

Bigtable: A Distributed Storage System for Structured Data

FAY CHANG, JEFFREY DEAN, SANJAY GHEMAWAT, WILSON C. HSIEH,
DEBORAH A. WALLACH, MIKE BURROWS, TUSHAR CHANDRA,
ANDREW FIKES, and ROBERT E. GRUBER
Google, Inc.

Bigtable is a distributed storage system for managing structured data that is designed to scale to a very large size: petabytes of data across thousands of commodity servers. Many projects at Google store data in Bigtable, including web indexing, Google Earth, and Google Finance. These applications place very different demands on Bigtable, both in terms of data size (from URLs to web pages to satellite imagery) and latency requirements (from backend bulk processing to real-time data serving). Despite these varied demands, Bigtable has successfully provided a flexible, high-performance solution for all of these Google products. In this article, we describe the simple data model provided by Bigtable, which gives clients dynamic control over data layout and format, and we describe the design and implementation of Bigtable.

Categories and Subject Descriptors: C.2.4 [**Computer Communication Networks**]: Distributed Systems—*distributed databases*

General Terms: Design

Additional Key Words and Phrases: Large-Scale Distributed Storage

ACM Reference Format:

Chang, F., Dean, J., Ghemawat, S., Hsieh, W. C., Wallach, D. A., Burrows, M., Chandra, T., Fikes, A., and Gruber, R. E. 2008. Bigtable: A distributed storage system for structured data. *ACM Trans. Comput. Syst.* 26, 2, Article 4 (June 2008), 26 pages. DOI = 10.1145/1365815.1365816. <http://doi.acm.org/10.1145/1365815.1365816>.

This article was originally published as an award paper in the *Proceedings of the 7th Symposium on Operating Systems Design and Implementation* [Chang et al. 2006]. It is being republished here with minor modifications and clarifications.

Authors' address: Google Inc., 1600 Amphitheatre Parkway, Mountain View, CA 94043; email: {fay, jeff, sanjay, wilsonh, kerr, m3b, tushar, fikes, gruber}@google.com.

Permission to make digital or hard copies of part or all of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or direct commercial advantage and that copies show this notice on the first page or initial screen of a display along with the full citation. Copyrights for components of this work owned by others than ACM must be honored. Abstracting with credits is permitted. To copy otherwise, to republish, to post on servers, to redistribute to lists, or to use any component of this work in other works requires prior specific permission and/or a fee. Permissions may be requested from the Publications Dept., ACM, Inc., 2 Penn Plaza, Suite 701, New York, NY 10121-0701 USA, fax +1 (212) 869-0481, or permission@acm.org.

© 2008 ACM 0734-2071/2008/06-ART4 \$5.00 DOI: 10.1145/1365815.1365816. <http://doi.acm.org/10.1145/1365815.1365816>.

ACM Transactions on Computer Systems, Vol. 26, No. 2, Article 4, Pub. date: June 2008.

1. INTRODUCTION

Beginning in late 2003, we designed, implemented, and deployed a distributed storage system for managing structured data at Google called Bigtable. Bigtable is designed to reliably scale to petabytes of data and thousands of machines. Bigtable has achieved several goals: wide applicability, scalability, high performance, and high availability. Bigtable is used by more than sixty Google products and projects, including Google Analytics, Google Finance, Orkut, Personalized Search, Writely, and Google Earth. These products use Bigtable for a variety of demanding workloads, which range from throughput-oriented batch-processing jobs to latency-sensitive serving of data to end users. The Bigtable clusters used by these products span a wide range of configurations, from a handful to thousands of servers, and store up to several hundred terabytes of data.

In many ways, Bigtable resembles a database: it shares many implementation strategies with databases. Parallel databases [DeWitt and Gray 1992] and main-memory databases [DeWitt et al. 1984] have achieved scalability and high performance, but Bigtable provides a different interface than such systems. Bigtable does not support a full relational data model; instead, it provides clients with a simple data model that supports dynamic control over data layout and format, and allows clients to reason about the locality properties of the data represented in the underlying storage. Data is indexed using row and column names that can be arbitrary strings. Bigtable also treats data as uninterpreted strings, although clients often serialize various forms of structured and semi-structured data into these strings. Clients can control the locality of their data through careful choices in their schemas. Finally, Bigtable schema parameters let clients dynamically control whether to serve data out of memory or from disk.

Section 2 describes the data model in more detail, and Section 3 provides an overview of the client API. Section 4 briefly describes the underlying Google infrastructure on which Bigtable depends. Section 5 describes the fundamentals of the Bigtable implementation, and Section 6 describes some of the refinements that we made to improve Bigtable’s performance. Section 7 provides measurements of Bigtable’s performance. We describe several examples of how Bigtable is used at Google in Section 8, and discuss some lessons we learned in designing and supporting Bigtable in Section 9. Finally, Section 10 describes related work, and Section 11 presents our conclusions.

2. DATA MODEL

A Bigtable *cluster* is a set of processes that run the Bigtable software. Each cluster serves a set of tables. A *table* in Bigtable is a sparse, distributed, persistent multidimensional sorted map. Data is organized into three dimensions: rows, columns, and timestamps.

$$(\text{row:}\text{string}, \text{column:}\text{string}, \text{time:}\text{int64}) \rightarrow \text{string}$$

We refer to the storage referenced by a particular row key, column key, and timestamp as a *cell*. Rows are grouped together to form the unit of load

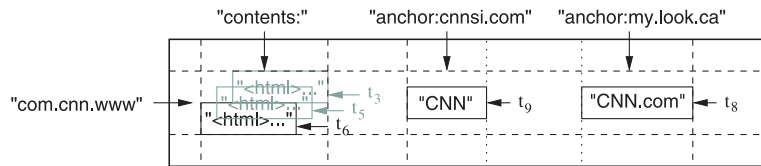


Fig. 1. A slice of an example table that stores Web pages. The row name is a reversed URL. The contents column family contains the page contents, and the anchor column family contains the text of any anchors that reference the page. CNN's home page is referenced by both the Sports Illustrated and the MY-look home pages, so the row contains columns named anchor:cnnsi.com and anchor:my.look.ca. Each anchor cell has one version; the contents column has three versions, at timestamps t_3 , t_5 , and t_6 .

balancing, and columns are grouped together to form the unit of access control and resource accounting.

We settled on this data model after examining a variety of potential uses of a Bigtable-like system. Consider one concrete example that drove many of our design decisions: a copy of a large collection of web pages and related information that could be used by many different projects. Let us call this particular table the *Webtable*. In *Webtable*, we would use URLs as row keys, various aspects of web pages as column names, and store the contents of the web pages in the contents: column under the timestamps when they were fetched, as illustrated in Figure 1.

Rows. Bigtable maintains data in lexicographic order by row key. The row keys in a table are arbitrary strings (currently up to 64KB in size, although 10-100 bytes is a typical size for most of our users). Every read or write of data under a single row key is serializable (regardless of the number of different columns being read or written in the row), a design decision that makes it easier for clients to reason about the system's behavior in the presence of concurrent updates to the same row. In other words, the row is the unit of transactional consistency in Bigtable, which does not currently support transactions across rows.

Rows with consecutive keys are grouped into *tablets*, which form the unit of distribution and load balancing. As a result, reads of short row ranges are efficient and typically require communication with only a small number of machines. Clients can exploit this property by selecting their row keys so that they get good locality for their data accesses. For example, in *Webtable*, pages in the same domain are grouped together into contiguous rows by reversing the hostname components of the URLs. We would store data for maps.google.com/index.html under the key com.google.maps/index.html. Storing pages from the same domain near each other makes some host and domain analyses more efficient.

Columns. Column keys are grouped into sets called *column families*, which form the unit of access control. All data stored in a column family is usually of the same type (we compress data in the same column family together). A column family must be created explicitly before data can be stored under any

column key in that family. After a family has been created, any column key within the family can be used: data can be stored under such a column key without affecting a table's schema. It is our intent that the number of distinct column families in a table be small (in the hundreds at most), and that families rarely change during operation; this limitation keeps widely shared metadata from being too large. In contrast, a table may have an unbounded number of columns.

Entire column families may be deleted by changing a table's schema, in which case the data stored under any column keys in that family is deleted. Since Bigtable does not support transactions across multiple rows, however, the data stored under a particular column key cannot be deleted atomically if it resides in multiple rows.

A column key is named using the following syntax: *family:qualifier*. Column family names must be printable, but qualifiers may be arbitrary strings. An example column family for Weetable is *language*, which stores the language in which a web page was written. We use only one column key with an empty qualifier in the *language* family to store each web page's language ID. Another useful column family for this table is *anchor*; each column key in this family represents a single anchor, as shown in Figure 1. The qualifier is the name of the referring site; the cell contains the text associated with the link.

Access control and both disk and memory accounting are performed at the column-family level. In our Weetable example, these controls allow us to manage several different types of applications: some that add new base data, some that read the base data and create derived column families, and some that are only allowed to view existing data (and possibly not even to view all of the existing families for privacy reasons).

Timestamps. Different cells in a table can contain multiple versions of the same data, where the versions are indexed by timestamp. Bigtable timestamps are 64-bit integers. They can be assigned implicitly by Bigtable, in which case they represent “real time” in microseconds, or they can be assigned explicitly by client applications. Applications that need to avoid collisions must generate unique timestamps themselves. Different versions of a cell are stored in decreasing timestamp order, so that the most recent versions can be read first.

To make the management of versioned data less onerous, we support two per-column-family settings that tell Bigtable to garbage-collect versioned data automatically. The client can specify either that only the last n versions of data be kept, or that only new-enough versions be kept (e.g., only keep values that were written in the last seven days).

In our Weetable example, we can set the timestamps of the crawled pages stored in the contents: column to the times at which these page versions were actually crawled. The garbage-collection mechanism described above enables us to tell Bigtable to keep only the most recent three versions of every page.

```

// Open the table
Table *T = OpenOrDie("/bigtable/web/webtable");

// Write a new anchor and delete an old anchor
RowMutation r1(T, "com.cnn.www");
r1.Set("anchor:www.c-span.org", "CNN");
r1.Delete("anchor:www.abc.com");
Operation op;
Apply(&op, &r1);

```

Fig. 2. Writing to Bigtable.

```

Scanner scanner(T);
ScanStream *stream;
stream = scanner.FetchColumnFamily("anchor");
stream->SetReturnAllVersions();
scanner.Lookup("com.cnn.www");
for (; !stream->Done(); stream->Next()) {
    printf("%s %s %lld %s\n",
           scanner.RowName(),
           stream->ColumnName(),
           stream->MicroTimestamp(),
           stream->Value());
}

```

Fig. 3. Reading from Bigtable.

3. API

The Bigtable API provides functions for creating and deleting tables and column families. It also provides functions for changing cluster, table, and column family metadata, such as access control rights.

Client applications can write or delete values in Bigtable, look up values from individual rows, or iterate over a subset of the data in a table. Figure 2 shows C++ code that uses a `RowMutation` abstraction to perform a series of updates. (Irrelevant details were elided to keep the example short.) The call to `Apply` performs an atomic mutation to the Webtable: it adds one anchor to `www.cnn.com` and deletes a different anchor.

Figure 3 shows C++ code that uses a `Scanner` abstraction to iterate over all anchors in a particular row. Clients can iterate over multiple column families, and there are several mechanisms for limiting the rows, columns, and timestamps traversed by a scan. For example, we could restrict the scan above to only produce anchors whose columns match the regular expression `anchor:*.cnn.com`, or to only produce anchors whose timestamps fall within ten days of the current time.

Bigtable supports several other features that allow the user to manipulate data in more complex ways. First, Bigtable supports single-row transactions,

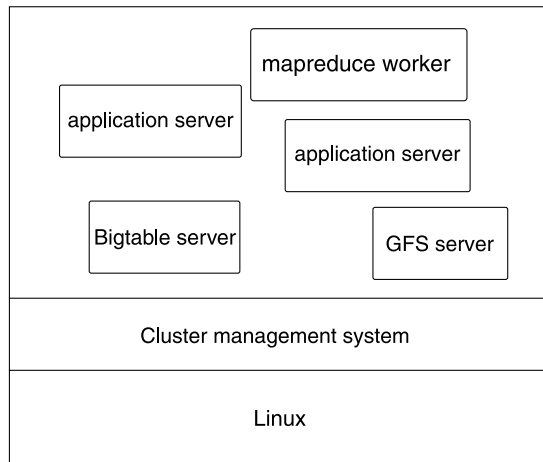


Fig. 4. A typical set of processes that run on a Google machine. A machine typically runs many jobs from many different users.

which can be used to perform atomic read-modify-write sequences on data stored under a single row key. Bigtable does not currently support general transactions across row keys, although it provides an interface for batching writes across row keys at the clients. Second, Bigtable allows cells to be used as integer counters. Finally, Bigtable supports the execution of client-supplied scripts in the address spaces of the servers. The scripts are written in a language called Sawzall [Pike et al. 2005], which was developed at Google for processing data. At the moment, our Sawzall-based API does not allow client scripts to write back into Bigtable, but it does allow various forms of data transformation, filtering based on arbitrary expressions, and summarization via a variety of operators.

Bigtable can be used with MapReduce [Dean and Ghemawat 2004], a framework for running large-scale parallel computations developed at Google. We have written a set of wrappers that allow a Bigtable to be used both as an input source and as an output target for MapReduce jobs.

4. BUILDING BLOCKS

Bigtable is built on several other pieces of Google infrastructure. A Bigtable cluster typically operates in a shared pool of machines that run a wide variety of other distributed applications. Bigtable depends on a Google cluster management system for scheduling jobs, managing resources on shared machines, monitoring machine status, and dealing with machine failures. Bigtable processes often share the same machines with processes from other applications. For example, as illustrated in Figure 4, a Bigtable server may run on the same machine as a mapreduce worker [Dean and Ghemawat 2004], application servers, and a server for the Google File System (GFS) [Ghemawat et al. 2003].

Bigtable uses GFS to store log and data files. GFS is a distributed file system that maintains multiple replicas of each file for greater reliability and availability.

The Google *SSTable* immutable-file format is used internally to store Bigtable data files. An *SSTable* provides a persistent, ordered immutable map from keys to values, where both keys and values are arbitrary byte strings. Operations are provided to look up the value associated with a specified key, and to iterate over all key/value pairs in a specified key range. Internally, each *SSTable* contains a sequence of blocks (by default each block is 64KB in size, but the size is configurable). A block index (stored at the end of the *SSTable*) is used to locate blocks; the index is loaded into memory when the *SSTable* is opened. A lookup can be performed with a single disk seek: we first find the appropriate block by performing a binary search in the in-memory index, and then read the appropriate block from disk. Optionally, an *SSTable* can be completely mapped into memory, which allows us to perform lookups and scans without touching disk.

Bigtable relies on a highly-available and persistent distributed lock service called Chubby [Burrows 2006]. A Chubby service consists of five active replicas, one of which is elected to be the master and actively serve requests. The service is live when a majority of the replicas are running and can communicate with each other. Chubby uses the Paxos algorithm [Chandra et al. 2007; Lamport 1998] to keep its replicas consistent in the face of failure. Chubby provides a namespace that consists of directories and small files. Each directory or file can be used as a lock, and reads and writes to a file are atomic. The Chubby client library provides consistent caching of Chubby files. Each Chubby client maintains a *session* with a Chubby service. A client's session expires if it is unable to renew its session lease within the lease expiration time. When a client's session expires, it loses any locks and open handles. Chubby clients can also register callbacks on Chubby files and directories for notification of changes or session expiration.

Bigtable uses Chubby for a variety of tasks: to ensure that there is at most one active master at any time; to store the bootstrap location of Bigtable data (see Section 5.1); to discover tablet servers and finalize tablet server deaths (see Section 5.2); and to store Bigtable schemas (see Section 5.5). If Chubby becomes unavailable for an extended period of time, Bigtable becomes unavailable. In August 2006, we measured this effect in 14 Bigtable clusters spanning 11 Chubby instances. The average percentage of Bigtable server hours during which some data stored in Bigtable was not available due to Chubby unavailability (caused by either Chubby outages or network issues) was 0.0047%. The percentage for the single cluster that was most affected by Chubby unavailability was 0.0326%.

5. IMPLEMENTATION

The Bigtable implementation has three major components: a library that is linked into every client, one master server, and many tablet servers. Tablet servers can be dynamically added (or removed) from a cluster to accommodate changes in workloads.

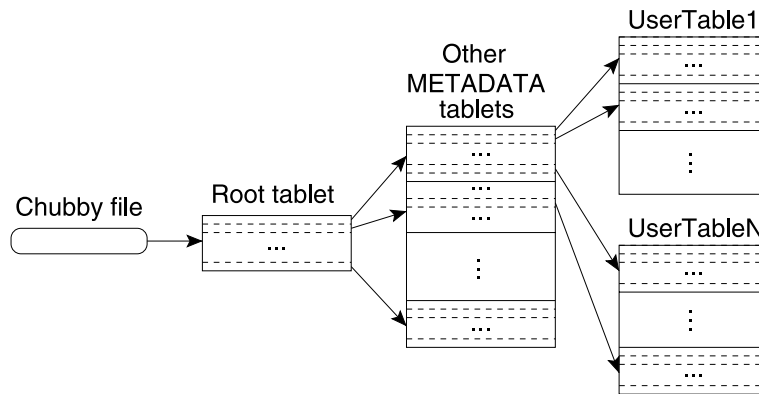


Fig. 5. Tablet location hierarchy.

The master is responsible for assigning tablets to tablet servers, detecting the addition and expiration of tablet servers, balancing tablet-server load, and garbage collecting files in GFS. In addition, it handles schema changes such as table and column family creations and deletions.

Each tablet server manages a set of tablets (typically we have somewhere between ten to a thousand tablets per tablet server). The tablet server handles read and write requests to the tablets that it has loaded, and also splits tablets that have grown too large.

As with many single-master distributed storage systems [Ghemawat et al. 2003; Hartman and Ousterhout 1993], client data does not move through the master: clients communicate directly with tablet servers for reads and writes. Because Bigtable clients also do not rely on the master for tablet location information, most clients never communicate with the master. As a result, the master is lightly loaded in practice.

A Bigtable cluster stores a number of tables. Each table consists of a set of tablets, and each tablet contains all of the data associated with a row range. Initially, each table consists of just one tablet. As a table grows, it is automatically split into multiple tablets, each approximately 1 GB in size by default.

Although our model supports arbitrary-sized data, the current Bigtable implementation does not support extremely large values well. Because a tablet cannot be split in the middle of a row, we recommend to users that a row contain no more than a few hundred GB of data.

In the remainder of this section we describe some of the details of the Bigtable implementation.

5.1 Tablet Location

We use a three-level hierarchy analogous to that of a B⁺-tree [Comer 1979] to store tablet location information (Figure 5). The first level is a file stored in Chubby that contains the location of the *root tablet*. The *root tablet* contains the locations of all of the tablets of a special METADATA table. Each METADATA tablet contains the location of a set of user tablets. The *root tablet* is treated

specially—it is never split—to ensure that the tablet location hierarchy has no more than three levels.

The METADATA table stores the location of a tablet under a row key that is an encoding of the tablet’s table identifier and its end row. Each METADATA row stores approximately 1KB of data in memory. With a modest limit of 128 MB METADATA tablets, our three-level location scheme is sufficient to address 2^{34} tablets (or 2^{61} bytes in 128 MB tablets).

The client library traverses the location hierarchy to locate tablets, and caches the locations that it finds. If the client does not know the location of a tablet, or if it discovers that cached location information is incorrect, then it recursively moves up the tablet location hierarchy. If the client’s cache is empty, the location algorithm requires three network round-trips, including one read from Chubby. If the client’s cache is stale, the location algorithm could take up to six round-trips, because stale cache entries are only discovered upon misses (which we expect to be infrequent because METADATA tablets should not move very frequently). Although tablet locations are stored in memory, so no GFS accesses are required, we further reduce this cost in the common case by having the client library prefetch tablet locations: it reads the metadata for more than one tablet whenever it reads the METADATA table.

We also store secondary information in the METADATA table, including a log of all events pertaining to each tablet (such as when a server begins serving it). This information is helpful for debugging and performance analysis.

5.2 Tablet Assignment

Each tablet is assigned to at most one tablet server at a time. The master keeps track of the set of live tablet servers, and the current assignment of tablets to tablet servers, including which tablets are unassigned. When a tablet is unassigned, and a tablet server with sufficient room for the tablet is available, the master assigns the tablet by sending a tablet load request to the tablet server. This assignment fails only if the tablet load request is not received before the next master failover: a tablet server only accepts tablet load requests from the current master. Therefore, once a master has sent a tablet load request, it can assume that the tablet is assigned until the tablet server dies, or the tablet server informs the master that it has unloaded the tablet.

Bigtable uses Chubby to keep track of tablet servers. When a tablet server starts, it creates and acquires an exclusive lock on a uniquely named file in a specific Chubby directory. The master monitors this directory (the *servers directory*) to discover tablet servers. A tablet server stops serving its tablets if it loses its exclusive lock: for example, a network partition might cause the server to lose its Chubby session. (Chubby provides an efficient mechanism that allows a tablet server to check whether it still holds its lock without incurring network traffic.) A tablet server attempts to reacquire an exclusive lock on its file as long as the file still exists. If its file no longer exists, then the tablet server will never be able to serve again, so it kills itself. Whenever a tablet server terminates (e.g., because the cluster management system is re-

moving the tablet server's machine from the cluster), it attempts to release its lock so that the master will reassign its tablets more quickly.

The master is responsible for detecting when a tablet server is no longer serving its tablets, and for reassigning those tablets as soon as possible. To detect when a tablet server is no longer serving its tablets, the master periodically asks each tablet server for the status of its lock. If a tablet server reports that it has lost its lock, or if the master was unable to reach a server during its last several attempts, the master attempts to acquire an exclusive lock on the server's file. If the master is able to acquire the lock, then Chubby is live and the tablet server is either dead or having trouble reaching Chubby, so the master ensures that the tablet server can never serve again by deleting its server file. Once a server's file has been deleted, the master can move all the tablets that were previously assigned to that server into the set of unassigned tablets. To ensure that a Bigtable cluster is not vulnerable to networking issues between the master and Chubby, the master kills itself if its Chubby session expires. Master failures do not change the assignment of tablets to tablet servers.

When a master is started by the cluster management system, it needs to discover the current tablet assignments before it can change them. The master executes the following steps at startup:

- (1) The master grabs a unique *master* lock in Chubby, which prevents concurrent master instantiations.
- (2) The master scans the servers directory in Chubby to find the live servers.
- (3) The master communicates with every live tablet server to discover what tablets are already assigned to each server, and to update their notion of the current master (so that any subsequently received tablet load requests from prior masters will be rejected).
- (4) The master scans the METADATA table to learn the set of tablets. Whenever this scan encounters a tablet that is not already assigned, the master adds the tablet to the set of unassigned tablets, which makes the tablet eligible for tablet assignment.

One complication is that the scan of the METADATA table cannot happen until the METADATA tablets have been assigned. Therefore, before starting this scan (Step (4)), the master adds the root tablet to the set of unassigned tablets if an assignment for the root tablet was not discovered during Step (3). This addition ensures that the root tablet will be assigned. Because the root tablet contains the names of all METADATA tablets, the master knows about all of them after it has scanned the root tablet.

The set of existing tablets only changes when a table is created or deleted, two existing tablets are merged to form one larger tablet, or an existing tablet is split into two smaller tablets. The master is able to keep track of these changes because it initiates all but the last. Tablet splits are treated specially since they are initiated by tablet servers. A tablet server commits a split by recording information for the new tablet in the METADATA table. After committing the split, the tablet server notifies the master. If the split notification is

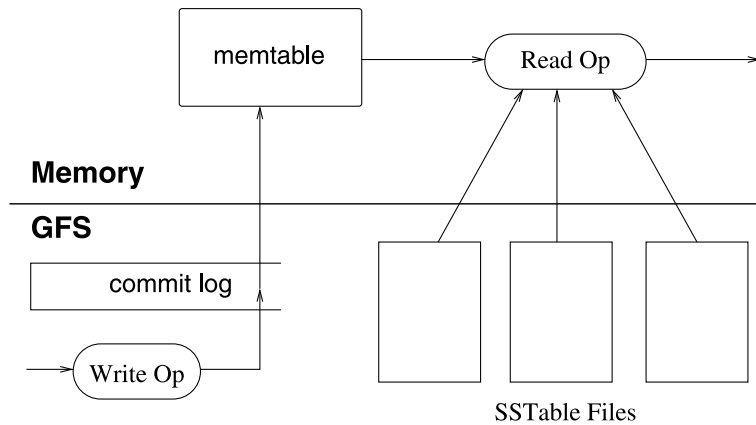


Fig. 6. Tablet representation.

lost (because the tablet server or the master died), the master detects the new tablet when it asks a tablet server to load the tablet that has now split. The tablet server will notify the master of the split, because the tablet entry it finds in the METADATA table will specify only a portion of the tablet that the master asked it to load.

5.3 Tablet Serving

The persistent state of a tablet is stored in GFS, as illustrated in Figure 6. Updates are committed to a commit log that stores redo records. The recently committed ones are stored in memory in a sorted buffer called a *memtable*. A memtable maintains the updates on a row-by-row basis, where each row is copy-on-write to maintain row-level consistency. Older updates are stored in a sequence of SSTables (which are immutable).

To recover a tablet, a tablet server reads its metadata from the METADATA table. This metadata contains the list of SSTables that comprise a tablet and a set of a redo points, which are pointers into any commit logs that may contain data for the tablet. The server reads the indices of the SSTables into memory and reconstructs the memtable by applying all of the updates that have committed since the redo points.

When a write operation arrives at a tablet server, the server checks that it is well-formed (i.e., not sent from a buggy or obsolete client), and that the sender is authorized to perform the mutation. Authorization is performed by reading the list of permitted writers from a Chubby file (which is almost always a hit in the Chubby client cache). A valid mutation is written to the commit log. Group commit is used to improve the throughput of small mutations [DeWitt et al. 1984; Gawlick and Kinkade 1985]. After the write has been committed, its contents are inserted into the memtable.

When a read operation arrives at a tablet server, it is similarly checked for well-formedness and proper authorization. A valid read operation is executed on a merged view of the sequence of SSTables and the memtable. Since the

SSTables and the memtable are lexicographically sorted data structures, the merged view can be formed efficiently.

Incoming read and write operations can continue while tablets are being split and merged. Reads and writes can also occur while tablets are being *compacted*; compactions are described in the next section.

5.4 Compactions

As write operations execute, the size of the memtable increases. When the memtable size reaches a threshold, the memtable is frozen, a new memtable is created, and the frozen memtable is converted to an SSTable and written to GFS. This *minor compaction* process has two goals: it shrinks the memory usage of the tablet server, and it reduces the amount of data that has to be read from the commit log during recovery if this server dies.

Every minor compaction creates a new SSTable. If this behavior continued unchecked, read operations might need to merge updates from an arbitrary number of SSTables. Instead, we bound the number of such files by periodically executing a *merging compaction* in the background. A merging compaction reads the contents of a few SSTables and the memtable, and writes out a new SSTable. The input SSTables and memtable can be discarded as soon as the compaction has finished.

A merging compaction that rewrites all SSTables into exactly one SSTable is called a *major compaction*. SSTables produced by non-major compactions can contain special deletion entries that suppress deleted data in older SSTables that are still live. A major compaction, on the other hand, produces an SSTable that contains no deletion information or deleted data. Bigtable cycles through all of its tablets and regularly applies major compactions to them. These major compactions allow Bigtable to reclaim resources used by deleted data, and also allow it to ensure that deleted data disappears from the system in a timely fashion, which is important for services that store sensitive data.

Bigtable read performance benefits from a locality optimization in GFS. When files are written, GFS attempts to place one replica of the data on the same machine as the writer. When GFS files are read, the reads are served from the nearest available replica. Therefore, in the common case of tablet servers sharing machines with GFS servers, tablet servers will compact data into SSTables that have a replica on local disk, which enables fast access to those SSTables when subsequent read requests are processed.

5.5 Schema Management

Bigtable schemas are stored in Chubby. Chubby is an effective communication substrate for Bigtable schemas because it provides atomic whole-file writes and consistent caching of small files. For example, suppose a client wants to delete some column families from a table. The master performs access control checks, verifies that the resulting schema is well formed, and then installs the new schema by rewriting the corresponding schema file in Chubby. Whenever tablet servers need to determine what column families exist, they simply read the appropriate schema file from Chubby, which is almost always available in

the server’s Chubby client cache. Because Chubby caches are consistent, tablet servers are guaranteed to see all changes to that file.

6. REFINEMENTS

The implementation described in the previous section required a number of refinements to achieve the performance, availability, and reliability required by our users. This section describes portions of the implementation in more detail in order to highlight these refinements.

Locality Groups. Each column family is assigned to a client-defined locality group, which is an abstraction that enables clients to control their data’s storage layout. A separate SSTable is generated for each locality group in each tablet during compaction. Segregating column families that are not typically accessed together into separate locality groups enables more efficient reads. For example, page metadata in Webtable (such as language and checksums) can be in one locality group, and the contents of the page can be in a different group; an application that wants to read the metadata does not need to read through all of the page contents.

In addition, some useful tuning parameters can be specified on a per-locality group basis. For example, a locality group can be declared to be in-memory. SSTables for in-memory locality groups are loaded lazily into the memory of the tablet server. Because SSTables are immutable, there are no consistency issues. Once loaded, column families that belong to such locality groups can be read without accessing the disk. This feature is useful for small pieces of data that are accessed frequently; we use it internally for the tablet-location column family in the METADATA table.

Compression. Clients can control whether or not the SSTables for a locality group are compressed, and if so, which compression format is used. The user-specified compression format is applied to each SSTable block (whose size is controllable via a locality-group-specific tuning parameter). Although we lose some disk space by compressing each block separately, we benefit in that small portions of an SSTable can be read without decompressing the entire file. Many Bigtable clients use a two-pass custom compression scheme. The first pass uses Bentley and McIlroy’s [1999] scheme, which compresses long common strings across a large window. The second pass uses a fast compression algorithm that looks for repetitions in a small 16 KB window of the data. Both compression passes are very fast—they encode at 100–200 MB/s, and decode at 400–1000 MB/s on modern machines.

Even though we emphasized speed instead of space reduction when choosing our compression algorithms, this two-pass compression scheme does surprisingly well. For example, in Webtable, we use this compression scheme to store Web page contents. In one experiment, we stored a large number of documents in a compressed locality group. For the purposes of the experiment, we limited ourselves to one version of each document instead of storing all versions available to us. The scheme achieved a 10-to-1 reduction in space. This is much better than typical Gzip reductions of 3-to-1 or 4-to-1 on HTML pages because

of the way Webtable rows are laid out: all pages from a single host are stored close to each other. This allows the Bentley-McIlroy algorithm to identify large amounts of shared boilerplate in pages from the same host. Many applications, not just Webtable, choose their row names so that similar data ends up clustered, and therefore achieve very good compression ratios. Compression ratios get even better when we store multiple versions of the same value in Bigtable.

Caching for Read Performance. To improve read performance, tablet servers use two levels of caching. The Scan Cache is a higher-level cache that caches the key-value pairs returned by the SSTable interface to the tablet server code. The Block Cache is a lower-level cache that caches SSTable blocks that were read from GFS. The Scan Cache is most useful for applications that tend to read the same data repeatedly. The Block Cache is useful for applications that tend to read data that is close to the data they recently read (e.g., sequential reads, or random reads of different columns in the same locality group within a hot row).

Bloom Filters. As described in Section 5.3, a read operation has to read from all of the SSTables that make up the state of a tablet. If these SSTables are not in memory, we may end up doing many disk accesses. We reduce the number of accesses by allowing clients to specify that Bloom filters [Bloom 1970] should be created for SSTables in a particular locality group. A Bloom filter allows us to ask whether an SSTable might contain any data for a specified row/column pair. For certain applications, the small amount of tablet server memory used for storing Bloom filters drastically reduces the number of disk seeks required for read operations. Our use of Bloom filters also avoids disk accesses for most lookups of non-existent rows or columns.

Commit-Log Implementation. If we kept the commit log for each tablet in a separate log file, a very large number of files would be written concurrently in GFS. Depending on the underlying file system implementation on each GFS server, these writes could require a large number of disk seeks in order to write to the different physical log files. In addition, having separate log files per tablet also reduces the effectiveness of the group commit optimization, since groups would tend to be smaller. To fix these issues, we append mutations to a single commit log per tablet server, which co-mingles mutations for different tablets in the same physical log file [Gray 1978; Hagmann 1987].

Using one log provides significant performance benefits during normal operation, but it complicates recovery. When a tablet server dies, the tablets that it served will be moved to a large number of other tablet servers; each server typically loads a small number of the original server's tablets. To recover the state for a tablet, the new tablet server needs to reapply the mutations for that tablet from the commit log written by the original tablet server. However, the mutations for these tablets were co-mingled in the same physical log file. One approach would be for each new tablet server to read this full commit log file and apply just the entries needed for the tablets it needs to recover. However, under such a scheme, if 100 machines were each assigned a single tablet

from a failed tablet server, then the log file would be read 100 times (once by each server).

We avoid duplicating log reads by first sorting the commit log entries by key (table, row name, log sequence number). In the sorted output, all mutations for a particular tablet are contiguous and can therefore be read efficiently with one disk seek followed by a sequential read. To parallelize the sorting, we partition the log file into 64-MB segments, and sort each segment in parallel on different tablet servers. This sorting process is coordinated by the master and is initiated when a tablet server indicates that it needs to recover mutations from some commit log file.

Writing commit logs to GFS sometimes causes performance hiccups for a variety of reasons (e.g., a GFS server machine involved in the write crashes, or is heavily loaded, or the network paths traversed to reach the particular set of GFS servers is suffering network congestion). To protect mutations from GFS latency spikes, each tablet server actually has two log writing threads, each writing to its own log file; only one of these two threads is actively in use at a time. If writes to the active log file are performing poorly, the log file writing is switched to the other thread, and mutations that are in the commit log queue are written by the newly active log writing thread. Log entries contain sequence numbers to allow the recovery process to elide duplicated entries resulting from this log switching process.

Speeding Up Tablet Recovery. Before unloading a tablet, a tablet server first does a minor compaction on that tablet. This compaction reduces recovery time by reducing the amount of uncompact state in the tablet server's commit log. After finishing this compaction, the tablet server stops serving the tablet. Before it actually unloads the tablet, the tablet server does another (usually very fast) minor compaction to eliminate any remaining uncompact state in the tablet server's log that arrived while the first minor compaction was being performed. After this second minor compaction is complete, the tablet can be loaded on another tablet server without requiring any recovery of log entries.

Exploiting Immutability. Besides the SSTable caches, various other parts of the Bigtable system have been simplified by the fact that all of the SSTables that we generate are immutable. For example, we do not need any synchronization of accesses to the file system when reading from SSTables. As a result, concurrency control over rows can be implemented very efficiently. The only mutable data structure that is accessed by both reads and writes is the memtable. To reduce contention during reads of the memtable, we make each memtable row copy-on-write and allow reads and writes to proceed in parallel.

Since SSTables are immutable, the problem of permanently removing deleted data is transformed to that of garbage collecting obsolete SSTables. Each tablet's SSTables are registered in the METADATA table. The master removes obsolete SSTables as a mark-and-sweep garbage collection [McCarthy 1960] over the set of SSTables, where the METADATA table contains the set of roots.

Finally, the immutability of SSTables enables us to split tablets quickly. Instead of generating a new set of SSTables for each child tablet, we let the child tablets share the SSTables of the parent tablet.

7. PERFORMANCE EVALUATION

We set up a Bigtable cluster with N tablet servers to measure the performance and scalability of Bigtable as N is varied. The tablet servers were configured to use 1 GB of memory and to write to a GFS cell consisting of 1786 machines with two 400 GB IDE hard drives each. N client machines generated the Bigtable load used for these tests. (We used the same number of clients as tablet servers to ensure that clients were never a bottleneck.) Each machine had two dual-core Opteron 2 GHz chips, enough physical memory to hold the working set of all running processes, and a single gigabit Ethernet link. The machines were arranged in a two-level tree-shaped switched network with approximately 100-200 Gb/s of aggregate bandwidth available at the root. All of the machines were in the same hosting facility and therefore the round-trip time between any pair of machines was less than a millisecond.

The tablet servers and master, test clients, and GFS servers all ran on the same set of machines. Every machine ran a GFS server. Some of the machines also ran either a tablet server, or a client process, or processes from other jobs that were using the pool at the same time as these experiments.

R is the distinct number of Bigtable row keys involved in the test. R was chosen so that each benchmark read or wrote approximately 1 GB of data per tablet server.

The *sequential write* benchmark used row keys with names 0 to $R - 1$. This space of row keys was partitioned into $10N$ equal-sized ranges. These ranges were assigned to the N clients by a central scheduler that assigned the next available range to a client as soon as the client finished processing the previous range assigned to it. This dynamic assignment helped mitigate the effects of performance variations caused by other processes running on the client machines. We wrote a single string under each row key. Each string was generated randomly and was therefore uncompressible. In addition, strings under different row keys were distinct, so no cross-row compression was possible. The *random write* benchmark was similar except that the row key was hashed modulo R immediately before writing so that the write load was spread roughly uniformly across the entire row space for the entire duration of the benchmark.

The *sequential read* benchmark generated row keys in exactly the same way as the sequential write benchmark, but instead of writing under the row key, it read the string stored under the row key (which was written by an earlier invocation of the sequential write benchmark). Similarly, the *random read* benchmark shadowed the operation of the random write benchmark.

The *scan* benchmark is similar to the sequential read benchmark, but uses support provided by the Bigtable API for scanning over all values in a row range. Using a scan reduces the number of RPCs executed by the benchmark since a single RPC fetches a large sequence of values from a tablet server.

Table I. Number of 1000-byte values read/written per second. The values are the rate per tablet server.

Experiment	# of Tablet Servers			
	1	50	250	500
random reads	1212	593	479	241
random reads (mem)	10811	8511	8000	6250
random writes	8850	3745	3425	2000
sequential reads	4425	2463	2625	2469
sequential writes	8547	3623	2451	1905
scans	15385	10526	9524	7843

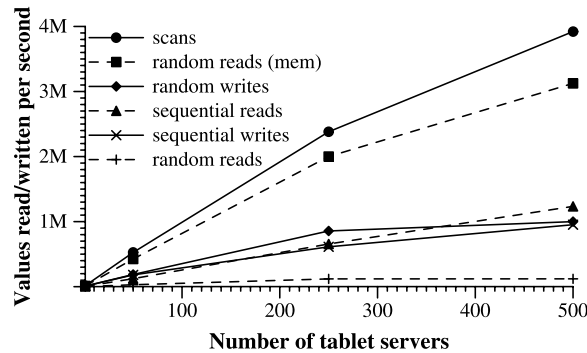


Fig. 7. Number of 1000-byte values read/written per second. The curves indicate the aggregate rate across all tablet servers.

The *random reads (mem)* benchmark is similar to the random read benchmark, but the locality group that contains the benchmark data is marked as *in-memory*, and therefore the reads are satisfied from the tablet server’s memory instead of requiring a GFS read. For just this benchmark, we reduced the amount of data per tablet server from 1 GB to 100 MB so that it would fit comfortably in the memory available to the tablet server.

Table I and Figure 7 provide two views on the performance of our benchmarks when reading and writing 1000-byte values to Bigtable. The table shows the number of operations per second per tablet server; the graph shows the aggregate number of operations per second.

Single Tablet-Server Performance. Let us first consider performance with just one tablet server. Random reads are slower than all other operations by an order of magnitude or more. Each random read involves the transfer of a 64 KB SSTable block over the network from GFS to a tablet server, out of which only a single 1000-byte value is used. The tablet server executes approximately 1200 reads per second, which translates into approximately 75 MB/s of data read from GFS. This bandwidth is enough to saturate the tablet server CPUs because of overheads in our networking stack, SSTable parsing, and Bigtable code, and is also almost enough to saturate the network links used in our system. Most Bigtable applications with this type of an access pattern reduce the block size to a smaller value, typically 8KB.

Random reads from memory are much faster since each 1000-byte read is satisfied from the tablet server's local memory without fetching a large 64-KB block from GFS.

Sequential reads perform better than random reads since every 64-KB SSTable block that is fetched from GFS is stored into our block cache, where it is used to serve the next 64 read requests.

Scans are even faster since the tablet server can return a large number of values in response to a single client RPC, and therefore RPC overhead is amortized over a large number of values.

Writes perform better than reads because each tablet server appends all incoming writes to a single commit log, and because we use group commit to stream these writes efficiently to GFS. Reads, on the other hand, must typically incur one disk seek for each SSTable accessed. Random writes and sequential writes have very similar performance; in both cases, all writes to the tablet server are recorded in the same commit log.

Scaling. Aggregate throughput increases dramatically, by over a factor of a hundred, as we increase the number of tablet servers in the system from 1 to 500. For example, the performance of random reads from memory increases by almost a factor of 300 as the number of tablet server increases by a factor of 500. This behavior occurs because the bottleneck on performance for this benchmark is the individual tablet server CPU.

However, performance does not increase linearly. For most benchmarks, there is a significant drop in per-server throughput when going from 1 to 50 tablet servers. This drop is caused by imbalance in load in multiple server configurations, often due to other processes contending for CPU and network. Our load balancing algorithm attempts to deal with this imbalance, but cannot do a perfect job for two main reasons: rebalancing is throttled to reduce the number of tablet movements (a tablet is unavailable for a short time, typically less than one second, when it is moved), and the load generated by our benchmarks shifts around as the benchmark progresses.

The random read benchmark shows the worst scaling (an increase in aggregate throughput by only a factor of 100 for a 500-fold increase in number of servers). This behavior occurs because (as explained above) we transfer one large 64KB block over the network for every 1000-byte read. This transfer saturates various shared 1-Gigabit links in our network and as a result, the per-server throughput drops significantly as we increase the number of machines.

8. REAL APPLICATIONS

As of August 2006, there are 388 non-test Bigtable clusters running in various Google machine clusters, with a combined total of about 24,500 tablet servers. Table II shows a rough distribution of tablet servers per cluster. Many of these clusters are used for development purposes and therefore are idle for significant periods. One group of 14 busy clusters with 8069 total tablet servers saw an aggregate volume of more than 1.2 million requests per second, with

Table II. Distribution of Number of Tablet Servers in Bigtable Clusters.

# of tablet servers		# of clusters
0 ..	19	259
20 ..	49	47
50 ..	99	20
100 ..	499	50
> 500		12

Table III. Characteristics of a Few Tables in Production Use.

Project name	Size (TB)	Comp. ratio	# (B) Cells	# Families	# Groups	% MMap	Frontend
<i>Crawl</i>	800	11%	1000	16	8	0%	No
<i>Crawl</i>	50	33%	200	2	2	0%	No
<i>Analytics</i>	20	29%	10	1	1	0%	Yes
<i>Analytics</i>	200	14%	80	1	1	0%	Yes
<i>Base</i>	2	31%	10	29	3	15%	Yes
<i>Earth</i>	0.5	64%	8	7	2	33%	Yes
<i>Earth</i>	70	–	9	8	3	0%	No
<i>Orkut</i>	9	–	0.9	8	5	1%	Yes
<i>Pers. Search</i>	4	47%	6	93	11	5%	Yes

Size (measured before compression) and *# Cells* indicate approximate sizes. *Comp. ratio* (compression ratio) is not given for tables that have compression disabled. *Frontend* indicates that the application's performance is latency-sensitive.

incoming RPC traffic of about 741 MB/s and outgoing RPC traffic of about 16 GB/s.

Table III provides some data about a few of the tables in use as of August 2006. Some tables store data that is served to users, whereas others store data for batch processing; the tables range widely in total size, average cell size, percentage of data served from memory, and complexity of the table schema. In the rest of this section, we briefly describe how three product teams use Bigtable.

8.1 Google Analytics

Google Analytics (analytics.google.com) is a service that helps webmasters analyze traffic patterns at their web sites. It provides aggregate statistics, such as the number of unique visitors per day and the page views per URL per day, as well as site-tracking reports, such as the percentage of users that made a purchase, given that they earlier viewed a specific page.

To enable the service, webmasters embed a small JavaScript program in their web pages. This program is invoked whenever a page is visited. It records various information about the request in Google Analytics, such as a user identifier and information about the page being fetched. Google Analytics summarizes this data and makes it available to webmasters.

We briefly describe two of the tables used by Google Analytics. The raw click table (~200 TB) maintains a row for each end-user session. The row name is a tuple containing the website's name and the time at which the session was created. This schema ensures that sessions that visit the same web site are

contiguous, and that they are sorted chronologically. This table compresses to 14% of its original size.

The summary table (~20 TB) contains various predefined summaries for each website. This table is generated from the raw click table by periodically scheduled MapReduce jobs. Each MapReduce job extracts recent session data from the raw click table. The overall system's throughput is limited by the throughput of GFS. This table compresses to 29% of its original size.

8.2 Google Earth

Google operates a collection of services that provide users with high-resolution satellite imagery of the world's surface. Users can access the images through the web-based Google Maps interface (maps.google.com) and through the Google Earth (earth.google.com) custom client software. These products allow users to navigate across the world's surface: they can pan, view, and annotate satellite imagery at many different levels of resolution. This system uses one table to preprocess data, and a different set of tables for serving client data.

The preprocessing pipeline uses one table to store raw imagery. During preprocessing, the imagery is cleaned and consolidated into final serving data. This table contains approximately 70 terabytes of data and therefore is served from disk. The images are efficiently compressed already, so Bigtable compression is disabled.

Each row in the imagery table corresponds to a single geographic segment. Rows are named to ensure that adjacent geographic segments are stored near each other. The table contains a column family to keep track of the sources of data for each segment. This column family has a large number of columns: essentially one for each raw data image. Since each segment is only built from a few images, this column family is very sparse.

The preprocessing pipeline relies heavily on MapReduce over Bigtable to transform data. The overall system processes over 1 MB/sec of data per tablet server during some of these MapReduce jobs.

The serving system uses one table to index data stored in GFS. This table is relatively small (~500 GB), but it must serve tens of thousands of queries per second per datacenter with low latency. As a result, this table is hosted across hundreds of tablet servers and contains in-memory column families.

8.3 Personalized Search

Personalized Search (www.google.com/psearch) is an opt-in service that records user queries and clicks across a variety of Google properties such as web search, images, and news. Users can browse their search histories to revisit their old queries and clicks, and they can ask for personalized search results based on their historical Google usage patterns.

Personalized Search stores each user's data in Bigtable. Each user has a unique userid and is assigned a row named by that userid. All user actions are stored in a table. A separate column family is reserved for each type of action (e.g., there is a column family that stores all web queries). Each data element uses as its Bigtable timestamp the time at which the corresponding user action

occurred. Personalized Search generates user profiles using a MapReduce over Bigtable. These user profiles are used to personalize live search results.

The Personalized Search data is replicated across several Bigtable clusters to increase availability and to reduce latency due to distance from clients. The Personalized Search team originally built a client-side replication mechanism on top of Bigtable that ensured eventual consistency of all replicas. The current system now uses a replication subsystem that is built into the servers.

The design of the Personalized Search storage system allows other groups to add new per-user information in their own columns, and the system is now used by many other Google properties that need to store per-user configuration options and settings. Sharing a table amongst many groups resulted in an unusually large number of column families. To help support sharing, we added a simple quota mechanism to Bigtable to limit the storage consumption by any particular client in shared tables; this mechanism provides some isolation between the various product groups using this system for per-user information storage.

9. LESSONS

In the process of designing, implementing, maintaining, and supporting Bigtable, we gained useful experience and learned several interesting lessons.

One lesson we learned is that large distributed systems are vulnerable to many types of failures, not just the standard network partitions and fail-stop failures assumed in many distributed protocols. For example, we have seen problems due to all of the following causes: memory and network corruption, large clock skew, hung machines, extended and asymmetric network partitions, bugs in other systems that we are using (Chubby for example), overflow of GFS quotas, and planned and unplanned hardware maintenance. As we have gained more experience with these problems, we have addressed them by changing various protocols. For example, we added checksumming to our RPC mechanism. We also handled some problems by removing assumptions made by one part of the system about another part. For example, we stopped assuming that a given Chubby operation could return only one of a fixed set of errors.

Another lesson we learned is that it is important to delay adding new features until it is clear how the new features will be used. For example, we initially planned to support general-purpose transactions in our API. Because we did not have an immediate use for them, however, we did not implement them. Now that we have many real applications running on Bigtable, we have been able to examine their actual needs, and have discovered that most applications require only single-row transactions. Where people have requested distributed transactions, the most important use is for maintaining secondary indices, and we plan to add a specialized mechanism to satisfy this need. The new mechanism will be less general than distributed transactions, but will be more efficient (especially for updates that span hundreds of rows or more) and will also interact better with our scheme for optimistic cross-data-center replication.

A practical lesson that we learned from supporting Bigtable is the importance of proper system-level monitoring (i.e., monitoring both Bigtable itself, as well as the client processes using Bigtable). For example, we extended our

RPC system to keep detailed traces for a sample of RPCs. This feature has allowed us to detect and fix many problems such as lock contention on tablet data structures, slow writes to GFS while committing Bigtable mutations, and stuck accesses to the METADATA table when METADATA tablets are unavailable. Another example of useful monitoring is that every Bigtable cluster is registered in Chubby. This allows us to track down all clusters, discover how big they are, see which versions of our software they are running, how much traffic they are receiving, and whether or not there are any problems such as unexpectedly large latencies.

The most important lesson we learned is the value of simple designs. Given both the size of our system (about 100,000 lines of non-test code), as well as the fact that code evolves over time in unexpected ways, we have found that code and design clarity are of immense help in code maintenance and debugging. One example of this is our tablet-server membership protocol. Our first protocol was simple: the master periodically issued leases to tablet servers, and tablet servers killed themselves if their lease expired. Unfortunately, this protocol reduced availability significantly in the presence of network problems, and was also sensitive to master recovery time. We redesigned the protocol several times until we had a protocol that performed well. However, the resulting protocol was too complex and depended on the behavior of Chubby features that were seldom exercised by other applications. We discovered that we were spending an inordinate amount of time debugging obscure corner cases, not only in Bigtable code, but also in Chubby code. Eventually, we scrapped this protocol and moved to a newer simpler protocol that depends solely on widely-used Chubby features.

10. RELATED WORK

The Boxwood project [MacCormick et al. 2004] has components that overlap in some ways with Chubby, GFS, and Bigtable, since it provides for distributed agreement, locking, distributed chunk storage, and distributed B-tree storage. In each case where there is overlap, it appears that the Boxwood's component is targeted at a somewhat lower level than the corresponding Google service. The Boxwood project's goal is to provide infrastructure for building higher-level services such as file systems or databases, while the goal of Bigtable is to directly support client applications that wish to store data.

Many recent projects have tackled the problem of providing distributed storage or higher-level services over wide area networks, often at "Internet scale." This includes work on distributed hash tables that began with projects such as CAN [Ratnasamy et al. 2001], Chord [Stoica et al. 2001], Tapestry [Zhao et al. 2001], and Pastry [Rowstron and Druschel 2001]. These systems address concerns that do not arise for Bigtable, such as highly variable bandwidth, untrusted participants, or frequent reconfiguration; decentralized control and Byzantine fault tolerance are not Bigtable goals.

In terms of the distributed data storage model that one might provide to application developers, we believe the key-value pair model provided by

distributed B-trees or distributed hash tables is too limiting. Key-value pairs are a useful building block, but they should not be the only building block one provides to developers. The model we chose is richer than simple key-value pairs, and supports sparse semi-structured data. Nonetheless, it is still simple enough that it lends itself to a very efficient flat-file representation, and it is transparent enough (via locality groups) to allow our users to tune important behaviors of the system.

Several database vendors have developed parallel databases that can store large volumes of data. Oracle’s Real Application Cluster database [oracle.com] uses shared disks to store data (Bigtable uses GFS) and a distributed lock manager (Bigtable uses Chubby). IBM’s DB2 Parallel Edition [Baru et al. 1995] is based on a shared-nothing [Stonebraker 1986] architecture similar to Bigtable. Each DB2 server is responsible for a subset of the rows in a table which it stores in a local relational database. Both products provide a complete relational model with transactions.

Bigtable locality groups realize similar compression and disk read performance benefits observed for other systems that organize data on disk using column-based rather than row-based storage, including C-Store [Abadi et al. 2006; Stonebraker et al. 2005] and commercial products such as Sybase IQ [French 1995; sybase.com], SenSage [sensesage.com], KDB+ [kx.com], and the ColumnBM storage layer in MonetDB/X100 [Zukowski et al. 2005]. Another system that does vertical and horizontal data partitioning into flat files and achieves good data compression ratios is AT&T’s Daytona database [Greer 1999]. Our locality groups do not support CPU-cache-level optimizations, such as those described by Ailamaki et al. [2001].

The manner in which Bigtable uses memtables and SSTables to store updates to tablets is analogous to the way that the Log-Structured Merge Tree [O’Neil et al. 1996] stores updates to index data. In both systems, sorted data is buffered in memory before being written to disk, and reads must merge data from memory and disk.

C-Store and Bigtable share many characteristics: both systems use a shared-nothing architecture and have two different data structures, one for recent writes, and one for storing long-lived data, with a mechanism for moving data from one form to the other. The systems differ significantly in their API: C-Store behaves like a relational database, whereas Bigtable provides a lower level read and write interface and is designed to support many thousands of such operations per second per server. C-Store is also a “read-optimized relational DBMS”, whereas Bigtable provides good performance on both read-intensive and write-intensive applications.

Bigtable’s load balancer has to solve some of the same kinds of load and memory balancing problems faced by shared-nothing databases (e.g., Copeland et al. [1988] and Stonebraker et al. [1994]). Our problem is somewhat simpler: (1) we do not consider the possibility of multiple copies of the same data, possibly in alternate forms due to views or indices; (2) we let the user tell us what data belongs in memory and what data should stay on disk, rather than trying to determine this dynamically; (3) we have no complex queries to execute or optimize.

11. CONCLUSIONS

We have described Bigtable, a distributed system for storing structured data at Google. Bigtable clusters have been in production use since April 2005, and we spent roughly seven person-years on design and implementation before that date. As of August 2006, more than sixty projects are using Bigtable. Our users like the performance and high availability provided by the Bigtable implementation, and that they can scale the capacity of their clusters by simply adding more machines to the system as their resource demands change over time.

Given the unusual interface to Bigtable, an interesting question is how difficult it has been for our users to adapt to using it. New users are sometimes uncertain of how best to use the Bigtable interface, particularly if they are accustomed to using relational databases that support general-purpose transactions. Nevertheless, the fact that many Google products successfully use Bigtable demonstrates that our design works well in practice.

We are in the process of implementing several additional Bigtable features, such as support for secondary indices and infrastructure for building cross-data-center replicated Bigtables with multiple master replicas. We have also begun deploying Bigtable as a service to product groups, so that individual groups do not need to maintain their own clusters. As our service clusters scale, we will need to deal with more resource-sharing issues within Bigtable itself [Banga et al. 1999; Bavier et al. 2004].

Finally, we have found that there are significant advantages to building our own storage solution at Google. We have gotten a substantial amount of flexibility from designing our own data model for Bigtable. In addition, our control over Bigtable's implementation, and the other Google infrastructure upon which Bigtable depends, means that we can remove bottlenecks and inefficiencies as they arise.

ACKNOWLEDGMENTS

We thank the anonymous reviewers for TOCS and OSDI, our OSDI shepherd Brad Calder, and David Nagle for their detailed suggestions for improvements on drafts of this paper.

The Bigtable system has benefited greatly from the feedback of our many users within Google. In addition, we thank the following people for their contributions to Bigtable: Shoshana Abrass, Dan Aguayo, Sameer Ajmani, Dan Birken, Xin Chen, Zhifeng Chen, Bill Coughran, Jeff de Vries, Bjarni Einarsson, Mike Epstein, Shane Gartshore, Frédéric Gobry, Healfdene Goguen, Robert Griesemer, Orla Hegarty, Jeremy Hylton, Josh Hyman, Nick Johnson, Alex Khesin, Marcel Kornacker, Joanna Kulik, Alberto Lerner, Shun-Tak Leung, Sherry Listgarten, Mike Maloney, Wee-Teck Ng, Abhishek Parmar, David Petrou, Eduardo Pinheiro, Kathy Polizzi, Richard Roberto, Deomid Ryabkov, Shoumen Saha, Yasushi Saito, Steven Schirripa, Cristina Schmidt, Lee Schumacher, Hao Shang, Jordan Sissel, Charles Spirakis, Alan Su, Chris Taylor, Harendra Verma, Kate Ward, Peter Weinberger, Rudy Winnacker, Frank Yellin, Yuanyuan Zhao, and Arthur Zwieginzew.

REFERENCES

- ABADI, D. J., MADDEN, S. R., AND FERREIRA, M. C. 2006. Integrating compression and execution in column-oriented database systems. *Proceedings of the ACM SIGMOD International Conference on Management of Data*. ACM, New York.
- AILAMAKI, A., DEWITT, D. J., HILL, M. D., AND SKOUNAKIS, M. 2001. Weaving relations for cache performance. *The VLDB J.* 169–180.
- BANGA, G., DRUSCHEL, P., AND MOGUL, J. C. 1999. Resource containers: A new facility for resource management in server systems. In *Proceedings of the 3rd Symposium on Operating Systems Design and Implementation*. 45–58.
- BARU, C. K., FECTEAU, G., GOYAL, A., HSIAO, H., JHINGRAN, A., PADMANABHAN, S., COPELAND, G. P., AND WILSON, W. G. 1995. DB2 parallel edition. *IBM Syst. J.* 34, 2, 292–322.
- BAVIER, A., BOWMAN, M., CHUN, B., CULLER, D., KARLIN, S., PETERSON, L., ROSCOE, T., SPALINK, T., AND WAWRZONIAK, M. 2004. Operating system support for planetary-scale network services. In *Proceedings of the 1st Symposium on Networked Systems Design and Implementation*. 253–266.
- BENTLEY, J. L. AND MCILROY, M. D. 1999. Data compression using long common strings. In *Data Compression Conference*. 287–295.
- BLOOM, B. H. 1970. Space/time trade-offs in hash coding with allowable errors. *Commun. ACM* 13, 7, 422–426.
- BURROWS, M. 2006. The Chubby lock service for loosely-coupled distributed systems. In *Proceedings of the 7th USENIX Symposium on Operating Systems Design and Implementation*. 335–350.
- CHANDRA, T., GRIESEMER, R., AND REDSTONE, J. 2007. Paxos made live — An engineering perspective. In *Proceedings of PODC*.
- CHANG, F., DEAN, J., GHEMAWAT, S., HSIEH, W. C., WALLACH, D. A., BURROWS, M., CHANDRA, T., FIKES, A., AND GRUBER, R. E. 2006. Bigtable: A distributed storage system for structured data. In *Proceedings of the 7th USENIX Symposium on Operating Systems Design and Implementation*. 205–218.
- COMER, D. 1979. Ubiquitous B-tree. *Computing Surveys* 11, 2 (June), 121–137.
- COPELAND, G. P., ALEXANDER, W., BOUGHTER, E. E., AND KELLER, T. W. 1988. Data placement in Bubba. In *Proceedings of the ACM SIGMOD International Conference on Management of Data*. ACM, New York, 99–108.
- DEAN, J. AND GHEMAWAT, S. 2004. MapReduce: Simplified data processing on large clusters. In *Proceedings of the 6th USENIX Symposium on Operating Systems Design and Implementation*. 137–150.
- DEWITT, D., KATZ, R., OLKEN, F., SHAPIRO, L., STONEBRAKER, M., AND WOOD, D. 1984. Implementation techniques for main memory database systems. In *Proceedings of the ACM SIGMOD International Conference on Management of Data*. ACM, New York, 1–8.
- DEWITT, D. J. AND GRAY, J. 1992. Parallel database systems: The future of high performance database systems. *Commun. ACM* 35, 6 (June), 85–98.
- FRENCH, C. D. 1995. One size fits all database architectures do not work for DSS. In *Proceedings of the ACM SIGMOD International Conference on Management of Data*. ACM, New York, 449–450.
- GAWLICK, D. AND KINKADE, D. 1985. Varieties of concurrency control in IMS/VS fast path. *Datab. Eng. Bull.* 8, 2, 3–10.
- GHEMAWAT, S., GOBIOFF, H., AND LEUNG, S.-T. 2003. The Google file system. In *Proceedings of the 19th ACM Symposium on Operating Systems Principles*. ACM, New York, 29–43.
- GRAY, J. 1978. Notes on database operating systems. In *Operating Systems — An Advanced Course*. Lecture Notes in Computer Science, vol. 60. Springer-Verlag, ACM, New York.
- GREER, R. 1999. Daytona and the fourth-generation language Cymbal. In *Proceedings of the ACM SIGMOD International Conference on Management of Data*. ACM, New York, 525–526.
- HAGMANN, R. 1987. Reimplementing the Cedar file system using logging and group commit. In *Proceedings of the 11th Symposium on Operating Systems Principles*. 155–162.

- HARTMAN, J. H. AND OUSTERHOUT, J. K. 1993. The Zebra striped network file system. In *Proceedings of the 14th Symposium on Operating Systems Principles*. ACM, New York, 29–43.
- KX.COM. kx.com/products/database.php. Product page.
- LAMPORT, L. 1998. The part-time parliament. *ACM Trans. Comput. Syst.* 16, 2, 133–169.
- MACCORMICK, J., MURPHY, N., NAJORK, M., THEKKATH, C. A., AND ZHOU, L. 2004. Boxwood: Abstractions as the foundation for storage infrastructure. In *Proceedings of the 6th USENIX Symposium on Operating Systems Design and Implementation*. 105–120.
- MCCARTHY, J. 1960. Recursive functions of symbolic expressions and their computation by machine. *Commun. ACM* 3, 4 (Apr.), 184–195.
- O’NEIL, P., CHENG, E., GAWLICK, D., AND O’NEIL, E. 1996. The log-structured merge-tree (LSM-tree). *Acta Inf.* 33, 4, 351–385.
- ORACLE.COM. www.oracle.com/technology/products/database/clustering/index.html. Product page.
- PIKE, R., DORWARD, S., GRIESEMER, R., AND QUINLAN, S. 2005. Interpreting the data: Parallel analysis with Sawzall. *Scientific Programming Journal* 13, 4, 227–298.
- RATNASAMY, S., FRANCIS, P., HANDLEY, M., KARP, R., AND SHENKER, S. 2001. A scalable content-addressable network. In *Proceedings of SIGCOMM*. ACM, New York, 161–172.
- ROWSTRON, A. AND DRUSCHEL, P. 2001. Pastry: Scalable, distributed object location and routing for large-scale peer-to-peer systems. In *Proceedings of Middleware 2001*. 329–350.
- SENSAGE.COM. sensation.com/products-sensation.htm. Product page.
- STOICA, I., MORRIS, R., KARGER, D., KAASHOEK, M. F., AND BALAKRISHNAN, H. 2001. Chord: A scalable peer-to-peer lookup service for Internet applications. In *Proceedings of SIGCOMM*. ACM, New York, 149–160.
- STONEBRAKER, M. 1986. The case for shared nothing. *Datab. Eng. Bull.* 9, 1 (Mar.), 4–9.
- STONEBRAKER, M., ABADI, D. J., BATKIN, A., CHEN, X., CHERNIACK, M., FERREIRA, M., LAU, E., LIN, A., MADDEN, S., O’NEIL, E., O’NEIL, P., RASIN, A., TRAN, N., AND ZDONIK, S. 2005. C-Store: A column-oriented DBMS. In *Proceedings of the 10th International Conference on Very Large Data Bases*. ACM, New York, 553–564.
- STONEBRAKER, M., AOKI, P. M., DEVINE, R., LITWIN, W., AND OLSON, M. A. 1994. Mariposa: A new architecture for distributed data. In *Proceedings of the 10th International Conference on Data Engineering*. IEEE Computer Society Press, Los Alamitos, CA, 54–65.
- SYBASE.COM. www.sybase.com/products/databaseservers/sybaseiq. Product page.
- ZHAO, B. Y., KUBIATOWICZ, J., AND JOSEPH, A. D. 2001. Tapestry: An infrastructure for fault-tolerant wide-area location and routing. Tech. Rep. UCB/CSD-01-1141, CS Division, University of California, Berkeley. Apr.
- ZUKOWSKI, M., BONCZ, P. A., NES, N., AND HEMAN, S. 2005. MonetDB/X100 — A DBMS in the CPU cache. *IEEE Data Eng. Bull.* 28, 2, 17–22.

Received December 2006; revised April 2008; accepted April 2008