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THE GOOGLE FILE SYSTEM

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Abstract: **Google File System, a scalable distributed file system is implemented for large distributed data-intensive applications. It provides fault tolerance while running on inexpensive commodity hardware, and it delivers high aggregate performance to a large number of clients. While sharing many of the same goals as previous distributed file systems, this design has been driven by observations of their application workloads and technological environment, both current and anticipated that reflect a marked departure from some earlier file system assumptions. This has led us to reexamine traditional choices and explore radically different design points. The file system has successfully met their storage needs. It is widely deployed within Google as the storage platform for the generation and processing of data used by our service as well as research and development efforts that require large data sets. The largest cluster to date provides hundreds of terabytes of storage across thousands of disks on over a thousand machines, and it is concurrently accessed by hundreds of clients. In this paper, I present file system interface extensions designed to support distributed applications by Google, discuss many aspects of their design, and report measurements from both micro-benchmarks and real world use.**

Keywords: **Google File System, large distributed data-intensive applications.**

1. INTRODUCTION

Google have designed and implemented the Google File System (GFS) to meet the rapidly growing demands of Google's data processing needs. GFS shares many of the same goals as previous distributed file systems such as performance, scalability, reliability, and availability. However, its design has been driven by key observations of their application workloads and technological environment, both current and anticipated that reflect a marked departure from some earlier file system design assumptions.

First, component failures are the norm rather than the exception. The file system consists of hundreds Or even thousands of storage machines built from inexpensive commodity parts and is accessed by a comparable number of client machines. The quantity and quality of the components virtually guarantee that some are not functional at any given time and some will not recover from their current failures. They have seen problems caused by application bugs, operating system bugs, human errors, and the failures of disks, memory, connectors, networking, and power supplies. Therefore, constant monitoring, error detection, fault tolerance, and automatic recovery must be integral to the system.

Second, files are huge by traditional standards. Multi-GB files are common. Each file typically contains many application objects such as web documents. When they are regularly working with fast growing data sets of many TBs comprising billions of objects, it is unwieldy to manage billions of approximately KB-sized files even when the file system could support it. As a result, design assumptions and parameters such as I/O operation and block sizes have to be revisited.

Third, most files are mutated by appending new data rather than overwriting existing data. Random writes within a file are practically non-existent. Once written, the files are only read, and often only sequentially. A variety of data share these characteristics. Some may constitute large repositories that data analysis programs scan through. Some may be data streams continuously generated by running applications. Some may be archival data. Some may be intermediate results produced on one machine and processed on another, whether simultaneously or later in time. Given this access pattern on huge files, appending becomes the focus of performance optimization and atomicity guarantees, while caching data blocks in the client loses its appeal.

Fourth, co-designing the applications and the file system API benefits the overall system by increasing our flexibility.

For example, they have relaxed GFS's consistency model to vastly simplify the file system without imposing an onerous burden on the applications. Google have also introduced an atomic append operation so that multiple clients can append concurrently to a file without extra synchronization between them. These will be discussed in more details later in the paper. Multiple GFS clusters are currently deployed for different purposes. The largest ones have over 1000 storage nodes, over 300 TB of disk storage, and are heavily accessed by hundreds of clients on distinct machines on a continuous basis.

2. DESIGN OVERVIEW

2.1 Assumptions:

In designing a file system for our needs, they have been guided by assumptions that offer both challenges and opportunities. We alluded to some key observations earlier and now lay out their assumptions in more details.

• The system is built from many inexpensive commodity components that often fail. It must constantly monitor itself and detect, tolerate, and recover promptly from component failures on a routine basis.

• The system stores a modest number of large files. We expect a few million files, each typically 100 MB or larger in size. Multi-GB files are the common case and should be managed efficiently. Small files must be supported, but they need not optimize for them.

• The workloads primarily consist of two kinds of reads: large streaming reads and small random reads. In large streaming reads, individual operations typically read hundreds of KBs, more commonly 1 MB or more. Successive operations from the same client often read through a contiguous region of a file. A small random read typically reads a few KBs at some arbitrary offset. Performance-conscious applications often batch and sort their small reads to advance steadily through the file rather than go back and forth.

• The workloads also have many large, sequential writes that append data to files. Typical operation sizes are similar to those for reads. Once written, files are seldom modified again. Small writes at arbitrary positions in a file are supported but do not have to be efficient.

• The system must efficiently implement well-defined semantics for multiple clients that concurrently append to the same file. Their files are often used as producer consumer queues or for many-way merging. Hundreds of producers, running one per machine, will concurrently append to a file. Atomicity with minimal synchronization overhead is essential. The file may be read later, or a consumer may be reading through the file simultaneously.

• High sustained bandwidth is more important than low latency. Most of their target applications place a premium on processing data in bulk at a high rate, while few have stringent response time requirements for an individual read or write.

2.2 Interface:

GFS provides a familiar file system interface, though it does not implement a standard API such as POSIX. Files are organized hierarchically in directories and identified by pathnames. They support the usual operations to create, delete, open, close, read, and write files.

Moreover, GFS has snapshot and record append operations. Snapshot creates a copy of a file or a directory tree at low cost. Record append allows multiple clients to append data to the same file concurrently while guaranteeing the atomicity of each individual client's append. It is useful for implementing multi-way merge results and producer consumer queues that many clients can simultaneously append to without additional locking. They have found these types of files to be invaluable in building large distributed applications. Snapshot and record append are discussed further in Sections 3.4 and 3.3 respectively.

2.3 Architecture:

A GFS cluster consists of a single master and multiple chunkservers and is accessed by multiple clients, as shown in Figure 1. Each of these is typically a commodity Linux machine running a user-level server process. It is easy to run both a chunkserver and a client on the same machine, as long as machine resources permit and the lower reliability caused by running possibly flaky application code is acceptable.

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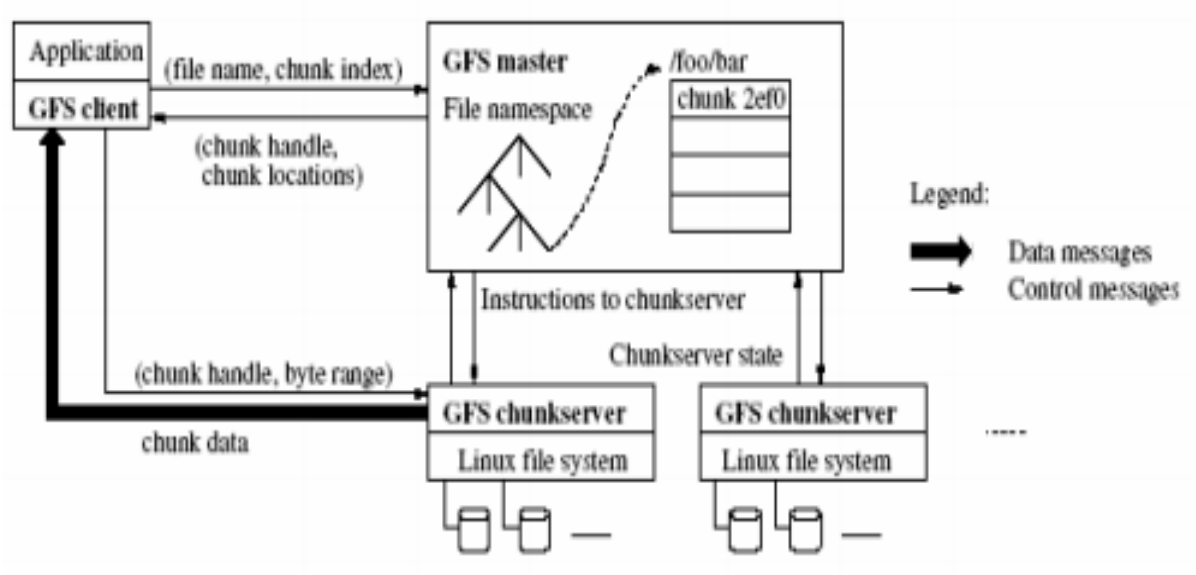
Files are divided into fixed-size chunks. Each chunk is identified by an immutable and globally unique 64 bit chunk handle assigned by the master at the time of chunkcreation. Chunkservers store chunks on local disks as Linux files and read or write chunkdata specified by a chunkhandle and byte range. For reliability, each chunk is replicated on multiple chunkservers. By default, they store three replicas, though users can designate different replication levels for different regions of the file namespace.

The master maintains all file system metadata. This includes the namespace, access control information, the mapping from files to chunks, and the current locations of chunks. It also controls system-wide activities such as chunklease management, garbage collection of orphaned chunks, and chunkmigration between chunkservers. The master periodically communicates with each chunkserver in HeartBeat messages to give it instructions and collect its state.

GFS client code linked into each application implements the file system API and communicates with the master and chunkservers to read or write data on behalf of the application. Clients interact with the master for metadata operations, but all data-bearing communication goes directly to the chunkservers. They do not provide the POSIX API and therefore need not hook into the Linux vnode layer.

Neither the client nor the chunkserver caches file data. Client caches offer little benefit because most applications stream through huge files or have working sets too large to be cached. Not having them simplifies the client and the overall system by eliminating cache coherence issues. (Clients do cache metadata, however.) Chunkservers need not cache file data because chunks are stored as local files and so Linux's buffer cache already keeps frequently accessed data in memory.



2.4 Single Master:

Having a single master vastly simplifies their design and enables the master to make sophisticated chunk placement and replication decisions using global knowledge. However, they must minimize its involvement in reads and writes so that it does not become a bottleneck. Clients never read and write file data through the master. Instead, a client asks the master which chunkservers it should contact. It caches this information for a limited time and interacts with the chunkservers directly for many subsequent operations.

Let us explain the interactions for a simple read with reference to Figure 1. First, using the fixed chunksize, the client translates the file name and byte offset specified by the application into a chunkindex within the file. Then, it sends the master a request containing the file name and chunk index. The master replies with the corresponding chunk handle and locations of the replicas. The client caches this information using the file name and chunkindex as the key.

The client then sends a request to one of the replicas, most likely the closest one. The request specifies the chunk handle and a byte range within that chunk. Further reads of the same chunk require no more client-master interaction until the cached information expires or the file is reopened. In fact, the client typically asks for multiple chunks in the same request

and the master can also include the information for chunks immediately following those requested. This extra information sidesteps several future client-master interactions at practically no extra cost.

2.5 Chunk Size:

Chunksize is one of the key design parameters. Google have chosen 64 MB, which is much larger than typical file system block sizes. Each chunk replica is stored as a plain Linux file on a chunkserver and is extended only as needed. Lazy space allocation avoids wasting space due to internal fragmentation, perhaps the greatest objection against such a large chunksize.

A large chunksize offers several important advantages. First, it reduces clients' need to interact with the master because reads and writes on the same chunk require only one initial request to the master for chunk location information. The reduction is especially significant for their workloads because applications mostly read and write large files sequentially. Even for small random reads, the client can comfortably cache all the chunk location information for a multi-TB working set. Second, since on a large chunk, a client is more likely to perform many operations on a given chunk, it can reduce network overhead by keeping a persistent TCP connection to the chunkserver over an extended period of time. Third, it reduces the size of the metadata stored on the master. This allows us to keep the metadata in memory, which in turn brings other advantages that we will discuss in Section 2.6.1.

On the other hand, a large chunksize, even with lazy space allocation, has its disadvantages. A small file consists of a small number of chunks, perhaps just one. The chunkservers storing those chunks may become hot spots if many clients are accessing the same file. In practice, hot spots have not been a major issue because their applications mostly read large multi-chunk files sequentially. However, hot spots did develop when GFS was first used by a batch-queue system: an executable was written to GFS as a single-chunk file and then started on hundreds of machines at the same time. The few chunkservers storing this executable were overloaded by hundreds of simultaneous requests. Google fixed this problem by storing such executables with a higher replication factor and by making the batch queue system stagger application start times. A potential long-term solution is to allow clients to read data from other clients in such situations.

2.6 Metadata :

The master stores three major types of metadata: the file and chunk namespaces, the mapping from files to chunks, and the locations of each chunk's replicas. All metadata is kept in the master's memory. The first two types (namespaces and file-to-chunk mapping) are also kept persistent by logging mutations to an operation log stored on the master's local disk and replicated on remote machines. Using a log allows us to update the master state simply, reliably, and without risking inconsistencies in the event of a master crash. The master does not store chunk location information persistently. Instead, it asks each chunkserver about its chunks at master startup and whenever a chunkserver joins the cluster.

	Write	Record Append
Serial success	*defined*	*defined* interspersed with *inconsistent*
Concurrent successes	*consistent* but *undefined*	
Failure	*inconsistent*	

Table 1: File Region State After Mutation

2.7 Consistency Model:

GFS has a relaxed consistency model that supports our highly distributed applications well but remains relatively simple and efficient to implement. We now discuss GFS's guarantees and what they mean to applications. We also highlight how GFS maintains these guarantees but leave the details to other parts of the paper.

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3. SYSTEM INTERACTIONS

We designed the system to minimize the master's involvement in all operations. With that background, we now describe how the client, master, and chunkservers interact to implement data mutations, atomic record append, and snapshot.

3.1 Leases and Mutation Order:

A mutation is an operation that changes the contents or metadata of a chunk such as a write or an append operation. Each mutation is performed at all the chunk's replicas. They use leases to maintain a consistent mutation order across replicas. The master grants a chunklease to one of the replicas, which they call the primary. The primary picks a serial order for all mutations to the chunk. All replicas follow this order when applying mutations. Thus, the global mutation order is defined first by the lease grant order chosen by the master, and within a lease by the serial numbers assigned by the primary.

The lease mechanism is designed to minimize management overhead at the master. A lease has an initial timeout of 60 seconds. However, as long as the chunk is being mutated, the primary can request and typically receive extensions from the master indefinitely. These extension requests and grants are piggybacked on the HeartBeat messages regularly exchanged between the master and all chunkservers. The master may sometimes try to revoke a lease before it expires (e.g., when the master wants to disable mutations on a file that is being renamed). Even if the master loses communication with a primary, it can safely grant a new lease to another replica after the old lease expires.

In Figure 2, we illustrate this process by following the control flow of a write through these numbered steps.

1. The client asks the master which chunkserver holds the current lease for the chunk and the locations of the other replicas. If no one has a lease, the master grants one to a replica it chooses (not shown).

2. The master replies with the identity of the primary and the locations of the other (secondary) replicas. The client caches this data for future mutations. It needs to contact the master again only when the primary becomes unreachable or replies that it no longer holds a lease.

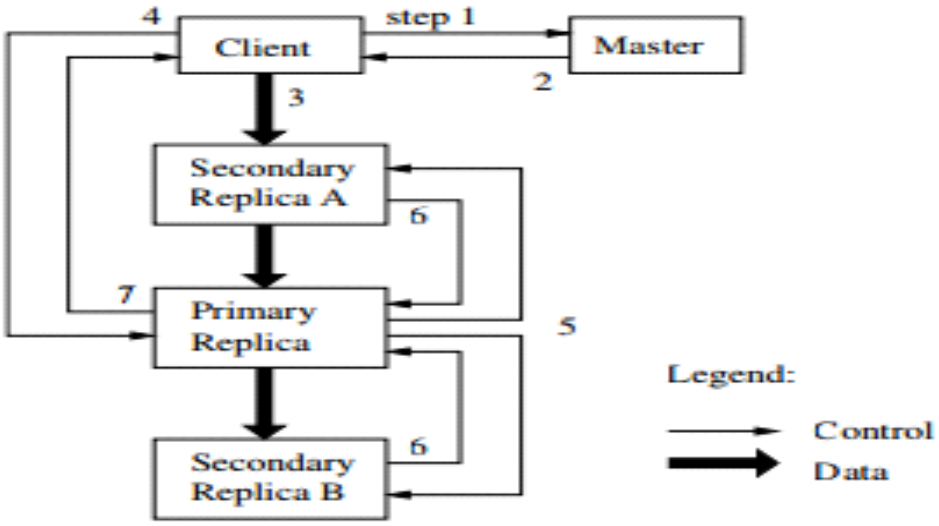

Figure 2: Write Control and Data Flow

3. The client pushes the data to all the replicas. A client can do so in any order. Each chunkserver will store the data in an internal LRU buffer cache until the data is used or aged out. By decoupling the data flow from the control flow, we can improve performance by scheduling the expensive data flow based on the network topology regardless of which chunkserver is the primary. Section 3.2 discusses this further.

4. Once all the replicas have acknowledged receiving the data, the client sends a write request to the primary. The request identifies the data pushed earlier to all of the replicas. The primary assigns consecutive serial numbers to all the mutations it receives, possibly from multiple clients, which provides the necessary serialization. It applies the mutation to its own local state in serial number order.

5. The primary forwards the write request to all secondary replicas. Each secondary replica applies mutations in the same serial number order assigned by the primary.

6. The secondary's all reply to the primary indicating that they have completed the operation.

7. The primary replies to the client. Any errors encountered at any of the replicas are reported to the client. In case of errors, the write may have succeeded at the primary and an arbitrary subset of the secondary replicas. (If it had failed at the primary, it would not have been assigned a serial number and forwarded.) The client request is considered to have failed, and the modified region is left in an inconsistent state. Our client code handles such errors by retrying the failed mutation. It will make a few attempts at steps (3) through (7) before falling back to a retry from the beginning of the write.

If a write by the application is large or straddles a chunk boundary, GFS client code breaks it down into multiple write operations. They all follow the control flow described above but may be interleaved with and overwritten by concurrent operations from other clients. Therefore, the shared file region may end up containing fragments from different clients, although the replicas will be identical because the individual operations are completed successfully in the same order on all replicas. This leaves the file region in consistent but undefined state.

3.2 Data Flow:

Google decouple the flow of data from the flow of control to use the network efficiently. While control flows from the client to the primary and then to all secondary's, data is pushed linearly along a carefully picked chain of chunkservers in a pipelined fashion. Their goals are to fully utilize each machine's network bandwidth, avoid network bottlenecks and high-latency links, and minimize the latency to push through all the data.

To fully utilize each machine's network bandwidth, the data is pushed linearly along a chain of chunkservers rather than distributed in some other topology (e.g., tree). Thus, each machine's full outbound bandwidth is used to transfer the data as fast as possible rather than divided among multiple recipients.

To avoid network bottlenecks and high-latency links (e.g., inter-switch links are often both) as much as possible, each machine forwards the data to the "closest" machine in the network topology that has not received it. Suppose the client is pushing data to chunkservers S1 through S4. It sends the data to the closest chunkserver, say S1. S1 forwards it to the closest chunkserver S2 through S4 closest to S1, say S2. Similarly, S2 forwards it to S3 or S4, whichever is closer to S2, and so on. Google's network topology is simple enough that "distances" can be accurately estimated from IP addresses.

Finally, latency is maximized by pipelining the data transfer over TCP connections. Once a chunkserver receives some data, it starts forwarding immediately. Pipelining is especially helpful to us because we use a switched network with full-duplex links. Sending the data immediately does not reduce the receive rate. Without network congestion, the ideal elapsed time for transferring B bytes to R replicas is B/T + RL where T is the network throughput and L is latency to transfer bytes between two machines. Our network links are typically 100 Mbps (T), and L is far below 1 ms. Therefore, 1 MB can ideally be distributed in about 80 ms.

3.3 Atomic Record Appends:

GFS provides an atomic append operation called record append. In a traditional write, the client specifies the off- set at which data is to be written. Concurrent writes to the same region are not serializable: the region may end up containing data fragments from multiple clients. In a record append, however, the client specifies only the data. GFS appends it to the file at least once atomically (i.e., as one continuous sequence of bytes) at an offset of GFS's choosing and returns that offset to the client. This is similar to writing to a file opened in O_ APPEND mode in UNIX without the race conditions when multiple writers do so concurrently.

Record append is heavily used by our distributed applications in which many clients on different machines append to the same file concurrently. Clients would need additional complicated and expensive synchronization, for example through a distributed lock manager, if they do so with traditional writes. In our workloads, such files often serve as multiple-producer/single-consumer queues or contain merged results from many different clients.

Record append is a kind of mutation and follows the control flow in Section 3.1 with only a little extra logic at the primary. The client pushes the data to all replicas of the last chunk of the file then, it sends its request to the primary. The

primary checks to see if appending the record to the current chunk would cause the chunk to exceed the maximum size (64 MB). If so, it pads the chunk to the maximum size, tells secondary's to do the same, and replies to the client indicating that the operation should be retried on the next chunk. (Record append is restricted to be at most one-fourth of the maximum chunksize to keep worst case fragmentation at an acceptable level.) If the record fits within the maximum size, which is the common case, the primary appends the data to its replica, tells the secondary's to write the data at the exact offset where it has, and finally replies success to the client.

If a record appends fails at any replica, the client retries the operation. As a result, replicas of the same chunk may contain different data possibly including duplicates of the same record in whole or in part. GFS does not guarantee that all replicas are byte wise identical. It only guarantees that the data is written at least once as an atomic unit. This property follows readily from the simple observation that for the operation to report success, the data must have been written at the same offset on all replicas of some chunk. Furthermore, after this, all replicas are at least as long as the end of record and therefore any future record will be assigned a higher offset or a different chunk even if a different replica later becomes the primary. In terms of our consistency guarantees, the regions in which successful record append operations have written their data are defined (hence consistent), whereas intervening regions are inconsistent (hence undefined).

3.4 Snapshot:

The snapshot operation makes a copy of a file or a directory tree (the "source") almost instantaneously, while minimizing any interruptions of ongoing mutations. Users use it to quickly create branch copies of huge data sets (and often copies of those copies, recursively), or to checkpoint the current state before experimenting with changes that can later be committed or rolled back easily.

Like AFS [5], we use standard copy-on-write techniques to implement snapshots. When the master receives a snapshot request, it first revokes any outstanding leases on the chunks in the files it is about to snapshot. This ensures that any subsequent writes to these chunks will require an interaction with the master to find the lease holder. This will give the master an opportunity to create a new copy of the chunk first.

After the leases have been revoked or have expired, the master logs the operation to disk. It then applies this log record to its in-memory state by duplicating the metadata for the source file or directory tree. The newly created snapshot files point to the same chunks as the source files.

The first time a client wants to write to a chunk C after the snapshot operation, it sends a request to the master to find the current lease holder. The master notices that the reference count for chunk C is greater than one. It defers replying to the client request and instead picks a new chunk handle C'. It then asks each chunkserver that has a current replica of C to create a new chunk called C'. By creating the new chunk on the same chunkservers as the original, we ensure that the data can be copied locally, not over the network (our disks are about three times as fast as our 100 Mb Ethernet links). From this point, request handling is no different from that for any chunk: the master grants one of the replicas a lease on the new chunk C' and replies to the client, which can write the chunk normally, not knowing that it has just been created from an existing chunk.

4. MASTER OPERATION

The master executes all namespace operations. In addition, it manages chunk replicas throughout the system: it makes placement decisions, creates new chunks and hence replicas, and coordinates various system-wide activities to keep chunks fully replicated, to balance load across all the chunkservers, and to reclaim unused storage. We now discuss each of these topics.

4.1 Namespace Management and Locking:

Many master operations can take a long time: for example, a snapshot operation has to revoke chunkserver leases on all chunks covered by the snapshot. We do not want to delay other master operations while they are running. Therefore, we allow multiple operations to be active and use locks over regions of the namespace to ensure proper serialization.

Unlike many traditional file systems, GFS does not have a per-directory data structure that lists all the files in that directory. Nor does it support aliases for the same file or directory (i.e., hard or symbolic links in UNIX terms). GFS logically represents its namespace as a lookup table mapping full pathnames to metadata. With prefix compression, this

table can be efficiently represented in memory. Each node in the namespace tree (either an absolute file name or an absolute directory name) has an associated read-write lock.

Each master operation acquires a set of locks before it runs. Typically, if it involves /d1/d2/.../dn/leaf, it will acquire read-locks on the directory names /d1, /d1/d2, ..., /d1/d2/.../dn, and either a read lock or a write lock on the full pathname /d1/d2/.../dn/leaf. Note that leaf may be a file or directory depending on the operation.

We now illustrate how this locking mechanism can prevent a file /home/user/foo from being created while /home/user is being snapshotted to /save/user. The snapshot operation acquires read locks on /home and /save, and write locks on /home/user and /save/user. The file creation acquires read locks on /home and /home/user, and a write lock on /home/user/foo. The two operations will be serialized properly because they try to obtain conflicting locks on /home/user. File creation does not require a write lock on the parent directory because there is no "directory", or inode-like, data structure to be protected from modification. The read lock on the name is sufficient to protect the parent directory from deletion.

One nice property of this locking scheme is that it allows concurrent mutations in the same directory. For example, multiple file creations can be executed concurrently in the same directory: each acquires a read lock on the directory name and a write lock on the file name. The read lock on the directory name suffices to prevent the directory from being deleted, renamed, or snapshotted. The write locks on file names serialize attempts to create a file with the same name twice.

Since the namespace can have many nodes, read-write lock objects are allocated lazily and deleted once they are not in use. Also, locks are acquired in a consistent total order to prevent deadlock: they are first ordered by level in the namespace tree and lexicographically within the same level.

4.2 Replica Placement:

A GFS cluster is highly distributed at more levels than one. It typically has hundreds of chunkservers spread across many machine racks. These chunkservers in turn may be accessed from hundreds of clients from the same or different racks. Communication between two machines on different racks may cross one or more network switches. Additionally, bandwidth into or out of a rack may be less than the aggregate bandwidth of all the machines within the rack. Multi-level distribution presents a unique challenge to distribute data for scalability, reliability, and availability.

The chunk replica placement policy serves two purposes: maximize data reliability and availability, and maximize network bandwidth utilization. For both, it is not enough to spread replicas across machines, which only guards against disk or machine failures and fully utilizes each machine's network bandwidth. We must also spread chunk replicas across racks. This ensures that some replicas of a chunk will survive and remain available even if an entire rack is damaged or offline (for example, due to failure of a shared resource like a network switch or power circuit). It also means that traffic, especially reads, for a chunk can exploit the aggregate bandwidth of multiple racks. On the other hand, write traffic has to flow through multiple racks, a tradeoff we make willingly.

4.3 Creation, Re-replication, Rebalancing:

Chunk replicas are created for three reasons: chunkcreation, re-replication, and rebalancing.

When the master creates a chunk, it chooses where to place the initially empty replicas. It considers several factors. (1) We want to place new replicas on chunkservers with below-average disk space utilization. Over time this will equalize disk utilization across chunkservers. (2) We want to limit the number of "recent" creations on each chunkserver. Although creation itself is cheap, it reliably predicts imminent heavy write traffic because chunks are created when demanded by writes, and in our append-once-read-many workload they typically become practically read-only once they have been completely written. (3) As discussed above, we want to spread replicas of a chunk across racks.

The master re-replicates a chunk as soon as the number of available replicas falls below a user-specified goal. This could happen for various reasons: a chunkserver becomes unavailable, it reports that its replica may be corrupted, one of its disks is disabled because of errors, or the replication goal is increased. Each chunk that needs to be re-replicated is prioritized based on several factors. One is how far it is from its replication goal. For example, we give higher priority to a chunk that has lost two replicas than to a chunk that has lost only one. In addition, we prefer to first re-replicate chunks

for live files as opposed to chunks that belong to recently deleted files (see Section 4.4). Finally, to minimize the impact of failures on running applications, we boost the priority of any chunk that is blocking client progress.

The master picks the highest priority chunk and "clones" it by instructing some chunkserver to copy the chunk data directly from an existing valid replica. The new replica is placed with goals similar to those for creation: equalizing disk space utilization, limiting active clone operations on any single chunkserver, and spreading replicas across racks. To keep cloning traffic from overwhelming client traffic, the master limits the numbers of active clone operations both for the cluster and for each chunkserver. Additionally, each chunkserver limits the amount of bandwidth it spends on each clone operation by throttling its read requests to the source chunkserver.

Finally, the master rebalances replicas periodically: it examines the current replica distribution and moves replicas for better disk space and load balancing. Also through this process, the master gradually fills up a new chunkserver rather than instantly swamps it with new chunks and the heavy write traffic that comes with them. The placement criteria for the new replica are similar to those discussed above. In addition, the master must also choose which existing replica to remove. In general, it prefers to remove those on chunkservers with below-average free space so as to equalize disk space usage.

4.4 Garbage Collection:

After a file is deleted, GFS does not immediately reclaim the available physical storage. It does so only lazily during regular garbage collection at both the file and chunk levels. We find that this approach makes the system much simpler and more reliable.

4.4.1 Mechanism:

When a file is deleted by the application, the master logs the deletion immediately just like other changes. However instead of reclaiming resources immediately, the file is just renamed to a hidden name that includes the deletion timestamp. During the master's regular scan of the file system namespace, it removes any such hidden files if they have existed for more than three days (the interval is configurable). Until then, the file can still be read under the new, special name and can be undeleted by renaming it back to normal. When the hidden file is removed from the namespace, it's in memory metadata is erased. This effectively severs its links to all its chunks.

In a similar regular scan of the chunk namespace, the master identifies orphaned chunks (i.e., those not reachable from any file) and erases the metadata for those chunks. In a HeartBeat message regularly exchanged with the master, each chunkserver reports a subset of the chunks it has, and the master replies with the identity of all chunks that are no longer present in the master's metadata. The chunkserver is free to delete its replicas of such chunks.

4.4.2 Discussion:

Although distributed garbage collection is a hard problem that demands complicated solutions in the context of programming languages, it is quite simple in our case. We can easily identify all references to chunks: they are in the file to-chunk mappings maintained exclusively by the master. We can also easily identify all the chunk replicas: they are Linux files under designated directories on each chunkserver. Any such replica not known to the master is "garbage."

4.5 Stale Replica Detection:

Chunk replicas may become stale if a chunkserver fails and misses mutations to the chunk while it is down. For each chunk, the master maintains a chunk version number to distinguish between up-to-date and stale replicas.

Whenever the master grants a new lease on a chunk, it increases the chunk version number and informs the up-to date replicas. The master and these replicas all record the new version number in their persistent state. This occurs before any client is notified and therefore before it can start writing to the chunk. If another replica is currently unavailable, its chunk version number will not be advanced. The master will detect that this chunkserver has a stale replica when the chunkserver restarts and reports its set of chunks and their associated version numbers. If the master sees a version number greater than the one in its records, the master assumes that it failed when granting the lease and so takes the higher version to be up-to-date.

The master removes stale replicas in its regular garbage collection. Before that, it effectively considers a stale replica not to exist at all when it replies to client requests for chunk information. As another safeguard, the master includes the chunk

version number when it informs clients which chunkserver holds a lease on a chunk or when it instructs a chunkserver to read the chunk from another chunkserver in a cloning operation. The client or the chunkserver verifies the version number when it performs the operation so that it is always accessing up-to-date data.

5. FAULT TOLERANCE AND DIAGNOSIS

One of the greatest challenges in designing the system is dealing with frequent component failures. The quality and quantity of components together make these problems more the norm than the exception: we cannot completely trust the machines, nor can we completely trust the disks. Component failures can result in an unavailable system or, worse, corrupted data. We discuss how we meet these challenges and the tools we have built into the system to diagnose problems when they inevitably occur.

5.1 High Availability:

Among hundreds of servers in a GFS cluster, some are bound to be unavailable at any given time. We keep the overall system highly available with two simple yet effective strategies: fast recovery and replication.

5.1.1 Fast Recovery:

Both the master and the chunkserver are designed to restore their state and start in seconds no matter how they terminated. In fact, we do not distinguish between normal and abnormal termination; servers are routinely shut down just by killing the process. Clients and other servers experience a minor hiccup as they time out on their outstanding requests, reconnect to the restarted server, and retry. Section 6.2.2 reports observed startup times.

5.1.2 Chunk Replication:

As discussed earlier, each chunkis replicated on multiple chunkservers on different racks. Users can specify different replication levels for different parts of the file namespace. The default is three. The master clones existing replicas as needed to keep each chunk fully replicated as chunkservers go offline or detect corrupted replicas through checksum verification (see Section 5.2). Although replication has served us well, we are exploring other forms of cross-server redundancy such as parity or erasure codes for our increasing read only storage requirements. We expect that it is challenging but manageable to implement these more complicated redundancy schemes in our very loosely coupled system because our traffic is dominated by appends and reads rather than small random writes.

5.1.3 Master Replication:

The master state is replicated for reliability. Its operation log and checkpoints are replicated on multiple machines. A mutation to the state is considered committed only after its log record has been flushed to disk locally and on all master replicas. For simplicity, one master process remains in charge of all mutations as well as background activities such as garbage collection that change the system internally. When it fails, it can restart almost instantly. If its machine or disk fails, monitoring infrastructure outside GFS starts a new master process elsewhere with the replicated operation log. Clients use only the canonical name of the master (e.g. gfs-test), which is a DNS alias that can be changed if the master is relocated to another machine.

Moreover, "shadow" masters provide read-only access to the file system even when the primary master is down. They are shadows, not mirrors, in that they may lag the primary slightly, typically fractions of a second. They enhance read availability for files that are not being actively mutated or applications that do not mind getting slightly stale results. In fact, since file content is read from chunkservers, applications do not observe stale file content. What could be stale within short windows is file metadata, like directory contents or access control information.

To keep itself informed, a shadow master reads a replica of the growing operation log and applies the same sequence of changes to its data structures exactly as the primary does. Like the primary, it polls chunkservers at startup (and infrequently thereafter) to locate chunk replicas and exchanges frequent handshake messages with them to monitor their status. It depends on the primary master only for replica location updates resulting from the primary's decisions to create and delete replicas.

5.2 Data Integrity:

Each chunkserver uses check summing to detect corruption of stored data. Given that a GFS cluster often has thousands of disks on hundreds of machines, it regularly experiences disk failures that cause data corruption or loss on both the read and write paths. (See Section 7 for one cause.) We can recover from corruption using other chunk replicas, but it would be impractical to detect corruption by comparing replicas across chunkservers. Moreover, divergent replicas may be legal: the semantics of GFS mutations, in particular atomic record append as discussed earlier, does not guarantee identical replicas. Therefore, each chunkserver must independently verify the integrity of its own copy by maintaining checksums.

A chunkis broken up into 64 KB blocks. Each has a corresponding 32 bit checksum. Like other metadata, checksums are kept in memory and stored persistently with logging, separate from user data.

5.3 Diagnostic Tools:

Extensive and detailed diagnostic logging has helped immeasurably in problem isolation, debugging, and performance analysis, while incurring only a minimal cost. Without logs, it is hard to understand transient, non-repeatable interactions between machines. GFS servers generate diagnostic logs that record many significant events (such as chunkservers going up and down) and all RPC requests and replies. These diagnostic logs can be freely deleted without affecting the correctness of the system. However, we try to keep these logs around as far as space permits.

The RPC logs include the exact requests and responses sent on the wire, except for the file data being read or written. By matching requests with replies and collating RPC records on different machines, we can reconstruct the entire interaction history to diagnose a problem. The logs also serve as traces for load testing and performance analysis.

The performance impact of logging is minimal (and far outweighed by the benefits) because these logs are written sequentially and asynchronously. The most recent events are also kept in memory and available for continuous online monitoring.

6. MEASUREMENTS

In this section we present a few micro-benchmarks to illustrate the bottlenecks inherent in the GFS architecture and implementation, and also some numbers from real clusters in use at Google.

6.1 Micro-benchmarks:

Google measured performance on a GFS cluster consisting of one master, two master replicas, 16 chunkservers, and 16 clients. Note that this configuration was set up for ease of testing. Typical clusters have hundreds of chunkservers and hundreds of clients.

All the machines are configured with dual 1.4 GHz PIII processors, 2 GB of memory, two 80 GB 5400 rpm disks, and a 100 Mbps full-duplex Ethernet connection to an HP 2524 switch. All 19 GFS server machines are connected to one switch, and all 16 client machines to the other. The two switches are connected with a 1 Gbps link.

6.1.1 Reads:

N clients read simultaneously from the file system. Each client reads a randomly selected 4 MB region from a 320 GB file set. This is repeated 256 times so that each client ends up reading 1 GB of data. The chunkservers taken together have only 32 GB of memory, so we expect at most a 10% hit rate in the Linux buffer cache. Our results should be close to cold cache results.

Figure 3(a) shows the aggregate read rate for N clients and its theoretical limit. The limit peaks at an aggregate of 125 MB/s when the 1 Gbps link between the two switches is saturated, or 12.5 MB/s per client when its 100 Mbps network interface gets saturated, whichever applies. The observed read rate is 10 MB/s, or 80% of the per-client limit, when just one client is reading. The aggregate read rate reaches 94 MB/s, about 75% of the 125 MB/s link limit, for 16 readers, or 6 MB/s per client. The efficiency drops from 80% to 75% because as the number of readers increases, so does the probability that multiple readers simultaneously read from the same chunkserver.

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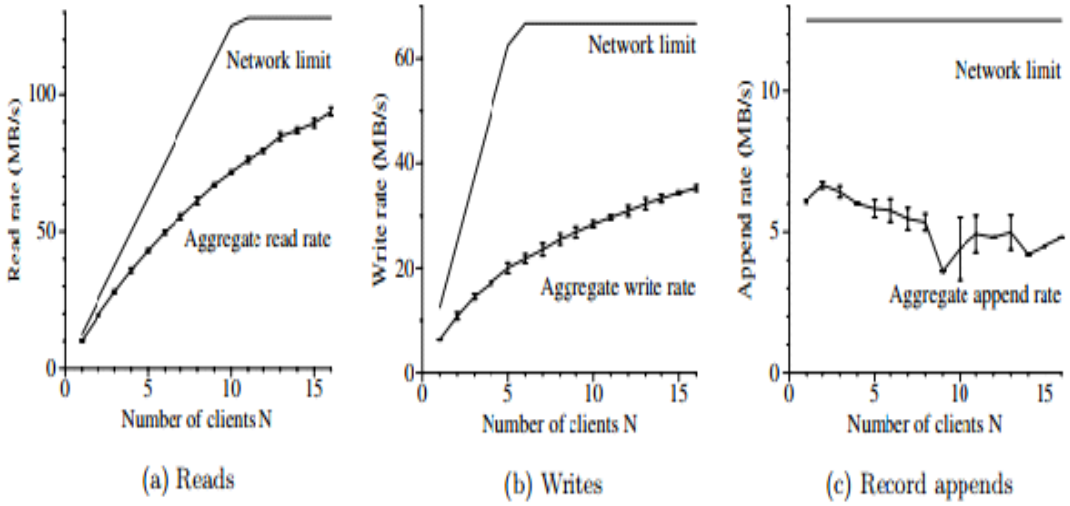

6.1.2 Writes:

N clients write simultaneously to N distinct files. Each client writes 1 GB of data to a new file in a series of 1 MB writes. The aggregate write rate and its theoretical limit are shown in Figure 3(b). The limit plateaus at 67 MB/s because we need to write each byte to 3 of the 16 chunk servers, each with a 12.5 MB/s input connection.

The write rate for one client is 6.3 MB/s, about half of the limit. The main culprit for this is our network stack. It does not interact very well with the pipelining scheme we use for pushing data to chunk replicas. Delays in propagating data from one replica to another reduce the overall write rate.

Aggregate write rate reaches 35 MB/s for 16 clients (or 2.2 MB/s per client), about half the theoretical limit. As in the case of reads, it becomes more likely that multiple clients write concurrently to the same chunkserver as the number of client's increases. Moreover, collision is more likely for 16 writers than for 16 readers because each write involves three different replicas.

Writes are slower than we would like. In practice this has not been a major problem because even though it increases the latencies as seen by individual clients, it does not significantly affect the aggregate write bandwidth delivered by the system to a large number of clients.

6.1.3 Record Appends:

Figure 3(c) shows record append performance. N clients append simultaneously to a single file. Performance is limited by the network bandwidth of the chunkservers that store the last chunk of the file, independent of the number of clients. It starts at 6.0 MB/s for one client and drops to 4.8 MB/s for 16 clients, mostly due to congestion and variances in network transfer rates seen by different clients.

Their applications tend to produce multiple such files concurrently. In other words, N clients append to M shared files simultaneously where both N and M are in the dozens or hundreds. Therefore, the chunkserver network congestion in our experiment is not a significant issue in practice because a client can make progress on writing one file while the chunkservers for another file are busy.

6.2 Real World Clusters:

We now examine two clusters in use within Google that are representative of several others like them. Cluster A is used regularly for research and development by over a hundred engineers. A typical task is initiated by a human user and runs up to several hours. It reads through a few MBs to a few TBs of data, transforms or analyzes the data, and writes the results back to the cluster. Cluster B is primarily used for production data processing. The tasks last much longer and continuously generate and process multi-TB data sets with only occasional human intervention. In both cases, a single "task" consists of many processes on many machines reading and writing many files simultaneously.

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Cluster	A	B
Chunkservers	342	227
Available disk space	72 TB	180 TB
Used disk space	55 TB	155 TB
Number of Files	735 k	737 k
Number of Dead files	22 k	232 k
Number of Chunks	992 k	1550 k
Metadata at chunkservers	13 GB	21 GB
Metadata at master	48 MB	60 MB

Table 2: Characteristics of two GFS clusters

6.2.1 Storage:

As shown by the first five entries in the table, both clusters have hundreds of chunkservers, support many TBs of disk space, and are fairly but not completely full. "Used space" includes all chunk replicas. Virtually all files are replicated three times. Therefore, the clusters store 18 TB and 52 TB of file data respectively.

The two clusters have similar numbers of files, though B has a larger proportion of dead files, namely files which were deleted or replaced by a new version but whose storage have not yet been reclaimed. It also has more chunks because its files tend to be larger.

6.2.2 Metadata:

The chunkservers in aggregate store tens of GBs of metadata, mostly the checksums for 64 KB blocks of user data. The only other metadata kept at the chunkservers is the chunk version number discussed in Section 4.5.

The metadata kept at the master is much smaller, only tens of MBs, or about 100 bytes per file on average. This agrees with our assumption that the size of the master's memory does not limit the system's capacity in practice. Most of the per-file metadata is the file names stored in a prefix-compressed form. Other metadata includes file ownership and permissions, mapping from files to chunks, and each chunk's current version. In addition, for each chunk we store the current replica locations and a reference count for implementing copy-on-write.

Each individual server, both chunkservers and the master, has only 50 to 100 MB of metadata. Therefore recovery is fast: it takes only a few seconds to read this metadata from disk before the server is able to answer queries. However, the master is somewhat hobbled for a period – typically 30 to 60 seconds – until it has fetched chunk location information from all chunkservers.

6.2.3 Read and Write Rates:

Table 3 shows read and write rates for various time periods. Both clusters had been up for about one week when these measurements were taken. (The clusters had been restarted recently to upgrade to a new version of GFS.) The average write rate was less than 30 MB/s since the restart. When we took these measurements, B was in the middle of a burst of write activity generating about 100 MB/s of data, which produced a 300 MB/s network load because writes are propagated to three replicas.

Cluster	A	B
Read rate (last minute)	583 MB/s	380 MB/s
Read rate (last hour)	562 MB/s	384 MB/s
Read rate (since restart)	589 MB/s	49 MB/s
Write rate (last minute)	1 MB/s	101 MB/s
Write rate (last hour)	2 MB/s	117 MB/s
Write rate (since restart)	25 MB/s	13 MB/s
Master ops (last minute)	325 Ops/s	533 Ops/s
Master ops (last hour)	381 Ops/s	518 Ops/s
Master ops (since restart)	202 Ops/s	347 Ops/s

Table 3: Performance Metrics for Two GFS Clusters

The read rates were much higher than the write rates. The total workload consists of more reads than writes as we have assumed. Both clusters were in the middle of heavy read activity. In particular, A had been sustaining a read rate of 580

MB/s for the preceding week. Its network con- figuration can support 750 MB/s, so it was using its resources efficiently. Cluster B can support peak read rates of 1300 MB/s, but its applications were using just 380 MB/s.

6.2.4 Master Load:

Table 3 also shows that the rate of operations sent to the master was around 200 to 500 operations per second. The master can easily keep up with this rate, and therefore is not a bottleneck for these workloads.

In an earlier version of GFS, the master was occasionally a bottleneck for some workloads. It spent most of its time sequentially scanning through large directories (which contained hundreds of thousands of files) looking for particular files. We have since changed the master data structures to allow efficient binary searches through the namespace. It can now easily support many thousands of file accesses per second. If necessary, we could speed it up further by placing name lookup caches in front of the namespace data structures.

6.2.5 Recovery Time:

After a chunkserver fails, some chunks will become under replicated and must be cloned to restore their replication levels. The time it takes to restore all such chunks depends on the amount of resources. In one experiment, we killed a single chunkserver in cluster B. The chunkserver had about 15,000 chunks containing 600 GB of data. To limit the impact on running applications and provide leeway for scheduling decisions, our default parameters limit this cluster to 91 concurrent cloning's (40% of the number of chunkservers) where each clone operation is allowed to consume at most 6.25 MB/s (50 Mbps). All chunks were restored in 23.2 minutes, at an effective replication rate of 440 MB/s.

In another experiment, we killed two chunkservers each with roughly 16,000 chunks and 660 GB of data. This double failure reduced 266 chunks to having a single replica. These 266 chunks were cloned at a higher priority, and were all restored to at least 2x replication within 2 minutes, thus putting the cluster in a state where it could tolerate another chunkserver failure without data loss.

6.3 Workload Breakdown:

In this section, we present a detailed breakdown of the workloads on two GFS clusters comparable but not identical to those in Section 6.2. Cluster X is for research and development while cluster Y is for production data processing.

6.3.1 Methodology and Caveats:

These results include only client originated requests so that they reflect the workload generated by our applications for the file system as a whole. They do not include inter server requests to carry out client requests or internal background activities, such as forwarded writes or rebalancing.

Statistics on I/O operations are based on information heuristically reconstructed from actual RPC requests logged by GFS servers. For example, GFS client code may break a read into multiple RPCs to increase parallelism, from which we infer the original read. Since our access patterns are highly stylized, we expect any error to be in the noise. Explicit logging by applications might have provided slightly more accurate data, but it is logistically impossible to recompile and restart thousands of running clients to do so and cumbersome to collect the results from as many machines.

One should be careful not to overly generalize from our workload. Since Google completely controls both GFS and its applications, the applications tend to be tuned for GFS, and conversely GFS is designed for these applications. Such mutual influence may also exist between general applications and file systems, but the effect is likely more pronounced in our case.

Operation	Read		Write		Record Append	
Cluster	X	Y	X	Y	X	Y
0K	0.4	2.6	0	0	0	0
1B..1K	0.1	4.1	6.6	4.9	0.2	9.2
1K..8K	65.2	38.5	0.4	1.0	18.9	15.2
8K..64K	29.9	45.1	17.8	43.0	78.0	2.8
64K..128K	0.1	0.7	2.3	1.9	< .1	4.3
128K..256K	0.2	0.3	31.6	0.4	< .1	10.6
256K..512K	0.1	0.1	4.2	7.7	< .1	31.2
512K..1M	3.9	6.9	35.5	28.7	2.2	25.5
1M..inf	0.1	1.8	1.5	12.3	0.7	2.2

Table 4: Operations Breakdown by Size (%). For reads, the size is the amount of data actually read and transferred, rather than the amount requested.

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Operation	Read		Write		Record Append	
Cluster	X	Y	X	Y	X	Y
1B..1K	< .1	< .1	< .1	< .1	< .1	< .1
1K..8K	13.8	3.9	< .1	< .1	< .1	0.1
8K..64K	11.4	9.3	2.4	5.9	2.3	0.3
64K..128K	0.3	0.7	0.3	0.3	22.7	1.2
128K..256K	0.8	0.6	16.5	0.2	< .1	5.8
256K..512K	1.4	0.3	3.4	7.7	< .1	38.4
512K..1M	65.9	55.1	74.1	58.0	.1	46.8
1M..inf	6.4	30.1	3.3	28.0	53.9	7.4

Table 5: Bytes Transferred Breakdown by Operation Size (%). For reads, the size is the amount of data actually read and transferred, rather than the amount requested. The two may differ if the read attempts to read beyond end of file, which by design is not uncommon in our workloads.

6.3.2 Chunkserver Workload:

Table 4 shows the distribution of operations by size. Read sizes exhibit a bimodal distribution. The small reads (under 64 KB) come from seek-intensive clients that look up small pieces of data within huge files. The large reads (over 512 KB) come from long sequential reads through entire files.

A significant number of reads return no data at all in cluster Y. Our applications, especially those in the production systems, often use files as producer-consumer queues. Producers append concurrently to a file while a consumer reads the end of file. Occasionally, no data is returned when the consumer outpaces the producers. Cluster X shows this less often because it is usually used for short-lived data analysis tasks rather than long-lived distributed applications.

Write sizes also exhibit a bimodal distribution. The large writes (over 256 KB) typically result from significant buffering within the writers. Writers that buffer less data, checkpoint or synchronize more often, or simply generate less data account for the smaller writes (under 64 KB).

As for record appends, cluster Y sees a much higher percentage of large record appends than cluster X does because our production systems, which use cluster Y, are more aggressively tuned for GFS.

Table 5 shows the total amount of data transferred in operations of various sizes. For all kinds of operations, the larger operations (over 256 KB) generally account for most of the bytes transferred. Small reads (under 64 KB) do transfer a small but significant portion of the read data because of the random seek workload.

6.3.3 Appends versus Writes:

Record appends are heavily used especially in our production systems. For cluster X, the ratio of writes to record appends is 108:1 by bytes transferred and 8:1 by operation counts. For cluster Y, used by the production systems, the ratios are 3.7:1 and 2.5:1 respectively. Moreover, these ratios suggest that for both clusters record appends tend to be larger than writes. For cluster X, however, the overall usage of record append during the measured period is fairly low and so the results are likely skewed by one or two applications with particular buffer size choices.

As expected, our data mutation workload is dominated by appending rather than overwriting. We measured the amount of data overwritten on primary replicas. This approximates the case where a client deliberately overwrites previous written data rather than appends new data. For cluster X, overwriting accounts for under 0.0001% of bytes mutated and under 0.0003% of mutation operations. For cluster Y, the ratios are both 0.05%. Although this is minute, it is still higher than we expected. It turns out that most of these overwrites came from client retries due to errors or timeouts. They are not part of the workload per se but a consequence of the retry mechanism.

Cluster	X	Y
Open	26.1	16.3
Delete	0.7	1.5
FindLocation	64.3	65.8
FindLeaseHolder	7.8	13.4
FindMatchingFiles	0.6	2.2
All other combined	0.5	0.8

Table 6: Master Requests Breakdown by Type (%)

6.3.4 Master Workload:

Table 6 shows the breakdown by type of requests to the master. Most requests ask for chunk locations (FindLocation) for reads and lease holder information (FindLeaseLocker) for data mutations.

Clusters X and Y see significantly different numbers of Delete requests because cluster Y stores production data sets that are regularly regenerated and replaced with newer versions. Some of this difference is further hidden in the difference in Open requests because an old version of a file may be implicitly deleted by being opened for write from scratch (mode "w" in UNIX open terminology).

FindMatchingFiles is a pattern matching request that supports "ls" and similar file system operations. Unlike other requests for the master, it may process a large part of the namespace and so may be expensive. Cluster Y sees it much more often because automated data processing tasks tend to examine parts of the file system to understand global application state. In contrast, cluster X's applications are under more explicit user control and usually know the names of all needed files in advance.

7. EXPERIENCES

In the process of building and deploying GFS, we have experienced a variety of issues, some operational and some technical.

Initially, GFS was conceived as the backend file system for our production systems. Over time, the usage evolved to include research and development tasks. It started with little support for things like permissions and quotas but now includes rudimentary forms of these. While production systems are well disciplined and controlled, users sometimes are not. More infrastructure is required to keep users from interfering with one another.

Some of our biggest problems were disk and Linux related. Many of our disks claimed to the Linux driver that they supported a range of IDE protocol versions but in fact responded reliably only to the more recent ones. Since the protocol versions are very similar, these drives mostly worked, but occasionally the mismatches would cause the drive and the kernel to disagree about the drive's state. This would corrupt data silently due to problems in the kernel. This problem motivated our use of checksums to detect data corruption, while concurrently we modified the kernel to handle these protocol mismatches.

Earlier we had some problems with Linux 2.2 kernels due to the cost of fsync (). Its cost is proportional to the size of the file rather than the size of the modified portion. This was a problem for our large operation logs especially before we implemented check pointing. We worked around this for a time by using synchronous writes and eventually migrated to Linux 2.4.

Another Linux problem was a single reader-writer lock which any thread in an address space must hold when it pages in from disk (reader lock) or modifies the address space in a mmap () call (writer lock). We saw transient timeouts in our system under light load and looked hard for resource bottlenecks or sporadic hardware failures. Eventually, we found that this single lock blocked the primary network thread from mapping new data into memory while the disk threads were paging in previously mapped data. Since we are mainly limited by the network interface rather than by memory copy bandwidth, we worked around this by replacing mmap () with pread () at the cost of an extra copy.

Despite occasional problems, the availability of Linux code has helped us time and again to explore and understand system behavior. When appropriate, we improve the kernel and share the changes with the open source community.

8. RELATED WORK

Like other large distributed file systems such as AFS [5], GFS provides a location independent namespace which enables data to be moved transparently for load balance or fault tolerance. Unlike AFS, GFS spreads a file's data across storage servers in a way more akin to xFS [1] and Swift [3] in order to deliver aggregate performance and increased fault tolerance.

As disks are relatively cheap and replication is simpler than more sophisticated RAID [9] approaches, GFS currently uses only replication for redundancy and so consumes more raw storage than xFS or Swift.

In contrast to systems like AFS, xFS, Frangipani [12], and Intermezzo [6], GFS does not provide any caching below the file system interface. Our target workloads have little reuse within a single application run because they either stream through a large data set or randomly seek within it or read small amounts of data each time.

Some distributed file systems like Frangipani, xFS, Minnesota's GFS [11] and GPFS [10] remove the centralized server and rely on distributed algorithms for consistency and management. We opt for the centralized approach in order to simplify the design, increase its reliability, and gain flexibility. In particular, a centralized master makes it much easier to implement sophisticated chunk placement and replication policies since the master already has most of the relevant information and controls how it changes. We address fault tolerance by keeping the master state small and fully replicated on other machines. Scalability and high availability (for reads) are currently provided by our shadow master mechanism. Updates to the master state are made persistent by appending to a write-ahead log. Therefore we could adapt a primary-copy scheme like the one in Harp [7] to provide high availability with stronger consistency guarantees than our current scheme.

We are addressing a problem similar to Lustre [8] in terms of delivering aggregate performance to a large number of clients. However, we have simplified the problem significantly by focusing on the needs of our applications rather than building a POSIX-compliant file system. Additionally, GFS assumes large number of unreliable components and so fault tolerance is central to our design.

GFS most closely resembles the NASD architecture [4]. While the NASD architecture is based on network-attached disk drives, GFS uses commodity machines as chunkservers, as done in the NASD prototype. Unlike the NASD work, our chunkservers use lazily allocated fixed-size chunks rather than variable-length objects. Additionally, GFS implements features such as rebalancing, replication, and recovery that are required in a production environment.

Unlike Minnesota's GFS and NASD, we do not seek to alter the model of the storage device. We focus on addressing day-to-day data processing needs for complicated distributed systems with existing commodity components.

The producer-consumer queues enabled by atomic record appends address a similar problem as the distributed queues in River [2]. While River uses memory-based queues distributed across machines and careful data flow control, GFS uses a persistent file that can be appended to concurrently by many producers. The River model supports m-to-n distributed queues but lacks the fault tolerance that comes with persistent storage, while GFS only supports m-to-1 queues efficiently. Multiple consumers can read the same file, but they must coordinate to partition the incoming load.

9. CONCLUSIONS

The Google File System demonstrates the qualities essential for supporting large-scale data processing workloads on commodity hardware. While some design decisions are specific to our unique setting, many may apply to data processing tasks of a similar magnitude and cost consciousness.

They have started by reexamining traditional file system assumptions in light of our current and anticipated application workloads and technological environment. Their observations have led to radically different points in the design space. We treat component failures as the norm rather than the exception, optimize for huge files that are mostly appended to (perhaps concurrently) and then read (usually sequentially), and both extend and relax the standard file system interface to improve the overall system.

Google's system provides fault tolerance by constant monitoring, replicating crucial data, and fast and automatic recovery. Chunk replication allows us to tolerate chunkserver failures. The frequency of these failures motivated a novel online repair mechanism that regularly and transparently repairs the damage and compensates for lost replicas as soon as possible. Additionally, we use check summing to detect data corruption at the disk or IDE subsystem level, which becomes all too common given the number of disks in the system.

Their design delivers high aggregate throughput to many concurrent readers and writers performing a variety of tasks. We achieve this by separating file system control, which passes through the master, from data transfer, which passes directly between chunkservers and clients. Master involvement in common operations is minimized by a large chunk size and by chunk leases, which delegates' authority to primary replicas in data mutations. This makes possible a simple, centralized master that does not become a bottleneck. We believe that improvements in our networking stack will lift the current limitation on the write throughput seen by an individual client.

GFS has successfully met Google's storage needs and is widely used within Google as the storage platform for research and development as well as production data processing. It is an important tool that enables us to continue to innovate and attack problems on the scale of the entire web.

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