Spanner Motivation

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Outline

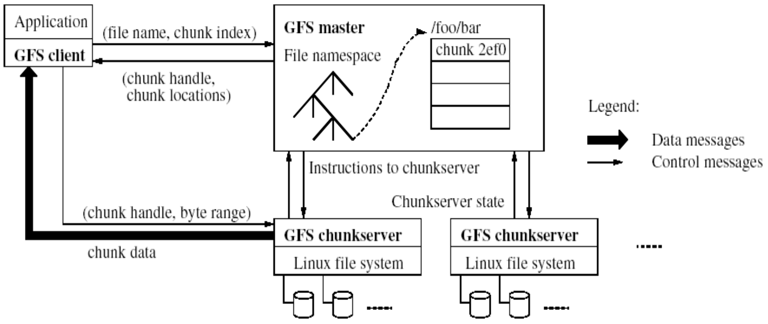
Last week:

- Chubby: coordination service
- BigTable: scalable storage of structured data
- GFS: large-scale storage for bulk data

Today/Friday:

- Lessons from GFS/BigTable
- Megastore: Multi-key, multi-data center NoSQL
- Spanner: Multi-key, multi-data center NoSQL using real-time

GFS Architecture



- each file stored as 64MB chunks
- each chunk on 3+ chunkservers
- single master stores metadata

At Least Once Append

- If failure at primary or any replica, retry append (at new offset)
  - Append will eventually succeed!
  - May succeed multiple times!
- App client library responsible for
  - Detecting corrupted copies of appended records
  - Ignoring extra copies (during streaming reads)
- Why not append exactly once?

Question

Does the BigTable tablet server use “at least once append” for its operation log?

Data Corruption

- Files stored on Linux, and Linux has bugs
  - Sometimes silent corruptions
- Files stored on disk, and disks are not fail-stop
  - Stored blocks can become corrupted over time
  - Ex: writes to sectors on nearby tracks
  - Rare events become common at scale
- Chunkservers maintain per-chunk CRCs (64KB)
  - Local log of CRC updates
  - Verify CRCs before returning read data
  - Periodic revalidation to detect background failures

~15 years later

- Scale is much bigger:
  - now 10K servers instead of 1K
  - now 100 PB instead of 100 TB
- Bigger workload change: updates to small files!
- Around 2010: incremental updates of the Google search index

GFS -> Colossus

- GFS scaled to ~50 million files, ~10 PB
- Developers had to organize their apps around large append-only files (see BigTable)
- Latency-sensitive applications suffered
- GFS eventually replaced with a new design, Colossus

Metadata scalability

- Main scalability limit: single master stores all metadata
- HDFS has same problem (single NameNode)
- Approach: partition the metadata among multiple masters
- New system supports ~100M files per master and smaller chunk sizes: 1MB instead of 64MB

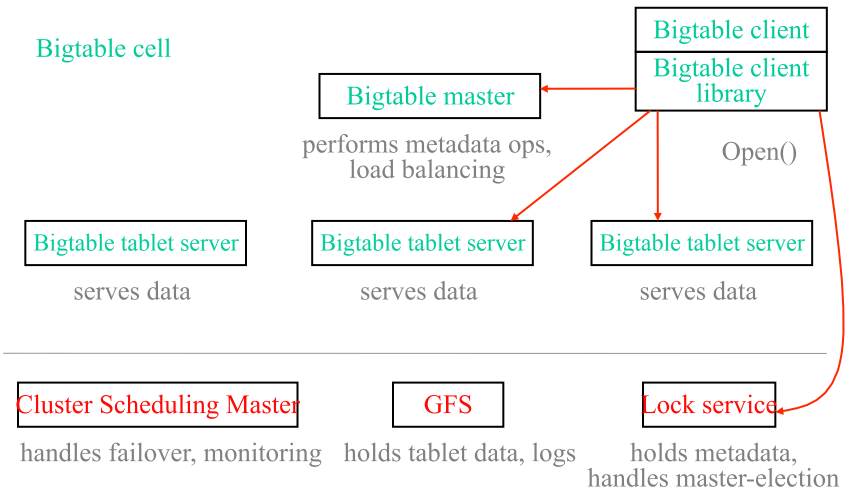
Reducing Storage Overhead

- Replication: 3x storage to handle two copies
- Erasure coding more flexible: m pieces, n check pieces
  - e.g., RAID-5: 2 disks, 1 parity disk (XOR of other two) => 1 failure w/ only 1.5 storage
- Sub-chunk writes more expensive (read-modify-write)
- Recovery is harder:
  usually need to get all the other pieces,
  generate another one after the failure

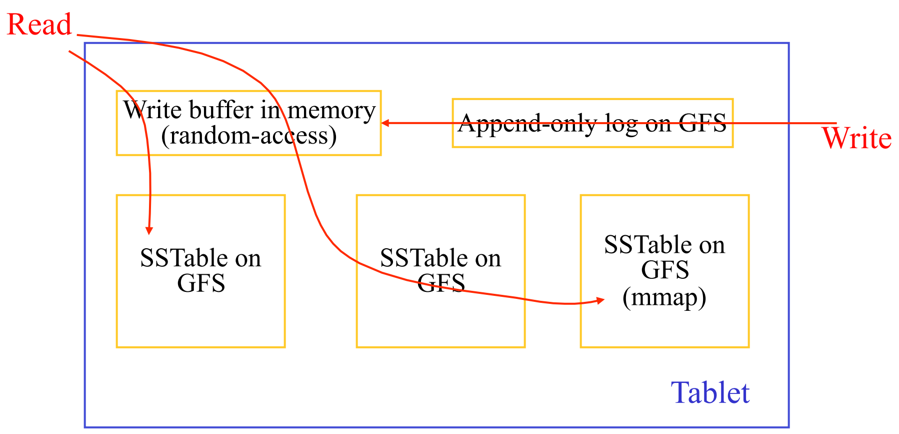
Erasure Coding

- 3-way replication:
  3x overhead, 2 failures tolerated, easy recovery
- Google Colossus: (6,3) Reed-Solomon code
  1.5x overhead, 3 failures
- Facebook HDFS: (10,4) Reed-Solomon
  1.4x overhead, 4 failures, expensive recovery
- Azure: more advanced code (12, 4)
  1.33x, 4 failures, same recovery cost as Colossus

BigTable System Structure



Tablet Representation



Read

Write buffer in memory
(random-access)

Append-only log on GFS

Write

SSTable on
GFS

SSTable on
GFS

SSTable on
GFS
(mmap)

Tablet

- SSTable: Immutable on-disk ordered map from string→string
- String keys: *<row, column, timestamp>* triples

Compactions

- Tablet state represented as set of immutable compacted SSTable files, plus tail of log (buffered in memory)
- Minor compaction:
  - When in-memory state fills up, pick tablet with most data and write contents to SSTables stored in GFS
    - Separate file for each locality group for each tablet
- Major compaction:
  - Periodically compact all SSTables for tablet into new base SSTable on GFS
    - Storage reclaimed from deletions at this point

Timestamps

- Used to store different versions of data in a cell
  - New writes default to current time, but timestamps for writes can also be set explicitly by clients
- Lookup options:
  - *"Return most recent K values"*
  - *"Return all values in timestamp range (or all values)"*
- Column families can be marked w/ attributes:
  - *"Only retain most recent K values in a cell"*
  - *"Keep values until they are older than K seconds"*

API

- Metadata operations
  - Create/delete tables, column families, change metadata
- Writes (atomic)
  - Set(): write cells in a row
  - DeleteCells(): delete cells in a row
  - DeleteRow(): delete all cells in a row
- Reads
  - Scanner: read arbitrary cells in a bigtable
    - Each row read is atomic
    - Can restrict returned rows to a particular range
    - Can ask for just data from 1 row, all rows, etc.
    - Can ask for all columns, just certain column families, or specific columns

Shared Logs

- Designed for 1M tablets, 1000s of tablet servers
  - 1M logs being simultaneously written performs badly
- Solution: shared logs
  - Write log file per tablet server instead of per tablet
    - Updates for many tablets co-mingled in same file
  - Start new log chunks every so often (64MB)
- Problem: during recovery, server needs to read log data to apply mutations for a tablet
  - Lots of wasted I/O if lots of machines need to read data for many tablets from same log chunk

Shared Log Recovery

Recovery:

- Servers inform master of log chunks they need to read
- Master aggregates and orchestrates sorting of needed chunks
  - Assigns log chunks to be sorted to different tablet servers
  - Servers sort chunks by tablet, writes sorted data to local disk
- Other tablet servers ask master which servers have sorted chunks they need
- Tablet servers issue direct RPCs to peer tablet servers to read sorted data for its tablets

Compression

- Many opportunities for compression
  - Similar values in the same row/column at different timestamps
  - Similar values in different columns
  - Similar values across adjacent rows

- Within each SSTable for a locality group, encode compressed blocks
  - Keep blocks small for random access (~64KB compressed data)
  - Exploit fact that many values very similar
  - Needs to be low CPU cost for encoding/decoding

Compression Effectiveness

- Experiment: store contents for 2.1B page crawl in BigTable instance
  - Key: URL of pages, with host-name portion reversed
    - **com.cnn.www/index.html:http**
  - Groups pages from same site together
    - Good for compression (neighboring rows tend to have similar contents)
    - Good for clients: efficient to scan over all pages on a web site

- One compression strategy: gzip each page: ~28% bytes remaining
- BigTable: BMDiff + Zippy

Type	**Count(B)**	**Space(TB)**	**Compressed**	**%remaining**
Web contents	2.1	45.1	4.2	9.2
Links	1.8	11.2	1.6	13.9
Anchors	126.3	22.8	2.9	12.7

Summary of BigTable Key Ideas

Unstructured key-value table data

- No need for having a schema in advance
- instead create columns when needed

Versioned data, with key-specific garbage collection

Maintain data locality on same tablet

Instead of consistent hashing, reconfigure tablet boundaries for load balancing

Tablets for lookup: key -> tablet

Efficient updates using log structure (store deltas)

BigTable in retrospect

- Definitely a useful, scalable system!
- Still in use at Google, motivated lots of NoSQL DBs
- Lack of distributed transactions: biggest mistake in design, per Jeff Dean
- Lack of multi-data center support

Question

How would you add multi-key transactions to BigTable?

- Easy if all keys are on the same tablet, or on different tablets on the same tablet server
- What if keys are on different tablet servers?

Multi-Key NoSQL Transactions

- Straw proposal: Two phase commit
  - Select one tablet server as coordinator
  - Add log entries for coordinator/participant actions
  - Check log if coordinator or participant fails
- What if coordinator/participant crashes?
  - BigTable master wait for lease timeout
  - Select new tablet server
  - New tablet server recovers in progress transactions using log
  - Abort/commit as appropriate

Performance of NoSQL 2PC

What is performance of multi-key transactions using two phase commit?

- Each tablet server orders operations to its own keys
- If coordinator, must lock or delay subsequent operations to that key, until participants reply
- If participant, must lock or delay subsequent ops to that key, until coordinator commits/aborts
- All ops to key are delayed, not just multi-key ones

- Stale reads to the rescue?

Question

How would you add support for multiple data centers to BigTable?

Multiple Data Center NoSQL

- Straw proposal: Paxos state machine replicas
  - Every data center has complete copy of data
  - One serves as Paxos leader (per tablet or per key)
  - Clients contact leader
  - Leader proposes ordering of client ops to tablet
- Paxos implies
  - correct despite data center failures, network partitions, etc.
  - Progress if a majority of data centers remain up and connected

Multi-Data Center Paxos Performance

- Assume Paxos is optimized: one round from leader to participants per operation (batched)
- Latency:
  - One RT from client to (remote) leader
  - One RT from leader to farthest data center
- Throughput
  - Every operation sent to every data center
  - N messages to coordinate Paxos ordering (batched)
- Per-transaction: two log operations at coordinator, two at each participant
- Stale reads to the rescue?

Megastore Motivation

- Many apps need atomicity across rows
  - Examples: gmail, google+, picasa, …
- Many apps need to span multiple data centers
  - Hide outages from end users
  - Low latency for every user on planet
- Goals:
  - Fast local reads
  - At cost of slower writes

Megastore Key Ideas

- BigTable as a service
  - No need to reimplement NoSQL
  - Two phase commit across keys
  - operation log stored in a BT column
- Use data center for testing
  - Extensive randomized testing of corner cases

Megastore Key Ideas

- Paxos with replica in each data center
  - Most operations are reads
  - For writes, rotating leader – wait turn to propose
- Special quorum rules
  - reads require one replica, can always be local
  - Writes require majority (of data centers) to commit
  - Writes require all replicas before return to client
  - If data center fails, wait for lease expire, then return to client