BigTable: A System for Distributed Structured Storage

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Motivation

- Lots of (semi-)structured data at Google
  - URLs:
    - Contents, crawl metadata, links, anchors, pagerank, …
  - Per-user data:
    - User preference settings, recent queries/search results, …
  - Geographic locations:
    - Physical entities (shops, restaurants, etc.), roads, satellite image data, user annotations, …
- Scale is large
  - billions of URLs, many versions/page (~20K/version)
  - Hundreds of millions of users, thousands of q/sec
  - 100TB+ of satellite image data

Why not just use commercial DB?

- Scale is too large for most commercial databases
- Even if it weren't, cost would be very high
  - Building internally means system can be applied across many projects for low incremental cost
- Low-level storage optimizations help performance significantly
  - Much harder to do when running on top of a database layer

Also fun and challenging to build large-scale systems :)

Goals

- Want asynchronous processes to be continuously updating different pieces of data
  - Want access to most current data at any time
- Need to support:
  - Very high read/write rates (millions of ops per second)
  - Efficient scans over all or interesting subsets of data
  - Efficient joins of large one-to-one and one-to-many datasets
- Often want to examine data changes over time
  - E.g. Contents of a web page over multiple crawls

BigTable

- Distributed multi-level map
  - With an interesting data model
- Fault-tolerant, persistent
- Scalable
  - Thousands of servers
  - Terabytes of in-memory data
  - Petabyte of disk-based data
  - Millions of reads/writes per second, efficient scans
- Self-managing
  - Servers can be added/removed dynamically
  - Servers adjust to load imbalance

Status

- Design/initial implementation started beginning of 2004
- Currently ~100 BigTable cells
- Production use or active development for many projects:
  - Google Print
  - My Search History
  - Orkut
  - Crawling/indexing pipeline
  - Google Maps/Google Earth
  - Blogger
  - …
- Largest bigtable cell manages ~200TB of data spread over several thousand machines (larger cells planned)

Background: Building Blocks

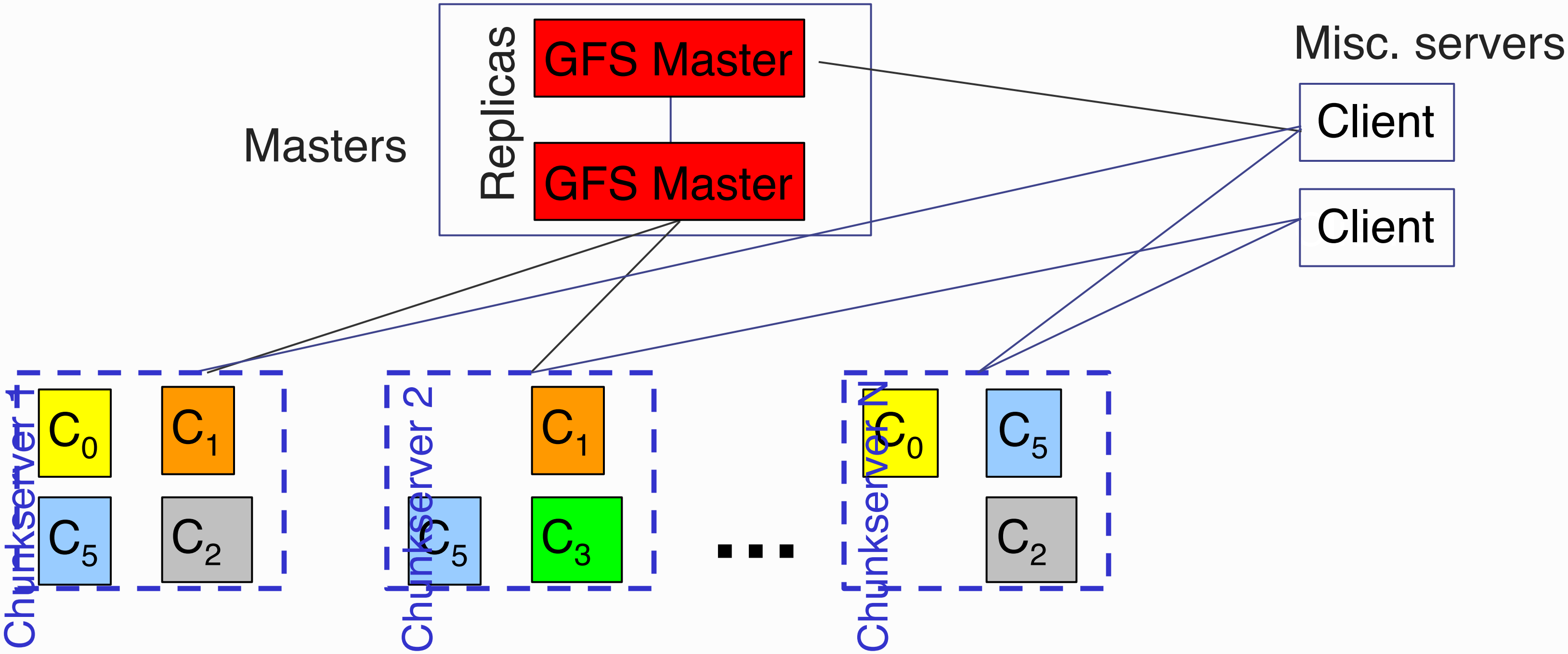
Building blocks:

- Google File System (GFS): Raw storage
- Scheduler: schedules jobs onto machines
- Lock service: distributed lock manager
  - also can reliably hold tiny files (100s of bytes) w/ high availability
- MapReduce: simplified large-scale data processing

BigTable uses of building blocks:

- GFS: stores persistent state
- Scheduler: schedules jobs involved in BigTable serving
- Lock service: master election, location bootstrapping
- MapReduce: often used to read/write BigTable data

Google File System (GFS)



- Master manages metadata
- Data transfers happen directly between clients/chunkservers
- Files broken into chunks (typically 64 MB)
- Chunks triplicated across three machines for safety
- See SOSP'03 paper at http://labs.google.com/papers/gfs.html

Google

MapReduce: Easy-to-use Cycles

Many Google problems: *"Process lots of data to produce other data"*

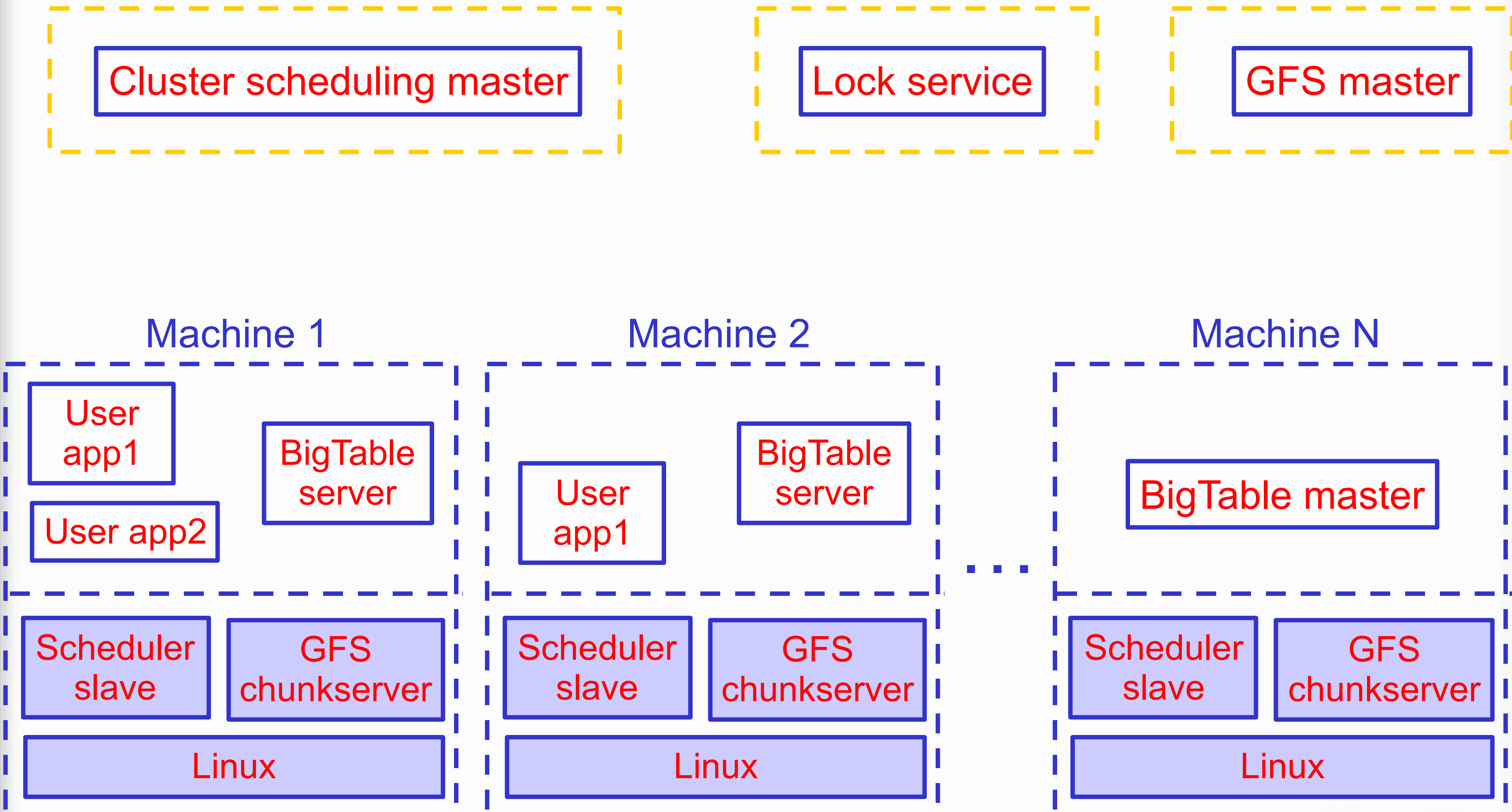
- Many kinds of inputs:
  - Document records, log files, sorted on-disk data structures, etc.
- Want to use easily hundreds or thousands of CPUs

- MapReduce: framework that provides (for certain classes of problems):
  - Automatic & efficient parallelization/distribution
  - Fault-tolerance, I/O scheduling, status/monitoring
  - User writes Map and Reduce functions
- Heavily used: ~3000 jobs, 1000s of machine days each day

See: “MapReduce: Simplified Data Processing on Large Clusters”, OSDI’04

BigTable can be input and/or output for MapReduce computations

Typical Cluster



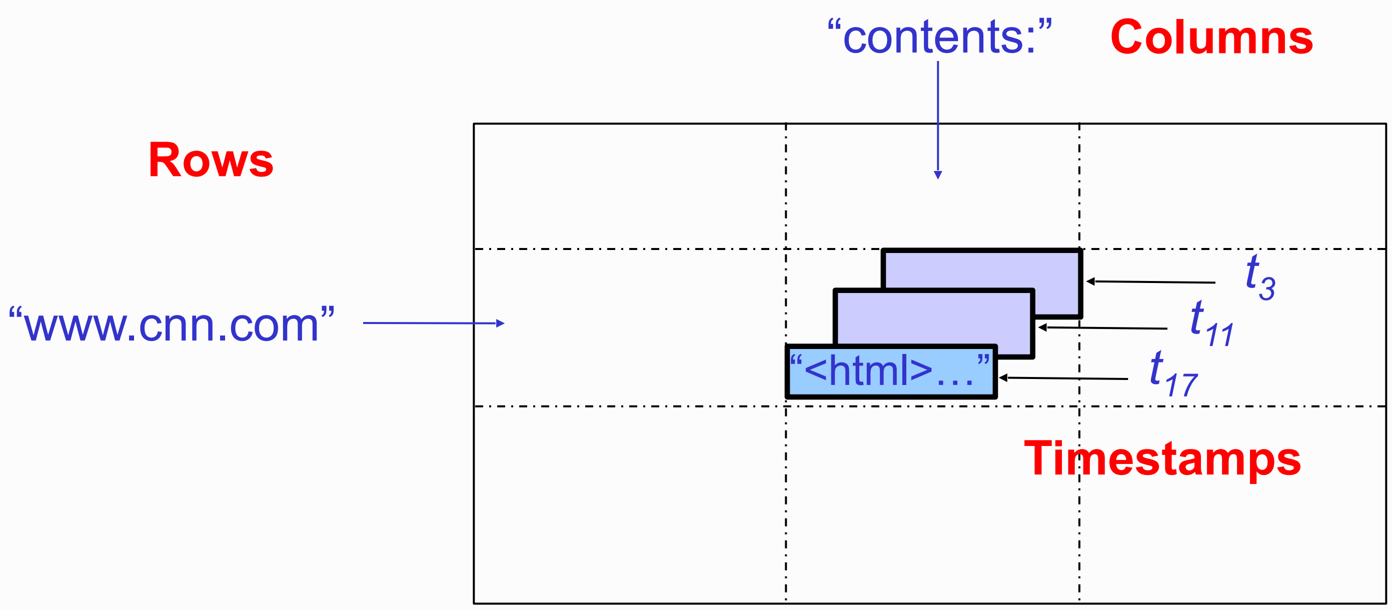
BigTable Overview

- Data Model
- Implementation Structure
  - Tablets, compactions, locality groups, …
- API
- Details
  - Shared logs, compression, replication, …
- Current/Future Work

Basic Data Model

- Distributed multi-dimensional sparse map

  (row, column, timestamp) → cell contents



- Good match for most of our applications

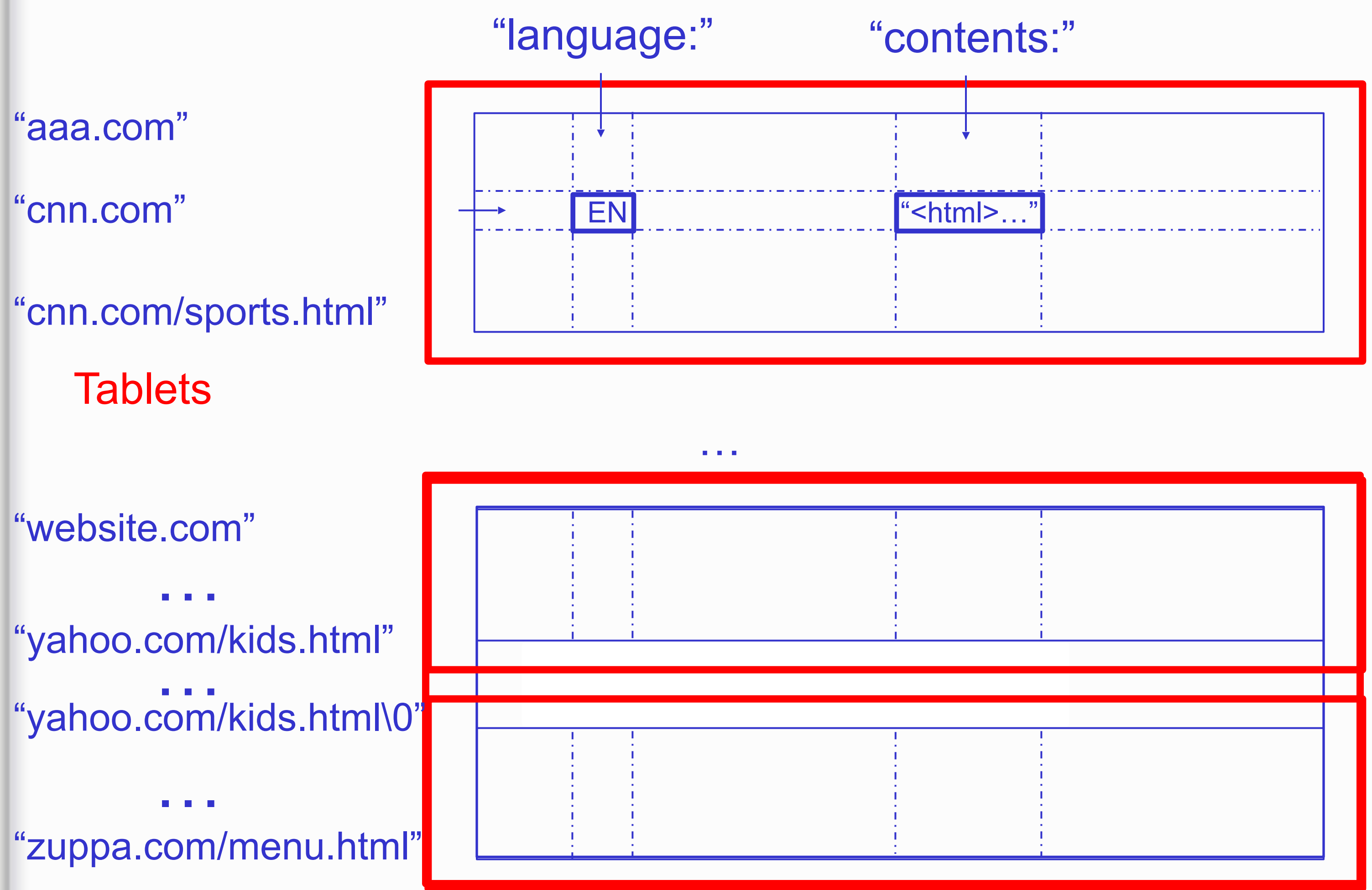
Rows

- Name is an arbitrary string
  - Access to data in a row is atomic
  - Row creation is implicit upon storing data
- Rows ordered lexicographically
  - Rows close together lexicographically usually on one or a small number of machines

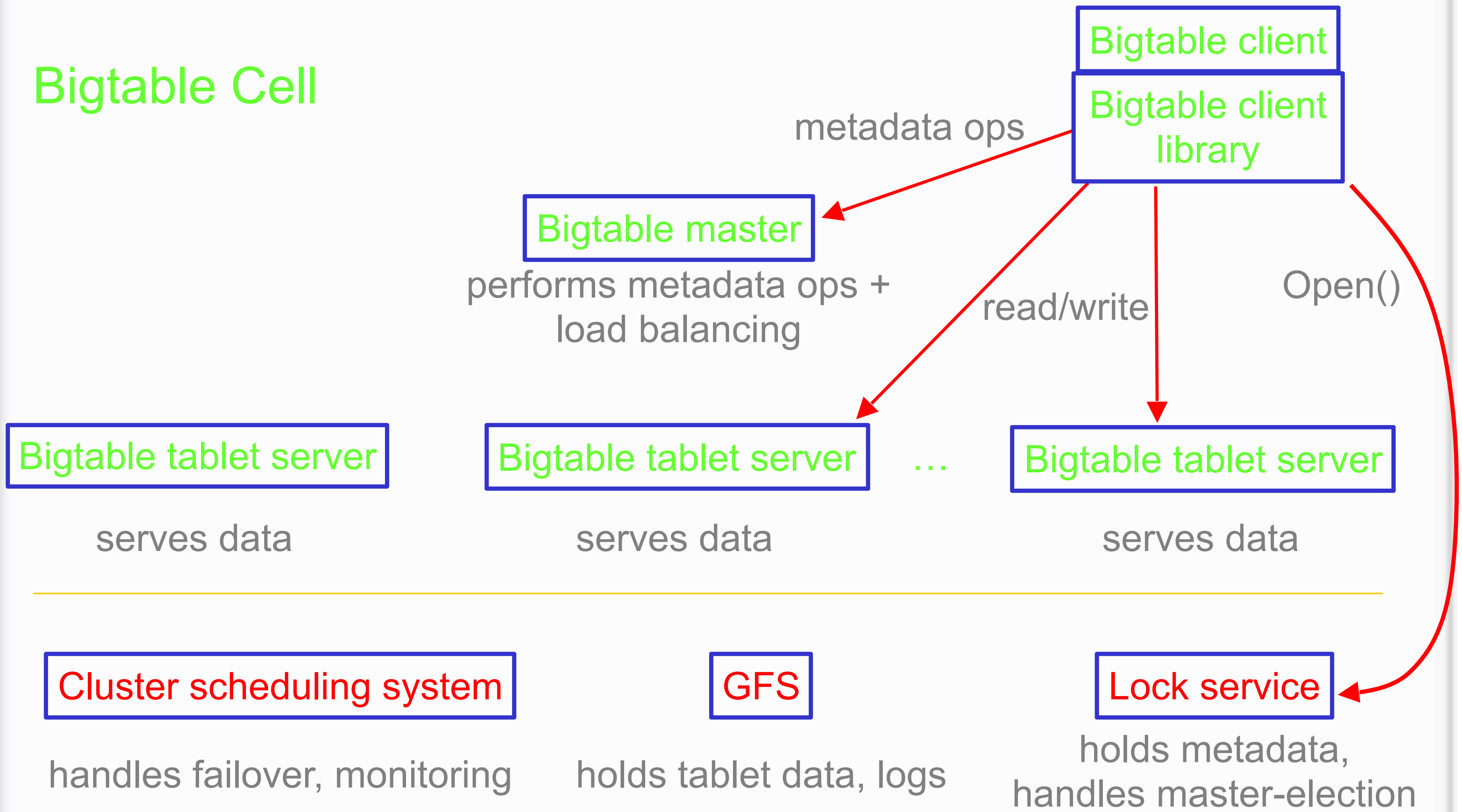
Tablets

- Large tables broken into ***tablets*** at row boundaries
  - Tablet holds contiguous range of rows
    - Clients can often choose row keys to achieve locality
  - Aim for ~100MB to 200MB of data per tablet
- Serving machine responsible for ~100 tablets
  - Fast recovery:
    - 100 machines each pick up 1 tablet from failed machine
  - Fine-grained load balancing:
    - Migrate tablets away from overloaded machine
    - Master makes load-balancing decisions

Tablets & Splitting



System Structure



Locating Tablets

- Since tablets move around from server to server, given a row, how do clients find the right machine?
  - Need to find tablet whose row range covers the target row

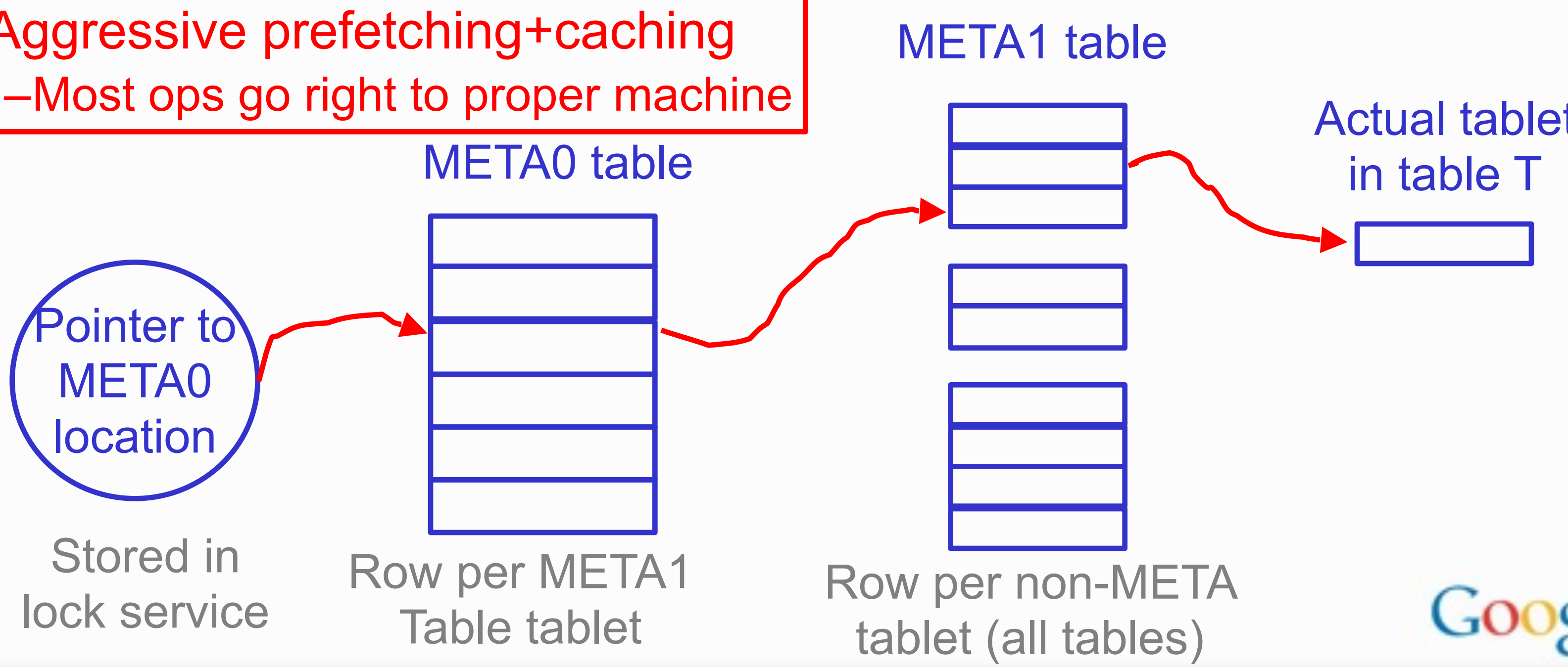
- One approach: could use the BigTable master
  - Central server almost certainly would be bottleneck in large system

- Instead: store special tables containing tablet location info in BigTable cell itself

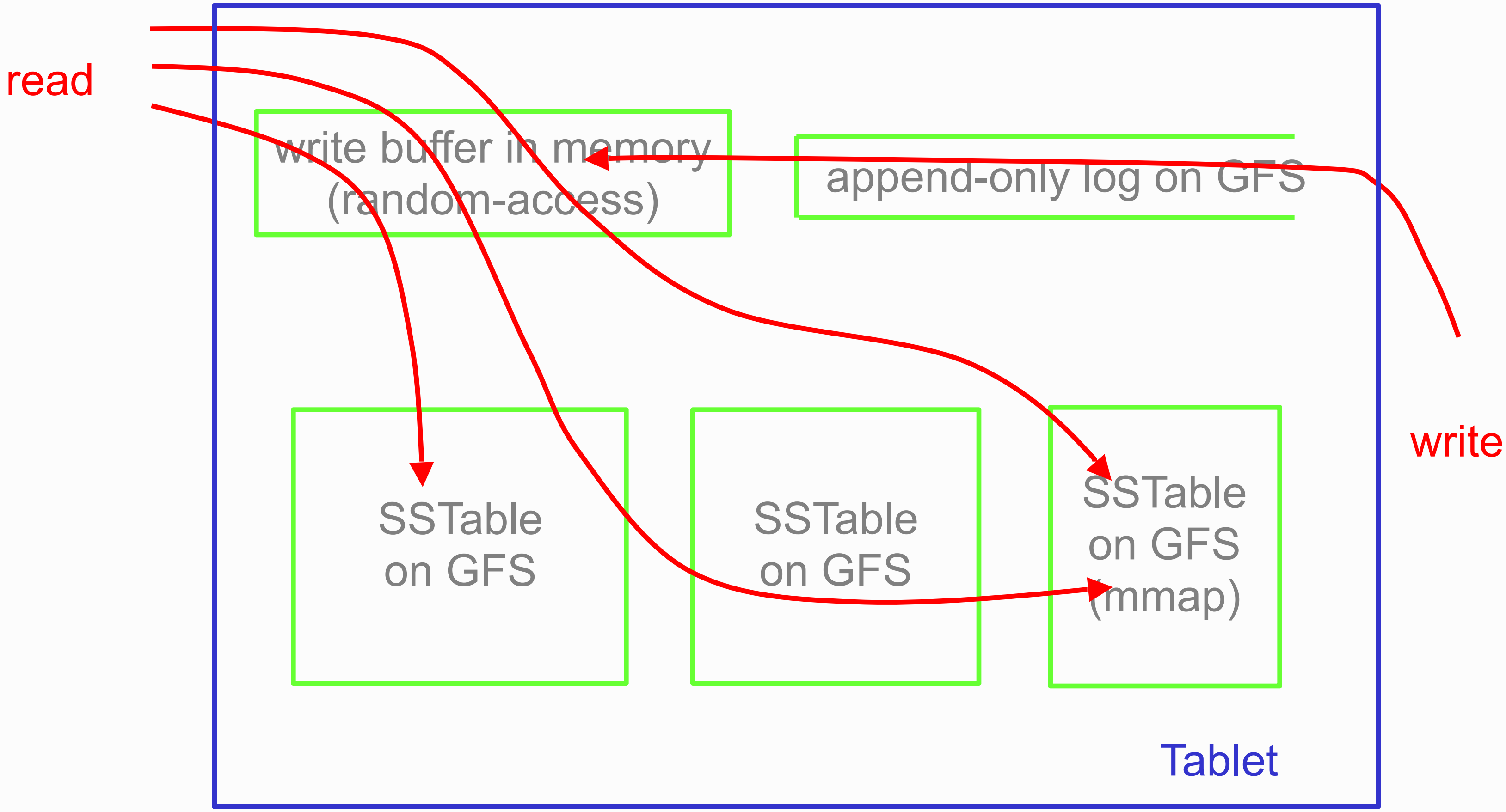
Locating Tablets (cont.)

- Our approach: 3-level hierarchical lookup scheme for tablets
  - Location is *ip:port* of relevant server
  - 1st level: bootstrapped from lock service, points to owner of META0
  - 2nd level: Uses META0 data to find owner of appropriate META1 tablet
  - 3rd level: META1 table holds locations of tablets of all other tables
    - META1 table itself can be split into multiple tablets

- Aggressive prefetching+caching
  - Most ops go right to proper machine



Tablet Representation

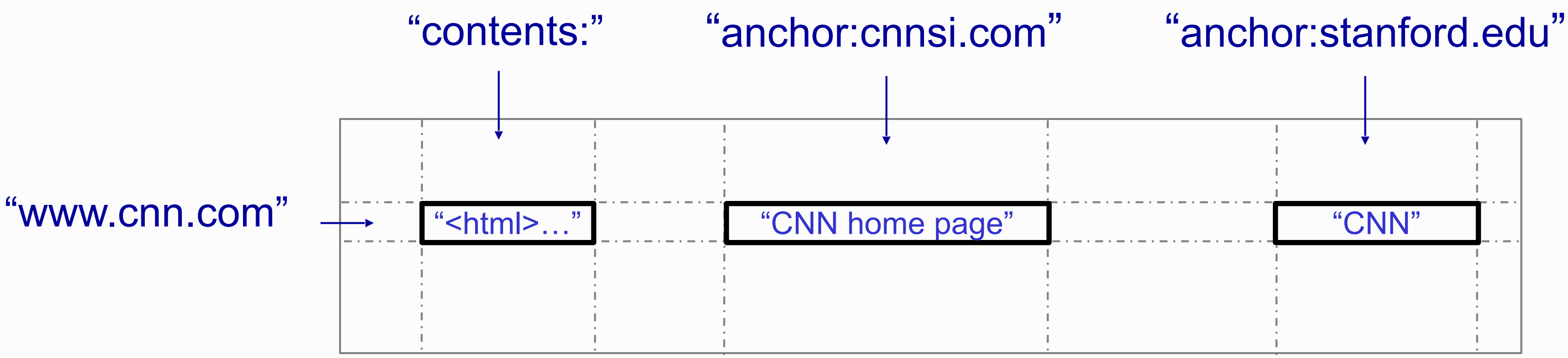


SSTable: Immutable on-disk ordered map from string->string
string keys: *<row, column, timestamp>* triples

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

Columns



- Columns have two-level name structure:
  - family:optional_qualifier
- Column family
  - Unit of access control
  - Has associated type information
- Qualifier gives unbounded columns
  - Additional level of indexing, if desired

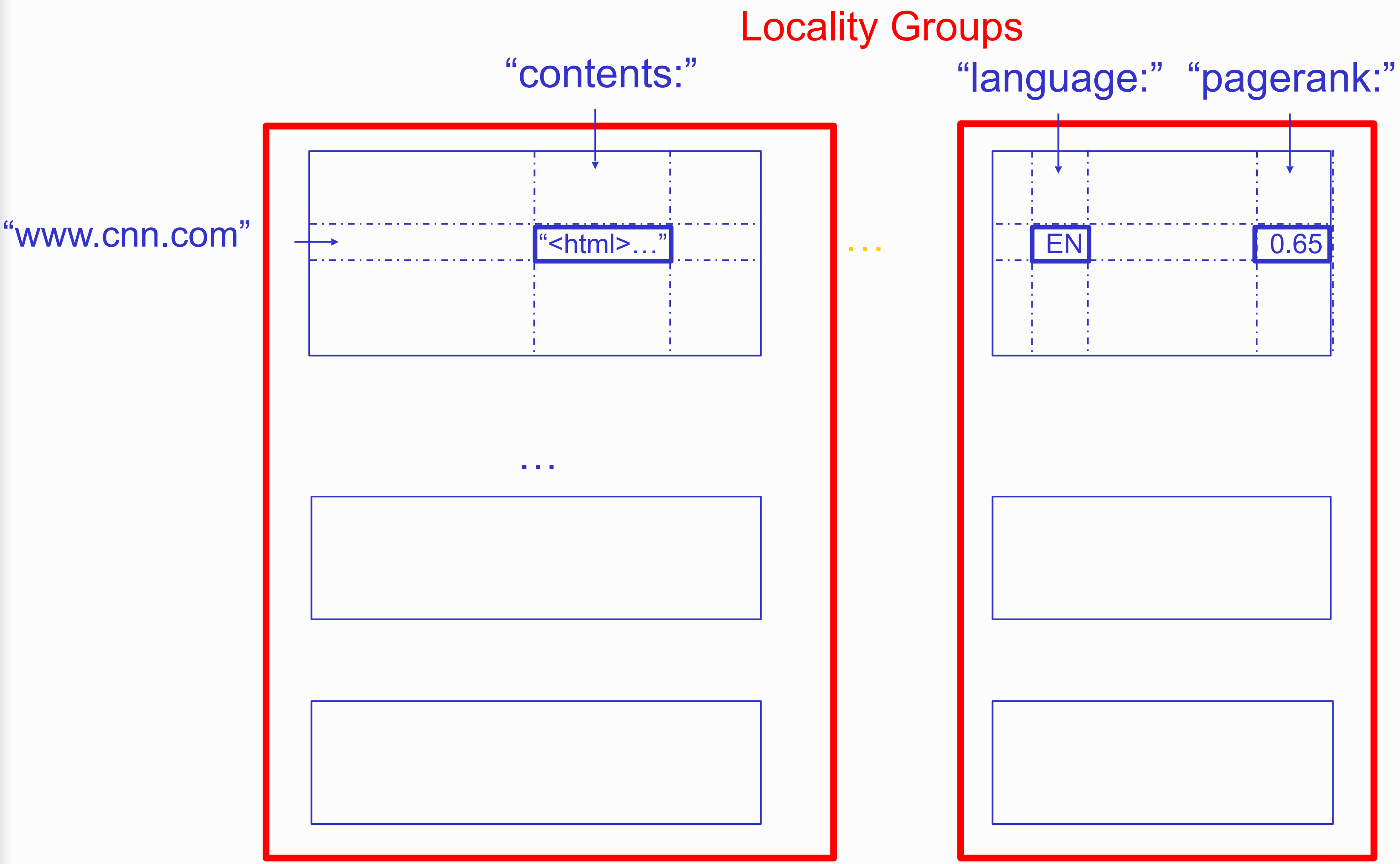
Timestamps

- 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 familes can be marked w/ attributes:
  – *"Only retain most recent K values in a cell"*
  – *"Keep values until they are older than K seconds"*

Locality Groups

- Column families can be assigned to a locality group
  - Used to organize underlying storage representation for performance
    - scans over one locality group are *O(bytes_in_locality_group)* , not *O(bytes_in_table)*
  - Data in a locality group can be explicitly memory-mapped

Locality Groups



Google

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 (64 MB)
- 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

Google

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

- Two building blocks: BMDiff, Zippy

BMDiff

- Bentley, McIlroy DCC'99: "*Data Compression Using Long Common Strings*"
- Input: dictionary + source
- Output: sequence of
  - COPY: <x> bytes from offset <y>
  - LITERAL: <literal text>

- Store hash at every 32-byte aligned boundary in
  - Dictionary
  - Source processed so far
- For every new source byte
  - Compute incremental hash of last 32 bytes
  - Lookup in hash table
  - On hit, expand match forwards & backwards and emit COPY
- Encode: ~ 100 MB/s, Decode: ~1000 MB/s

Zippy

- LZW-like: Store hash of last four bytes in 16K entry table
- For every input byte:
  - Compute hash of last four bytes
  - Lookup in table
  - Emit COPY or LITERAL

- Differences from BMDiff:
  - Much smaller compression window (local repetitions)
  - Hash table is not associative
  - Careful encoding of COPY/LITERAL tags and lengths
- Sloppy but fast:

Algorithm	**% remaining**	**Encoding**	**Decoding**
Gzip	13.4%	21 MB/s	118 MB/s
LZO	20.5%	135 MB/s	410 MB/s
Zippy	22.2%	172 MB/s	409 MB/s

BigTable Compression

- Keys:
  - Sorted strings of (Row, Column, Timestamp): prefix compression
- Values:
  - Group together values by “type” (e.g. column family name)
  - BMDiff across all values in one family
    - BMDiff *output* for values 1..*N* is dictionary for value *N*+1
- Zippy as final pass over whole block
  - Catches more localized repetitions
  - Also catches cross-column-family repetition, compresses keys

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 page contents	2.1	45.1 TB	4.2 TB	9.2%
Links	1.8	11.2 TB	1.6 TB	13.9%
Anchors	126.3	22.8 TB	2.9 TB	12.7%

Google

In Development/Future Plans

- More expressive data manipulation/access
  – Allow sending small scripts to perform read/modify/write transactions so that they execute on server?
- Multi-row (i.e. distributed) transaction support
- General performance work for very large cells
- BigTable as a service?
  – Interesting issues of resource fairness, performance isolation, prioritization, etc. across different clients

Conclusions

- Data model applicable to broad range of clients
  - Actively deployed in many of Google's services
- System provides high performance storage system on a large scale
  - Self-managing
  - Thousands of servers
  - Millions of ops/second
  - Multiple GB/s reading/writing
- More info about GFS, MapReduce, etc.: http://labs.google.com/papers

Google

Backup slides

Bigtable + Mapreduce

- Can use a Scanner as MapInput
  - Creates 1 map task per tablet
  - Locality optimization applied to co-locate map computation with tablet server for tablet
- Can use a bigtable as ReduceOutput