Enhancing Data Processing on Clouds with Hadoop/HBase

by

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A thesis
presented to the University of Waterloo
in fulfilment of the
thesis requirement for the degree of
Doctor of Philosophy
in
Computer Science

Waterloo, Ontario, Canada, 2011

AUTHOR'S DECLARATION

I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

I understand that my thesis may be made electronically available to the public.

Chen Zhang

Abstract

In the current information age, large amounts of data are being generated and accumulated rapidly in various industrial and scientific domains. This imposes important demands on data processing capabilities that can extract sensible and valuable information from the large amount of data in a timely manner. Hadoop, the open source implementation of Google's data processing framework (MapReduce, Google File System and BigTable), is becoming increasingly popular and being used to solve data processing problems in various application scenarios. However, being originally designed for handling very large data sets that can be divided easily in parts to be processed independently with limited inter-task communication, Hadoop lacks applicability to a wider usage case. As a result, many projects are under way to enhance Hadoop for different application needs, such as data warehouse applications, machine learning and data mining applications, etc. This thesis is one such research effort in this direction. The goal of the thesis research is to design novel tools and techniques to extend and enhance the large-scale data processing capability of Hadoop/HBase on clouds, and to evaluate their effectiveness in performance tests on prototype implementations. Two main research contributions are described. The first contribution is a light-weight computational workflow system called "CloudWF" for Hadoop. The second contribution is a client library called "HBaseSI" supporting transactional snapshot isolation (SI) in HBase, Hadoop's database component.

CloudWF addresses the problem of automating the execution of scientific

workflows composed of both MapReduce and legacy applications on clouds with Hadoop/HBase. CloudWF is the first computational workflow system built directly using Hadoop/HBase. It uses novel methods in handling workflow directed acyclic graph decomposition, storing and querying dependencies in HBase sparse tables, transparent file staging, and decentralized workflow execution management relying on the MapReduce framework for task scheduling and fault tolerance.

HBaseSI addresses the problem of maintaining strong transactional data consistency in HBase tables. This is the first SI mechanism developed for HBase. HBaseSI uses novel methods in handling distributed transactional management autonomously by individual clients. These methods greatly simplify the design of HBaseSI and can be generalized to other column-oriented stores with similar architecture as HBase. As a result of the simplicity in design, HBaseSI adds low overhead to HBase performance and directly inherits many desirable properties of HBase. HBaseSI is non-intrusive to existing HBase installations and user data, and is designed to work with a large cloud in terms of data size and the number of nodes in the cloud.

Acknowledgements

I would like to thank my supervisor, Professor Hans De Sterck, for the inspirational instructions and guidance as well as the superb diligence, kindness and patience in his involvement of my PhD research.

I would like to thank my PhD Committee members for giving me valuable advice and suggestions. Professor Ashraf Aboulnaga's course on cloud computing inspired my work on transactional snapshot isolation on HBase. He also provided great advice on the paper about the Hadoop case study in solving a scientific computing problem. Professor Kenneth Salem, who is an expert on snapshot isolation, provided excellent suggestions on my research on the "HBaseSI" project as well as insightful comments on the "CloudBATCH" project. He also arranged three public seminars for me to present my work to faculty members and students in the David R. Cheriton School of Computer Science. Both of them offered extremely helpful feedback and critique during my proposal defence and arranged meetings.

I would like to thank the many excellent collaborators and fellow students, without whom my graduate studies would not have been the same. I also want to give thanks to the University of Waterloo Faculty of Mathematics, David R. Cheriton School of Computer Science, SHARCNET and Cybera for providing generous support for my research work.

Finally, I would like to thank my wife, who has been supporting me whole-heartedly in numerous ways, for her tolerance and love.

Dedicated to my wife,

Jing Wu,

for her love.

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Chapter 1

Introduction

Nowadays, large amounts of data are being generated daily from various sources: web posts on social network sites like Facebook, transactional data at Amazon and Walmart, data generated by search engines like Google, astronomy and weather data gathered by NASA, drug testing data at pharmaceutical companies, etc. These data are also called "Big Data" in some contexts. Big Data are either structured data that can be stored in relational databases, or unstructured data that may include audio, video, images, web pages, and many other forms. A common trait associated with these data is the large scale in terms of data size and the ever-increasing demand for new techniques to process and make sense of the data in a timely and scalable[1] manner.

The immense data processing scale has posed challenging requirements on existing distributed programming paradigms and execution environments, and on the underlying hardware infrastructure, particularly concerning easy programmability, scalability, fault tolerance and on-demand resource availability. Under this background, Google was a pioneer in designing a software framework

[1] In this thesis, two aspects of scalability are of importance: 1. scalability in terms of automatically handling hardware failures that occur with increased frequency for larger systems; and 2. scalability in terms of performance as problem sizes and cloud sizes increase.

[12, 18, 4] for processing large-scale data sets in a scalable and fault tolerant way. Amazon revolutionarily commercialized an economical way for companies and the general public to acquire on-demand computing resources through renting virtual machine instances based on a pay-per-use model [15]. The resources provided in this way are now referred to as "public clouds". The resources in traditional clusters and grids belonging to the same organization are referred to as "private clouds" if the resources are used in similar on-demand and expandable ways like public clouds. A resource pool consisting of a combination of public cloud and private cloud resources is called a "hybrid cloud". The term "cloud computing" is used to refer to this new way of doing computation over cloud resources.

Hadoop [34], the open source implementation of Google's system, is a popular open source cloud computing framework that has shown to perform well in various usage scenarios (e.g., see [32]). Its MapReduce framework offers transparent distribution of compute tasks and data with optimized data locality and task level fault tolerance; its Hadoop Distributed File System (HDFS) offers a single global interface to access data from anywhere with data replication for fault tolerance; and its HBase [21] sparse data store allows to manage structured data on top of HDFS.

Similar to Google's original system, Hadoop is designed for the processing of very large data sets that can be divided easily in parts that can be processed independently with limited inter-task communication over homogeneous computing environment. As Hadoop becomes popular, people find that Hadoop can also be extended or enhanced to solve a wide spectrum of problems beyond the original type of computing problems it was designed for. As a result, many related projects are created to cater to different application needs. For example, "Hive" [6] is a data warehouse infrastructure that provides data summarization and ad hoc querying; "Pig" [23] is a high-level dataflow language and execution

framework for parallel computation; and "Mahout" [28] is a scalable machine learning and data mining library, etc.

Among these efforts in enhancing Hadoop, some research problems remain open for further investigation. For example, there exists no out-of-the-box support for database transactions involving multiple data rows in HBase sparse tables; there exist no well-established cloud environment computational workflow systems on top of Hadoop to easily build and run computational workflows composed of MapReduce and existing legacy programs; Hadoop is incompatible with existing cluster batch job queuing systems and lacks support for user access control, accounting, and legacy batch job processing facilities comparable to existing cluster job queuing systems, etc.

In this thesis, we focus on research questions pertaining to enhancing software frameworks for cloud computing. More specifically, we design novel tools and techniques to extend and enhance the large-scale data processing capability of Hadoop/HBase on clouds, and to evaluate their effectiveness in performance tests on prototype implementations.

1.1 Thesis Statement

This thesis addresses the problem of enhancing large-scale data processing on clouds with Hadoop/HBase in handling computational workflows and maintaining strong transactional data consistency. The two major contributions we report on in this thesis are as follows.

1. A light-weight computational workflow system, called "CloudWF", is presented, automating the execution of scientific workflow jobs on clouds with Hadoop/HBase. CloudWF tackles the problem of easily building and running computational workflows composed of MapReduce and existing legacy programs. It is the first workflow management system that is built

entirely on top of Hadoop/HBase and targeted to take advantage of the new Hadoop/HBase architecture for scalability, fault tolerance and ease of use.

2. A client library, called "HBaseSI", is presented, supporting multi-row distributed transactions with global strong snapshot isolation (SI) on HBase. HBaseSI tackles the problem of maintaining strong transactional data consistency in HBase tables under concurrent access in a shared environment. It is the first snapshot isolation solution for HBase, and it is built entirely on bare-bones HBase instead of implementing an extra middleware layer atop.

CloudWF (presented in [46]) is the first workflow management system closely integrated with Hadoop/HBase that allows the user to build and run computational workflows composed of both MapReduce and legacy applications on clouds. The novelties in the design of CloudWF are: 1. A new way to describe workflow components as self-contained and independent building blocks, separating executable blocks from connectors; this facilitates easier storage, dependency handling, file staging, and distribution; 2. A new method to store workflow component information as well as workflow graph structure (dependencies) in HBase sparse tables with an efficient way to query and reconstruct dependencies at run time; 3. A new method to automate file staging between workflow blocks transparently; 4. A new method to manage multiple workflow instance executions using a single workflow engine (composed of a set of global HBase tables and several decentralized distributed system components), while other workflow systems normally feature one workflow engine process per workflow executed, which makes load balancing and execution coordination more difficult [39].

HBaseSI is the first distributed transactional system with global SI for HBase. Our initial version of HBaseSI provided weak SI [48]; the new version presented in [49] is significantly improved and provides strong SI. Our work on SI for HBase

was published independently and at the same time as Google's Percolator system for supporting transactions with SI in BigTable. While HBaseSI shares some important design ideas with Percolator, there are also significant differences (e.g., Percolator is intrusive to user data tables, uses data locks and complicated straggler handling mechanisms, may have blocking reads, etc.). Also, Percolator relies on the "single-row transaction" functionality specific to BigTable, and therefore cannot be directly implemented on HBase. The major novelties in HBaseSI are: 1. Non-intrusive to both server configuration and client data - no modifications are required; 2. A new method in handling distributed transaction commits without using a central commit engine or traditional distributed coordination methods such as consensus-based protocols, explicit atomic broadcast, and transactional data locks. Instead, transactions make commit decisions autonomously; 3. A new method to guarantee non-blocking start of transactions with fresh and consistent snapshots as well as strict global commit ordering, relying on a novel distributed queuing mechanism implemented by standard HBase tables; 4. A new method to handle straggling and failed transactions without the need for any roll back/-forward procedures. The approaches followed in HBaseSI can also be applied to other column-oriented data stores that feature similar data organization as HBase.

1.2 Thesis Organization

The remaining chapters of the thesis are organized as follows.

Chapter 2 introduces some necessary background information. We will talk about grids and clouds, key components in Google's large-scale data processing framework, Hadoop and HBase.

Chapter 3 describes the preliminary and supportive work I did in the early stages of my PhD research. This motivates the two main contributions of the thesis. A brief overview is given of the research projects I have done during my

PhD study, showing how they are related as well as their relevance to the main theme of the thesis. Some details are provided for some of the preliminary and supportive work.

Chapter 4 describes the CloudWF system for building and running computational workflows. The design and implementation of the system are described in detail, and the advantages of the new design over existing systems are discussed.

Chapter 5 describes the HBaseSI system for achieving transactional snapshot isolation on Hadoop clouds. The detailed system design and implementation are described as well as a complete protocol walkthrough under an example application scenario, and performance evaluations using Amazon EC2.

Chapter 6 gives conclusions and describes future research directions.

1.3 Publications Related to Thesis Work

1.3.1 Main Contributions

The publications below are related to the two main contributions of the thesis: CloudWF and HBaseSI. The conference paper in CloudCom2009 describes the design and implementation of the CloudWF system (See Chapter 4). The journal paper describes the significantly improved HBaseSI system with strong SI whereas the conference paper published in Grid2010 describes the initial HBaseSI system with weak SI (See Chapter 5).

Journal Publications

1. Chen Zhang and Hans De Sterck. HBaseSI: A Solution for Multi-row Distributed Transactions with Global Strong Snapshot Isolation on Clouds. Special Issue: New Directions in Cloud and Grid Computing, Scalable Computing: Practice and Experience, Vol. 12, No. 2, 2011.

Conference Publications

1. CloudCom2009: Chen Zhang and Hans De Sterck. CloudWF: A Computational Workflow System for Clouds Based on Hadoop. The First International Conference on Cloud Computing, Dec 1-4, 2009, Beijing, China. (27% acceptance)

2. Grid2010: Chen Zhang and Hans De Sterck. Supporting Multi-row Distributed Transactions with Global Snapshot Isolation Using Bare-bones HBase. The 11th ACM/IEEE International Conference on Grid Computing, Oct 25-29, 2010, Brussels, Belgium. (23% acceptance)

1.3.2 Other Contributions

The following publications are related to preliminary and supportive work I have done during my PhD (See Chapter 3). The journal paper in RNA, the conference paper in BLSC2007 and the book chapter are results of my involvement in the research on GridBASE, a light-weight grid computing framework, at the early stage of my PhD study. At that time, cloud computing was still at its very infancy while grid computing prevailed. The paper in HPCS2009 describes one of the first few research attempts at the time it was published to apply Hadoop in solving scientific computing problems with customized input formats. The paper published in CloudCom2010 describes supportive work on CloudBATCH, a system attempting to enable Hadoop with the capability to manage traditional batch job submissions in clusters.

Journal Publications

1. Ryan Kennedy, Manuel E. Lladser, Zhiyuan Wu, Chen Zhang, Michael Yarus, Hans De Sterck, and Rob Knight. Natural and Artificial RNAs Occupy the Same Restricted Region of Sequence Space. RNA, 16:280-289, 2010.

Conference and Workshop Publications

1. CloudCom2010: Chen Zhang and Hans De Sterck. CloudBATCH: A Batch Job Queuing System on Clouds with Hadoop and HBase. The Second IEEE International Conference on Cloud Computing Technology and Science, Nov 30 - Dec 3, 2010, Indianapolis, Indiana, USA. (25% acceptance)

2. HPCS2009: Chen Zhang, Ashraf Aboulnaga, Hans De Sterck, Haig Djambazian, and Rob Sladek. Case Study of Scientific Data Processing on a Cloud Using Hadoop. High Performance Computing Symposium, June 14-17, 2009. Kingston, Ontario, Canada.

3. BLSC2007: Hans De Sterck, Chen Zhang, and Aleks Papo. Database-driven Grid Computing with GridBASE. The 2007 IEEE International Symposium on Bioinformatics and Life Science Computing. May 21-23, 2007. Niagara Falls, Ontario, Canada.

Book Chapter

1. Hans De Sterck, Alex Papo, Chen Zhang, Micah Hamady, and Rob Knight. Database-driven Grid Computing and Distributed Web Applications: A Comparison. In "Grids for Bioinformatics and Computational Biology". Wiley, December 2007. ISBN: 978-0-471-78409-8.

Chapter 2

Background

2.1 Grids and Clouds

Grid computing is an abstract concept of orchestrating heterogeneous computing resources across virtual organizations (VO's) [17] to solve problems that are normally computation-intensive and/or data-intensive and cannot be solved efficiently on a single computer. Grid computing has the objective to provide an ideal combination of high performance, high reliability and ease of programming. While the grid computing idea was attractive for certain applications and substantial effort has been dedicated to working out this concept by various research groups around the world, it has also turned out that the idea was not easy to realize in practice. Among the stumbling blocks encountered we could mention security and privacy concerns, lack of hardware or software compatibility between heterogeneous computing resources, and the general inertia of legacy computing environments against change. In fact, the intrinsic difficulties of optimizing the use of heterogeneous resources and dealing with different administrative domains within and across VO's have made it complicated and difficult to adopt the technology outside of research and educational institutions.

Additionally, grids are normally shared by many users at the same time by using existing queuing systems instead of granting dedicated usage on a per user basis. This introduces extra complexity in resource discovery, reservation and monitoring, which further makes the wide adoption of grids difficult. There thus remained a clear need for transparent, user-friendly and efficient distributed computing systems with a reasonable degree of scalability and fault tolerance for various usage scenarios.

Cloud computing is closely related to grid computing. While grid computing has a heavy academic flavor, cloud computing has been developed more in a commercial context. The term "cloud computing" is currently most closely associated with the "public cloud" concept pioneered by Amazon [15]. With Amazon's pay-per-use resource renting model, it becomes very easy for companies and the general public to get an expandable pool of computing resources on demand under their full control for dedicated usage without the need to purchase or maintain actual hardware. The resources in public clouds can be configured exactly according to users' needs using virtualization technologies. It is also potentially beneficial to resource providers like Amazon to gain profit by renting out idling cycles of their own compute farms.

Although cloud computing concepts are closely related to the general ideas and goals of grid computing, there are some specific characteristics that make cloud computing promising as a paradigm for transparently scalable distributed computing. In particular, two important properties that many cloud systems share are the following:

1. Clouds can provide a homogeneous operating environment (for instance, identical operating system (OS) and libraries on all cloud nodes, possibly via virtualization).

2. Clouds can provide full control over dedicated resources on-demand (in many cases, the cloud is set up such that the application has full control

over exactly the right amount of dedicated resources, and more dedicated resources may be added as the needs of the application grow).

While these two properties lead to systems that are less general than what is normally considered in the grid computing context, they significantly simplify the technical implementation of cloud computing solutions, possibly to the level where feasible, easily deployable technical solutions can be worked out. The fact that cloud computing solutions, after only a short time, have already become commercially viable would point in that direction. Indeed, the first property above removes the complexity of dealing with versions of application code that can be executed in a large variety of software operating environments, and the second property removes the complexity of dealing with resource discovery, security protocol negotiations, etc., which are the characteristics of shared environments with heterogeneous resources.

Cloud computing is thus a promising paradigm for transparently scalable distributed computing and is now receiving more and more attention in both the commercial and academic arenas. Cloud resource services provide on-demand hardware availability for dedicated usage. Cloud computing software frameworks manage cloud resources and provide scalable and fault tolerant computing utilities with globally uniform and hardware-transparent user interfaces.

While public cloud service providers allow users to rent computing resources on-demand for dedicated usage, one may argue that the aspects of cloud computing most important for scalable distributed computing with large datasets were actually rather pioneered in Google's "private cloud" systems: Google used its own resources as "private clouds" and developed a cloud computing framework for doing large-scale data processing on its private clouds. Google's "private clouds" share important properties of Amazon's "public clouds", including a homogeneous environment and dedicated usage with on-demand increase in resources, but on top of that, Google's systems also provide a cloud computing

framework that facilitates very large-scale distributed data processing. In fact, compared to existing cluster and grid resource management systems whose task is to orchestrate computing resources for distributed computing job executions, Google's software framework provides not only the basic resource management functionality but also a software stack composed of several key components that make scalable and fault tolerant data processing of very large data sets easy to program and manage.

2.2 Google's Cloud Software Framework

There has been a lot of research and development on cloud computing software frameworks at Google. One of the core components among those developments is Google's MapReduce software framework which has proven to be an efficient and powerful data processing solution as demonstrated by Google's success in handling gigantic amounts of data. Google's MapReduce framework (in the broad sense) is composed of the following three major components:

1. MapReduce [12], a scalable and reliable programming model and execution environment for processing large data sets.

2. Google File System (GFS) [18], a scalable and reliable distributed file system for large data sets.

3. BigTable [4], a scalable and reliable distributed storage system for sparse structured data.

Google's MapReduce system is tailored to specific applications running on its internal compute farms. GFS can deal efficiently with large input files that are normally written once and read many times. MapReduce handles large processing jobs that can be parallelized easily: the input normally consists of a very long sequence of atomic input records that can be processed independently,

at least in the first phase. Results can then be collected (reduced) in a second processing phase, with key-value pair communication between the two phases. MapReduce features a simple but expressive programming paradigm, which hides parallelism and fault-tolerance. The large input files can be divided automatically into smaller file splits that are processed on different compute nodes, normally by dividing files at the boundaries of GFS data blocks that are stored on different compute nodes. These file splits are normally distributed over all the compute nodes, and MapReduce attempts to move computation to the nodes where the data records reside. Scalability is obtained by the ability to use more resources as demand increases, and reliability is obtained by fault-tolerance mechanisms based on replication and redundant execution.

Note that Google's MapReduce system achieves its high performance by treating compute nodes as homogeneous and taking full control over all the compute nodes for dedicated usage, which is a suitable assumption for its own compute farms but not necessarily for the general computing communities that have been using distributed heterogeneous resources in clusters and grids under shared usage.

2.3 Hadoop

Hadoop [34] is the open source implementation of important parts of Google's data processing systems. Corresponding to Google's systems, Hadoop also contained three major components when it was created:

1. Hadoop's MapReduce: corresponding to Google's MapReduce programming paradigm and execution environment.

2. Hadoop's Distributed File System (HDFS): corresponding to Google File System.

3. The HBase storage system for sparse structured data: corresponding to Google's BigTable.

The MapReduce model is designed to process large-scale input data that is divisible into a long sequence of atomic input records that each can be processed independently. Hadoop's MapReduce provides a suitable platform to run MapReduce applications because it hides all the details about splitting input data, reserving compute nodes, scheduling computation with data locality concerns on available compute nodes, and gathering the final result data. Users only need to write their program using the MapReduce API provided by Hadoop, put their input data into HDFS and simply execute a command to run their application automatically in parallel on the compute nodes with fault tolerance handled transparently by the MapReduce environment. Hadoop's HDFS is a flat-structure distributed file system. It is visible to all cloud nodes and provides a uniform global view for file paths in a traditional hierarchical structure. File contents are not stored hierarchically, but are divided into low level data chunks and stored in datanodes with replication. Data chunk pointers for files are linked to their corresponding datanode locations at namenode. HBase is the database component of Hadoop. Any metadata information such as descriptions or comments for jobs can be easily stored and queried in HBase. Hadoop is used extensively by companies like Yahoo, Facebook, etc., and is proven to scale and perform well [32], like the original implementation by Google.

2.4 HBase

HBase [21] is a column-oriented store implemented as the open source version of Google's BigTable system. Column-oriented data stores (column stores) are gaining attention in both academia and industry because of their architectural support for extensive data scalability as well as data access efficiency and fault

tolerance on clouds. Data in typical column stores such as Google's BigTable system are organized internally as nested key-value pairs and presented externally to users as sparse tables. Each row in the sparse tables corresponds to a set of nested key-value pairs indexed by the same top level key (called "row key"). The second level key is called "column family" and the third level key is called "column qualifier". Each column in a row corresponds to the data value (stored as an uninterpreted array of bytes) indexed by the combination of a second and third level key. Scalability is achieved by transparently range-partitioning data based on row keys into partitions of equal total size following a shared-nothing architecture. These data partitions are dispatched to be hosted at distributed servers. As the size of data grows, more data partitions are created. In theory, if the number of hosting servers scales, the data hosting capacity of the column store scales. Concerning data access, at each data hosting server, data are physically stored in units of columns or locality groups formed by a set of co-related columns rather than on a per row basis. Column stores derive their name from this property. This makes scanning a particular set of columns less expensive since the data in other columns need not be scanned. Persistent distributed data storage systems (for example, with file replication on disk) are normally used to store all the data for fault tolerance purposes.

In HBase, applications store data into sparse tables, which are tables with rows having varying numbers of columns. Every data row has a unique and sortable row key. Rows in each table are automatically sorted by row keys. Columns are grouped into column families. The data for the same column family are stored physically close on disk for efficient querying. The data value for each row-column combination is uniquely determined by the row key, column and timestamp. The timestamp facilitates multiple data versions. Timestamps are either explicitly passed in by the user when the data value is inserted, or implicitly assigned by the system. Table 2.1 shows an example HBase table taken

Table 2.1: An example HBase table taken from the HBase website (slightly modified). A column is specified by the concatenation of a column family name and a column qualifier. For example, in the first column, "anchor" is the name of a column family and "cnnsi.com" is a column qualifier. The symbols "ts8" and "ts9" denote timestamps.

Row Key	anchor: cnnsi.com	anchor: my.look.ca
com.cnn	ts9: cnn	ts9: cnn.com ts8: bbc.com

from the HBase website (slightly modified). The table contains one row with row key "com.cnn" and columns "anchor: cnnsi.com" and "anchor:my.look.ca" grouped by column family "anchor:". Each HBase row-column pair, for example, row "com.cnn" and column "anchor:my.look.ca", is assigned a timestamp (a Java Long type number).

HBase employs a master-slave topology. Tables are split horizontally for distributed storage into row-wise "regions". The regions are stored on slave machines called "region servers". Each region server hosts distinct row regions with region data stored in persistent storage (HDFS). A pool of multiple masters is supported eliminating a single point of failure. When a region server fails, its data can be recovered from HDFS and be hosted by a new replacement region server. The scalability of HBase is attributed to the shared-nothing architecture of data regions hosted by distributed region servers. However, there could still be bottlenecks in the system in the case when a single region server gets overloaded by too many requests on the same data region. In fact, at each region server, all the read/write requests to a particular row in a table region are serialized.

Currently, only simple queries using row keys and timestamps are supported in HBase, with no SQL or join queries. It is also possible to scan and iterate through a set of columns row by row within a row range. However inadequate the query

capability may seem, if the tables are formulated properly, some efficient problem-specific search methods can be developed, especially for data with graph-like structures such as directed acyclic graphs for workflows, which is the topic of Chapter 4.

Chapter 3

Preliminary and Supportive Work

3.1 Research Overview

The PhD research project reported on in this thesis started in September 2006. At that time, cloud computing was just emerging as a concept and the term "grid computing" was still used more commonly. The author's first research project was on the "GridBASE" system [11]. GridBASE is a previously developed database-driven light-weight distributed job execution system for running task-farmable applications on clusters/grids. The core concept behind GridBASE is to use computing power on-demand in a similar way to how electricity is provided in a power grid, treating every node in the system as homogeneous. The author refined GridBASE's coding in terms of modularity and portability to use other database systems rather than Oracle alone, and demonstrated its applicability in [11] and [10]. The application of GridBASE to RNA folding, a real-world large-scale bioinformatics application, resulted in a journal paper [25]. This project raised the author's interest in cloud computing which shares a similar philosophy of using resources on-demand. The next step was to investigate Google's MapReduce framework and its at that time newly-developed open

source implementation - Hadoop.

The initial Hadoop project [45] was a case study on live cell image processing. It tackled the problem of executing legacy applications (MATLAB) with non-standard Hadoop input formats (i.e. image files instead of textual inputs) through the Hadoop MapReduce framework. The legacy applications were executed by Map-only MapReduce program wrappers scheduled through Hadoop based on program execution and file staging metadata maintained in HBase. This research was one of the earliest efforts to apply Hadoop to large-scale scientific data processing, since early Hadoop applications were focused on server side computations such as web indexing, etc. The method to execute MATLAB applications in a MapReduce environment in this case study is also used in later projects to execute general legacy applications/scripts that can be invoked through simple commandline execution.

Through the previous study, the author discovered the need for a Hadoop-based data processing framework that is backward compatible with legacy applications and easy to use for scientists lacking programming skills. This motivated the design of CloudWF [46], a light-weight computational workflow system to handle workflow jobs composed of multiple MapReduce/legacy applications, which is the subject of Chapter 4. With CloudWF, workflows can be easily constructed using a simple workflow description method to stitch together existing commandline invocations and scripts. This is the first workflow management system targeted to take advantage of the Hadoop/HBase architecture for scalability, fault tolerance and ease of use. Firstly, CloudWF does not require any centralized workflow engine process to control the execution flow of each workflow instance. Instead, it uses a novel way to store the workflow graph structure into HBase sparse tables for efficient querying and workflow dependency management. In addition, to easily farm out workflows to cloud compute nodes, CloudWF splits each workflow instance into independently executable blocks (for program exe-

cution) and connectors (for file staging and event notification). Compared with other computational workflow systems that require one workflow execution controller process per workflow instance executed, CloudWF makes load balancing, execution coordination and fault tolerance easier.

Through developing CloudWF, it was noticed that some distributed components need to concurrently update data stored in shared tables in HBase at the risk of generating inconsistent data. However, there wasn't any simple transactional data management system available for HBase to handle this issue. This led the author to the design of HBaseSI, a non-intrusive client library supporting multi-row distributed transactions with global strong snapshot isolation (SI) on HBase, which is the subject of Chapter 5. HBaseSI is the first SI solution for HBase, and it functions on top of bare-bones HBase rather than implementing and deploying an extra middleware layer over HBase. It requires no changes to server configuration and no extra programs to be deployed. Unlike traditional ways of handling distributed transactions, HBaseSI allows clients to make commit decisions autonomously through the client library based on transaction metadata stored in a separate set of system tables, avoiding the need to modify existing user tables as well as the overhead of using complicated consensus-based protocols, explicit atomic broadcast, or transactional locks on data for distributed synchronization and concurrency control. In this way, an easy-to-employ solution is provided that is non-intrusive to server configuration and client data. A novel distributed queuing mechanism implemented by standard HBase tables was employed to guarantee consistent and fresh global snapshots as well as strict global commit ordering. Consequently, the system supports non-blocking start of transactions with fresh data snapshots and non-blocking reads. Furthermore, HBaseSI allows transactions to perform writes to user data tables without waiting till commit time, and it employs a simple and effective straggler handling mechanism. The approach adopted for HBaseSI can be widely applied to other

column stores that feature similar data organization as HBase. The initial version of the SI system was published in [48], and a significantly improved version in [49]. It is worth noting that Google researchers published independently and at the same time the Percolator system [36] for supporting multi-row distributed transactions with SI on BigTable. While the systems share some important design ideas, there are also significant differences. Additionally, Percolator relies on the "single-row transaction" functionality specific to BigTable, and therefore cannot directly be implemented for HBase.

Having worked extensively with Hadoop, the author found it practically difficult to operate a Hadoop cluster on existing cluster systems because Hadoop's concept is incompatible with cluster batch job queuing systems. Given this, the author designed the CloudBATCH system [47] to use Hadoop/HBase as a cluster management system in lieu of batch job queuing systems to accept both MapReduce and legacy batch job submissions, removing the complexity and overhead of making the two kinds of systems compatible. CloudBATCH provides a nice alternative to easily configure a set of resources to cater for both MapReduce and legacy application needs.

The main contributions of this thesis, CloudWF and HBaseSI, are presented in Chapters 4 and 5, respectively, and some details on the preliminary and supportive work for the thesis are given in the remainder of this chapter.

3.2 Preliminary Work

3.2.1 GridBASE

As continuation of a predecessor project called TaskSpaces [9], a new grid computing system was developed by De Sterck and collaborators, called GridBASE [11]. The purpose of GridBASE was to make it easy to grid-enable a certain class of (task-farmable) applications. GridBASE was designed as a lightweight

and portable grid computing solution. Industry-strength database technology played a key role in the design of the framework. The general idea was to use a database server as a central node for task and data control. More specifically, the database was used as a reliable and remotely accessible component both for storing and organizing the configuration information of the grid, and for managing information related to the grid users and the jobs and tasks they submit for execution. Users are only concerned with submitting jobs and getting results through a simple interface that hides the heterogeneity of the grid. Scheduling and load-balancing are taken care of automatically by the database component which acts as a superqueue. In this way, decentralization in space and time is achieved.

GridBASE has four types of components: worker, broker, database operator, and client application. Their roles in GridBASE are shown in the figure below. The thick lines represent information transfer through database access. The thin lines represent direct control interactions between system components.

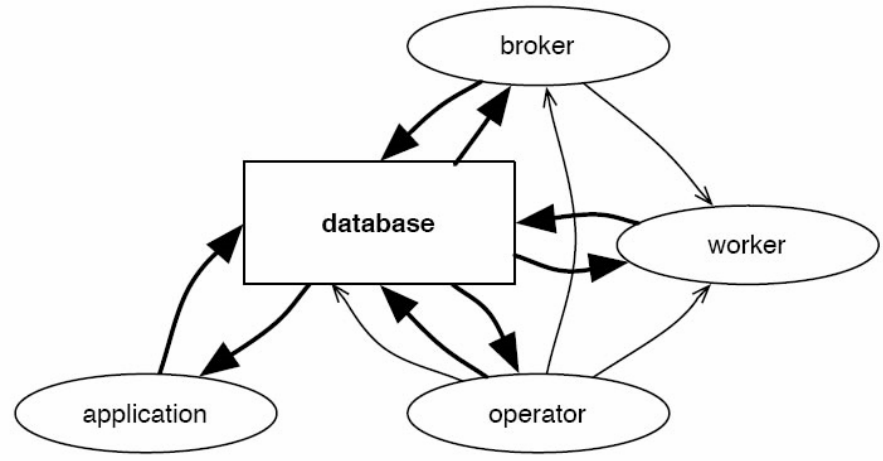


Figure 3.1: GridBase design overview.

Grid users use the client application to submit their jobs to the central

database. Each job is composed of tasks and their program files and input data. Workers register with the database when they are available. Brokers periodically query the database and match available tasks with available workers. After matching, brokers notify the workers that have been assigned to tasks. Workers then download tasks from the database, execute them, and upon task completion place the results back into the database. The "operator" role is conceptually responsible for providing computing resources and assuring system availability and maintenance.

GridBASE is generally suitable for users requiring the execution of big jobs that can be decomposed into independent sub-tasks. These types of applications are also referred to as task-farmable applications. Application code can be written in any language, and simple workflow support is provided. In our prototype implementation we experimented with code delivery and input and output file delivery via the database component. Some usage scenarios are bioinformatics problem solving, multi-tier web server hosting, web-based applications requiring a high throughput front end and an easy-to-deploy backend, etc. The original prototype of GridBASE was built by a former student of the research group. The author contributed to the later phases of the GridBASE project, fixing some system defects, rewriting part of the system and better encapsulating the database operations of GridBASE into more extensible structures. One conference paper [11] and one book chapter [10] were published about GridBASE.

GridBASE was a distributed computing framework that already tried to accomplish several goals that cloud computing environments typically target, such as on-demand scalability, reliability, user transparency and ease of use. We used GridBASE for distributing RNA folding tasks over a collection of clusters, and for organizing the tasks and their input and output in collaboration with researchers from the University of Colorado, Boulder. The results have been published in the journal RNA [25].

3.2.2 Hadoop Case Studty

The GridBASE project was completed at the end of 2008. By that time, cloud computing was starting to emerge as a promising new paradigm. As a logical next step, we decided to explore cloud computing for scientific applications.

We performed a case study of scientific data processing using Hadoop and published a conference paper [45]. The purpose was to explore the use of Hadoop-based cloud computing for scientific data processing problems. At that time, it was one of the few research efforts in the direction of applying Hadoop to problems other than what it was designed for. We used Hadoop to develop a simple user application that allows processing of scientific data (live cell image files) with MATLAB on cloud nodes. The scientific data processing problem considered in this case study is simple: the workload is divisible, without the need for communication between tasks. There is only one processing phase, and thus there is no need to use the "reduce" phase of Hadoop's MapReduce. Nevertheless, our solution relies on many of the other features offered by the cloud concept and Hadoop, including scalability, reliability, fault-tolerance, easy deployability, etc. At the same time, we developed a small extension to Hadoop's MapReduce which allows it to easily handle various input formats for scientific data processing applications. Our approach can be generalized easily to more complicated scientific data processing jobs (such as jobs with input data stored in a relational database, jobs that require a reduce phase after the map phase, scientific workflows, etc.).

As a motivation for scientific data processing on clouds, we briefly describe the application problem. The scientific goal of the case study was to investigate the complex molecular interactions that regulate biological systems. To achieve this scientists from McGill University developed an imaging platform to acquire and analyze live cell data at single cell resolution from populations of cells studied under different experimental conditions. The key feature of the acquisition

system is its capability to record data in high throughput both in the number of images that can be captured for a single experimental condition and the number of different experimental conditions that can be studied simultaneously. This is achieved by using an automated bright field and epifluorescence microscope in combination with miniaturized printed live cell assays. The acquisition system has a data rate of 1.5 MBps, and a typical 48 hour experiment can generate more than 260 GB of images, recorded as hundreds of multichannel videos each corresponding to a different treatment (Figure 3.2).

The data analysis task for this platform is daunting: thousands of cells in the videos need to be tracked and characterized individually. The output consists of precise motion, morphological and gene expression data of each cell at many different timepoints. While image analysis is the bottleneck in the data processing pipeline, it happens to be a good candidate step for parallelization. The data processing can be broken up into hundreds of independent video analysis tasks. The image analysis task uses computationally intensive code written in MATLAB to both analyze the data and generate result files. The analysis method solves the segmentation and tracking problem by first running a watershed segmentation algorithm. We then perform tracking by matching the segmented areas through time by using information about the cell shape intensity and position. As a final step we detect cell division events. The output data of the analysis is represented as a set of binary trees, each representing a separate cell lineage, where each node stores detailed information about a single cell at all time points.

For each experiment (a specific set of parameters for the live cells under study), several data acquisitions may be performed. Typically, each acquisition generates 600 folders (one per field, see Figure 3.2), in which 900 acquired images are stored. Each image has a resolution of 512 x 512 16-bit pixels (512 KB), resulting in a total data size of 260 GB per acquisition. Different types of analysis (or data processing) jobs may be performed on the data gathered in

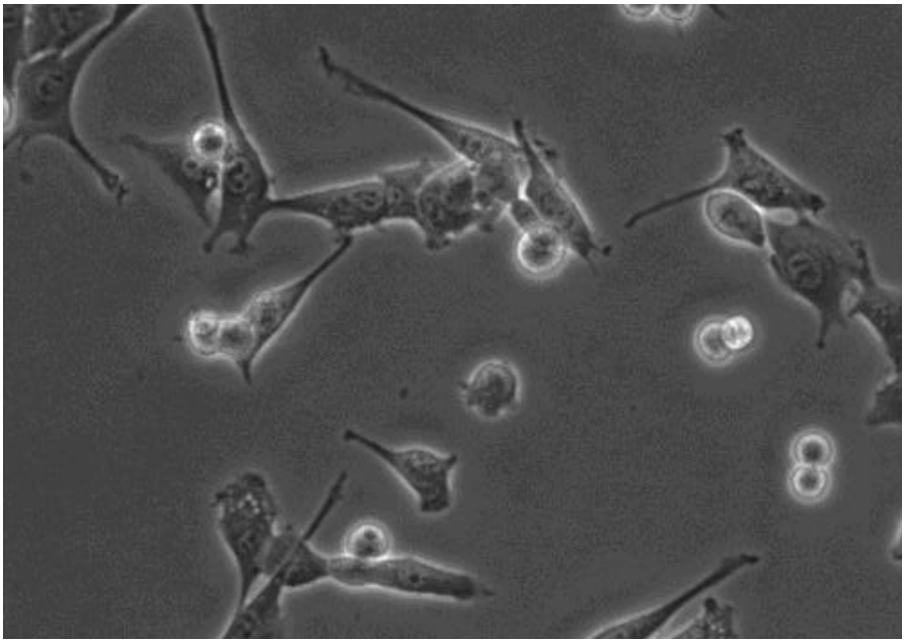


Figure 3.2: Single microscope image with about two dozen cells on a grey background. Some interior structure can be discerned in every cell (including the cell membrane, the dark grey cytoplasm, and the lighter cell nucleus with dark nucleoli inside). Cells that are close to division appear as bright, nearly circular objects. In a typical experiment images are captured concurrently for 600 of these "fields". For each field we acquire about 900 images over a total duration of 48 hours, resulting in 260 GB of acquired data per experiment. The data processing task consists of segmenting each image and tracking all cells individually in time. The cloud application is designed to handle concurrent processing of many of these experiments and storing all input and output data in a structured way.

each acquisition. Analysis jobs are normally performed using MATLAB programs, and the analysis can be parallelized easily, since each field can be processed independently.

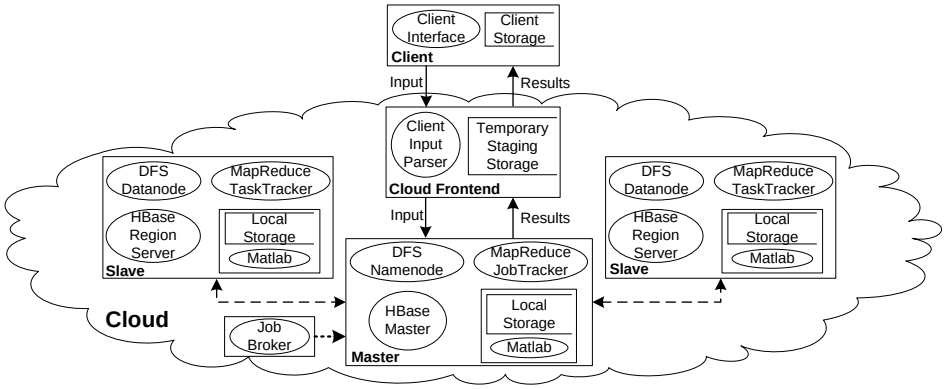


Figure 3.3: System design overview for the Hadoop case study project.

Figure 3.3 shows the design of our Hadoop-based system for processing the data gathered in the live cell experiments. Our system puts all essential functionality inside a cloud, while leaving only a simple Client at the experiment side for user interaction. In the cloud, we use HDFS to store data, we use two HBase tables, called "Data" and "Analysis", to store metadata for data and for analysis jobs, respectively, and we use the MapReduce environment to schedule computation. Each row in the "Data" table represents a piece of experiment data with the path in HDFS and the data descriptions; each row in the "Analysis" table represents an analysis job submission with its completion status. The Client can issue three types of simple requests to the cloud application (via the Cloud Frontend): a request for transferring experiment data (an acquisition) into the cloud's HDFS, a request for performing an analysis job on a certain acquisition using a certain analysis program, and a request for querying/viewing analysis results. The Cloud Frontend processes Client requests. When it receives a data transfer request, it starts a Secure Copy (scp) connection to the Client's local

storage, and transfers data to its Temporary Staging Storage. It then puts the staged data from the Temporary Staging Storage into the HDFS. It also updates the "Data" table in HBase to record the metadata that describes the acquisition (including the range of fields recorded in the acquisition, and the HDFS path to the folder containing the fields). If the request is job submission or query, it inserts a record into the "Analysis" table or queries the "Analysis" table for the required information. The Job Broker shown in the bottom left corner of Figure 3.3 polls the "Analysis" table through regular "heart-beat" intervals to discover newly inserted unprocessed jobs, and submits the Mapper-only MapReduce jobs to the MapReduce environment. In our case, since MATLAB is a native program that cannot use HDFS files directly but requires its input and output files to reside on the local file system, we need to get files out of HDFS and copy them to local storage before MATLAB can start processing. Therefore, each Mapper first stages the needed data to the local storage and then invokes the MATLAB application through commandline. After MATLAB processing completes, the results are put back into HDFS, and when all Map tasks have been completed the "Analysis" table is updated accordingly to mark the status of job completion.

In order to use Hadoop for our problem, it was necessary to extend the default way how Hadoop handles input data formats, how it handles the way input data is split into parts for processing by the map workers, and how it handles the extraction of atomic data records from the split data. For our scientific data processing application, an atomic data record is a folder of images corresponding to one field (total data size 512KB x number of images in that folder). The granularity is thus much coarser than in standard Hadoop applications, and when we split the input, we may require just a few atomic input records per split (i.e., per map worker). In this case, it is more convenient and efficient to let the user control the number of splits, and to perform the split exactly at the boundary of the atomic input records rather than at HDFS block boundaries as is standard in

Hadoop. Also, it is more natural to provide the input indirectly, via paths to the HDFS folders that contain the image files, rather than providing the complete data set serialized into a single large file for all map tasks. We implemented this approach by writing new classes that implement the Hadoop interfaces for handling input and input splits.

Our prototype system performed satisfactorily and provided good insight into how Hadoop can be extended to support simple scientific computing scenarios [45]. Considering the desirable properties of Hadoop and its good prospects in large-scale data processing, we decided to further investigate the possibility of enhancing Hadoop for performing more complicated data processing tasks in the future phases of the PhD research.

3.3 Supportive Work

3.3.1 CloudBATCH

As MapReduce becomes more and more popular in data processing applications, the demand for Hadoop clusters grows increasingly. However, Hadoop's concept is incompatible with existing cluster batch job queuing systems and it is designed under the assumption that it has a dedicated cluster under its full control. Hadoop also lacks support for user access control, accounting, fine-grain performance monitoring and legacy batch job processing facilities comparable to existing cluster job queuing systems, making dedicated Hadoop clusters less amenable for administrators, and for users with hybrid computing needs involving both MapReduce and legacy applications. As a result, getting a properly suited and sized Hadoop cluster has not been easy in organizations with existing clusters. Under this background, we have worked on a prototype solution called "CloudBATCH", enabling Hadoop to function as a traditional batch job queuing system with enhanced management functionality for cluster resource management [47].

With CloudBATCH, a complete shift to Hadoop for managing an entire cluster to cater for hybrid computing needs becomes feasible.

There are two existing solutions to compare CloudBATCH with, each representing a typical research direction to solve Hadoop's incompatibility issue with legacy cluster management systems. One is Hadoop on Demand (HOD) [20], which extends Hadoop to make it compatible with legacy systems, and the other is Sun Grid Engine (SGE) with Hadoop integration [35], which adapts a legacy job queuing system to make it compatible with Hadoop. However, neither of these existing solutions are natural or elegant.

HOD is added to Hadoop for dynamically creating and using Hadoop clusters through existing queuing systems. The idea is to make use of the existing cluster queuing system to schedule multiple jobs that each run a Hadoop daemon on a compute node. These running daemons together create an on-demand Hadoop cluster. After the Hadoop cluster is set up, user-submitted MapReduce applications can be executed. A simple walkthrough of the process for creating a Hadoop cluster and executing user-submitted MapReduce jobs through HOD is as follows:

1. User requests from cluster resource management system a number of nodes on reserve and submits a job called RingMaster to be started on one of the reserved nodes. MapReduce jobs to be executed on Hadoop cluster are submitted as well.

2. Nodes are obtained and RingMaster is started on one of the reserved nodes.

3. RingMaster starts one process called HodRing on each of the reserved nodes.

4. HodRing brings up on-demand Hadoop daemons (namenode, jobtracker, tasktracker, etc.) according to the specifications maintained by RingMaster in configuration files.

5. The MapReduce jobs that were originally submitted by the user are executed on the on-demand cluster.

6. Upon completion of the MapReduce jobs, the Hadoop cluster gets torn down and resources are released.

As seen from the above walkthrough of an HOD process, data locality of the external HDFS is not exploited because the reservation and allocation of cluster nodes does not take into account where the data to be processed are stored, violating an important design principle and reducing the advantage of the MapReduce framework. Another problem with HOD is that the HodRing processes are started through ssh by RingMaster, and the cluster resource management system is unable to track resource usage and to perform thorough cleanup when the cluster is torn down.

SGE with Hadoop Integration is released by Oracle, enabling SGE to work with Hadoop without requiring a separate dedicated Hadoop cluster. The core design idea is similar to HOD in that it also tries to start an on-demand Hadoop cluster by running Hadoop daemons through the cluster resource management system on a set of reserved compute nodes. The difference with HOD is that SGE takes into account data locality when scheduling tasktrackers and supports better resource usage monitoring and cleanup because tasktrackers are directly started by SGE as opposed to be started by HodRing in HOD. The main problem, apart from locking users down to using SGE, lies in its mechanism of exploiting data locality and the non-exclusive usage of compute nodes.

Figure 3.4 illustrates how SGE with Hadoop integration works:

1. A process called Job Submission Verifier (JSV) talks to the namenode of an external HDFS to obtain a data locality mapping from the user submitted MapReduce program's HDFS paths to data node locations in blocks and racks. Note that the "Load Sensors" are responsible for reporting on the

block and rack data for each execution host where an SGE Execution Daemon runs.

2. The SGE scheduler starts the Hadoop Parallel Environment (PE) with a jobtracker and a set of tasktrackers as near the data nodes containing user application input data as possible.

3. MapReduce applications that were originally submitted by the user are executed. Because several tasktrackers might have been started on the same physical node, physical nodes could be overloaded when user applications start to be executed.

4. Upon completion of the MapReduce jobs, the Hadoop cluster gets torn down and resources are released.

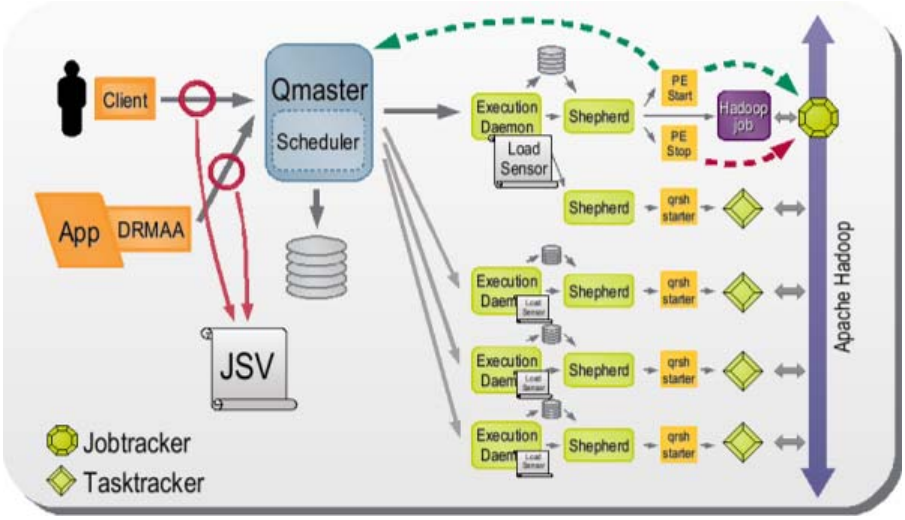


Figure 3.4: SGE Hadoop Integration (taken from online blog post by Oracle).

As seen above, the major advantage of SGE compared to HOD is the utilization of data locality information for scheduling tasktrackers. However, a compute node could get overloaded because multiple tasktrackers may be started on

the same node for data locality concerns to execute tasks. In other words, performance isolation is sacrificed for data locality. This type of problem was reported by users in their real-world applications. In this case, an unpredictable number of Hadoop speculative tasks [44] may be started on the other idling nodes where data do not reside, incurring extra overhead in data staging and waste of resources for executing the otherwise unnecessary duplicated tasks. The unbalanced mingled execution of normal and speculative tasks may further mix up Hadoop schedulers built in with the dynamically created Hadoop cluster which are unaware of the higher level scheduling decisions made by SGE, harming performance in unpredictable ways. Even if the default Hadoop speculative task functionality is turned off, the potential danger of overloading a node persists, which could further contribute to unbalanced executions of Map tasks that result in wasting cluster resources as explained below. SGE also has an exclusive host access facility. But if this facility is required, then the data locality exploitation mechanism would be much less useful because normally a data node would potentially host data blocks needed by several user applications while only one of them can benefit from data locality in the case with exclusive host access.

Most importantly, both HOD and SGE suffer from the same major problem intrinsic to the idea of creating a Hadoop cluster on-the-fly for each user MapReduce application request. The problem is a possible significant waste of resources in the Reduce phase, where nodes might be idling when the number of Reduce tasks to be executed is much smaller than the number of Map tasks that were executed in the first stage. This is because each of the on-demand clusters is privately tailored to a single user MapReduce application submission and the size of the Hadoop cluster is fixed at node reservation time. If the user MapReduce application requires far more Map tasks than Reduce tasks and the number of nodes are reserved matching the Map tasks (which is usually what users would request), many of the machines in the on-demand Hadoop cluster will be idling

when the much smaller number of Reduce tasks are running at the end. The waste of resources could also occur in the case of having unbalanced executions of Map tasks, in which case a portion of Map tasks get finished ahead of time and wait for the others to finish before being able to enter the Reduce phase. On a dedicated Hadoop cluster, all these effects are smoothed out because it typically processes multiple MapReduce jobs from multiple users at the same time, resulting in much higher efficiency.

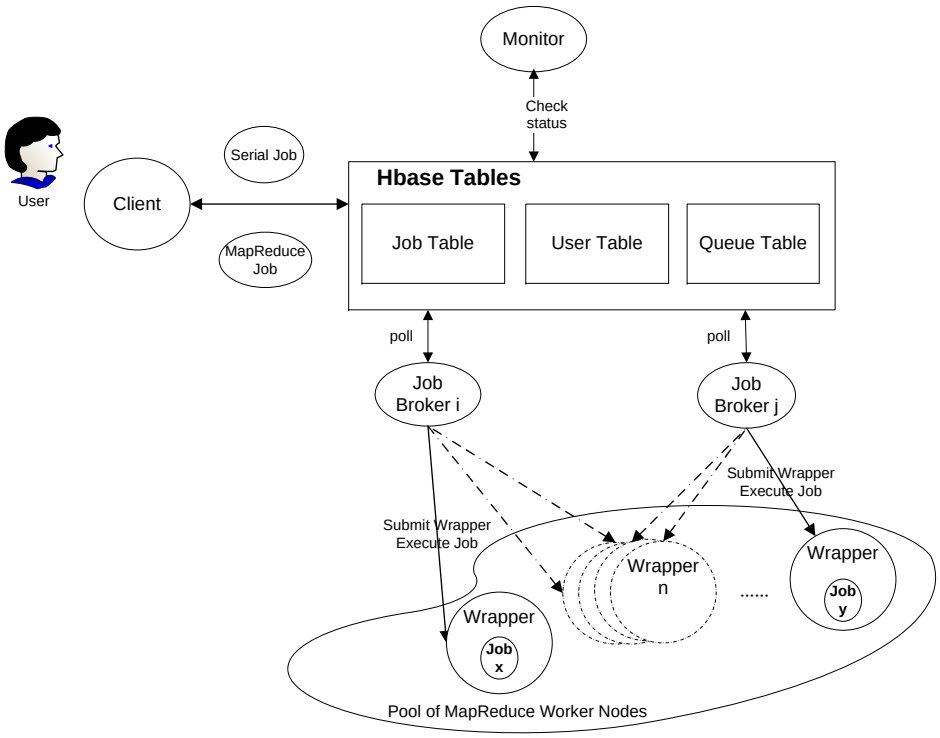


Figure 3.5: CloudBATCH architecture overview.

Different from other existing solutions, CloudBATCH [47] is designed as a fully distributed batch system on top of Hadoop and HBase. It uses a set of globally accessible HBase tables across all the nodes to manage metadata for jobs and resources, and run jobs through Hadoop MapReduce for transparent data and computation distribution. More specifically, it uses a dedicated Hadoop

cluster to avoid the efficiency problems identified above, it enables simple legacy applications by a commandline approach, and it adds basic user access control and accounting. Figure 3.5 shows the architecture overview of the CloudBATCH system. CloudBATCH has several distributed components: Clients, Job Brokers, Wrappers and Monitors. The general sequence of job submission and execution using CloudBATCH is as follows: Users use Clients to submit jobs to the system. Job information with proper job status is put into HBase tables by the Client. In the meantime, a number of Job Brokers are polling for the HBase tables to find jobs ready for execution. If a job is ready, a Wrapper containing the job is submitted to Hadoop MapReduce by the Job Broker. The Wrapper is responsible for executing the job through commandline invocation and monitoring the execution status of the job as well as updating relevant records concerning job and resource information in HBase tables. The Wrapper is also responsible for enforcing some job policies such as execution time limit. Monitors are responsible for detecting and handling failures after Wrappers are submitted to Hadoop. Since CloudBATCH is not a focus of this thesis, the interested reader is referred to [47] for further details, and we suffice here with the above discussion illustrating the difficulties of integrating MapReduce and legacy applications and outlining some possible approaches.

Chapter 4

CloudWF

This chapter describes CloudWF, the first lightweight computational workflow system naturally integrated with the Hadoop MapReduce environment for building and running computational workflows composed of both MapReduce and existing legacy programs on Hadoop clouds. It directly inherits several desirable properties from Hadoop, such as fault tolerance and scalability in terms of data size. The major novelty of the CloudWF design lies in several aspects: a simple workflow description method that encodes workflow blocks and block-to-block dependencies separately as standalone executable components, making it easy to reuse existing workflow components and perform runtime workflow structure change; a file relaying mechanism through the use of HDFS, achieving automatic and transparent file staging between connected workflow blocks; a new workflow storage method that uses HBase to store workflow information for efficient workflow block dependency reconstruction at runtime, enabling multiple workflow instances to be executed concurrently with no need for a director per workflow instance which incurs less resource utilization per workflow instance execution.

4.1 Introduction

Due to the scalability, fault tolerance, transparency and easy deployability inherent in the cloud computing concept, Hadoop has proven highly successful in the context of the processing of very large data sets that can be divided easily in parts that can be processed with limited inter-task communication. However, Hadoop does not support workflow jobs and there exist no well-established computational workflow systems on top of Hadoop for automatic execution of complex workflows with large data sets in a cloud environment.

Computational workflows are essential in scientific application scenarios. The main purpose of computational workflows is to streamline and automate complex computational processes that require multiple interdependent computing steps and data staging in between. In general, computational workflows are directed graphs where the nodes represent computational components and the edges represent the temporal order of component executions as well as the data that flow between components. The particular type of computational workflow we target is described as follows:

1. Each workflow is represented as a directed acyclic graph (DAG). Nodes in a DAG are called "blocks"; edges are called "connectors". Each block represents a single executable program. Each connector represents either the data staging between the connected blocks or just the temporal order of block executions (dependencies).

2. The executable program in each block is either a Hadoop MapReduce program or an existing legacy program (programs not built by using the Hadoop MapReduce API) such as a FORTRAN or MATLAB program, invoked by a commandline command or script.

3. A block can only become active and start execution once, not before all

the block's incoming connectors finish execution. This is different from dataflow applications where every block is scheduled to start running at the beginning and stays active at all times, waiting for input data. In this thesis, we distinguish dataflows from workflows by this trait.

Many scientific workflow systems on clusters and grids exist for various usage needs such as the systems described in [27, 29, 30, 13], see also the review paper [43]. With the advent of cloud computing, those existing systems still work well according to their design if clouds are used in the same way as clusters and grids [24]. However, it is not easy to deploy those systems on top of newly developed cloud computing frameworks such as Hadoop and make them work well. This is because the new cloud computing frameworks and the existing systems are designed with different emphasis under different backgrounds. The new cloud computing frameworks emphasize massive scalability and fault tolerance. As a result, they normally employ simplifications in resource management and job scheduling policies, such as providing users with dedicated and homogeneous resources within a single Virtual Organization (VO) [17], providing a distributed file system to remove the need for manual file transfer between cloud compute nodes with various protocols (such as ftp, sftp, etc.), and hiding away as many details of the underlying resources as possible (such as machine locations and configurations) so that complex resource discovery and reservation due to resource heterogeneity are no longer necessary. Indeed, faced by peta-scale data processing needs with easy-to-access machines at very large scales (for example, machines provided by Amazon [15]), the paramount issue now is how to simply run data processing jobs worry-free. On the contrary, the existing systems are designed for use on clusters and grids, and emphasize orchestrating heterogeneous resources that are each of limited scale with various hardware and software configurations. As a result, the workflow execution mechanisms of the existing systems need to be designed to handle the complexity and heterogeneity of the

resources, requiring a lot of detailed information about the underlying computing environments for resource management and job scheduling to obtain optimized performance on workflow executions, which would become further complicated in large-scale systems where managing dynamic resource information in real-time for each participating node is very difficult. Clouds provide better solutions for these issues. Additionally, for example, the systems described in [27, 29, 30] all need a workflow execution director role for every running workflow instance for managing the resource mapping and execution sequence of workflow components, which means extra resources are needed for running the director. The directors may become performance bottlenecks especially when handling many concurrent and large-scale workflow executions. Most importantly, existing workflow solutions do not easily handle Hadoop MapReduce jobs since the required Hadoop clusters are not compatible with the queuing systems that most existing workflow solutions are designed around.

Currently, there exist no well-established cloud environment computational workflow systems on top of Hadoop to easily build and run computational workflows composed of MapReduce and existing legacy programs (See Section 4.4). Our research was motivated by the lack of workflow systems in Hadoop concerning the type of workflow applications we target, and the need for such a system for automating large-scale data processing tasks in various fields, such as bioinformatics, space weather simulation, phone-log processing, etc. Our CloudWF system was designed with the following target use case in mind: A group of scientists collaborating in a research lab frequently runs workflows of existing scientific applications (divisible or MapReducible workloads) with large data volumes. What CloudWF wants to achieve is to provide scientists who set up a private cloud on their lab cluster or use public cloud resources, with an easy way to build and execute workflows transparently on their cloud.

CloudWF is a lightweight computational workflow system for clouds based

on Hadoop. It is the first workflow system that can handle both MapReduce and legacy applications on Hadoop clouds, and directly inherits several desirable properties from Hadoop, such as fault tolerance (task fault tolerance achieved through the automatic failed-task recovery mechanism of the Hadoop MapReduce execution environment; file fault tolerance achieved through the use of the redundant distributed file system HDFS) and scalability in terms of data size. CloudWF accepts from the user workflow description XML files having workflow blocks and connectors as workflow components, stores the component information in Hadoop HBase, and processes the components using the Hadoop MapReduce framework with workflow data and processing programs stored in HDFS. In CloudWF, each workflow block contains either a MapReduce or a legacy program; each workflow connector contains a block-to-block dependency which may involve file copying between connected blocks. HDFS is used as an intermediary for staging files between blocks that may execute on different cloud nodes. Both blocks and connectors can be executed independently with no concern of which workflow they belong to, while each of the workflow-wise block dependency trees is maintained and reconstructed implicitly based on the HBase records of the workflow components at runtime. As a result, there is no separate execution control for each workflow instance to keep track of dependencies: blocks and connectors of all workflows that are being executed at a given time are scheduled by the CloudWF system in a uniform way. This allows for efficient parallel execution of multiple workflows at the same time. With CloudWF and a Hadoop cloud environment, users can easily connect MapReduce or general unix commandline program invocations into workflows with almost no need to rewrite any commands to adapt to the workflow description method used. The details of file staging between blocks are hidden for the user: files used in workflow instance executions can be assumed to have already been staged to the local machine with no worries about file path and access protocol heterogeneity.

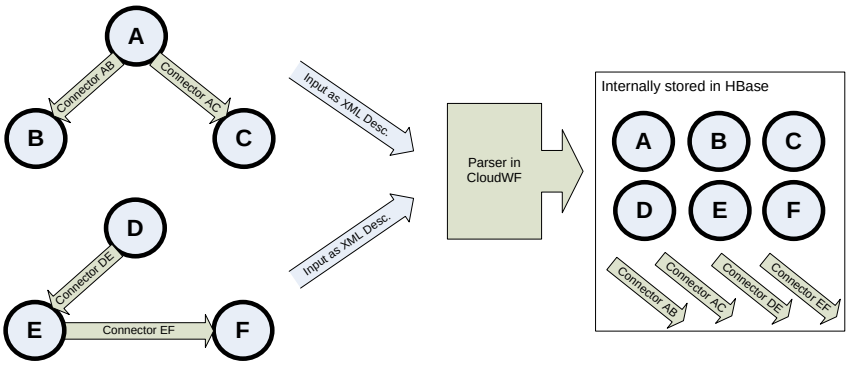


Figure 4.1: Breaking up the components of two workflows into independent blocks and connectors. The HBase tables store the dependencies between components implicitly.

The novelty of CloudWF design mainly lies in the following aspects.

1. It adopts a simple prototype workflow description method that encodes workflow blocks and block-to-block dependencies separately as standalone executable components, as illustrated in Figure 4.1. Using this method, existing workflow blocks can be simply reused and it is also easy to perform runtime workflow structure change because changing the structure of a workflow only requires adding, removing, or modifying some standalone connector without affecting any other parts of the workflow.

2. It adopts a new workflow storage method that uses HBase sparse tables to store workflow information internally and reconstruct workflow block dependencies at runtime. The directed acyclic graphs (DAGs) of the workflows are encoded in the sparse HBase tables, which are a natural data structure for encoding graphs and allow for efficient querying of the graph connections. As a result, there is no need for execution control per workflow instance to explicitly direct the flow of data, which incurs less resource utilization and enhances scheduling efficiency and scalability.

3. It adopts HDFS for transparent file staging between connected blocks. The

CloudWF system handles file relaying and re-naming in the background, isolated from users. Because of employing HDFS, users and the workflow system have a globally accessible file repository. Using HDFS to store and relay files is convenient and reduces the complexity of handling files in a distributed environment: the uniformity of the cloud environment allows for simple file handling solutions.

4. It uses Hadoop's MapReduce framework for simple scheduling and task level fault tolerance. This avoids conflicting schedules as described in [39] and allows for a seamless integration of both MapReduce and legacy applications: MapReduce applications can naturally run on Hadoop while legacy applications can be simply executed by Map-only MapReduce jobs with the Mappers calling the legacy applications through commandline invocation.

The remaining sections of this chapter are organized as follows. Section 4.2 describes the design and implementation of the CloudWF system in detail. Section 4.3 briefly describes an application usage scenario, followed by a discussion of related work in Section 4.4. Section 4.5 gives conclusions and describes future work.

4.2 CloudWF

As shown in Figure 4.2, CloudWF puts all essential functionalities inside a cloud, while leaving the user with a very simple interface for submitting workflow XML description files for specification of workflows, and commands to start workflows and monitor their execution. The user also has to place any input and program files into the user area of the cloud HDFS, and can retrieve workflow output from the HDFS as well. (Note that the HDFS is divided into two parts, a system part that is used by CloudWF to relay files between workflow blocks, and a user part

that users employ for workflow input and output.)

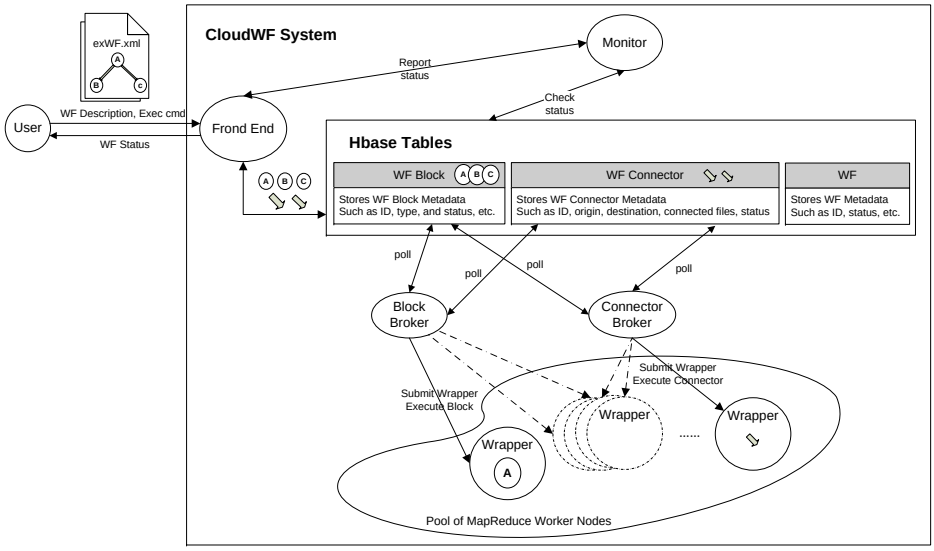


Figure 4.2: CloudWF system overview.

When the cloud Front End receives a user workflow description file, it parses the file into independent workflow components and stores the components into three HBase tables. In the workflow table ("WF"), we store workflow metadata, such as workflow IDs. In the workflow block table ("WFBlock"), we store block metadata such as ID and execution status. In the workflow connector table ("WFConnector"), we store block-to-block dependency information, including any file transfers that are required from the origin block to the destination block. The Block Broker polls the "WFBlock" table at small time intervals, submits Wrappers to execute ready-for-execution blocks, and manages some block status changes. The Connector Broker polls the "WFConnector" table, submits Wrappers to execute ready-for-execution connectors, and manages connector status changes. The pool of MapReduce worker nodes executes submitted blocks and connectors using the MapReduce framework and updates the corresponding block/connector status in the "WFBlock" and "WFConnector" tables so that Block Broker and Connector Broker can easily detect the results of the Wrappers' execution by

HBase queries. Real-time workflow execution status is obtained by the Monitor. When the Front End receives commands to retrieve workflow status, it calls the Monitor which in turn obtains information from the three HBase tables and sends back the results through the Frond End to users.

4.2.1 Expressing Workflows

CloudWF uses its own prototype workflow description method. The design objective is to allow users to easily and quickly construct cloud workflows from existing MapReduce and legacy unix commandline program invocations with minimum changes. The motivation for creating this new description method is threefold. First, we find that there exist few very lightweight languages that are straightforward to use and not much more complicated than scripting languages like bash scripts. Second, we want to deal specifically with both legacy and MapReduce program invocations. Third, we want to describe workflows in a way so that no extra overhead resulting from processing the language would be added when workflow executions are to be massively scaled up in Hadoop cloud environments.

To make the discussion specific, we consider two example commandline invocations, on each of the two types of commands (MapReduce and legacy unix commandline) that we want to embed in our workflows:

1. legacy unix commandline: cat inC1 inC2 > outC

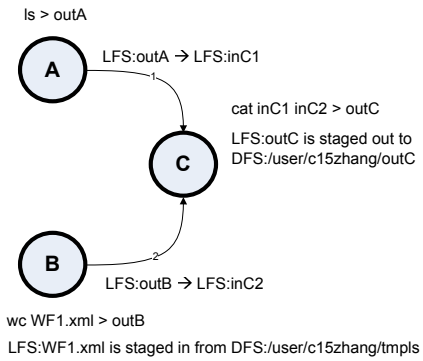
2. MapReduce commandline:
   /HadoopHome/bin/hadoop jar wordcount.jar org.myorg.WordCount
   /user/c15zhang/wordcount/input /user/c15zhang/wordcount/output

The first example is a simple unix cat with two input files and one output file that are stored in the working directory on the unix local file system (LFS) of the cloud node on which it executes, and the second is a simple Hadoop wordcount with

one HDFS input file and one HDFS output file (HDFS files are always referenced by their absolute HDFS path, since there is no concept of "working directory" in HDFS or Hadoop.). Note that, in the second example, the "hadoop" executable resides on the LFS of the cloud node on which it executes, and "wordcount.jar" (which contains org.myorg.WordCount) resides in the unix current working directory on the LFS of the cloud node on which the hadoop invocation executes.

In the rest of this section, we will explain CloudWF based on two simple example workflows, presented in Figures 4.3 and 4.4. The first example workflow (Figure 4.3) is composed of legacy blocks (type "legacy" in the XML file). Blocks A, B and C perform simple unix commands, and output files from blocks A and B are used as input for block C. CloudWF automatically stages these files from the cloud nodes on which A and B are executed, to the cloud node on which C executes, using HDFS as an intermediary. To this end, the user designates these files as outputs in their origin blocks in the XML file (blocks A and B), and as inputs in the XML description of block C. The user then describes connector components in the XML file that describe the order of execution in the workflow (C depends on A and C depends on B) and the files that have to be "connected" between the blocks. The input file of block B is staged into the workflow system from the user HDFS area, and the output file of block C is staged out from the workflow system to the user HDFS area. The precise mechanisms by which file staging is accomplished are described in Section 4.2.3, together with a more detailed explanation of the entries in the XML description file. For now we can just point out that the workflow ID of the first example workflow is "exWF", and that blocks and connectors in this workflow will be referred to as, for example, "exWF.A" and "exWF.connector1" in the HBase tables.

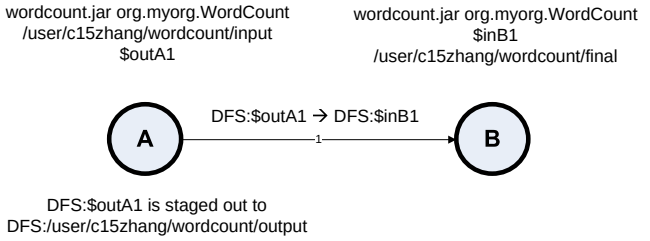
The second example workflow (Figure 4.4) is similar, but has blocks of MapReduce type. In block A a simple MapReduce wordcount is executed on a file that resides in the HDFS user directory (/user/c15zhang/wordcount/input),




```
<WF ID="exWF">
<block name="A" type="legacy">
    <command>ls > outA</command>
    <output1>LFS:outA</output1>
</block>
<block name="B" type="legacy">
    <command>wc WF1.xml > outB</command>
    <input1 from="DFS:/user/c15zhang/tmpls">LFS:WF1.xml</input1>
    <output1>LFS:outB</output1>
</block>
<block name="C" type="legacy">
    <command>cat inC1 inC2 > outC</command>
    <input1>LFS:inC1</input1>
    <input2>LFS:inC2</input2>
    <output1 to="DFS:/user/c15zhang/outC">LFS:outC</output1>
</block>
<connector name="connector1" origin="A" dest="C">
    <connect from="output1" to="input1"/>
</connector>
<connector name="connector2" origin="B" dest="C">
    <connect from="output1" to="input2"/>
</connector>
</WF>
```

Figure 4.3: First example workflow and XML file (legacy blocks).

and the result is stored in a HDFS file in a system location (referred to by $outA1 in block A). This result file is also staged out to a file in the user HDFS area (/user/c15zhang/wordcount/output). Note that the first part of the full Hadoop command is omitted in the XML command description such that the CloudWF user does not need to know the details about where Hadoop is installed on the cloud nodes. The user specifies in a connector in the XML file that $outA1 will also serve as input to block B, and CloudWF then makes the files accessible to block B (by a mechanism to be explained in Section 4.2.3). Block B performs a wordcount on the output file of block A, and puts the result in file /user/c15zhang/wordcount/final in the HDFS user area. Note that the HDFS files that have to be passed from block A to block B in Figure 4.4 are parametrized by placeholders $outA1 and $inB1, and CloudWF replaces these placeholders by absolute HDFS paths at execution time. It is explained in Section 4.2.3 why and how this is done, and why this is not necessary when files are passed between legacy blocks.




```
<WF ID="exMR">
<block name="A" type="mapreduce">
   <command>wordcount.jar org.myorg.WordCount /user/c15zhang/wordcount/input $outA1
   </command>
   <programFile1 from="DFS:/user/c15zhang/wordcount.jar">
      LFS:wordcount.jar
   </programFile1>
   <output1 to="DFS:/user/c15zhang/wordcount/output"> DFS:$outA1 </output1>
</block>
<block name="B" type="mapreduce">
   <command>wordcount.jar org.myorg.WordCount $inB1 /user/c15zhang/wordcount/final
   </command>
   <programFile1 from="DFS:/user/c15zhang/wordcount.jar">LFS:wordcount.jar
   </programFile1>
   <input1>DFS:$inB1</input1>
</block>
<connector name="connector1" origin="A" dest="B">
      <connect from="output1" to="input1"/>
</connector>
</WF>
```

Figure 4.4: Second example workflow and XML file (MapReduce blocks).

4.2.2 Storing Workflows in HBase Tables

CloudWF uses HBase to store workflow component information. There are three main reasons to use HBase. First, we need a database-like reliable metadata store to manage various types of workflow information that is important for workflow execution control, as well as to save intermediate results for fault tolerance and future reuse. Second, we have designed a set of sparse tables and find them very suitable for easily expressing and searching for workflow information and connectivity, which results in efficient processing without invoking complex database-like queries, thus voiding the need for specialized relational database systems. Finally, HBase is tightly coupled with the Hadoop framework and can be scaled and deployed more easily than mainstream database systems.

In HBase, we use three tables: the "WF" table, the "WFBlock" table and the "WFConnector" table (Figure 4.5). CloudWF relies on these tables to store workflow metadata and control execution. Additionally, the block dependency DAG of a workflow is implicitly stored within the "WFBlock" and "WFConnector" tables and is used for fast discovery of the next block/connector ready for execution. The following explains how we achieve that.

WFBlock Table

ID: blockID	ID: exWF	ID: blockType	ID: dependencyCount	Program: command	Program: input	Program: output
exWF.A	Y	legacy	0	ls > outA		(output1,LFS:outA)
exWF.B	Y	Legacy	0	wc WF1.xml > outB	(input1,DFS: /user/c15zhang/tmpls)	(output1,LFS: outB)
exWF.C	Y	legacy	2	cat inC1 inC2 > outC	(input1,LFS:inC1) (input2,LFS:inC2)	(output1,LFS:outC)

Status: readyForExecution	Status: inExecution	Status: readyForConnectors	Status: done

WFConnector Table

ID:connectorID	ID:exWF	Link:origin	Link:destination	Link:fromToList
exWF.connector1	Y	exWF.A	exWF.C	(output1, input1)
exWF.connector2	Y	exWF.B	exWF.C	(output1, input2)

Origin: exWF.A	Origin: exWF.B	Status: readyForExecution	Status: inExecution	Status: readyForBlock	Status: done
Y					
	Y				

WF Table

ID:WFID	ID:exWF	Status: readyForExecution	Status: inExecution	Status: done
exWF	Y			

Figure 4.5: HBase tables for the example workflow of Figure 2.2.

Figure 4.5 shows the HBase tables that correspond to the first example workflow (Figure 4.3) before execution is started. In WFBlock, every block has one entry. There are three HBase column families: ID, Program and Status. The

first column in the ID column family, ID:blockID, gives the block ID. The second column indicates that the blocks belong to workflow exWF. Note that, every time a workflow is added, an additional sparse column is created for that workflow (for example, ID:exWF2): the sparse columns ID:exWF and ID:exWF2 can be used for fast querying of the columns of workflows exWF and exWF2, respectively. The fourth column lists the dependency count of the blocks. Block C depends on A and B, so its count is 2. The dependency count will be reduced as blocks finish (see Section 4.2.4), and when it reaches 0 the block is detected as being ready for execution. The first column in the Program column family gives the commands, and the next two contain the lists of input and output files that have to be passed between blocks (specified by the <input> and <output> blocks in the XML file in Figure 4.3) The Status column family is used during execution (see Section 4.2.4).

Similarly, the WFConnector table has one entry per connector in the workflow, with ID, Link, Origin and Status column families. The ID and Status families function as above. The Link family lists the origin and destination block of each connector, and the descriptors for the files that need to be connected. The Origin column family appears redundant but is crucial for good performance: every workflow block that has a connector originating from it has its own (sparse) column in this family, thus allowing for very fast searching of which connectors have to be activated when a given workflow block finishes. This is important for performance when very large amounts of blocks and connectors are stored in the tables. Indeed, the sparse table concept of HBase allows us to create sparse columns for every block without much storage overhead (each column will only have one "Y" entry), and HBase provides a very fast mechanism to return all records in a table that are non-null in a given column. These features of HBase sparse tables allow us to store and query the connectivity of the workflow DAG in a natural and efficient way.

The third Table, WFTable, is used to store workflow information.

4.2.3 Staging Files Transparently with HDFS

File staging is a major issue in workflow management. CloudWF makes this easy by using HDFS as a globally accessible file repository so that files that appear on workflow component commandlines can be staged between any two cloud machines by relaying through HDFS. In CloudWF, we consider two types of file staging. The first type of file staging is between blocks, as described by the connector components in Figures 4.3, 4.4 and 4.5. The second type is staging files in from the user HDFS area into the workflow, and staging files out from the workflow to the user HDFS area. As already discussed before, the HDFS is divided into a user area and a CloudWF system area, and similarly, a CloudWF system area is also created on the local file system (LFS) of each cloud node.

During workflow execution, CloudWF creates two working directories for each block that is executed: one HDFS working directory in the system part of the globally accessible HDFS, and one LFS working directory in the system part of the LFS of the cloud node on which the block executes. The MapReduce Wrapper and its commandline invocation (which itself is legacy or MapReduce) are executed from the LFS working directory. The HDFS working directory is used for staging files between blocks, and for staging files in or out. For example, the HDFS and LFS paths to the HDFS and LFS working directories for block A in workflow exWF are given by

- HDFS working directory: /DFSHomePrefix/exWF/exWF.A/
- LFS working directory: /LFSHomePrefix/exWF/exWF.A/

The file staging for the workflows in Figures 4.3 and 4.4 then works as follows. As we said before, files that appear on commandlines and have to be staged between blocks have to be specified in <input> and <output> blocks

in the XML file, and are tagged as LFS files or HDFS files depending on their nature (consistent with their use in the commandline). Inside the <input> and <output> blocks, only relative paths can be used. These relative paths refer to the working directory of the block for which the <input> or <output> is specified. For unix legacy commandlines, the file names in the commandlines can simply be given relative to the unix working directory of the block, and commandlines need no change.

Let us consider the connector from block A to C in Figure 4.3. The block-to-block staging works as follows: after the commandline execution of block A, the CloudWF Wrapper copies outA to the HDFS working directory of block A. When connector 1 is executed, it copies outA from the HDFS working directory of block A to the HDFS working directory of block C. When block B starts, the CloudWF Wrapper copies the file from the HDFS working directory of block C to the LFS working directory of block C (with name inC1), and then C's commandline can be invoked. This mechanism is transparent to the user, who only has to provide the "connectors" in the XML file. The use of this connector mechanism allows highly parallel execution of multiple workflows at the same time, see Section 4.2.4.

For workflows with MapReduce blocks (see Figure 4.4) the situation is somewhat more complicated. Let us consider the connector from blocks A to B, which connects the HDFS output file from A to the HDFS input file of B. CloudWF again uses the HDFS working directory of block A and the HDFS working directory of block B to relay the file, but the problem is now that the MapReduce commandline requires absolute paths for HDFS files (because MapReduce does not have a HDFS working directory concept). We want to hide the system absolute paths to the HDFS working directories of blocks A and B from the user (because in practice they may not be known in advance, and it is not desirable that the user would have to know the details of paths used by the system), and to this end we provide

placeholders like $outA1, which are to be used for HDFS files on commandlines and in <input> and <output> blocks, and which CloudWF replaces by absolute HDFS paths to the block's HDFS working directory at runtime.

In this way, the user can stage HDFS files block-to-block in a way that is similar to staging LFS files: the only difference is that HDFS files are referred to using placeholders. The overhead in copying multiple HDFS files in order to get them from one block to another is small, since Hadoop HDFS uses copy-on-write, and most large HDFS input files are not written to. Users can also relay files themselves via the user section of HDFS, but then the user has to do all the bookkeeping and has to make sure that all necessary directories are available at runtime, which is cumbersome, so the transparent block-to-block file staging mechanism that CloudWF provides is attractive.

The mechanism for staging files into and out of the workflow is the same for Figures 4.3 and 4.4: the "from" and "to" fields in <input> and <output> blocks can contain absolute HDFS or LFS paths, and inside the <input> and <output> blocks the files are tagged as "DFS" or "LFS" depending on their use on the commandline, and placeholders are used for HDFS files.

In short, CloudWF uses HDFS to achieve transparent file staging in the background. For large and frequently used files, users can choose to populate the files to all cloud nodes beforehand to optimize system performance.

4.2.4 Executing Workflows

CloudWF executes blocks and connectors whenever they are ready for execution. For example, for the workflow of Figures 4.3 and 4.4, the user initiates execution through the Front End, after which blocks A and B (which have dependency count 0) are set to "readyForExecution" in the WFBlock table. Upon polling, the Block broker (Figure 4.2) finds the blocks that are ready for execution and submits Wrappers to the cloud pool. When block A finishes, the connectors that originate

from A (obtained by a fast query of WFConnector) are set as "readyForExecution", and are then picked up by the Connection broker and submitted for execution. Upon completion of the connector from A to C, the dependency count of C is decreased by one. When both connectors have executed, C then becomes ready for execution. If any Wrapper fails, it is restarted by the MapReduce framework automatically for six times by default. If all retries fail, the task (block or connector) fails and thus the entire workflow fails. If the Wrapper is alive and the submitted component execution fails, the Wrapper detects this failure and restarts the failed component command once. If the command fails again, the Wrapper marks the component status to fail and thus the entire workflow fails. In the future, more advanced failure handling mechanisms will be introduced to better cope with workflow failures.

4.2.5 Optimization: Virtual Start and End Blocks

In the prototype system, users need to explicitly start all the workflow start blocks to kickstart the workflow execution, and the system needs to check if all the workflow end blocks are finished to determine whether the workflow execution is successfully completed. This is especially inefficient for workflows with many start blocks or many end blocks. To enable easy start of workflow execution and easy detection of successfully completed workflow execution, we introduce virtual start and end blocks (Figure 4.6), blocks that are inserted by the system automatically in the background to each workflow instance at the start of execution. With virtual start blocks, starting a workflow execution can be as easy as starting one block (the virtual start block). Likewise, detecting the end of a workflow execution can be achieved easily by looking at the status of only one block (the virtual end block) no matter how complex a workflow is.

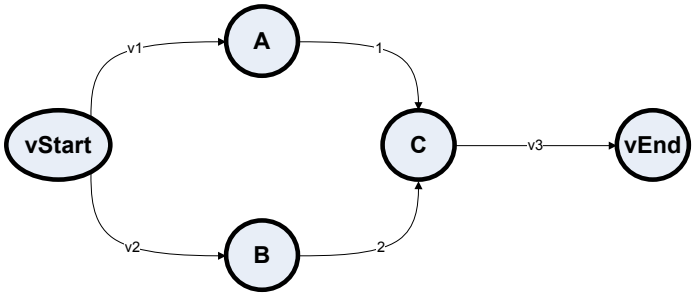


Figure 4.6: Virtual start and virtual end blocks.

4.3 Example Scientific Workflow Application Scenario

The prototype CloudWF system was tested with simple model workflows on a small departmental cluster. It is clear that the tests conducted so far are not enough to demonstrate how effective CloudWF is in handling workflows with large scale data processing. For now, we have tested to use the CloudWF system for processing the data gathered in the Hadoop case study project in processing live cell images mentioned in Chapter 3. Each MATLAB execution step is viewed as a workflow block. The result data generated by each step is staged as a workflow connector file copying operation. Because the applications use large data sets, file staging and caching mechanisms become crucial for performance. Additionally, because the MATLAB programs are not MapReduce applications and require all the data to be put into the local file system instead of DFS before processing, the file handling capability of CloudWF may be pushed to its limits and further optimizations could be necessary in the future.

4.4 Related Work

With the advent of clouds, it is possible to develop easy-to-use lightweight workflow systems that can take advantage of the desirable properties clouds can provide, such as scalability, fault tolerance, transparency and easy deployment.

Our CloudWF system tries to achieve this goal and it is the first workflow system that can easily handle both MapReduce and legacy application executions on Hadoop clouds.

4.4.1 Dataflow and Workflow Systems for Hadoop

At the time of writing, there exist two dataflow systems on clouds, Cascading [3] and Pig [23], and one workflow system, Yahoo! Oozie [33], is under development. Cascading is a dataflow system and is intended for expert programmers to build dataflows using the provided API as monolithic programs (each dataflow instance gets executed separately). This makes it complicated for users to reuse existing programs directly and it is not easy to parallelize the execution of multiple dataflows with varying length of execution (each dataflow instance needs its own scheduler). In other words, Cascading is not intended for application users who are not programming specialists since it does not provide a simple way to build and run workflows by composing existing MapReduce or legacy programs without extra programming. Pig is a platform for analyzing large data sets that provides a high-level language called Pig Latin [31] for expressing data analysis programs. With Pig, users can chain up data analysis jobs into dataflows. However, Pig is not a workflow platform to work on arbitrary datasets that are not structured into relations. In essence, Pig is designed to mimic the behavior of a relational database in which data are organized into relations and flows of operations on relations will output relations as well. If the data source and intermediate result data are mostly relational and need SQL-type operations all along the dataflow, then Pig may be a suitable platform, provided that all the relational data are written and stored in Pig-recognized formats, and all the original SQL queries (if they exist) or data manipulation commands are re-written using Pig Latin syntax. Apparently, Pig is not suitable for the type of workflows we target because we need a system that is more general and non-intrusive for cloud-enabling existing

legacy and MapReduce programs without any modification to those programs and without any restriction on the type or format of data those programs are using. Yahoo! Oozie is intended to be a comprehensive workflow management and coordination system for Hadoop to support many different job types that can run on clouds, such as MapReduce, Pig, Hadoop Streaming [41], HDFS, etc. It was started at almost the same time as our computational workflow system and became inactive shortly afterward. Its design is similar to existing workflow systems on grids, with the exception that jobs are run on Hadoop and the job files are put in HDFS. It hard-codes dependency in each workflow block (making it difficult to do isolated modifications to a block and avoid implications on other parts of the workflow) and mainly targets MapReduce-type applications (one needs to write extra action executors to support arbitrary types of applications), making compatibility with existing legacy programs more difficult. However, if Oozie sees more development action in the future, it may become relevant to what our system tries to achieve.

4.4.2 Legacy Workflow Systems

Additionally, in terms of general workflow organization, our system is novel compared to existing major computational workflow systems in several aspects. For ease of discussion, we re-state some of the novelties of CloudWF besides the seamless integration with Hadoop as follows: first, it encodes workflow blocks and block-to-block dependencies separately as standalone executable components which enables decentralized workflow execution management, in a way that is naturally suitable for cloud environments; second, it employs a new way to store workflow dependencies in HBase sparse tables such that they become efficiently searchable and enables multiple workflow instances to be executed concurrently with no need for a separate director to drive through each workflow instance execution; third, it uses HDFS for staging files between

workflow blocks transparently such that users do not need to be concerned about specific file transfer protocols or file naming conflicts. File renaming can also be handled automatically if applications have particular requirements on a certain naming convention.

There are several major computational workflow systems, such as Condor DAGMan [16], Kepler [27], and Pegasus [38], each targeted to certain usage scenarios but none closely integrated with Hadoop for running MapReduce-type applications.

Condor DAGMan is a workflow engine designed to manage workflows composed of Condor [37] jobs. A DAGMan process is started as a normal compute job submitted to Condor (one DAGMan process per workflow instance). Workflows are coded as workflow description files using DAGMan's own syntax. After an instance of DAGMan is started, it reads a workflow description file and submits jobs to Condor according to the block ordering determined by the workflow dependency read from the workflow description file. It monitors the log files for each block submission and determines based on the return values of the finished blocks whether or not to submit the next available jobs according to the dependency.

Kepler [27] is a GUI-based workflow composition and execution environment, focusing on the automation of workflow Actor executions controlled by Directors. A Kepler workflow is composed of a set of connected Actors. An Actor is an independent functional unit, such as a program, a file transfer manager (i.e., a program specialized in transferring files, such as a scp file manager taking inputs composed of a source and destination string and user password), etc. Each Actor has a number of input/output ports. Ports belonging to different Actors are connected by Channels. A Channel is just a GUI line drawn to connect the ports, representing the data flow or event notification sequence. Each workflow instance execution is controlled by one Director. The Directors are not responsible

for file transfers or resource mapping; such tasks are off-loaded to specialized Actors such as file transfer Actors and grid job submission Actors. Remote job execution on clusters and grids are done just as if by hand (explicit user credentials and submission commands must be coded in the job submission Actor). Furthermore, one cannot run arbitrary Actors on clusters/grids unless all the required files of the Actors are wrapped in submission scripts acceptable for the target clusters/grids batch job queuing system.

CloudWF is different from DAGMan and Kepler in several aspects. First, in CloudWF, there is no need for separate director roles for each workflow instance execution, saving valuable compute resources. Second, CloudWF stores workflow dependencies in HBase sparse tables for efficient queries and easy workflow execution management. Third, CloudWF supports transparent and protocol neutral file staging between blocks. Finally, CloudWF seamlessly supports both MapReduce and legacy applications, while executing MapReduce jobs with DAGMan and Kepler is not straightforward.

4.4.3 The Pegasus Workflow System

Pegasus [38] is a grid workflow system that has some conceptual similarity to CloudWF. Therefore, we now give a more detailed comparison to Pegasus.

Pegasus is a system that allows users to write resource independent (no actual physical file paths are included) workflow description files (called DAX - Directed Acyclic graph workflow XML), and then automatically transforms the DAX into DAGMan description files and submits DAGMan jobs to Condor which executes the workflows. Figure 4.7 shows the architecture of Pegasus. Pegasus uses Abstract Workflows, which contain resource neutral bindings for files. In other words, no physical file paths are used in the abstract workflows but only abstract file names. There is a central data registry containing information about the mappings of each file to different physical paths at different compute nodes.

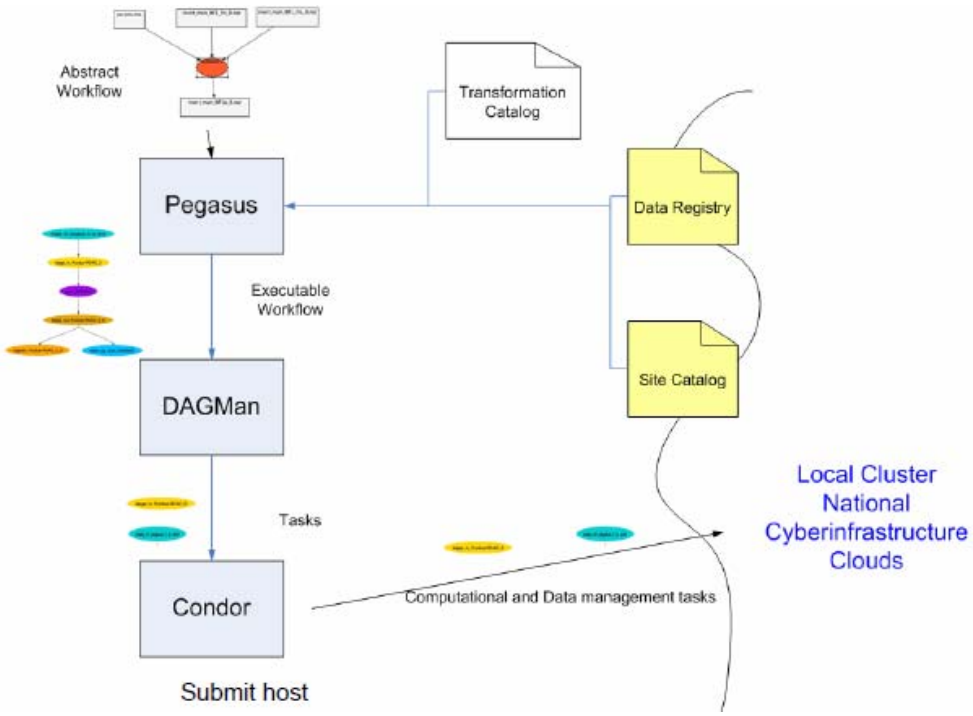


Figure 4.7: Pegasus system overview (taken from [38]).

Each compute node has a local Site Catalog containing the files it has and the corresponding mappings to the local physical file paths. For example, a file named a.file may exist under different file paths at different machines. Then the central catalog will have information about which machines have a.file, and at each machine, the Site Catalog will have information about the actual local physical paths for a.file. The task for Pegasus is to take such DAX files, transform them into the DAGMan description format, and then submit DAGMan jobs to Condor for execution. The purpose for Pegasus is thus to facilitate portability of workflows and handle heterogeneous file paths in distributed locations. Another benefit of Pegasus is that, because there are Catologs recording detailed whereabouts for

all files, if a host already contains a certain file, that file can be re-used and there is no need to stage that file multiple times when used by multiple workflows at that host. However, users need to take care of properly naming the files and keeping track of file changes at all replicas, which may become cumbersome.

Pegasus is somewhat similar to CloudWF in its file staging approach. Recall that Pegasus converts abstract workflow description files to condor DAGMan files for execution. During the conversion, Pegasus inserts data stage-in and stage-out processes as additional separate blocks for each original workflow block if files are to be staged. As a result, a block in the original abstract workflow may be converted to a group of blocks containing several input staging blocks, an executable block, and several output staging blocks. For input staging blocks, the file catalog will be queried using the logical file identifiers and the corresponding physical files will be staged to the local compute node. For output staging blocks, files will be staged back to the compute node where the block's corresponding DAGMan job is submitted for execution and relayed to subsequent blocks as their inputs via intermediate file storage locations when necessary. CloudWF also uses a file relaying mechanism to stage outputs of preceding blocks to their subsequent blocks as inputs. A difference is that Pegasus uses the local storage of the compute node where the DAGMan job is submitted as the basis to relay files, whereas CloudWF uses HDFS as a globally viewable and accessible file repository to relay files. Both of the two systems can transparently relay files between connected blocks alleviating users from the burden of hardcoding any file staging operations by actual physical file paths combined with specific file transfer protocols.

Pegasus is different from CloudWF in several aspects. Pegasus does not work with Hadoop by default, whereas CloudWF naturally integrates with Hadoop MapReduce and is oriented towards workflows composed of both legacy and MapReduce applications. Pegasus uses DAGMan which requires an extra exe-

cution monitoring process per workflow instance incurring extra resource use and the complexities concerning the scalability and fault tolerance of those monitoring processes, whereas CloudWF uses a novel way to efficiently store and manage workflow dependencies using HBase sparse tables such that there is no need for an extra workflow director role per workflow instance to manage the workflow execution graph. Furthermore, modifying a Pegasus workflow would cause the entire workflow to be re-compiled and the condor submission files to be re-generated before the new workflow can be executed, whereas the method to treat workflow blocks and connectors as independent executables in CloudWF makes it potentially easy to modify any block/connector without affecting other blocks/connectors in the same workflow, even at runtime. Finally, Pegasus requires many other heavy-weight grid tools (e.g. globus services, gridftp on each file hosting site, condor, and many Pegasus components) to be deployed whereas CloudWF only requires Hadoop and HBase.

4.5 Conclusions and Future Work

CloudWF is a computational workflow system specifically targeted at cloud environments where Hadoop is installed. It uses Hadoop components for job execution, file staging and workflow information storage. The novelty of the system lies in several aspects: its new workflow description method that separates out workflow component dependencies as standalone executable components such that there is no need for execution control per workflow instance to explicitly direct the flow of data, which improves resource utilization and enhances efficient scheduling; the directed acyclic graphs (DAGs) of the workflows are encoded in sparse HBase tables, which are a natural data structure for encoding graphs and allow for efficient querying of the graph connections; using HDFS to conveniently store and relay files reduces the complexity of handling files in a distributed environment – the uniformity of the cloud environment allows for simple file

handling solutions that are fully transparent to the user.

The current prototype CloudWF system can support building and running simple workflows composed of both MapReduce and legacy applications. Concerning future work, several other advanced features are planned to be built to further improve the prototype CloudWF system, namely:

1. Reusing workflow/block templates and nested workflows.
2. Execution steering with conditional branching and loops.
3. Runtime interactive workow change with instance clones.

CloudWF can also be extended to cloud computing frameworks other than Hadoop, as long as there is a distributed file system providing a global view and a metadata store like HBase supporting sparse tables.

Chapter 5

Snapshot Isolation for Column Stores on Clouds

This chapter presents the "HBaseSI" client library, which provides global strong snapshot isolation (SI) for multi-row distributed transactions in HBase. This is the first SI mechanism developed for HBase. HBaseSI uses novel methods in handling distributed transactional management autonomously by individual clients. These methods greatly simplify the design of HBaseSI and can be generalized to other column-oriented stores with similar architecture as HBase. As a result of the simplicity in design, HBaseSI adds low overhead to HBase performance and directly inherits many desirable properties of HBase. HBaseSI is non-intrusive to existing HBase installations and user data, and is designed to work with a large cloud in terms of data size and the number of nodes in the cloud.

5.1 Introduction

Column stores provide database-like table views, and it would be desirable if distributed transactions can be supported on them so that applications that used

to be built around traditional database management systems (DBMS) can make use of cloud column stores for transactional data processing, with improved scalability. Indeed, many applications, such as a large number of collaborative Web 2.0 applications, would benefit from transactional multi-row access to the underlying data stores [1]. In fact, those modern applications pose high requirements on scalability and fault tolerance and there are currently no existing DBMS solutions (even parallel database systems) to fully cater to those requirements due to the overhead of managing distributed transactions and the fact that it is impossible for DBMSs to guarantee transactional properties in the presence of various kinds of failures without limiting system scalability and availability [1, 5, 22]. Unfortunately, no out-of-the-box support for transactions involving multiple data rows exists in column stores. This is mainly because multi-row transactions in column stores are intrinsically distributed transactions [16] and traditional approaches, such as standard 2-phase commit protocols [2], consensus-based commits [26], atomic broadcast [14], and explicit data locking [7], would suffer from similar problems as in existing distributed DBMS solutions if they are directly applied to column stores.

This chapter presents a novel light-weight transaction system with global strong snapshot isolation on top of HBase (which is a representative open source column store modeled after Google's BigTable system), without using traditional methods of handling distributed transactions. A preliminary version of our system, providing weak SI for HBase, was presented in [48]. The solution presented in this chapter is called "HBaseSI". HBaseSI recycles some of the design principles of the initial system from [48] but uses a different, more efficient solution for handling distributed synchronization, with added support for global strong (and not weak) SI and an efficient failure handling mechanism. Our work in [48] described the first ever SI system for column-stores. Independently and at the same time, the Google Percolator system was presented in [36]. Percolator

provides global strong SI for Google's column store system, BigTable. Percolator shares many design principles with our SI system, but there are also many important differences in design goals. Several other research efforts have been made to investigate solutions for supporting multi-row distributed transactions on HBase (see Section 5.5). However, none of those solutions provide transaction support with global snapshot isolation.

HBaseSI targets the same type of OLTP (Online Transaction Processing) workloads as HBase, taking advantage of HBase's random data access performance. It is implemented as a client library and does not require any extra programs to be deployed or running in addition to existing HBase servers. In addition, HBaseSI is non-intrusive to existing user data that have already been stored in HBase since it does not require modifications to existing user data tables. Therefore, it is very easy for current HBase users to employ the system for transactions on their existing data. In HBaseSI, transactional management metadata are written by each transaction to a separate set of HBase tables. There is no central "commit engine" that decides which of the transactions that are ready to commit can actually commit; instead, the transaction processes decide autonomously, in a distributed fashion, whether they can commit or have to fail, using the information stored in the additional metadata HBase tables. As a result, little performance overhead pertaining to distributed synchronization is added by the transactional management logic. Many of HBase's desirable properties are directly inherited as well, such as fault tolerance, access transparency and high throughput. In its current design, HBase does not target scalability in terms of the number of transactions per unit of time.

The main contributions of HBaseSI are: 1. HBaseSI is the first distributed transactional system with global SI for HBase. The system design can be applied to other column stores similar to HBase, which means a broader set of applications can use column stores, namely, the ones that need to use transactional SI;

2. HBaseSI uses novel methods in how distributed transactions are managed autonomously by individual clients, without using complicated synchronization protocols as in traditional distributed transaction management. These methods greatly simplify the design of HBaseSI and can be generalized to other column-oriented stores with similar architecture as HBase.

The remainder of this chapter is structured as follows: in Section 5.2 we introduce some background information about snapshot isolation and the reason why we choose to use HBase for SI on clouds. In Section 5.3 we describe the design and implementation of HBaseSI in detail. In Section 5.4 we evaluate the performance of HBaseSI. Section 5.5 gives comparison to related work. Section 5.6 concludes and describes future work.

5.2 Background

5.2.1 Snapshot Isolation

For our purposes, we can describe Snapshot isolation (SI) as follows.

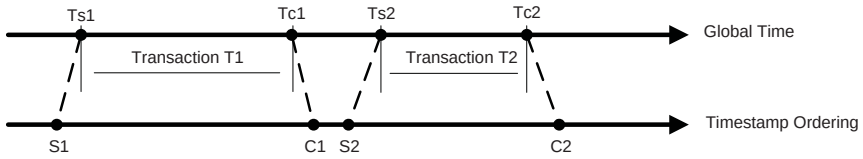


Figure 5.1: Illustration of SI.

A transaction Ti acquires a start timestamp, S(Ti), at the beginning of its execution (before performing any read or update operations), and acquires a commit timestamp, C(Ti) at the end of its execution (after finishing any read or update operations). We will also use the shorthand notation Si=S(Ti) and Ci=C(Ti) in what follows. The timestamps Si and Ci are ordered: they inherit their ordering from the ordering of real global times Tsi and Tci to which they correspond (Figure 5.1). This ordering implies in particular that all read and

write operations of Ti happen (in real, global time) after the time corresponding to Si, and all write operations of Ti happen (in real, global time) before the time corresponding to Ci. Transactions Ti and Tj are called concurrent if their lifespan intervals (Si,Ci) and (Sj,Cj) overlap. A transaction Ti that commits successfully is called a successful or committed transaction.

Global Strong SI can then be described as follows. A transaction history H satisfies global strong SI, if its (successful) transactions satisfy the following two conditions: 1. Read operations in any transaction Ti see the database in the state after the last commit before Si. In other words, all updates made by the committed transaction Tj which has the last Cj <= Si are visible to Ti. However, read operations in transaction Ti that read data items that have previously been written by transaction Ti itself, see the data values that were last written by Ti; 2. Concurrent transactions have disjoint writesets.

We add the qualifier "global" when we define strong SI because we want to investigate Snapshot Isolation for a distributed system in this chapter, and want to stress that the definition above applies to the global system. Additionally, the above definition does not regulate the behavior when two concurrent transactions with overlapping writesets both try to commit. In many occasions, a rule called the "first-committer-wins" rule [19] is employed, which will cause the failure of the transaction that is second in attempting to commit. To illustrate this rule, let's look at an example set of transactions as shown in Figure 5.2. T1 and T2 must have disjoint writesets in order to both commit successfully. If they have overlapping writesets, only T1 will successfully commit and T2 will abort, because T1 attempts to commit before T2.

The strong notion of SI as defined above is different from the original definition of SI [19], which allows Si to be chosen corresponding to any time in the past before the first read or update operation in transaction Ti. This relaxed version of SI is also called weak SI in [8]. To illustrate this difference, we assume

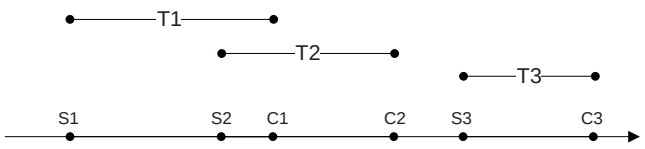


Figure 5.2: An example SI scenario.

that T1 and T2 in Figure 5.2 have disjoint writesets and both commit successfully. According to the definition of strong SI, T3 must see all the committed results as of timestamp S3, which include the commits for both T1 and T2. However according to weak SI, it is allowed that T3 use a snapshot between C1 and C2 that includes only the committed results from T1. Typically, versions of the strong notion of SI are implemented in stand-alone, non-distributed commercial databases. SI is not included in the ANSI/ISO SQL standard but versions of it are adopted by major DBMSs due to its better performance than Serializablity at the cost of having a potential write-skew anomaly [19].

5.2.2 HBase

Our choice of using HBase as the basis for investigating transactional SI solutions for clouds is not arbitrary. HBase enjoys several desirable properties that are important for simple and efficient SI implementations. First, HBase offers a single global system view with access transparency, meaning that clients access all the HBase tables as if they are hosted at a centralized server without knowing that they are actually contacting different distributed region servers for fractions of data. Recall that one of the most complex operations of managing distributed transactions is the synchronization between distributed servers hosting part of the data that the transactions would access. With the single global view that HBase provides, this complexity is hidden from the user (at the cost of some performance loss in practice). As such, the original difficult problem of managing distributed transactions involving multiple servers is virtualized into managing

shared data access at a centralized server, significantly reducing the complexity of transactional protocol implementation. This significantly reduces the complexity of transactional protocol implementation. Second, HBase provides multi-version data support distinguished by the timestamp the data item is written with. In other words, snapshots of data identified by write timestamps are naturally kept in HBase. This feature can directly facilitate the SI protocol implementation. Third, HBase guarantees single atomic row operations (reads/writes) with strong data consistency in the global table view. This means that a data item, once successfully written, is guaranteed to show a consistent value seen globally by all clients. This is a very important property for transactions to rely on for data consistency. Imagine if HBase were to support only eventual data consistency in its global table view: it would then be impossible to make clear guarantees on the availability of any data items.

Note that HBase does not guarantee that two messages sent in a certain order (for example, messages sent in the form of calling the insertRow method to add a row into a global system table) will be delivered in the same order (in the form of rows appearing in the global table), no matter whether the message sending order is determined by real time or a centralized timestamp. More specifically, it is possible that, if a client calls the method to insert row1 before another client calls the method to insert row2 into the same global table, row2 appears in the global table first. In fact, any row could take arbitrarily long to appear and it may even never appear, with atomicity guaranteed. This is also why in the HBaseSI protocol, we cannot solely rely on the order of data row appearance to order arrival of transactional information in the tables.

5.3 HBaseSI

5.3.1 System Design

A major design goal of HBaseSI is to provide transactional SI for HBase with minimum add-ons to existing HBase installations and administration. It may also be an advantage if it is possible for HBase users with existing data tables to employ HBaseSI with minimum effort. To this end, HBaseSI is implemented as a client library in Java with no extra programs to be deployed. Applications that need to do transactions use the client library to interact with HBase instead of using the standard HBase API. Each transaction writes its own transactional metadata (e.g. transaction ID, commit timestamp, commit request, etc.) to a set of global system HBase tables (separate from existing user data tables), and queries those tables to obtain information about other transactions. Based on the information obtained, and by accessing this information with atomic read/write operations provided by HBase, a transaction can autonomously decide to commit or abort. From a user's point of view, using HBaseSI requires no modification to any existing data tables and only requires switching to a new client API with semantics similar to the HBase API. From a system administrator's point of view, using HBaseSI incurs no change to the existing HBase administration.

HBaseSI employs several HBase tables in addition to the user's data tables. These additional system tables are three Counter tables (Tables 5.1, 5.2 and 5.3) for providing globally unique counters, a CommitRequestQueue table (Table 5.4) that acts as a queue for transactions that are submitting requests to commit, a CommitQueue table (Table 5.5) that acts as a queue for transactions that have been cleared to commit, and a Committed table (Table 5.6) that keeps track of successfully committed transactions and their writesets.

The Counter tables are intended to serve as a set of centralized locations for issuing globally unique IDs that may be used as well-ordered counters. Each

Table 5.1: W counter table. W stands for "HBase write timestamp".

Row Key	Counter
W	86

Table 5.2: R counter table. R stands for "commit request ID".

Row Key	Counter
R	78

of the tables is a single-row-single-column table. The HBase atomic incrementColumnValue function is used on the column "Counter" to dispense globally unique and strictly incremental time labels to transactions atomically. The W Counter table (Table 5.1) issues a unique ID to each transaction at the start of the transaction. W stands for "HBase write timestamp". This ID will be used as the unique ID for the transaction, and as HBase write timestamp when writing data to HBase tables (note that in this chapter we use two types of timestamps: "HBase write timestamps" are used as write timestamps for HBase to distinguish different data versions, and "transaction timestamps" are timestamps used for transaction ordering purposes). The order of the W counter values is not important, as long as each W counter value is unique. The R Counter table (Table 5.2) issues unique commit request ordering IDs dispensed to transactions that are attempting to commit, establishing an order among the transactions attempting to commit, which is, among other things, used for enforcing the "first-committer-wins" rule. R stands for "commit request ID". The C Counter table (Table 5.3) issues the final unique commit timestamps, each of which is used as the actual commit

Table 5.3: C counter table. C stands for "commit timestamp".

Row Key	Counter
C	54

Table 5.4: CommitRequestQueue table.

Row Key	writeset item 1	writeset item 2	writeset item 3	RequestOrderID
W1	Y		Y	R1
W2	Y	Y		

timestamp of a transaction. Different from W counter values, the strict global ordering of the R and C counter values is essential for the correctness of the HBaseSI protocol.

The CommitRequestQueue table (Table 5.4) is used as a queue for ordering commit attempts and checking for conflicting updates among concurrent transactions that try to commit at almost the same time. A transaction Ti, when trying to commit, enters this queue table by first inserting a row containing its unique transaction ID Wi (obtained from the "W Counter table") as the row key and its writeset as the columns. (The writeset column names are unique identifiers for the data locations in the user data tables. We use the concatenation of table name, row ID and column name of a data item as its unique identifier for the data location.) After this row is inserted, the transaction requests and obtains a commit request counter value Ri (from the "R counter table") and then enters Ri into the "RequestOrderID" column of its row. The sequence of first inserting a row, then getting a Ri counter value, and finally putting it under the "RequestOrderID" column is essential for the queuing mechanism of our SI protocol as we will explain later. The transaction's writeset items are marked as "Y", and this information is used to detect conflicting updates. The "RequestOrderID" column is used to order the commit attempts and enforce the "first-committer-wins" rule.

The CommitQueue table (Table 5.5) is a queue for transactions that are already cleared for committing but are just waiting for their turns to be actually committed according to the ordering of their commit timestamps. Each row in

Table 5.5: CommitQueue table.

Row Key	CommitTimestamp
W1	C1
W2	

Table 5.6: Committed table.

Row Key	writeset item 1	writeset item2	writeset item3
C1	W1	W1	
C2	W2		W2

this table corresponds to a transaction and is indexed by the unique transaction ID obtained from the "W Counter table" (Table 5.1). The "CommitTimestamp" column stores the timestamp obtained from the "C Counter" table (Table 5.3) which is used as the commit timestamp of the transaction. Note that a transaction Ti first writes a row in this table with row key Wi, then requests and obtains its CommitTimestamp Ci, and finally adds Ci to its row. This sequence is again essential for the queuing mechanism to work properly, as explained below.

The Committed table (Table 5.6) stores the metadata records for all the committed transactions. Each row in this table represents a successfully committed transaction indexed by the commit timestamp as the row key with the writeset data items as columns, containing the HBase timestamps used to actually write the data to the user's HBase data tables. In fact, for any transaction, successfully inserting a row into this table means that the transaction is committed atomically and the data becomes durable. Moreover, any row key of the table can identify a consistent snapshot because the rows in the table are strictly ordered and automatically sorted by row keys, and committed transactions are guaranteed to arrive in the Committed table in order due to the queuing mechanism, as explained below. The Committed table is also used by transactions in various functional ways, such as looking for the most recently committed version of data

when reading, and checking for writeset conflicts at commit time against previously committed records. Note that HBase's sparse column nature is crucial here for efficiency: the table can contain many columns, but each column typically contains only few elements, and can be scanned efficiently.

In HBaseSI, each transaction sees a consistent snapshot of all the data in HBase user tables, identified by the start timestamp of the transaction. When a transaction Ti starts, it first gets its start timestamp by reading the last row of the Committed table at the time it starts, and uses the row key of that row Cj as the start timestamp. So we have Si=Cj, and Ti will see all data committed by Tj, and any transaction committed before Tj. Transaction Ti also obtains a unique ID Wi from the "W Counter" table as its transaction ID. Then it performs reads/writes based on the snapshot identified by the start timestamp. Data being read/written are first saved in in-memory readset/writeset data structures so that repeated reads can be efficiently served from memory, except for the first read/write of a certain data item. In this way, it is guaranteed that the transaction reads its own writes at all times. Writes are applied to the user data tables immediately (speculatively) using the transaction ID Wi as the unique timestamp to write to HBase (recall that a timestamp can be specified when writing data to HBase). At commit time, the transaction puts itself into the CommitRequest table, may wait for its turn if there are any conflicting commit attempts, then checks for conflicts with committed transactions, and finally enters the CommitQueue table if it is cleared to commit. It then waits for all the other concurrent transactions in the CommitQueue table with smaller commit timestamp Ci to commit, and finally commits by atomically inserting a simple record row into the Committed table to make its writes durable. The pseudocode of the protocol is provided in Listing 5.1.

It is important to understand in detail how HBaseSI handles distributed synchronization among concurrent transactions concerning the global ordering of

transaction commit requests and commits. HBaseSI makes use of distributed queues to manage transaction commits and to guarantee the "first-committer-wins" rule, instead of using other traditional methods such as data locks or consensus-based protocols. The benefit is simplicity in design and implementation. HBaseSI makes use of two queues, implemented as two HBase tables. One is the CommitRequestQueue (Table 5.4); the other is the CommitQueue (Table 5.5). The protocol to ensure a correct sequence of entering and exiting a queue is the same for the two queues and therefore we explain the protocol using one queue, the CommitRequestQueue, as an example. Recall that when a transaction Ti makes a request to start the commit process, it first inserts a row indexed by its unique transaction ID Wi (obtained from the "W Counter table"), then gets a commit request counter value Ri and puts it under the "RequestOrderID" column of its row. The Ri value determines the order of Ti in the queue. This sequence of operations is of essential importance to guarantee that no concurrent transaction will leave the queue out of order, as we explain now. After transaction Ti inserts counter value Ri into its row in the CommitRequestQueue table, it reads all records in the table once. It then waits until all rows of transactions Tj it has read obtain Rj values in the table. This is essential to allow the queue to function based on the order of the R counter values: Ti is guaranteed to see any transaction Tj still in the queue that may have Rj<Ri, even if Rj appears in the table after Ri. This is so because Ti reads the table *after* it has obtained Ri, and any Tj still in the queue that may have Rj<Ri is guaranteed to have its row in the table at that time, because it inserted its row *before* requesting Rj. Ti will not proceed to the commit process until all Tj with Rj<Ri have left the queue, guaranteeing that transactions are processed in order and establishing the "first-committer-wins" rule. Based on the strict sequence of transactions entering the queue table, the protocol to ensure the ordering of exiting the queue is shown in Listing 5.1: pseudocode line 49 to 69. The pseudocode contains

an optimization of the basic queuing protocol: transactions in the queue only need to wait for transactions that have a conflicting writeset. The same queuing protocol, using C counter values Ci, is also used to guarantee that transactions that are cleared to commit arrive in the order of the commit timestamp Ci in the Committed table, see lines 71-89 in the pseudocode. Using this queuing protocol, we can make sure that transactions follow the exact order as specified by their globally unique and well-ordered counter values. With the queuing mechanism, we can easily enforce a strict global ordering of transaction commits.

```
1  Transaction {
   Writeset {(dataLocation(n),value(n))}; //containing N items
3  Readset {(dataLocation(m),value(m))}; //containing M items
   Long Wi, Si; //Wi is transaction ID, Si is start timestamp
5  Long Ri; //Ri is request order ID
   Long Ci; //Ci is commit timestamp
7
   //method called at the start of transaction
9  Start() { //transaction starts
       Wi = GetTimestamp (W counter);
11     Si = LastLineFromCommittedTable().getRowKey();
   }
13
   //method to read data value
15 Read(dataTable, dataRow, dataColumn) {
       dataLocation = dataTable + dataRow + dataColumn;
17     if (dataLocation in WriteSet) {read from WriteSet; return dataValue;} //
           read own writes
       if (dataLocation in ReadSet) {read from ReadSet; return dataValue;} //
           repeated read-only value
19     committedRecord = ScanForMostRecentRow (in Committed table, range [0, Si]
           containing column dataLocation); //Scan in range [0, Si] (row keys are
            C counter values not less than 0), and return the last record in the
           list
       Wread = committedRecord.valueAtColumn(dataLocation); //find the latest data
            version in snapshot. If the data item is not in the Committed table,
           Wread will be set to null
21     dataValue = readData(in dataTable, in dataRow, in dataColumn, with
           timestamp Wread); //read data. If Wread is null, no timestamp will be
```

```
        specified in the HBase read (recall that it is optional to specify a
            timestamp in reading from HBase)
        ReadSet.add (dataLocation, dataValue);
23      return dataValue;
    }
25
    //method to write data value
27  Write(dataLocation, dataValue) {
        WriteSet.add(dataLocation, dataValue);
29      writeToDataTable (dataLocation, dataValue, using timestamp Wi); //directly
            write to data tables with HBase timestamp Wi
    }
31
    //method for commit attempt
33  boolean Commit() {
        EnqueueForCommitRequest(); //queue up for requesting to commit
35      CheckConflictsInCommittedTable (from Si+1, with conflicting WriteSet); //
            scan the Committed table for writeset columns in range [Si + 1, +
            INFINITY) and verify that there are no writeset conflicts
        If (clearedToCommit) {
37          EnqueueForCommitting(); //when cleared to commit, queue up to finally
                commit
        } else {
39          doCleanup(); //abort transaction, remove rows in system tables and
                data items written to user tables
        }
41  }

43  //method to get a counter value
    GetTimestamp(HBaseTimestampTable) {
45      IncrementColumnValue (HBaseTimestampTable) //the mechanism to issue
            globally unique and well-ordered timestamps from a central HBase table
    }
47
    //method to enqueue for commit request
49  EnqueueForCommitRequest() {
        WriteHBaseTableRow (into CommitRequestQueue Table, row Wi, columns WriteSet
            );
51      Ri = GetTimestamp(R counter);
        WriteHBaseTableRow (into CommitRequestQueue Table, row Wi, column Ri);
```

```
53      PendingCommitRequests = GetRowsWithConflictingWriteSet(From
            CommitRequestQueue Table); //one-time scan
        while (PendingCommitRequests.isNotEmpty()) { //there exist requests to
            update conflicting data
55          select a row from PendingCommitRequests;
          if (row has disappeared from table) {
57              remove row from PendingCommitRequests; //the other transaction has
                    moved on
          } else {
59              wait until Ri appears in the row;
                if (row.Ri is larger than its own Ri) { //the other request is
                    later than self
61                  remove row from PendingCommitRequests; //no need to consider
                } else { //the other request is earlier than self
63                  wait until row disappears; //wait till the other request is
                        handled
                    remove row from PendingCommitRequests;
65              }
            }
67      }
    }
69
    //method to enqueue for committing
71  EnqueueForCommitting() {
        WriteHBaseTableRow (into CommitQueue Table, row Wi);
73      Ci = GetTimestamp(C counter);
        WriteHBaseTableRow (into CommitQueue Table, row Wi, Ci);
75      PendingCommits = GetAllRows (From CommitQueue Table); //one-time scan
        while (PendingCommits.isNotEmpty()) {
77          select a row from PendingCommits;
          if (row has disappeared from table) {
79              remove row from PendingCommits; //the other transaction has moved
                    on
          } else {
81              wait until Ci appears in the row;
                if (row.Ci is larger than its own Ci) {
83                  remove row from PendingCommits; //no need to consider
                } else {
85                  wait until row disappears;
                    remove row from PendingCommits;
```

```
87              }
            }
89      }
        //proceed to commit
91      WriteHBaseTableRow (into Committed Table, row Ci, columns WriteSet each
            containing value Wi); //atomic commit operation
        DeleteOwnRecordIn(CommitQueue table);
93      DeleteOwnRecordIn(CommitRequestQueue table);
    }
95
    Main() {
97      Start();
        ... //do reads and writes
99      Commit();
    }
101
    }
```

Listing 5.1: Pseudocode for the HBaseSI protocol.

Transactions in HBaseSI satisfy ACID properties as well as strong SI. Atomicity is provided by the underlying HBase atomic row write functionality because the final commit process only requires a single row write to the Committed table (Listing 5.1: pseudocode line 91). Durability is guaranteed by the underlying persistent data storage mechanism, i.e., Hadoop HDFS, because all the data in HBase are stored in HDFS. Consistency is maintained because only valid data is inserted into the HBase tables through the provided APIs and transactions never leave HBase in a half-finished state. The isolation level provided by HBaseSI is strong snapshot isolation. Strong SI requires that a transaction reads/writes in isolation upon a consistent snapshot of data identified by a start timestamp. Seen from the protocol above, our system guarantees that a transaction can see all the updates committed before it starts (start timestamps are row keys from the Committed table and any row key in the Committed table can identify a consistent snapshot containing all the previous committed updates). Our system also guarantees that transactions can only commit (atomically) if no conflicting

updates have been inserted by previously committed concurrent transactions. Therefore strong SI holds. In Section 5.3.5 we will give a formal proof that global strong SI holds for HBaseSI.

5.3.2 Protocol Walkthrough by Example

We now describe the transactional SI protocol along with the system table usage in more detail by walking through the process of handling two concurrent transactions with conflicting updates under a concrete example scenario. In this example scenario, Alice and Bob intend to purchase smart phones from an online shop. They make their purchases by doing transactions involving several data tables of the shop stored in HBase, for example, item inventory, billing, etc. For simplicity, we limit their transactions to updating the same "Shop" table containing information about the number of available smart phones in stock. Transactions involving more tables/rows work in the same way.

Initially, the Shop table shows that the stock is updated with 1 iPhone4 and 3 BlackBerrys (Table 5.7) by a transaction with unique ID W6 and commit timestamp C6 (Table 5.8) (recall that the unique transaction ID is also used as the timestamp to write data into HBase). The Committed table contains a record for this stock update. Bob and Alice start transactions Ta and Tb concurrently, with start timestamps Sa=C6 and Sb=C6 (note that snapshots of different transactions can be the same, such as in this case). Transaction IDs are Wa and Wb, respectively (recall that unique transaction IDs are handed out from the W Counter table). Now let's assume that Alice and Bob both read the stock of iPhone4 and BlackBerry, and then Alice decides to buy 1 iPhone4 while Bob would like to buy both an iPhone4 and a BlackBerry. What happens in the background is that, in order to first read a proper version of data according to the snapshot, transactions Ta and Tb need to query the Committed table using the start timestamps Sa=C6 and Sb=C6 to get the most recently committed

Table 5.7: Shop table.

Row Key	iPhone4	BlackBerry
Stock	1	3

Table 5.8: Committed table.

Row Key	Shop:Stock:iPhone4	Shop:Stock:BlackBerry
C6	W6	W6

version of the stock data of both types of phones. They will both obtain HBase timestamp W6 and use W6 to read the stock from the Shop table and put the results into their readsets. (Listing 5.1: pseudocode line 15 to 23) After that they perform writes to update the stock and put data into their writesets (Listing 5.1: pseudocode line 27 to 31). Note that writes are applied to the Shop table immediately using timestamp Wa by Ta and Wb by Tb respectively, which is facilitated by the multi-version support of HBase. We choose to write the data into the data tables speculatively to make the eventual commit process faster. The writes become visible to other transactions only after the transaction has successfully committed.

When they are ready to attempt to commit, Ta and Tb use their transaction ID (Wa for Ta and Wb for Tb) as the row key to add a row to the CommitRequestQueue table with their writeset items as columns (Table 5.9). Both transactions enter into the CommitRequestQueue table a row with values for their writesets, and then request their commit request ID from the R Counter table. Then they put the commit request IDs, Ra and Rb, under the RequestOrderID column and perform a scan of the entire CommitRequestQueue table for all other row records with conflicting writeset items. This is to find any conflicting concurrent commit requests that may have Rj<Ra or Rj<Rb in the queue. In our example, assume that Tb finishes inserting Rb into its row and that the row for Ta has not appeared in the table yet. Tb then scans the CommitRequestQueue and

finds no conflicts (Ta has not inserted its row yet). Then Tb can proceed to scan the Committed table to check if there are any conflicting committed transactions with commit timestamp larger than its start timestamp (C6). Assume there are none. Tb is now cleared for committing and atomically (line 91) adds a row with its transaction ID Wb as the row key to the CommitQueue table (Table 5.10). After adding the row, it requests and obtains a commit timestamp Cb and then puts it into its row under the CommitTimestamp column. It then waits in the CommitQueue for its turn according to the CommitTimestamp to finally commit. This wait in the CommitQueue guarantees that all committed transactions Ti appear in the Committed table in the order of their commit timestamps Ci, and thus that all the records appearing in the Committed table are well ordered. Therefore, the last row of the Committed table can always identify a consistent snapshot containing all the previous committed updates. After Tb finishes committing (see the resulting Committed table in Table 5.11), it deletes its row in both the CommitQueue and CommitRequestQueue (Listing 5.1: pseudocode line 92-93). In the meantime, assume Ta finishes inserting its row into the CommitRequestQueue a bit later, and after it scans the CommitRequestQueue table for rows with conflicting columns, it sees that Tb has already entered the CommitRequestQueue with a conflicting writeset and RequestOrder ID Rb. Since Rb<Ra, Ta waits until row Tb disappears (meaning that Tb has either been committed or aborted) before proceeding (Listing 5.1: pseudocode line 54-65). While row Tb is still present, Ta could alternatively decide to abort immediately in this case of writeset conflict instead of waiting. However, it is possible that Tb may have to abort when checking on conflicting committed updates in the Committed table on a portion of the overlapping writeset disjoint with Ta's writeset such that, in the end, Ta would be able to commit after Tb aborts. For this reason, we choose to let Ta wait to avoid aborting transactions that could have committed successfully. For example, assume there is a third transaction, Tc, which committed soon after

Table 5.9: CommitRequestQueue table.

Row Key	Shop:Stock: iPhone4	Shop:Stock: BlackBerry	RequestOrderID
Wa	Y		Ra
Wb	Y	Y	Rb

Table 5.10: CommitQueue table.

Row Key	CommitTimestamp
Wb	Cb

Tb started and which updated the "BlackBerry" column only. Tb would then be in conflict with Tc, but Ta would not be. In that case, Ta should be able to go through to commit after Tb aborts. Because the check for conflicting committed transactions in the Committed table is a quick HBase scan operation, there is no harm to let Ta wait a short period of time in the CommitRequestQueue rather than aborting it immediately after seeing Tb in the queue.

5.3.3 Read Optimization

An optimization for performance to the protocol above is necessary because the size of the Committed table grows linearly as transactions commit (each committed transaction creates a corresponding row that persists in the Committed table). Recall that when reading a data item, HBaseSI needs to scan all the rows in the Committed table up to the snapshot start timestamp and iterate through

Table 5.11: Committed table.

Row Key	Shop:Stock: iPhone4	Shop:Stock: BlackBerry
C6	W6	W6
Cb	Wb	Wb

Table 5.12: Version table. For example, the most recently read version of the data item stored in user data location DataLocation1 was committed by the transaction with commit timestamp C17.

Row Key	CommittedTimestamp
DataLocation1	C17
DataLocationM	C8

the records in the result list of the scan to find the most recent data version. As shown in Figure 5.6 below, the time it takes for scanning and iterating through the records grows linearly as the number of rows containing the target columns to scan increases. It would be good if only a small range of the committed table needs to be scanned by newly arrived transactions if the most recently known committed data version is kept somewhere globally visible. Following this idea, an extra system table called "Version table" is created (Table 5.12). Each row in the version table corresponds to a data item that has been written to, identified by its table, row and column name combination. Instead of using a centralized system component to constantly update the Version Table records, every transaction is responsible to update the records when new versions of data are read. In other words, it becomes a collaborative effort among all the transactions to keep the data versions in the Version table up to date. With the Version table, when a transaction Ti tries to read any data item, it needs to query the version table first to see if there is a data version record. If there is a record and the commit timestamp Cj in the record is before Si, then Ti only scans the Committed table in the range [Cj, Si]. If the data item is a frequently accessed one, the range of scan will be very small. If no previous version is found or the version found is more recent than the snapshot time Si, a full scan of the Committed table up to the snapshot point Si is necessary. Whichever the case for the scanning range, if a newer version is detected and read, the reading

transaction updates the Version table record after reading the data item.

The adjusted pseudocode for reading with Version table can be found in Listing 5.2.

```
1 Read(dataTable, dataRow, dataColumn) {
    dataLocation = dataTable + dataRow + dataColumn;
3   if (dataLocation in WriteSet) {read from WriteSet; return dataValue;}
    if (dataLocation in ReadSet) {read from ReadSet; return dataValue;}
5   Cj = ScanVersionTable (dataLocation); //if the data item doen't exist in
        the Version table, Cj = 0
    if (Cj <= Si) {
7       committedRecord = ScanForMostRecentRow (in Committed table, range [Cj,
            Si] containing column dataLocation); //Scan in range [Cj, Si], and
             return the last record in the list
    } else {
9       committedRecord = ScanForMostRecentRow (in Committed table, range [0,
            Si] containing column dataLocation); //Scan in range [0, Si] (row
            keys are C counter values not less than 0), and return the last
            record in the list
    }
11  if (committedRecord > Cj) {
        UpdateVersionTable (dataLocation, committedRecord);
13  }
    Wread = committedRecord.valueAtColumn(dataLocation); //find the latest data
         version in snapshot. If the data item is not in the Committed table,
        Wread will be set to null
15  dataValue = readData(in dataTable, in dataRow, in dataColumn, with
        timestamp Wread); //read data. If Wread is null, no timestamp will be
        specified in the HBase read (recall that it is optional to specify a
        timestamp in reading from HBase)
    ReadSet.add (dataLocation, dataValue);
17  return dataValue;
}
```

Listing 5.2: Read with Version table.

5.3.4 Handling Stragglers

In the protocol above, a transaction needs to wait in two queues, the CommitRequestQueue and the CommitQueue. Due to many possible failure conditions, transactions could stay in waiting forever if one or more of the previously submitted transactions get stuck in the commit process and never delete their corresponding rows in the above two queue tables. We call those transactions that do not terminate properly in a timely manner "stragglers". Detecting and handling such stragglers is difficult due to the large variety of possible failures. Also, false positives can be problematic (treating some slow transactions as dead whereas they may come back to an active state at some undetermined time in the future). Measures must be taken to not only prevent such stragglers from hampering the other active transactions, but also to avoid any potential data inconsistency issues caused by re-appearing transactions that had been deemed to be dead.

HBaseSI handles stragglers by adding a timeout mechanism to the waiting transactions. More specifically, the waiting transactions can kill and remove straggling/failed transactions from the CommitRequestQueue or CommitQueue based on the clock of the waiting transaction if a preconfigured timeout threshold is reached. A problem associated with this method is that a straggler may come back to life and try to resume the rest of its commit process after its records in either queues are removed, which could cause data inconsistencies and incorrect SI handling. The solution to this problem is to use the HBase atomic CheckAndPut method on two rows at once in the Committed table when doing the final commit rather than only using a simple atomic row write operation on one row. The difference between CheckAndPut and simple row write is that the former method guarantees an atomic chain of two operations involving checking a row and writing to a possibly different row in the same HBase table, whereas the latter method only guarantees atomicity for a single row write operation. To use

the CheckAndPut method, we first add an extra row called "timeout" in the Committed table (Table 5.13). When it starts, each transaction first marks the column named after its unique transaction ID Wi (obtained from the W Counter table) in the "timeout" row as "N", meaning that the transaction is not in timeout by default (a non-empty initial value "N" must be set because the CheckAndPut method does not work with empty column values). Later, in the commit process, if a transaction is deemed a straggler, other transactions will put a "Y" under the column named after the unique transaction ID of the straggler in the "timeout" row, and then delete the corresponding records of the straggler in both the CommitRequestQueue and the CommitQueue. (Note that the sequence of first marking the straggler in the Committed table and only then deleting rows in the two queues is essential to the correctness of the SI mechanism). When a healthy transaction commits, it performs an atomic CheckAndPut: it checks for "N" in the "timeout" row, and if the check is successful, it puts its row into the Committed table. If the value under its corresponding column is still marked as "N", it can indeed successfully insert its row into the Committed table; otherwise it knows it has been marked as a straggler and should abort by deleting its records in both the CommitRequestQueue and the CommitQueue tables, if those records still exist. In this way, HBaseSI can make sure that no transaction can commit once it is marked as a straggler. There is no problem if after a transaction commits successfully by inserting a row into the Committed table, it fails to delete the corresponding rows in the queues on time; those records will be removed by waiting transactions after the timeout and SI is not compromised. Note that for garbage cleaning purposes, after a transaction successfully commits, it can remove the corresponding column value in the row "timeout".

Table 5.13: Committed table.

Row Key	writeset item 1	writeset item 2	W6	Wi	Wj
T6	W6	W6			
timeout			N	N	Y

5.3.5 SI Proof

We now give a proof according to the definition of SI that HBaseSI satisfies global strong SI, by proving the following Lemmas and theorems.

Lemma 5.1

In HBaseSI, for any two transactions Ti and Tj in the CommitRequestQueue, let Ri be the request order ID of Ti, Ω_i be the writeset of Ti, Rj be the request order ID of Tj, and Ω_j be the writeset of Tj. If Ri $<$ Rj, and Ti and Tj have conflicting writesets ($\Omega_i \cap \Omega_j \neq \emptyset$), then Ti is guaranteed to have committed or aborted before Tj can exit the CommitRequestQueue.

Proof Ti and Tj enter the CommitRequestQueue by inserting a row into the CommitRequestQueue table (Listing 5.1, line 50) before obtaining their request order IDs (Listing 5.1, line 51). If Ri $<$ Rj holds, and Ti and Tj have conflicting writesets, Ti must have finished inserting a row into the CommitRequestQueue table before Tj obtains the request order ID Rj. Then after Tj obtains the request order ID Rj and performs a full table scan of the CommitRequestQueue table for rows with conflicting writesets (Listing 5.1, line 53), the resultset of Tj's scan (the PendingCommitRequests list) must contain the row inserted by Ti if Ti has not committed or aborted yet. As long as PendingCommitRequests is not empty, Tj can not exit the CommitRequestQueue (Listing 5.1, line 54). By the time

PendingCommitRequests is empty such that Tj can exit the CommitRequestQueue, Ti is guaranteed to have committed or aborted because only in those two cases will the row corresponding to Ti be deleted from the CommitRequestQueue (having Ti's row deleted from the CommitRequestQueue table because of the straggler handling mechanism also means Ti has aborted). Therefore, the Lemma holds.

Lemma 5.2

In HBaseSI, for any two transactions Ti and Tj in the CommitQueue, let Ci be the commit timestamp of Ti and Cj be the commit timestamp of Tj. If Ci < Cj, then Ti is guaranteed to have committed or aborted before Tj can exit the CommitQueue.

Proof Ti and Tj enter the CommitQueue by inserting a row into the CommitQueue table (Listing 5.1, line 72) before obtaining their commit timestamps (Listing 5.1, line 73). If Ci < Cj holds, Ti must have finished inserting a row into the CommitQueue table before Tj obtains the commit timestamp Cj. Then after Tj obtains the commit timestamp Cj and performs a full table scan of the CommitQueue table (Listing 5.1, line 75), the resultset of Tj's scan (the PendingCommits list) must contain the row inserted by Ti if Ti has not committed or aborted yet. As long as PendingCommits is not empty, Tj can not exit the CommitQueue (Listing 5.1, line 76). By the time PendingCommits is empty such that Tj can exit the CommitQueue, Ti is guaranteed to have committed or aborted because only in those two cases will the row corresponding to Ti be deleted from the CommitQueue (and having Ti's row deleted from the CommitQueue table because of the straggler handling mechanism also means Ti has aborted). Therefore, the Lemma holds.

Lemma 5.3

In HBaseSI,

Part A: for any two transactions Ti and Tj, let Si be the start timestamp of Ti and Cj be the commit timestamp of Tj. Then all updates made by the committed transaction Tj which has the last Cj <= Si, as well as updates made by committed transactions with commit timestamps smaller than Cj, are visible to Ti when Ti starts;

Part B: all data items that have previously been written by transaction Ti itself are visible to Ti.

Proof Part A: Let Ty be the transaction committed with commit timestamp Cy which is the largest row key when Ti starts. Then Si = Cy. This means, Ty has left the CommitQueue and committed by inserting a row into the Committed table. We now prove by contradiction that all previously committed transactions are also visible. Let Tx be some committed transaction with commit timestamp Cx <= Si but assume the updates committed by Tx are not visible to Ti when Ti starts. In other words, at the time Ti starts, the Committed table does not contain a row with row key Cx. This would mean that Tx, with a commit timestamp Cx < Cy (commit timestamps are unique according to the label issuing mechanism of HBaseSI), has not yet committed. This contradicts Lemma 5.2. Therefore, Part A holds.

Part B: All data items that have previously been written by transaction Ti itself are stored in the writeset of Ti (Listing 5.1, line 28). The writeset of Ti is always accessed first by read operations and will return the desired data value if the data item is in the writeset (Listing 5.1, line 17). Therefore, Part B holds.

Lemma 5.4

In HBaseSI, for any two transactions Ti and Tj that are committed, let Si be the start timestamp of Ti, Ci be the commit timestamp of Ti, Sj be the start timestamp of Tj, and Cj be the commit timestamp of Tj. Then if (Si, Ci] $\cap$ (Sj, Cj] $\neq \emptyset$, the writesets of Ti and Tj are guaranteed to be disjoint.

Proof We prove by contradiction as follows. Assume that Ti and Tj have conflicting writesets and are both committed. Let Ri be the request order ID of Ti, and Rj be the request order ID of Tj. Without loss of generality, let Ri $<$ Rj (request order IDs are unique and strictly ordered). According to Lemma 5.1, Ti is guaranteed to have committed before Tj can exit the CommitRequestQueue. Then we have Sj $<$ Ci $<$ Cj. Here, Sj $<$ Ci must hold because otherwise (Si, Ci] $\cap$ (Sj, Cj] $= \emptyset$, and commit timestamps are unique and strictly ordered so that Ci $<$ Cj holds. After Ti commits, Tj may exit the CommitRequestQueue and performs a scan of the Committed table in row range (Sj, ∞) (Listing 5.1, line 35). The resultset must contain row Ci with writeset conflicting with Tj. Tj is then forced to abort instead of being able to commit, which contradicts our assumption. Therefore, the lemma holds.

Theorem 5.5

If Lemmas 5.3 and 5.4 are true, then HBaseSI satisfies global strong SI.

Proof We prove global strong SI according to the definition given in Section 5.2.1. For all the committed transactions in the transaction history, according to Lemma 5.3, read operations in any transaction Ti see the data tables in the state after the last commit before Si and can see the writes of Ti itself; according to

Lemma 5.4, concurrent transactions have disjoint writesets. Therefore, HBaseSI satisfies global strong SI.

Theorem 5.6

The Version table optimization and straggler handling mechanism do not affect the global strong SI guarantee of HBaseSI.

Proof The Version table optimization does not affect the upper bound of the scan range (the upper bound equals the start timestamp Si of Ti, see Listing 5.2, line 7 and 9) in the Committed table for reads, nor does it affect the sequence of reading from writeset first when reading a data item (Listing 5.2, line 3). Therefore, Lemma 5.3 still holds. This optimization only concerns reads. Therefore, Lemma 5.4 still holds. According to Theorem 5.5, global strong SI still holds for HBaseSI.

The straggler handling mechanism deletes rows from the CommitRequestQueue and CommitQueue table only after the "timeout" row has been marked in the columns of the Committed table corresponding to the straggling transactions. The atomicity of the HBase row write and checkAndPut operations guarantees that once a row in the Committed table has received a "timeout" mark, the straggling transaction cannot commit anymore, but can only abort. Therefore, Lemmas 5.1 and 5.2 still hold, and as a result, Lemmas 5.3 and 5.4 hold. According to Theorem 5.5, global strong SI still holds for HBaseSI.

5.3.6 Discussion

In the previous sections, the detailed protocol of HBaseSI was elaborated with an example scenario where Alice and Bob purchase smartphones. The Version table optimization and straggler handling mechanism improve the efficiency and robustness of the protocol. In this section, some further issues about the

HBaseSI design and usage are discussed. First, there is no roll back or roll forward mechanism in HBaseSI and there is no explicit transaction log either. It is interesting to ponder on how HBaseSI supports ACID transactions, even in the face of failures, without those traditional mechanisms used in DBMSs. In fact, this can all be attributed to two very important HBase properties. The first one is that HBase stores many versions of data and allows reads/writes of data using a specific timestamp. This HBase property makes it possible for every concurrent transaction to write preliminary versions of data but only the successfully committed transactions get to publish the write timestamps they used in the Committed table for future reads. In other words, no roll back is necessary because uncommitted data won't be used in any case. The other property is the atomicity of the HBase row write and CheckAndPut methods. Using these atomic methods, HBase guarantees that once a row is inserted into the Committed table successfully, it becomes durable and is guaranteed to survive failures (media failure is handled by HDFS which stores data replicated across distributed locations).

Second, we discuss some design choices that affect performance such as scalability and disk usage. HBaseSI inherits many of the desirable properties of HBase because it is only a client library and imposes little overhead concerning system deployment. However, users need to be aware that in order to achieve several design goals, HBaseSI sacrifices some performance. For example, four important goals HBaseSI tries to achieve are: 1. global strong SI across table boundaries; 2. non-intrusive to user data tables; 3. non-blocking start of transactions with snapshots that are as fresh as possible (strong SI), and non-blocking reads; 4. strict "first-committer-wins" rule without lost transactions (transactions only abort when there is no chance they will be able to commit successfully). In order to achieve goal 2, HBaseSI is designed to use a separate set of system HBase tables for maintaining transactional metadata for all user tables instead

of creating extra columns in each separate user table, which inevitably creates potential performance bottlenecks at the small number of global system tables. HBaseSI is therefore not designed to provide scalability in terms of the number of transactions per unit time, but its target is to provide scalability in terms of cloud size and user data size. HBaseSI makes the final commit process as short as possible and allows writes to insert preliminary data into the user data tables as the transaction proceeds rather than waiting till the commit time to apply all the updates (note that when a transaction aborts, it should remove its written items from user tables), avoiding possible large waiting latency incurred by transactions with large writesets to be applied at commit time. In essence, HBaseSI trades disk space for high throughput in transaction commits. Additionally, it is important that the number of data versions HBase table locations can hold is set sufficiently high. For example, for data items that are likely to be updated concurrently by many clients, the number of versions allowed should be set to some larger value than default so that all the concurrent client writes can succeed. Furthermore, since multiple versions of old committed data may accumulate (the uncommitted data are already cleared by transactions when they abort), a dedicated garbage cleaning mechanism should be created for optimizing disk usage, with a policy on maximum transaction duration (such a policy is important to guarantee that the data that gets garbage-cleaned is not needed by any long-running transactions in their snapshots taken some time ago).

Third, we discuss the efficiency of having transactions wait in queues when committing. Recall that in the HBaseSI protocol, update transactions first wait in the CommitRequestQueue for the purpose of establishing an order in committing transactions and guaranteeing the "first-committer-wins" rule, and then wait in the CommitQueue after they are cleared for committing for the purpose of guaranteeing a correct global sequence of commits so that each row in the Committed table can identify a consistent snapshot of the data tables. This allows

new transactions to immediately obtain a start timestamp and start reading (non-blocking reads). Note that the first wait is only for transactions with conflicting writesets, but the second wait results in sequential processing of all concurrent transactions, no matter whether the writesets are in conflict or not. Although these two waits are essential for the commit queuing mechanism to work so that global strong SI can be achieved, it may sometimes be more efficient to relax the second wait to the extent that a transaction only waits for other transactions that use the same set of user tables. This would require transactions to declare in advance which groups of tables they use. This relaxation is reasonable in real-world applications. More specifically, for example, online e-commerce sites need to worry about the data consistency for a certain product in stock accessed by concurrent buyers through the same online portal (which means calling the same transactional routine concurrently). Those transactions shouldn't be waiting for the ones updating employee records or salaries in the back end. HBaseSI can be very easily adapted to such extended usage scenarios to make transactions more efficient in terms of minimizing unnecessary wait times in the CommitQueue. The decision of whether to use the extended scheme would be at the users' discretion. Also, in this case users cannot be allowed to write to tables outside the set they have declared. The benefit of using the extended scheme is a possible boost in performance, especially in the face of a large number of concurrent update requests.

Finally, we discuss the cost of adopting HBaseSI and the easiness of reverting back to non-SI default HBase. Normally, once one starts to use HBaseSI, all the read/write operations must be performed through the HBaseSI API rather than the default HBase API. Otherwise, the most recently updated data versions will not be maintained and used. Only through the HBaseSI API can a transaction find the correct timestamp used in writing the most up-to-date data, or make its committed updates accessible. This is because the timestamps used by HBaseSI

could be smaller than the default timestamps HBase uses when no explicit timestamps are specified for reads/writes. However, it is very easy to write a small tool to help restore the user data tables back to a state that users can use their data tables in the default HBase manner. The tool only needs to write the latest version of committed data to all the user data tables once, without specifying timestamps (so that the HBase default timestamps are used). The tool should also delete all the tables used by HBaseSI storing transactional metadata to make sure that no transactions could use the outdated transactional metadata leading to errors. The next time users want to use HBaseSI again, they can simply re-initialize the HBase tables for holding transactional metadata and start using HBaseSI without any required changes to existing user data.

5.4 Performance Evaluation on Amazon EC2

The general purpose of this performance evaluation section is to quantify the cost of adopting the HBaseSI protocol in handling concurrent transactions. Therefore tests are performed on each critical step of the HBaseSI protocol, with comparison to the performance of bare-bones HBase when possible. Additionally, because HBaseSI is the first system that achieves global strong SI on HBase, there are no other similar systems to compare with for some of the properties. As a result, for those properties, the tests serve the purpose of showing the users the expected behavior of the system. Furthermore, as mentioned in Section 5.3 above, HBaseSI uses a set of global system tables that facilitate non-blocking reads and a strict "first-committer-wins" rule, but may become performance bottlenecks if accessed by many concurrent transactions. The test results are thus expected to reflect the system performance under varying loads.

We use 20 Amazon machines in total to perform the tests and we are aware that performance variations may be observed in Amazon instances [40]. The test results may be affected by this to some extent but should be sufficient for

proof-of-concept purposes. A high memory 64-bit linux instance with 15 GB memory, 8 EC2 Compute Units (4 virtual cores with 2 EC2 Compute Units each) and high I/O performance is used to host the Hadoop namenode, jobtracker and the HBase master system component. Up to 19 other high CPU 64-bit linux instances with 7 GB of memory, 20 EC2 Compute Units (8 virtual cores with 2.5 EC2 Compute Units each) and high I/O performance are used to host Hadoop datanodes, HBase regionservers and run client transactions. The reason to choose a high memory instance to be the master server is because of the observation that under heavy loads from many concurrent clients, the mostly consumed resource at the server is memory. For instances running client transactions, however, the mostly consumed resource is CPU cycles, which is why the other 19 instances are chosen to be high CPU instances so that multiple client transactions can be run on each one of them. All these machines are in the same Amazon availability zone so that the network conditions for each instance are assumed to be similar.

In the tests, each machine instance runs a single client program issuing transactions if the total number of clients is less than 19. If the total number of clients is more than 19, an equal number of concurrent clients are run at each machine instance. For example, each machine instance can run 1, 2, or more clients with the total number of transactions being 19, 38, etc. At each client, transactions are issued consecutively one after another. In other words, a new transaction will only be issued when the previous one has finished executing, having either committed or aborted. Each transaction is executed for 3 times and the performance measure for the corresponding transaction is calculated as the average of the measures obtained from the 3 runs. We do this to average out the short-term performance variance of the Amazon EC2, which is further discussed at the end of this section. Additionally, we perform all the different tests (described below) in a single large batch on the same virtual cluster, in order to minimize the potential effects of long term performance variance (e.g.,

performance variance between days, weeks, etc.) in Amazon EC2. A batch of tests takes about 16 hours on Amazon EC2.

The goal of Test 1 is to measure the performance of the timestamp issuing mechanism in terms of throughput. In the test, each client connects to the server and requests a new timestamp directly after being granted one. After a starting flag is marked in an Indicator table, all clients run for a fixed period of time and stop. The throughput is calculated by dividing the total number of timestamps issued by the length of the fixed time period. Figure 5.3 shows the result of this test. Apparently the server gets saturated at a total throughput of about 360 timestamps per second, or about 30 million timestamps per day. Note that the timestamp generating mechanism currently used by HBaseSI is the most straightforward solution a user can get by using bare-bones HBase functionality. Other more efficient timestamp generating mechanisms with much higher throughput can also be adopted if the user desires, such as the one used by Google's Percolator system [36] which generates 2 million timestamps per second from a single machine.

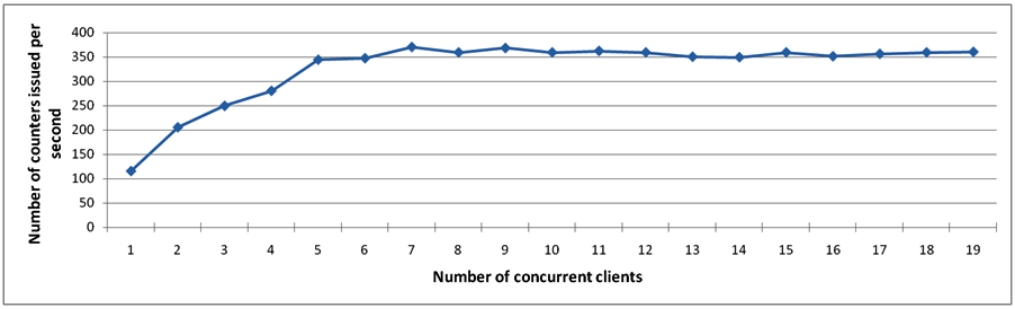


Figure 5.3: Test 1, performance of the timestamp issuing mechanism through counter tables.

The goal of Test 2 is to measure the performance of the start timestamp issuing mechanism via the Committed table in terms of throughput, i.e., how

many transactions can be allowed to start per second (in order for a transaction to start, a start timestamp must be issued first) with an increasing number of concurrent clients. Recall that the mechanism to obtain a start timestamp is different from getting a unique counter value from one of the counter tables. Instead, a transaction needs to read the last row of the Committed table at the time it starts and use the row key as its start timestamp. In this test, the clients all connect to the server first and then wait for a signal in the Indicator table to start at the same time. During the test, a program is run at the EC2 instance running the HBase server inserting a new row to the Committed table continuously, mimicking the real-world scenario where the Committed table keeps growing in size because of newly committed transaction records. The throughput is calculated in the same way as Test 1. Figure 5.4 shows the result for Test 2. The throughput stabilizes at about 420 timestamps per second due to server saturation, slightly higher than the result obtained from Test 1. The higher performance is expected because in Test 1 an atomic function call to increment a common column value is issued each time a counter value is to be obtained by each concurrent client, potentially causing a blocking write conflict at the HBase server, while in Test 2, only scanning the last row of the Committed table is necessary. The performance is thus satisfactory to the extent that the start timestamp mechanism is not the limiting bottleneck for starting new transactions even if the mechanism requires that every transaction should read from the Committed table at starting time.

The goal of Test 3 is to study the comparative performance of transactions with SI that contain a set of read/write operations, against executions of the same number of read/write operations with bare-bones HBase, for varying numbers of operations per transaction. In the test, we run 1 client only, vary the number of operations per transaction and measure the time spent on each read/write operation. Additionally, in order to control the performance overhead associated

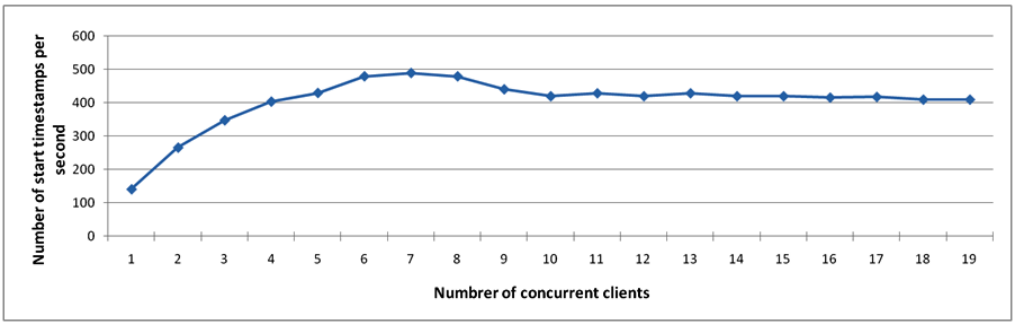


Figure 5.4: Test 2, performance of the start timestamp issuing mechanism.

with scanning a growing Committed table (recall that each SI read needs to scan the Committed table first to get the most up to date data version before actually reading the data), after each client run, the Committed table is manually cleaned. (In this test, no previous data versions exist, because the Committed table is cleaned up after each previous transaction execution and data locations are only written to once, but a quick scan is still executed for every read). The result of the test quantifies the performance overhead of transaction SI over bare-bones HBase. The results in Figure 5.5 show the startup/commit overhead of the protocol and how it can be amortized as the number of read/write operations per transaction grows. This indicates that the protocol is more efficient for transactions involving a larger number of operations per transaction or transactions with longer inter-operation intervals (user "think time" during user interactions) to better amortize the transaction startup/commit overhead.

The goal of Test 4 is to measure the time needed to scan the same column in a data table over a growing row range (each row contains a data value in the column scanned). The expected result is a linear growth of time corresponding to the number of table rows scanned. The result is used to show the necessity of using the Version table when performing reads in order to avoid costly full scans of the Committed table on every read. In this test, a single client is executed

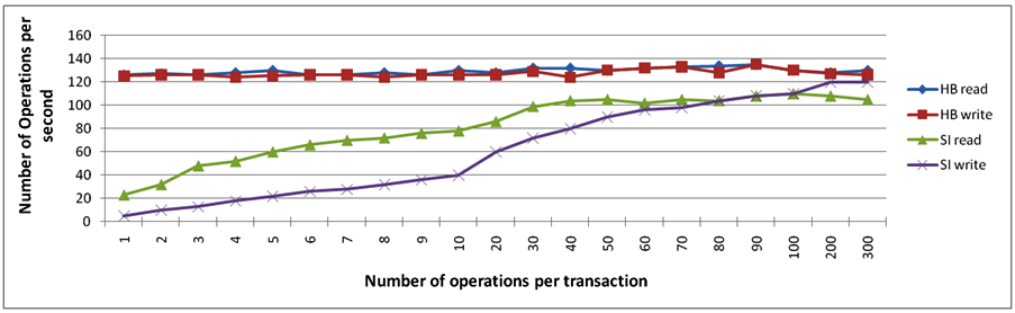


Figure 5.5: Test 3, comparative performance of executing transactions with SI against bare-bones HBase without SI.

to scan a data table with a continuously growing row range. The test result is shown in Figure 5.6 and is exactly according to expectation with linear growth in time.

We also perform two other tests on the performance of reads with the Version table. Recall that for data items written only once (a scan in the Committed table only returns 1 result), bare-bones HBase already has an efficient method to read those data items no matter how large the table is (since column scans are fast), and therefore the Version table is not needed in this case. However, for data items that are modified frequently (a scan in the Committed table can return many results), the use of the Version table is expected to reduce the size of the resultset from the scan of particular data columns in the Committed table for individual read operations, if there are other read operations previously performed on the same data items. Therefore, we design the following two tests.

In the first test, to show that the Version table is not needed for reading data items that are written once, we make two tables: one is a single-column table with only 1 row and the other is a double-column table with 10000 rows containing data only in column A and 1 extra row at the end of the table containing data only in column B. Then we measure the time it takes to scan the single-column

table with only 1 row and the time to scan column B in the double-column table without the use of the Version table. Table 5.14 shows the result of this test. As we can see, scanning the single-column table with only 1 row and scanning column B of the double-column table takes about the same time, verifying that the Version table optimization is not needed for reading data items that are written only once.

In the second test, we use the Version table on all the read operations. First, we make a single-column table with 1 row and measure the time it takes to read the column data value. Next we perform 10000 transactions each containing a single write operation to insert a new row to the table with data in the same column. As a result of these update transactions, the Committed table now contains many rows. Then we measure the time it takes to run a read-only transaction to read the most recent version of the data value in the same single column. After this, we run another batch of 10000 transactions each containing a write and a read operation on the same column. Because the Version table is used, the range to scan in the Committed table for each read operation is 1. Table 5.15 shows the results of this test. We can see that the time it takes to read the single-row-single-column table is the same as the time it takes to read the data value when many other reads on the same data item are previously performed, whereas the time to read a data item that has not been read by previous transactions is much longer. This indicates that the Version table is effective as expected.

The goal of Test 5[1] is to measure the comparative performance of transactional SI with the use of the Version table on workloads with different read/write ratios. We use several different kinds of workloads with mixed read/write operations corresponding to real-world e-commerce scenarios, such as online shopping. A "95/5

[1] Starting from Test 5 and for all the tests that follow, we use a 200 millisecond timeout threshold for the straggler handling mechanism, which causes some transactions to abort. More detailed discussions about this effect are given later in the section.

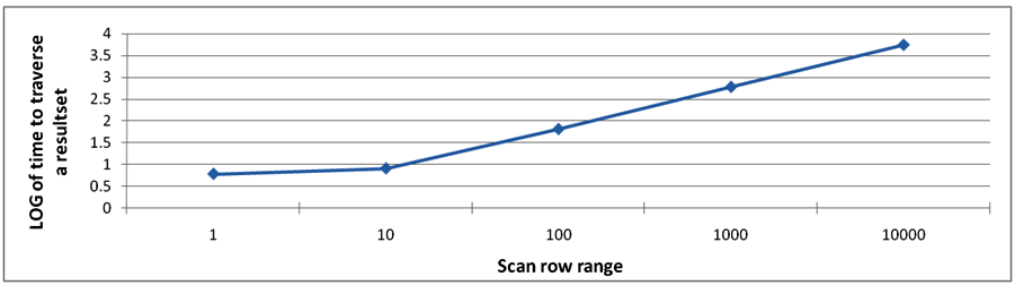


Figure 5.6: Test 4, time to traverse a resultset against a varying number of rows to scan.

Table 5.14: Test to show that the Version table is not needed for reading data items that are written only once. The time recorded in each column is the time of scanning the table using bare-bones HBase scan.

	Scanning a single column on the single-row table	Scanning column B of the multi-row-double-column table
Time (ms)	17	18

Table 5.15: Test to show that the Version table is effective to reduce the scan range in the Committed table. The time recorded in each column is the total time of running a transaction containing one read operation using HBaseSI.

	Reading a data item that is written once	Reading a data item that is written 10000 times but not read	Reading a data item that is written and read 10000 times
Time (ms)	877	4046	896

mix" is composed of transactions containing 95% read and 5% write operations; a "80/20 mix" is composed of 80% reads and 20% writes; and an "50/50 mix" is composed of 50% reads and 50% writes. In the test, we run clients executing the above three kinds of workloads with a varying number of concurrent clients, each executing a random number of reads/writes according to the above specifications with an average of 15 operations per transaction, upon a table with 10,000 data rows. We measure two things: throughput (number of transactions per second) and average commit time for successful update transactions (the average time spent in the commit process). There are two kinds of throughput to be measured. One is the overall throughput including both successful and aborted transactions, which shows the general system capacity in handling concurrent transactions. The other is the throughput for successfully committed transactions only, which can be used to calculate the ratio of successful transactions. This ratio, multiplied by the throughput of running the same set of read/write operations using bare-bones HBase, can be used to estimate the overhead of adopting HBaseSI to obtain correctness in transactions compared to bare-bones HBase performance for the successful transactions. It is also interesting to see how much time is spent in the CommitRequestQueue and the CommitQueue separately because for different types of mixed workloads, the ratio of the number of update transaction requests and the number of actually committed transactions is different. The result for total throughput is shown in Figure 5.7. An interesting point for this result is the comparative performance between these types of workloads. As we can see, as the number of concurrent clients grows, the "80/20 mix" and the "50/50 mix" have similar throughput, lower than the "95/5 mix". The reason why the "80/20 mix" has the lowest throughput is because the "80/20 mix" actually has the most number of successful update transactions processed among the three mix types: the "95/5 mix" doesn't have many costly update transactions, and the "50/50 mix" doesn't have many successfully committed update transactions

either because of the higher probability of having conflicts (recall that we count both successful and failed transactions in the total throughput). The throughput of the server saturates as the number of concurrent clients increases.

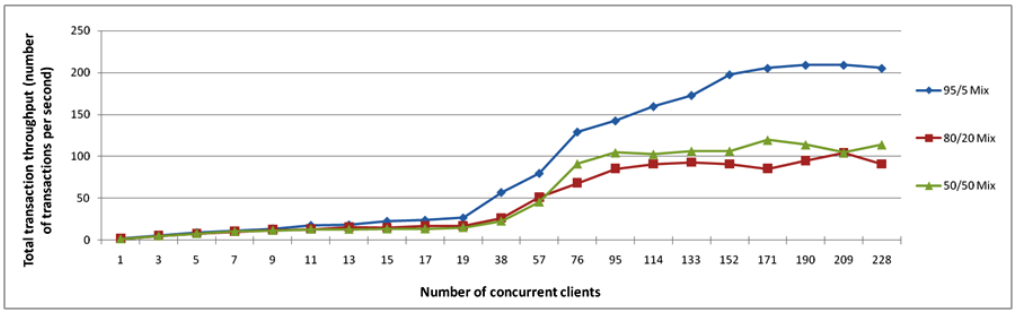


Figure 5.7: Test 5, general performance (total throughput) of executing transactions with SI under different workloads.

Figures 5.8, 5.9, and 5.10 show the estimated overall cost of adopting HBaseSI in comparison to using bare-bones HBase in handling the three types of workloads, namely, the "95/5", "80/20" and "50/50" mix. Figure 5.11 shows the ratio of the successful transactions. The general purpose of showing these test results is to give users an idea of the performance tradeoff for transactional correctness. The test compares the total transaction throughput and successfully committed transaction throughput using SI against the throughput of the estimated number of correct transactions using bare-bones HBase. The estimation is done by first calculating the ratio of "number of successful transactions/number of total transactions" using SI, and then multiplying that ratio with the total throughput of doing the same total set of read/write operations using bare-bones HBase. Generally, the throughput for estimated correct transactions using bare-bones HBase is about 5 times the throughput using HBaseSI.

Note that the low success ratios shown in Figure 5.11 are attributed to transactions that failed because of having conflicts with other concurrent transactions

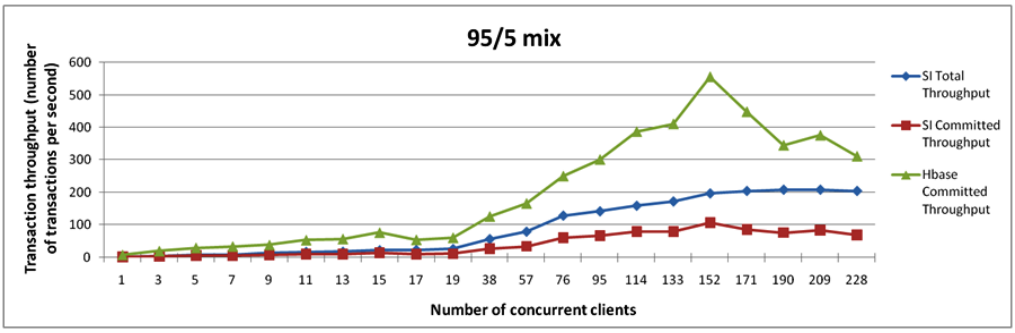


Figure 5.8: Test 5, comparative throughput between SI and estimated successful HBase transactions under the "95/5 mix".

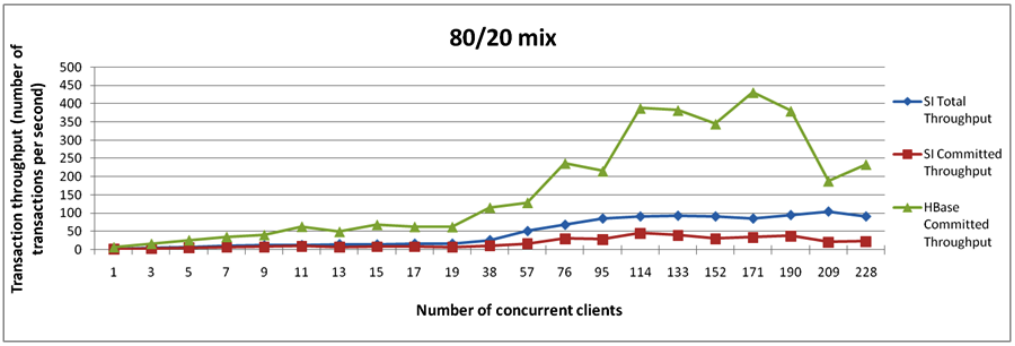


Figure 5.9: Test 5, comparative throughput between SI and estimated successful HBase transactions under the "80/20 mix".

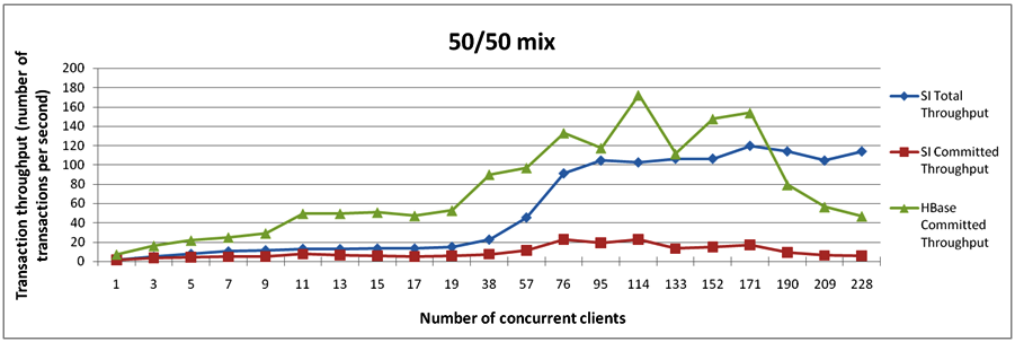


Figure 5.10: Test 5, comparative throughput between SI and estimated successful HBase transactions under "50/50 mix".

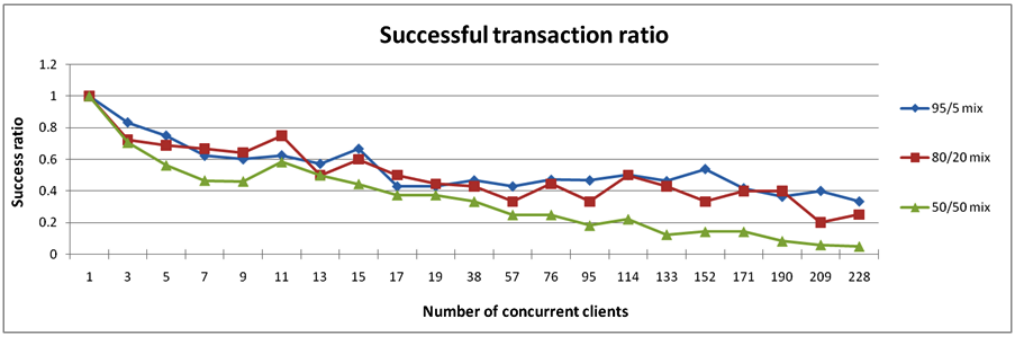


Figure 5.11: Test 5, successful transaction ratio under different types of workloads.

and transactions that were terminated by the straggler handling mechanism [2]. As mentioned earlier, we use 200 milliseconds as the timeout threshold for the straggler handling mechanism. The timeout threshold is chosen as twice the average wait time a transaction spends in the queue (in the case when there is only 1 client issuing transactions). Figure 5.12[3] shows the percentage of failing transactions that fail due to the straggler handling mechanism with timeout threshold 0 and 200 milliseconds (ms) under the "50/50 mix" for a small number of concurrent clients (the negative effects of choosing an improper timeout threshold value such as 0 ms are apparent). With 0 ms as the timeout threshold, a large portion of the transaction aborts are false aborts (no conflicting writesets) even when there are only a few concurrent clients; whereas with 200 ms as the timeout threshold, the false aborts only start to be significant after there are more concurrent clients issuing transactions that get queued up in the two queues. Therefore, the timeout threshold used in the straggler handling mechanism should be set properly according to the system capacity to control the false abort rate. Although choosing a timeout threshold is complicated and the timeout threshold may need to be adjusted according to the real-time workload of the system, the benefits still outweigh the drawbacks because otherwise client transactions might wait for stragglers forever.

Results for the average commit time for all three types of mixed workloads are shown in Figures 5.13, 5.14 and 5.15, respectively. As for the "95/5 mix" (Figure 5.13), write operations are relatively rare (5%). Therefore conflict probability is low. Transactions that get queued in the CommitRequestQueue are also likely to be able to commit successfully in the end. Therefore transactions tend to spend almost the same (short) time on average staying in both queues. As for the

[2]Another factor to consider is that in our tests we obtain average results from 3 trials, which is a rather small sample that could introduce variance. However, the choice of the small sample does not affect the general scaling trend of our test results, which is the actual focus of the tests.

[3]This test is done in a separate batch using a total of one EC2 Extra Large instance (m1.xlarge).

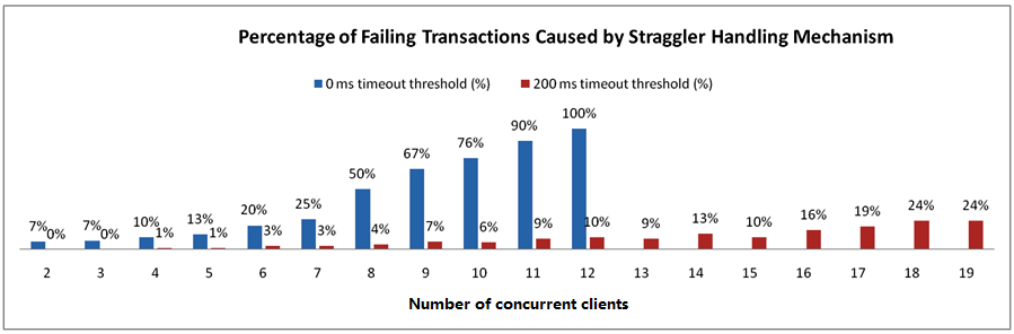


Figure 5.12: Test 5, percentage of failing transactions that fail due to the straggler handling mechanism with 0 and 200 milliseconds as timeout thresholds respectively.

"80/20 mix" (Figure 5.14), more update transactions (than in the "95/5 mix") are queued up for committing after passing the commit request checking stage at the CommitRequestQueue. Since the conflict rate increases as the number of concurrent clients increases (especially because of the fixed total number of data items under shared access), many transactions are queued in the CommitRequestQueue. Because the write operation rate for the "80/20 mix" (20%) is still much lower than in the "50/50 mix" (50%), most transactions queued up in the CommitRequestQueue eventually move on to the CommitQueue, resulting in a higher wait time in the CommitQueue than in the CommitRequestQueue due to the extra processing time in the final commit process. As for the "50/50 mix" (Figure 5.15), because there is a much higher conflict probability than for the other two mix workloads, more transactions are queued and finally aborted at the checking stage in the CommitRequestQueue. Only a few transactions can enter the CommitQueue, therefore the time spent in the CommitQueue is comparably much less than in the CommitRequestQueue.

The goal of Test 6 is to test the effectiveness of the straggler handling mechanism. We use the "80/20 mix" from Test 5 with 19 concurrent clients and add

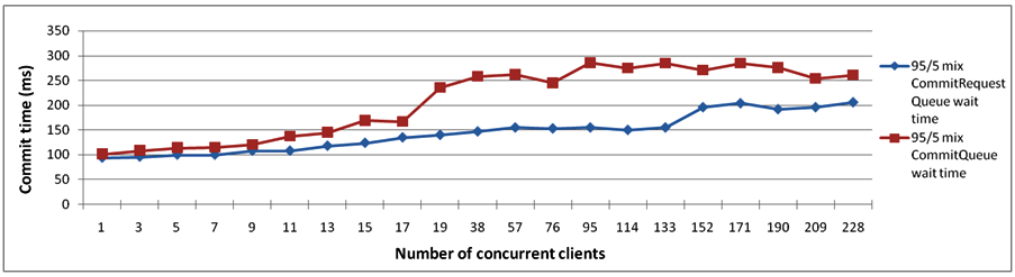


Figure 5.13: Test 5, "95/5 mix" wait time in both CommitRequestQueue and CommitQueue.

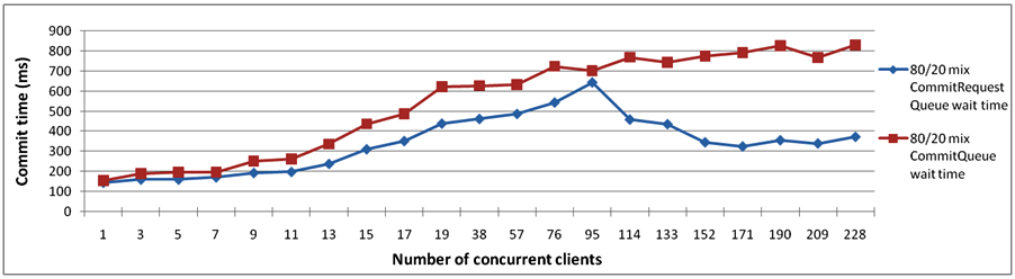


Figure 5.14: Test 5, "80/20 mix" wait time in both CommitRequestQueue and CommitQueue.

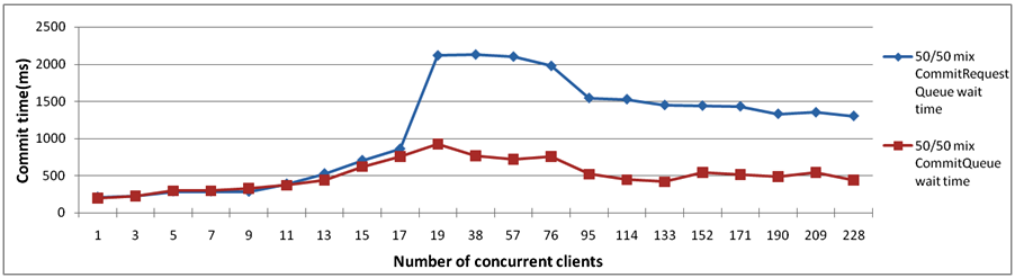


Figure 5.15: Test 5, "50/50 mix" wait time in both CommitRequestQueue and CommitQueue.

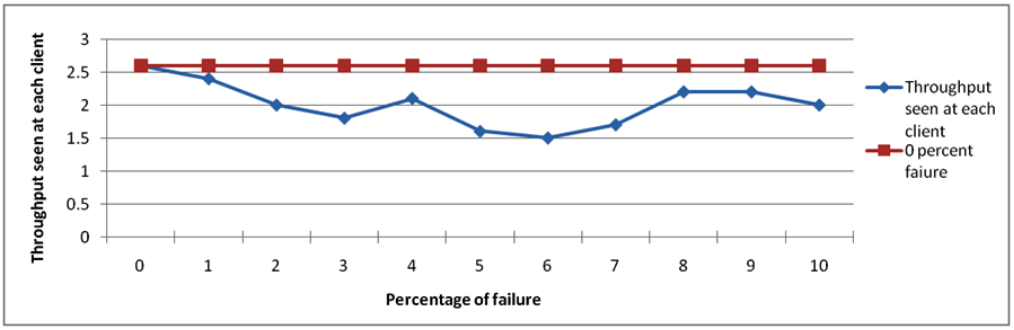


Figure 5.16: Test 6, throughput seen at each client under a varying failure ratio.

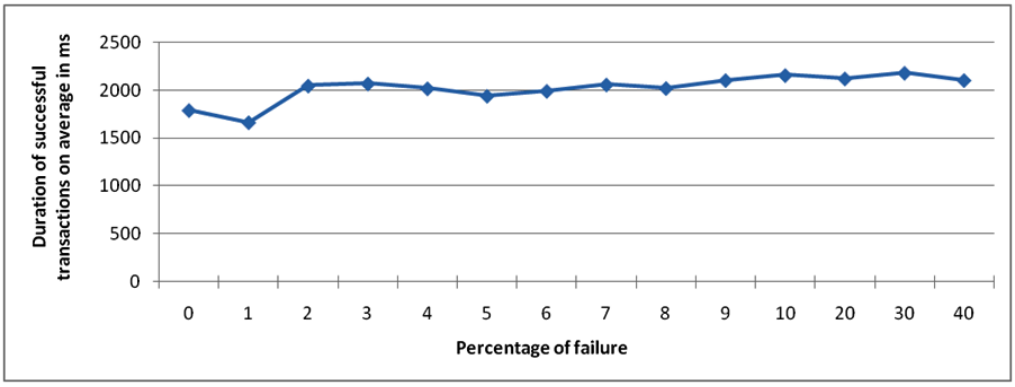


Figure 5.17: Test 6, average duration of successful transactions under a varying failure ratio.

an abort ratio at the end of each transaction. With an increasing abort ratio, we measure the total throughput in terms of transactions per second. Because the artificially inserted aborts occur at the end of transactions while transactions wait in the CommitRequestQueue after completing all the reads/writes, we still count the aborted transaction into the calculation of the throughput. The failed transactions become stragglers in the CommitRequestQueue table that have to be removed by live transaction processes. The results show how random transaction faults affect the performance of the SI protocol. As seen in Figure 5.16, the system achieves throughput similar to the case with no artificially inserted faults (because we also count the aborted transactions in the throughput calculation). We can also see from Figure 5.17 that the duration of successful transactions stays almost constant in the face of failures, indicating that the straggler handling mechanism is effective in bounding healthy transaction duration.

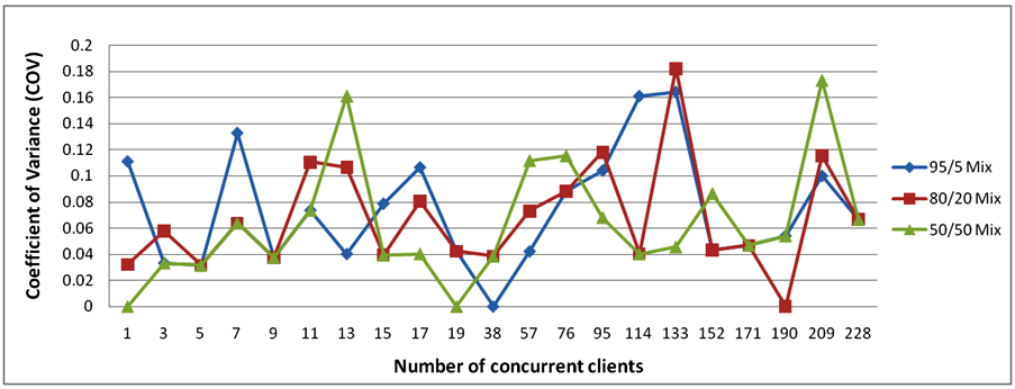


Figure 5.18: Coefficient of Variance (COV) calculated from data collected in Test 5.

We also measure the variance of Amazon EC2 performance in our tests with the Coefficient of Variance (COV) metric used in [40]. The COV is calculated by formula 5.1. Here N is the total number of measurements; x_1, .., x_n are the

Large instances								
$\overline{x}_{\mathrm{COV}_{G_i}}$	All		Day		HourOfDay		DayOfWeek	
	US	EU	US	EU	US	EU	US	EU
Startup Time	2.022	0.479	0.330	0.330	0.812	0.416	1.192	0.451
S3 Upload Time	0.395	0.481	0.356	0.406	0.371	0.448	0.383	0.472
Bonnie Seq Out	0.226	0.191	0.227	0.183	0.227	0.192	0.317	0.189
Bonnie Random Read	0.114	0.149	0.112	0.141	0.114	0.148	0.113	0.147
CPU	0.237	0.243	0.208	0.222	0.235	0.242	0.236	0.242
Memory	0.108	0.097	0.093	0.085	0.105	0.096	0.107	0.095
Iperf	0.201	0.124	0.204	0.121	0.196	0.122	0.205	0.123

Figure 5.19: Coefficient of Variance (COV) of Amazon EC2 performance reported in [40].

measured results; and $\overline{x}$ is the mean of those measurements:

$$COV = \frac{1}{\overline{x}} \sqrt{\frac{1}{N-1} \sum_{i=0}^{N} (x_i - \overline{x})^2} \tag{5.1}$$

Figure 5.18 shows the COV calculated for the data obtained in Test 5 (the total throughput numbers of Figure 5.7). As mentioned in the beginning of this section, every test is executed 3 times. Because the 3 repetitive runs of each transaction happen in the same hour, we compare our COV with the "HourOfDay" COV (as shown in Figure 5.19) reported in [40] and the results are consistent. The COV observed in Figure 5.18 also indicates that the short-term variance of Amazon EC2 in the same region is not large and we argue that our tests generate results that are sufficiently accurate to support our conclusions, especially because our analysis focuses on the effects of scaling.

5.5 Related Work

Several transactional systems exist for HBase, but none provide SI. The HBase project itself includes a contributed package for transactional table management, but it does not support recovering transaction states after region server failures. However, it is not fully implemented for reliable and practical transactional

processing due to the lack of support for recovering transaction states after region server failures and the possibility of lost updates for transactions with blind writes. G-store [5] supports groups of correlated transactions over a pre-defined set of data rows (called "Key Group") specified for each group of transactions respectively. G-store does not support general transactions across all the data tables and is suitable for applications that require transactional access to Key Groups that are transient in nature with an assumption that the number of keys in a Key Group must be small enough to be owned by a single node. CloudTPS [42] implements a server-side middleware layer composed of programs called local transaction managers (LTMs), but introduces extra overhead of middleware deployment, data synchronization, and fault handling. Each LTM is responsible for on-demand caching a subset of all data items. A transaction must specify the row keys of all the data to be accessed at transaction start time and then sends transaction request to any LTM to start a 2-phase commit protocol among all the LTMs serving parts of the data items accessed by the transaction. CloudTPS basically recreates another layer of small HBase-like region servers with data loaded on-demand on top of HBase, introducing extra overhead of middleware deployment, data synchronization, and fault handling. None of these systems provides SI.

Only recently two relevant papers were published independently at almost the same time about achieving snapshot isolation for distributed transactions, for HBase and for BigTable: we published a paper describing our initial system (the predecessor of the system described in this chapter) to support transactions with SI on top of HBase [48], and Google published a paper about their system called "Percolator" [36] supporting transactions with SI on top of BigTable. The two systems share many design ideas yet are different in some major design choices.

HBaseSI is an extended and improved version of our initial system of [48]. It is similar to the initial system and similar to Google's Percolator [36] in

that: all three systems are implemented as a client library rather than a set of middleware programs and allow client transactions to decide autonomously when they can commit (there is no central process to decide on commits); they all rely on the multi-version data support from the underlying column store for achieving snapshot isolation, and store transactional management data in column store tables; they all make use of some centralized timestamp issuing mechanism for generating globally well-ordered timestamps; and after starting using either of the systems, users must use the systems for all the subsequent data processing operations in order to guarantee data consistency. HBaseSI is superior to the initial system of [48] in that: HBaseSI is the first system on HBase to support global strong SI rather than the "gap-less" weak SI in the initial system; it uses a completely different mechanism in handling distributed synchronization (HBaseSI uses distributed queues to guarantee a correct sequence of transaction execution, while the initial system uses a complicated and rather inefficient mechanism to obtain snapshots); the initial system is inefficient because its PreCommit table grows without bound and has to be searched in its entirety by transactions attempting to commit; HBaseSI provides a simple mechanism for handling stragglers, whereas handling stragglers for the system proposed in [48] would be overly complicated.

In addition to the similarities listed above, HBaseSI shares with Percolator its support of global strong SI. HBaseSI and Percolator are also very different in several other aspects: HBaseSI focuses on random access performance with low latency whereas Percolator focuses on analytical workloads that tolerate larger latency; HBaseSI is non-intrusive to existing user data tables and stores the version information and transaction information in extra system tables, whereas Percolator is intrusive to existing user data and stores the same information in two extra columns in every user tables (but this design decision of HBaseSI makes it less scalable than Percolator concerning the number of concurrent

transactions), because Percolator distributes the transactional metadata to the individual user data tables, rather than using a common set of global system tables as in HBaseSI); HBaseSI supports non-blocking starts of transactions and does not block reads, whereas Percolator may block reads while data is being committed which may harm performance; HBaseSI strictly follows the "first-committer-wins" rule, whereas Percolator does not and two concurrent transactions with conflicting writesets could both fail; HBaseSI uses distributed queues in handling synchronization and concurrency rather than using traditional techniques such as data locks as in Percolator; and two concurrently committing transactions could unnecessarily both fail in Percolator but not in HBaseSI. In short, the two systems are designed with different purposes in mind and each may excel at one aspect and not another. Note also that the protocol described in Percolator cannot be trivially ported onto HBase, because HBase does not support BigTable's atomic single-row transactions, allowing multiple read-modify-write operations to be grouped into one atomic transaction as long as they are operating on the same row. HBase does not support the same functionality, but rather, only supports single atomic row read or row write operations one at a time, based on the row lock functionality (locking down a row exclusively against concurrent reads/writes from all other parties).

5.6 Conclusions and Future Work

This chapter presents HBaseSI, a light-weight client library for HBase, enabling multi-row distributed transactions with global strong SI on HBase user data tables. There exists no other systems providing the same level of transactional isolation on HBase yet. HBaseSI tries to achieve several design goals: achieving global strong SI across table boundaries; being non-intrusive to existing user data tables; strictly enforcing the "first-committer-wins" rule for SI; supporting highly responsive transactions with no blocking reads; and employing an effective

straggler handling mechanism. The performance overhead of HBaseSI over HBase is modest, especially for longer non-conflicting transactions involving a larger number of read and write operations per transaction. Future research directions may include implementing some helpful tools to optimize disk usage and possibly extending HBaseSI to increase its scalability by distributing the transactional metadata tables.

Concerning future work, HBaseSI can be further extended to support more general range queries efficiently. We also plan to apply its design to other column stores sharing similar architecture as HBase.

Chapter 6

Conclusions and Future Research

The theme of this thesis is enhancing data processing with Hadoop/HBase on clouds. The PhD research started when cloud computing research was still in its infancy and grid computing prevailed. Several preliminary research projects were conducted around a light-weight grid computing system called "GridBASE", as well as an early cloud computing case study for investigating the applicability of using Hadoop to solve customized scientific data processing problems on clouds. After these initial projects, Hadoop was chosen as the candidate framework for further developing cloud data processing techniques. In the meantime, research efforts were initiated by other researchers in the direction of enhancing Hadoop for various data processing scenarios. This PhD thesis presents two main research contributions in this research area.

The first contribution is CloudWF, a computational workflow system specifically targeted at cloud environments where Hadoop is installed. CloudWF is the first workflow management system targeted to take advantage of the Hadoop/HBase architecture for scalability, fault tolerance and ease of use. It uses Hadoop components to perform job execution, file staging and workflow information storage. The novelty of the system lies in its ability to take full advantage of

what the underlying cloud computing framework can provide, and in its new workflow description method that separates out workflow component dependencies as standalone executable components for decentralized job execution and transparent file staging over the MapReduce environment.

The second contribution is HBaseSI, a lightweight client library for HBase, enabling multi-row distributed transactions with global strong SI on HBase user data tables. HBaseSI is the first SI solution for HBase, and is implemented on top of bare-bones HBase rather than deploying an extra middleware layer. HBaseSI tries to achieve several design goals: achieving global strong SI across table boundaries; being non-intrusive to existing user data tables; strictly enforcing the "first-committer-wins" rule for SI; supporting highly responsive transactions with no blocking reads; and employing an effective straggler handling mechanism. The performance overhead of HBaseSI over HBase is modest, especially for longer transactions involving a larger number of read and write operations per transaction.

Apart from the two major contributions in the direction of enhancing Hadoop/HBase, we have also worked on a solution called "CloudBATCH" as supportive work to tackle the problem of Hadoop's incompatibility with existing cluster batch job queuing systems. CloudBATCH uses Hadoop/HBase to assume the core functionality of a cluster batch job queuing system, removing the complexity and overhead of making the two kinds of systems compatible. We did not go into details about CloudBATCH in this thesis because it deals with a rather practical problem. But the issue CloudBATCH addresses is of practical importance and has recently gained interest from researchers who are actively seeking for customized solutions to be applied on TeraGrid, one of the major grid computing platforms in the world.

Through these research contributions, we obtained fruitful results in designing novel tools and techniques to extend and enhance the large-scale data processing

capability of Hadoop/HBase. As cloud computing becomes more and more popular in academia and industry, we believe that there are promising future research opportunities in further extending the data processing capability of Hadoop/HBase on clouds for a wide spectrum of usage scenarios. In the following sections, we will briefly describe some general future research directions.

6.1 Wireless Sensor Networks and Clouds

Wireless sensor networks (WSNs) are gaining increasing attention in various application scenarios, such as environment monitoring, animal habitat surveillance, the Internet of Things, etc. The potentially large amount of data gathered by sensors and transmitted back to PC-hosts calls for novel and efficient data storage and processing methods. Furthermore, a user-friendly programming model and a corresponding task execution environment are still lacking, impeding fast deployment and reprogramming of applications.

As a result, we consider wireless sensor network as a compelling application area that will become a source of large amounts of data in the coming era of ubiquitous mobile networks and the Internet of Things. It will be very interesting to investigate the applicability of designing an integrated sensor network data processing and programming platform backed by clouds, involving efficient methods in storing and querying sensor data using HBase sparse tables, novel methods based on HBase queries for extracting topology and routing information and novel applications using the integrated environment, etc.

More specifically, for example, it may be interesting to design and implement a cloud data processing system for sensor-gathered data. The system will make use of existing hardware infrastructure (clusters/grids/clouds) for host data processing. Due to the sparse nature of the sensor data, HBase sparse tables will be used to manage data storage and querying. Hadoop MapReduce or existing cluster batch job queuing system will be used to execute computing jobs. A

prototype task execution environment deployable to sensors (with TinyOS) can also be developed, allowing users to program sensor actions.

6.2 Mobile Cloud

It is a trend that computing is becoming more and more mobile. How to efficiently organize and make use of various types of mobile and smart devices may become a next major research direction in cloud computing. Both hardware and software platforms are needed to properly form a mobile cloud. Large industrial players are moving into the mobile cloud area by leading industrial initiatives, such as Google's Cloud Printing, Microsoft's SkyDrive and its "Project Hawaii" initiative encouraging students at a selected number of universities to explore how to "use the cloud to enhance the user experience on mobile devices." The new HTML5 language is also believed to provide a convenient programming method for developing and maintaining cloud-based mobile applications. Apart from various enthusiastic efforts, many challenges still lie ahead. For example: how to minimize data transfer over the air while pushing as much application logics as possible into the cloud, how to agree on a unified set of programming primitives across heterogenous mobile infrastructures for easy application development and deployment, how to efficiently process data exploiting data locality and idling mobile computing resources, etc. It is promising that some of the techniques developed in grid/cloud computing can be exploited in the new mobile computing context, which may further inspire novel methods rooted in the native mobile computing infrastructure itself.

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