LogBase: A Scalable Log-structured Database System in the Cloud

[Technical Report]

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ABSTRACT

Numerous applications such as financial transactions (e.g., stock trading) are write-heavy in nature. The shift from reads to writes in web applications has also been accelerating in recent years. Write-ahead-logging is a common approach for providing recovery capability while improving performance in most storage systems. However, the separation of log and application data incurs write overheads observed in write-heavy environments and hence adversely affects the write throughput and recovery time in the system.

In this paper, we introduce LogBase – a scalable log-structured database system that adopts log-only storage for removing the write bottleneck and supporting fast system recovery. It is designed to be dynamically deployed on commodity clusters to take advantage of elastic scaling property of cloud environments. LogBase provides in-memory multiversion indexes for supporting efficient access to data maintained in the log. LogBase also supports transactions that bundle read and write operations spanning across multiple records. We implemented the proposed system and compared it with HBase and a disk-based log-structured record-oriented system modeled after RAMCloud. The experimental results show that LogBase is able to provide sustained write throughput, efficient data access out of the cache, and effective system recovery.

1. INTRODUCTION

There are several applications that motivate the design and implementation of LogBase, such as logging user activity (e.g., visit click or ad click from high volume web sites) and financial transactions (e.g., stock trading). The desiderata for the backend storage systems used in such write-heavy applications include:

- **High write throughput.** In these applications, a large number of events occur in a short period of time and need to be durably stored into the backend storage quickliest possible so that the system can handle a high rate of incoming data.

- **Dynamic scalability.** It is desirable that the storage systems are able to support dynamic scalability for the increasing workload, i.e., the ability to scale out and scale back on demand based on load characteristics.

- **Efficient multiversion data access.** The support of multiversion data access is useful since in these applications users often perform analytical queries on the historical data, e.g., finding the trend of stock trading or users' behaviors.

- **Transactional semantics.** In order to relieve application developers from the burden of handling inconsistent data, it is necessary for the storage system to support transactional semantics for bundled read and write operations that possibly access multiple data items within the transaction boundary.

- **Fast recovery from machine failures.** In large-scale systems, machine failures are not uncommon, and therefore it is important that the system is able to recover data and bring the machines back to usable state with minimal delays.

Storage system for photos, blogs, and social networking communications in Web 2.0 applications also represents well-suited domains for LogBase. The shift from reads to writes has been accelerating in recent years as observed at Yahoo! [34]. In addition, such data are commonly written once, read often, and rarely modified [6]. Therefore, it is desirable that the storage system is optimized for sustained write throughput, low read response time, faut-tolerance and cost-effectiveness, i.e., less expensive than previous designs in storage usage while offering similar data recovery capability.

Previous designs for supporting data durability and improving system performance, which we will discuss in detail in Section 2, do not totally fit the aforementioned requirements. Copy-on-write strategy used in System R [20] incurs much overhead of copying and updating data pages, and therefore affects the write throughput. In POSTGRES [35], a delta record is added for each update, which would increase read latency since records have to be reconstructed from the delta chains. Write-ahead-logging (WAL) [27] is widely adopted in most storage systems. In this approach, in order to improve system performance while ensuring data durability, updates are first recorded into the log presumably stored in "stable storage", before being buffered into the memory, which can be flushed into data structures on disks at later time. We refer to this strategy as WAL+Data approach. Although this approach can defer writing data to disks, sooner or later all the data have to be persisted into the physical storage, which would result in the write bottleneck observed in write-heavy applications. In addition, the need to replay log records and update corresponding data structures when recovering from machine failures before the system becomes ready for serving new requests is another source of delay.

LogBase instead adopts log-only approach, in which the log serves as the unique data repository in the system, in order to remove the write bottleneck. The essence of the idea is that all write operations are appended to the end of a log file without the need to be reflected, i.e., updated in-place, into any data file. There are some immediate advantages from this simple design choice. First, the number of disk I/Os will be reduced since the data only need to be written once into the log file, instead of being written into both log and data files like the WAL+Data approach. Second, all data will be written to disk, i.e., the log file, with sequential I/Os, which is much less expensive than random I/Os when performing in-place updates in data files. As a consequence, the cost of write operations with log-only approach is reduced considerably, and therefore LogBase can provide the much needed high write throughput for write-heavy applications. Note that reducing the number of writes not only improves system write throughput but also increases the working life of storage devices, especially when storing data in new types of storage such as solid-state drive (SSD) and phase-change memory (PCM). A third benefit of log-only approach is the cost-effective storage usage since the system does not need to store two copies of data in both log and data files.

Given the large application and data size, it is desirable that the system can be dynamically deployed in a cluster environment so that it is able to adapt to changes in the workload while leveraging commodity hardware. LogBase adopts an architecture similar to HBase [2] and BigTable [11] where a machine in the system, referred to as tablet server, is responsible for some tablets, i.e., partitions of a table. However, LogBase is different in that it leverages the log as its unique data repository. Specifically, each tablet server uses a single log instance to record the data of the tablets it maintains. LogBase stores the log in an underlying distributed file system (DFS) that implements RAID-like erasure code when replicating data blocks across nodes in the cluster to guarantee that the probability of data loss is extremely unlikely, except catastrophic failures of the whole cluster. Consequently, LogBase's capability of recovering data from machine failures, which will be discussed in detail in Section 3.4, is similar to traditional WAL+Data approach that typically uses RAID methods [32] to simulate "stable storage" for maintaining the log.

Since data are written into the log in sequence and not well-clustered, it is challenging to process read operations efficiently. To solve this problem, tablet servers in LogBase build an index per tablet for retrieving the data stored in the log. Each index entry is a $< key, ptr >$ pair where key is the primary key of the record and ptr is the offset that points to the location of that record in the log. The index of each tablet can be comfortably stored in memory since it only contains the $< key, ptr >$ pairs whose size is much smaller than the record's size. The in-memory index is especially useful for handling long tail requests, i.e., queries that access data not available in the read cache, as it avoids I/O costs of reading index blocks and data blocks from data files as in the WAL+Data approach.

To recover the indexes from machine failures, the restarted server just scans its log and reconstructs the in-memory index for the tablets. In addition, LogBase regularly performs checkpoint operations and persists the indexes into the DFS in order to reduce the cost of recovery. The interference of reads over the log is affordable since reads do not occur frequently in write-heavy applications. As machines in commodity cluster environments are commonly not equipped with dedicated disks for logging, most scalable cloud systems such as BigTable [11] and HBase [2] also store both log and application data in a shared DFS, and therefore observe similar interferences of reads and writes over the log and data files.

LogBase utilizes the log records to provide multiversion data access since all data are written into the log together with their version number, which is the commit timestamp of the transactions that write the data. To facilitate reads over multiversion data, the indexes are also multiversioned, i.e., the key of index entries now is composed of two parts: the primary key of the record as the prefix and the commit timestamp as the suffix. LogBase supports the ability to bundle a collection of read and write operations within a transaction boundary, providing transactional semantics – standard snapshot isolation – for updates spanning across multiple records. Read-only transactions access the recent snapshot of the database while update transactions operate on the latest version of the data.

In summary, the contributions of the paper are as follows.

- We propose LogBase – a scalable log-structured database system that can be dynamically deployed in the cloud. It provides similar recovery capability to traditional write-ahead-logging approach while offering highly sustained throughput for write-heavy applications.

- We design a multiversion index strategy in LogBase to provide efficient access to the multiversion data maintained in the log. The in-memory index can efficiently support long tail requests that access data not available in the cache.

- We further enhance LogBase to support transactional semantics for read-modify-write operations and provide snapshot isolation – a widely accepted correctness criterion.

- We conducted an extensive performance study on LogBase and used HBase [2] and LRS, a log-structured record-oriented system that is modeled after RAMCloud [31] but stores data on disks, as our baselines. The results confirm its efficiency and scalability in terms of write and read performance, as well as effective recovery time in the system.

The remaining of the paper is organized as follows. In Section 2, we review background and related work. In Section 3, we present the design and implementation of LogBase in detail. We evaluate the performance of LogBase in Section 4 and conclude the paper in Section 5.

2. BACKGROUND

In this section, we briefly describe previous design choices for supporting data durability while improving system performance. We also discuss why they do not totally fit the aforementioned requirements of write-heavy applications.

2.1 No-overwrite Strategies

Early database systems such as System R [20] use shadow paging strategy to provide the feature of data durability in which logging is not required. In this approach, the database is treated as a collection of pages and accessed through a page table, which maps page ids into disk addresses. When a transaction updates a page, it makes a copy, i.e., a shadow, of that page and operates on that. When the transaction commits, it updates the page table by mapping the page ids into the new addresses. Shadow paging is similar to purely functional data structures in that in-place updates are avoided. Although this approach does not require any logging for system recovery from failures, the overheads of page copying and updating are much higher for each transaction, and adversely affect the overall system performance.

Another no-overwrite strategy for updating records is employed in POSTGRES [35]. In particular, each data page in POSTGRES maintains an anchor table which is used to retrieve records stored in that page. When a record is inserted for the first time, space is allocated for the record. For data modification, instead of performing updating in-place in the page, a delta record is added to store the changes from the previous version of the record. When reading a record the system has to traverse and process the whole chain from the first version of the record. POSTGRES is initially optimized for small records, and delta records should be on the same page with the initial record. Although POSTGRES introduces many novel ideas, the performance is lower than expected due to the way records are stored, which requires read operations to reconstruct records from the delta chains. Further, POSTGRES uses a force buffer policy, i.e., all pages modified by a transaction are written into disk at commit. Such high cost of write operations is inadequate for write-heavy applications.

2.2 Log-structured Systems

Log-structured file systems (LFS) pioneered by Ousterhout and Rosenblum [33] for write-heavy environments have been well studied in the OS community. More recently, BlueSky [38], a network file system that adopts log-structured design and stores data persistently in a cloud storage provider, has been proposed.

Although LogBase employs the ideas of LFS, it provides a database abstraction rather than a file-system abstraction on top of the segmented log. That is, LogBase provides fine-grained access to data records instead of data blocks as in LFS. LogBase uses files, which are append-only, to implement its log segments, while LFS uses fixed size disk segments for its log. More importantly, LogBase maintains in-memory indexes for efficient record retrieval, and hence its log management is simpler than LFS as the log does not need to store metadata (e.g., inode structure) to enable random data access. To further facilitate database applications, LogBase clusters related records of a table during its log compaction for efficient support of clustering access.

Contemporary log-structured systems for database applications include Berkeley DB (Java Edition) and PrimeBase[1] – an open source log-structured storage engine for MySQL. Both systems are currently developed for single machine environment and use disk-resident indexes, which restricts system scalability and performance. Storing data in a sequential log is used as a way to maintain historical versions of data in temporal databases [26]. The log-only principle is also employed in Vagabond [29], a temporal object database system. These log-structured temporal database systems are also designed for centralized environments.

Recent research systems for scalable log-structured data management include Hyder [8] and RAMCloud [31]. Hyder takes advantage of new advent of modern hardware such as solid-state drives and high-speed network for shared-flash environments. In contrast, LogBase aims to exploit commodity hardware in a shared-nothing cluster environment. Similarly, RAMCloud is a DRAM-based storage system that requires servers with large memory and very high-speed network to meet latency goals, while LogBase is a disk-based storage system that is inherently designed for large-scale commodity clusters. OctopusDB [17] is another research proposal that uses the log as its primary data repository. Embracing the idea of "one size fits all", OctopusDB creates various storage views over the log to serve different applications. Developing an "one size fits all" system, though interesting, might reduce the needed performance for all applications.

Following no-overwrite strategies introduced by early database systems, log-structured merge tree (LSM-tree [30]), which is a hierarchy of indexes spanning across memory and disk, is proposed for maintaining real-time indexes at low I/O cost. The log-structured history data access method (LHAM [28]) is an adaptation of LSM-tree for hierarchical storage systems that store a large number of components on archival media. bLSM-tree [34], an optimization of LSM-tree that uses Bloom filters to improve read performance, has been recently proposed. LSM-tree and bLSM-tree complement our work and can be exploited to extend the index capability of LogBase when the memory of a tablet server is scarce. We shall investigate this option in our experiments.

It is also noteworthy that LSM-trees are designed to be compatible with external write ahead logs in mind. Therefore, although some cloud storage systems, such as HBase [2] and Cassandra [23], have adopted LSM-trees for maintaining their data, instead of performing in-place updates as in traditional DBMSes, they have not totally removed potential write bottlenecks since the separation of log and application data still exists in these systems.

2.3 WAL+Data

ARIES [27] is an algorithm designed for database recovery and enables no-force, steal buffer management, and thus improves system performance since updates to data can be buffered in memory without incurring "update loss" issues. The main principle of ARIES is write-ahead-logging (WAL), i.e., any change to a record is first stored in the log which must be written to "stable storage" before being reflected into the data structure.

WAL is a common approach in most storage systems ranging from traditional DBMSes, including open source databases like MySQL and commercial databases like IBM DB2, to the emerging cloud storage systems, a.k.a distributed key-value stores such as BigTable [11], HBase [2] and Cassandra [23]. One of the main reasons why this approach is popular is that while the log cannot be re-ordered, the data can be sorted or clustered in any order to exploit data locality for better I/O performance (e.g., clustering access via clustered indexes). However, this feature is not necessary for all applications. In addition, the separation of log and application data in this approach might incur potential overheads that would reduce the write throughput and increase the time for system recovery.

In particular, although this design defers writing the application data to disks in order to guarantee system response time, sooner or later all the data buffered in memory have to be reflected into the physical storage, which could result in write bottlenecks. Therefore, the system might not be able to provide high write throughput for handling a large amount of incoming data in write-heavy applications. In addition, when recovering from machine failures the system needs to replay relevant log records and update the corresponding application data before it is ready for serving new user requests. As a consequence, the time to bring the failed machine back to usable state is delayed.

2.4 Discussion

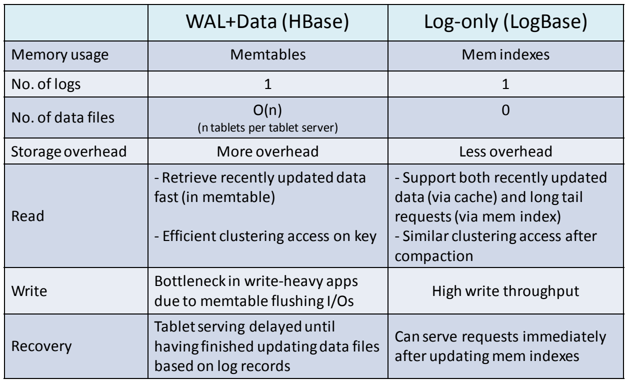
Having reviewed previous designs, we now discuss the advantages of log-only approach for write-heavy applications. In particular, we look especially at the WAL+Data approach used in HBase [2] and compare it with the log-only used in LogBase. Table 1 summarizes the comparison in term of various aspects such as storage overhead, write and read performance, and recovery time.

Both approaches need similar number of I/Os and storage consumption for logging operation, and similar memory usage (memtables for buffering data in HBase, and in-memory indexes for locating data in LogBase). Nevertheless, the WAL+Data approach in HBase eventually incurs more storage overhead due to the use of additional storage for application data. More importantly, its

[1] http://sourceforge.net/projects/pbxt/

frequent flushing of memtables into physical storage, which is the norm in write-heavy applications, results in write bottlenecks. On the contrary, the log-only approach in LogBase avoids such cost and therefore is able to provide the desired high write throughput.

Table 1: WAL+Data vs. Log-only.



	WAL+Data (HBase)	Log-only (LogBase)
Memory usage	Memtables	Mem indexes
No. of logs	1	1
No. of data files	O(n) (n tablets per tablet server)	0
Storage overhead	More overhead	Less overhead
Read	- Retrieve recently updated data fast (in memtable) - Efficient clustering access on key	- Support both recently updated data (via cache) and long tail requests (via mem index) - Similar clustering access after compaction
Write	Bottleneck in write-heavy apps due to memtable flushing I/Os	High write throughput
Recovery	Tablet serving delayed until having finished updating data files based on log records	Can serve requests immediately after updating mem indexes

Retrieving data that have recently been updated is fast in both approaches since they are cached in memory. However, for long tail requests that do not query recently updated data, the log-only approach can be more efficient since it uses in-memory indexes for directly locating and retrieving data from the log while in the other approach, application data and its index blocks need to be fetched from data files, which incurs more disk I/Os. Note that after a log compaction process (cf. Section 3.6.5), data of a table in the log are clustered based on its primary key, and hence the log-only approach can support similar data access to the WAL+Data approach.

3. DESIGN AND IMPLEMENTATION

In this section, we present various issues of the design and implementation of LogBase including data model, partitioning strategy, log repository, multiversion index, basic data operations, transaction management, and system recovery method.

3.1 Data Model

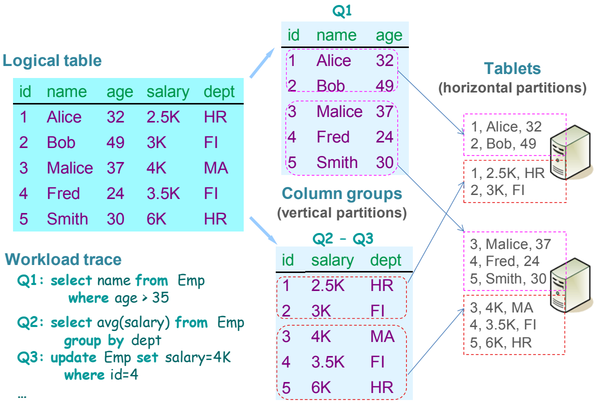
Cloud storage systems, as surveyed in [10], represent a recent evolution in building infrastructure for maintaining large-scale data, which are typically extracted from Web 2.0 applications. Most of these systems such as Cassandra [23] and HBase [2] employ key-value model or its variants and make a trade-off between system scalability and functionality. Recently, some systems such as Megastore [5] adopt a variant of the abstracted tuples model of an RDBMS where the data model is declared in a schema and with strongly typed attributes. Pnuts [12] is another large-scale distributed storage system that uses the tuple-oriented model.

Since LogBase aims to provide storage service for database-centric applications, its data model is also based on the widely-accepted relational data model where data are stored as tuples in relations, i.e., tables, and a tuple comprises of multiple attributes' values. However, LogBase further adapts this model to support column-oriented storage model in order to exploit the data locality property of queries that frequently access a subset of attributes in the table schema. This adaptation is accomplished by the partitioning strategy presented in the below section.

3.2 Data Partitioning Strategy

LogBase optionally divides columns of a table schema into several *column groups*. Each column group comprises of columns that are frequently accessed together by a set of queries in the workload. Column groups are stored separately in different physical data segments so that the system can exploit data locality when processing queries. Such vertical partitioning benefits queries which often require access to only a subset of columns within a table since it saves significant I/O cost compared to the approach that stores all columns of the table schema into a single physical table.

Consider the example in Figure 1. The original table has an abstracted schema with five columns $(id, name, age, salary, dept)$. The workload trace includes three queries $\{Q_1, Q_2, Q_3\}$ as listed in Figure 1. It is beneficial to partition the schema into two column groups, namely $CG1(id, name, age)$ and $CG2(id, salary, dept)$, and store them in separate physical tables in order to minimize I/O cost of the given workload since Q_1 mainly accesses data in CG_1 while Q_1 and Q_3 mainly access data in CG_2.



id	name	age	salary	dept
1	Alice	32	2.5K	HR
2	Bob	49	3K	FI
3	Malice	37	4K	MA
4	Fred	24	3.5K	FI
5	Smith	30	6K	HR

```
Q1: select name from Emp
        where age > 35
Q2: select avg(salary) from Emp
        group by dept
Q3: update Emp set salary=4K
        where id=4
...
```

id	name	age
1	Alice	32
2	Bob	49
3	Malice	37
4	Fred	24
5	Smith	30

id	salary	dept
1	2.5K	HR
2	3K	FI
3	4K	MA
4	3.5K	FI
5	6K	HR

1, Alice, 32
2, Bob, 49

1, 2.5K, HR
2, 3K, FI

3, Malice, 37
4, Fred, 24
5, Smith, 30

3, 4K, MA
4, 3.5K, FI
5, 6K, HR

Figure 1: Data partitioning strategy.

The above partitioning strategy is similar to data morphing technique [22] and vertical partitioning in main memory database Hyrise [21] which also partition the table schema into column groups. Nevertheless, the main difference is that these two approaches aim at determining a CPU cache-efficient column layout while the partitioning strategy in LogBase focuses on exploiting data locality for minimizing I/O cost of a query workload. In particular, given a table schema with a set of columns, multiple ways of grouping these columns into different partitions are enumerated. The I/O cost of each assignment is computed based on the query workload trace and the best assignment is selected as the vertical partitions of the table schema.

Note that if the table schema includes many columns, the number of possible ways of grouping columns may result in a combinatorial explosion and in such cases it is not efficient to enumerate all the groupings. In that case, we can employ a local search algorithm to obtain approximate best candidate for partitions as in the data morphing technique [22]. Also note that since we have designed the vertical partitioning scheme based on the trace of query workload, tuple re-construction is only necessary in the worst case. Moreover, each column group still embeds the primary key of data records as one of its componential columns, and therefore to reconstruct the tuple, LogBase collects the data in all column groups using the primary key as selection predicate.

In order to facilitate parallel query processing while offering scale out capability, LogBase further splits the data in each column group into horizontal partitions, referred to as tablets, as illustrated in Figure 1. A carefully designed horizontal partitioning scheme can help to reduce or even eliminate distributed transactions across machines, and thus simplify the transaction management in the system. Typically, users tend to operate on their own data which form an entity group or a key group as characterized in [5, 15, 37]. By cleverly designing the key of data so that all data related to a user have the same key prefix which is the user's identity. Hence, data accessed by a transaction are usually clustered on a physical machine. In this case, executing transactions is not expensive since a full two-phase commit (2PC) protocol is not needed.

For scenarios where the application data cannot be naturally partitioned into entity groups, we can implement a group formation protocol that enables users to explicitly cluster data records into key groups [15]. Another alternative solution is workload-driven approach for data partitioning [14]. This approach models the transaction workload as a graph in which data records are vertices and transactions are edges and uses a graph partitioning algorithm to split the graph into sub partitions while reducing number of cross-partition transactions.

3.3 Architecture Overview

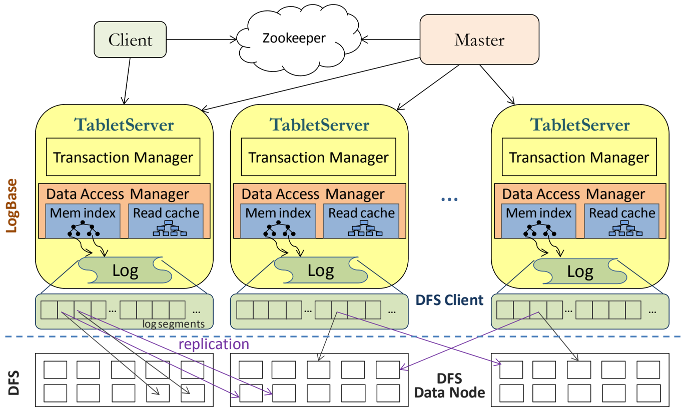


Figure 2: System architecture.

Figure 2 illustrates the overall architecture of LogBase. In this architecture, each machine – referred to as tablet server – is responsible to maintain several tablets, i.e., horizontal partitions of a table. The tablet server records the data, which might belong to the different tablets that it maintains, into its single log instance stored in the underlying distributed file system (DFS) shared by all servers. Overall, a tablet server in LogBase consists of three major functional layers, including transaction manager, data access manager, and log repository.

Log Repository. At the bottom layer is the repository for maintaining log data. Instead of storing the log in local disks, the tablet servers employ a shared distributed file system (DFS) to store log files and provide fault-tolerance in case of machine failures. The implementation of Log Repository is described in Section 3.4.

Data Access Manger. This middle layer is responsible to serve basic data operations including Insert, Delete, Update, and Get a specific data record. Data Access Manager also supports Scan operations for accessing records in batches, which is useful for analytical data processing such as programs run by MapReduce [1, 16]. Tablet severs in LogBase employs in-memory multiversion indexes (cf. Section 3.5) for supporting efficient access to the data stored in the log. The processing of data operations is discussed in Section 3.6.

Transaction Manager. This top layer provides interface for applications to access the data maintained in LogBase via transactions that bundles read and write operations on multiple records possibly located on different machines. The boundary of a transaction starts with a Begin command and ends with a Commit or Abort command. Details of transaction management is presented in Section 3.7.

The master node is responsible for monitoring the status of other tablet servers in the cluster, and provides the interface for updating metadata such as create a new table, add column groups into a table, and assign tablets to tablet servers. To avoid critical point of failures, multiple instances of master node can be run in the cluster and the active master is elected via Zookeeper [3], a distributed coordination service. If the active master fails, then one of the remaining masters will take over the master role. The master node is not the bottleneck of the system since it does not lie on the main path of read or write operations. The general processing flow is that a new client first contacts the Zookeeper to retrieve the master node information. With that information it can query the master node to get the tablet server information and finally retrieve data from the tablet server that maintains the records of its interest. Information of both master node and tablet servers are cached and only looked up once.

Although LogBase employs a similar architecture to HBase [2] and Bigtable [11], it introduces several major different designs. First, LogBase uses the log as data repository in order to remove the write bottleneck of the WAL+Data approach observed in write-heavy applications. Second, tablet servers in LogBase build an in-memory index for each column group in a tablet to support efficient data retrieval from the log. Finally, LogBase provides transactional semantics for bundled read and write operations accessing multiple records.

3.4 Log Repository

As discussed in Section 1, the approach that uses log as the unique data repository in the system benefits write-heavy applications in many ways, including high write throughput, fast system recovery and multiversion data access. Nevertheless, there could be questions about how this approach can guarantee the property of data durability in comparison to the traditional write-ahead-logging, i.e., WAL+Data approach.

GUARANTEE 1. ***Stable storage.*** *The log-only approach provides similar capability of recovering data from machine failures compared to the WAL+Data approach.*

Recall that in the WAL+Data approach, data durability is guaranteed with the "stable storage" assumption, i.e., the log file must be stored in a stable storage with zero probability of losing data. Unfortunately, implementing stable storage is theoretically impossible. Therefore, some methods such as RAID (Redundant Array of Independent Disks [32]) have been proposed and widely accepted to simulate stable storages. For example, a RAID-like erasure code is used to enable recovery from corrupted pages in the log repository of Hyder [8], which is a log-structured transactional record manager designed for shared flash.

To leverage commodity hardware and dynamic scalability designed for cluster environment, LogBase stores the log in HDFS[2] (Hadoop Distributed File System), which is an open-source distributed file system modeled after GFS (Google File System [19]). HDFS employs n-way replication to provide data durability (n is a configurable parameter – most distributed storage systems use 3-way replication as default setting since it has been a consensus that

[2] http://hadoop.apache.org/hdfs

maintaining three replicas is enough for providing high data availability in distributed environment). The log can be considered as an infinite sequential repository which contains contiguous segments. Each segment is implemented as a sequential file in HDFS whose size is also configurable. We set the default size of segments to 64 MB as in HBase [2].

Replicas of a data block in HDFS are synchronously maintained. That is, a write operation to a file is consistently replicated to n machines before returning to users. This is equivalent to RAID-1 level or mirroring disks [32]. Further, the replication strategy in HDFS is rack-aware, i.e., it distributes replicas of a data block across the racks in the cluster, and consequently guarantees that the probability of data loss is extremely unlikely, except catastrophic failures of the whole cluster. Therefore, the use of log-only approach in LogBase does not reduce the capability of recovering data from machine failures compared to the other systems. Note that HBase [2] also stores its log data (and its application data) in HDFS.

Each tablet server in LogBase maintains several tablets, i.e., partitions of a table, and record the log data of these tablets in HDFS. There are two design choices for the implementation of the log: (i) a single log instance per server that is used for all tablets maintained on that server and (ii) the tablet server maintains several log instances and each column group has one log instance. The advantages of the second approach include:

- **Data locality.** Since LogBase uses log as the unique data repository, it needs to access the log to retrieve the data. If a log instance contains only the data that are frequently access together, e.g., all rows of a column group, it's likely to improve the I/O performance for queries that only access that column group. On the contrary, in the first approach, the system needs to scan the entire log containing rows of all column groups.

- **Data recovery.** If a tablet server fails, its tablets will be assigned to other servers. In the second approach, one log represents one column group, and therefore, other servers only need to reload the corresponding index file and check the tail of that log (from the consistent point immediate after the latest checkpoint). Otherwise, in the first approach, the log has to be sorted and split by column group, and then scanned by the corresponding servers as in BigTable [11] and HBase [2].

However, the downside of the second approach is that, the underlying distributed file system has to handle many read/write connections that are used for multiple log instances. In addition, it also consumes more disk seeks to perform writes to different logs in the physically storage. Since LogBase aims at write-heavy applications that require high write throughput, we choose the first approach, i.e., each tablet server uses a single log instance for storing the data from multiple tablets that it maintains. Moreover, this approach still can support data locality after the log compaction process (cf. Section 3.6.5) which periodically scans the log, removes out-of-date data and sorts the log entries based on column group, primary key of the record, and timestamp of the write. That is, all data related to a specific column group will be clustered together after the log compaction.

A log record comprises of two components $< LogKey, Data >$. The first component, $LogKey$, stores the information of a write operation, which includes log sequence number (LSN), table name, and tablet information. LSN is used to keep track of updates to the system, and is useful for checkpointing and recovery (cf. Section 3.8). LSN either starts at zero or at the last known LSN persisted in the previous consistent checkpoint block. The second component, $Data$, is a pair of $< RowKey, Value >$ where $RowKey$ represents the id of the record and $Value$ stores the content of the write operation. $RowKey$ is the concatenation of the record's primary key and the column group updated by the write operation, along with the timestamp of the write. Log records are to be persisted into the log repository before write operations can return to users.

3.5 In-memory Multiversion Index

Since LogBase records all writes sequentially in the log repository, there is no clustering property of data records stored on disks. As a result, access to data records based on their primary keys is inefficient as it is costly to scan the whole log repository only for retrieving some specific records. Therefore, LogBase builds indexes over the data in the log to provide efficient access to the data.

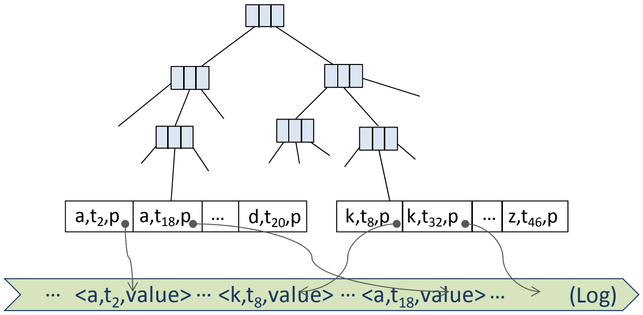


Figure 3: Multiversion index over the log repository.

In particular, tablet servers build a multiversion index, as illustrated in Figure 3, for each column group in a tablet. LogBase utilizes the log entries to provide multiversion data access since all data are written into the log together with their version numbers, i.e., the timestamp of the write. To facilitate reads over multiversion data, the indexes are also multiversioned. The indexes resemble B^{link}-trees [24] to provide efficient key range search and concurrency support. However, the content of index entries is adapted to support multiversion data. In our indexes, each index entry is a pair of $< IdxKey, Ptr >$. The $IdxKey$ is composed of two parts: the primary key of the record as the prefix and the timestamp as the suffix. Ptr is the offset that points to the location of a data record in the log, which includes three information: the file number, the offset in the file, the record's size.

We design an index key as a composite value of record id and timestamp so that the search for current as well as historical versions of particular data records, which is the major access pattern in our applications, can be done efficiently. Historical index entries of a given record id, e.g., key a in Figure 3, are clustered in the index and can be found by performing an index search with the data key a as the prefix. Among the found entries, the one that has the latest timestamp contains the pointer to the current version of the data record in the log.

The ability to search for current and historical versions efficiently is useful when developing the multiversion concurrency control for concurrently executing transactions in LogBase (cf. Section 3.7). Although multiversion indexes can be implemented with other general multiversion access methods, e.g., Time-Split B-tree (TSB-tree) [25], these methods are mainly optimized for temporal queries by partitioning the index along time and attribute value dimensions, which increases the storage space and insert cost considerably.

The indexes in LogBase can be stored in memory since they only contain the $< IdxKey, Ptr >$ pairs whose size are much smaller than the record's size. For example, while the size of records, e.g., blogs' content or social communications, could easily exceed 1 KB, the $IdxKey$ only consumes about 16 bytes (including the record id and timestamp of long data type) and Ptr consumes about 8 bytes (including the file number and record size as short data type, and the file offset as integer data type), which makes a total size of 24 bytes each index entry. Assuming that the tablet server can reserve 40% of its 1 GB heap memory for in-memory indexes (HBase [2] uses a similar default setting for its memtables), the indexes of that server can maintain approximately 17 million entries.

There are several methods to scale out LogBase's index capability. A straight-forward way is to increase either the heap memory for the tablet server process or the percentage of memory usage for indexes (or both). Another solution is to launch more tablet server processes on other physical machines to share the workload. Finally, LogBase can employ a similar method to log-structured merge-tree (LSM-tree) [30] for merging out part of the in-memory indexes into disks.

A major advantage of the indexes in LogBase is the ability to efficiently process long tail requests, i.e., queries that access data not available in read cache. LogBase uses in-memory indexes for directly locating and retrieving data records from the log with only one disk seek, while in the WAL+Data approach (e.g., in HBase [2]) both application data and index blocks need to be fetched from disk-resident files, which incurs more disk I/Os.

The downside of in-memory indexes is that their content are totally lost when machines crash. To recover the indexes from machine failures, the restarted server just scans its log and reconstructs the in-memory index for the tablets it maintains. In order to reduce the cost of recovery, LogBase performs checkpoint operation at regular times. In general, tablet servers periodically flush the in-memory indexes into the underlying DFS for persistence. As a consequence, at restart time the tablet server can reload the indexes quickly from the persisted index files back into memory. We describe the details of LogBase's recovery technique in Section 3.8.

3.6 Tablet Serving

Now we present the details of a tablet server in LogBase, which uses only log files to facilitate both data access and recovery. As illustrated in Figure 4, each tablet server manages two major components, including (i) the single log instance (consisting of sequential log segments) which stores data of multiple tablets maintained by the server, and (ii) the memory index for each column group which map the primary key of data records to their location in the log. Another major component (not shown) is the transaction manager whose details will be described in the next section.

LogBase differs from HBase [2] on every aforementioned component. More specifically, HBase stores data in data files which are separate with the log and uses memtables to buffer recently updated data, in addition to the fact that it does not support transactional semantics for bundled read and write operations. The benefits of the log-only approach compared to the WAL+Data approach when serving write-heavy applications have been discussed in Section 2.4. In the following, we will describe how LogBase performs basic data operations such as write, read, delete, and scan over the tablets as well as tablet compaction operation.

3.6.1 Write

When a write request (Insert or Update) arrives, the request is first transformed into a log record of $< LogKey, Data >$ format, where $LogKey$ contains meta information of the write such as log sequence number, table name, and tablet information while $Data$ stores the content of the write, including the record's primary key, the updated column group, the timestamp of the write, and the new value of data. Then the tablet server writes this log record into the log repository.

After the log record has been persisted, its starting offset in the log along with the timestamp are returned so that the tablet server subsequently updates the in-memory index of the corresponding updated column group. This guarantees that the index are able to keep track of historical versions of the data records. The indexes are used to retrieve the data records in the log at later time. In addition, the new version of data can also be cached in a read buffer (not shown in Figure 4) so that LogBase can efficiently serve read requests on recently updated data. While the in-memory index is a major component and is necessary for efficient data retrieval from the log, read buffer is only an optional component whose existence and size are configurable parameters. The read buffer in LogBase is different from the memtable in HBase [2] in that the read buffer is only for improving the read performance whereas the memtable stores data and needs to be flushed into disks whenever the memtable is full, which incurs write bottlenecks in write-intensive applications.

A counter is maintained to record the number of updates that have occurred to the column group of a tablet. If the number of updates reaches a threshold, the index can be merged out into an index file stored in the underlying DFS and the counter is reset to zero. Persisting indexes into index files helps to provide a faster recovery from failures, since the tablet servers do not need to scan the entire log repository in order to rebuild the indexes. Note that the DFS with 3-way synchronous replication is sufficient to serve as a stable storage for index files (as the case of log files that we have discussed in Section 3.4).

3.6.2 Read

To process a Get request, which retrieves data of a specific record given its primary key, the tablet server first checks whether the corresponding record exists in the read buffer. If the value is found, it is returned and the request is completed. Otherwise, the server obtains the log offset of the requested record from the in-memory index. With this information, the data record is retrieved from the log repository, and finally returned to clients. By default, the system will return the latest version of the data of interest. To access historical versions of data, users can attach a timestamp t_q with the retrieval request. In this case, LogBase fetches all index entries with the requested key as the prefix and follows the pointer of the index entry that has the latest timestamp before t_q to retrieve the data from the log.

Meanwhile, the read buffer also caches the recent fetched record for serving possible future requests. Since there is only one read buffer per tablet server and the size of the read buffer is limited, a good replacement strategy is needed to guarantee the read buffer is fully exploited while reducing the number of cache misses. In our implementation, we employ the LRU strategy which discards the least recently used records first. However, we also design the replacement strategy as an abstracted interface so that users can plug in new strategies that fit their application access patterns. With the use of read buffer, LogBase can quickly answer requests for data that have recently been updated or queried in addition to the ability to process long tail requests efficiently via in-memory indexes.

Note that the vertical partitioning scheme in LogBase, as discussed in Section 1, is designed based on the workload trace, and therefore most queries and updates will access data within a column group. In the case where tuple reconstruction is necessary, LogBase collects componential data of a record from all corresponding column groups.

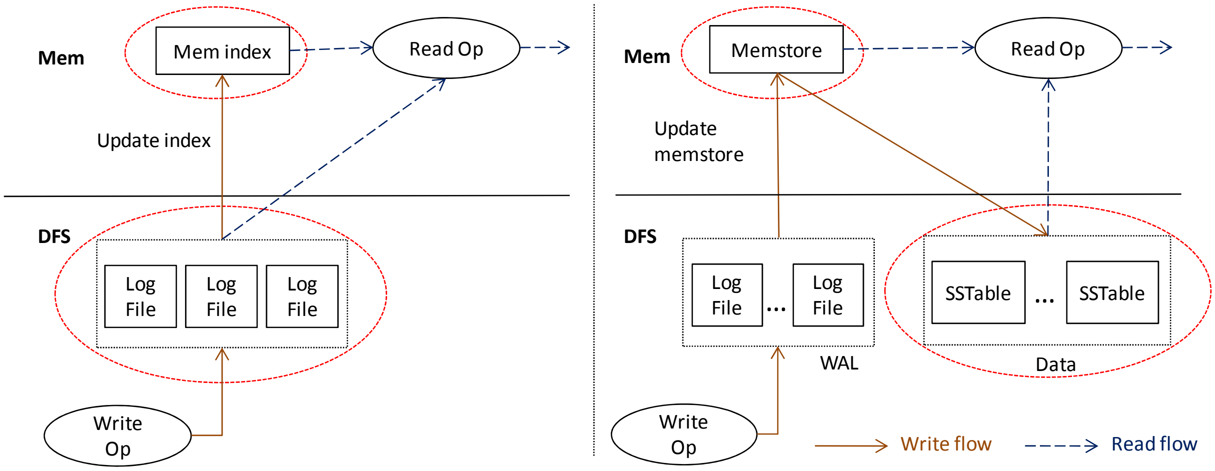


Figure 4: Tablet serving of LogBase (left) vs. HBase (right).

3.6.3 *Delete*

A tablet server in `LogBase` performs a *Delete* operation given a record primary key in two steps. First, it remove all index entries associated with this record key from the in-memory index. By doing this all incoming queries at later time cannot find any pointer from the index in order to access the data record in the log repository. However, in the event of tablet server's restart after failures, the index is typically reloaded from the previous consistent checkpoint file, which still contains the index entries that we have attempted to remove in the first step.

Therefore, in order to guarantee durable effect of the *Delete* operation, `LogBase` performs a second step which persists a special log entry, referred to as invalidated log entry, into the log repository to record the information about this *Delete* operation. While this invalidated log entry also contains $LogKey$ similar to normal log entries, its $Data$ component is set to $null$ value in order to represent the fact that the corresponding data record has been deleted. As a consequence, during the restart of the tablet server, this invalidated log entry will be scanned over and its deletion effect will be reflected into the in-memory index again.

3.6.4 *Scan*

`LogBase` supports two types of scan operations, including range scan and full table scan. A range scan request takes a start key and an end key as its input. If the query range spans across tablet servers, it will be divided into subranges which are executed in parallel on multiple servers. Each tablet server process a range scan as follows. First, it traverses the in-memory index to enumerate all index entries that satisfies the query range. Then, it follows the pointers in the qualified index entries to retrieve the data from the log repository. Since the data in the log are not clustered based on the search key, it is not efficient when handling with large range scan queries. However, `LogBase` periodically performs log compaction operation which will be discussed below. After this compaction, data in the log are typically sorted and clustered based on the data key. Therefore, `LogBase` can support efficient range scan queries, i.e., clustering access on the primary key of data records, if the log compaction operation is done at regular times.

In contrast to range scan queries, full table scans can be performed efficiently in `LogBase` without much optimization. Since full table scans do not require any specific order of access to data records, multiple log segments, i.e., log files, in the log repository of tablet servers are scanned in parallel. This function is similar to the parallel scan method adopted in MapReduce-based processing systems.

3.6.5 *Compaction*

In the log-only approach, updates (and even deletes) are sequentially appended as a new log entry at the end of the log repository. After a period of time, there could be obsolete versions of data that are not useful for any query, but they still consume storage capacity in the log repository. Therefore, it is important to perform a vacuuming process, referred to as compaction, to discard out-of-date data and uncommitted updates from the log repository and reclaim the storage resources.

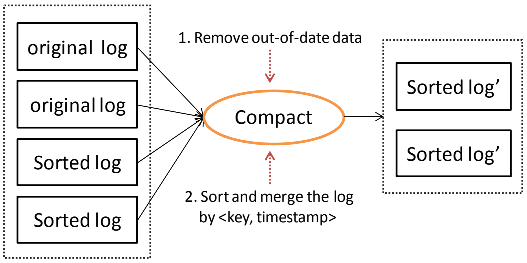


Figure 5: Log compaction.

Compaction could be done periodically as background process or more frequently when the system has spare CPU and I/O bandwidth. Figure 5 illustrates the compaction process performed by a tablet server in `LogBase`. In particular, `LogBase` performs a MapReduce-like job which takes the current log segments (some of them are sorted log segments, resulted from the previous compaction) as its input, removes all obsolete versions of data and invalidated records, and finally sorts the remaining data based on the following criteria (listed from the highest to lowest priority): table name, column group, record id, and timestamp. The result of this job is a set of sorted log segments in which data are well-clustered. Then, each tablet server builds the in-memory indexes over these new log segments. After the indexes have been built, the tablet server now can efficiently answer clients' queries on the clustered data in the sorted log segments.

Note that until this time point, old log segments and in-memory indexes are still in use and all clients' update requests from the start of the running compaction process are stored in new log segments which will be used as inputs in the next round of compaction. That is, LogBase can serve clients' queries and updates as normal during the compaction process. After the compaction process has finished, i.e., the resulted sorted segments and in-memory indexes are ready, the old log segments and in-memory indexes can be safely discarded.

An additional optimization can be adopted during the compaction process to decrease the storage consumption of log segments and further improve I/O performance for queries. Specifically, since the data in the resulting log segments are clustered by table name and column group already, it is not necessary to store this information in every log entries any more. Instead, the tablet server only needs to maintain a metadata which maps the table name and column group information to a list of log segments that store its data.

3.7 Transaction Management and Correctness Guarantees

In the previous section, we have presented LogBase's basic data operations, which only guarantee single row ACID properties similar to other cloud storage systems such as Pnuts [12], Cassandra [23] and HBase [2]. We now present how LogBase ensures ACID semantics for bundled read and write operations spanning across multiple records.

3.7.1 Concurrency Control

The Rationale of MVOCC. Recall that LogBase is designed with a built-in function of maintaining multiversion data. In addition, the careful design of the data partitioning scheme in LogBase, which is based on application semantics and query workload (cf. Section 3.2), clusters data related to a user together, and thus reduces the contention between transactions as well as the number of distributed transactions. Consequently, we employ a hybrid scheme of multi-version and optimistic concurrency control (MVOCC) to implement isolation and consistency for transactions in LogBase.

A major advantage of MVOCC is the separation of read-only transactions and update transactions so that they will not block each other at runtime. That is, read-only transactions access a recent consistent snapshot of the database while update transactions operate on the latest version of the data. Therefore, read-only transactions always commit successfully without the need to check conflicts with other transactions. In contrast, an update transaction after finishing its read phase has to validate its possible conflicts with other concurrently executing update transactions before being allowed to enter the write phase.

While traditional OCC needs to store old write-sets of committed transactions just for the purpose of verifying data conflicts [4], the MVOCC in LogBase provides another advantage that in the validation phase of update transactions, the transaction manager can use the version numbers of data records to check for conflicts with other update transactions. In particular, to commit an update transaction T, the transaction manager checks whether T's write set are updated by other concurrent transactions that have just committed by comparing the versions of the records in T's write set that T has read before (there is no blind write) with the current version of the records maintained in the in-memory indexes. If there is any change in the record versions, then the validation fails and T is restarted. Otherwise, the validation return success and T is allowed to enter the write phase and commit.

Validation with Write Locks. Concurrent writes might incur consistency issues: if two conflicting transactions perform validation concurrently, they might both succeed since the corresponding data versions have not been changed by any transaction; however, when these transactions enter the write phase, inconsistencies might occur. In order to avoid this problem, LogBase embeds write locks into the validation phase of MVOCC, as shown in Algorithm 1. Particularly, an update transaction first executes its read phase as per normal; however, at the beginning of validation phase, the transaction manager will request write locks over the data records for its intention writes (lines 3 - 6). If all the locks can be obtained and the validation succeeds (lines 7 - 8), the transaction is allowed to start the commit process (line 10) which executes its write phase and finally releases the locks. On the contrary, if the transaction manager fails to acquire all necessary write locks, it will still hold the existing locks while re-executing the read phase (line 12) and trying to request again the locks that it could not get in the first time. This means that the transaction keeps pre-claiming the locks until it obtains all the necessary locks, so that it can enter the validation phase and write phase safely.

Algorithm 1 : Validation with write lock

```
Input: write-set ($WS$) of the validating transaction $T$
Input: server $S$ where $T$ is validated
Output: $valid\_state$ of the validation process
 1. $valid\_state := true$
 2. for all data record $R$ in $WS(T, S)$ do
 3.   if $lock\_conflict(R)$ then
 4.     $valid\_state := false$
 5.   else
 6.     Acquire $lock(R)$
 7.   if $read\_version(T, R) < latest\_version(R)$ then
 8.     $valid\_state := false$
 9. if $valid\_state = true$ then
10.   Send COMMIT message to the transaction manager
11. else
12.   Send RESTART message to the transaction manager
13. return $valid\_state$
```

Deadlock can be avoided by enforcing each transaction to always request the locks in the same sequence, e.g., based on the order of records' key. For instance, if both $T1$ and $T2$ desire to lock a write set $\{x, y\}$ where $x < y$, each of them has to request $lock(x)$ and $lock(y)$ in sequence so that no transaction requests and waits for locks on new items while still locking other transactions' desired items.

Note that although LogBase employs write locks in its algorithm, it is different from traditional two-phase locking (2PL) in that the transaction only holds write locks for a short time during validation and write phase rather than the whole transaction execution time as in 2PL. LogBase delegates the task of managing distributed locks to a separate service, Zookeeper [3], which is widely used in distributed storage systems, such as Cassandra [23] and HBase [2], for providing efficient distributed synchronization. In addition, LogBase employs Zookeeper as a timestamp authority to establish a global counter for generating transaction's commit timestamps and therefore ensuring a global order for committed update transactions.

Snapshot Isolation in LogBase. The locking method during validation ensures "first-committer-wins" rule [7]. Therefore, the MVOCC in LogBase provides similar consistency and isolation level to standard snapshot isolation [7] (see detailed proof below).

Since snapshot isolation is a widely accepted correctness criterion and adopted by many database systems such as InterBase, Oracle, PostgreSQL, and SQL Server, we hypothesize that it is also useful for large-scale environments. If strict serializability is required, read locks also need to be acquired by transactions [4, 36], but that will adversely affect transaction performance as read locks block the writes and void the advantage of snapshot isolation. Another method which detects potential cyclic "read-write" dependency at runtime and restarts one of the involving transactions [9] also introduces performance overhead and might abort transactions unnecessarily.

GUARANTEE 2. ***Isolation.*** *The hybrid scheme of multiversion optimistic concurrency control (MVOCC) in* `LogBase` *guarantees snapshot isolation.*

PROOF. The MVOCC in LogBase is able to eliminate inconsistent reads, including "Dirty read", "Fuzzy read", "Read skew" and "Phantom", and inconsistent writes, including "Dirty write" and "Lost update", while still suffers from "Write skew" anomaly, thereby follows strictly the properties of Snapshot Isolation as formalized in [7]. □

The definitions of these phenomena from [7] are shown below:

Dirty read. $w_1[x]...r_2[x]...((c_1$ or $a_1)$ and $(c_2$ or $a_2)$ in any order)

Fuzzy read. $r_1[x]...w_2[x]...((c_1$ or $a_1)$ and $(c_2$ or $a_2)$ in any order)

Read skew. $r_1[x]...w_2[x]...w_2[y]...c_2...r_1[y]...(c_1$ or $a_1)$

Phantom. $r_1[P]...w_2[y$ in $P]...c_2...r_1[P]...c_1$

Dirty write. $w_1[x]...w_2[x]...((c_1$ or $a_1)$ and $(c_2$ or $a_2)$ in any order)

Lost update. $r_1[x]...w_2[x]...w_1[x]...c_1$

Write skew. $r_1[x]...r_2[y]...w_1[y]...w_2[x]...(c_1$ and $c_2)$

Intuitively, in LogBase multiversions of a data item are timestamped and reads of a transaction access data in the consistent snapshot as of the time that the transaction starts. Therefore, phenomena such as Dirty read, Fuzzy read and Read skew cannot occur, since a transaction will read the same value of a data item even there is an intervening update by another transaction – this update will create a later version of the data item. Similarly, LogBase can also avoid Phantom, i.e., a transaction will see the same old set of data items when rereading a predicate.

The MVOCC in LogBase delays writes until commit time and writes will create new versions. In other words, an update of a transaction is never overwritten by another concurrent transaction, and hence LogBase precludes Dirty write. Most importantly, LogBase is able to prevent Lost update by the use of write locks during validation phase. The first transaction (among other write-conflicting transactions) that can obtain the write locks will win and commit safely, i.e., its updates will be durable. This mechanism ensures "First-Committer-Wins" rule in Snapshot Isolation.

Likewise Snapshot Isolation, the MVOCC in LogBase cannot prevent Write skew: suppose there is an integrity constraint between x and y. T_1 reads x and y first, and then T_2 reads x and y, writes x, and commits. Then T_1 writes y and commits. Although the integrity constraint can be satisfied in the snapshot of each T_1 and T_2, it might be violated in the final state of the database.

In the folling, we provide the detailed formal proof. The *multiversion histories* representing the aforementioned phenomena when executing transactions in `LogBase` are listed below. We use subscripts to denote different versions of a record, e.g., x_i refers to a version of x written by transaction T_i. By convention, T_0 is an originator transaction which installs the initial values of all records in the system.

Dirty read. $w_1[x_1]...r_2[x_0]...((c_1$ or $a_1)$ and $(c_2$ or $a_2)$ in any order) (1)

Fuzzy read. $r_1[x_0]...w_2[x_2]...((c_1$ or $a_1)$ and $(c_2$ or $a_2)$ in any order) (2)

Read skew. $r_1[x_0]...w_2[x_2]...w_2[y_2]...c_2...r_1[y_0]...(c_1$ or $a_1)$ (3)

Phantom. $r_1[P]...w_2[y_2$ in $P]...c_2...r_1[P]...c_1$ (4)

Dirty write. $w_1[x_1]...w_2[x_2]...((c_1$ or $a_1)$ and $(c_2$ or $a_2)$ in any order) (5)

Lost update. $r_1[x_0]...w_2[x_2]...w_1[x_1]...c_1$ (6)

Write skew. $r_1[x_0]...r_2[y_0]...w_1[y_1]...w_2[x_2]...(c_1$ and $c_2)$ (7)

Under dependency theory [18], we put an edge from transaction T_1 to transaction T_2 in the *multiversion serialization graph* (MVSG) in three senarios:

ww**-dependency.** T_1 installs a version of x and T_2 installs a later version of x.

wr**-dependency.** T_1 installs a version of x and T_2 reads this (or a later) version of x.

rw**-dependency.** T_1 reads a version of x and T_2 installs a later version of x.

Based on the dependency theory, we prove the snapshot isolation property of the MVOCC in `LogBase`.

Dirty read. In formula (1), there is a rw-dependency from T_2 to T_1 on record x. Hence, its MVSG includes only one edge ($T_2 -rw(x)\dashrightarrow T_1$) and is acyclic, showing that "Dirty read" does not occur in `LogBase`.

That is, T_1 installs a new version of x while T_2 reads an older version of x from a previous consistent snapshot.

Fuzzy read. Similarly, in formula (2), there is a rw-dependency from T_1 to T_2 on record x. Hence, its MVSG includes only one edge ($T_1 -rw(x)\dashrightarrow T_2$) and is acyclic, showing that "Fuzzy read" does not occur in `LogBase`.

That is, T_2 installs a new version of x while T_1 reads an older version of x from a previous consistent snapshot.

Read skew. In formula (3), there are two rw-dependencies from T_1 to T_2 on record x and y respectively. Hence, its MVSG includes two edges ($T_1 -rw(x)\dashrightarrow T_2$, and $T_1 -rw(y)\dashrightarrow T_2$) and is acyclic, showing that "Read skew" does not occur in `LogBase`.

That is, T_2 installs a new version of x and y while T_1 reads an older of version x and y from a previous consistent snapshot.

Phantom. In formula (4), there is a rw-dependency from T_1 to T_2 on record y. Hence, its MVSG includes only one edge ($T_1 -rw(y)\dashrightarrow T_2$) and is acyclic, showing that "Phantom" does not occur in `LogBase`.

That is, T_2 installs a new version of y belonging to predicate P while T_1 reads an older version of records belonging to predicate P from a previous consistent snapshot.

Dirty write. In formula (5), there is a ww-dependency from T_1 to T_2 on record x. Hence, its MVSG includes only one edge ($T_1 -ww(x)\rightarrow T_2$) and is acyclic, showing that "Dirty write" does not occur in `LogBase`.

Due to the "First-Committer-Wins" (enforced by locking during validation), either T_1 or T_2 is aborted if the other transaction has committed successfully.

Lost update. In formula (6), there is a ww-dependency from T_2 to T_1 on record x. Hence, its MVSG includes only one edge ($T_2 -ww(x)\rightarrow T_1$) and is acyclic, showing that "Lost update" does not occur in `LogBase`.

Due to the "First-Committer-Wins" (enforced by locking during validation), T_2 will be aborted if it attempts to commit at later time because T_1 has committed already.

Write skew. In formula (7), there is a rw-dependency from T_1 to T_2 on record x (i.e., $T_1 -rw(x)\dashrightarrow T_2$), and a rw-dependency from T_2 to T_1 on record y (i.e., $T_2 -rw(y)\dashrightarrow T_1$). Its MVSG, depicted in Figure 6, contains a cycle between T_1 and T_2, showing that the MVOCC in `LogBase` suffers from this anomaly.

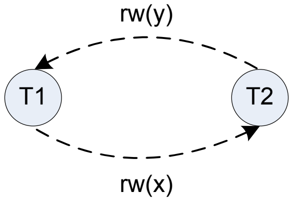


Figure 6: Multiversion serialization graph for write skew.

3.7.2 Commit Protocol and Atomicity

GUARANTEE 3. ***Atomicity.*** *`LogBase`'s commit protocol guarantees similar atomicity property to the WAL+Data approach.*

The commit procedure for an update transaction T proceeds as follows. After executing T's read phase, the transaction manager runs the validation algorithm to determine if T conflicts with other committed transactions or not. If the validation fails, then T is restarted. Otherwise, the transaction manager gets a commit timestamp from the timestamp authority and persists T's writes along with the commit record into the log repository. In addition, relevant in-memory index entries are updated accordingly to reflect the changes, and all the write locks held by T are released.

Note that if the transaction manager fails to persist the final commit record into the log repository (due to errors of the log), T is still not completed as in the WAL+Data approach. Although uncommitted writes could have been written to the log, they are not reflected in the index and thus cannot be accessed by users. Scan operations also check and only return data whose corresponding commit record exists. The uncommitted writes will be totally removed out of the log when the system performs log compaction. In summary, all or none of the updates of a transaction are recorded into the system, i.e., `LogBase` guarantees similar atomicity property to the WAL+Data approach. We also discuss how `LogBase` ensures data durability in the next section.

If the writes of a transaction involves multiple servers, the transaction manager will perform two-phase-commit (2PC) protocol and collect vote messages from participating servers as illustrated in Algorithm 2. Since the MVOCC in `LogBase` defers update effect until commit time, it piggy-backs concurrency control information for validation phase on the messages of the commit protocol, and hence the message cost for transaction management is minimized. Also note that the number of distributed transactions has been reduced at most by the use of smart data partitioning (cf. Section3.2), the above costly 2PC protocol is only necessary in the worst case. `LogBase` also embeds an optimization technique that processes commit and log records in batches similar to group commits in a database, instead of individual log writes, in order to reduce the log persistence cost and therefore improve write throughput.

Algorithm 2 : Commit protocol

```
Send validation requests to participants
Collect vote messages from participants
if all validation successful then
    Get commit timestamp from the timestamp authority
    Persist log records and commit record to the log
    Send COMMIT message to participants
else
    Send RESTART message to participants
```

3.8 Failures and Recovery

In the previous section, we have shown how `LogBase` ensures atomicity, consistency and isolation property. In the following, we present the data durability property of `LogBase`, which guarantees all modifications that have been confirmed with users are persistent in the storage.

GUARANTEE 4. ***Durability.*** *`LogBase`'s recovery protocol guarantees similar data durability property to the WAL+Data approach.*

When a crash occurs, the recovery is simple in `LogBase` since it does not need to restore the data files as in the WAL+Data approach. Instead, the only instance in `LogBase` that needs to be recovered is the in-memory indexes. As a straightforward way, the restarted server can scan its entire log and rebuild the in-memory indexes accordingly. However, this approach is costly and infeasible in practice. In order to reduce the cost of recovery, `LogBase` performs checkpoint operation at regular times or when the number of updates has reached a threshold.

In the checkpoint operation, tablet servers persist two important information into the underlying DFS to enable fast recovery. First, the current in-memory indexes are flushed into index files stored in DFS for persistence. Second, necessary information, including the current position in the log and the log sequence number (LSN) of the latest write operation whose effects have been recorded in the indexes and their persisted files in the first step, are written into checkpoint blocks in DFS so that `LogBase` can use this position as a consistent starting point for recovery.

With the checkpoint information, recovery in `LogBase` can be performed fast since it only need to do an analysis pass from the last known consistent checkpoint to the end of the log where the crash occurred. In particular, at restart time the tablet server can reload the indexes quickly from the persisted index files back into the memory. Then a redo strategy is employed to bring the indexes up-to-date, i.e., the tablet server analyzes the log entries from the recovery starting point and updates the in-memory indexes accordingly. If the LSN of the log entry is greater than the corresponding index entry in the index, then the pointer in the index entry is updated to this log address. Note that performing redo is sufficient for system recovery since `LogBase` adopts optimistic concurrency control method, which defers all modifications until commit time.

All uncommitted log entries are ignored during the redo process and will be discarded from the log repository when the system performs log compaction (cf. Section 3.6.5). In addition, in the event of repeated restart when a crash occurs during the recovery, the system only needs to redo the process.

It is also important to note that if a tablet server fails to restart within a predefined period after its crash, the master node will consider this as permanent failures and re-assign the tablets maintained by this failed server to other healthy tablet servers in the system. The log of the failed servers, which is stored in the shared DFS, is scanned (from the consistent recovery starting point) and split into separate files for each tablet according to the tablet information in the log entries. Then the healthy tablet server scans its assigned log files to perform the recovery as discussed above.

4. PERFORMANCE EVALUATION

We now evaluate the implementation of `LogBase` using a variety of benchmarks. First, we perform micro-benchmarks to examine the performance of basic data operations in `LogBase`. Second, we test the efficiency and scalability of `LogBase` with the Yahoo! cloud data serving benchmark (YCSB) [13] and compare it with HBase [2], a scalable cloud storage system that uses WAL+Data approach. Third, we study transaction performance of `LogBase` with the TPC-W benchmark[3]. Fourth, we evaluate the cost of checkpointing and system recovery time. Finally, we compare `LogBase` with other log-structured record-oriented systems.

4.1 Experimental Setup

Experiments were performed on an in-house cluster including 24 machines, each with a quad core processor, 8 GB of physical memory, 500 GB of disk capacity and 1 gigabit ethernet. `LogBase` is implemented in Java, inherits basic infrastructures from HBase open source, and adds new features for log-structured storages including access to log files, in-memory indexes, log compaction, transaction management and system recovery. We compare the performance of `LogBase` with HBase (version 0.90.3). All settings of HBase are kept as its default configuration, and `LogBase` is configured to similar settings. Particularly, both systems use 40% of 4 GB heap memory for maintaining in-memory data structures (the memtables in HBase and in-memory indexes in `LogBase`), and 20% of heap memory for caching data blocks. Both systems run on top of Hadoop platform (version 0.20.2) and store data into HDFS. We keep all settings of HDFS as default, specifically the chunk size is set to 64 MB and the replication factor is set to 3.

Each machine runs both a data node and a tablet server process. The size of datasets is proportional to the system size, and for every experiment we bulkload 1 million of 1KB records for each node (the key of each record takes its value from $2 * 10^9$ which is the max key in YCSB benchmark [13]). For scalability experiments, we run multiple instances of benchmark clients, one for each node in the system. Each benchmark client submits a constant workload into the system, i.e., a completed operation will be immediately followed by a new operation. The benchmark client reports the system throughput and response time after finishing a workload of 5,000 operations. Before running every experiments, we execute about 15,000 operations on each node to warm up the cache. The default distribution from which the accessed keys are selected is Zipfian distribution with the co-efficient set to 1.0.

4.2 Micro-benchmarks

In this part, we study the performance of basic data operations including sequential write, random read, sequential scan and range scan of `LogBase` with a single tablet server storing data on a 3-node HDFS. We shall study the performance of `LogBase` with mixed workloads and bigger system sizes in the next section.

4.2.1 *Write Performance*

Figure 7 plots the write overhead of inserting 1 million records into the system. The results show that `LogBase` outperforms HBase by 50%. For each insert operation, `LogBase` flushes it to the log and then update the memory index. It thus only writes the data to HDFS once. On the contrary, besides persisting the log information (which includes the record itself) into HDFS, HBase has to insert the record into a memtable, which will be written to the data file in HDFS when the memtable is full (64 MB as default setting). As a result, HBase incurs more write overhead than `LogBase`.

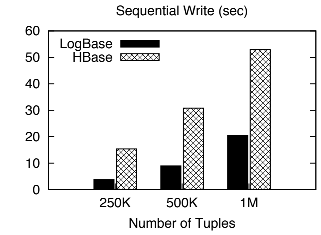


Figure 7: Write performance.

4.2.2 *Random Access Performance*

Figure 8 shows the performance of random access without any cache used in both systems. The performance of `LogBase` is superior to HBase, because `LogBase` maintains a dense in-memory index and each record has a corresponding index entry containing its location in the log. With this information, `LogBase` is able to seek directly to the appropriate position in the log and retrieve the record. In contrast, HBase stores separate sparse block indexes in different data files, and hence after seeking to the corresponding block in one data file, it loads that block into memory and scan the block to get the record of interest. Further, the tablet server in HBase has to check its multiple data files in order to get the proper data record. Therefore, `LogBase` can efficiently support long tail requests that access data not available in the cache.

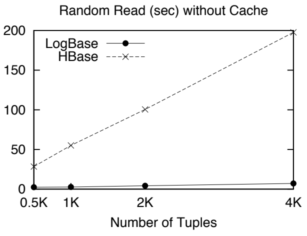


Figure 8: Random access (without cache).

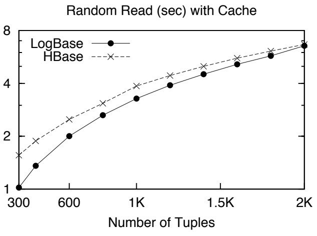


Figure 9: Random access (with cache).

As shown in Figure 9, the performance gap between `LogBase` and HBase reduces when the block cache is adopted in the system. The main reason is that, if the block containing the record to be accessed is cached from previous requests, HBase does not need to seek and read the entire block from HDFS. Instead, it only reads the proper record from the cached block. Note that with larger data domain size in distributed YCSB benchmark as will be discussed in the next section, the cache has less effect and `LogBase` provides better read latency for the support of in-memory indexes.

[3] http://www.tpc.org/tpcw/

4.2.3 Scan Performance

Sequential scan. Figure 10 illustrates the result of sequential scan the entire data. The performance of LogBase is slightly slower than HBase. LogBase scans the log files instead of the data files as HBase, and each log entry contains additional log information besides the data record such as the table name and column group. As such, a log file has larger size than a data file and LogBase has to spend slightly more time to scan the log file.

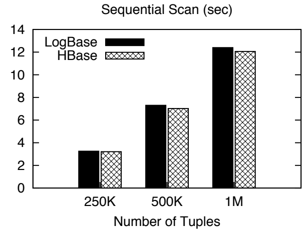


Figure 10: Sequential scan.

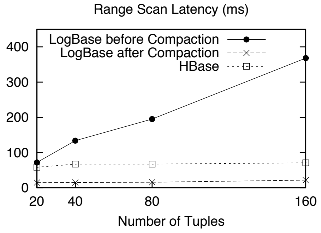


Figure 11: Range scan.

Range scan. The downside of LogBase is that it is not as efficient as HBase when processing range scan query as shown in Figure 11. In HBase, data in memtables are kept sorted by key order and persisted into data files, and hence facilitates fast range scan query. LogBase, on the contrary, sequentially writes data into the log without any clustering property and might need to perform multiple random access to process a single range scan query. However, it is notable that after the compaction process, data in the log are well-clustered and LogBase is able to provide even better range scan performance than HBase for its ability to load the correct block quickly with the support of dense in-memory indexes.

4.3 YCSB Benchmark

In the following, we examine the efficiency and scalability of LogBase with mixed workloads and varying system sizes using YCSB benchmark [13]. The system size scales from 3 to 24 nodes and two write-heavy mix workloads (95% and 75% of update in the workload) are tested. We do not focus on read-heavy mix workloads because with the support of cache, the difference in performance is reduced as shown in the previous experiments.

In the loading phase of the benchmark, multiple instances of clients are launched to insert benchmark data in parallel. Like the result of sequential write in the micro-benchmark, Figure 12 shows that LogBase outperforms HBase when parallel loading data and only spends about half of the time to insert data. This confirms that LogBase can provide the needed high write throughput for write-heavy environments.

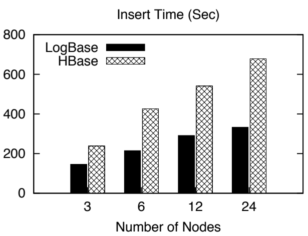


Figure 12: Data loading time.

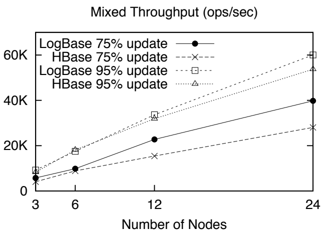


Figure 13: Mixed throughput.

In the experiment phase, the benchmark client at each node will continuously submit a mixed workload into the system. An operation in this workload either reads or updates a certain record that has been inserted in the loading phase. The system overall throughput with different mixes is illustrated in Figure 13 and the corresponding latency of update and read operations is shown in Figure 14 and Figure 15 respectively. The results show that both LogBase and HBase achieve higher throughput with the mix that has higher percentage of update since both systems process write more efficient than read.

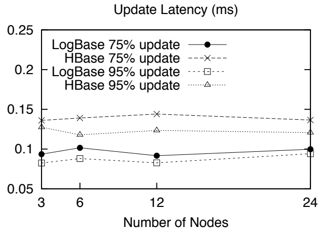


Figure 14: Update latency.

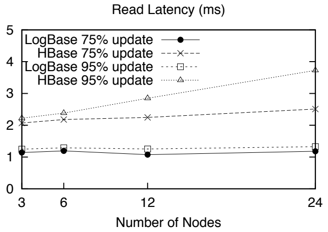


Figure 15: Read latency.

In addition, for each mix, LogBase achieves higher throughput than HBase for its ability to support both write and read efficiently. In HBase, if the memtable is full and a minor compaction is required, the write has to wait until the memtable is persisted successfully into HDFS before returning to users and hence the write response time is delayed. LogBase provides better read latency for the support of in-memory indexes as we have shown in the micro-benchmarks. Although HBase employs cache to improve read performance, the cache has less effect in this distributed experiment since both data domain size and experimental data size are large while there are less read operations in the workload.

Figure 14 and Figure 15 also illustrate the elastic scaling property of LogBase where the system scales well with flat latency. That is, the more workload can be served by adding more nodes into the system.

4.4 TPC-W Benchmark

In this experiment, we examine the performance of LogBase when accessing multiple data records possibly from different tables within the transaction boundary. In particular, we experiment LogBase with TPC-W benchmark which models a webshop application workload. The benchmark characterizes three typical mixes including browsing mix, shopping mix and ordering mix that have 5%, 20% and 50% update transactions respectively.

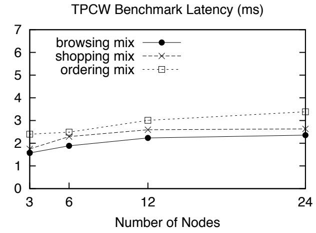


Figure 16: Transaction latency.

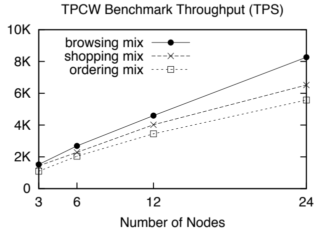


Figure 17: Transaction throughput.

A read-only transaction performs one read operation to query the details of a product in the item table while an update transaction executes an order request which bundles one read operation to retrieve the user's shopping cart and one write operation into the orders table. Each node in the system is bulk loaded with 1 million products and customers before the experiment. We stress test the system by using a client thread at each node to continuously submit transactions to the system and then benchmark the transaction throughput and latency.

As can be seen in Figure 16, under browsing mix and shopping mix, LogBase scales well with nearly flat transaction latency when the system size increases and as a result, the transaction throughput (shown in Figure 17) scales linearly under these two workloads. It is because of the fact that in these two workloads, most of the transactions are read-only and have no commit overhead for the use of MVOCC in LogBase.

4.5 Checkpoint and Recovery

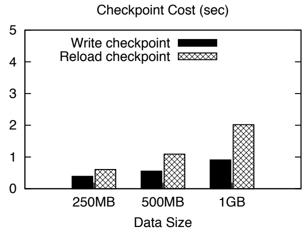


Figure 18: Checkpoint cost.

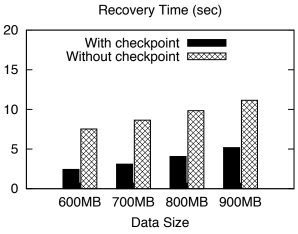


Figure 19: Recovery time.

We now study the cost of checkpoint operation and the recovery time in a system of 3 nodes. Figure 18 plots the time to write a checkpoint and reload a checkpoint with varying thresholds at which a tablet server performs the checkpoint operation. LogBase takes less time to write a checkpoint (persist in-memory indexes) than to reload a checkpoint (reload the persisted index files into memory) because HDFS is optimized for high write throughput. This is useful because checkpoint writing is to be performed more frequently in LogBase, whereas checkpoint loading only happens when the system recovers from tablet servers' failures.

The time to recover varying amount of data maintained by a failed tablet server is shown in Figure 19. The checkpoint was taken at a threshold of 500 MB before we purposely killed the tablet server when its amount of data reached 600 MB to 900 MB. The results show that the recovery time in the system with checkpoint is significantly faster than without checkpoint. In the former approach, the system only needs to reload the checkpoint and scan a little additional log segments after the checkpoint time to rebuild the in-memory indexes, whereas in the latter approach the system has to scan the entire log segments.

LogBase does not support as efficient recovery time as RAMCloud [31] because the two systems make different design choices for targeting at different environments. In RAMCloud, both indexes and data are entirely stored in memory while disks only serve as data backup for recovery purpose. Therefore, RAMCloud backups log segments of a tablet dispersedly to hundreds of machines (and disks) in order to exploit parallelism for recovery. In contrast, LogBase stores data on disks and hence cannot scatter log segments of a tablet to such scale in order to favor recovery as it would adversely affect the write and read performance of the system.

4.6 Comparison with Log-structured Systems

As we have reviewed in Section 2, recent scalable log-structured record-oriented systems (LRS) such as RAMCloud [31] and Hyder [8] target at different environments with LogBase. Specifically, RAMCloud stores its data and indexes entirely in memory while Hyder scales its database in shared-flash environments without data partitioning. Therefore, we cannot compare their performance directly with LogBase. Here, for comparison purpose as well as exploring the opportunity of scaling the indexes beyond memory, we examine a system, referred to as LRS, which has a distributed architecture and data partitioning strategy similar to RAMCloud and LogBase but stores data on disks and indexes in log-structured merge trees (LSM-tree [30]) in order to deal with scenarios where the memory of tablet servers is scarce. Particularly, in this experiment we use LevelDB [4], a variant LSM-tree open source by Google, with all settings kept as default.

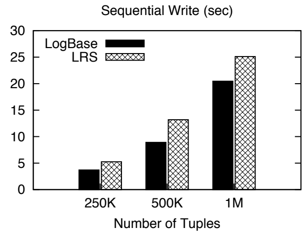


Figure 20: Sequential write.

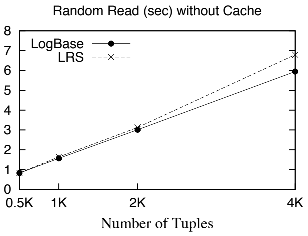


Figure 21: Random access.

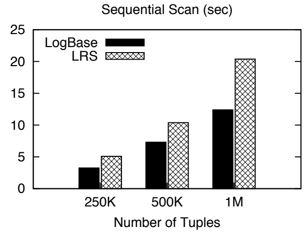


Figure 22: Sequential scan.

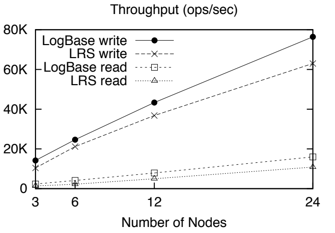


Figure 23: Throughput.

The results of comparison between LogBase and LRS in a system of 3 nodes are shown in Figure 20, Figure 21, and Figure 22 respectively for sequential write, random access, and sequential scan. The comparison results with varying system sizes are also plotted in Figure 23. Overall, the sequential write and random access performance of LRS are only slightly lower than that of LogBase because LevelDB is highly optimized for a variety of workloads and can provide efficient write and read performance with moderate write and read buffer (4 MB and 8 MB respectively in the experiment). This leads us to conclude that it is possible for LogBase to scale its indexes beyond memory (by the use of LSM-trees) without paying much cost of reduction in the system throughput.

LogBase also achieves higher sequential scan performance than LRS. For each scanned record, the system needs to check its stored version against the current version maintained in the indexes to determine whether the record contains the latest data. Such cost of accessing indexes is attributed to the difference in the scan performance of the two systems. Note that after log compaction, historical versions of a record are clustered together and the number of version checking with indexes is minimized, which would reduce the scan performance gap.

5. CONCLUSION

We have introduced a scalable log-structured database system called LogBase, which can be elastically deployed in the cloud and provide sustained write throughput and effective recovery time in the system. The in-memory indexes in LogBase support efficient data retrieval from the log and are especially useful for handling long tail requests. LogBase provides the widely accepted snapshot isolation for bundled read-modify-write transactions. Extensive experiments on an in-house cluster verifies the efficiency and scalability of the system. Our future works include the design and implementation of efficient secondary indexes and query processing for LogBase.

[4] http://code.google.com/p/leveldb/

Acknowledgments

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6. REFERENCES

[1] Hadoop mapreduce. http://hadoop.apache.org/mapreduce.

[2] Hbase. http://hbase.apache.org.

[3] Zookeeper. http://zookeeper.apache.org.

[4] D. Agrawal, A. J. Bernstein, P. Gupta, and S. Sengupta. Distributed optimistic concurrency control with reduced rollback. *Distributed Computing*, 2(1):45–59, 1987.

[5] J. Baker, C. Bond, J. Corbett, J. J. Furman, A. Khorlin, J. Larson, J.-M. Leon, Y. Li, A. Lloyd, and V. Yushprakh. Megastore: Providing scalable, highly available storage for interactive services. In *Proc. of CIDR*, pages 223–234, 2011.

[6] D. Beaver, S. Kumar, H. C. Li, J. Sobel, and P. Vajgel. Finding a needle in haystack: facebook's photo storage. In *Proc. of OSDI*, pages 1–8, 2010.

[7] H. Berenson, P. Bernstein, J. Gray, J. Melton, E. O'Neil, and P. O'Neil. A critique of ansi sql isolation levels. In *Proc. of SIGMOD*, pages 1–10, 1995.

[8] P. A. Bernstein, C. W. Reid, and S. Das. Hyder - a transactional record manager for shared flash. In *Proc. of CIDR*, pages 9–20, 2011.

[9] M. J. Cahill, U. Röhm, and A. D. Fekete. Serializable isolation for snapshot databases. In *Proc. of SIGMOD*, pages 729–738, 2008.

[10] R. Cattell. Scalable sql and nosql data stores. *SIGMOD Rec.*, 39:12–27, 2011.

[11] F. Chang, J. Dean, S. Ghemawat, W. C. Hsieh, D. A. Wallach, M. Burrows, T. Chandra, A. Fikes, and R. E. Gruber. Bigtable: a distributed storage system for structured data. In *Proc. of OSDI*, pages 205–218, 2006.

[12] B. F. Cooper, R. Ramakrishnan, U. Srivastava, A. Silberstein, P. Bohannon, H.-A. Jacobsen, N. Puz, D. Weaver, and R. Yerneni. Pnuts: Yahoo!'s hosted data serving platform. *PVLDB*, 1(2):1277–1288, 2008.

[13] B. F. Cooper, A. Silberstein, E. Tam, R. Ramakrishnan, and R. Sears. Benchmarking cloud serving systems with ycsb. In *Proc. of SoCC*, pages 143–154, 2010.

[14] C. Curino, E. Jones, Y. Zhang, and S. Madden. Schism: a workload-driven approach to database replication and partitioning. *Proc. VLDB Endow.*, 3:48–57, 2010.

[15] S. Das, D. Agrawal, and A. El Abbadi. G-store: a scalable data store for transactional multi key access in the cloud. In *Proc. of SOCC*, pages 163–174, 2010.

[16] J. Dean and S. Ghemawat. Mapreduce: simplified data processing on large clusters. In *Proc. of OSDI*, pages 10–10, 2004.

[17] J. Dittrich and A. Jindal. Towards a one size fits all database architecture. In *Proc. of CIDR*, pages 195–198, 2011.

[18] A. Fekete, D. Liarokapis, E. O'Neil, P. O'Neil, and D. Shasha. Making snapshot isolation serializable. *ACM Trans. Database Syst.*, 30(2):492–528, 2005.

[19] S. Ghemawat, H. Gobioff, and S.-T. Leung. The google file system. In *Proc. of SOSP*, pages 29–43, 2003.

[20] J. Gray, P. McJones, M. Blasgen, B. Lindsay, R. Lorie, T. Price, F. Putzolu, and I. Traiger. The recovery manager of the system r database manager. *ACM Comput. Surv.*, 13:223–242, 1981.

[21] M. Grund, J. Krüger, H. Plattner, A. Zeier, P. Cudré-Mauroux, and S. Madden. Hyrise - a main memory hybrid storage engine. *PVLDB*, 4(2):105–116, 2010.

[22] R. A. Hankins and J. M. Patel. Data morphing: an adaptive, cache-conscious storage technique. In *Proc. of VLDB*, pages 417–428, 2003.

[23] A. Lakshman and P. Malik. Cassandra: a decentralized structured storage system. *SIGOPS Oper. Syst. Rev.*, 44(2):35–40, 2010.

[24] P. L. Lehman and S. B. Yao. Efficient locking for concurrent operations on b-trees. *ACM Trans. Database Syst.*, 6:650–670, 1981.

[25] D. B. Lomet and B. Salzberg. Access methods for multiversion data. In *Proc. of SIGMOD*, pages 315–324, 1989.

[26] D. B. Lomet and B. Salzberg. Exploiting a history database for backup. In *Proc. of VLDB*, pages 380–390, 1993.

[27] C. Mohan, D. Haderle, B. Lindsay, H. Pirahesh, and P. Schwarz. Aries: a transaction recovery method supporting fine-granularity locking and partial rollbacks using write-ahead logging. *ACM Trans. Database Syst.*, 17:94–162, 1992.

[28] P. Muth, P. O'Neil, A. Pick, and G. Weikum. The lham log-structured history data access method. *The VLDB Journal*, 8:199–221, 2000.

[29] K. Nrvåg. The vagabond approach to logging and recovery in transaction-time temporal object database systems. *IEEE Trans. on Knowl. and Data Eng.*, 16:504–518, 2004.

[30] P. O'Neil, E. Cheng, D. Gawlick, and E. O'Neil. The log-structured merge-tree. *Acta Inf.*, 33:351–385, 1996.

[31] D. Ongaro, S. M. Rumble, R. Stutsman, J. Ousterhout, and M. Rosenblum. Fast crash recovery in ramcloud. In *Proc. of SOSP*, pages 29–41, 2011.

[32] D. A. Patterson, G. Gibson, and R. H. Katz. A case for redundant arrays of inexpensive disks (raid). In *Proc. of SIGMOD*, pages 109–116, 1988.

[33] M. Rosenblum and J. K. Ousterhout. The design and implementation of a log-structured file system. *ACM Trans. Comput. Syst.*, 10:26–52, 1992.

[34] R. Sears and R. Ramakrishnan. blsm: A general purpose log structured merge tree. In *Proc. of SIGMOD*, pages 217–228, 2012.

[35] M. Stonebraker and L. A. Rowe. The design of postgres. In *Proc. of SIGMOD*, pages 340–355, 1986.

[36] A. Thomasian. Distributed optimistic concurrency control methods for high-performance transaction processing. *IEEE Trans. on Knowl. and Data Eng.*, 10:173–189, 1998.

[37] H. T. Vo, C. Chen, and B. C. Ooi. Towards elastic transactional cloud storage with range query support. *Proc. VLDB Endow.*, 3(1-2):506–514, 2010.

[38] M. Vrable, S. Savage, and G. M. Voelker. Bluesky: A cloud-backed file system for the enterprise. In *Proc. of FAST*, pages 237–250, 2012.