data accessing means access all records holding a particular attribute value.

item, but also other needed data items of potential operations are fetched into memory. Thus, *Range partitioning* makes disk I/Os more efficient.

Hash partitioning is ideally suitable for applications that access data in a sequential manner. Hash partitioning also needs an attribute as the partitioning attribute. Records are assigned to a particular partition by applying a *hash* function over the partitioning key attribute of each record. Hash partitioning works well with both sequential data access applications and associative data access ones. It can also handle data with no particular order, such as alphanumeric product code keys.

The problem with horizontal partitioning is that it might cause data skew, where all required data for a query is put in one partition. Hash partitioning and round-robin partitioning are less possible to causes data skew, but range partitioning is relatively easy to cause this issue.

2.3.1.2 Vertical Partitioning

Another data partitioning method is vertical partitioning, which divides the original table, index or materialized view into multiple partitions containing fewer columns. Each partition has full number of records, but partial attributes. As each record has fewer attributes, the size of record is smaller. Thus, each disk page can hold more records, which allows query processing to reduce disk I/Os. When the cardinality of the original table is large, this benefit is more obvious.

However, vertical partitioning has some disadvantages. Firstly, updating (insert or delete) records in a vertically partitioned table involves operations over more processors. Secondly, vertical partitioning breaks the record integrality. Nevertheless, vertical partitioning is useful in some specific contexts. For example, it can separate frequently updated data (dynamic data) columns from static data columns; the dynamic data can be physically stored as a new table. In the processing of data read-intensive OLAP queries, vertical partitioning has its proper advantages:

- With isolating certain columns, it is easier to access data, and create index over these columns (45; 44).
- Column-specific Data compression, like run-length encoding, can be directly performed (24).

- Multiple values from a column can be passed as a block from one operator to the next. If existing attributes have fix-length values, then they can be iterated as array (24).
- For some specific data set with a high dimension number, vertical partitioning is more reasonable in terms of time and space costs (74).

2.3.2 Data Replication

Data replication technique is usually used together with data partitioning. Data replication is used to increase the liability. Multiple identical copies of data are stored over different machines. Once the machine holding the primary copy is down, then the data can still be accessed on machines holding the copies. In general, data replication and distribution are not necessary together with data partitioning. They are the technologies can be used alone. In the work of (29), the author proposed an adaptive virtual partitioning for OLAP query processing based on shared-nothing architecture. In their approach, the data set is replicated over all the nodes in the shared-nothing cluster. The virtual partitioning does not physically partition the data set, instead, it creates a set of sub-queries including different predicates. By applying these predicates, the original data set is virtually partitioned, the original query is run only on the data items belonging to the partition.

2.3.3 Horizontally Partitioning Multidimensional Data Set

The multidimensional data set usually has a large volume. But the calculations over them are expected running rapidly. As one of the OLAP query optimizing approaches, data partitioning makes it possible to process queries in a parallel and distributed fashion. Also, it can reduce irrelevant data accesses, improve the scalability, and ease data management. In this sub-section, we summarize the applications of horizontal partitioning in OLAP query processing. By horizontal partitioning, we refer to the partitioning method that conserves the record integrality. According to the ways for storing data, OLAP tools can be categorized into Relational OLAP (ROLAP) and Multidimensional OLAP (ROLAP). In ROLAP, data is stored in form of relations under star-schema. In MOLAP, data is stored in form of cubes or multidimensional arrays i.e. data cubes. We separately specify the data partitioning approaches designed for these two different data models.

2.3.3.1 Partitioning Multidimensional Array Data

In a MOLAP, data cube is represented as a multidimensional space, stored in optimized multidimensional array storage. In the multidimensional space, each *dimension* is represented as an axis; the distinct values of each dimension are various coordinate values on the corresponding axis. The *measures* are loaded form each record in the original data set into the cells of this multidimensional space, each cell being indexed by the unique values of each attributes of the original record. Partitioning a data cube into dimensions and measures is a design choice (93).

Partitioning data cubes should support equal or near-equal distributions of work (i.e. the various aggregate computations for a set of cuboids) among processors. The partitioning approach should be dimension-aware, which means that it should provide some regularity for supporting dimension-oriented operations. Partitioning can be performed over one or more dimensions(93; 58). That is to say, the basic multidimensional array is partitioned on one or more dimensions. The dimensions over which the partitioning is performed are called partitioning dimensions. After partitioning, each processor holds a smaller multidimensional array, where the number of distinct values held in each partitioning dimension is smaller than in the whole multidimensional array. Thus, the distinct values over each partitioning dimension are not be overlapped among the sub-multidimensional arrays held by each processor. In order to obtain the coarsest partitioning grain possible, the dimension(s) having largest number of distinct values is chosen to be the partitioning dimension. Assume a data set with 5 attributes (A, B, C, D, M), among them A, B, C, D are the dimensions (axis) in the multidimensional array, and M is the measure stored in each cell of multidimensional array. D_a, D_b, D_c and D_d are number of distinct values in each dimension, respectively, with $D_a \geq D_b \geq D_c \geq D_d$ established. This data set will be partitioned and distributed over p processors, numbered $P_0 ... P_{n-1}$. Thus, an one-dimension partitioning will partition on A, since the A has the biggest number of distinct values[1]; this partitioning also builds an order on A, which means if $A_x \in P_i$ and $A_y \in P_j$ then $A_x \leq A_y$ for $i < j$.

[1]Similarly, a two-dimension partitioning will partition on A, B, since A and B have the biggest number of distinct values.

The sub-cubes are constructed over processors with their local sub-data set (i.e. partition). In order to guarantee that each partition does not have overlaps over the partitioning dimension's distinct values, the sampling-like record distributing methods, such hash-based or sort-based method can be used to distribute records to various processors as described in (93).

Constructing the sub-cube is performed by scanning sub-data set attributed to the local processor. In reference (93), the sub-data-set is scanned twice. The first scan obtains the distinct values for each dimension contained in the sub-data-set, and constructs a hash-table for various dimensions' distinct values. The second scan loads the records into the multidimensional array. Record loading (the second scan) works together with probing the hash-tables created earlier. During this process, the method chosen for partitioning and distributing the original data set, will affected the performance because the way to access data is slightly different.

Another thing to be noted is that data partitioning determines the amount of data movement during the aggregates' computations of the aggregates (58). As the computations of various cuboids involve multiple aggregations over any combination of dimensions, some cuboid computations are non-local. They need to newly partition over a dimension and distribute the partitions. Assume that the multidimensional array of the 4 dimensional cube is partitioned over A, B, then the aggregation of over dimension C from $\underline{AB}C$[1] to $\underline{AC}$ involves aggregations over dimension B, and requires partitioning and distribution over dimension C.

2.3.3.2 Partitioning Star-schema Data

In ROLAP, data is organized under star-schema. Horizontal partitioning was considered an effective method compared to vertical partitioning for star schema data (70). In the centralized Data Warehouse, data is stored in form of star schema. In general, star schema is composed of multiple dimension tables and one fact table. Since horizontal partitioning addresses the issue of reducing irrelevant data access, it is helpful to avoid unnecessary I/O operations. One of the features about data analysis queries run on Data Warehouse is they involve multiple join operations between dimension tables and the fact table. The derived horizontal partitioning, developed for optimizing relational database operations, can be used to efficiently processed these join operations.

[1]The letters with underlines represents the dimensions being partitioned and distributed.

Partitioning only fact table

This partitioning scheme partitions only the fact table, and replicating the dimension tables, since the fact table is generally large.

The reference (34) proposed stripping-partitioning approach. In this approach, the dimension tables are fully replicated over all compute nodes without being partitioned, as they are relatively small. The fact table is partitioned using round-robin partitioning and each partition is distributed to a compute node. Defining N as the number of computers, each computer stores $1/N$ fraction of total amount of records. Records of fact table are striping-partitioned by N computers, then queries can be executed in parallel. In this way, they guaranteed a nearly linear speed-up and significantly improvement of query response time.

The size of each partition determines the workload attributed to a processor. The partition size needs to be tuned according to variant queries. A virtual partitioning method (28) was proposed for this purpose. It allows greater flexibility on node allocation for query processing than physical data partitioning. In this work, the distributed Data Warehouse is composed of several database systems running independently. Data tables are replicated over all nodes, and each query is broken into sub-queries by appending range predicates specifying an interval on the partitioning key. Each database system receives a sub-query and is forced to process a different subset of data of the same size. However, the boundaries limiting each subset are very hard to compute, and dispatching the one sub-query per node makes it difficult to realize dynamic load balancing. A fine-grained virtual partitioning (FGVP) (31) was proposed addressing this issue. FGVP decomposes the original query into a large number of sub-queries instead of one query per database system. It avoids fully scanning table and suffers less from the individual database system internal implementation. However, determining appropriate partition size is still difficult. Adaptive Virtual Partitioning (AVP) (29) adopted an experimental approach to obtain the appropriate partitioning size. An individual database system process the first received sub-query with a given small partitioning size. Each time it starts to process a new sub-query, it increases the partitioning size. This procedure repeats until the execution time does not shorten any more, then the best partitioning size is found. Performing AVP needs some metadata information. Metadata information includes clustered index of the relations, names and cardinalities of relations, attributes on which a clustered index is built, the range of values of such attributes. The meta data information is stored in a catalog in the work of (69).

Partitioning dimension tables & fact table

This partitioning scheme works with star-schema is partitions both dimension tables and fact table. Often, the dimension tables are horizontally partitioned into various fragments, and the fact table is also horizontally partitioned according to the partitioning results of dimension tables. This scheme takes in to account of the star-join requirements.

The number of the fact table partitions depends on the partition number of each dimension table. Assume N is the number of fact table partitions, $p_1...p_d$ are the partition numbers of dimension tables $1...d$. If fact table partitioning considers all partitioning performed on the dimension table, then $N = p_1 \times ... \times p_d$. That means, along with augment of $p_1...p_d$, N will explosively increase. The work of (32) focus on finding the optimal number of fact table partitions, in order to satisfy two objectives:

- avoid an explosion of the number of the fact table partitions;
- ensure a good performance of OLAP queries.

A generic algorithm is adopted for selecting an horizontal schema in their work.

2.3.4 Vertically Partitioning Multidimensional Data set

Multidimensional data set usually contains many attributes. With the entire record being stored on the disk (in case of horizontal partitioning), the data access over multidimensional data set may become inefficient, even though some indexing technique, like B-tree applied on it. Vertical partitioning is needed in some special cases. Imagine the following extreme scenario where a query scans only the values of one particular attribute of each record. Clearly, in this case, scanning the required attribute separately is much more efficient than scanning the whole table. From the literature, we summarized two types of data set, for which vertical partitioning is very suitable, high dimension data set and read-oriented data set.

The advantages of vertical partitioning versus horizontal one are, firstly, it can reduce the dimensionality, which in turn enhance the data accessibility; secondly, it enables a set of optimization, like index and compressing easily, to be performed, which in turn improves the efficiency.

2.3.4.1 Reducing Dimensionality by Vertical Partitioning

In a data set with high dimensionality, the number of dimensions is very large, but the number of records is moderate. The queries run over such data set concerns only several dimensions. Although OLAP queries involve high-dimension space, retrieving data of all dimensions occurs very rarely. Based on this, the authors of reference (74) employed a vertically partitioning method in their work. They vertically partitioned the data set into a set of disjoint low dimensional data sets, called fragment. For each fragment, the local data cube is calculated. These local data cubes are on-line assembled when queries concerning multiple fragments need to be processed. In this work, an inverted index based indexing technique and data compressing technique are applied for accelerating the on-line data cube assemblage[1].

2.3.4.2 Facilitating Index and Compression by Vertical Partitioning

In a vertically partitioned data set, data is stored in a column-oriented style. Different from the row-oriented storage where, records are stored one after another, in the column-oriented storage, attribute values belonging to the same column stored contiguously, compressed, and densely packed (26). OLAP applications are generally read-intensive, where the most common operation is to read data from disk, the update operation also occurs, but not frequently. For such read-intensive applications, the most important performance-affecting factor is the I/O efficiency.

For a multidimensional data set, the traditional indexing techniques, such as B-tree indexing, are not appropriate. Simply scanning the vertically partitioned data tables is often more efficient than using B-tree based indexes to answer ad hoc range queries (100). Using the traditional indexing techniques to process queries involving only a subset of attributes suffers from the high dimensionality of the data set, since the size of index increase super-linearly with the augment of the dimension number. With the vertical partitioning method, the high dimensionality issue is resolved. However, facing the new data storage structure, not all the traditional indexing techniques are

[1]Refer to 2.2.4 Inverted index for more information.

appropriate. Bitmap index data structure is mostly used for answering read-intensive OLAP queries (38), but not optimized for insert, delete or update operations. Having this characteristic, Bitmap is considered to be the most suitable index for working with vertical partitioned data. For large data set, Bitmap index can have millions to billions of bits. It is imperative to compress bitmap index. The authors of (100) have compared some of the compression schemes such as Byte-aligned Bitmap Code (BBC), Word-Aligned Hybrid run-length code (WAH), and Word-aligned Bitmap Code (WBC). They found that WAH is the most efficient in answering queries because it is much more CPU-efficient.

Compared to row-oriented storage, column-oriented storage presents a number of opportunities to improve performance by compression techniques. In such a column-oriented storage, compression schemes encoding multiple values within one time are natural. For example, many popular modern compression schemes, such as Run-length encoding, make use of the similarity of adjacent data to compress. However, in a row-oriented storage system, such schemes do not work well, because an attribute is stored as a part of an entire record. Compression techniques reduces the size of data, thus it improves the I/O performance in the following ways (23):

- In a compressed format, data is stored nearer to each other, the seek time is reduced;
- The transfer time is reduced also because there is less data to be transferred;
- The buffer hit rate is increased because a larger fraction of retrieved data fits in the buffer pool.

Especially, compression ratios are usually higher in column-oriented storage because consecutive values of a same column are often quite similar to each other.

2.4 Query Processing Parallelism

Parallelizing query processing over partitioned data set using multiple processors can significantly reduce the response time. The query processing parallelism has shown a good speed-up and scale-up for OLTP query, it is worthwhile to investigate parallelism research for processing OLAP query. In the sequential database systems, such as relational database system, queries are often parsed into graphs during the processing. These graphs are called query execution plan or query plan, which is composed of various operators.

A lot of parallel query processing work has been done in parallel database machines, such as Gamma (54), Bubba (35), Volcano (59) etc. The main contributions of their work were parallelization of data manipulations and design of the specific hardware. Even though parallel database machines were not really put into use, they leaded database technology toward a good direction, and its research work became the basis of parallel query processing techniques. The general description of query processing parallelization is as follows: a query is transformed into N partial queries that are executed in an independent way in each of N computers. Generally, we can distribute the same query to all computers, but some types of queries require rewriting.

2.4.1 Various Parallelism Forms

There exist several forms of parallelism that are interesting to designers and implementers of query processing systems (60). *Inter-query parallelism* means multiple queries are processed concurrently. For example, several queries contained in a transaction are executed concurrently in a database management system. For this form of parallelism, the resource contention is an issue. Basing on the algebraic operators parallelization, the parallelism forms can be further refined.

Inter-operator parallelism means parallel execution of different operators in a single query. It has two sub-forms, i.e. *horizontal inter parallelism* and *vertical inter parallelism. Horizontal inter parallelism* means splitting a tree of query execution plan into several sub-trees, each sub-tree is executed by a processor individually. It can easily be implemented by inserting a special type of operators, *exchange*, into the query execution plan, in order to parallelize the query processing. We will talk about *exchange* operator in the following content. *Vertical inter-parallelism* is also called *pipeline*, in which operators are organized into a series of *producers* and *customers*. Parallelism is gained by processing records as a stream. Records being processed by producers are sent customers. The authors of reference (52) argued that, in a relational database system, the benefit of pipeline parallelism is limited. The main reasons was: 1) very long pipelines are rare in query processing based on SQL operators; 2) some SQL operators do not emit the first item of output until they consumed all items of input, such as aggregate and sort operators; 3) there often exist one operator which takes much longer time than other operators, which makes the speed-up by pipeline parallelism be very limited.

Another form of parallelism is *Intra-operator parallelism*, which means executing an operator using several concurrent processes running on different processors. It is based on data partitioning. The precondition of *intra operator parallelism* is that query should focus on *sets*. Otherwise, if data being queried represents a sequence, for example, time sequence in a scientific database, then such a parallelism form could not be directly used, and some additional synchronization should be processed at the result-merging phase.

2.4.2 Exchange Operator

Exchange operator was proposed in Volcano system (59). It is a parallel operator inserted into a sequential query execution plan so as to parallelize the query processing. It is similar to the operators in the system, like *open*, *next*, *close*; other operators are not affected by the presence of *exchange* in the query execution plan. It does not manipulate data. On the logical level, *exchange* is "no-op" that has no place in logical query algebra such as the relational algebra. On the physical level, it provides the "control" functions that the other operators do not offer, such as, processes management, data redistribution, flow control. *Exchange* provides only "control" parallelisms, but it does not determine or presuppose the policies applied for using these mechanisms, such as degree of parallelism, partitioning functions, attributing processes to processors. In Volcano, the optimizer or user determines these policies. The Figure 2.3 shows a parallel query execution plan with *exchange* operators.

2.4.3 SQL Operator Parallelization

Query running over the partitioned data set can achieve parallelism, which is also called partitioned parallelism. The algorithms used to implement various operators in parallel are different from those used in a sequential query execution plan's implementations. In the following content, we will summarize the parallelization issues for different operators.

Various SQL operators parallelization algorithms has been introduced in the literature (52; 60; 68), such as, *parallel scan*, *parallel selection* and *update*, *parallel sorting*,

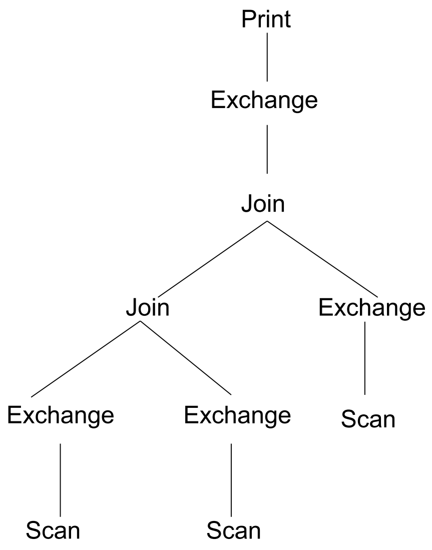


Figure 2.3: A parallel query execution plan with *exchange* operators.

parallel aggregation and duplicate removal, *parallel join and binary matching.* Apart from these traditionally used SQL operators, some operators specifically designed for parallel query processing, such as *merge*, *split*, are also introduced. We summarize these algorithms in this section.

2.4.3.1 Parallel Scan

Scan is a basic operator used in query processing. It involves a large number of disk I/Os, which is also the most expensive operation. Therefore, it is significant to parallelize *scan* operator in order to share I/O cost. After partitioning data, each *parallel scan* operator performs over one partition. The output of *parallel scans* working over partitions of a same relation are then processed by a *merge* operator, which merges multiple scanning outputs into one output and send it to the application or to the next operator in the query execution plan.

2.4.3.2 Merge and Split

Merge operator is to collect data. A *merge* operator is equipped several input ports and one output port. The input data streams are received at the input ports of *merge* operator, and the merging result exits from the output port. If a multi-stage parallel processing is required, then a data stream need to be split into individual sub-streams.

Split operator serves this purpose. *Split* is used to partition or duplicate a record stream into multiple ones. For example, record's various attributes are sent to different destination processes through attribute *split* operator. A *split* operators partition the input record stream by applying round-robin, hash partitioning methods, or any other partitioning methods. *Split* allows the auto parallelism of new added operators of system, and it supports various kinds of parallelism.

2.4.3.3 Parallel Selection and Update

Parallel selection operator partitions the workload of selection over several I/O devices, each being composed of one single disk or an array of disks. *Selection* operator concurrently perform over all required data partitions, and retrieve matching records. If the partitioning attribute is also the selection attribute, then all disks holding partitions will not contain the selection results. Thus, the numbers of processes and that of activated disks are limited. Local index can still bring high efficiency for *parallel selection* operator.

Data movement could be caused by *update* operator in the case of updating the value of the partitioning attribute of one record. The modified data might need to be moved to a new disk or node in order to maintain the partitioning consistency. Since moving data is expensive operation, it is more practical to choose an immutable attribute as the partitioning attribute in case where the original data set contains dynamic data.

2.4.3.4 Parallel Sorting

Sorting is one of the most expensive operators in database systems. Lots of research has addressed *parallel sorting*. Without loss of generality, assume a *parallel sorting* operator with multiple inputs and multiple outputs, and further, assume records are aligned in a random order on the sorting attribute in each input, and the output has to be range-partitioned with records being sorted within each range. The algorithms implementing *Parallel sorting* generally include two phases, local sorting phase and data exchange phase. In the local sorting phase, records are sorted within multiple processes. In the data exchange phase, records are sent to a set of processes. The target process, to which a record is sent, will produce an output partition with the range of sorting attribute value comprising the record's sorting attribute value. In other words, the sent records should contribute to the output produced by the target process. In practice, we can first run data exchange, then local sorting; or, run local sorting first, then data exchange. If data exchange runs first, then the knowledge of quantile should be available in order to ensure load balancing. If local sorting runs first, records are sent, at the end of local sorting, to the right receiving processes, according to the range that each sent record's sorting attribute value belongs to.

One of the possible problems during this procedure is deadlock. The reference (60) summarized the five necessary conditions of deadlock, cited as follows, i.e. if all these conditions establish, then deadlock will occur. Assume that a couple of *parallel sort* operators play with other operators in a relationship of producers and consumers, then the necessary conditions of deadlock are:

- multiple consumers feed multiple producers;
- each producer produces a sorted stream and each consumer merges multiple sorted streams;
- some key-based partitioning rule (i.e., hash partitioning) is used other than range partitioning, ;
- flow control is enabled;
- the data distribution is particularly unfortunate.

Deadlock can be avoided by guaranteeing one of the above conditions does not establish. Among them, the second condition—each producer produces a sorted stream and each consumer merges multiple sorted streams—is most easily to be avoided. For instance, if the sending process (producer) does not perform sorting, or each individual input stream of receiving process (consumer) is not sorted, then deadlock can be avoided. That is, moving the sorting operation from producer operator to consumer operator can resolve deadlock problem.

Deadlocks can also occur during the execution of a *sort-merge-join*, and they can be similarly avoided by moving the sorting operation from the producer operator to the consumer operator. However, this happens when the sorting operation is not possible to be moved from producer (sort) to consumer (merge-join), for example, reading data from a B-tree index makes the records being sorted when they are retrieved from disk. In such a case, it is necessary to find alternative methods that do not require re-partitioning and merging of sorted data between the producers and consumers. The first alternative method is moving the consumer's operations into the producer. Assume the original data is sorted and partitioned with range- or hash-partitioning method, with the partitioning attribute being exactly the attribute considered by the operations of consumer process, e.g. join attribute in case of consumer operator being merge-join, then the process boundaries and data exchange can entirely be removed from consumer. This means producer operator, i.e. B-tree scan and consumer operator, i.e. merge-join, are all performed in a same group of processes. The second method utilizes fragment-and-replicate to perform join operation. Assume that records of input stream are sorted over a relevant attribute within each partition, but partitioned either round-robin or over a different attribute. For such a data distribution, fragment-and-replicate strategy is applicable. During the join operation with fragment-and-replicate strategy, one input of join is partitioned over multiple processes and another input of join is replicated across these processes[1]. The join operations are running within the same processes as the processes producing sorted output. Thus, the sorting and join operations are running in one operator, and deadlocks can be avoided.

2.4.3.5 Parallel Aggregation and Duplicate Removal

There are three commonly used methods for parallelizing *aggregation and duplicate removal*. *Centralized Two Phase* method first does aggregations on each of the multiprocessors over the local partition, then the partial results are sent to a centralized coordinator node, which merges these partial results and generates the final result. *Two Phase* method parallelizes the processing of the second phase of the *Centralized Two Phase* method. The third method is called *Re-partitioning*. It first redistributes the relation on the group by attributes, and then it does the aggregation and generates the final results in parallel over each node. Shatdal et al. (96) argued that those three methods do not work well for all queries. Both of the *Two Phase* methods only work well when the number of result records is small. On the contrary, the *Re-partitioning* method works well only when the number of distinct values of group-by attributes is

[1]In typical fragment-and-replicate join processing, the larger input is partitioned, and the smaller input is replicated.

large. They proposed a hybrid method that changes/decides the method according to the workload and the number of the distinct values of group-by attributes being computed. A bucket overflow optimization of *Two Phase* methods was discussed in (60). For hash-based aggregation, a special technique to improve performance is that they do not create the overflow file[1], and the records can be directly moved to the final nodes, because in resent shipping records to other node is faster than writing record into disk. The disk I/O operations are caused when the aggregate output is too large to fit into memory.

2.4.3.6 Parallel Join

Join operators include different kinds of join operators, which are realized in different approaches. For instance, *semi-join*, *outer-join*, *non-equi-join* etc. are all *join* operators. Different from above mentioned operators, join operators are binary operators, which involve two inputs.

Executing distributed join operator in parallel indispensably involves *send* and *receive* operation. These operations are based on protocols like TCP/IP or UDP. *Row blocking* is a commonly used technique for shipping records to reduce cost. Record shipping is done in a block-wise way. Instead of being shipped one by one, records are shipped block by block. This method compensates for the brute in the arrival of data up to a certain point (68).

Parallel joins over horizontally partitioned data can be achieved by multiple ways. Assuming relation R is partitioned into R_1 and R_2: $R = R_1 \bigcup R_2$, then the join between relations R and S can be computed by $(R_1 \bigcup R_2) \bowtie S$ or $(R_1 \bigcup S) \bowtie (R_2 \bigcup S)$. If R is partitioned into 3 partitions, and S is replicated, then more methods can be adopted. For instance, the join can be calculated by $((R_1 \bigcup R_2) \bowtie S) \bigcup (R_3 \bowtie S))$, with one replica of S is placed near to R_1 and R_2, another replica of B is placed near to R_3. If $R_i \bowtie S_j$ is estimated to be, then this partial calculation can be removed to reduce the overhead.

Sort-merge-join is a conventional method for computing joins. Assume still R and S are two input relations for join. In *sort-merge-join* method, both of the input relations are first sorted over the join attribute. Then these two intermediate relations sorted are compared, and the matching records are output. *Hash-join* is an alternative of

[1]Overflow file means the common overflowing zone of hash table.

sort-merge-join. *Hash-join* breaks a join into several smaller joins. The two input relations R and S are hash-partitioned on the join attributes. One partition of relation R is hash into memory, the related partition of relation S is scanned. Each of the records in this S partition is compared against the partition of R held in memory. Once a record is matched, it is outputed. *Double-pipelined-hash-join* improved the conventional *hash-join*. It is a symmetric, incremental join. *Double-pipelined-hash-join* creates two in-memory hash-tables, each for one of the input relations. Initially, both hash-tables are empty. The records of R and S are processed one by one. For processing one record of R, the hash-table of S is probed, if the record is matched records, then it is outputed immediately. Simultaneously, the record is inserted into the hash-table of R for matching the unprocessed records of S. Thus, at any point in time, all the encountered records are joined. *Double-pipelined-hash-join* has two advantages. Firstly, it allows delivering the first results of a query as early as possible. Secondly, it makes it possible to fully exploit pipelined parallelism, and in turn reduce the overall execution time.

Symmetric partitioning and *fragment-and-replicate* are two basic techniques for paralelizing binary operators. In *symmetric partitioning*, both of the inputs are partitioned over the join attribute, and then the operations will be run on every node. This method is used in Gamma(54). In *fragment-and-replicate* method, one of the two inputs is partitioned; the other input is broadcasted to all other nodes. In general, the larger input is partitioned in order not to move it. This method is realized in the early database systems, because the communication cost overshadowed the computation cost. Sending small input to a small number of nodes costs less than partitioning both larger input and small input. To be noted, *fragment-and-replicate* cannot correctly work for *semi-join*, and other binary operators, like, *difference union*, because when a record is replicated, it will contribute multiple times to the output.

Semi-join is used to process join between relations placed on different nodes. Assume two relations R and S are placed on nodes r and s, respectively. *Semi-join* sends the needed columns for join of relation R from node r to s, then finds the records qualifying the join from relation S and sends these records back to r. The join operation is executed on node r. *Semi-join* can be expressed as: $R \bowtie S = R \bowtie (S \ltimes_{\pi} (R))$. *Redundant-semi-join* is a technique for reducing network traffic used in distributed databases for join processing. This method is used in distributed memory parallel systems. Assume two relations R and S having a common attribute A, are each stored on nodes r and s separately. *Redundant-semi-join* sends the duplicate-free projection on A to s, executes a *semi-join* to decide which records of S will contribute to the join result, and then ships these records to r. Basing on the law of relational algebra $R \bowtie S = R \bowtie (S \ltimes R)$, there is no need of shipping S, which reduces communication overhead, at the cost of adding the overhead of projecting, shipping the column A of R and executing the semi-join. Such a reduction can be applied on R or S, or both of them. The operations included during this process, such as *projection*, *duplicate removal*, *semi-join* and *final join* can be parallelized not only on nodes s and r, but also on more than two nodes.

Symmetric fragment-and-replicate is proposed by Stamos et al. (98) which is applicable for *non-equi-joins* and *N-way-join*. For parallelizing a *non-equi-join*, processors are organized into rows and columns. One input relation is partitioned over rows, and its partitions are replicated over each processor row. The other input relation is partitioned over columns, and its partitions are replicated over each processor column. A record of one input relation only matches with one record from the other input relation. The global join result is the concatenation of all partial results. This method improves *fragment-and-replicate* method by reducing the communication cost.

For joins in a parallel Data Warehouse environment, the *parallel star-join* is discussed by Datta et al. in (44). This parallel join processing is based on a special data structure, *Data Index*[1], proposed in the same work. Recall that *Basic DataIndex* (*BDI*) is simply a vertical partition of the fact table, which may include more than one column and the *Join DataIndex* (*JDI*) is designed to efficiently process join operations between fact table and dimension table. *JDI* is an extension of *BDI*. *JDI* is composed of *BDI* and a list of RecordIDs indicating the matching records in the corresponding dimension table. Assume that F represents the fact table, and D represents the set of dimension tables, then $\mid D \mid = d$, which means that there are d dimension tables. Let G represents a set of processor groups, and $\mid G \mid = d + 1$. Dimension table D_i and the fact table partition *JDI* corresponding to the key value of D_i are distributed to the processor group i. And the fact table partition *BDI* after containing measures is

[1]DataIndex is discussed in section 2.2.6

distributed to processor group $d+1$. Basing on the above data distribution, the *parallel star-join* processing involves only rowsets and projection columns.

In (101) a more complex join operator *General Multiple Dimension Join* (GMDJ) is discussed in a distributed Data Warehouse environment. GMDJ is a complex OLAP operator being composed of relational algebraic operators and other GMDJ operators. These GMDJ operator-composed queries need a multi-round processing. GMDJ operator clearly separates group-by definition and aggregate definition, which allows expressing various kinds of OLAP queries. An OLAP query expressed in GMDJ expressions is translated into a multi-rounded query plan. During each round, each site of distributed Data Warehouse executes calculations and communicates its results with the coordinator; the coordinator synchronize the partial results into a global result, then transfer the global result to distributed Data Warehouse sites. When a distributed Data Warehouse site receives an OLAP query, it transforms the OLAP query into GMDJ operators, then these operators are optimized using distributed computation. Taking the efficiency into account, the synchronization at the end of each round is started when the faster sites' partial results arrive on the coordinator, instead of waiting all partial results' arrivals before starting the synchronization. Although this work described how to generate a distributed query plan, it did not support on-line aggregation.

2.4.3.7 Issues of Query Parallelism

During the parallelization of query processing, some issues will appear, such as *data skew* and *load balance*. Pipeline parallelism does not easily lend itself to load balancing, since each processor in the pipeline is loaded proportionally to the amount of data it has to process. This amount of data cannot be predicated very well. For partitioning-based parallelism, load balancing are optimal, if the partitions are all of equal size. However, load balancing can be hard to achieve in case of data skew. Range partitioning risks *data skew*, where all the data is placed in one partition, and all the calculations. However, hashing and round-robin based partitioning suffers less from data skew.

2.5 New Development in Multidimensional Data Analysis

Recently, some new technologies are adopted in the multi-dimensional data analysis application. These new technologies include: in-memory query processing, search engine technologies, enhanced hardware.

SAP BI Accelerator (BIA)(72) is a commercial multi-dimensional data analysis product using these new technologies. BIA is running on a couple of blade servers[1]. BIA does not adopt the traditional pre-calculation way (store pre-calculated results into materialized views) to accelerate query processing. On the contrary, it compresses data to fit into the memory. Before a query is answered, all the data needed to answer it is copied to memory. All the query processing are in-memory.

Aside from in-memory query processing, BIA adopted the search engine technology to accelerate the query processing. They used a **metamodel** in order to bridge the gap between the structured data cube and search engine technology, which is originally developed to work with unstructured data. In this metamodel, the data originally stored under star-schema are represented as a join graphs expressing the joins between fact table and required dimension tables. This pre-defined joins (stored in the metamodel) are materialized at run time by the accelerator engine.

2.6 Summary

In this chapter, we first described the features of multidimensional data analysis queries and three distributed system architectures, including shared-memory, shared-disk and shared-nothing. Secondly, we gave a survey for existing work in accelerating data analytical query processing. Three approaches were discussed, pre-computing, data indexing and data partitioning. Pre-computing is an approach to barter storage space for computing time. The aggregates of all possible dimension combination are calculated and stored to rapidly answer the forthcoming queries. We discussed some related issues of pre-computing, including data cube construction, sparse cube, query result re-usability, data compressing. For indexing technologies, we discussed several indexes appearing in the literature, including B-tree/B^+-tree index, projection index, Bitmap index, Bit-Sliced index, join index, inverted index etc. A special type of index used in distributed architecture was also presented. For data partitioning technology, we introduced two basic data partitioning methods, horizontal partitioning and vertical partitioning, as well as their advantages and disadvantages. Then we presented the

[1]A blade server is equipped with high performance CPUs (e.g. Dual Intel Xeon), memory of up to 8 gigabytes, 3 level caches ranging from 512 kilobytes to 2 megabytes, modest board storage, or external disk, 2 or 3 Ethernet interfaces with high speed internet.

application of partitioning methods on the multidimensional data set. After that, the parallelism of query processing was described. We focused on parallelization of various operators, including, *scan*, *merge*, *split*, *selection*, *update*, *sorting*, *aggregation*, *duplicate removal* and *join*. At the end of this chapter, we introduced some new developments in multidimensional data analysis.

3

Data Intensive Applications with MapReduce

Along with the development of hardware and software, more and more data are generated at a rate much faster than ever. Although data storage is cheap, and the issues for storing large volume of data can be resolved, processing large volume of data is becoming a challenge for data analysis software. The feasible approach to handle large-scale data processing is to *divide and conquer*. People look for solutions based on parallel model, for instance, the parallel database, which is based on the shared-nothing distributed architectures. Relations are partitioned into pieces of data, and the computations of one relational algebra operator to be proceeded in parallel on each piece of data (52). The traditional parallel attempts in data intensive processing, like parallel database, was suitable when data scale is moderate. However, parallel database does not scale well. MapReduce is a new parallel programming model, which turns a new page in data parallelism history. MapReduce model is a parallel data flow system that works through data partitioning across machines, each machine independently running the single-node logic (64). MapReduce initially aims at supporting information pre-processing over a large number of web pages. MapReduce can handle large data set with the guarantee of scalability, load balancing and fault tolerance. MapReduce is applicable to a wide range of problems. According to different problems, the detailed implementations are varied and complex. The following are the some of possible problems to be addressed:

- How to decompose a problem into multiple sub-problems?

- How to ensure that each sub-task obtain the data it needs?
- How to cope with intermediate output so as to benefit from MapReduce's advantages without loosing efficiency?
- How to merge the sub-results into a final results?

In this chapter, we will focus on the MapReduce model. Firstly, we describe the logic composition of MapReduce model as well as its extended model. The relative issues about this model, such as MapReduce's implementation frameworks, cost analysis, etc., will also be addressed. Secondly, we will talk about the distributed data access of MapReduce. A general presentation on data management applications in the cloud is given before the discussion about large-scale data analysis based on MapReduce.

3.1 MapReduce: a New Parallel Computing Model in Cloud Computing

In parallel distributed computing, the most troublesome part of programming is to handle the system-level issues, like communication, error handling, synchronization etc. Some parallel computing models, such as MPI, OpenMP, RPC, RMI etc., are proposed to facilitate the parallel programming. These models provide a high-level abstraction and hide the system-level issues, like communication and synchronization issues.

Message Passing Interface (MPI) defines a two-sided message-passing library (between sender and receiver). Otherwise, the one-sided communications are also possible. Note that in MPI, a send operation does not necessarily have an explicit reception. Remote Procedure Call (RPC) and Remote Method Invocation (RMI) are based on the one-side communication. Open Multi-Processing (OpenMP) is designed for shared memory parallelism. It automatically parallelizes programs, by adding the synchronization and communication controls during compiling time. Although these models and their implementations have undertaken much system-level work, they are rather designed for realizing processor-intensive applications. When using these models for large-scale data processing, programmers still need to handle low-level details.

MapReduce is a data-driven parallel computing model proposed by Google. The first paper on MapReduce model (47) described one possible implementation of this model based on large clusters of commodity machines with local storage. The paper (71) gave a rigorous description of this model, including its advantages, in Google's domain-specific language, Sawzall. One of the most significant advantages is it provides an abstraction which hides the system-level details from programmers. Having this high-level abstraction, developers do not need to be distracted by solving how computations are carried out and finding the input data that the computations need. Instead, they can focus on the processing of the computations.

3.1.1 MapReduce Model Description

MapReduce is a parallel programming model proposed by Google. It aims at supporting distributed computation on large data sets by using a large number of computers with scalability and fault tolerance guarantees. During the map phase, the master node takes the input, and divides it into sub-problems, then distributes them to the worker nodes. Each worker node solves a sub-problem and sends the intermediate results are ready to be processed by reducer. During the reduce phase, intermediate are processed by reduce function on different worker nodes, and the final results are generated.

This type of computation is different from parallel computing with shared memory, which emphasizes that computations occur concurrently. In parallel computing with shared memory, the parallel tasks have close relationships between each other. Computations supported by MapReduce are suitable for parallel computing with distributed memory. Indeed, MapReduce executes the tasks on a large number of distributed computers or nodes. However, there is a difference between the computations supported by MapReduce and the traditional parallel computing with distributed memory. For the latter, the tasks are independent, which means that the error or loss of results from one task does not affect the other tasks' results, whereas in MapReduce, tasks are only relatively independent and loss or error do matter. For instance, the mapper tasks are completely independent between each other, but the reducer tasks cannot start until all mapper tasks are finished, i.e. reducer tasks' start-up is restricted. The loss of task results or failed execution of task also produces a wrong final result. With MapReduce, complex issues such as fault-tolerance, data distribution and load balancing are all hidden from the users. MapReduce can handle them automatically. In this way, MapReduce programming model simplifies parallel programming. This simplicity is retained in all frameworks that implement MapReduce model. By using these frameworks, the users only have to define two functions *map* and *reduce* according to their applications.

3.1.1.1 Fundamentals of MapReduce Model

MapReduce's idea was inspired from high-order function and functional programming. *Map* and *reduce* are two of primitives in functional programming languages, such as Lisp, Haskell, etc. A *map* function processes a fragment of key-value pairs list to generate a list of intermediate key-value pairs. A *reduce* function merges all intermediate values associated with a same key, and produces a list of key-value pairs as output. Refer to the reference (47) for a more formal description. The syntax of MapReduce model is the following: `map(key1,value1)` → `list(key2,value2)`
reduce`(key2,list(value2)` → `list(key2,value3)`

In the above expressions, the input data of *map* function is a large set of `(key1,value1)` pairs. Each key-value pair is processed by the *map* function without depending on other peer key-value pair. The map function produces another pair of key-value, noted as `(key2,value2)`, where, the key (denoted as `key2`) is not the original key as in the input argument (denoted as `key1`). The output of the map phase are processed before entering the reduce phase, that is, key-value pairs `(key2,value2)` are grouped into lists of `(key2,value2)`, each group having the same value of `key2`. These lists of `(key2,value2)` are taken as input data by the *reduce* function, and the *reduce* function calculates the aggregate value for each `key2` value. Figure 3.1 shows the logical view of MapReduce.

The formalization given in the first article of MapReduce (47) was simplified. It omitted the detailed specification for intermediate results processing part in order to hide the complexities to the readers. However, this might cause some confusion. The author of reference (71) took a closer look at the Google's MapReduce programming model and gave a clearer explanation for the underlying concepts of the original MapReduce. The author formalized the MapReduce model with the functional programming language, Haskell. The author also analyzed the parallel opportunities existing in MapReduce model and its distribution strategy. The parallelization may exist in the processing of mapper's input, the grouping of the intermediate output, the reduction

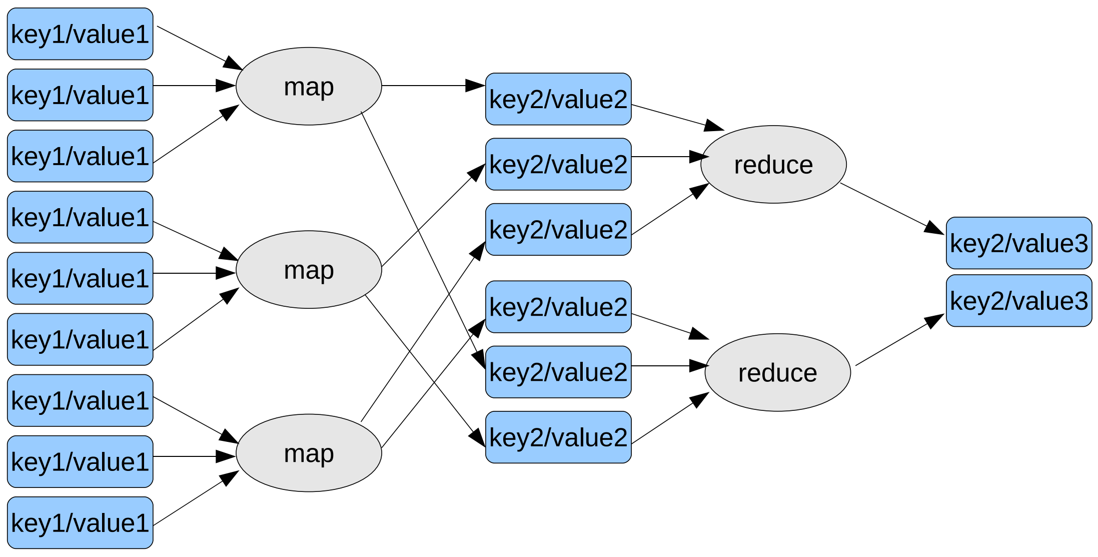


Figure 3.1: Logical view of MapReduce model.

processing over groups and the reduction processing inside each group during the reduce phase. In the strategy of MapReduce model, network bandwidth is considered as the scarce resource. This strategy combines parallelization and large data set distributed storage to avoid saturating the network bandwidth.

Note that the keys used in map phase and reduce phase can be different, i.e. developers is free to decided which part of data will be keys in these two phases. That means this data form of key-value pair is very flexible, which is very different from the intuitive feel. As keys are user-definable, one can ignore the limitation of key-value. Thus, a whole MapReduce procedure can be informally described as follows:

- Read a lot of data;
- Map: extract useful information from each data item;
- Shuffle and Sort;
- Reduce: aggregate, summarize, filter, or transform;
- Write the results.

3.1.1.2 Extended MapCombineReduce Model

MapCombineReduce model is an extension of MapReduce model. In this model, an optional component, namely the **combiner**, is added to the basic MapReduce model. This combiner component is proposed and adopted in Hadoop project (11). The intermediate output key-value pairs are buffered and periodically flushed onto disk. At the end of the processing procedure of the mapper, the intermediate key-value pairs are already available in memory. However, these key-value pairs are not written into a single file. These key-value pairs are split into R buckets based on the key of each pair. For the sake of efficiency, we sometimes need to execute a reduce-type operation within each worker node. Whenever a reduce function is both associative and commutative, it is possible to "pre-reduce" each bucket without affecting the final result of the job. Such a "pre-reduce" function is referred to as **combiner**. The optional combiner component collects the key-value pairs from the memory. Therefore, the key-value pairs produced by the mappers are processed by the combiner instead of being written into the output immediately. In such a way, the intermediate output amount is reduced. This makes sense when the bandwidth is relatively small and the volume of transferred data over the network is large. Figure 3.2 shows the logical view of MapCombineReduce model.

3.1.2 Two MapReduce Frameworks: GridGain vs Hadoop

Hadoop(11) and GridGain (10) are two different open-source implementations of MapReduce. Hadoop is designed for processing applications. The response time is relatively long, for instance, from several minutes to several hours. One example of such an application is the finite element method calculated over a very large mesh. The application consists into several steps; each step uses the data generated by the previous steps. The processing of Hadoop includes transmitting the input data to the computing nodes. This transfer must be extremely fast to fulfill the users' need. Hadoop is an excellent MapReduce supporting tool and a Hadoop cluster gives high throughput computing. However, it has a high latency since Hadoop is bound with the Hadoop distributed file system (HDFS). The Hadoop's MapReduce component operates on the data or files stored on HDFS, and these operations take a long time to be performed. For this reason, Hadoop cannot provide a low latency.

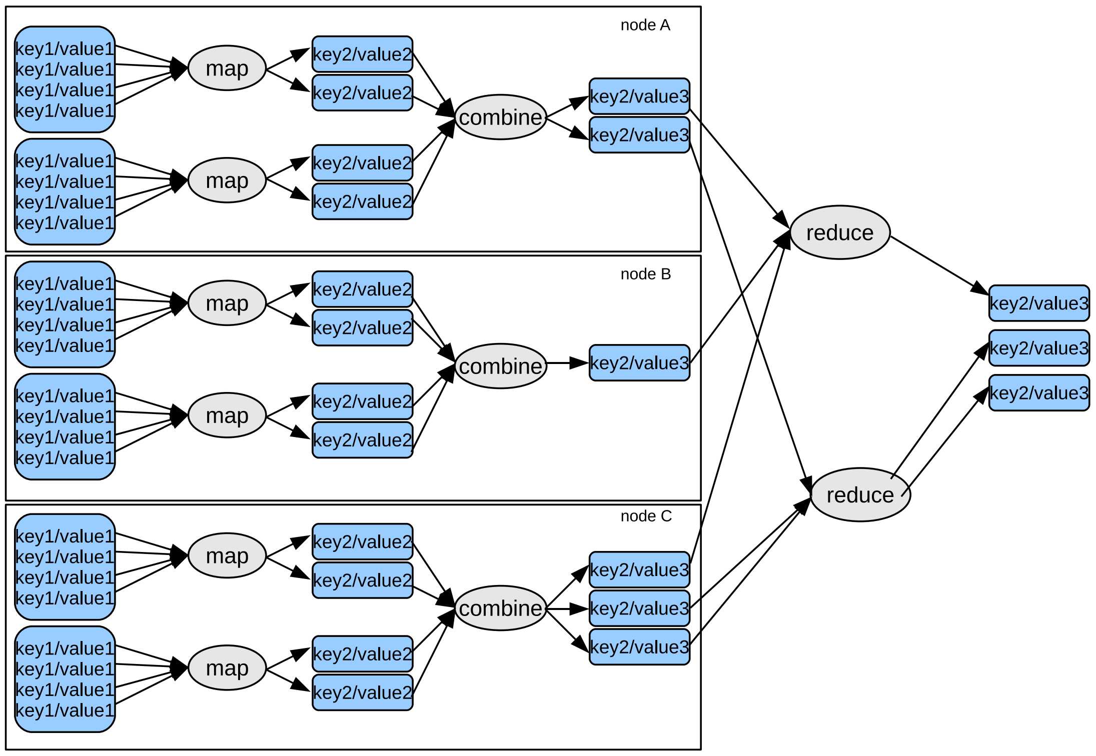


Figure 3.2: Logical view of MapCombineReduce model.

However, what we are trying to perform in parallel is a great number of queries on one large data set. The data set involved is not modified, and the query processing should be interactive. In fact, low latency is essential for interactive applications. In order to be compatible with the application's interactive requirements, the response time is strictly limited, for instance, within five seconds. In contrast to Hadoop, GridGain is not bound with file system and offers low latency. It is a MapReduce computational tool. GridGain splits the computing task into small jobs and executes them on the grid in parallel. During the task execution, GridGain deals with the low-level issues, such as nodes discovery, communication, jobs collision resolution, load balancing, etc. Being compared with Hadoop, GridGain is more flexible. Instead of accessing data stored on distributed file system, GridGain can process data stored in any file system or database. In addition, GridGain has some other advantages. For instance, it does not need application deployment and can be easily integrated with other data grid products. In particular, it allows programmers to write their programs in pure Java language.

3.1.3 Communication Cost Analysis of MapReduce

In parallel programming, a computation is partitioned into several tasks, which are allocated to different computing nodes. The communication cost issues must be considered since the data transmission between the computing nodes represents a non-negligible part. The communication cost is directly linked with the degree of parallelism. If the tasks are partitioned with a high degree of parallelism, the communication cost will be large. On the other hand, if the degree of parallelism is small, the communication cost will be limited.

In MapReduce parallel model, the communication cost exists in several phases. For the basic MapReduce model, without a combiner component, the communication cost consists in three distinct phases. The first phase is the launching phase, during which all the tasks are sent to the mappers. The second phase, located between mappers and reducers, consists in sending the output from mappers to reducers. The third phase is the final phase, which produces the results and where the outputs of the reducers are sent back. For the extended MapCombineReduce model, the communication consists in four phases. The first phase is still the launching phase. The second phase, located between mappers and combiners, consists to send the intermediate results from mappers to combiners located on the same node. The third phase, located between the combiner and the reducer, consists to send the output of combiners to reducers. The fourth phase is the final phase, which produces the results. The size of the output data exchanged between the components strongly impacts the communication cost. In reference (62), the author described an analysis for the communication cost in a parallel environment, depending on the amount of data exchanged between the processes. Basing on their work we analyzed the case of MapReduce, we summarized the following factors influencing the communication cost.

(i) The first one is the amount of intermediate data to be transferred, from the mappers to the reducers (case without a combiner component) or from the combiners to the reducers (case of a combiner component).

(ii) The second factor is the physical locations of the mappers, the combiners and the reducers. If two communicating components are on the same node, the communication cost is low; otherwise the cost is high. If two communicating components are located on two geographically distant nodes, the communication cost could be extremely high!

(iii) The third factor to be considered is the number of mappers, combiners and reducers respectively. Usually, the user defines the number of mappers according to the scale of the problem to be solved and the computing capacity of the hardware. The number of combiners is usually equal to the number of nodes participating to the calculation, as are devoted to collect local intermediate result of a node. Whether or not the number of reducers can is user-definable depends on the design of the implemented MapReduce framework. For example Hadoop allows the user to specify the number of reducers. Opposite, GridGain fixes the value of the number of reducers to one.

(iv) The fourth factor is the existence of a direct physical connection between two communicating components. A direct physical connection between two components means that two nodes respectively holding the two components are physically connected to each other.

(v) The last factor is the contention over the communicating path. When two or more communications are executed at the same time, the contention of the bandwidth will appear. A possible scenario of this contention with MapReduce model could be described as follows. The mappers on various nodes are started at almost the same time. Since the nodes in a cluster are usually of identical type, they almost have the same capability. As a consequence, the mappers complete their work on each node at the same time. The outputs of these mappers are then sent to the reducers. In this scenario, the contention of the communicating path is caused by the transmission requests arriving almost simultaneously.

Since the actions of transferring the data from the master node to the worker nodes are generally much more costly than the actions of transferring the mappers from the master to the workers, we usually transfer the mapper job code towards the location of data. Thus, the geographical locations of the data have a strong impact on the efficiency.

3.1.4 MapReduce Applications

MapReduce was initially proposed to support the search operation among a large amount of web pages. It is naturally capable of handling large-scale unstructured data, i.e. data-intensive text processing. An example of data-intensive text-processing is website log analysis. Website uses log to record users' behaviours or activities, which generates a large volume of data. Analysing this information allows providing additional services. For example, with log analysing, an on-line selling website may recommend the new products to a client which is relative to the product that he or she already purchased.

The large-scale structured data analysis applications, such as OLAP query processing can benefit from MapReduce. For utilizing MapReduce to serve data analysis applications, there still exist some challenges. Firstly, MapReduce does not directly support relational algebraic operators and query optimization. Secondly, being compared with the high-level declarative data query and manipulation language SQL, MapReduce is only a low-level procedural programming paradigm. In order to benefit from MapReduce, a combination of MapReduce and SQL is expected for data intensive applications in a near future. The combination between MapReduce and SQL consists in realizing and optimizing each relational algebra operator. Some SQL queries can be directly and naturally realized using MapReduce, for example, such as select queries.

The other queries are more difficult to realize. For instance, a group by query involves multiple operations, such as selecting, grouping and aggregating. It is more complex to realize it in MapReduce. In addition, in a MapReduce-based application, the processing over input data, intermediate output and final output should also be handled. Some research work on how to translate relational algebra operators into MapReduce programs are carried out. For instance, the work of reference (65) uses an extended MapReduceMerge model to efficiently merge data already partitioned and sorted.

MapReduce model is also applied to machine learning. In reference (102) the authors used MapReduce in machine learning field. They showed the speed-up on a variety of learning algorithms parallelized with MapReduce. Instead of running on a cluster of computers, their program was running on the multi-core hardware.

MapReduce is used for data mining in (86; 61). The objective of data mining is to find final models from a lot of raw data. As data set is increasingly gathering volume, data mining also need to address the scalability issue. In this context, a data set consists of unstructured or semi-structured data, for example, a corpus of text documents, a large web crawl, or system logs, etc. The traditional way needs to convert unstructured data into structured data. However, getting data in the appropriate form is not trivial. As MapReduce can naturally process unstructured data, it is advantageous to be applied in data mining. MapReduce allows a large class of computations to be transparently executed in a distributed architecture. Distributed data mining process involves several steps, including data gathering, pre-processing, analysis and post-processing. MapReduce is suitable to for almost all these processing steps.

Comparing all these MapReduce applications, we can see that they have a common feature, i.e. they all have a "big-top-small-bottom processing structure", the Figure 3.3 illustrates this structure. This means that these MapReduce-applicable applications all take a large data set as input, but generate a small-sized output compared to the size of input. We can imagine that all the applications having such a feature can benefit from using MapReduce model.

3.1.5 Scheduling in MapReduce

In traditional parallel computing, where storage nodes and computing nodes are connected via a high-performance network, one form of parallelization is task parallelism. Task parallelism means dispatching tasks across different parallel computing nodes,

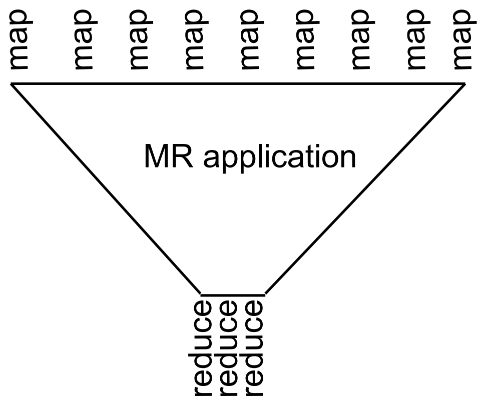


Figure 3.3: Big-top-small-bottom processing structure of MapReduce suitable applications

which involves *moving data* to nodes where the computations occur. The task parallelism, characterized by moving data, is not suitable for data-intensive applications. The workload of data-intensive applications will suffer from network congestion when moving large amount of data across network, which causes a bottleneck of system. Another form of parallelism is data parallelism. Data parallelism focuses on distributing data across different computing nodes. In a system of multiple computing nodes, Data Parallelism is achieved when each node performs a task over a piece of distributed data.

MapReduce follows the same idea as Data Parallelism, moving programs instead of moving data. In a distributed architecture running MapReduce, computing nodes and storage nodes co-locate on same machines. Computation is sent to a node having or close to the received data and execute on it. MapReduce assumes a distributed architecture being composed of one master node and many worker nodes. For a MapReduce procedure, a common scheduling is described as following.

1. The input is split into M blocks, each block is processed by a *mapper*;
2. *Mappers* are assigned and started on free worker nodes;
3. Each *mapper* produces R local files containing intermediate data;

4. *Reducers* are assigned and started when all mappers were finished, processing intermediate data read from *mapper* workers.

When the master node assigns *mapper* to a free worker node, it takes into account the locality of data to the worker node. The worker nodes closest to or having the needed data are chosen. The output of each *mapper* is partitioned into R local files containing intermediate key-value pairs. A shuffle over all intermediate key-value pairs is automatically run after all the intermediate outputs are available, before starting the *reducer*. When the master node assigns *reducer* to a free worker node, the worker node reads the intermediate key-value pairs from remote worker nodes where were running mappers. Worker node then sorts and applies reduce logic which produces the final output.

Comparing with traditional scheduling used in parallel computing, the job scheduling within a MapReduce processing need to mainly consider two additional aspects(79):

- the need for data locality (running computing where the data is);
- the dependence between *mapper* and *reducer*.

In Hadoop, one of the implemented MapReduce frameworks, a speculative task execution is realized. This speculative execution is aiming to address the *straggler* nodes. As a barrier exists between *map* phase and *reduce* phase, the *reducer* cannot be started until all *mappers* finished. Thus, the speed of MapReduce fully depends on the slowest node running *mapper*, which is called *straggler* node. With speculative execution, an identical mapper of *straggler* node is executed on a different worker node, and the framework simply uses the result of the first task attempt to finish. Both *mappers* and *reducers* can be speculatively executed. Hadoop uses a *slots* model for task scheduling over one worker node. Each worker node has a fixed number of *mapper slots* and *reducer slots*. When a slot becomes free, the scheduler will scan through tasks ordered by priority and submit time to find a task to fill the slot. The scheduler also considers the data locality when it assigns a task of *mapper*[1]

Another framework implementing MapReduce model, GridGain, has a limitation over the *reducer* number. The number of reducer is fixed as *one*, which means only one

[1]Scheduler chooses the node holding the needed data block, if it is possible. Otherwise, scheduler chooses a node within a same rack as the neede data blocks holding node.

reducer is run when all *mappers* were finished their computations. The *reducer* is run on the master node. In such a context, the scheduling is simplified. GridGain provides several policies for scheduling *mappers*. Especially, GridGain provides a Data affinity policy for dispatching jobs over nodes. If a previous mapper using a data block, saying A, is assigned to a worker node, noted as a, then the next task using the same data block A will still be assigned to the worker node a.

When there are multiple jobs to be executed, Hadoop schedules these jobs following the FIFO policy. The reference (57) considers a multi-user environment. Their work designed and implemented a fair scheduler for Hadoop. The fair scheduler gives each user an illusion of owning a private Hadoop cluster, letting user to start jobs within seconds and run interactive queries, while utilizing an underlying shared cluster efficiently.

Some jobs need not only one time MapReduce procedure, but multiple times MapReduce procedures. In this case, one MapReduce job cannot accomplish the whole job, and then a chain of MapReduce can be used to realize such large jobs, i.e. multi-stage MapReduce.

3.1.6 Efficiency Issues of MapReduce

The efficiency of MapReduce is a matter of debate for data analysis. The fundamental reason is that MapReduce is not initially designed for data analysis system over structured data. The typical calculations involved in MapReduce are scanning over a lot of unstructured data, like web page. In contrast, the data analysis applications typically accesses structured data. Comparing to the brute-force scan over unstructured data, the measures for accelerating query over structured data are abundant, such index, materialized view, column-oriented store. However, people argued that the lack of data structure is not a limitation, because MapReduce skip the data-loading phase, and immediately read data off of the file system and answer query on the fly, without any kind of loading stage. In the traditional data analysis, the data-loading phase is to load data using a pre-defined schema. Still, the optimization, like index and materialized view can unquestionably improve the performance. Especially, these optimization only need to be done one-time, and are reusable for all processing of query. In fact, data loading phase could also be exploited in MapReduce. For example, data compression can be done in data loading phase, which can accelerate brute-force scan. Without data loading, MapReduce needs to parse data each time it accesses data, instead of parsing data only once as load time. The efficiency of MapReduce depends on the applications in which it is used. For complex analysis of unstructured data, where brute-force scan is the right strategy, MapReduce is suitable. On the contrary, for business-oriented data analysis market, special MapReduce-based algorithms need to be created to obtain high efficiency.

3.1.7 MapReduce on Different Hardware

MapReduce is typically running across multiple machines connected in a shared-nothing fashion. People tried to run MapReduce over other different hardware. MapReduce can be run on shared-memory, multicore and multi-processor systems. In the reference (90), the author realized a specific implementation of MapReduce for shared-memory system. This shared-memory MapReduce automatically manages thread creation, dynamic task scheduling, and fault tolerance across processor nodes. Another specific implementation of MapReduce running on Cell BE architecture is introduced in (46). MapReduce can also run on graphics processors (GPUs). A GPU specialized MapReduce framework, Mars, was proposed in (63).

3.2 Distributed Data Storage Underlying MapReduce

The data-driven nature of MapReduce requires a specific underlying data storage support. High-Performance Computing's traditional separating storage component from computations is not suitable for processing large size data set. MapReduce abandons the approach of separating computation and storage. In the runtime, MapReduce needs to either access data on local disk, or access data stored closely to the computing node.

3.2.1 Google File System

Google uses a distributed Google File System (GFS) (57; 87) to support MapReduce computations. Hadoop provides an open-source implementation of GFS, which is named Hadoop Distributed File System (HDFS) (12). In Google, MapReduce is implemented on top of GFS and running over within clusters. The basic idea of such GFS is to divide a large data set into chunks, then replicate each chunk across different nodes. The chunk size is much larger than in the traditional file system. The default chunk size is 64M in GFS and HDFS.

The architecture of GFS follows master-slave model. The master node is responsible of maintaining file namespace, managing and monitoring the cluster. Slave nodes manage their actual chunks. Data chunks are replicated across slave nodes, with 3 replicas by default. When an application wants to read a file, it needs to consult the metadata information about chunks by contacting the master node to know on which slave nodes the required chunk is stored. After that, application contacts the specific slave nodes to access data. The size of chunk is a crucial factor influencing the amount of data that the master node needs to handle. The default chunk size considers a trade-off between trying to limit resource usage and master interaction times on the one hand and accepting an increased degree of internal fragmentation on the other hand.

GFS is different from the general applicative File System, such as NFS or AFS. GFS assumes that data is updated in an append-only fashion(36), and data access is mainly long streaming reads. GFS is optimized for workload characterized of the above-mentioned features. The following summarizes GFS's characteristics:

- GFS is optimized for the usage of large files, where the space efficiency is not very important;
- GFS files are commonly modified by being appended data;
- Modifying at file's arbitrary offset is infrequent operation;
- GFS is optimized of large streaming reads;
- GFS supports great throughput, but has long latency;
- Client's caching techniques are considered as ineffective.

A weakness of GFS master-slave is the single master node. The master node plays a crucial role in GFS. It does not only manage metadata, but also maintains the file namespace. In order to avoid the master node becoming a bottleneck, the master has been implemented using multi-threading and fine-grained locking. Additionally, in order to alleviate the workload of master node, master node is designed to only provide metadata to locate chunks, and it does not participate the following data accessing.

Rick of single point of failure is another weakness of GFS. Once the master node crushes, the whole file system will stop working. For handling master's crush, a *shadow masters* design is adopted. The shadow master holds a copy of the newest operation log. When master node crushes, the shadow master provides read-only access of metadata.

3.2.2 Distributed Cache Memory

The combination of MapReduce and GFS guarantee high throughput since GFS is optimized for sequential reads and appends on large files. However, such a combination has a high latency. GFS-based MapReduce heavily use disk, in order to alleviate the affect brought by failures. However, this produces a large amount of disk I/O operations. The latency for disk access is much higher than that of memory access. In GFS-based MapReduce, memory was not fully utilized (110). In the GFS open-source implementation, HDFS, reading data also suffers from high latency. Reading a random chunk in HDFS involves multiple operations. For instance, it needs communicating with master to get the data chunk location. If data chunk is not located on the node where read operation occurs, then that also requires performing data transfer. Each of these operations leads to higher latency(76).

The authors of reference (110) argued that small-scale MapReduce clusters, which have no more than dozen of machines, are very common in most companies and laboratories. Node failures are infrequent in clusters of such size. So it is possible to construct a more efficient MapReduce framework for small-scale heterogeneous clusters using distributed memory. The author of the reference (76) also proposed the idea of utilizing distributed memory. Both of these works have chosen the open-source distributed in-memory object caching system, *memcached* to provide an in-memory storage to Hadoop.

In the work of (76), the whole data set, in form of key-value pair, is loaded into *memcached* from HDFS. Once the whole data set is in *memcached*, the subsequent MapReduce programs access data with the client API of *memcached*. Each mapper or reducer maintains connections to the *memcached* servers. All requests happen in parallel and are distributed across all *memcached* servers.

In the work of (110), only the output of mappers is loaded into *memcached*. The cached mapper's output is attached with a key. Such a key is made up of a mapper id and its target reducer id. Once a reducer is started, it checks whether the outputs for it are in *memcached*. If that is true, then it gets them from *memcached* server.

3.2.3 Manual Support of MapReduce Data Accessing

If a MapReduce framework without being attached with a distributed file system is used, then data locating needs to be taken charge of developers. GridGain is such a pure MapReduce computing framework, and it is not attached with any distributed storage system. Although this forces developers to do the low-level work of data locating, to some extent, this provides some flexibility. Data accessing does not need to consult the file namespace any more; the other data forms than files can also be the representation of distributed stored data, e.g. data can be stored in database on each computing node.

GridGain's MapReduce is composed of one master node and multiple worker nodes. GridGain provides useful mecanism for users to add user properties, which is visible to master. Master node can identify worker nodes from the added properties. The additional properties defined by user can be used for different purposes, such as, logical name of node, role name of node etc. As we adopted GridGain as the MapReduce framework, we give an example coming from our work. In this work, we added to each worker node a property representing the identifier of data fragment stored in the current worker node.

In the manual approach, a data pre-processing phase is indispensable. During this phase, data set is divided into blocks, and distributed/replicated across different worker nodes. Using the method mentioned above, a user-defined property representing data fragment identifier is added to each worker node. As being visible to master node, this user-defined property is used for locating data chunks. An illustration is given in the Figure 3.4. As this manual approach decouples underlying storage from the computations, it provides the possibility to choose various underlying data storages. Mappers can access third-part data source. As developer can personally control data locating, then data transfer between worker nodes is less frequent than in the GFS-based MapReduce system. More importantly, the optimization over data accessing can be performed without being limited by a particular file system.

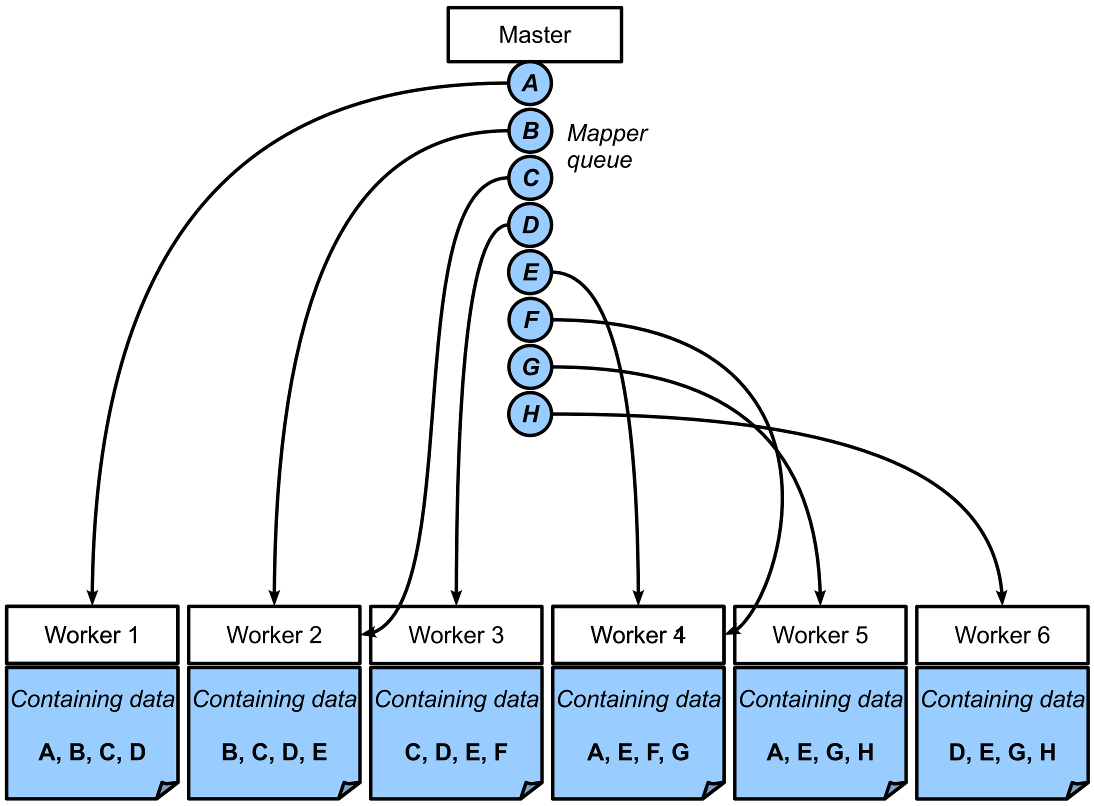


Figure 3.4: Manual data locating based on GridGain: circles represent mappers to be scheduled. The capital letter contained in each circle represents the data block to be processed by a specific mapper. Each worker has a user-defined property reflecting the *contained data*, which is visible for master node. By identifying the values of this property, the master node can locate data blocks needed by each mapper.

3.3 Data Management in Cloud

Cloud computing is an internet-based computing system, which integrates resources ranging from computer processing, storage and software available across network. Amazon, Google, Microsoft all put forward the concept of Cloud Computing. So far, there already exist multiple commercial products. Amazon Simple Storage Service (Amazon S3) (2) and Amazon Elastic Compute Cloud (Amazon EC2) (1) provide small-scale enterprises with computing and storage services. Google App Engine (7) allows running the third-part parallel programs on its cloud. Microsoft's Windows Azure Platform (22) provides a Windows-based environment for running applications and storing data on servers in data centers. More details can be find in reference (109), an article on state-of-the-art of cloud computing.

Data storage in the new cloud platform is different than before. Replicated and distributed are two of main characteristics of data stored in cloud. Data is automatically replicated without the interference of users. Data availability and durability are achieved through replication. Large cloud provider may have data centers spread across the world.

3.3.1 Transactional Data Management

Data stored in fashion of cloud—replicated and distributed—is considered to be unsuitable for *transactional data management* applications(25). In traditional data management system, a transaction should support ACID, which means all computations contained in a transaction should be Atomicity, Consistency, Isolation and Durability. Such a guarantee is important for write-intensive applications. However, the ACID guarantee is difficult to be achieved on replicated and distributed data storage. Among full-fulfilled database products, shared-nothing architecture is not commonly used for transactional data management. Realizing a transaction on a shared-nothing architecture involves complex distributed locking which is non-trivial work. The advantage of scalability coming with shared-nothing architecture is not an urgent need for transactional data management.

3.3.2 Analytical Data Management

Analytical data management applications are commonly used in business planning problem solving, and decision support. Data involved by analytical data management is often historical data. Historical data usually has large size, and is read-mostly (or read-only), and occasionally batch updated. Analytical data management applications can benefit from cloud data storage. Analytical data management applications are argued to be well-suited to run in a Cloud environment (25), since analytical data management matches well with shared-nothing architecture, and ACID guarantees are not needed for it.

3.3.3 BigTable: Structured Data Storage in Cloud

BigTable(37) is a distributed structured data storage system. Hadoop provided HBase (13), an open-source implementation of BigTable. BigTable provided a flexible, high-performance solution for various Google applications with varied demands. MapReduce is one of applications using BigTable. Different applications in Google could be latency-sensitive or they need high-throughputs. A BigTable is a sparse, distributed, persistent multidimensional sorted map, indexed by a row key, column key and a time-stamp. Thus, it shares characteristics of both row-oriented storage and column-oriented storage. GFS is used to store log and data files in BigTable. The cluster management takes charge of job scheduling, resource managing on shared machines, dealing with machine failures, as well as monitoring machine status. BigTable API provides functions for creating and deleting tables and column families[1], changing cluster, table, and column family metadata.

3.4 Large-scale Data Analysis Based on MapReduce

Data analysis applications or OLAP applications are encountering scalability issue. Facing more and more generated data, OLAP software should be able to handle data sets much larger than ever. MapReduce naturally has good scalability, and people argued that MapReduce approach is suitable for data analysis workload. The key is to choose an appropriate implementation strategy for the given data analysis application. For choosing an appropriate implementation strategy to process an data analysis

[1]Column family refers to several column keys being grouped into sets.

query, two types of questions need to be answered. The first question is about the data placement. This short term includes several sub-questions: What is the most suitable data-partitioning scheme? To which degree we will partition the data set? What is the best data placement strategy of data partitions? The second question is how to efficiently perform the query over the distributed data partitions? In a MapReduce based system, the query's calculation is transformed to another problem, how to implement the query's processing with MapReduce? To answer to these questions, the specific analysis addressing various queries needs to be undertaken.

3.4.1 MapReduce-based Data Query Languages

Hadoop's rudimentary support for MapReduce, promoted the development of MapReduce-based high-level data query languages. A data query language PigLatin (40), was originally designed by Yahoo, and later became an open-source project. It is designed as a bridge between low-level, procedural style of MapReduce and high-level declarative style of SQL. It is capable of handling structured and semi-structured data. Program written in PigLatin is translated into physical plans being composed of MapReduce procedures during compiling. The generated physical plans are then executed over Hadoop.

Similarly, another open-source project, Hive (14) of Facebook, is a Data Warehouse infrastructure built on top of Hadoop. It allows aggregating data, processing ad hoc query, and analysing data stored in Hadoop files. HiveQL is an SQL-like language, which allows querying over large data set stored as HDFS files.

Microsoft developed MapReduce-based declarative and extensible scripting language, SCOPE (Structured Computations Optimized for Parallel Execution) (91), targeted for massive data analysis. This language is high-level declarative, and the compiler together with optimizer can improve SCOPE scripts through compiling and optimizing. SCOPE is extensible. Users are allowed to create customized extractors, processors, aggregators and combiners by the extending built-in C# components.

3.4.2 Data Analysis Applications Based on MapReduce

An attempt of MapReduce-based OLAP system was described in (39). The following description of their work lays out a clear example of doing data analysis with MapReduce. The data set used in their work is a data cube. In particular, the data cube was coming from a web log, which is employed to analyse the web search activities. More specifically, the data cube is composed of 2 dimensions (keyword k and time t) and 2 measures (page count: $pageCount$ and advertisement count: $adCount$). During data partitioning, the data cube is divided over dimensions of keyword and time. The cells having the same value of k and t are put into one block. Similar to the MOLAP, the hierarchy concept is applied over the data cube in their work. These different hierarchy levels in *time* dimension allow partitioning data cube with different granularities. Support of dynamic data partitioning granularity is a unique feature of this work. As queries processed in their work are correlated, the results generated for one query can serve as the input for another query. However, the granularity of the second query is not necessarily the same as in the first query, and then the change of granularity is needed. The MapReduce-based query processing concerns two groups of nodes: nodes running *mappers*, and nodes running *reducers.* The group of nodes is done at the beginning of query processing. *Mapper* fetches part of data set and generates *key-value* pairs from individual record. The *key* field is related to different granularities, which in turn depends on the query, and it can be computed using the given algorithms. The *value* field is the exact copy of the original data record. These *key-value* pairs are shuffled, and dispatched to *reducers.* The pairs with the same *key* go to the same *reducer. Reducer* performs an external sorting to group pairs with the same value. Then it produces an aggregated result for each group.

Regarding the commercial software, MapReduce was integrated into some commercial software products. Greenplum is a commercial MapReduce database, which enables programmers to perform data analysis on petabyte-scale data sets inside and outside of it (8). Aster Data Systems, a database software company has recently announced the integration of MapReduce with SQL. Aster's *nCluster* allows implementing flexible MapReduce functions for parallel data analysis and transformation inside the database (3).

3.4.3 Shared-Nothing Parallel Databases vs MapReduce

Although being able to run on different hardware, MapReduce is typically running on a shared-nothing architecture where computing nodes are connected by network without memory or disk sharing among each other. Many parallel databases adopted shared-nothing architecture, like in the parallel database machines, Gamma (54) and Grace (56).

Though MapReduce and parallel databases target different users, it is in fact possible to write almost any parallel processing task as either a set of database queries or a set of MapReduce jobs (88). This led to controversies about which system is better for large-scale data processing. Among them, there are also criticizing voice of new-rising MapReduce. Some researchers in the database field even argued that MapReduce is a step backward in the programming paradigm for large-scale data intensive applications (53). However, more and more commercial database software begun to integrate the cloud computing concept into their products. Existing commercial shared-nothing parallel databases suitable for doing data analysis application in cloud are: Teradata, IBM DB2, Greenplum, DATAllego, Vertica and Aster Data. Among others, DB2, Greenplum, Vertica and Aster Data are naturally suitable since their products could theoretically run in the data centers hosted by cloud computing provider (25). It is interesting to compare the features of both systems.

3.4.3.1 Comparison

We compare shared-nothing parallel database and MapReduce in the following aspects:

Data partitioning In spite of having a lot of differences, shared-nothing parallel database and MapReduce do share one feature: the data set is all partitioned in both systems. However, as in shared-nothing parallel database data is structured in tables, data partitioning is done with specific data partitioning methods. Partitioning take into account the data semantic, and is running under control of user. On the contrary, data partitioning in a typical MapReduce system is automatically done by system, where user can only participate data partitioning with limitations. For example user can configure the size of block. But the semantic of data is not considered during partitioning.

Data distribution In shared-nothing parallel database, the knowledge of data distribution is available before query processing. This knowledge can help query optimizer to achieve load-balancing. In MapReduce system, the detail data distribution remains unknown, since distribution is automatically done by system.

Support for schema Shared-nothing parallel databases require data conform to a well-defined schema; data is structured with rows and columns. In contrast, MapReduce permits data to be any arbitrary format. MapReduce programmer is free of schema, and data can even have no structure at all.

Programming model Like other DBMSs, shared-nothing parallel database supports a high-level declarative programming language, i.e. SQL, which is known for and largely accepted by both professional and non-professional users. With SQL, users only need to declare what they want to do, but do not need to provide a specific algorithms to realize it. However, in MapReduce system, developers must provide an algorithm in order to realize the query processing.

Flexibility SQL is routinely criticized for its insufficient expressive power. In order to mitigate flexibility, shared-nothing parallel databases allow user-defined functions. MapReduce has good flexibility by allowing developers to realize all calculations in the query processing.

Fault tolerance Both parallel database and MapReduce use replication to deal with disk failures. However, parallelism databases cannot handle node failures, since they do not save intermediate results, once a node fails, the whole query processing should be restarted. MapReduce is able to handle node failure during the execution of MapReduce computation. The intermediate results (from mappers) are stored before launching reducers in order to avoid starting the processing from zero in case of node failure.

Indexing Parallel databases have many indexing techniques, such hash or B-tree, to accelerate data access. MapReduce does not have built-in indexes.

Support for Transactions The support for transactions requires the processing to respect ACID. Shared-nothing parallel databases support transaction, since it can easily respect ACID. But it is difficult for MapReduce to respect such a principle. Note that, in large-scale data analysis, the ACID is not really necessary.

Scalability Shared-nothing parallel database can scale well to tens of nodes, but difficult to go any further. MapReduce has very good scalability, which is proved by Google's use. It can scale to thousands nodes.

Adaptability over heterogeneous environment As shared-nothing parallel database is designed to run in homogeneous environment, it is not suited to run in heterogeneous environment. MapReduce is able to run in heterogeneous environment.

Execution strategy MapReduce has two phases, map phase and reduce phase. Reducers need to pull each of its input data from the nodes where mappers were run. Shared-nothing parallel databases uses a *push* approach to transfer data instead of *pull*.

Table 3.1 summarizes the differences between parallel database and MapReduce with short descriptions.

	Parallelism database	**MapReduce**
Data partitioning	Use specific methods consider data semantic	Done automatically do not consider data semantic
Data distribution	Known for developers	Unknown
Schema support	Yes	No
Programming model	Declarative	Direct realize
Flexibility	Not good	Good
Fault tolerance	Handle disk failures	Handle disk and node failures
Indexing	Support	Have no built-in index
Transaction support	Yes	No
Scalability	Not good	Good
Heterogeneous environment	Unsuitable	Suitable
Execution strategy	Push mode	Pull mode

Table 3.1: Differences between parallel database and MapReduce

3.4.3.2 Hybrid Solution

MapReduce-like software, and shared-nothing parallel databases have their own advantages and disadvantages. People look for a hybrid solution that combines the fault tolerance, heterogeneous cluster, and ease of scaling of MapReduce and the efficiency, performance, and tool plug-ability of shared-nothing parallel database.

HadoopDB (27) is one of the attempts for constructing such a hybrid system. It combines parallel databases and MapReduce to exploit both the high performance from the parallel database and scalability from MapReduce. The basic idea behind HadoopDB is to use MapReduce as the communication layer above multiple nodes running single-node DBMS instances. Queries are expressed in SQL, translated into MapReduce by extending existing tools, and as much work as possible is pushed into the higher performing single node databases. In the experiments their work, they tested several frequently used SQL-queries, such as select query, join query, simple group-by query, etc. over one or more of the three relations.

Another way to realize such a hybrid solution is to integrate parallel database optimization as a part of calculations running with MapReduce. Since MapReduce does not give any limitations over the implementations, such a hybrid solution is totally feasible. Our work's approach also belongs to the hybrid solution.

3.5 Related Parallel Computing Frameworks

Like MapReduce, Dryad system (66) also provides an abstraction that hides system-level details from developers. The system-level details include fine-grain concurrency control, resource allocation, scheduling, component failures etc. Dryad provides an appropriate abstraction level for developers to write the scalable applications. In Dryad, a job is expressed as a directed acyclic graph where each vertex represents developer-specified subroutines and edges represent data channels that caption dependencies. Dryad allows developers to write sub-routines as sequential programs. Such a logical computation graph is then mapped onto physical resources by the framework.

DryadLINQ (108) is high-level language programming environment based on Dryad. DryadLINQ combines Dryad and .NET Language Integrated Query (LINQ). LINQ allows developers to write large-scale data parallel application in a SQL-like query language. DryadLINQ translates LINQ programs into distributed Dryad computations that are run within Dryad system.

An academic research project, YvetteML (YML) (49), is a framework aiming to exploit distributed computing architectures and peer-to-peer systems. YML, together with various low-level middlewares addressing different distributed architectures, provides users with an easy way to utilize these distributed architectures. The provided workflow language Yvette allows describing an application with a directed acyclic graph, with the vertex representing component[1] and edges represents the timing relationship between components when being executed. Developers need to write components and the Yvette program when realizing a distributed application over YML framework.

3.6 Summary

In this chapter, we first introduced the basic idea and related issues of MapReduce model and its extended model, MapCombineReduce. Two implementation frameworks of MapReduce, Hadoop and GridGain were presented. They have different latency. Hadoop has high latency, while GridGain has low latency. Under the interactive response time requirement, GridGain is a suitable choice for our work. MapReduce model hides the underlying communication details. We specially analysed the communication cost of MapReduce procedure, and discussed the main factors that influence the communication cost. We then discussed the job-scheduling issues in MapReduce. In MapReduce job-scheduling, two more things need to be considered than in other cases, data locality and dependence between *mapper* and *reducer*. Our discussion also involves MapReduce efficiency and its application on different hardware. Secondly, we described the distributed data storage underlying MapReduce, including distributed filesystems, like GFS and its open source implementation—HDFS, and efficient enhanced storage system basing on cache mechanism. Another approach is manual support of MapReduce data access adopted in our work. The third topic addressed in this chapter is data management in cloud. The suitability of being processed with MapReduce was discussed for transactional data management and analytical data management. The latter was thought to be able to benefit from MapReduce model. Relying on this, we further addressed large-scale data analysis based on MapReduce. We presented the MapReduce-based data query languages and data analysis related work with MapReduce. As shared-nothing parallel database and MapReduce system use similar hardware, we specially did the comparison between them, followed by presenting the related work of a hybrid solution of combining these two into one system. Finally, we introduced related parallel computing frameworks.

[1]A component is a pre-compiled executable which realizes the user-defined computations

4

Multidimensional Data Aggregation Using MapReduce

In this chapter, we will present the MapReduce-base multidimensional data aggregation. We will first describe the background of our work, as well as the organization of data used in our work. Then we will introduce *Multiple Group-by* query, which is also the calculation that we will parallelize relying on MapReduce. We will give two implementations of *Multiple Group-by* query, one is based on MapReduce, and the other is based on MapCombineReduce. The job definitions for each implementation will be specifically described. We also will present the performance measurement and execution time analysis.

4.1 Background of This Work

In the last ten years, more and more BI products use data visualization technique to support decision-making. Data visualization means using computer-supported, interactive, visual representation of abstract data to reinforce cognition, hypothesis building and reasoning. Facing to the growing volume of historical data, data visualization is becoming an indispensable tool helping decision-maker to extract useful knowledge from large amount of data. Typically, the abstract data is represented as dashboards, charts, maps, and scatter-plots etc. Data represented in these forms become easier to be understood and explore. There is no need to become a data expert to navigate among data, make comparison and share findings. The data visualization techniques have impacted the BI modern analytic techniques (78). Interactive data explorations, such as zooming, brushing, and filtering become basic computations supported by BI software.

Data exploration consists in operations related to the dimensionality of multidimensional data set. OLTP techniques implemented in DBMSs are not the right solution for data exploration, since they are optimized for transaction processing and neglect the dimensionality of data. On the contrary, OLAP is argued to be suitable for data exploration (43), since OLAP systems organize data into multidimensional cubes, which equips data structure itself with dimensionality. A data cube is composed of *measures* and *dimensions*. Measures contain static numeric values aggregated from raw historical data, such as margin, quantity sold, which are classified by dimensions. Dimensions contain "text" values, and they form the axes of cube, such as, product, city etc. The values within one dimension can be further organized in a containment type hierarchy to support multiple granularities. During data exploration, a set of multidimensional aggregation queries are involved. Usually, user starts from an overview of data set, and then goes further to browse more detailed data aggregates of smaller grain. Citing the example of SAP BusinessObjects Explorer (20), at the beginning of data exploration, the first view displayed for user shows the aggregates over several dimensions selected by default. The aggregated values shown in such a view are calculated by a set of multidimensional aggregated queries. Next, when user selects a certain distinct value of one dimension, then measures are filtered and re-aggregated in another multidimensional aggregation query.

4.2 Data Organization

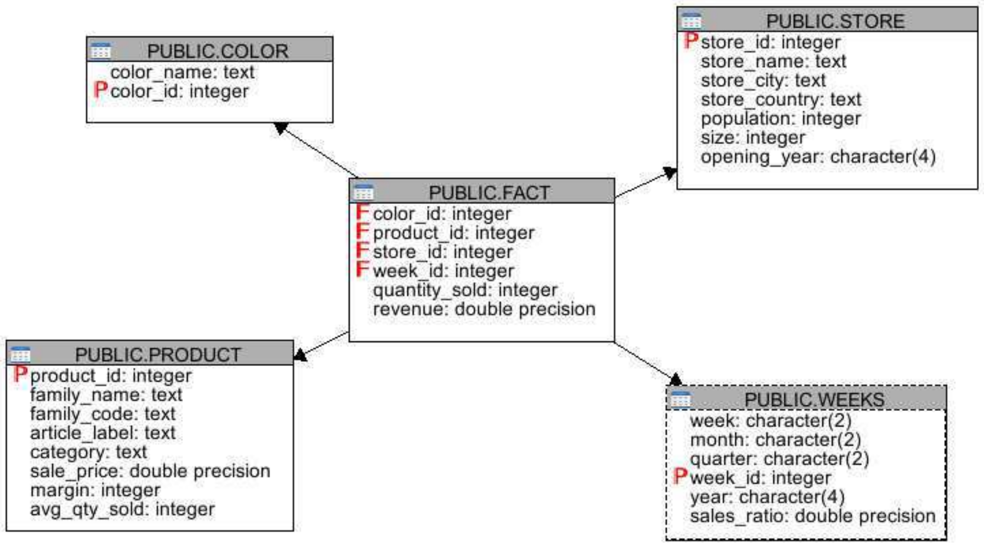
The traditional data cube is stored either in form of multidimensional data array (in MOLAP) or under star-schema (in ROLAP). MOLAP suffers from sparsity of data. When the number of dimensions increases, the sparsity of the cube also increases at a rapid rate. Sparsity a insurmountable obstacle in MOLAP. In addition, MOLAP precompute all the aggregates. When the amount of data is large enough, pre-computation will take long time. Thus, MOLAP is only suitable for data sets of small and moderate size. In contrast, ROLAP is more suitable for data sets of large size. In ROLAP, one of traditional query accelerating approaches is pre-computing[1]. Pre-computing approach requires all the aggregated values contributing to the potential queries are computed before processing queries. For this purpose, the database administrators need to identify the frequently demanded queries from numerous passed queries, and then build materialized views and indexes for these queries. Figure 4.1 shows the data organization in case of employing materialized views. Certainly, query's response time is reduced by this approach. However, the computations involved in this approach are heavy, more calculations are needed for choosing optimal one from multiple materialized views during query processing. Materialized views can only help to accelerate processing of a certain set of pre-chosen queries, not to accelerate the processing of all queries. Another disadvantage of materialized view is that they take up a lot of storage space.

An alternative approach for organizing data is to store one overall materialized view. The materialized view is a result of join operation among all dimension tables and the fact table. Assume a data set from an on-line apparel selling system, recording the sales records of all products in different stores during the last three years. This data set is originally composed of 4 dimension tables (COLOR, PRODUCT, STORE, WEEKS) and 1 fact table (FACT). Refer to the sub-figure (a) of Figure 4.1 for the star-schema definition of the data set. The overall materialized view is named as ROWSET. Each record stored in ROWSET contains values of all measures retrieved from original FACT table associated with the distinct values of different dimensions retrieved from dimension tables. The List 4.1 shows the SQL statements used to generate the materialized view, ROWSET. Those SQL statements are written in *psql*, which can be interpreted and executed in PostgreSQL. A graphic illustration is available in Figure 4.2:

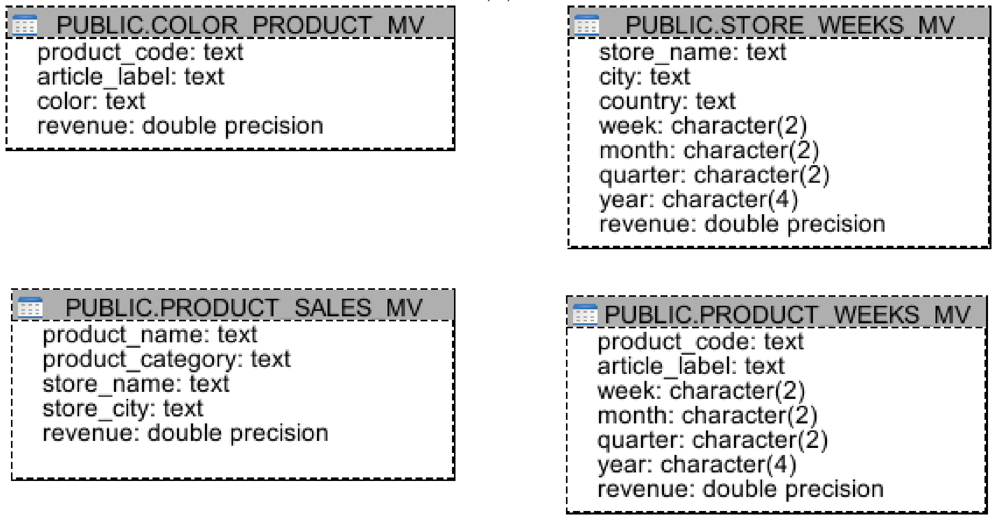
Listing 4.1: SQL statements used to create materialized view—ROWSET

```
DROP TABLE IF EXISTS "ROWSET" CASCADE;
CREATE TABLE "ROWSET" AS
SELECT c."color_name" AS color,
       p."family_name" AS product_family,
       p."family_code" AS product_code,
       p."article_label" AS article_label,
       p."category" AS product_category,
       s."store_name" AS store_name,
       s."store_city" AS store_city,
```

[1]Refer to section 2.1 for more information.

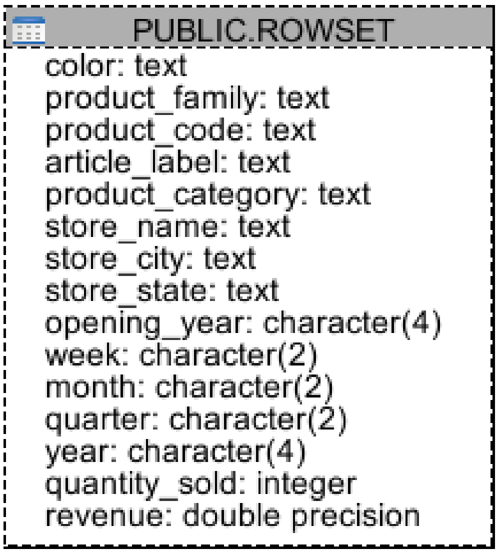


(a)



(b)

Figure 4.1: Storage of original data set and the pre-computed materialized views for the identified frequently demanded queries: sub-figure (a) shows original data set under star-schema; sub-figure (b) shows several materialized views created based on the original data set represented in (a).



PUBLIC.ROWSET
color: text
product_family: text
product_code: text
article_label: text
product_category: text
store_name: text
store_city: text
store_state: text
opening_year: character(4)
week: character(2)
month: character(2)
quarter: character(2)
year: character(4)
quantity_sold: integer
revenue: double precision

Figure 4.2: Overall materialized view—*ROWSET*

```
         s."store_country" AS store_state,
         s."opening_year" AS opening_year,
         w."week" AS week,
         w."month" AS "month",
         w."quarter" AS quarter,
         w."year" AS "year",
         f."quantity_sold" AS quantity_sold,
         f."revenue" AS revenue
FROM     "WEEKS" w JOIN
         ("COLOR" c JOIN
         ("PRODUCT" p JOIN
         ("STORE" s JOIN
          "FACT" f ON (f."store_id"=s."store_id"))
                   ON (f."product_id"=p."product_id"))
                   ON (f."color_id"=c."color_id"))
                   ON (w."week_id"=f."week_id");
```

In this work, the data organization of single overall materialized view is adopted. It has several advantages. Firstly, comparing with multiple materialized views approaches, the required storage space is reduced. Secondly, the overall materialized view is not created for optimizing a set of pre-chosen queries, instead, all queries can benefit from this materialized view. Thirdly, with one materialized view, the emerging search engine techniques could be easily applied. In particular, in this work, one materialized view approach greatly simplifies data partitioning and indexing work.

Term specification From now on, the terms *dimension* and *measure* are slightly different from the recognized terms with common names in OLAP field. In order to avoid confusion, we would like to newly declare the definitions of these two terms. If not additionally specified, the following occurrences of the two terms adopt the definitions below.

- *Dimension* is a type of columns, of which the distinct values are of type *text*.
- *Measure* is a type of columns, of which the distinct values are of type *numeric*.

To be noted, *hierarchy* is not adopted in this terminology.

4.3 Computations Involved in Data Explorations

In SAP BusinessObjects data explorer, user selects an information space, and then enters into a relevant exploration panel. The first page displayed in exploration panel shows aggregated measures dimension by dimension. User can selected various aggregate functions, such as COUNT, SUM, AVERAGE, MAX, MIN, etc, by clicking a drop-list. Assuming the aggregate function SUM applied on all the measures, then the computations involved within the display of the first page actually is equivalent to execution of SQL statement of the List 4.2.

Listing 4.2: SQL statements used for displaying the first page of exploration panel.

```
DROP VIEW IF EXISTS page_0 CASCADE;
CREATE VIEW page_0 AS
SELECT * FROM "ROWSET"
;
DROP VIEW IF EXISTS dimension_0;
CREATE VIEW dimension_0 AS
SELECT "page_0"."color" AS distinct_value,
       SUM(page_0."quantity_sold") AS quantity_sold,
       SUM(page_0."revenue") AS revenue
FROM "page_0"
GROUP BY "distinct_value"
;
DROP VIEW IF EXISTS dimension_1;
```

```
CREATE VIEW dimension_1 AS
SELECT "page_0"."product_family" AS distinct_value,
       SUM(page_0."quantity_sold") AS quantity_sold,
       SUM(page_0."revenue") AS revenue
FROM "page_0"
GROUP BY "distinct_value"
;
DROP VIEW IF EXISTS dimension_2;
CREATE VIEW dimension_2 AS
SELECT "page_0"."product_category" AS distinct_value,
       SUM(page_0."quantity_sold") AS quantity_sold,
       SUM(page_0."revenue") AS revenue
FROM "page_0"
GROUP BY "distinct_value"
;
-----------repeate for all the dimensions---------
```

If user finds an anomalous aggregated value, for example, a certain product category, say, ”swimming hats” has a too low quantity sold, and he/she wants to see the detail data over the specific product category, then a detailed exploration is performed and the second page is generated. The second page displays the ”swimming hats” related measures aggregated over different dimensions. The computation involved in displaying the second page of exploration panel is equivalent to execution of SQL statement in List 4.3.

Listing 4.3: SQL statements used for displaying the second page of exploration panel.

```
DROP VIEW IF EXISTS page_1 CASCADE;
CREATE VIEW page_1
AS
SELECT * FROM "page_0"
WHERE "product_category"='Swimming hats'
;
DROP VIEW IF EXISTS dimension_0;
CREATE VIEW dimension_0 AS
SELECT "page_1"."color" AS distinct_value,
       SUM(page_1."quantity_sold") AS quantity_sold,
       SUM(page_1."revenue") AS revenue
FROM "page_1"
GROUP BY "distinct_value"
;
DROP VIEW IF EXISTS dimension_1;
CREATE VIEW dimension_1 AS
```

```
SELECT "page_1"."product_family" AS distinct_value,
       SUM(page_1."quantity_sold") AS quantity_sold,
       SUM(page_1."revenue") AS revenue
FROM "page_1"
GROUP BY "distinct_value"
;
DROP VIEW IF EXISTS dimension_2;
CREATE VIEW dimension_2 AS
SELECT "page_1"."product_category" AS distinct_value,
       SUM(page_1."quantity_sold") AS quantity_sold,
       SUM(page_1."revenue") AS revenue
FROM "page_1"
GROUP BY "distinct_value"
;
-----------repeate for all the dimensions---------
```

Similarly, further exploration can be achieved by applying both the current *WHERE* condition `"product_category"='Swimming hats'` and the new condition coming from the exploration panel.

As seen from the above illustration, a typical computation involved in data exploration is the *Group-by* query, on different dimensions, with aggregates using various aggregate functions. Without considering other features of data explorer, we could say that the computations involved in a data exploration are composed of a couple of elementary *Group-by* query having the following form:

```
SELECT DimensionA,
       aggregate_funtion(Measure1),
       aggregate_funtion(Measure2)
FROM "ROWSET"
WHERE DimensionB=b
GROUP BY DiemnsionA;
```

Group-by query is a typical OLAP query. Because of OLAP queries wide application, a lot of research work has been done. The characteristics of these queries are summarized in (75). The two important characteristics of OLAP query—including *Group-by* query—are:

- most of them include aggregate functions;
- they usually include selection clauses.

Going any further from the two characteristics, one *Group-by* query involves two processing phases, *filtering* and *aggregating*. During filtering phase, the WHERE condition is applied to filter the records of materialized view. During the aggregating phase, the aggregate function is performed over the filtered records.

4.4 Multiple Group-by Query

For being able to response user's exploration, multiple *Group-by* queries need to be calculated simultaneously, instead of one single *Group-by* query. The term *Multiple Group-by query* is able to more clearly express the characteristics of the query addressed in this work. For defining the *Multiple Group-by* query, we describe it as follows: *Multiple Group-By* query is a set of Group-by queries using the same select-where clause block. More formally, *Multiple Group-By* query can be expressed in SQL with the following form:

```sql
SELECT X, SUM(*),
FROM R WHERE condition
GROUP BY X
ORDER BY X;
```

where X is a set of columns on relation R.

Some commercial database systems support a similar *Group-by* construct named *GROUPING SETS*, and it allows the computation of multiple Group-by queries using a single SQL statement (111). Comparing with the *Multiple Group by* query addressed in this work, GROUPING SETS query is slightly different. Each Group-by query contained in GROUPING SETS query could have more than one group-by dimension, i.e. one Group-by query aggregates over more than one dimension, whereas in this work, one Group-by query aggregates over only one dimension.

4.5 Challenges

In data exploration environment, processing *Multiple Group-by* query has several challenges. The first challenge is large data volume. In a very common case, the historical data set is often of large size. The generated materialized view also is of large size. In order for user to do analysis as comprehensively as possible, the historical data set contains many dimensions. It is not rare that the generated overall materialized view has more than 10 dimensions. The second challenge is the requirement of short response time. It is a common demand for all the interactive interface application, including data exploration. *Multiple Group-by* queries aggregating over all dimensions is repeatedly invoked and processed during data exploration, then it is required that each query is answer within a very short time, for example, not more than 5 seconds, ideally, within hundreds of milliseconds. Summarizing these challenges' description—doing time and resource consuming computations in short time.

Parallelization is the solution to address these challenges: partition the large materialized view ROWSET into smaller blocks, then processed query over each of them, finally merge the results. One particular thing of this work is that we utilize cheap commodity hardware instead of expensive supercomputer. This is also the significant side of this work. This particularity brings further challenges, scalability and fault tolerance issues. For addressing these challenges, we adopt MapReduce model, and the detailed specifications will be given later in this chapter.

4.6 Choosing a Right MapReduce Framework

There exist several researches and projects focusing on building specific MapReduce frameworks for various hardware and different distributed architectures. In our work, we adopt the shared-nothing clusters, which are available for free[1]. Some well-designed MapReduce frameworks are already realized for this type of hardware architecture. We need to the right framework for satisfying the specific requirement.

4.6.1 GridGain Wins by Low-latency

Interactivity, i.e. short response time is the basic requirement in this work. In order to meet this requirement, while the application-level optimization is essential, choosing a right underlying MapReduce framework is also important. At our framework choosing moment, there were two different open-source MapReduce frameworks available, Hadoop (11) and GridGain (10).

[1]Grid'5000, for more information, refer to(9)

At first, Hadoop has been chosen as the MapReduce supporting framework. We successfully installed and configured Hadoop in a cluster of two computers, and run several simple tests over Hadoop. The experiment execution time over Hadoop was not satisfying. An application of filtering materialized view of small size with a given condition took already several seconds, which is too slow for interactive interface. This phenomenon was then diagnosed as a consequence of the high latency of Hadoop. Actually, high latency is consistent with the initial design of Hadoop. Hadoop is designed to address batch-processing application. Batch-processing application only emphasizes high-throughput. In such a context, high-latency is insignificant. The high-latency is also a side effect of Hadoop's "MapReduce + HDFS" design, of which more explanation can be found in Subsection 3.1.2.

Another MapReduce framework, GridGain, is finally adopted as the underlying framework in this work. GridGain offers a low latency since it is a pure MapReduce engine without being associated with a distributed file system. Therefore, data partitioning and distributing should be manually managed. Although this increases the workload of programmers, they have a chance to do optimizations at the data access level. Additionally, GridGain provides several pre-defined scheduling policies including data affinity scheduling policy, which can be beneficial for processing multiple continuous queries.

4.6.2 Terminology

In GridGain, a **Task** is a MapReduce processing procedure; a **Job** is either a Map procedure or a Reduce procedure. In Hadoop, the two terms are used inversely. A MapReduce procedure is called a **Job** in Hadoop, and a Map or a Reduce procedure is called a **Task**. In this dissertation, we adopt the terminology of GridGain.

4.6.3 Combiner Support in Hadoop and GridGain

Combiner is an optional component, which is located between the **mapper** and the **reducer**. In Hadoop, combiner component is implemented, and user can choose to use or not to use it freely. The combiner is physically located on each computing node. Its function is to locally collect the intermediate output from the mappers running on current node before these intermediate outputs being sent over the network. In certain

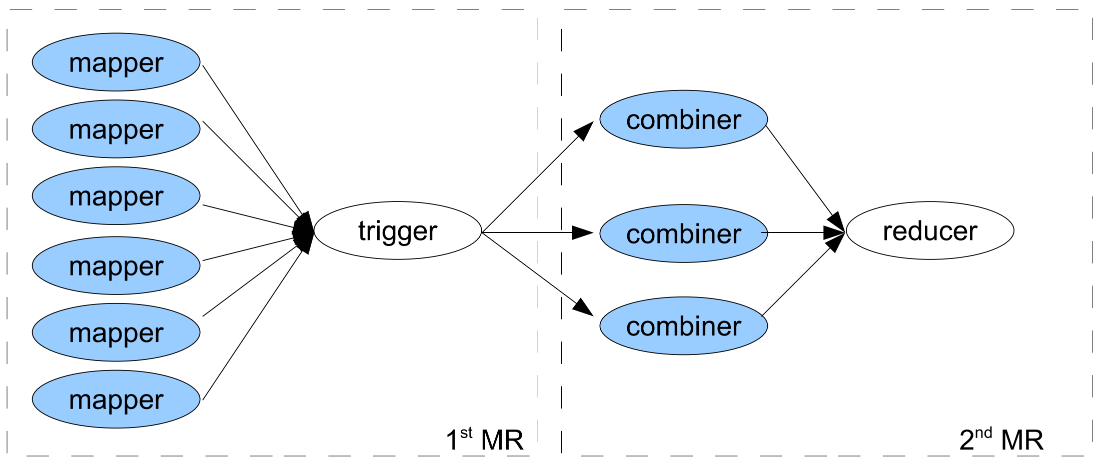


Figure 4.3: Create the task of MapCombineReduce model by combining two GridGain MapReduce tasks.

case, using this combiner component can optimize the performance of the entire model. The objective of using combiner is to reduce the intermediate data transfer.

This optional component **combiner** is not implemented in GridGain. In this work, we propose a bypass method to make GridGain supporting combiner. Although this method is implemented on top of GridGain, it is not limited to work with GridGain. The same idea can also be carried out on other MapReduce frameworks. We illustrate this method in the Figure 4.3. A GridGain MapReduce is composed of multiple mappers and one reducer. In this method, we utilized two successive GridGain MapReduce tasks. In the first MapReduce task, the mappers correspond to the mapper component of MapCombineReduce model, and its reducer acts as a trigger to activate the second MapReduce task, once the first MapReduce's mappers have all finished their works. The mappers of the second MapReduce task actually act as the combiner component of MapCombineReduce model. The reducer of the second MapReduce task does the job of the reducer component of MapCombineReduce model.

4.6.4 Realizing MapReduce Applications with GridGain

GridGain provides developers with Java-based technologies to develop and to run grid applications on private or public clouds. In order to implement a MapReduce application, there are mainly two classes need to define in GridGain, i.e. **Task**, and

Job. Task class's definition requires developer realizing `map()` and `reduce()` functions. Job class's definition requires developer realizing `execute()` function. The name of `map()` might be confusing. This name misleads people to think it defines the calculations to be carried out in mapper. But in fact, the `map()` function is responsible for establishing the mappings between mappers and worker nodes. This function could be utilized to apply user-defined job-scheduling policy. GridGain provides some pre-defined implementations of map() function, which support various job-scheduling policies, including data affinity, round robin, weighted random, etc. The web site of GridGain (10) gives to the readers more descriptions about GridGain's supported job-scheduling policies. `execute()` is actually the function specifying operations performed by mapper. `execute()` contains the distributed computations which will be executed in parallel with other instances of *execute()* function. When a mapper arrives at a remote worker node, a collision resolving strategy will look into a queue of existing mappers on this worker node to either reject the current mapper or leave it waiting in the queue. When the mapper got run, the `execute()` function will be executed. `Reduce` function contains the actions of reducer, collecting mappers intermediate outputs and calculate the final result. It usually is composed of some aggregate-type operations. `Reduce()` function's execution is activated by the arrival of the mappers' intermediate outputs. According to the policy defined by the user, `reduce()` can be activated once the first intermediate output from mapper arrives at the master node, or after the sub-results of all the mappers arrived. The default policy is to wait all the mappers to finish their works and then to activate the `reduce()` method. In addition, developer also need to define a task loader program, which takes charge of initializing the parameters, starting a grid instance, launching user's application, and then waiting and collecting the results.

4.6.5 Workflow Analysis of GridGain MapReduce Procedure

GridGain's MapReduce is composed of multiple mappers and one reducer. The mappers are sent to and run on worker nodes, and the reducer run on master node. For fully understanding the procedure of GridGain's MapReduce, we analyzed the log file of GridGain and also did the profiling work when running MapReduce application. The following description of GridGain MapReduce workflow is based on this analysis.

The Figure 4.4 shows the workflow of a GridGain's MapReduce task. When master starts a MapReduce task, it in fact starts a thread for this task. The thread does the start-up work and closure work for the task. The start-up work includes the following steps.

1. Firstly, master creates mappings between user-defined jobs (mappers) and available worker nodes;
2. Secondly, master serializes mappers in a sequential way ;
3. Once all mappers are serialized, master sends each mapper to the corresponding worker node.

After all the mappers being sent, the thread terminates and the master enters into a "waiting" status. This "waiting" status continues until the master node receives the mappers' intermediate outputs. When the master node receives a mapper's intermediate output, it begins to de-serialize this intermediate output immediately. After all the intermediate outputs are de-serialized, then it starts the reducer. The de-serialization and reducer execution compose the task's closure.

On the other side, the worker node listens to the messages after the GridGain instance is started. When it receives a message containing serialized mapper object, it will de-serialize the message, thereby it obtains mapper's object. Then, the mapper is put into a queue waiting for being executed once one or more CPU becomes available. After the mapper's execution is accomplished, the intermediate output is serialized and sent back to the master node.

4.7 Paralleling Single Group-by Query with MapReduce

Before addressing the parallelization of *Multiple Group-by* query, we describe the processing of the elementary query—single Group-by query—in MapReduce. Intuitively, single Group-by query could be well matched with MapReduce model. A single Group-by query can be executed in two phases: the first phase is filtering, and the second phase is aggregating. The other operations (regroup) can be incorporated into the aggregating phase. The filtering phase corresponds to the mapper'work in MapReduce, and the aggregating phase corresponds to its reducer's work.

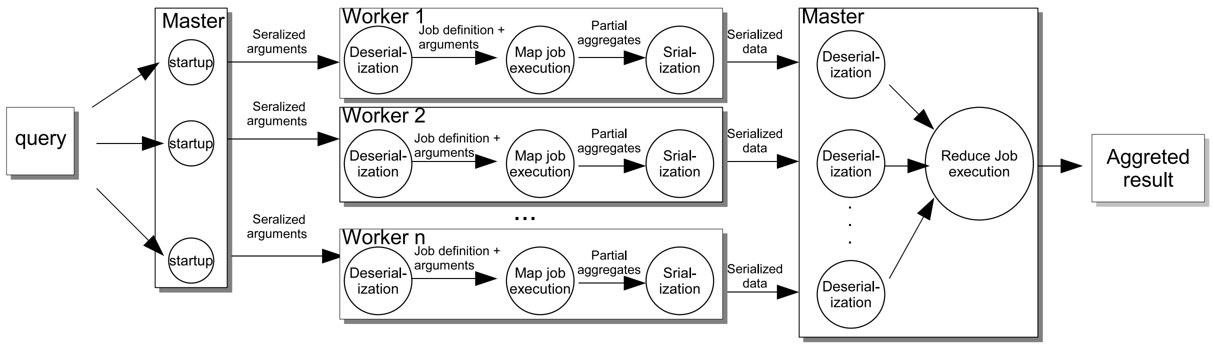


Figure 4.4: Work flow diagram of MapReduce-based application in GridGain.

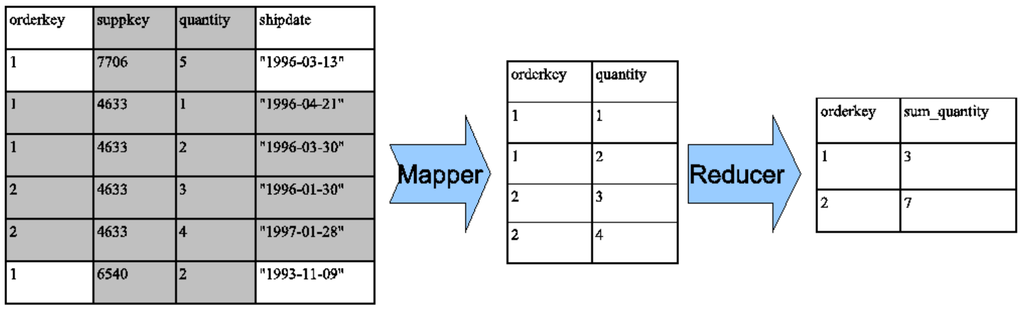
As an example of Group-by query, we consider another materialized view LINEITEM with two dimensions and one measure, LINEITEM(OrderKey,SuppKey,Quantity), and one Group-by query of the form:

```
SELECT "Orderkey", SUM("Quantity")
FROM "LINEITEM"
WHERE "Suppkey" = '4633'
GROUP BY Orderkey
```

The above query performs the following operations on the materialized view, `LINEITEM`. The first operation is **filtering**, which makes records to be filtered by the WHERE condition. Only the records matching the condition ”`"Suppkey" = '4633'`” are retained for the subsequent operations. Within the next operation, these tuples are **re-grouped** into groups according to the distinct values stored in the dimension `OrderKey`. The last operation is a SUM aggregation, which adds up the values of the measure `Quantity`. The SUM aggregation is executed on each group of tuples. Figure 4.5 illustrates how this MapReduce model-based processing procedure is organized.

4.8 Parallelizing Multiple Group-by Query with MapReduce

A *Multiple Group-by* query can also be implemented in these two phases. In a *Multiple Group-by* query, multiple single Group-by queries, having the same WHERE condition, we propose that the mapping phase performs the computation for filtering data accord-



orderkey	suppkey	quantity	shipdate
1	7706	5	"1996-03-13"
1	4633	1	"1996-04-21"
1	4633	2	"1996-03-30"
2	4633	3	"1996-01-30"
2	4633	4	"1997-01-28"
1	6540	2	"1993-11-09"

orderkey	quantity
1	1
1	2
2	3
2	4

orderkey	sum_quantity
1	3
2	7

Figure 4.5: Single Group-by query's MapReduce implementation design. This design corresponds to the SQL query `SELECT Orderkey SUM(Quantity) FROM LINEITEM WHERE Suppkey = 4633 GROUP BY Orderkey`.

ing to the condition defined by the common WHERE clause. The aggregating phase still corresponds to a set of reduce-type operations. For a *Multiple Group-by* query, the aggregating phase consists of a couple of aggregating operations performed on several different Group-by dimensions. In this work, we first use the reducer to implement the aggregating phase at first, and then we propose an optimized implementation based on the extended MapCombineReduce model. The following content in this section will give more details about these two implementations.

4.8.1 Data Partitioning and Data Placement

The materialized view ROWSET used in our tests is composed of 15 columns, including 13 dimensions and 2 measures. We partition this materialized view into several blocks. The horizontal partitioning method (99) is used to equally divide ROWSET. As a result, each block has an equal number of records, and each record keeps all the columns from the original ROWSET. All the data blocks are replicated on every participating worker node. This is inspired from the Adaptive virtual partitioning method proposed in (29). Such a method allows conveniently realizing the distribution of data without worrying about the accessibility problem caused by a data placement strategy. With all the data blocks available on all the worker nodes, the data location work is simplified.

4.8.2 Determining the Optimal Job Grain Size

The size of the data block actually determines the job grain size, since the data block is processed as the input data by each job. A too big grain size leads to an unbalanced load, on the contrary, a too small grain size will lead to waste much more time on the start-up overhead and job closure overhead. An optimal job grain size on a given computing node is determined by the computing power of the node. Then defining an appropriate data block size can get the nodes to work more efficiently. The optimal or near-optimal data block size could be evaluated by the minimization of the value of cost function working under current investigation. In practice, it can also be obtained through experiments. In this work, we perform the experiments on top of IBM eServer 325 machines. According to the experimental results, the optimal block sizes are 16000 and 32000 lines (in one block) on this type of hardware.

4.8.3 Initial MapReduce Model-based Implementation

The initial implementation of the MapReduce model-based *Multiple Group-by* query we have developed is shown in Figure 4.6. In this implementation, the mappers perform the filtering phase, and the reducer performs aggregating phase. In order to realize the filtering operations, each mapper first opens and scans a certain data block file locally stored on the worker node, and then selects the records which meet the conditions defined in the WHERE clause. In this way, each mapper filters out a group of records. After that, all the records filtered by the mappers are then sent to the reducer as intermediate outputs. The Algorithm 1 describes this processing with pseudo-code.

The reducer realizes the aggregating operations as follows. Firstly, the reducer creates a set of aggregate tables to save the aggregate results. Each aggregate table corresponds to a Group-by dimension. The **aggregate table** is a structure designed to store aggregate value for one dimension. In addition to the distinct values of the dimension, the aggregate table also stores aggregate values calculated by applying user defined aggregate functions over different measures. As shown in figure 4.7, the first column stores the distinct values of dimension, and the corresponding aggregate values are stored in the rest columns. The number of aggregate functions (denoted as nb_{agg}) contained in the query determines the total number of columns. There are $nb_{agg} + 1$ columns in aggregate table in total.

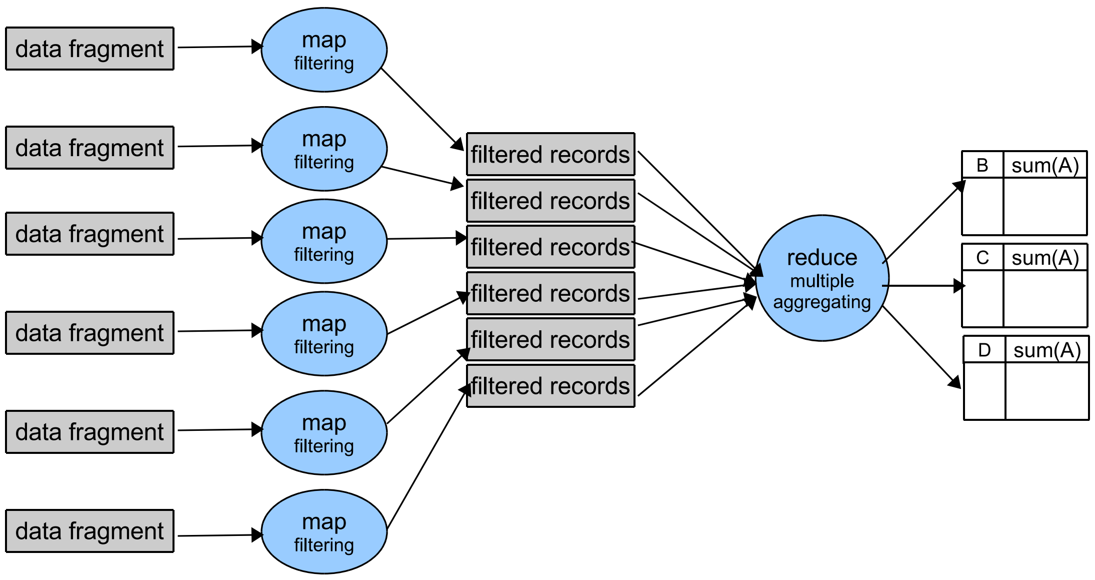


Figure 4.6: The initial *Multiple Group-by* query implementation based on MapReduce model.

DV of Dimension	agg_func_1 (msr_x)	agg_func_2 (msr_y)	...
DV_1	agg_val_DV_1	agg_val_DV_1	...
DV_2	agg_val_DV_2	agg_val_DV_2	...
...	...	...	...

Figure 4.7: Aggregate table structure

As an example, we specify the construction of **aggregate tables** for the *Multiple Group-by* query below:

```
SELECT SUM("revenue"), SUM("quantity_sold"), "product_family"
FROM "ROWSET"
WHERE "color"='Pink'
GROUP BY "product_family"
;
SELECT SUM("revenue"), SUM("quantity_sold"), "store_name"
FROM "ROWSET"
WHERE "color"='Pink'
GROUP BY "store_name"
;
SELECT SUM("revenue"), SUM("quantity_sold"), "year"
FROM "ROWSET"
WHERE "color"='Pink'
GROUP BY "year"
;
```

This *Multiple Group-by* query includes three single Group-by queries; each query includes two aggregate functions. Thus, we need to create three *aggregate tables.* For the first Group-by query aggregating over dimension `product_family`, the *aggregate table* has three columns. The first column is used to store different distinct values appearing in the records which meet the WHERE condition `E > e`. The second and third columns are used to store the corresponding aggregate values for each distinct value of the dimension `product_family`. In this example, the two aggregate functions are both `SUM`. The *aggregate table* for the second and third Group-by queries, are constructed in a similar way. *Aggregate table* is implemented as Hashtable in over program.

Secondly, the reducer scans all intermediate results, and simultaneously the reducer updates the **aggregate tables** by aggregating the new arriving aggregate values onto some records in the **aggregate tables**. The final result obtained by the reducer is a group of aggregate result tables, each table corresponding to one Group-by query. The Algorithm 2 describes this processing in pseudo-code.

In this initial implementation, the reducer works on all the records filtered by the WHERE condition. The most important calculations, i.e. the aggregations, are performed in the reducing phase. It takes all the filtered records as its input data. Such an implementation is a general approach for realizing a MapReduce application. However,

Algorithm 1 Filtering in Mapper

```
Input: data block, *Multiple Group-by* query
Output $selectedRowSet$
Load data block into $rawData$
**for** $record \in rawData$ **do**
  **if** $record$ passes WHERE condition **then**
    $recordID \rightarrow matchedRecordIDs$
  **end if**
**end for**
**for** $recordID \in matchedRecordIDs$ **do**
  copy $rawData[recordID]$ to $selectedRowSet$
**end for**
```

Algorithm 2 Aggregating in Reducer

```
Input: $selectedRowSet$
Output: $agg$s
**for** $dimension \in GroupByDimension$s **do**
  create a aggregate table: $agg$
**end for**
**for** $record \in selectedRowSet$ **do**
  **for** $dimension \in GroupByDimension$s **do**
    **if** (value of $dimension$ in $record$) $\in agg$ of $dimension$ **then**
      assuming existing record is $r$
      **for** *agg_func()* $\in$ *agg_func_list* **do**
        update $r.field(1 + a)$ with *agg_func(r)*
      **end for**
    **else**
      Insert into $agg$ a new record $rr$ where
      $rr.field1$ = value of $GroupByDimension$
      **for** *agg_func()* $\in$ *agg_func_list* **do**
        $rr.field(1 + a)$ = *agg_func(rr)*
      **end for**
    **end if**
  **end for**
**end for**
```

it is not fully suitable for GridGain. Because of the limitation of GridGain (only one reducer), all the filtered records should be transfer over the network. This could cause high overhead when the bandwidth is limited.

4.8.4 MapCombineReduce Model-based Optimization

In the initial implementation, all the intermediate outputs produced by the mappers (i.e. all the records matching the WHERE condition), are sent to the reducer over the network. If query selectivity [1] under the given WHERE condition is relatively small, for instance 1%[2], then output of mapping phase will be moderate, and the initial implementation is suitable. However, if the query selectivity is larger, for instance, 9%, then the number of records will be great and the volume of data being transferred over the network will become large, which causes a higher communication cost. As a consequence, the initial implementation is not suitable for queries with relatively large selectivity.

In order to reduce the network overhead caused by the intermediate data transmission for queries with larger selectivity value, we propose a MapCombineReduce model-based implementation. We let the combiner component to act as a pre-aggregator on each worker node. In this work, the number of combiner of each worker node is one. In optimized MapCombineReduce model-based implementation, the mapper first performs the same operations of the filtering phase as in the initial implementation. However, the result of the filtering phase will be put into the local cache instead of being sent over the network immediately. The mapper then sends out a signal when it finished its work. The trigger (i.e. reducer in the first MapReduce task) will receive this signal. When the trigger receives all the *work finished* signals, then it activates the second MapReduce task. In the second MapReduce task, the combiner (i.e. the mapper of the second MapReduce task) does the aggregating operations locally within each worker node. Each of the combiners generates a portion of aggregate the results, i.e. a set of partial aggregate tables. Then they send out their partial results to the reducer. After merging all the partial results, the reducer generates the final aggregate tables of the *Multiple Group-by* query. Thus, the volume of data to be transferred is reduced

[1]Here, a selectivity of a select query means the ratio value between the number of records satisfying the predicate defined in the WHERE clause and the cardinality of the relation.

[2]This means that only 1% of the records are selected out from the data source table.

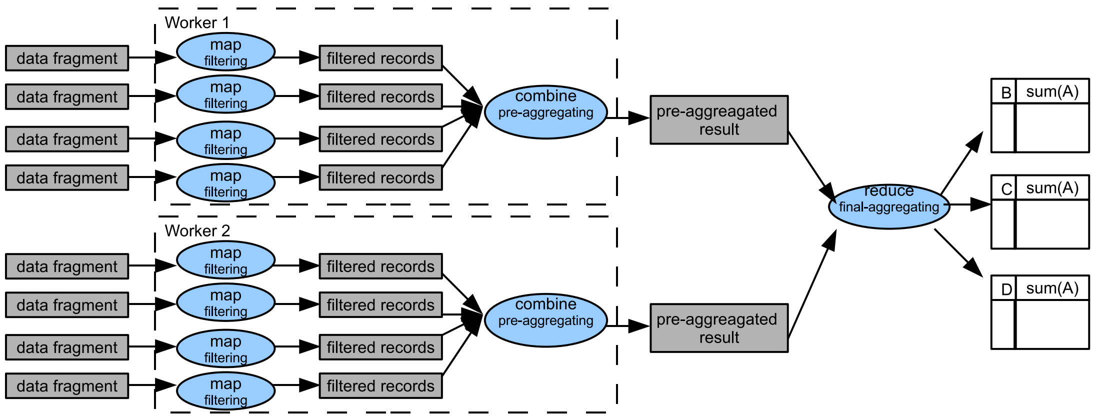


Figure 4.8: The optimized *Multiple Group-by* query implementation based on MapCombineReduce model.

during the pre-aggregation phase, which in turn reduces the total communication cost. Figure 4.8 illustrates the MapCombineReduce model-based *Multiple Group-by* query processing.

4.8.5 Performance Measurements

We have developed two implementations of *Multiple Group-by* query. The initial implementation uses a basic MapReduce model without combiner. The optimized implementation adopts the combiner component to do the pre-aggregation over the output of the mappers before sending the intermediate data to the reducer.

4.8.5.1 Experiment Platform: Grid'5000

To evaluate the proposed approaches, we did a first performance measurement on Grid'5000 (9) a French project that provides a large-scale reconfigurable grid infrastructure to support distributed and parallel experiments. Grid'5000 is composed of 9 sites geographically distributed in France featuring a total of 5000 processors. In Grid'5000, users can reserve a number of computers within one cluster or across several clusters. Users can freely install his/her own software, such as operating system (OS) on the reserved computers. Grid'5000 provides a series of tools and commands to support computer reservation, rapid software installation experiment deployment, and node status monitoring. For instance, with the Kadeploy (15) tool, it is possible to generate customized images of operating systems and applications, store and automatically or interactively load them through the job scheduler tool OAR (17).

For the experiments in this work, we ran the version 2.1.1 of GridGain over Java 1.6.0 on top of computers in one cluster located in the Sophia site. In this cluster, all the computers are of model IBM eServer 325. The total number of nodes in this cluster is 49 and each node is equipped with two AMD Opteron 246 2.0GHz processors, 2GB of RAM and network card of Myrinet-2000, running under the 64-bit Debian. We reserve from 1 to 20 nodes according to the experiment requirements. GridGain instances are started at master node and worker nodes, the JVM maximum of heap size were set to 1536MB. In the following experiments, we were mainly interested in the two performance aspects of our *Multiple Group-by* query implementations, the speed-up and the scalability.

4.8.5.2 Speed-up

In our work, the materialized view was stored as a plain text CSV file. We use a materialized view of 640 000 records which is composed of 15 columns, including 13 dimensions and 2 measures. Each record is stored as a different line of the CSV file. We partitioned this materialized view with 5 different block sizes: 1000, 2000, 4000, 8000 and 16000. Several *Multiple Group-by* queries with different selectivities[1] (1.06%, 9.9%, 18.5%) were executed on the materialized view. Each query includes 7 Group-by queries. In order to test the speed-up, We firstly ran a sequential test on one machine in the cluster, then we launched the parallel tests realized with GridGain on 5, 10, then on 15, and finally on 20 worker nodes. Each test is run 5 times and the average execution time was recorded. Figure 4.9 shows the speed-up of the initial implementation and the optimized one comparing with the sequential execution time.

As seen from this figure, no good speed-up is obtained with small block sizes such as 1000 and 2000. However, an obvious acceleration can be observed when using larger block size like 4000, 8000 and 16000. The explanation of this phenomenon is that, for each job running on a worker node, there are some initial costs to start (job start-up) and to close the job (job closure). The actions in job start-up include receiving data or parameters from the calling node (usually this is the master node), preparing the

[1]The selectivity of a select query means the ratio value between the number of records satisfying the predicate defined in the WHERE clause and the cardinality of the relation

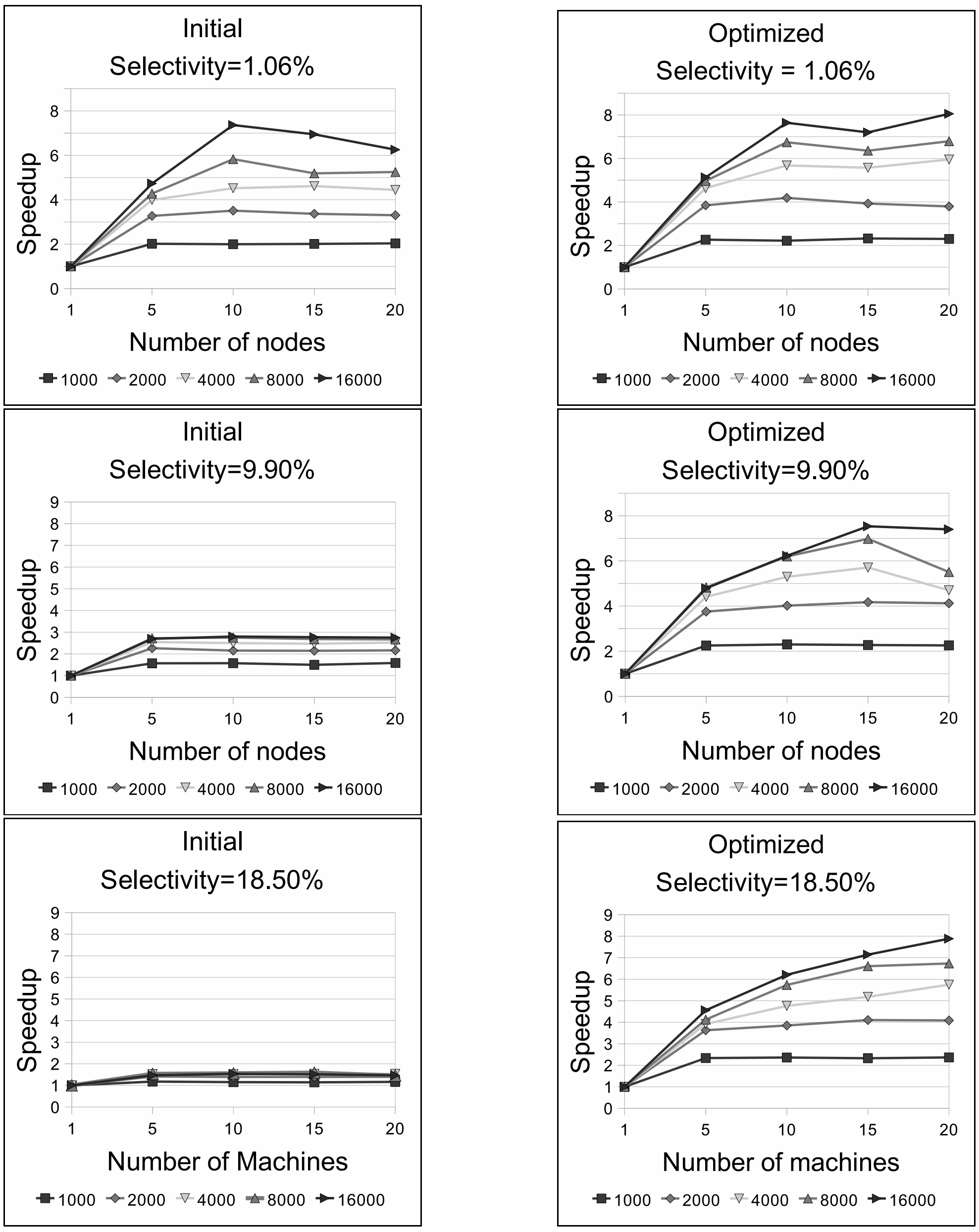


Figure 4.9: Speed-up versus the number of machines and the block size (1000, 2000, 4000, 8000, 16000).

input data or reading the input data from an indicated place, etc. The job closure cost consists in establishing a connection with the master node in order to send back the intermediate outputs on worker side, and receiving and pre-processing each intermediate output on the master side. The smaller the block size is, the larger the job number is. When the block size is equal to 1000 or 2000, the number of jobs is large and the job start-up/closure cost becomes important ...

The results shown in the two first figures consider a query with selectivity equal to 1.06%. With this small selectivity, the output of the mappers is not large enough, and the optimized implementation does not exhibit its advantage over the initial implementation. However, increasing the query selectivity (e.g. 9.9% and 18.5%), makes the intermediate data being transferred in the initial implementation considerably larger than those transferred in the optimized implementation. As a consequence, the optimized implementation shows a better speed-up performance than the initial implementation.

4.8.5.3 Scalability

For the scalability, we used several materialized views having the same dimensions and measures, but containing several times more records than the one of the speed-up tests. We used materialize views of 640 000, 1 280 000, 1 920 000 and 2560000 records, respectively. The tests performed using the materialized view of 640 000 records were run on 5 machines, those using the materialized view of 1 280 000 records were run on 10 machines, those using materialized view of 1 920 000 records were run on 15 machines, and those using materialized view of 2 560 000 records were run on 20 machines. According to the previous test case, the executions with block size as 16000 had better performance than the other ones. Therefore, we defined the block size of 16000, and we used queries with the same selectivities as used in speed-up experiments. Figure 4.10 shows the obtained results.

These figures show that the optimized implementation has very good scalability. With an increasing the data scale, the executions spend almost the same time (the difference is smaller than 1 seconds). As seen from the first figure, for the case of query selectivity equal to 1.06%, the workload is relatively small and both the optimized implementation and the initial implementation gave acceptable execution time, i.e. within 3 seconds. Note that in case of a small selectivity, the communication cost was not dominant and the pre-aggregation work did not bring an obvious optimizing

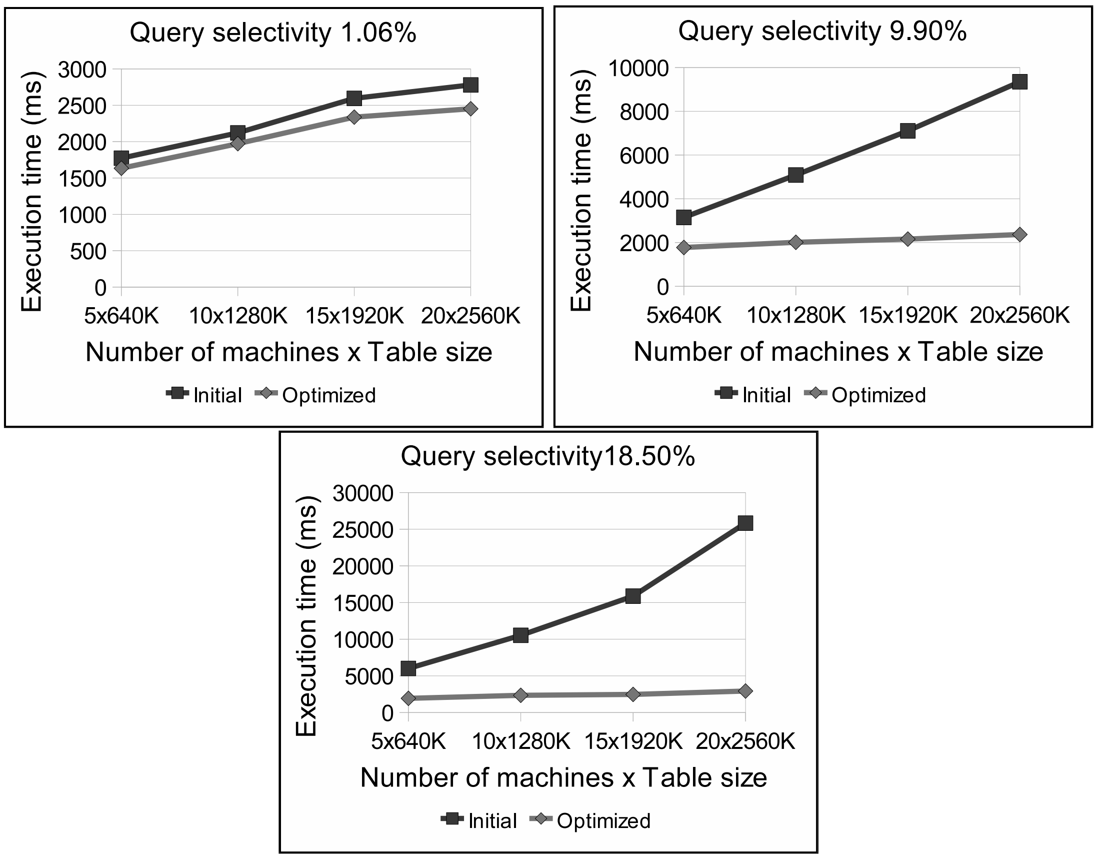


Figure 4.10: Comparison of the execution time upon the size of the data set and the query selectivity.

effect. In the rest of the figures, the query selectivities have larger values. This enables more records to be selected and implies larger communication costs for transferring intermediate output. As a consequence, the optimized implementation always shows better performance than the initial implementation, and the curve if the optimized implementation stands upper the curve of the initial implementation. This behaviour is clearly outlined for query selectivity equal to 9.9% and 18.5%.

4.9 Execution Time Analysis

In this section, we will describe a basic analysis of execution time of the *Multiple Group-by* query. These cost analysis respectively address the initial implementation based on the MapReduce and optimized implementation based on the MapCombineReduce. As mentioned earlier, a GridGain MapReduce task's calculation is composed of the start-up and closure on the master node, and the mapper executions over worker nodes. In this work, we are also interested in the optimization over communication cost, thus, communication time is considered, but we ignore the extra cost brought by the resource contention over each worker node when running multiple mappers.

4.9.1 Cost Analysis for Initial Implementation

Assume that the Multiple Group-by query runs over a materialized view of N records, and the query has nb_{GB} Group-by dimensions. We use MapReduce-based method to parallelize query processing. The parallel *Multiple Group-by* query's total cost is composed of four parts:

- start-up cost(on master node), denoted as C_{st};
- mapper's execution (on workers), denoted as C_m;
- closure cost (on master node), denoted as C_{cl};
- communication cost, denoted as C_{cmm}.

In start-up, the master does the preparation of mappers, including the mappings from mappers to available worker nodes, and then sequentially performs the serializations of mappers with their attached arguments. We use C_{mpg} to denote the time for building mapping between mappers and worker nodes, C_s the time for serializing one unit size of data, $size_m$ the size of mapper object, nb_m the number of mappers. The notations that are used for expressing the cost analysis are listed in the Table 4.1.

Without considering the low-level details of serialization[1], we simply assume that the serialization time is proportional to the size of data being serialized, i.e. a bigger mapper object consumes more time during the serialization. Therefore, a MapReduce task of GridGain, the start-up cost C_{st} over master node is:

$$C_{st} = (C_{mpg} + C_s \cdot size_m) \cdot nb_m$$

When a worker node receives a message containing mapper, it first serializes the mapper as well as its arguments, it then launches the execution of mapper. When

[1]The details of serialization will be discussed in Chapter 5.

Table 4.1: Notations used for describing the cost analysis

Notation	Description
N	records number of whole data set
C_{st}	start-up cost
C_{st}^{m}	mapper's start-up cost (optimization)
C_{st}^{c}	combiner's start-up cost (optimization)
C_{w}^{m}	cost spend on worker for executing mapper (optimization)
C_{w}^{c}	cost spend on worker for executing combiner (optimization)
C_{cl}	closure cost
C_w	cost spent on one worker
C_{mpg}	cost for creating a mapping from mapper to a worker node
C_{cmm}	communication cost
C_m	mapper's cost
C_r	reducer's cost
C_c	combiner's cost
C_s	one unit data's serialization cost
C_d	one unit data's de-serialization cost
C_l	cost for loading a record into memory
C_n	network factor, cost for transferring a unit of data
C_f	cost for filtering a record
C_a	cost for aggregating a record
C_i	total cost of initial implementation
$size_m$	size of mapper object
$size_c$	size of combiner object
$size_{rslt}$	size of mapper's intermediate result
nb_{GB}	Group-by dimension number
DV_i	the i_{th} distinct value
nb_m	mapper number
nb_{node}	worker node number
$\frac{N}{nb_m}$	block size
S	query's selectivity

the mapper is finished, it serializes the mapper's output. Therefore, the cost of this procedure is expressed as:

$$C_w = C_d \cdot size_m + C_m + C_s \cdot size_{rslt}$$

Similarly, let's assume that the de-serialization cost is proportional to $size_m$, and the cost for serializing the intermediate result generated by a mapper is proportional to $size_{rslt}$ by assumption.

The closure consists of de-serializing of the mappers' outputs and executing user-defined reducer. The de-serialization is run over all the records filtered by user-defined condition in the query. Therefore, we know the total record number contained in all intermediate outputs for being serialized is equal to the number of all the filtered records: $N \times S$, (S represents the query's selectivity). Thus, we express the closure cost as below:

$$C_{cl} = C_d \cdot N \cdot S + C_r$$

The communication cost is composed of two parts. One is the cost for sending mappers from master node to worker nodes; the other is that for worker nodes sending intermediate output to the master node. The size of messages and the network status are two factors considered in this cost analysis. Thus, we express the communication cost as:

$$C_{cmm} = C_n \cdot (nb_m \cdot size_m + N \cdot S)$$

The analysis of C_m and C_r are related to various applications. In the MapReduce-based initial implementation, the mappers perform filtering operations. They firstly load the data block from the disk into the memory, and then filter loaded data with condition defined in the query. For the mappers used in initial implementation, the cost analysis of the C_m is as follows:

$$C_m = \frac{N}{nb_m} \cdot (C_l + C_f \cdot S)$$

The reducer aggregates over the records filtered by mappers. It concerns the number of records that it processes. We express reducer's cost as below:

$$C_r = N \cdot S \cdot C_a$$

With the mapper and reducer's cost analysis, we obtain the total cost analysis of the initial implementation. We consider that mapper object's size is small comparing with the intermediate outputs, and it can be ignored when the data set is large, the costs concerning mappers' mapping, serialization, de-serializations and transmission can be removed. Thus, the analysis as below is obtained:

$$C_i = \frac{N}{nb_m} \cdot (C_l + C_f \cdot S) + C_s \cdot size_{rslt} + (C_d + C_a + C_n) \cdot N \cdot S \qquad (1)$$

4.9.2 Cost Analysis for Optimized Implementation

For MapCombineReduce-based optimization of multiple-group-by query, the total cost is considered to be composed of:

- Mapper's start-up (on master), denoted as C_{st}^m;
- Cost spend on one worker for executing a mapper, denoted as C_w^m;
- Combiners' start-up (on master), denoted as C_{st}^c;
- Cost spend on one worker for executing a combiner, denoted as C_w^c;
- Closure (on master), denoted as C_{cl};
- Communication, denoted as C_{cmm}.

The start-up of mappers is similar to that of MapReduce, we mark two superscripts m and c in order to distinguish mapper's start-up from combiner's start-up:

$$C_{st}^m = (C_{mpg} + C_s \cdot size_m) \cdot nb_m$$

The mappers do the same calculations as in initial implementation. However, the output's size of each mapper is estimated as 0, because the mapper stores the selected records into the worker's memory and returns null. Thus, the cost for running a mapper is expressed as below:

$$C_w^m = C_d \cdot size_m + C_m + 0$$

where

$$C_m = \frac{N}{nb_m} \cdot (C_l + C_f \cdot S)$$

The combiner's start-up is similar to the mapper's start-up, however, the number of combiners is equal to the number of worker nodes in that the combiners collect the intermediate data from all the worker nodes, one combiner per worker node is sufficient. Thus, the combiner's start-up cost is expressed as below:

$$C^c_{st} = (C_{mpg} + C_s \cdot size_c) \cdot nb_{node}$$

The combiner's execution over one worker node can be analyzed similarly as in the analysis of mapper's execution. However, the size of combiner's result can be precisely expressed as $\sum_{i=1}^{nb_{GB}} DV_i$, which is the result size of pre-aggregations on any worker node. Thus, we have the following analysis for combiner's execution cost:

$$C^c_w = C_d \cdot size_c + C_c + C_s \cdot \sum_{i=1}^{nb_{GB}} DV_i$$

where the combiner's cost is expressed as:

$$C_c = \frac{N}{nb_{node}} \cdot S \cdot C_a$$

The closure includes the de-serialization of combiners' output and the cost of reducer:

$$C_{cl} = C_d \cdot \sum_{i=1}^{nb_{GB}} DV_i \cdot nb_{node} + C_r$$

where the reducer's cost is expressed as:

$$C_r = nb_{node} \cdot \sum_{i=1}^{nb_{GB}} DV_i \cdot C_a$$

As an additional combiner is added, the communication cost's analysis is correspondingly modified:

$$C_{cmm} = C_n \cdot (nb_m \cdot size_m + nb_{node} \cdot size_c + \sum_{i=1}^{nb_{GB}} DV_i * nb_{node})$$

The following analysis of total cost is obtained after ignoring the mapping, serialization/deserialization and transmission cost of mappers and combiners:

$$C_o = \frac{N}{nb_m} \cdot (C_l + C_f \cdot S) + \frac{N}{nb_{node}} * S \cdot C_a +$$

$$(C_n + C_d + C_a) \cdot nb_{node} \cdot \sum_{i=1}^{nb_{GB}} DV_i + C_s \cdot \sum_{i=1}^{nb_{GB}} DV_i \quad (2)$$

4.9.3 Comparison

Comparing the equations (1) and (2), we can see that the optimized implementation surpass the initial one in two aspects. Firstly, it decreases the communication cost by reducing it from the scale of $N \times S$ to $nb_{node} \cdot \sum_{i=1}^{nb_{GB}} DV_i$. Secondly, a part of aggregating calculations are parallelized over worker nodes. We call the aggregation parallelized over worker nodes as pre-aggregation. The aggregating phase's calculation in initial implementation had scale of $N \times S$, and it is reduced to $(\frac{N}{nb_{node}} \cdot S + nb_{node} \cdot \sum_{i=1}^{nb_{GB}} DV_i)$ in the optimized implementation. However, another part of aggregation (post-aggregation) is inevitably to be done by master node, fortunately, the post-aggregation is small relative to the whole aggregation.

A disadvantage of the optimized implementation can be observed. A part of cost is increased with the growth of worker node number, including communication cost. With this knowledge, the compression of intermediate output is considered to be important.

4.10 Summary

In this chapter, we firstly introduced the data explorer background of this work and identified the *Multiple Group-by* query as the elementary computation to be parallelized under this background. Then we described for why we chose GridGain over Hadoop as the MapReduce framework in our work. We used GridGain as the MapReduce supporting framework because of its low latency. A detailed workflow analysis over the GridGain MapReduce procedure has been done. We realized two implementations of *Multiple Group-by* query based on MapReduce, initial and optimized implementations. The initial implementation of the *Multiple Group-by* query is based on a direct realization, which implemented filtering phase within mappers and aggregating phase within the reducer. In the optimized implementation of *Multiple Group-by* query, we adopted a combiner as a pre-aggregator, which does the aggregation (pre-aggregation) on a local computing node level before starting reducer. With such a pre-aggregator, the amount of intermediate data transferred over the network is reduced. As GridGain does not support a combiner component, we constructed the combiner through merging two successive GridGain's MapReduces. The experiments were run on a public academic platform named Grid'5000. The experimental results showed that the optimized version has better speed-up and better scalability for reasonable query selectivity. At the end of this chapter, a formal analysis of execution time is given for both implementations. A qualitative comparison between these implementations was presented. According to the qualitative comparison, the optimized implementation has decreased the communication cost by reducing the intermediate data; it has also reduced the aggregating phase's calculation by parallelizing a part of aggregating calculation. These analysis are also valuable reference for other MapReduced applications.

5

Performance Improvement

In this chapter, we will present some methods to improve the performance of MapReduce-based *Multiple Group-by* query processing. In a distributed shared-nothing architecture, like MapReduce system, there are two approaches to optimize query processing. The first one is to choose optimal job-scheduling policy in order to complete the calculation within minimum time. Load balancing, data skew, straggler node etc. are the issues involved in job-scheduling. The second approach focuses on the optimization of individual jobs constituting the parallel query processing. Individual job optimization needs to consider the characteristics of involved computations, including the low-level optimization over detailed operations. The optimization of individual job sometimes affects the job-scheduling policy. Although the two optimizing approaches are at different level, they have influences between each other. In this chapter, we will first discuss the optimization work for accelerating individual jobs during the parallel processing procedure of the *Multiple Group-by* query. Then, we will identify the performance affecting factors during this procedure. The performance measurement work will be presented. The execution time estimation models are proposed for query executions based on different data partitioning method. An alternative compressed data structure will be proposed at the end of this chapter. It enables to realize more flexible job scheduling.

5.1 Individual Job Optimization: Data Restructure

In this work, a specific *data restructure* phase is adopted for realizing the distributed data storage. During data restructure phase, a data index and compressing procedure is performed after data partitioning. The objective of data restructure is to improve data access efficiency. GridGain needs developer to provide an underlying distributed data storage scheme since it is not coming with an attached distributed file system. To some extent, this provides flexibility, although this forces developers to do the low-level work. In this section, we first describe the applied data partitioning method and corresponding data partition's placement policies used in this work, and then we describe index and compressing data structure.

5.1.1 Data Partitioning

Data partitioning is one of the major factors that significantly affect the performance in traditional parallel database systems. Using data partitioning, a data table is divided into disjoint blocks and placed on different computing nodes. There mainly exist two principal data partitioning methods, horizontal partitioning and vertical partitioning. Horizontal partitioning means dividing a data table into multiple blocks with different rows in each block. Vertical partitioning means dividing a data table into multiple blocks with different columns in each block. In Chapter 2, we discussed advantages and disadvantages of two data partitioning methods. The type of calculation determines the choice between horizontal and vertical partitioning. For *Multiple Group-by* query, neither data partitioning method has an overwhelming advantage over another one. We adopted both horizontal and vertical partitioning into this work.

5.1.1.1 With Horizontal Partitioning

With horizontal partitioning, we divide the materialized view ROWSET into a certain number of equal-sized horizontal partitions, each partition holding the same number of entire records. Each record contains the dimensions and measures. With entire records in each partition, one benefit is that the aggregations over multiple dimensions can be performed within one pass of data scanning. However, this partitioning method does not exclude the dimensions unrelated to the query from being accessed.

5.1.1.2 With Vertical Partitioning

With the vertical partitioning, we divide ROWSET into vertical partitions. One vertical partition contains only one dimension and all measures. Since one dimension together with measures can supply enough information for aggregating phase calculation of a Group by query. Thus, the number of vertical partitions is equal to the number of dimensions. Taking the ROWSET as an example, ROWSET consists of 13 dimensions and 2 measures. The entire ROWSET is divided into 13 partitions, with each partition including one dimension and two measures. The advantage of this vertical partitioning is that unrelated data accessing is excluded. However, the measures are duplicated accessed in every vertical partition.

5.1.1.3 Data Partition Placement

After partitioning, data partitions will be respectively placed on different worker nodes. Data placement policy also affects workload distribution across worker nodes during query processing.

In case of horizontal partitioning, an equal number of data partitions are placed on every worker node. Additionally, we place the partitions containing successive records on each worker node. It means that in the original data set, these records were aligned together, one after another. The advantage of such a data distribution is that load balancing across worker nodes can be achieved if no data skew or workload skew exists.

In case of vertical partitioning, the number of worker nodes is considered during data placement. Data partitions are distributed according to the following policies:

- *If the number of worker nodes is small, then all vertical partitions are placed (replicated) on every worker node.* We can judge a number of worker nodes to be "small", if it is smaller than the average number of single Group-by queries contained in a *Multiple Group-by* query. For example, we often create a *Multiple Group-by* query with 5 single Group-by queries in our experiments, and then 5, or less than 5 worker nodes are considered as a small number of worker nodes. In a practical data exploration system, one exploring action will invoke a set of single Group-by queries, each corresponding to one dimension. Thus, the number of single Group-by queries is equal to or smaller than the number of dimensions in reality. Then, worker node number smaller than the dimension number is considered to be small. Otherwise, the worker node number is considered as large.

- *If worker node number is big, then each vertical partition is further horizontally divided into smaller blocks. Worker nodes are accordingly grouped into regions. Block is replicated over worker nodes within its corresponding region.* Consider an example shown in Figure 5.1, given a ROWSET with 3 000 000 records under the same scheme as before, we divide it into 13 vertical partitions using our vertical partitioning method, and each partition includes three columns (one dimension and two measures). Assuming that there are 15 worker nodes available. In this case of big number of worker nodes, each vertical partition of 3 000 000 records is further divided into 3 blocks of 1 000 000 records. The worker nodes are accordingly regrouped into 3 regions, with each region containing 5 worker nodes. As a result, the first block of every vertical partition is replicated across worker nodes within the region one; the second block of all the vertical partition is replicated across worker nodes within the region two; and so on. In this case, each vertical partition is further divided in a horizontal fashion, thus it actually is hybrid partitioning.

5.1.2 Data Restructure Design

As discussed in the preceding chapters, *Multiple Group-by* query processing is a data-intensive application, since it contains many data scanning operations. For instance, in previous work, *filtering* phase performed scanning operations over each data partition to identify records satisfying the given WHERE condition. These operations involve disk I/O, which is recognized as one type of the most costly operations. Using more efficient way to access data will be significant for accelerating query processing. Our restructuring data approach is based on inverted index and data compressing techniques.

5.1.2.1 Using Inverted Index

Indexing techniques are widely used for accelerating data access in database systems. These index techniques were rather designed for quickly locating one specific record or a small number of records. However, in data analysis applications, including *Multiple Group-by* query, there are a large number of records that needed to be located. Under

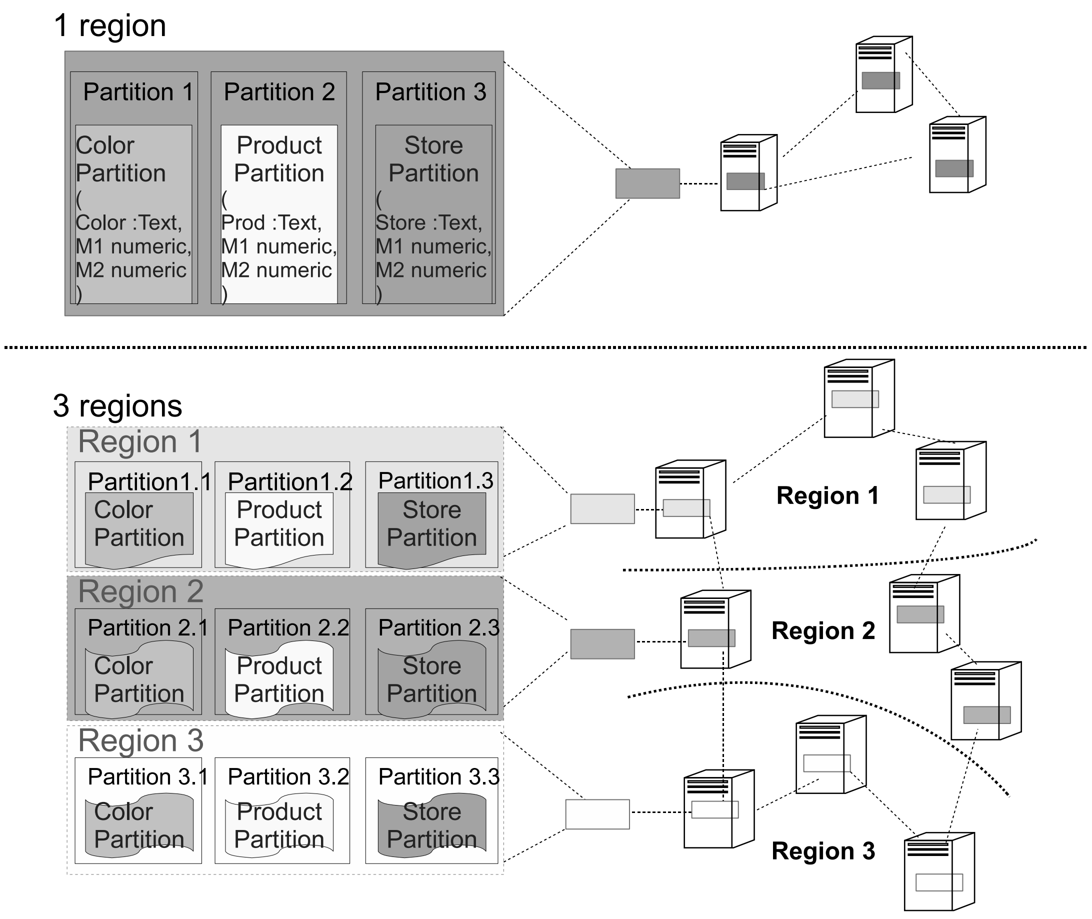

1 region
Partition 1
Partition 2
Partition 3
Color Partition (Color :Text, M1 numeric, M2 numeric)
Product Partition (Prod :Text, M1 numeric, M2 numeric)
Store Partition (Store :Text, M1 numeric, M2 numeric)
3 regions
Region 1
Partition1.1 Color Partition
Partition1.2 Product Partition
Partition1.3 Store Partition
Region 2
Partition 2.1 Color Partition
Partition 2.2 Product Partition
Partition 2.3 Store Partition
Region 3
Partition 3.1 Color Partition
Partition 3.2 Product Partition
Partition 3.3 Store Partition
Region 1
Region 2
Region 3

Figure 5.1: Data placement for the vertical partitions.

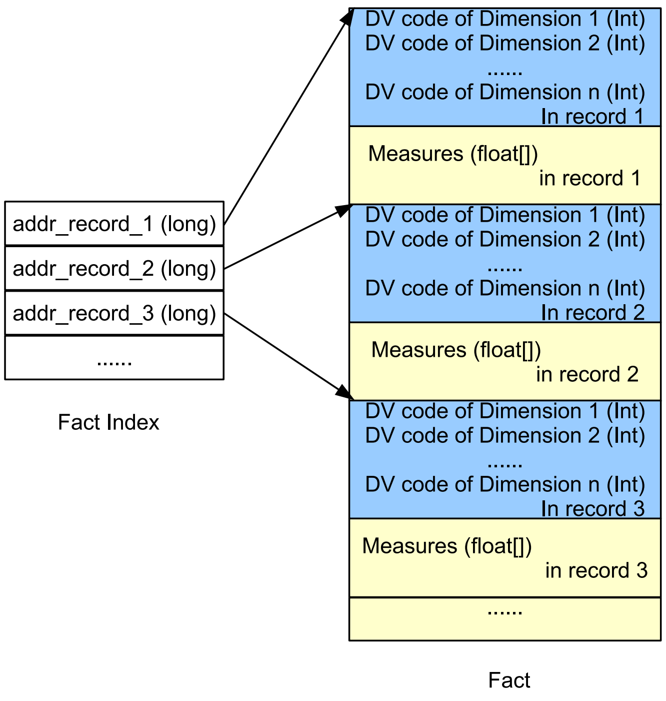
this circumstance, the inverted indexing technique is more suitable, since its special structure allows for retrieving data in a batch fashion. Refer to Section 2.2.4 for details on inverted index.

Inverted index was originally designed to handle unstructured data, such as data contained in web pages. Apache Lucene (16) realized the inverted indexing technique. The concepts used in Lucene are based on unstructured data. For example, in Lucene, a *Document* is a collection of Fieldables; a *Fieldable* is a logical representation of a user's content that needs to be indexed or stored. In order to utilize Lucene to index structured data, a record is considered as a Document of Lucene, and each column's value of the record is considered as a Fieldable. Thus, recordID corresponds *DocumentID* of Lucene. When searching a keyword of a certain column in an inverted index, we get a set of recordIDs with which associate the records containing this keyword.

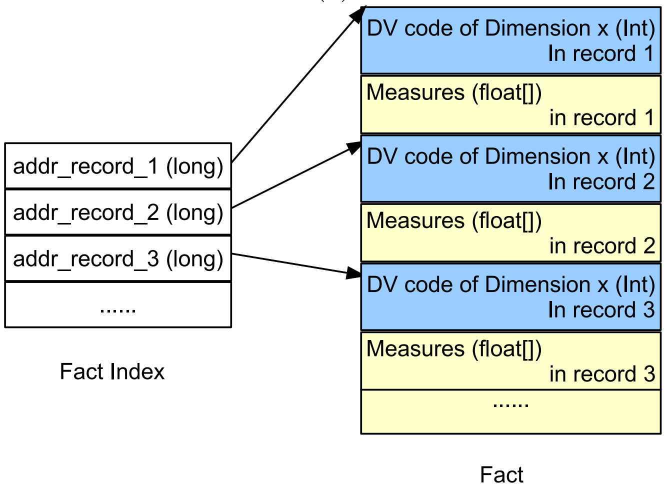
5.1.2.2 Data Compressing

In this work, the data restructuring procedure does not only realize the Lucene-based inverted indexation, but also realize a data compressing procedure. For the *Dimensions*, the "text" type distinct value is converted into an integer. We call this integer as the code of the distinct value. Both of these integer values and float values of *Measures* are compressed into bytes before written to the disk.

For each horizontal partition, the compressed data is stored in two files, *FactIndex* and *Fact*. Fact file stores distinct values of each dimension and the measure values contained in each record. These values are organized record by record in Fact file. The FactIndex file stores a set of addresses. Each *address* pointing to the position of each record stored in Fact file. Figure 5.2(a) shows the compressed data storage for horizontal partitions. Similarly, for each vertical partition, the compressed data is also stored in *FactIndex* and *Fact*. Instead of storing integer values for all dimensions, only one integer value is stored for each record. The float values of all measures are still stored for each record. Figure 5.2(b) shows the compressed data files for vertical partitions.


DV code of Dimension 1 (Int)
DV code of Dimension 2 (Int)
......
DV code of Dimension n (Int)
In record 1
Measures (float[])
in record 1
DV code of Dimension 1 (Int)
DV code of Dimension 2 (Int)
......
DV code of Dimension n (Int)
In record 2
Measures (float[])
in record 2
DV code of Dimension 1 (Int)
DV code of Dimension 2 (Int)
......
DV code of Dimension n (Int)
In record 3
Measures (float[])
in record 3
......
addr_record_1 (long)
addr_record_2 (long)
addr_record_3 (long)
......
Fact Index
Fact

(a)



(b)

Figure 5.2: (a) Compressed data files for one horizontal partition. (b) Compressed data files for one vertical partition of dimension x. (DV means Distinct Value)

5.2 Mapper and Reducer Definitions

Processing a *Multiple Group-by* query consists of filtering and aggregating phases. Over the restructured data, the computations involved in these two phases are different than before. Instead of a raw data scanning, filtering phase performs a *search* operation over inverted index with a keyword coming from the WHERE condition. Such a *search* operation retrieves from inverted index a list of recordIDs, indicating the records satisfying the given condition. With the recordID list, the aggregating phase can locate the selected records and compute aggregates by reading filtered data from their compressed data file.

In the previous work, we learned that performing aggregating phase within combiners could reduce execution time. Lately, we realized that aggregating phase could be moved into mappers for purpose of reducing the size of the intermediate output from mappers. As a result, we let mappers perform filtering and aggregating phases, and reducer merges the aggregate tables from mappers and generates the final result.

Under different data partitioning methods, data organization is different, and the job definitions are not the same. In our implementation under the horizontal partitioning, the mapper applies the WHERE condition and then aggregates for all dimensions appearing in Group-by dimensions over each data partition. In our implementation under the vertical partitioning, mapper performs the filtering operations, and then aggregates for one dimension, since each vertical partition includes only one dimension. We present the detailed Mapper and Reducer definition in the following content.

5.2.1 Under Horizontal Partitioning

Mapper

Under the horizontal partitioning, a mapper starts with the filtering phase. In filtering phase, records are filtered with the WHERE condition through a "search" operation which looks for the given keyword within the Lucene index file (denoted as *index*). As a result, a recordID list (denoted as *slctRIDs*) in type of BitSet (5) is produced. In filtering phase, dimensions are also filtered. Only those dimensions appearing in the Group-by clauses (denoted as *GBDims*) are selected.

After that, processing enters into the aggregating phase. Multiple aggregate tables are created for selected dimensions (denoted as *slctDims*). These tables are initialized with distinct values of corresponding dimension. We designed a new data structure of aggregate table and enhanced its functionality. The basic functionality of new aggregate table remains the same as in Chapter 4, which means storing for each Group-by dimension distinct values and the corresponding aggregate values for each distinct value. Differently, the new structure can additionally record the aggregate function list given in query, and it provides implementations for various aggregate functions, which allows computing aggregate values by calling the built-in functions. Besides, the new aggregate table structure stores the name of dimension.

Since in one mapper, aggregating phase only aggregates over one partition of the entire ROWSET, the aggregate table only contains a partial of the aggregates, and we mark the partial aggregate table as *agg_part*. The *text* type distinct value of all the selected dimensions, as well as the *numeric* values of all the measures in the selected records is read from the compressed data (CD) file. The following computations are performed each time one selected record is retrieved. Values of all Group-by dimensions are read from the retrieved record. For every Group-by dimension, the aggregated value associated with the read distinct value is updated by the measure values from the retrieved record. It is necessary to distinguish two cases. In one case, the current record is the first one that contributes to the aggregate values of one distinct value. In this case, we compute the aggregates with newly arrived measure values, and insert a new record with the computed aggregate values. Otherwise, the current record is not the first contributing one, then recalculate aggregate values by aggregating the existing aggregate values with newly arrived measure values, and update them. The pseudo-code in Algorithm 3 describes this procedure.

Reducer

The reducer collects all the intermediate outputs, i.e. partial aggregate tables produced by mappers. Each mapper produces multiple aggregate tables, each aggregate table for one Group-by dimension. One mapper processes aggregations over multiple dimensions. If we mark the number of Group-by queries as nb_{GB}, then each mapper produces nb_{GB} partial aggregate tables, noted as, $agg\_part[nb_{GB}]$. Assuming that there are, in total, nb_m mappers, the number of intermediate aggregate tables is equal to the product of the mapper number and the Group-by dimension number, i.e. $nb_m \times nb_{GB}$. The intermediate output from the same mapper is sent back in one message. Reducer

Algorithm 3 Mapper under Horizontal Partitioning

```
Input: $index$, $(CD)$
Output: $agg\_part[nb_{GB}]$
//filtering
$slctRIDs = index.search(keyword)$
$slctDims = GBDims$
//aggregating
for $d = 0$ to $nb_{GB} - 1$ do
  create and initialize $agg\_part[d]$
end for
for $RID \in slctRIDs$ do
  retrieve $dimValues[nb_{GB}]$ of $RID$th-record from $CD$
  retrieve $msrValues[nb_{msr}]$ of $RID$th-record from $CD$
  for $d = 0$ to $nb_{GB} - 1$ do
    if in $agg\_part[d]$, $aggValues[..]$ for $dimValues[d] = \{0.0..0.0\}$ then
      for $a = 0$ to $|agg\_func[..]| - 1$ do
        $aggVal[a] = agg\_func[a](msrValues[x])$,
        where $x \in [0..nb_{msr} - 1]$
        $aggValues[a] = aggVal[a]$
      end for
    else
      for $a = 0$ to $|agg\_func[..]| - 1$ do
        $aggVal[a] = agg\_func[a](msrValues[x], aggValues[a])$,
        where $x \in [0..nb_{msr} - 1]$
        $aggValues[a] = aggVal[a]$
      end for
    end if
  end for
end for
```

processes the intermediate outputs mapper by mapper. After creating a set of empty aggregate tables, denoted as $agg[nb_{GB}]$, then it calls the merge function to merge the partial aggregate tables produced by each mapper with the initialized aggregate tables. The pseudo-code in Algorithm 4 describes this processing procedure.

Algorithm 4 Reducer under Horizontal Partitioning

```
Input: $mp\_output[nb_m] < agg\_part[nb_{GB}] >$ //$nb_m$: mapper number
Output: $agg[nb_{GB}]$
for $g = 0$ to $nb_{GB} - 1$ do
  create $agg[g]$ //create the $g$th aggregate table
end for
for $m = 0$ to $nb_m - 1$ do
  $agg\_part[..] \leftarrow mp\_output[m]$
  for $g = 0$ to $nb_{GB} - 1$ do
    merge $agg\_part[g]$ with $agg[g]$
  end for
end for
```

5.2.2 Under Vertical Partitioning

Mapper

Under the vertical partitioning, the index and compressed data is organized partition by partition. The processing a Group-by query actually involves data of two partitions, since filtering with the WHERE condition needs to access one partition, aggregating phase needs to access another partition. This is the usual case. It is uncommon that a Group-by query aggregates over a dimension which appears in the WHERE condition.

In filtering phase, mapper applies condition by searching the given *keyword* within Lucene index of the partition concerned by WHERE condition, and produces a selected recordID-list. As mentioned above, the aggregating phase works on a different partition, which is the corresponding partition of the Group-by dimension. The selected recordID-list is used to interactively retrieve dimension value and measure values from the compressed data file. At the same time, the aggregate computations are performed. When a record being retrieved, the aggregate functions are performed to calculate the new aggregate values. The aggregate function either aggregates over the newly read measure values and the existing aggregate values, or, if the current record is the first contributor to the aggregate value of current distinct value, the aggregate function compute the aggregate values only with the new measured values. The aggregate values are updated into the aggregate table.

Note that, we use the same mapper computation both vertically partitioned data and hybrid partitioned data. The only difference is in the generated intermediate aggregate table. Mapper working over a complete vertical partition produces an complete aggregate table. The aggregate table contains aggregate values for all distinct value. It is not necessary to aggregate such an aggregate table with other aggregate tables to generate the final result in reducer. On the contrary, the mapper working on a hybrid partition can only produce a partial aggregate table. For generating the final result, multiple partial aggregate tables need to be re-aggregated in reducer. This difference is automatically managed in our program. In order to distinguish from the final aggregate table, which is noted as *agg*, we still mark the output of mapper as *agg_part* for both cases. The detailed mapper pseudo-code is listed in Algorithm5.

Algorithm 5 Mapper under Vertical Partitioning

```
Input: $index$, $CD$, $dim$ // CD: Compressed Data
Output: $agg\_part$
//filtering phase
$slctRIDs = index.search(keyword)$
//aggregating phase
for all $RID \in slctRIDs$ do
  retrieve $dimValue$ of RIDth-record from $CD$)
  retrieve $msrValues[nb_{msr}]$ of $RID$th-record from $CD$
  if in $agg\_part$, $aggValues[..]$ for $dimValue = \{0.0..0.0\}$ then
    for $a = 0$ to $|agg\_func[..]| - 1$ do
      $aggVal[a] = agg\_func[a](msrValues[x])$
      where $x \in [0..nb_{msr} - 1]$
      $aggValues[a] = aggVal[a]$
    end for
  else
    for $a = 0$ to $|agg\_func[..]| - 1$ do
      $aggVal[a] = agg\_func[a](msrValues[x], aggValues[a])$
      where $x \in [0..nb_{msr} - 1]$
      $aggValues[a] = aggVal[a]$
    end for
  end if
end for
```

Reducer

The reducer collects aggregate tables *agg_parts* produced by all mappers. Under vertical partitioning, the total number of intermediate aggregate tables is equal to the number of mappers. That is much smaller comparing with the number of *agg_part* produced by mappers over horizontal partitions. At the beginning of reducer, we create and initialize nb_{GB} aggregate tables, which will be updated during the calculation and "outputed" as the final result at the end of reducer. For each partial aggregate table, we first identify the aggregate table $agg[x]$ serving for the same dimension. Then we merge the aggregate values within the partial aggregate table to the final aggregate table.

As mentioned above, one mapper may produce a complete aggregate table or a partial aggregate table. However, reducer handles them using the same computation. If an aggregate table is complete, then there will be no other aggregate table, which corresponds to the same dimension. Thus, no aggregate table will be merged with it. This is achieved automatically. For a partial aggregate table, there are naturally other partial aggregate tables be merged with it. The pseudo-code in Algorithm 6 describes this procedure.

Algorithm 6 Reducer under Vertical Partitioning

```
Input: $mp\_output[nb_m] < agg\_part >$
where $nb_m$ is number of mappers
Output: $agg[nb_{GB}]$
for $g = 0$ to $nb_{GB} - 1$ do
    create $agg[g]$
end for
for $m = 0$ to $nb_m - 1$ do
    identify the target $agg[x]$, where $agg[x]$
    serves the same dimension as $agg\_part[m]$
    aggregate $agg[x]$ with $agg\_part[m]$
end for
```

5.3 Data-locating Based Job-scheduling

GridGain is a Multiple-Map-One-Reduce framework. It provides an automatic job-scheduling scheme, which assumes all nodes are equally suitable for executing job. Unfortunately, that is not the case of our work. We provide a data-locating job-scheduling scheme. This scheme can be simply described as sending job to where its input data is.

5.3.1 Job-scheduling Implementation

Our job-scheduling implementation helps mapper to accurately locate data partition. This is especially important in case of no existence of data redundancy. One wrong mapping will cause computational errors. With the data placement procedure performed during data restructuring, this job-scheduling scheme is converted to a data location issue. We utilize the user-definable attribute mechanism provided by GridGain to address this issue. For example, we add a user-defined attribute "fragment" into each worker's GridGain configuration, and attribute it a value representing the data partitions' identifiers that it holds. When the worker nodes' GridGain instances are started, the "fragment" attribute is visible to the master node's GridGain instance and the other worker nodes' GridGain instances. It is used to identify the right worker node.

In the case of horizontal partitioning, worker node identifiers (i.e. hostnames) are utilized to locate data partitions. In this case, an equal number of partitions are placed on each worker node. The partitions containing successive records are placed over one worker node. That is, partitions are distributed on worker nodes in a sequential order. Then, the identifier of worker node is used as the identifier of data partitions that it holds. In this way, worker node identifiers are used to locate data partitions. For example, assuming that ROWSET is horizontally divided into 10 partitions, these partitions are placed over 5 worker nodes. Thus, worker node A holds partitions 1, 2; worker node B holds partitions 3, 4, and so on. In this scenario, 10 mappers need to be dispatched. As partitions 1 and 2 locate on worker node A, then mappers 1 and 2 are sent to worker node A. The rest of mappers are scheduled in the same way.

In case of vertical partitioning, a user-defined attribute, "region identifier" is utilized to locate data partitions. When worker node number is small (case of 1 region), vertical partitions are replicated across all worker nodes. When worker node number is large, further, vertical partitions are horizontally divided into regions. Worker nodes are accordingly re-organized into regions. The worker nodes of the same region have the same "region identifier". Partitions are replicated across worker nodes within the same region. Thus, the region identifiers of worker nodes are utilized for data partitions. As an example, 13 vertical partitions from ROWSET having 10 000 000 records, are horizontally divided into 2 regions. The records 1 to 5 000 000 are put in region 1, and the records 5 000 001 to 10 000 000 are put in region 2. 10 worker nodes are accordingly re-organized into 2 regions, each containing 5 worker nodes. 10 mappers aggregate over 5 different dimensions in two different regions respectively. For load balancing reason, we use round-robin policy within region to keep the job number running over each worker as balanced as possible.

5.3.2 Discussion on Two-level Scheduling

We actually realize a two-level scheduling in MapReduce computations, i.e. task-level scheduling and job-level scheduling. Task-level scheduling means dispatching each mapper to the corresponding worker node. It considers how to distribute mappers, and ignores the calculation details within each job (mapper). Several elements should be considered in the task-level scheduling, such as mapper number, worker node number, load balancing. In order to achieve load balancing, it is necessary to take into account worker node's performance and status, and the input data location, etc. As one job is run on one worker node, job-level scheduling takes place within a worker node, since one job runs on one worker node. Job-level scheduling considers the organization of calculations within a mapper. The main calculations can be encapsulated into reusable classes, and stored in a local jar file on each worker. Mapper calls the methods of these classes to run those calculations. Job-level scheduling is closely related to calculations that a job should execute. For this reason, the job-level scheduling should be tuned according to different queries; on the contrary, the task-level scheduling could be unchanged or slightly changed for different queries. Our mapper job definitions can be considered as a job-level scheduling.

5.3.3 Alternative Job-scheduling Scheme

An alternative job-scheduling scheme is to perform filtering phase on the master node and aggregating phase over worker nodes. This job-scheduling scheme is feasible since the restructured data allows loosely coupled computations. In the preceding implementation, filtering phase and aggregating phase are not separable, since aggregating phase computations consume filtering computations' output. With restructured data, we can see that the computations of these two phases are clearly decoupled, since they use different files as input data. In filtering phase, a *search* operation is performed via accessing only inverted index files (Lucene generated files). In aggregating phase, aggregation is performed over filtered records identified by a list of recordID calculated by filtering phase, and it only needs to accesses the compressed data files (FactIndex and Fact files). As these two phases are decoupled, they can be scheduled and optimized separately, which provides more flexibility for job-scheduling. This is especially helpful in case of vertical partitioning, where the selected recordIDs is commonly usable for multiple dimensions' aggregations.

5.4 Speed-up Measurements

We evaluated our MapReduce-based *Multiple Group-by* query over restructured data in a cluster of Grid'5000 located in Orsay site[1]. Also, we use the version of GridGain 2.1.1 over Java 1.6.0. The JVM's maximum of heap size is set to 1536MB on both master node and worker nodes. We ran our applications over 1 to 15 nodes. Although the worker nodes were small-scaled, the ROWSET processed in these experiments is not extremely large, and it fits well with the amount of nodes used in our work. ROWSET was composed of 10 000 000 records with each including 15 columns. The size of ROWSET was 1.2 GB. We partition the data set with both horizontal partitioning and vertical partitioning. All the partitions had already been indexed with Lucene and compressed before launching the experiments.

We chose queries having different selectivity. Selectivity is a factor that controls the amount of data being processed in the aggregating phase. Four *Multiple Group-by* queries' selectivities are 1.06%, 9.9%, 18.5% and 43.1% respectively. These queries all had the same five Group-by dimensions. Before starting the parallel experiments, we ran a group of sequential versions for each of these queries and measured the execution times, which were used as the baseline of the speed-up comparison.

5.4.1 Under Horizontal Partitioning

Under the horizontal partitioning, we partitioned the ROWSET with different sizes. We ran concurrently different number of mappers over each worker node in different experiments. Thus, we could compare the performance of running a few of big-grained

[1]The cluster located in Sophia site had unfortunately retired after doing our first part of experiments. The currently chosen cluster has the same hardware configuration as retired cluster of Sophia.

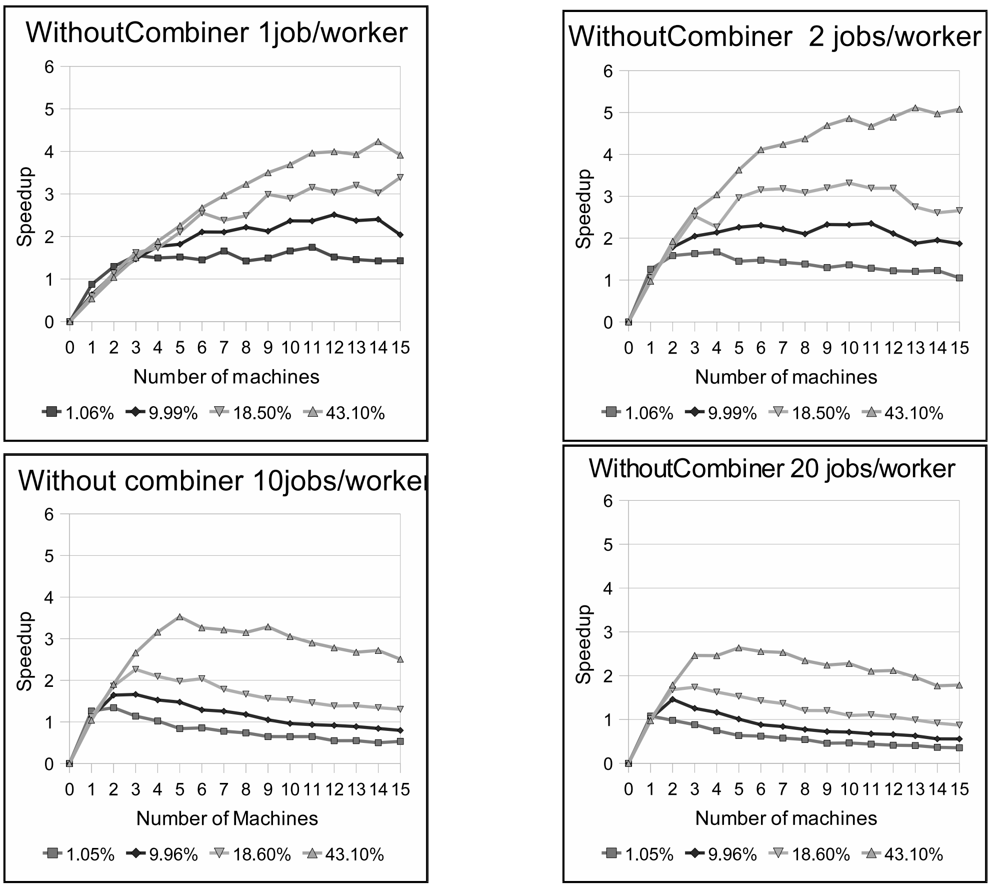


Figure 5.3: Speed-up of MapReduce *Multiple Group-by* query over horizontal partitions.

jobs per node against that of running multiple small-grained jobs on one node. Our experiments with the horizontal partitioning-based implementation was organized in 4 groups, in the first group, there was only 1 mapper being dispatched to a worker node and run on it. In the second group, 2 mappers were running on one worker node. In the third group, we ran 10 mappers on each worker node, and in the fourth group, 20 mappers per worker node. The Figure 5.3 shows the speed-up performance of the MapReduce-based *Multiple Group-by* query over horizontal partitions. We also realized a MapCombineReduce-based implementation. The MapCombineReduce-based implementation was for the case where more than one mappers running on one node. Combiner performed the same computations as reducer. The Figure 5.4 shows the speed-up performance measurement of the MapCombineReduce-based multiple Group-by aggregation over horizontal partitions.

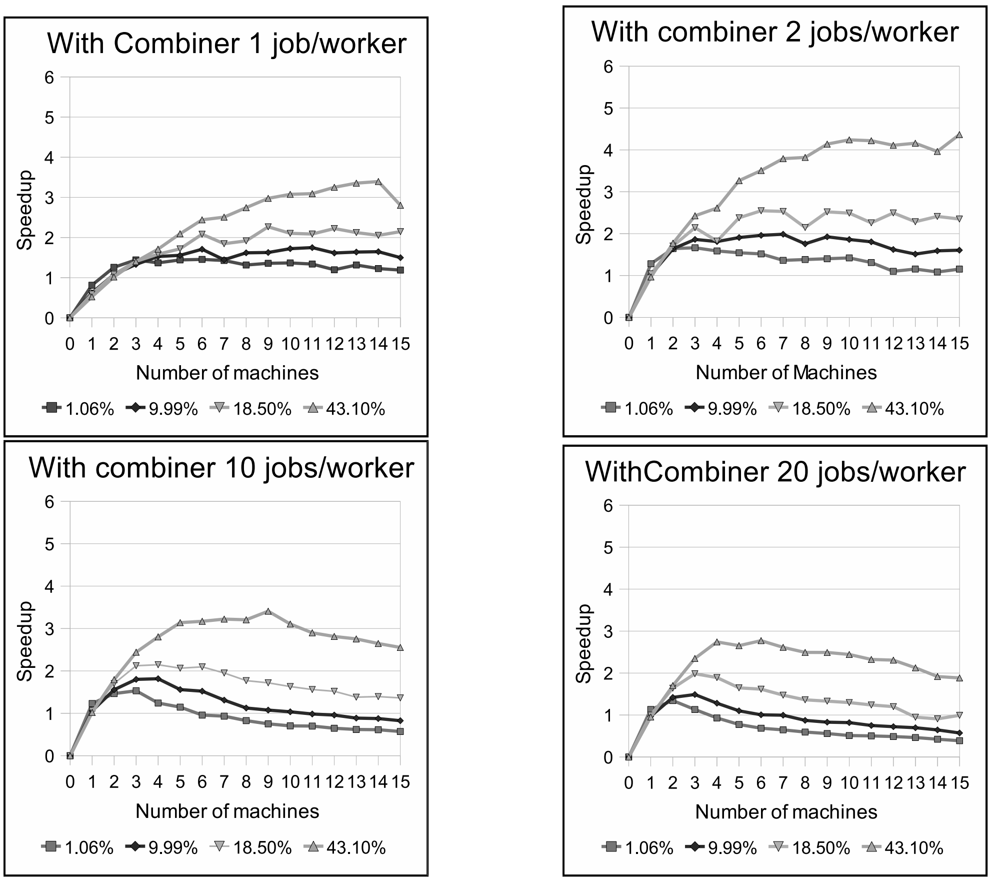


Figure 5.4: Speed-up of MapCombineReduce *Multiple Group-by* query over horizontal partitions.

Observation and Comparison

For the MapReduce-based implementation, the first observation of the speed-up measurement is that the queries with big selectivity shows better speed-up performance than the queries with small selectivity. A query with certain selectivity has a fixed workload of calculation. Some parts of this workload are parallelizable, but others are not. The reason why the big selectivity queries have better speed-up performance is the parallelizable portion in their workload is greater than that in the small selectivity queries. The second observation is the speed-up performances of smaller job number per node (1 and 2 jobs/node) experiments surpass that of bigger job number per node (10 and 20 jobs/node) experiments. Multiple jobs concurrently running over one node were considered to be able to more efficiently utilize the CPU cycles, and can run faster. But in reality, this is not always true. We will discuss the issue of multiple jobs concurrently running on one worker node later in this chapter.

The speed-up of MapCombineReduce-based implementation is similar to that of MapReduce-based one. Comparing these two implementations, we can see that the speed-up performance of MapReduce-based implementation is better than that of MapCombineReduce-based one in the experiments of small job number per node. In contrast, for experiments of big job number per node, the MapCombineReduce-based implementation speeds up better than MapReduce-based one. That is due to the necessity of combiner for different job number per node. For the job number per node smaller or around the CPU number per node (e.g. 1 and 2), the pre-final-aggregation (combiner's work) is not necessary, in that the number of intermediate outputs is not big. On the contrary, when the number of job per node is big (e.g. 10 and 20), the combiner is necessary. In this case, the speed-up of MapCombineReduce-based implementation is slightly better than the MapReduce-based implementation.

5.4.2 Under Vertical Partitioning

Under vertical partitioning, we dispatched the vertical partitions using the policies described in Section 5.1.1.3. Similarly, we realized a MapReduce based implementation and MapCombineReduce based one. We measured the speed-up performance for both of them. During the experiments, we increased the number of worker nodes from 1 to 15, and divided the experiments into 3 groups. In experiments of group 1, we had a small worker node number, denoted as w, $w \in [1..5]$, we organized vertical partitions into one region. If we note region number as nb_r, then $nb_r = 1$. In this case, each mapper aggregates over one entire Group-by dimension. Thus, then in case of 1 region, the number of mappers is equal to the number of Group-by dimensions ($nb_m = nb_{GB} = 5$). In the second group of experiments, we increased the number of region to two ($nb_r = 2$) in order to utilize till 10 worker nodes. We ran the queries over 2, 4, 6, 8 then 10 worker nodes (i.e. $w \in [2, 4, 6, 8, 10]$), and measured the execution time in case of each vertical partition being cut into two regions. As the number of mapper equals to the number of partitions, then we have $nb_m = nb_{GB} \cdot nb_r = 10$. In the third group of experiments, we increased the number of region to three, i.e. $nb_r = 3$. We had worker nodes number $w \in [3, 6, 9, 12, 15]$ in different experiments. The number of mapper $nb_m = 15$. The mappers were evenly distributed within each region.

As we fixed the Group-by dimension number as 5, the total mapper number was $5 \times nb_r$, and the number of mappers per node was varying with node number per region: $nb_{job/node} = \lfloor 5/nb_{node/region} \rfloor$ or $\lceil 5/nb_{node/region} \rceil$ For example, if $nb_{node} = 1$, $nb_r = 1$, then each node was assigned 5 mappers; if $nb_{node} = 10$, $nb_r = 2$, then each node is assigned 1 mapper; if $nb_{node} = 2$, $nb_r = 1$, then one node was assigned 2 mappers, the other 3 mappers, etc. We illustrate the speed-up performance measurements in the Figure 5.5.

Observation and Comparison

As shown in this figure, the speed-up is increasing with the raise of worker number regardless of the number of regions. The MapReduce-based implementation speeds up better than the MapCombineReduce-based one, because the number of job per node is small (i.e. < 5). The queries with bigger selectivity, like, 9.9%, 18.5%, 43.1%, benefit more from the parallelization than the queries with smaller selectivity, like 1.06%.

For most of queries, the biggest speed-up appears in the third group of experiments with 3 regions, for both the implementations MapReduce-based one and MapCombineReduce-based one. Comparing the speed-up under vertical partitioning and that under the horizontal partitioning, we can see the best speed-up appears in experiments under the vertical partitioning. Under vertical partitioning, each mapper aggregates over only one dimension; the obtained intermediate output is the aggregates of one dimension. The size of the intermediate outputs with using vertical partitioning is much smaller than those with using the horizontal partitioning. Imagining a scenario where 10 worker

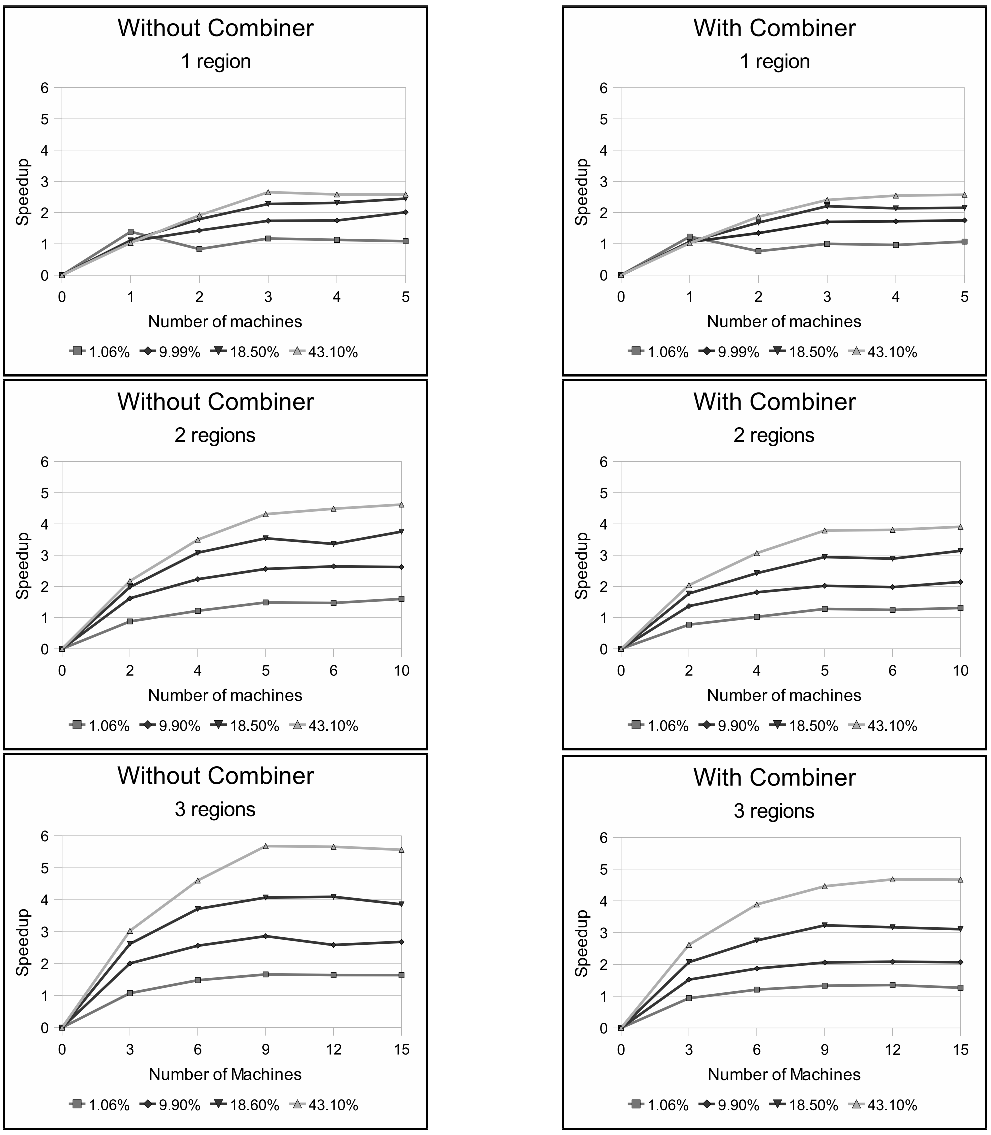


Figure 5.5: Speed-up of MapReduce *Multiple Group-by* aggregation over vertical partitions, MapReduce-based implementation is on the left side. MapCombineReduce-based implementation is on the right side.

nodes are available. Under horizontal partitioning, one mapper works on one horizontal partition on one worker node. As each mapper aggregates over 5 dimensions, then, the number of intermediate aggregate tables from all the mappers are $10 \times 5 = 50$. Under vertical partitioning, 10 available workers are organized into 2 regions. Also, there are in total 10 mappers. But each mapper aggregates over one dimension. Thus the number of intermediate aggregate tables is exactly the number of mappers 10. If we simply suppose that an aggregate table of an arbitrary Group-by dimension is of size 20K, then 1000K intermediate output is generated under horizontal partitioning, while 200K intermediate output is generated under vertical partitioning. Thus, with vertical partitioning, the intermediate data volume to be transferred is reduced with regard to the experiments with the horizontal partitioning.

5.5 Performance Affecting Factors

In this section, we will discover the performance affecting factors in the *Multiple Group-by query* processing. Some of them are concerning the computations themselves, others are related to the exterior condition, such as hardware, network, etc. Discovering of these factors is helpful for locating the bottlenecks, and in turn increasing the system efficiency. The performance affecting factors addressed in this section include, query selectivity, running multiple jobs over one worker node, hitting data distribution, intermediate output size, serialization algorithms, network status, combiner's utilization as well as data partitioning methods.

5.5.1 Query Selectivity

Query selectivity is a factor that controls the records filtered out during the selecting phase. Also, it determines the amount of data that the aggregating phase should process. For big selectivity, query's aggregating phase takes up a majority of the whole calculation. In addition, the aggregating calculation is parallelizable. Thus the query with big selectivity benefits more from the parallelization than query with small selectivity. Query selectivity sometimes is related with workload skew. In some particular cases a query selects a lot of records from some partitions, but very limited records from the other partitions. Therefore, most aggregate operations are performed only on a part of worker nodes, while the other nodes keep idle, which causes the

Job number on 1 node	1 Mapper's Average Execution time (ms)
1	170
2	208
3	354
4	417
5	537

Table 5.1: Average execution time of multiple mappers jobs on 1 node.

workload skew. This happens more frequently with range data partitioning than in other cases.

5.5.2 Side Effect of Running Multiple Mappers on One Node

In our experiments, we ran a different number of mappers on each worker node so as to measure different effects for acceleration. Intuitively, the more mappers concurrently run on one worker node, the more efficiently the CPU(s) should be utilized. However, mappers run degradedly when contentions are provoked. More importantly, this retards the execution of reducer, since the reducer does not start until all mappers have been finished. Thus, from the point of view of the whole query processing, running multiple mappers on one worker node may degrade the performance of individual mapper. This will in turn degrade the whole MapReduce procedure. Table 5.1 shows a list of average execution time of one individual mapper when multiple mappers running concurrently on one node. The workload of each mapper was as follows: searching in the inverted index to filter the data partition and obtaining a list of recordIDs with which associated the records satisfying the WHERE condition; aggregating over one vertical partition. The total record number of the partition is 3 333 333, and the number of records selected out accounts for 1 percent of the total records. These mappers were executed on one same worker node.

These mappers are concurrently running as different threads. They do not communicate among each other, and they have different inputs and outputs. This means that each mapper will bring new input data into the memory and generate the output data of it. The workload of data aggregation is typically data-intensive, and contentions may occur different resources, such as the contentions of disk I/O or memory bandwidth. As shown in this table, when running only one mapper over one worker node, the execution time is relatively small (170 ms). When concurrently running 2 mappers over one worker node, the average execution time of one individual mapper is lightly dragged (37 ms longer). When concurrently running 3 or more mappers over one worker node, the execution time shows a relatively large delay (from 184 ms to 367 ms). We can see that, on one worker node with 2 CPUs, having 2 concurrently running mappers, the average execution time is the most interesting. After that, when we continuously increased the number of mappers on the worker node, the more mappers were concurrently running on one worker node, the longer time an individual mapper takes.

5.5.3 Hitting Data Distribution

The data intensive application involves a large number of data read operations. The execution time is affected by the hitting data's distribution. By hitting data, we mean the data item that a read operation is going to locate and read. The hitting data's distribution means the distribution of all the hitting data items' storage positions in one file. If the distribution of hitting data items is concentrated, then less operations of disk I/O are invoked. Otherwise, if the distribution of hitting data items is dispersed, then more operations of disk I/O are invoked.

This is a result of using the buffering technique, which is widely used to realize read operations. Buffering technique can help to reduce the number of disk I/O operations. Buffer is actually a region in memory of a given size, for example, 1024 Bytes. The data stored in the buffer is fetched within one disk read operation. When a read operation with a given file read position is invoked, it will first check whether the data item of the give position is already loaded into the buffer. If that is the case, then the read operation will directly read the data item from the buffer. If the given file read position is exceeded the data scope held in buffer, then a buffer *refill* operation will be invoked. Thus, a disk read operation is caused. It seeks in the file stored on disk and then continuously fetches data items from this position to the buffer, until the buffer is filled.

In the processing of *Multiple Group-by* query, the computations in aggregating phase involves reading data of each selected records. The selected records distribution in stored file becomes a factor that affects the execution time. This is relatively more obvious in the experiments using horizontal data partitioning than in the experiments

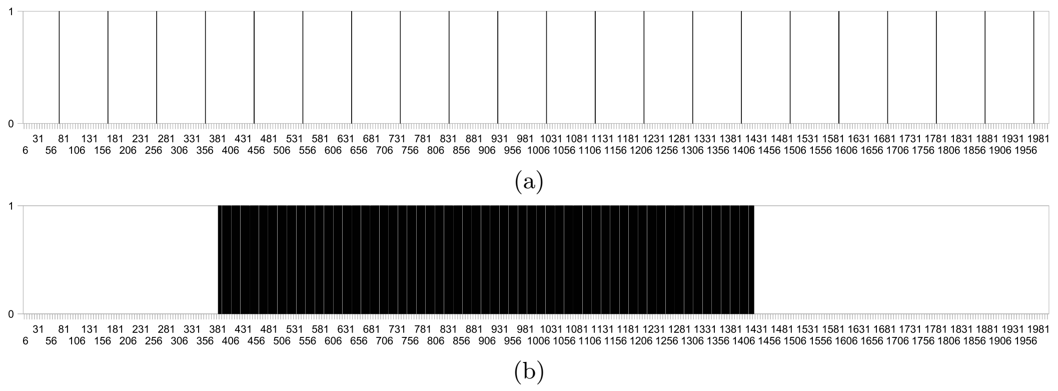


Figure 5.6: Hitting data distribution: (a) Hitting data distribution of qurey with WHERE condition "Color='Pink' "(selectivity=1.06%) in the first 2000 records of ROWSET; (b) Hitting data distribution of query with WHERE condition "Product Family='Accessories' "(selectivity=43.1%) in the first 2000 records of ROWSET.

using vertical partitioning. Taking an example in our work, in order to do aggregation, we aggregated over various Group-by dimensions after read each selected record. Regarding the execution time, the worst case appeared in our experiments is the query with the WHERE condition of "Color='Pink'"(selectivity=1.06%). In this case, hitting data items are very dispersed, and the average time for aggregating one record is 5500 nanoseconds. On the contrary, for the query with WHERE condition "Product Family='Accessories' "(selectivity=43.1%), the average time for aggregating one selected records is 1000 nanoseconds. In order to be more illustrative, we visualize the distribution of hitting data of these two cases in Figure 5.6. The axis x represents the recordID, and a vertical black line represents that the record hits the WHERE condition. We visualize only the first 2000 records in these figures.

A simple calculation can make this clearer. In the compressed data file, we stored for each record the compressed dimension values, and measure values. In our case of horizontal partitioning, one record is composed of 13 dimension values of "text" type, and 2 measure values of float type. Under the compressed data format, one dimension value is first replaced by an integer and then converted into 1 byte data; one float measure value is converted into 4 bytes data. Thus, one record is converted into 21 bytes (13×1 bytes + 2×4 bytes = 21 bytes) in the compressed format. A buffer of 1024 bytes is capable of accommodating $1024 \div 21 \approx 49$ records. In case of the sub-figure (a), where 1.06% records are selected, and the hitting data distribution is very dispersed.

In this case, one buffer refill (i.e. disk read operation) is caused for processing each selected record. In case of the sub-figure (b) 43.1% records are selected. The hitting data distribution is rather concentrated, there even exists a lot of selected records that are contiguously stored. In this extreme case (continuous storage), processing 21 selected records will only cause one buffer refill. Disk read is one of the most expensive operations. That explains the big difference of the average per record processing time between these two cases. The similar case also occurred in the filtering phase. We observed a various difference among the average time for retrieving one recordID of selected records when processing queries with different selectivities.

5.5.4 Intermediate Output Size

Except for the overhead for computing the aggregates, the cost for transferring intermediate output is also an overhead that we cannot ignore. Without considering the uncontrollable factor of available network bandwidth, the main factor controlling this overhead is the size of intermediate output. In our work, distinct value number of each Group-by dimension, aggregate function number, mapper number and data partitioning method affect the size of intermediate aggregate tables.

Distinct value number of one dimension and aggregate function number determines the size of current dimensions aggregate table. The distinct value number of a certain dimension determines the number of rows composing the corresponding aggregate table. Each row stores the aggregates values for one distinct value. The number of aggregate functions determines the number of columns composing the aggregate table. In each row, one cell stores distinct value, and for each aggregate function, one additional cell is used for storing the data item calculated by the aggregate function. As a result, one row stores 1 value of type integer plus $|agg\_func[..]|$ values of type float.

While the first two factors determine the individual aggregate table size. Mapper number and data partitioning method affect the total size of all the intermediate aggregate tables. Under horizontal partitioning, each mapper produces multiple aggregate tables, where the number of aggregate tables is the product of Group-by dimension number (denoted as nb_{GB}) and mapper number (denoted as nb_m). Under vertical partitioning, each mapper produces one aggregate table for a particular dimension, and the number of aggregate tables is the number of mappers. Similarly, under hybrid partitioning, the number of aggregate tables is also the number of mappers.

In practice, individual aggregate tables concerning to different dimensions have different size. If we note the total number of distinct values for all the Group-by dimensions (nb_{DV}), we can calculate the intermediate output size under horizontal partitioning as follows: $nb_m \times nb_{DV} \times nb_{GB} \times [sizeof(int) + sizeof(float) \times |agg\_func[..]|]$

Under vertical partitioning, the mapper number is closely correlated with the number of region number (nb_r). A set of aggregate tables—each for a Group-by dimension—are produced by one region's mappers. Then we have the intermediate output size as: $nb_r \times nb_{DV} \times nb_{GB} \times [sizeof(int) + sizeof(float) \times |agg\_func[..]|]$

5.5.5 Serialization Algorithms

Serialization is a process for converting a data structure or an object into a sequence of bytes so in order to transmit it across network and be restored to the original state. De-serialization is the inverse process of serialization. They are crucial for distributed applications. In our experiments, we noticed that a portion of time non-ignorable is used to serialize and de-serialize the data being transferred. Sometimes, this portion of time reaches 50% of the total execution time.

There exist various serialization algorithms. For example, some of them are designed for message sending based applications, where objects are smaller and infrequently repeated; some others of them are designed for streaming protocol based applications, where the objects are big and usually repeated. Some algorithms are time-efficient; others are space-efficient. Also, a serialization can either be performed during runtime or during the compile-time (89). GridGain provides three alternatives of serialization/de-serialization, one is based on JBoss serialization, one is based on JDK serialization, and the other is based on XStream[1]. We adopted JBoss serialization based one, since it is the default choice and the most time-efficient one among them.

Regarding the size of serialized object, the serialized object size is usually larger than the original object. A serialized object needs contain sufficient information to restore the original object. The class description of current object and its supper-class description, as well as the other serializable objects referenced by current object should be included in the generated serialized object. As a result, the serialized object is larger than its original object. There exist some work trying to reduce the size of serialized object, like in (81).

[1]XStream is a library to serialize objects to XML and back again.

In our work, two types of data are serialized and transmitted, i.e., mapper objects and aggregate tables. The serialization of mapper objects happens during the start-up phase of a MapReduce task. The mappers are sequentially serialized one after another on the master node. The serialization for the first instance of mapper class takes much longer time than the following instances of the same mapper class. The aggregate tables are also sequentially de-serialized when they arrived at the master node. The de-serialization times for aggregate tables are varying, and we did not observe regularity over their changes. Over the worker nodes, we observed a small overhead for de-serializing the mapper instance, but a non-ignorable serialization time for aggregate tables.

Taking a close look at the two main types of transmitted data, we find that mapper object and aggregate tables are of different type. Mapper object has a complex structure, being composed of many super classes, references and parameters. This will cause a big overhead for rewriting the class descriptions. Fortunately, in our case, the serialization process is repeated multiple times within one process, for serializing mapper objects with different status, which make it possible to do optimization. In contrast, aggregate table's structure is relatively simple, but contains big size of data. The data types are mostly primitive, like integers and floats. Therefore, the desirable serialization/de-serialization algorithms for our application need to be compatible to both types of data. The future work will address this issue.

5.5.6 Other Factors

Except for the above performance affecting factors, there exist some other factors, such as network status, utilization of combiner, and data partitioning methods. We have already discussed them is earlier work, here we only want to give a short summary for them.

Network status

Network status together with the size of serialized objects determines the execution time of data transmission. It involves not only the available bandwidth over network, but also the physical location of two communicating components. The data transfer takes longer time if two communicating components are located in different clusters than if they are within the same cluster. In our experiments, we adopted a single cluster, where the network bandwidth is stable. By observation, the execution times for sending mapper objects did not significantly change[1].

Use or not Combiner

Using combiner component reduces a lot the execution time in the work of Chapter 4. In this previous work, we ran a relatively large number of mappers over one worker node. Also, the intermediate output's data structure (i.e. aggregate table) was not compact. However, combiner component's utilization is not always favorable. As we can see in the resent work, the combiner component's utilization did not significantly reduce the execution time. On the contrary, it caused more overheads in certain cases. In case where the number of mappers over one worker node is small, it is not necessary to use the combiner component. However, our MapCombineReduce construction using two successive MapReduce tasks is still significant, since it allows executing a MapCombineReduce job in GridGain.

Data partitioning methods

In our work, the data partitioning methods determines multiple issues concerning the execution of mappers and reducer. Firstly, it determines the index creation and data compressing in data restructure phase. It, in turn, determines the computations performed during MapReduce procedure. Finally, it determines the size of intermediate output.

5.6 Cost Estimation Model

In this section, we give a cost estimation model for the execution time during the whole MapReduce-based query processing on the restructured data. For the sake of time limitation, we worked only on the cost estimation for the MapReduced-based implementation, and the cost estimation for MapCombineReduce-based implementation is not addressed in this work. The above-mentioned performance effecting factors and observation based on our experiments are maximally considered for constructing the cost estimation model.

[1]The size of mapper is constant. For this reason, we use it to observe execution time changes

We still consider the four parts of cost in a MapReduce procedure, start-up, mapper's execution, closure and communication. In start-up, the master prepares the mappers, including mapping mappers to available worker nodes, then serializing mapper objects. The serialization for the first mapper object takes longer time than the serializations for the other mapper objects. The formal cost estimation for start-up is as follows:

$$C_{st} = C_{mpg} \cdot nb_m + C_s \cdot size_m + C'_s \cdot (nb_m - 1) \cdot size_m$$

If there is no additional specification, the notations used in the formulas of this chapter can be referred in Table 4.1. In above formula, we estimate the cost for computing the mappings as $C_{mpg} \cdot nb_m$, the serialization time for the first mapper object as $C_s \cdot size_m$, the serialization time for the rest of mapper objects as $C_s \cdot (nb_m - 1) \cdot size_m$

When a worker receives a message of mapper, it de-serializes the mapper object, then executes mapper job. When finished, it serializes aggregate table produced by mapper. Taking into account the factor of running multiple mappers on one worker node, we add a function of mapper number per node (denoted as $f(nb_{m/node})$) into the estimation. Thus, the execution time of this process is estimated as:

$$C_w = f(nb_{m/node}) \cdot (C_d \cdot \gamma \cdot size_m + C_m + C_s \cdot size_{agg})$$

Here, $\gamma \cdot size_m$, $(\gamma > 1)$ is used to represent the size of serialized mapper object. A serialized object is always bigger than the original one, so, we have $\gamma > 1$. Also, γ is varying according to the composition of object. The notation $size_{agg}$ means the size of generated aggregate table. The mapper execution cost C_m and aggregate table size $size_{agg}$ are varying according to the adopted partitioning methods. We will respectively give the detailed estimations for the horizontal partitioning-based implementation and the vertical partitioning-based one lately.

The closure includes de-serialization of the intermediate aggregate tables and user-defined reducer's execution. We estimate the closure cost as below:

$$C_{cl} = C_d \cdot \sum_{i=1}^{nb_m} \gamma \cdot size_{agg\_i} + C_r$$

where the reducer cost (denoted as C_r) is varying with different applications. We will give the estimation of reducer lately.

In our work, the data communication is composed of master node sending mappers to the worker nodes, and worker nodes sending intermediate aggregate tables to master node. Considering the size of transmitted data and the network status we estimate the communication cost as:

$$C_{cmm} = C_n \cdot (nb_m \cdot \gamma \cdot size_m + \sum_{i=1}^{nb_m} \gamma \cdot size_{agg\_i})$$

where $size_{agg\_i}$ represents the size of the ith aggregate table produced by mappers.

5.6.1 Cost Estimation of Implementation over Horizontal Partitions

For the implementation over horizontal partitions, the mapper takes a horizontal partition as input data, searches in its Lucene index, read values of dimensions and aggregates with measures over the distinct values of Group-by dimensions. We assume there exist D dimensions and M measures in ROWSET, over which we run the query aggregating on nb_{GB} Group-by dimensions. The mapper cost is estimated as below:

$$C_m = S \cdot \frac{N}{nb_m} \cdot \{\alpha \cdot C_f + \beta \cdot (nb_{GB} + 4M) \cdot C_{rd} + nb_{agg} \cdot nb_{GB} \cdot C_a\}$$

where C_f estimates the average execution time for successfully obtaining one recordID of the selected records by searching Lucene index; C_{rd} represents the execution time for retrieve 1 byte from compressed file; nb_{agg} means the number of aggregate functions defined in the query. A distinct value is represented as an integer (i.e. distinct value code) of size 1 byte[1], and a measure value as a float sized 4 bytes. As mentioned before, record filtering and record reading operations are impacted by hitting data distribution issue, which means, the average time for processing one unit of data is varying with query selectivity. Therefore, two parameters α and β are applied over the corresponding items. Their values are varying with different queries.

Under horizontal partitioning, each mapper produces aggregate tables for all Group-by dimensions. The size of aggregate table can be estimated as follows:

[1]In our work, distinct value number of any dimension is smaller than 256, thus, 1 byte is sufficient to represent all distinct value code in integer of any dimension.

$$size_{agg} = \sum_{i=1}^{nb_{GB}} nb_{DV_i} \cdot (1 + 4nb_{agg})$$

where nb_{DV_i} represents the number of distinct values of the ith Group-by dimension. $1 + 4nb_{agg}$ is the number of bytes containing in one row of aggregate table.

As the reducer takes all intermediate outputs of mappers as input and performs aggregation over them, we estimate cost of reducer as:

$$C_r = C_a \cdot nb_{agg} \cdot nb_m \cdot \sum_{i=1}^{nb_{GB}} nb_{DV_i} \qquad (1)$$

With these detailed estimation, we ignore the function $f(nb_{m/node})$, since we address on the small job per node cases, which is the most common case. Thus, we obtain the total execution time estimation of the horizontal partitioning-based *Multiple Group-by* query as below:

$$Cost_{hp} = C_{mpg} \cdot nb_m + C_s \cdot size_m + C'_s \cdot (nb_m - 1) \cdot size_m + C_d \cdot \gamma \cdot size_m +$$

$$S \cdot \frac{N}{nb_m} \cdot [\alpha \cdot C_f + \beta \cdot (nb_{GB} + 4M) \cdot C_{rd} + nb_{agg} \cdot nb_{GB} \cdot C_a] + C_s \cdot \sum_{i=1}^{nb_{GB}} nb_{DV_i} \cdot (1 + 4nb_{agg}) +$$

$$C_d \cdot nb_m \cdot \sum_{i=1}^{nb_{GB}} nb_{DV_i} \cdot (1 + 4nb_{agg}) + C_a \cdot nb_{agg} \cdot nb_m \sum_{i=1}^{nb_{GB}} nb_{DV_i} + C_n \cdot nb_m \cdot \gamma \cdot size_m + C_n \cdot \gamma \cdot \sum_{i=1}^{nb_m} size_{Sagg_i}$$

If we note the average size of serialized aggregate table as $\gamma \cdot \sum_{i=1}^{nb_{GB}} nb_{DV_i} \cdot 1 + 4nb_{agg}$. We estimate the value of parameters as described in table 5.2. As it is difficult to accurately estimate the serialization/de-serialization execution time for a unit of data, we estimate the serialization/de-serialization time for the really used data in our experiments. Therefore, the estimation values for these parameters are accompanied with the size of data being serialized or de-serialized.

In order to test the accuracy of our execution time estimation model, we compare the speed-up curve calculated from our model to the measured speed-up curve. The Figure 5.7 are two speed-up curves for MapReduce based query processing on horizontal partitions, with the number of worker nodes gradually increasing from 1 to 15. We chose the case where only one mapper concurrently running on a worker node. In this case, the application related parameter can be determined, such as, total record number

Table 5.2: Parameters and their estimated values (in ms)

Notation	Estimated value	Cost for...
C_{mpg}	2.34×10^{-1}	creating a mapping between mapper and a worker node
$C_s \cdot size_m$	83.51	serializing first mapper instance
$C'_s \cdot size_m$	1.21	serializing non-first mapper instance
$C_d \cdot \gamma \cdot size_m$	2.45	de-serializing mapper
C_a in mapper	0	aggregation, ignorable, since we use small number aggregate functions (only 2) in our work; aggregate operation is right after retrieving the operand.
C_a in reducer	0.001	aggregating in reducer
C_s	6.67×10^{-3}	serializing one byte of aggregate table on average in mapper
$C_d \cdot \gamma$	5.0×10^{-3}	de-serializing for one byte of aggregate tables on average in reducer
$C_n \cdot \gamma \cdot size_m$	0.403	transmitting one mapper
$C_n \cdot \gamma$	8.82×10^{-4}	transmitting one byte of aggregate table
For query *selectivity* = 1.06%		
$\alpha \cdot C_f$	7.24×10^{-4}	filtering per record in average
$\beta \cdot C_r d$	4.33×10^{-4}	reading one byte from compressed data
For query *selectivity* = 9.9%		
$\alpha \cdot C_f$	1.15×10^{-4}	filtering per record in average
$\beta \cdot C_r d$	7.20×10^{-5}	reading one byte from compressed data
For query *selectivity* = 18.5%		
$\alpha \cdot C_f$	5.30×10^{-5}	filtering per record in average
$\beta \cdot C_r d$	7.60×10^{-5}	reading one byte from compressed data
For query *selectivity* = 43.1%		
$\alpha \cdot C_f$	5.30×10^{-5}	filtering per record in average
$\beta \cdot C_r d$	7.60×10^{-5}	reading one byte from compressed data

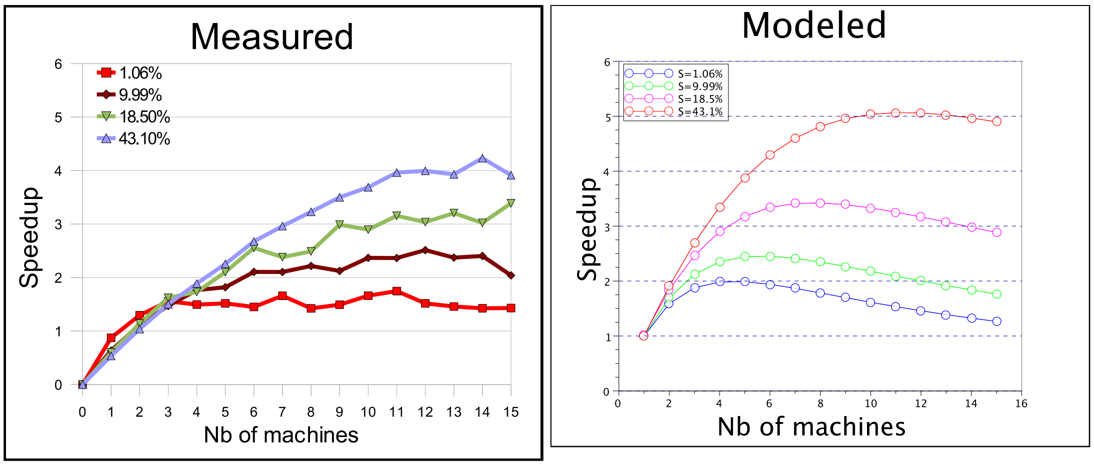


Figure 5.7: Measured speedup curve vs. Modeled speedup curve for MapReduce based query on horizontal partitioned data, where the each work node runs one mapper.

N=10 000 000, aggregate function number $nb_{agg} = 2$, total distinct values number $\sum_{i=1}^{nb_{GB}} nb_{DV_i} = 511$, Group-by dimension number $nb_{GB} = 5$, measure values contained in one record $M = 2$, etc.

5.6.2 Cost Estimation of Implementation over Vertical Partitions

We also estimate the cost of the implementation under the vertical partitioning in a similar way. The mapper's cost is estimated as:

$$C_m = S \cdot \frac{N}{nb_{rgn}} \cdot [C_f + (4M + 1) \cdot C_{rd} + C_a \cdot nb_{agg}]$$

where nb_{rgn} means the number regions.

With vertical partitioning, each mapper aggregates over one dimension d then the intermediate aggregate table size is estimated as:

$$size_{agg_d} = nb_{DV_d} \cdot (1 + 4nb_{agg})$$

where, $nb_{nb_{DV_d}}$ means the distinct value number of current Group-by dimension d; $(1 + 4nb_{agg})$ is the estimated size in byte of each row in aggregate table.

The reducer aggregates over a list of aggregate results; each of them is the aggregate result of one dimension or a part of dimension in case of $nb_{rgn} > 1$. The estimation of the reducer is:

$$C_r = C_a \cdot nb_{rgn} \cdot nb_{agg} \cdot \gamma \cdot \sum_{i=1}^{nb_{GB}} nb_{DV_i} \qquad (2)$$

By summing up the above estimations, we obtain the total cost estimation of *Multiple Group-by* query processing over vertical partitions:

$$Cost_{vp} = C_{mpg}\cdot nb_m + C_s\cdot size_m + C_d\cdot\gamma\cdot size_m + S\cdot\frac{N}{nb_{rgn}}\cdot[C_f + (4M+1)\cdot C_{rd} + nb_{agg}\cdot C_a] +$$

$$C_s\cdot nb_{DV_d}\cdot(1+4nb_{agg}) + C_d\cdot\gamma\cdot nb_{rgn}\cdot\sum_{i=1}^{nb_{GB}} nb_{DV_i}\cdot(1+4nb_{agg}) + C_a\cdot nb_{rgn}\cdot nb_{agg}\sum_{i=1}^{nb_{GB}} nb_{DV_i} +$$

$$C_n \cdot (nb_m \cdot \gamma \cdot size_m + \gamma \cdot nb_{rgn} \cdot \sum_{i=1}^{nb_{GB}} nb_{DV_i} \cdot (1 + 4nb_{agg})$$

Here we replaced $\sum_{i=1}^{nb_m} size_{agg_i}$ by $nb_{rgn}\cdot\sum_{i=1}^{nb_{GB}} nb_{DV_i}\cdot(1+4nb_{agg})$ since the partial aggregate tables from different region effectively construct nb_{rgn} times aggregates for all Group-by dimensions. The same estimation for parameter values could also be done for vertical partitioning base query processing. We will have this done in the future work.

5.6.3 Comparison

Note that, for the same ROWSET partitioned horizontally and vertically, the number of partitions in horizontal partitioning is larger than the number of regions in vertical partitioning, that is, $HP.nb_{pttn} > VP.nb_{rgn}$. The reason is, in horizontal partitioning, partition number is equal to mapper number, and we let mapper number equal to a multiple of node number, so as to utilize all the available nodes. However, with vertical partitioning, the region number is usually a sub-multiple of nodes number. Given this established facts, $HP.nb_{pttn} > VP.nb_{rgn}$, we see that the reducer cost of vertical partitioning-based implementation, which is expressed with formula (1), is smaller than that of the horizontal partitioning-based one, which is expressed with formula (2). As shown by the estimation, under both horizontal partitioning and vertical partitioning, a great part of calculation is parallelized. We make the calculation reduced from scale of ROWSET size N to fragment size $\frac{N}{nb_m}$ (in case of horizontal partitioning) or $\frac{N}{nb_{rgn}}$ (in case of vertical and hybrid partitioning). However, the transfer and serialization/de-serialization of intermediate data still form an important part of the cost. This cost is caused by parallelization. On the contrary, we can imagine that a further compression for intermediate outputs of mappers can optimize the calculation.

5.7 Alternative Compressed Data Structure

In the previous work, we used a data partition locating policy as the job-scheduling policy. Although this worked well, we still need a more flexible job-scheduling policy. An imaginable job-scheduling policy is based on distinct values. That means, each mapper works for aggregating only one or a part of distinct values of one certain dimension, then the intermediate aggregate tables produced by mappers are assembled in reducer. For supporting such a distinct-value-wise job scheduling, we propose an alternative compressed data structure in this section. This data structure works with the vertical partitioning.

5.7.1 Data Structure Description

In order to facilitate distinct-value-wise job scheduling, we need the aggregate value of one distinct value can be calculated within one continuous process. Thus, if the measures values corresponding to the same distinct value are successively stored, then aggregation for one distinct value can be processed in a continuous mode. This is the basic idea of the new compressed structure. In this new compressed data structure, we regroup the measure values' storage order. Measures corresponding to the same distinct value are stored together successively. As the stored order of measures is different than in the original ROWSET, we provide a data structure recording the records' old positions in the original ROWSET. Relying on the above description, we design the compressed data structure as follows. To be noted, this structure is designed specifically for vertical partition. The compressed data is still composed of two files, *FactIndex* and *Fact*. For each distinct value, Fact file stores a recordID-list with each recordID indicating the old position of records containing the current distinct value. Then, it stores a set of measures contains the current distinct value. FactIndex stores for each distinct value the distinct value code, and an address pointing to a position in

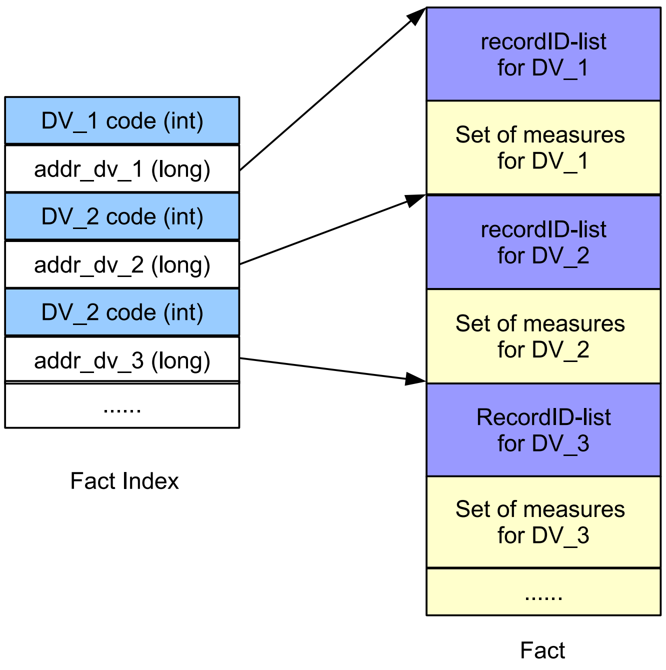


Figure 5.8: Compressed data files suitable for distinct value level job scheduling with measures for each distinct value are stored together.

Fact file where the recordID-list and a set of measures covered by the current distinct value start to store. Figure 5.8 illustrates this structure. For aggregating with using this data structure, each mapper will be scheduled to aggregate over one distinct value. FactIndex file is accessed to obtain the given distinct value's storage position in Fact file. Then, the mapper identifies the selected records covered by the given distinct values by retrieving the common recordIDs of selected recordID-list from the filtering phase and the recorID-list retrieved from Fact file. At last, the selected records covered by the current value are aggregated using the measure values covered by current distinct value retrieved from the Fact file.

5.7.2 Data Structures for Storing RecordID-list

Integer Array and Bitmap are two alternative data types can be used to store recordID list. In case of using Integer Array, each recordID is stored as an element of the array. In case of using Bitmap, we create a Bitmap being composed of a sequence of bits. The number of bits is equal to the cardinality of the original ROWSET. One bit in

Bitmap corresponds one record. The value of each bit is either 0 or 1. If we use 1 to indicate that the current record's id is in current distinct value's recordID-list, we obtain a Bitmap with all 1 positions indicating the whole recordID-list.

Considering the use of storage space, Integer Array and Bitmap are very different. When the recordID-list contains a small number of elements, Integer Array takes smaller storage spaces. In the opposite case, where the recordID-list contains a large number of elements, Bitmap is more storage efficient.

5.7.3 Compressed Data Structures for Different Dimensions

Taking into account the above features, we distinguish two categories of dimensions: dimensions having a small number of distinct values and dimensions having a large number of distinct values. For those dimensions with a small number of distinct values, then many records are covered by one certain distinct value. In turn, a large number of recordIDs need to be stored. In this case, Bitmap is more space-saving and makes access more efficient than Integer Array. For those dimensions with a large number of distinct values, only a few recordIDs need to be stored. For this case, Integer Array provides is more space-saving and provides more access efficiency.

But how to define the "small" and "large" over the number of distinct values for one dimension? Let's do a concrete calculation. Imagine that we have a ROWSET containing 10^7 records. One recordID stored as integer takes 4 bytes. Assume that a dimension includes V distinct values. Thus each distinct value covers $10^7/V$ records. If we store the recordID-list in Integer Array, for one certain distinct value, $4 \times 10^7/V$ bytes are needed, on average. Then, we need to store $4 \times 10^7/V$ bytes in total in order to store all recordIDs containing all distinct values. If we use a Bitmap to store recordID-list of one distinct value, then the Bitmap takes 1.25×10^6 bytes. As a result, the critical point of distinct value number V is 32. If $V = 32$, then two storage take the same space; if $V < 32$, Bitmap takes smaller space; if $DV > 32$, then Integer Array takes smaller space. Thus, if the number of distinct values is larger than 32, then we considered it as "large"; otherwise, if the number of distinct value is smaller than or equal to 32, then we consider it as "small". After defining the data structure of recordID-list, we specify the concrete storage for those two dimensions. For dimensions having a large number of distinct values, the composed data is composed of 2 files, FactIndex and Fact. Data stored in the FactIndex file includes, the code of each distinct value of integer and an

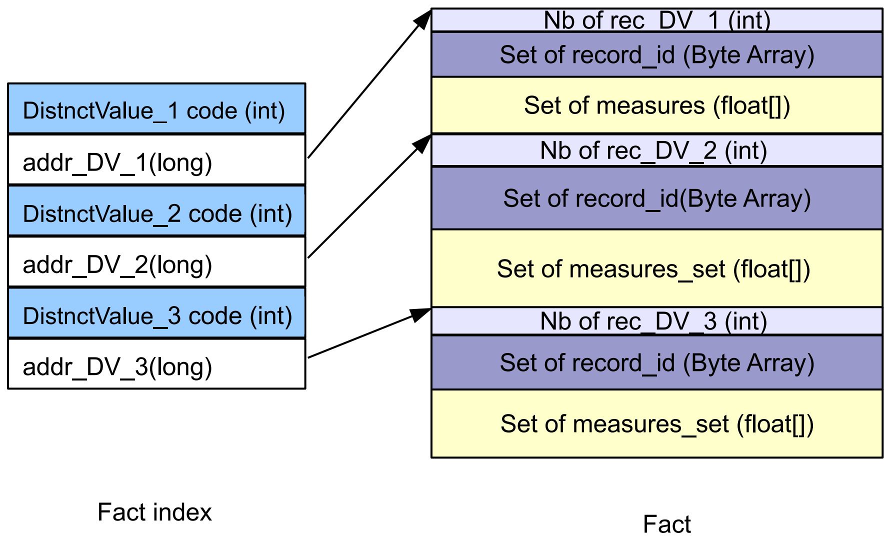

DistnctValue_1 code (int)
addr_DV_1(long)
DistnctValue_2 code (int)
addr_DV_2(long)
DistnctValue_3 code (int)
addr_DV_3(long)
Nb of rec_DV_1 (int)
Set of record_id (Byte Array)
Set of measures (float[])
Nb of rec_DV_2 (int)
Set of record_id(Byte Array)
Set of measures_set (float[])
Nb of rec_DV_3 (int)
Set of record_id (Byte Array)
Set of measures_set (float[])
Fact index
Fact

Figure 5.9: Compressed data structure storing recordID list as Integer Array for dimension with a large number of distinct values

address of long integer pointing to a position in the Fact file where the data related to this distinct value is stored. Data stored in the Fact file includes three parts. The first one is an integer representing the number of records covered by current distinct value. The second one is an Integer Array compressed in Byte Array representing the recordID-list for records covered by current distinct value. The third one is a Float Array representing the measure values for records having the current distinct value. Refer to Figure 5.9 for the illustration of this structure.

For dimension having small number of distinct values, the compressed data is also composed of FactIndex file and Fact file. The FactIndex file stores the code of the current distinct value in integer and an address in long integer, in long type, pointing to a position in the Fact file where data related to this distinct value is stored. The Fact file stores, for each distinct value, a Bitmap indicating the records covered by the current distinct value, as a Byte Array, and the measure values for records having the current distinct value in type of Float Array. Refer to Figure 5.10 for the illustration of this structure.

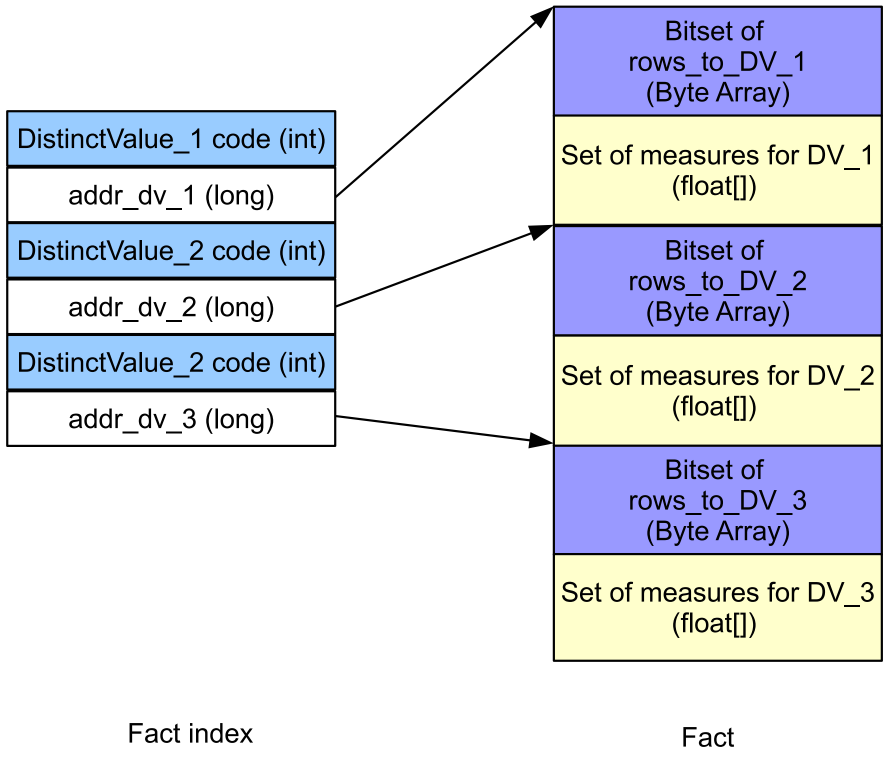

DistinctValue_1 code (int)
addr_dv_1 (long)
DistinctValue_2 code (int)
addr_dv_2 (long)
DistinctValue_2 code (int)
addr_dv_3 (long)
Bitset of rows_to_DV_1 (Byte Array)
Set of measures for DV_1 (float[])
Bitset of rows_to_DV_2 (Byte Array)
Set of measures for DV_2 (float[])
Bitset of rows_to_DV_3 (Byte Array)
Set of measures for DV_3 (float[])
Fact index
Fact

Figure 5.10: Compressed data structure storing recordID list as Bitmap for dimension with a small number of distinct values (In Java, Bitmap is implemented as Bitset)

5.7.4 Measurements

We tested these two compressed data using a single machine, which is equipped with a 4-core CPU running at 2.5GHz and 4 Go RAM. The objective is to measure the efficiency provided by using these two different data structure over all dimensions. Table 5.3 shows the execution time for four single Group-by queries having the following form:

```
SELECT group_by_dimension, SUM("quantity_sold"), SUM("revenue")
FROM   "ROWSET"
WHERE condition
GROUP BY group_by_dimension
```

Those four single Group-by queries aggregates over dimensions, Product Family, Product Category, Article Label and Store City, respectively. These four dimensions have different distinct value number varying from 12 to 244. As shown in this table, the first compressed data structure works well for aggregations over dimensions having large number of distinct values and dimensions having small number of distinct values. For the second compressed data structure, the aggregation over dimensions having small number of distinct values is much faster than the aggregation over dimensions having large number of distinct values. Even though, the aggregations over the second compressed data are always slower than those over the first compressed data. The compressed data using Bitmap did not provide the same efficiency as we imagined.

5.7.5 Bitmap Sparcity and Compressing

The low efficiency of Bitmap, i.e. the second compressed data used in above experiments is caused by the sparcity. Even for a dimension having small number of distinct values, for example, 12, the Bitmap is very sparse, since only 1/12 bits are set to 1. A Bitmap compressing is crucial for improving the storage efficiency. There exist already some Bitmap compressing algorithms that we can take advantage of. These methods typically employ Run-length-encoding, such as Byte-aligned Bitmap Code, Word-Aligned Hybrid code and Position List Word Aligned Hybrid (4). Run-length-encoding stores the sequence in which the same data value occurs in many consecutive positions, namely run, as one single data value and count, instead of storing them as the original run(19). We will address the Bitmap compressing methods in the future work in order to improve our Bitmap's storage efficiency.

	RecordID list stored as Integer Array				**RecordID list stored as Bitmap**			
Group-by dimension	Product Family	Product Category	Article Label	Store City	Product Family	Product Category	Article Label	Store City
DV nb / WHERE	12	34	209	244	12	34	209	244
Color=Pink (S=1.06%)	547	500	516	453	968	1313	4219	3922
Product Family= Shirt Waist(S=9.9%)	*469*	*453*	438	437	*562*	*797*	3235	3812
Opening Year= 2001(S=18.5%)	678	688	563	531	1031	1390	4344	3062
Product Family= Accessories(S=43.1%)	*860*	*859*	859	844	*1079*	*1625*	4203	4281
ALL (S=100%)	1844	1578	1531	1516	2344	2422	5484	5547

Table 5.3: Execution Times in ms of Group-by queries with different selectivities (S) using new compressed data structures. The numbers shown in italic represents that the corresponding aggregations run over the dimensions correlated to the WHERE condition involved dimension. For example, Product Family and Product Category are correlated dimensions.

5.8 Summary

In this work, we realized *Multiple Group-by* query on restructured data, using MapReduce model to parallelize the calculation. We introduced the data partitioning, indexation and data compressing processing in data restructuring phase. The materialized view ROWSET is partitioned respectively using two principal partitioning methods, horizontal partitioning and vertical partitioning. The index that we created using Lucene over ROWSET is an inverted index, which allows rapidly accessing and filtering the records with WHERE condition. We measured our *Multiple Group-by* query implementations over ROWSET, and compared the speed-up performance of implementations over horizontally partitioned data and that over vertically partitioned data. In most cases, they showed similar speed-up performance, however, the best speed-up appeared in the vertical partitioning-base implementation. Basing on the measured result observations and analysis, we discovered several interesting factors that affect query processing performance, including query selectivity, concurrently running mapper number on one node, hitting data distribution, intermediate output size, adopted serialization algorithms, network status, whether or not using combiner as well as the data partitioning methods. We gave an estimation model for the query processing's execution time, and specifically estimated the values of various parameters for data horizontal partitioning-based query processing. In order to support distinct-value-wise job-scheduling, we designed a new compressed data structure, which works with vertical partition. It allows the aggregations over one certain distinct value to be performed within one continuous process. However, such a data structure is only an initial design. We will address the optimization issues, like Bitmap compressing, in the future work.

6

Conclusions and Future Directions

The objective of this Ph.D work is to propose a cheap solution for interactive large-scale multidimensional data analysis applications using commodity hardware. We propose to adopt MapReduce to achieve this target. MapReduce helps to solve scalability and fault tolerance issues of in parallel and distributed computing environment, especially in case of using unstable commodity hardware. However, MapReduce only is a low-level procedural programming paradigm. In order for data intensive applications to benefit from MapReduce, a combination of MapReduce and SQL is expected. The combination between MapReduce and SQL consists in realizing and optimizing relational algebra operators. In this work, we address a typical multidimensional data analysis query, *Multiple Group by* query.

6.1 Summary

In our work, we try to utilize methods of Cloud Computing to satisfy commercial software requirements. In addition to realize a concrete multidimensional data analysis query with MapReduce, we mostly focus on the performance optimization. It is an important aspect in designing Cloud Computing-based solution for business software. The main contributions of this work are summarized as follows:

- We identify *Multiple Group by* query as the elementary computation under data explorer background of our work.

- We choose GridGain over Hadoop as MapReduce framework to realize *Multiple Group by* query since GridGain has lower latency. A detailed workflow analysis of the GridGain MapReduce procedure has been done.

- We realize two implementations of *Multiple Group by* query over plain text data format with MapReduce. In the initial MapReduce-based implementation, we realize filtering phase within mappers and aggregating phase within the reducer. In the optimized MapCombineReduce-based implementation, the aggregation (pre-aggregation) is performed within combiner on a local computing node level before starting reducer. As GridGain does not support combiner component, we realize the combiner by merging two successive GridGains MapReduces.

- The experimental results show that the optimized version has better speed-up and better scalability for reasonable query selectivity. We formally analyze the execution time of these two implementations in a qualitative way. The qualitative comparison shows that the optimized implementation decreases the communication cost by reducing the intermediate data quantity, and it also reduces the aggregating phases calculation by parallelizing a part of aggregating calculation.

- We further optimize the individual jobs' execution of parallelized *Multiple Group by* query by running them over restructured data format. We introduce a data restructuring phase, within which the data partitioning, indexation and data compressing processing are performed.

- We measure and compare the speed-up performance of *Multiple Group by* query over horizontally partitioned data set and vertically partitioned data set. They show similar speed-up performance but the best speed-up appears in the vertical partitioning-base implementation.

- We discover several interesting factors that affect query processing performance, including query selectivity, concurrently running mapper number on one node, hitting data distribution, intermediate output size, adopted serialization algorithms, network status, whether or not using combiner as well as the data partitioning methods.

- We give an estimation model for *Multiple Group-by* query processings execution time, and specifically estimated the values of various parameters for data horizontal partitioning-based query processing.
- We design a new compressed data structure, which is working with vertical partition, in order to support more flexible distinct-value-wise job-scheduling.

6.2 Future Directions

In order to utilize Cloud Computing to serve as the infrastructure of multidimensional data analysis applications, the combination of traditional parallel database optimization mechanisms and Cloud computing is expected. In our work, we combine MapReduce with several optimization techniques coming from parallel database. This approach does not depend on a third-part product, and it can guarantee the performance application. There are still some performance issues to be addressed.

- Choosing suitable serialization/de-serialization algorithms to deal with mapper objects and intermediate results is an important issue. Since these procedures are repeatedly performed, it is closely related to the performance. In our distinct-value-wise job-scheduling, Bitmap compressing is needed for reducing storage requirement and improving the efficiency of data access. We will address these issues in our near future work.
- In this work, we focused on a specific type of query, *Multiple Group by* query. However, our work is still limited for processing all kinds of data analytical queries. For addressing different queries, we could define concrete MapReduce job and add suitable optimization mechanisms in a similar way. This work will also be addressed in the future.
- Extending our calculation to a larger computing scale is another interesting direction. In this work, all the experiments were running over one single cluster. However, running experiments over one cluster is a bit far from exploiting a real Cloud platform. In order to further address a more realistic large-scaled multidimensional data analytical query processing, multiple clusters or even the real Cloud experimental platform need to be exploited during in the experiments. The hardware update will allow us to handle larger data sets.

- Utilizing Cloud Computing to process large data set involves another hard problem—data privacy. This topic was not covered in our work. However, it is still an important aspect. People or enterprises will not want to put their data over the Cloud until their private data can be protected from unauthorized accesses. Some authorization and authentication technologies have already been developed earlier in Grid Computing. They are very useful for the Cloud platform's data accessing protection requirement. However, the authorization and authentication of Cloud platform are more challenging than in Grid platform, since it is a commercialized, shared computing platform, users will require more fine authorization and authentication mechanisms.

- MapReduce was employed as a parallel model in our work. For this work, MapReduce is used as a tool. In fact, a lot of research work inside MapReduce model has been done recently. Scheduling strategies of Map jobs and Reduce jobs are one of the addressed problems. Job-scheduling strategies have a considerable impact on the computing efficiency of a specific calculation. Being limited by the fixed Reducer number of GridGain framework's design, we did not sufficiently addressed the job-scheduling issues. However, along with the development of MapReduce frameworks and the new emergence of new frameworks, we should have more participation into MapReduce's job-scheduling.

There is much more other interesting work to do for integrating MapReduce model into or utilizing Cloud Computing in resolving the real problems, including industrial applications as well as scientific computations. For instance, MapReduce's combination with web techniques, re-designing of various algorithms for fitting MapReduce execution style, etc. are all interesting research subjects. We believe that the performance issue addressed in this work represents an important aspect in Cloud computing. We hope that our work can provide a useful reference for people who want to study and utilize MapReduce and Cloud Computing platform.

Appendices

Appendix A

Applying Bitmap Compression

We talked about Bitmap sparsity and compressing earlier in section 5.7.5. Compressing Bitmap is helpful for reducing the aggregation time of Group-by query over vertically partitioned data. Recall that we have described two methods for store the list of recordIDs which correspond to a specific distinct value. The first method is to store recordID list as Integer Array. The second method is to store recordID list as Bitmap. From the measured execution time of a couple of Group-by query, we can see that the Bitmap storage method suffered from the Bitmap sparsity and was not sufficiently efficient. That is the why we introduce Bitmap compressing technique.

Word-Aligned Hybrid (WAH) method (105) is one of Bitmap Compression techniques. We adopt it this technique in our work. WAH method encodes Bitmap in words which better matches current CPUs. Bitmaps compressed with WAH method can directly participate in bitwise operations without decompression. Other alternative Bitmap compressing techniques are also applicable, including Byte-aligned Bitmap Code (30) and Position List Word Aligned Hybrid (PLWAH)(50), etc.

A.1 Experiments and Measurements

Similar to the experiments described in section 5.7.4, we tested Group-by queries over three compressed structures. The first compressed data structure stores recordID list as Integer Array. The second compressed data structure stores recordID list as non-compressed Bitmap. The third compressed data structure stores recordID list as compressed Bitmap. We measured the execution times of the same four single Group-by queries over a single machine which is equipped with a 4-core CPU running at 2.66GHz and 4Go RAM. Table A.1 shows the measured results.

As shown in this table, among the three compressed data structures, the first data structure works best for aggregations over dimensions having large number of distinct values. The first data structure works well for aggregations over dimensions having small number of distinct values. However, comparing with the third data structure, the first data structure makes Group-by queries to take longer execution time. That means the third compressed data structure, storing recordID list as compressed Bitmap, is the best one for the aggregations over dimensions having small number of distinct values. The measurements over the second compressed data structure still shows longer execution time for aggregations over large distinct value number dimensions, comparing with the other two compressed data structures. Based on these observations, we can summarize that, for single Group-by queries over dimensions having small distinct value number, the data structure storing recordID list as compressed Bitmap offers best performance; for single Group-by queries over dimensions having large distinct value number, the data structure storing recordID list as Integer Array offers best performance. Up to here, our original objective is achieved.

	RecordID list stored as Integer Array				**RecordID list stored as Bitmap**				**RecordID list stored as compressed Bitmap**			
Group-by dimension	Product Family	Product Category	Article Label	Store City	Product Family	Product Category	Article Label	Store City	Product Family	Product Category	Article Label	Store City
DV nb / WHERE	12	34	209	244	12	34	209	244	12	34	209	244
Color=Pink (S=1.06%)	434	420	387	447	581	937	2589	2411	198	289	981	934
Product Family= Shirt Waist(S=9.9%)	*395*	*394*	375	394	*444*	*638*	2255	2440	*234*	*292*	902	841
Opening Year= 2001(S=18.5%)	498	466	479	473	661	913	2694	2361	229	327	974	857
Product Family= Accessories(S=43.1%)	*710*	*706*	626	647	*848*	*1055*	2880	2811	*317*	*386*	1048	949
ALL (S=100%)	794	758	869	783	1282	1500	3267	3217	195	302	1138	870

Table A.1: Execution Times in ms of Group-by queries with different selectivities (S) using three compressed data structures. The numbers shown in italic represents that the corresponding aggregations run over the dimensions correlated to the WHERE condition involved dimension. For example, Product Family and Product Category are correlated dimensions.

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