Distributed Storage Systems

Theory and practice

Pietro Michiardi

Eurecom

Introduction

Overview

- The CAP Theorem
- Amazon Dynamo
- Apache HBase
- Apache Cassandra

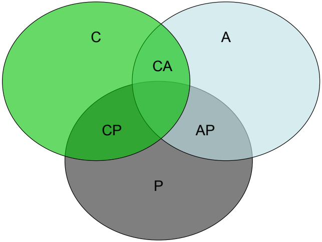
The CAP Theorem

The CAP Theorem

- **Frequently cited distributed systems theorem**
- **Relates the following three properties**
  - C: Consistency
    - One-copy semantics, linearizability, atomicity, total-order
    - Every operation must appear to take effect in a single indivisible point in time between its invocation and response
  - A: Availability
    - Every client's request is served (receives a response) unless a client fails (despite a strict subset of server nodes failing)
  - P: Partition-tolerance
    - A system functions properly even if the network is allowed to lose arbitrarily many messages sent from one node to another

The CAP Theorem

- **In the folklore interpretation, the theorem says:**
  C, A, P: pick two



Precautions: be careful with CA

- **Sacrificing P (partition tolerance)**
- **Negating:** A system functions properly even if the network is allowed to lose arbitrarily many messages sent from one node to another
- **Yields:** A system does not function properly even if the network is allowed to lose arbitrarily many messages sent from one node to another
  - This implies sacrificing C or A, *i.e.,* the system does not work

Precautions: be careful with CA

- **Negating P:** A system function properly if the network is not allowed to lose arbitrarily many messages
- **However, in practice:** It is not possible to choose whether the network will lose messages! This either happens or not
- **One can argue that not "arbitrarily" many messages will be lost**
  - But "a lot" of them might be (before the network repairs)
  - In the meantime, either C or A is sacrificed

CAP in practice

- **In practical distributed systems:**
  - Partitions may occur
  - This is not under your control, as a system designer
- **Designer's choice:**
  - You choose whether you want your system in C or A, when/if (temporary) partitions occur
- **In summary:**
  - CAP is a fundamental theorem stating the tradeoffs among different system properties
  - Practical distributed systems are either in CP or AP
  - **The choice (C vs. A) depends on your application logic**

CAP in theory

- **Historical notes:**
  - First stated by Eric Brewer at the PODC 2000 keynote
  - Formally proved by Gilbert and Lynch, 2002
- **GL Theorems:**
  - Asynchronous / partially synchronous network models
  - Read/Write data objects
  - Finer definitions of Availability and Consistency
- **Further readings:**
  - (Fischer, Lynch and Patterson) FLP impossibility result
  - t-connected CAP

CAP: some illustrative choices

- **CP:**
  - BigTable (Google), HBase, MongoDB, Redis, Memcachedb, ...
  - (sometimes classified in CA) Paxos, Zookeeper, RDBMSs, ...
- **AP:**
  - Amazon Dynamo, CouchDB, Cassandra, SimpleDB, Riak, Voldmort (LinkedIn), ...

Amazon Dynamo

Amazon Web Services

- **Amazon's cloud computing services**
  - S3, EC2, RedShift, SimpleDB, Elastic MR, and many, many more
  - Combined, they allow constructing Internet-scale applications

- **Infrastructure services requirements:**
  - Security, scalability, availability, performance, cost-efficiency
  - Serve millions of customers worldwide, continuously

Amazon Web Services

- **Important observations**
  - No emphasis on consistency
  - AWS is in AP, sacrificing consistency

- **AWS follows the BASE philosophy**
  - BASE vs. ACID
  - Basically Available
  - Soft state
  - Eventually consistent

Why favoring Availability over Consistency?

- **Even the shortest outage has significant financial consequences and impact customer trust**

- **Clearly, consistency violations may as well have a big impact**
  - But not in several Amazon's services
  - Billing is a separate story

Amazon Dynamo

- **Works behind the scenes in the context of AWS**
  - Used to power client-facing services such as S3, and others
  - Used to power internal Amazon services such as: shopping cart, customer session management, product catalog, recommendations, order fulfillment, sales rank, fraud detection, ...

- **What is Dynamo?**
  - Highly available key-value storage system
  - Favors availability over consistency under failures

What is a key-value store?

- **Think about Hash tables or dictionaries**
  - Simple API: **get(key)**, **put(key, value)**
  - Sometimes referred to read/write operations
- **Specifics of Dynamo API**
  - Uses an additional argument to pass a “context”
  - Context holds critical metadata
  - Typically stores small objects (< 1 MB)
- **Specifics of services using Dynamo**
  - Do not need transactions
  - Often need only primary-key access to data

Amazon Dynamo: Features

- **Main characteristics**
  - Low latency
  - Scalable (hundreds of machines)
  - Always-on available (especially for writes)
  - Partition/Fault tolerance
  - Eventually consistent

- **How such features are obtained**
  - General distributed systems toolbox
  - We review some of them here

Amazon Dynamo: Key Techniques (1)

- **Consistent hashing** [Karger97]
  - For data partitioning, replication and load balancing
- **Sloppy Quorums**
  - Boosts availability in presence of failures
  - May result in inconsistent versions of keys (data)

Amazon Dynamo: Key Techniques (2)

- **Vector clocks** [Fidge88/Mantern88]
  - For tracking causal dependencies among different versions of the same key (data)
- **Gossip-based group membership**
  - For maintaining information about alive nodes
- **Anti-entropy protocol based on Merkle trees**
  - Background synchronization of divergent replicas

Amazon Dynamo: Design Decisions

- **Always writable data store**
  - E.g., think shopping cart service
- **How to handle data changes?**
  - Replication, required for fault/disaster tolerance
  - Allow multiple versions of data
  - Reconcile and resolve conflicts during reads
- **How to reconcile data?**
  - Application-side: depending on business logic
  - Dynamo: deterministic, e.g., “last-write” wins

Amazon Dynamo: Architecture

Amazon Dynamo Architecture

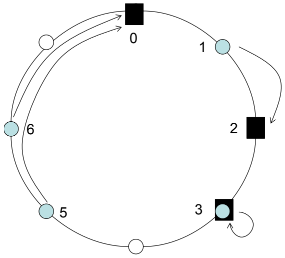
- **Scalable and robust components for:**
  - **Load balancing and data partitioning**
  - **Membership, fault detection**
  - Failure recovery
  - **Replica synchronization**
  - Overload Handling
  - State transfer
  - Concurrency management
  - Scheduling
  - Request marshalling and routing
  - System monitoring
  - Configuration management

Amazon Dynamo: Data Partitioning

- **Data partitioning**
  - Dynamic partitioning of keys over a set of storage nodes
  - Technique used for DHTs, e.g., Chord
- **Consistent Hashing**
  - Hashes of keys give key m-bit identifiers
  - Hashes of nodes give m-bit identifiers
  - Identifiers are ordered in an identifier circle
- **Key assignment to storage nodes**
  - A key is assigned to the closest successor node ID
  - Key k is assigned to the first node whose ID $\geq k$
  - If such node does not exist, navigate the circle and find node with the smallest ID

Consistent Hashing Example

- Assume: $m = 3$ bit, 3 storage nodes (0,2,3), 4 keys (1,3,5,6)



Consistent Hashing: Key Properties (1)

- **Dynamic membership management**
  - Storage nodes can come and go
  - Allows incremental scalability

- **Storage node arrival/departures**
  - *n* `Joins`: all keys previously assigned to node *n*'s successor are now assigned to *n*
  - *n* `Leaves`: all keys currently assigned to node *n* are assigned to its successor

Consistent Hashing: Key Properties (2)

- **Load balancing** [Karger97]
  - Each node is responsible for at most $(1+\epsilon)K/N$ keys
  - When a new node joins, only $O(K/n)$ keys must be moved (optimal)

- **Virtual Nodes**
  - Each physical storage node mapped multiple times to the circle

  $\rightarrow$ Improves load balancing

  $\rightarrow$ Allows heterogeneous storage nodes

Amazon Dynamo: Data Replication

- **Goal: achieve high availability and durability**
  - Each data item (key) replicated at N nodes
  - Virtual nodes: same physical node skipped
  - N is a configurable parameter per Dynamo instance

- **Example:**
  - Assume $N = 3$
  - For key k, B is the "coordinator" node
  - B replicates k to $N - 1$ other successor nodes (C and D)

$\rightarrow$ B, C, D are a **preference list** for k

Amazon Dynamo: Data Versioning (1)

- **Data replication performed after an ACK is sent to a client `put` request**
  - Asynchronous replication
  - May result in inconsistencies under partitions
  - → Read does not return the last value

- **Operations should not be lost!**
  - "Add to cart" should not be rejected but also not forgotten
  - If it is performed when the latest version is not available, then it is performed on a stale version of the data
  - → We may have different version of a key/value pair

Amazon Dynamo: Data Versioning (2)

- **Precautions**
  - Once a partition heals, versions are merged
  - New versions subsume previous ones
  - Applications must be designed with data versionin in mind

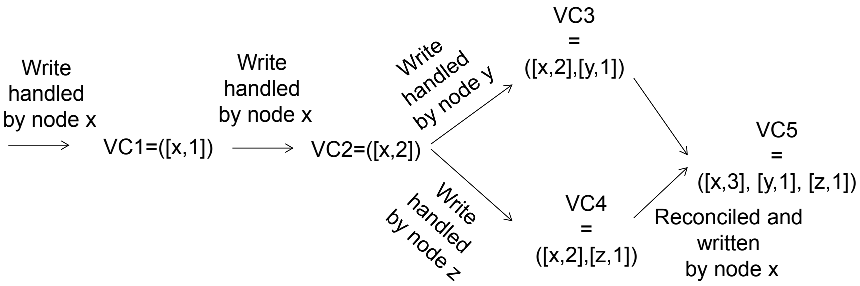
- **Key technique for versioning**
  - Vector clocks
  - Capture causality between different versions of an object

Vector Clocks (in Dynamo) (1)

- **In theory:**
  - Each `write` to a key k associated to a vector clock $VC(k)$
  - $VC(k)$ is an array (map) of integers
  - In theory, one entry $VC(k)[i]$ for each storage node i
  - When node i handles a write for key k it increments $VC(k)[i]$

- **In practice:**
  - $VC(k)$ will not have many entries $\rightarrow$ only node from the preference list should have entries
  - Dynamo truncates entries if more than a threshold

Vector Clocks (in Dynamo) (2)



NB: one VC per key

Anatomy of `put` and `get` operations

- **Storage nodes can receive requests for any key**
  - Generic load balancer may chose a random node, not necessarily the coordinator
  - Application may directly contact the coordinator in a preference list

- **Request routing**
  - Node serves request only if in preference list
  - Otherwise, routes the request to the first node in preference list
  - 0-hop DHT routing: all nodes know all other nodes
  - → Not the most scalable, but excellent for low-latency

- **Extended preference list**
  - Accounts for node failures

Amazon Dynamo: Quorums

- **Two important parameters**
  - R: number of nodes involved in a get
  - W: number of nodes involved in a put
  - Quorum system: $R + W > N$, where N is the number of replicas
- **Handling put (by coordinator)**
  - Generate new VC, write new version locally
  - Send value, VC, to N nodes from preference list
  - Wait for $W - 1$ acknowledgments
- **Handling get (by coordinator)**
  - Send get to N selected nodes from preference list
  - Wait for R responses
  - Select highest versions using VC, reconcile/merge different versions
  - Writeback reconciled version

Choosing R, W

- R, W **smaller than** N
  - To decrease latency
  - Slowest replica dictates query latency
- $W = 1$
  - Always available for writes
  - Yields $R = N \rightarrow$ reads pay the penalty
- **Typical values in Dynamo**
  - $W, R, N = 2, 2, 3$

Handling Failures

- ***N* selected nodes are the first *N* healthy nodes**
  - Might change from request to request
  - Hence the term “sloppy” quorums
- **Sloppy vs. strict quorums**
  - Allow availability under a much wider range of partitions
  - Sacrifice consistency
- **Data-center wide failures**
  - Power outages, cooling failures, network failures, ...
  - Preference lists account for this

Handling Temporary Failures

- **Hinted Handoff**
  - If a replica in the preference list is down, then a new replica is created on a new node
  - Coordinator selects a new replica node, but hints that the role is temporary
  - When the new replica learns about failure recovery, it handles data to the node in the preference list

Amazon Dynamo: Anti-Entropy Synchronization

- **Uses Merkle Trees**
  - A tree in which every non-leaf node is labelled with the hash of the labels of its children nodes

- **Storage nodes**
  - Keep a Merkle tree for each of its key ranges (virtual nodes)
  - Compare root of the tree with replicas
  - If equal, replicas are in sync
  - Otherwise, traverse the tree and synchronize keys that differ

Amazon Dynamo: Membership Management

- **Membership management initiated by administrator**

- **Gossip protocol to propagate membership changes**
  - Nodes contact a random node every second
  - 2 nodes reconcile membership information
  - Gossiping also used to handle metadata

Failure Detection

- **Unreliable failure detection**
  - Detection is triggered by read/write requests
  - Called “in-band” failure detection
  - → No dedicated component

- **Example:**
  - With steady load on node A
  - Node A periodically checks the status of nodes in the extended preference list
  - Does not make the distinction between faults and partitions

Amazon Dynamo: Summary

- **Eventually consistent, highly available key value store**
  - In the CAP space, it is in AP
- **Focuses on low-latency**
  - Writes are super fast
  - Reconciliation in reads
- **Built atop of fundamental techniques in distributed systems**
  - Consistent hashing
  - Sloppy quorum-based replication
  - Merkle-tree based synchronization
  - Vector clocks, and gossip membership management

HBASE

Introduction

Why yet another storage architecture?

- **Relational Databse Management Systems (RDBMS)**:
  - Around since 1970s
  - Countless examples in which they actually do make sense
- **The dawn of Big Data**:
  - Previously: ignore data sources because no cost-effective way to store everything
    - One option was to prune, by retaining only data for the last *N* days
  - Today: store everything!
    - Pruning fails in providing a base to build useful mathematical models

Batch processing

- **Hadoop and MapReduce**:
  - Excels at storing (semi- and/or un-) structured data
  - Data interpretation takes place at analysis-time
  - Flexibility in data classification
- **Batch processing: A complement to RDBMS**
  - Scalable sink for data, processing launched when time is right
  - Optimized for large file storage
  - Optimized for “streaming” access
- **Random Access**:
  - Users need to “interact” with data, especially that “crunched” after a MapReduce job
  - This is historically where RDBMS excel: random access for structured data

Column-Oriented Databases

- **Data layout**:
  - Save their data grouped by columns
  - Subsequent column values are stored contiguously on disk
  - This is substantially different from traditional RDBMS, which save and store data by row

- **Specialized databases for specific workloads**:
  - Reduced I/O
  - Better suited for compression $\rightarrow$ Efficient use of bandwidth
    - Indeed, column values are often very similar and differ little row-by-row
  - Real-time access to data

- **Important NOTE**:
  - HBase is not a column-oriented DB in the typical term
  - HBase uses an on-disk column storage format
  - Provides key-based access to specific cell of data, or a sequential range of cells

Column-Oriented and Row-Oriented storage layouts

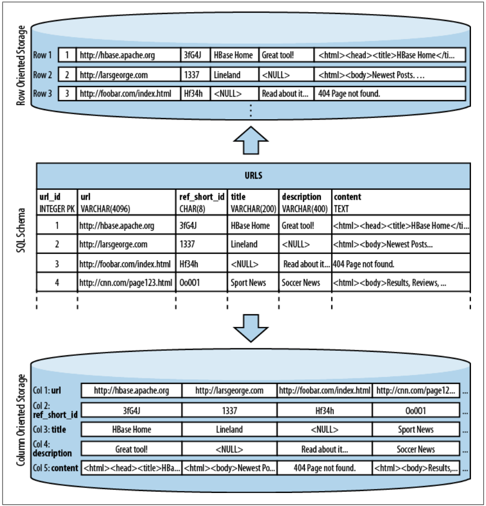


Figure: Example of Storage Layouts

The Problem with RDBMS

- **RDBMS are still relevant**
  - Persistence layer for frontend application
  - Store relational data
  - Works well for a limited number of records
- **Example: Hush**
  - Used throughout this course
  - URL shortener service
- **Let's see the "scalability story" of such a service**
  - Assumption: service must run with a reasonable budget

The Problem with RDBMS

- **Few thousands users: use a LAMP stack**
  - *Normalize data*
  - Use foreign keys
  - Use Indexes

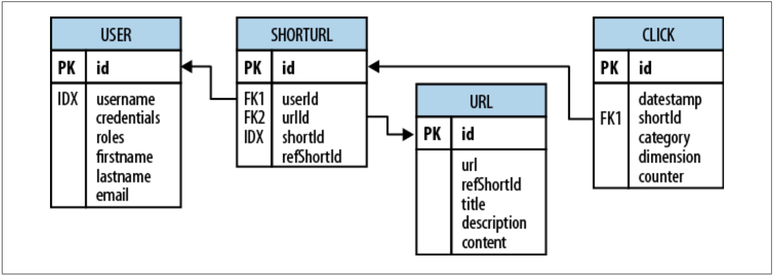


Figure: The Hush Schema expressed as an ERD

The Problem with RDBMS

- **Find all short URLs for a given user**
  - `JOIN` `user` and `shorturl` tables
  - Use the `WHERE` clause to select the given user
- **Stored Procedures**
  - Consistently update data from multiple clients
  - Underlying DB system guarantees coherency
- **Transactions**
  - Make sure you can update tables in an *atomic* fashion
  - RDBMS $\rightarrow$ *Strong Consistency* (ACID properties)
  - *Referential Integrity*

The Problem with RDBMS

- **Scaling up to tens of thousands of users**
  - Increasing pressure on the database server
  - Adding more application servers is easy: they share their state on the same central DB
  - CPU and I/O start to be a problem on the DB

- **Master-Slave architecture**
  - Add DB server so that `READS` can be served in parallel
  - Master DB takes all the writes (which are fewer in the Hush application)
  - Slaves DB replicate Master DB and serve all reads (but you need a load balancer)

The Problem with RDBMS

- **Scaling up to hundreds of thousands**
  - `READS` are still the bottlenecks
  - Slave servers begin to fall short in serving clients requests
- **Caching**
  - Add a caching layer, e.g. Memcached or Redis
  - Offload `READS` to a fast in-memory system

  → You lose consistency guarantees

  → Cache invalidation is critical for having DB and Caching layer consistent

The Problem with RDBMS

- **Scaling up more**
  - `WRITES` are the bottleneck
  - The master DB is hit too hard by `WRITE` load
  - *Vertical scalability*: beef up your master server
  - $\rightarrow$ This becomes costly, as you may also have to replace your RDBMS

- **SQL `JOINs` becomes a bottleneck**
  - Schema de-normalization
  - Cease using stored procedures, as they become slow and eat up a lot of server CPU
  - Materialized views (they speed up `READS`)
  - Drop secondary indexes as they slow down `WRITES`

The Problem with RDBMS

- **What if your application needs to further scale up?**
  - Vertical scalability vs. Horizontal scalability
- **Sharding**
  - Partition your data across multiple databases
    - ★ Essentially you break horizontally your tables and ship them to different servers
    - ★ This is done using fixed boundaries
    - → Re-sharding to achieve load-balancing
  - → This is an operational nightmare
  - Re-sharding takes a huge toll on I/O resources

Non-Relational DataBases

- **They originally do not support SQL**
  - In practice, this is becoming a thin line to make the distinction
  - One difference is in the data model
  - Another difference is in the consistency model (ACID and transactions are generally sacrificed)

- **Consistency models and the CAP Theorem**
  - Strict: all changes to data are atomic
  - Sequential: changes to data are seen in the same order as they were applied
  - Causal: causally related changes are seen in the same order
  - Eventual: updates propagates through the system and replicas when in steady state
  - Weak: no guarantee

Dimensions to classify NoSQL DBs

- **Data model**
  - How the data is stored: key/value, semi-structured, column-oriented, ...
  - How to access data?
  - Can the schema evolve over time?
- **Storage model**
  - In-memory or persistent?
  - How does this affect your access pattern?
- **Consistency model**
  - Strict or eventual?
  - This translates in how fast the system handles `READS` and `WRITES` [2]

Dimensions to classify NoSQL DBs

- **Physical Model**
  - Distributed or single machine?
  - How does the system scale?
- **Read/Write performance**
  - Top-down approach: understands well the workload!
  - Some systems are better for `READS`, other for `WRITES`
- **Secondary indexes**
  - Does your workload require them?
  - Can your system emulate them?

Dimensions to classify NoSQL DBs

- **Failure Handling**
  - How each data store handle server failures?
  - Is it able to continue operating in case of failures?
    - This is related to Consistency models and the CAP theorem
  - Does the system support “hot-swap”?

- **Compression**
  - Is the compression method pluggable?
  - What type of compression?

- **Load Balancing**
  - Can the storage system seamlessly balance load?

Dimensions to classify NoSQL DBs

- **Atomic `read-modify-write`**
  - Easy in a centralized system, difficult in a distributed one
  - Prevent race conditions in multi-threaded or shared-nothing designs
  - Can reduce client-side complexity

- **Locking, waits and deadlocks**
  - Support for multiple client accessing data simultaneously
  - Is locking available?
  - Is it wait-free, hence deadlock free?

Impedance Match

"One-size-fits-all" has been long dismissed: need to find the perfect match for your problem.

Database (De-)Normalization

- **Schema design at scale**
  - A good methodology is to apply the DDI principle [8]
    - Denormalization
    - Duplication
    - Intelligent Key design

- **Denormalization**
  - Duplicate data in more than one table such that at `READ` time no further aggregation is required

- **Next: an example based on Hush**
  - How to convert a classic relational data model to one that fits HBase

Example: Hush - from RDBMS to HBase

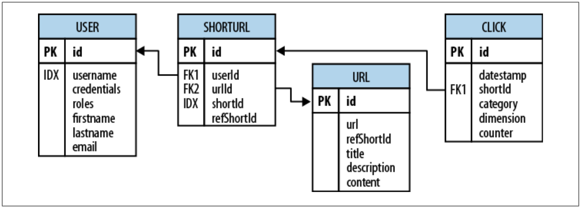


Figure: The Hush Schema expressed as an ERD

- `shorturl` table: contains the short URL
- `click` table: contains click tracking, and other statistics, aggregated on a daily basis (essentially, a counter)
- `user` table: contains user information
- `URL` table: contains a replica of the page linked to a short URL, including META data and content (this is done for batch analysis purposes)

Example: Hush - from RDBMS to HBase

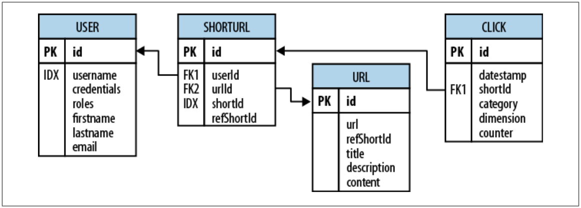


Figure: The Hush Schema expressed as an ERD

- `user` table is indexed on the `username` field, for fast user lookup
- `shorturl` table is indexed on the short URL (`shortId`) field, for fast short URL lookup

Example: Hush - from RDBMS to HBase

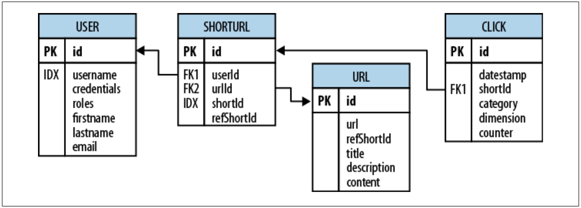


Figure: The Hush Schema expressed as an ERD

- `shorturl` and `user` tables are related through a foreign key relation on the `userId`
- `URL` table is related to `shorturl` table with a foreign key on the URL id
- `click` table is related to `shorturl` table with a foreign key on the short URL id
- NOTE: a web page is stored only once (even if multiple users link to it), but each users maintain separate statistics

Example: Hush - from RDBMS to HBase

Table: shorturl		
Row Key:	shortId	
Family:	data:	Columns: url, refShortId, userId, clicks
	stats-daily: **[ttl: 7days]**	Columns: YYYYMMDD, YYYYMMDD\x00<country-code>
	stats-weekly: **[ttl: 4weeks]**	Columns: YYYYWW, YYYYWW\x00<country-code>
	stats-monthly: **[ttl: 12months]**	Columns: YYYYMM, YYYYMM\x00<country-code>

Table: url		
Row Key:	MD5(url)	
Family:	data: **[compressed]**	Columns: refShortId, title, description
	content: **[compressed]**	Columns: raw

Table: user-shorturl		
Row Key:	username\x00shortId	
Family:	data:	Columns: timestamp

Table: user		
Row Key:	username	
Family:	data:	Columns: credentials, roles, firstname, lastname, email

Figure: The Hush Schema in HBase

- `shorturl` table: stores each short URL, usage statistics (various time-ranges in separate *column-families* with distinct *TTL* settings)
  - Note the dimensional postfix appended to the time information
- `url` table: stores the downloaded page, and the extracted details
  - This table uses compression

Example: Hush - from RDBMS to HBase

Table: shorturl		
Row Key:	shortId	
Family:	data:	Columns: url, refShortId, userId, clicks
	stats-daily: **[ttl: 7days]**	Columns: YYYYMMDD, YYYYMMDD\x00<country-code>
	stats-weekly: **[ttl: 4weeks]**	Columns: YYYYWW, YYYYWW\x00<country-code>
	stats-monthly: **[ttl: 12months]**	Columns: YYYYMM, YYYYMM\x00<country-code>

Table: url		
Row Key:	MD5(url)	
Family:	data: **[compressed]**	Columns: refShortId, title, description
	content: **[compressed]**	Columns: raw

Table: user-shorturl		
Row Key:	username\x00shortId	
Family:	data:	Columns: timestamp

Table: user		
Row Key:	username	
Family:	data:	Columns: credentials, roles, firstname, lastname, email

Figure: The Hush Schema in HBase

- `user-shorturl` table: this is a lookup table (basically an index) to find all shortIDs for a given user
  - Note that this table is filled at *insert time*, it's not automatically generated by HBase
- `user` table: stores user details

Example: Hush - RDBMS vs HBase

- **Same number of tables**
  - Their meaning is different
  - `click` table has been absorbed by the `shorturl` table
  - statistics are stored with the date as the key, so that they can be accessed *sequentially*
  - The `user-shorturl` table is replacing the foreign key relationship, making user-related lookups faster

- **Normalized vs. De-normalized data**
  - Wide tables and column-oriented design eliminates `JOINs`
  - *Compound keys* are essential
  - Data partitioning is based on keys, so a proper understanding thereof is essential

HBase building blocks

- **The backdrop: BigTable**
  - GFS, The Google FileSystem [6]
  - Google MapReduce [4]
  - BigTable [3]

- **What is BigTable?**
  - BigTable is a distributed storage system for managing structured data designed to scale to a very large size
  - BigTable is a sparse, distributed, persistent multi-dimensional sorted map

- **What is HBase?**
  - Essentially it's an open-source version of BigTable
  - Differences listed in [5]

HBase building blocks

Tables, Rows, Columns, and Cells

- **The most basic unit in HBase is a *column***
  - Each column may have multiple versions, with each distinct value contained in a separate *cell*
  - One or more columns form a *row*, that is addressed uniquely by a *row key*

- A table is a collection of rows
  - All rows are always *sorted lexicographically* by their row key

```
hbase(main):001:0> scan 'table1'
ROW                           COLUMN+CELL
row-1                          column=cf1:, timestamp=1297073325971 ...
row-10                         column=cf1:, timestamp=1297073337383 ...
row-11                         column=cf1:, timestamp=1297073340493 ...
row-2                          column=cf1:, timestamp=1297073329851 ...
row-22                         column=cf1:, timestamp=1297073344482 ...
row-3                          column=cf1:, timestamp=1297073333504 ...
row-abc                        column=cf1:, timestamp=1297073349875 ...
7 row(s) in 0.1100 seconds
```

HBase building blocks

Tables, Rows, Columns, and Cells

- **Lexicographical ordering of row keys**
  - Keys are compared on a binary level, byte by byte, from left to right
  - This can be thought of as a primary index on the row key!
  - Row keys are *always unique*
  - Row keys can be any *arbitrary array of bytes*
- **Columns**
  - Rows are composed of columns
  - Can have millions of columns
  - Can be compressed or tagged to stay in memory

HBase building blocks

Tables, Rows, Columns, and Cells

- **Column Families**
  - Columns are grouped into *column families*
  - → Semantical boundaries between data
  - Column families and columns stored together in the same low-level storage file, called an *HFile*
  - Defined when table is created
  - Should not be changed too often
  - The number of column families should be reasonable [WHY?]
  - Column family name composed by printable characters

- **References to columns**
  - Column “name” is called `qualifier`, and can be any arbitrary number of bytes
  - Reference: `family:qualifier` (also called the column key)

HBase building blocks

Tables, Rows, Columns, and Cells

- **A note on the `NULL` value**
  - In RDBMS `NULL` cells need to be set and occupy space
  - In HBase, `NULL` cells or columns are simply not stored

- **A *cell***
  - Every column value, or cell, is timestamped (implicitly or explicitly)
    - This can be used to save multiple versions of a value that changes over time
    - Versions are stored in decreasing timestamp, most recent first
  - Cell versions can be constrained by *predicate deletions*
    - Keep only values from the last week

HBase building blocks

Tables, Rows, Columns, and Cells

- **Access to data**
  - `(Table, RowKey, Family, Column, Timestamp)` → `Value`
  - `SortedMap<RowKey, List<SortedMap<Column, List<Value, Timestamp>>>>`

  - The first `SortedMap` is the table, containing a `List` of column families
  - The families contain another `SortedMap`, representing columns and a `List` of value, timestamp tuples

- **A note on consistency:**
  - Row data access is **atomic** and includes any number of columns
  - There is no further guarantee or transactional feature spanning multiple rows

  → HBase is strictly consistent

HBase building blocks

Automatic Sharding

- **Region**
  - This is the basic unit of scalability and load balancing
  - Regions are contiguous ranges of rows “stored together” $\rightarrow$ they are the equivalent of *range partitions* in sharded RDBMS
  - Regions are *dynamically split* by the system when they become too large
  - Regions can also be merged to reduce the number of storage files

- **Regions in practice**
  - Initially, there is one region
  - System monitors region size: if a threshold is attained, `SPLIT`
    - Regions are split in two at the *middle key*
    - This creates roughly two equivalent (in size) regions

HBase building blocks

Automatic Sharding

- **Region Servers**
  - Each region is served by *exactly one Region Server*
  - Region servers can serve multiple regions
  - The number of region servers and their sizes depend on the capability of a single region server
- **Server failures**
  - Regions allow for fast recovery upon failure
  - Fine-grained Load Balancing is also achieved using regions as they can be easily moved across servers

HBase building blocks

Storage API

- **No support for SQL**
  - CRUD operations using a standard API, available for many “clients”
  - Data access is not declarative but imperative
- **Scan API**
  - Allows for fast iteration over ranges of rows
  - Allows to limit the number and which column are returned
  - Allows to control the version number of each cell
- **Read-modify-write API**
  - HBase supports single-row transactions
  - Atomic read-modify-write on data stored in a single row key

HBase building blocks

Storage API

- **Counters**
  - Values can be interpreted as counters and **updated atomically**
  - Can be read and modified in one operation
  - $\rightarrow$ Implement global, strictly consistent, sequential counters

- **Coprocessors**
  - These are equivalent to stored-procedures in RDBMS
  - Allow to push user code in the address space of the server
  - Access to server local data
  - Implement lightweight batch jobs, data pre-processing, data summarization

HBase building blocks

HBase implementation

- **Data Storage**
  - *Store* files are called `HFiles`
  - Persistent and ordered **immutable** maps from key to value
  - Internally implemented as sequences of blocks with an index at the end
  - Index is loaded when the `HFile` is opened and kept in memory
- **Data lookups**
  - Since `HFiles` have a block index, lookup can be done with a single disk seek
  - First, the block possibly containing a given lookup key is determined with a **binary search** in the in-memory index
  - Then a block read is performed to find the actual key
- **Underlying file system**
  - Many are supported, usually HBase deployed on top of HDFS

HBase building blocks

HBase implementation

- **`WRITE` operation**
  - First, data is written to a commit log, called WAL (write-ahead-log)
  - Then data is moved into memory, in a structure called `memstore`
  - When the size of the `memstore` exceeds a given threshold it is flushed to an `HFile` to disk
- **How can HBase write, while serving `READS` and `WRITES`?**
  - Rolling mechanism
    - new/empty slots in the `memstore` take the updates
    - old/full slots are flushed to disk
  - Note that data in `memstore` is sorted by keys, matching what happens in the `HFiles`
- **Data Locality**
  - Achieved by the system looking up for server hostnames
  - Achieved through intelligent key design

HBase building blocks

HBase implementation

- **Deleting data**
  - Since HFiles are immutable, how can we delete data?
  - A delete marker (also known as *tombstone marker*) is written to indicate that a given key is deleted
  - During the read process, data marked as deleted is skipped
  - Compactions (see next slides) finalize the deletion process

- **`READ` operation**
  - Merge of what is stored in the `memstores` (data that is not on disk) and in the `HFiles`
  - The WAL is never used in the `READ` operation
  - Several API calls to read, scan data

HBase building blocks

HBase implementation

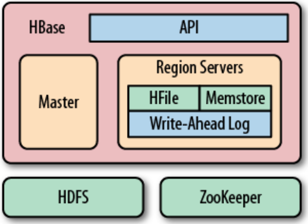
- **Compactions**
  - Flushing data from `memstores` to disk implies the creation of new `HFiles` each time
  - $\rightarrow$ We end up with many (possibly small) files
  - $\rightarrow$ We need to do housekeeping [WHY?]

- **Minor Compaction**
  - Rewrites small `HFiles` into fewer, larger `HFiles`
  - This is done using an *n*-way merge[1]

- **Major Compaction**
  - Rewrites all files within a column family or a region in a new one
  - Drop deleted data
  - Perform predicated deletion (e.g. delete old data)

[1] What is MergeSort?

HBase: a glance at the architecture



- **Master node: `HMaster`**
  - Assigns regions to region servers using ZooKeeper
  - Handles load balancing
  - Not part of the data path
  - Holds metadata and schema
- **Region Servers**
  - Handle `READs` and `WRITEs`
  - Handle region splitting

Architecture

Seek vs. Transfer

- **Fundamental difference between RDBMS and alternatives**
  - B+Trees
  - Log-Structured Merge Trees

- **Seek vs. Transfer**
  - Random access to individual cells
  - Sequential access to data

B+ Trees

- **Dynamic, multi-level indexes**
  - Efficient insertion, lookup and deletion
  - Q: What's the difference between a B+ Tree and a Hash Table?
  - Frequent updates may imbalance the trees $\rightarrow$ Tree optimization and re-organization is required (which is a costly operation)
- **Bounds on *page size***
  - Number of keys in each branch
  - Larger fanout compared to binary trees
  - Lower number of I/O operations to find a specific key
- **Support for range scans**
  - Leafs are linked and represent an in-order list of all keys
  - No costly tree-traversal algorithms required

LSM-Trees

- **Data flow**
  - Incoming data is first stored in a logfile, *sequentially*
  - Once the log has the modification saved, data is pushed in memory
    - In-memory store holds most recent updates for fast lookup
  - When memory is "full", data is flushed in a store file to disk, as a sorted list of `key` $\rightarrow$ `record` pair
  - At this point, the log file can be thrown away

- **How store files are arranged**
  - Similar idea of a B+ Tree, but optimized for sequential disk access
  - All nodes of the tree try to be filled up completely
  - Updates are done in a **rolling merge** fashion
    - The system packs existing on-disk multi-page blocks with in-memory data until the block reaches full capacity

LSM-Trees

- **Clean-up process**
  - As flushes take place over time, a lot of store files are created
  - Background process aggregates files into larger ones to limit disk seeks
  - All store files are always sorted by key $\rightarrow$ no re-ordering required to fit new keys in

- **Data Lookup**
  - Lookups are done in a merging fashion
    - First lookup in the in-memory store
    - If miss, the lookup in the on-disk store

- **Deleting data**
  - Use a *delete marker*
  - When pages are re-written, deleted markers and keys are eventually dropped
  - Predicate deletion happens here

B+ Tree vs. LSM-Trees

- **B+ Tree [1]**
  - Work well when there are not so many updates
  - The more and the faster you insert data at random locations the faster pages get fragmented
  - **Updates and deletes are done at disk seek rates, rather than transfer rates**

- **LSM-Tree [7]**
  - Work at disk transfer rate and scale better to huge amounts of data
  - Guarantee a consistent insert rate
    - They transform random into sequential writes
  - Reads are independent from writes
  - Optimized data layout which offers predictable boundaries on disk seeks

Storage

Overview

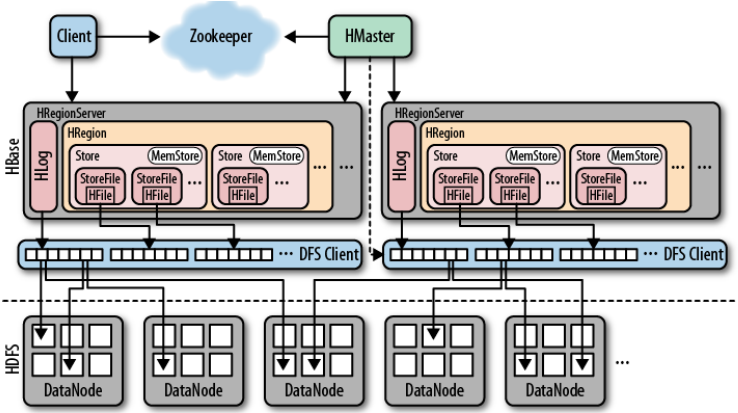


Figure: Overview of how HBase handles files in the filesystem

Storage

Overview

- **HBase handles two kinds of file types**
  - One is used for the WAL
  - One is used for the actual data storage

- **Who does what**
  - `HMaster`
    - Low-level operations
    - Assigns region servers to key space
    - Keeps metadata
    - Talks to ZooKeeper
  - `HRegionServer`
    - Handles the WAL and `HFiles`
    - These files are divided in to blocks and stored into HDFS
    - Block size is a parameter

Storage

Overview

- **General communication flow**
  - A client contacts ZooKeeper when trying to access a particular row
  - Recovers from ZooKeeper the server name that host the `-ROOT-` region
  - Using the `-ROOT-` information the client retrieves the server name that host the `.META.` table region
    - The `.META.` table region contains the row key in question
  - Contact the reported `.META.` server and retrieve the server name that has the region containing the row key in question
- **Caching**
  - Generally, lookup procedures involve caching row key locations for faster subsequent lookups

Storage

Overview

- **Important Java Classes**
  - `HRegionServer` handles one or more regions and create the corresponding `HRegion` object
  - When an `HRegion` object is opened it creates a `Store` instance for each `HColumnFamily`
  - Each `Store` instance can have:
    - One or more `StoreFile` instances
    - A `MemStore` instance
  - `HRegionServer` has a shared `HLog` instance

Storage

Write Path

- **External client insert data in HBase**
  - Issues an `HTable.put(Put)` request to `HRegionServer`
  - `HRegionServer` hands the request to the `HRegion` instance that matches the request [Q: What is the matching criteria?]

- **How the system reacts to a write request**
  - Write data to the WAL, represented by the `HLog` class
    - The WAL stores `HLogKey` instances in a HDFS `SequenceFile`
    - These keys contain a sequence number and the actual data
    - In case of failure, this data can be used to replay not-yet-persisted data
  - Copy data in the `MemStore`
    - Check if MemStore size has reached a threshold
    - If yes, launch a *flush request*
    - Launch a thread in the `HRegionServer` and flush `MemStore` data to an `HFile`

Storage

HBase Files

- **What and where are HBase files (including WAL, `HFile`,...) stored?**
  - HBase has a root directory set to "`/hbase`" in HDFS
  - Files can be divided into:
    - ⋆ Those that reside under the HBase root directory
    - ⋆ Those that are in the *per-table* directories

- `/hbase`
  - `.logs`
  - `.oldlogs`
  - `.hbase.id`
  - `.hbase.version`
  - `/example-table`

Storage

HBase Files

- `/example-table`
  - `.tableinfo`
  - `.tmp`
  - `"...Key1..."`
    - `.oldlogs`
    - `.regioninfo`
    - `.tmp`
    - `colfam1/`
- `colfam1/`
  - `"....column-key1..."`

Storage

HBase: Root-level files

- **`.logs` directory**
  - WAL files handled by `HLog` instances
  - Contains a subdir for each `HRegionServer`
  - Each subdir contains many `HLog` files
  - All regions from that `HRegionServer` share the same HLog files
- `.oldlogs` directory
  - When data is persisted to disk (from `Memstores`) log files are decommissioned to the `.oldlogs` dir
- **`hbase.id` and `hbase.version`**
  - Represent the unique ID of the cluster and the file format version

Storage

HBase: Table-level files

- **Every table has its own directory**
  - `.tableinfo`: stores the serialized `HTableDescriptor`
    - This include the table and column family schema
  - `.tmp` directory
    - Contains temporary data

Storage

HBase: Region-level files

- **Inside each table dir, there is a separate dir for every region in the table**
  - The name of each of this dirs is the MD5 hash of a region name
    - Inside each region there is a directory for each column family
    - Each column family directory holds the actual data files, namely `HFiles`
    - Their name is just an arbitrary random number
  - Each region directory also has a `.regioninfo` file
    - Contains the serialized information of the `HRegionInfo` instance

- **Split Files**
  - Once the region needs to be split, a `splits` directory is created
    - This is used to stage two daughter regions
    - If split is successful, daughter regions are moved up to the table directory

Storage

HBase: A note on region splits

- **Splits triggered by store file (region) size**
  - Region is split in two
  - Region is closed to new requests
  - `.META.` is updated
- **Daughter regions initially reside on the same server**
  - Both daughters are compacted
  - Parent is cleaned up
  - `.META.` is updated
- **Master schedules new regions to be moved off to other servers**

Storage

HBase: Compaction

- **Process that takes care of re-organizing store files**
  - Essentially to conform to underlying filesystem requirements
  - Compaction check when memstore is flushed

- **Minor and Major compactions**
  - Always from the oldest to the newest files
  - Avoid all servers to perform compaction concurrently

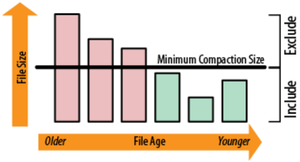


Figure: A set of store files showing the minimum compaction threshold

Storage

HFile format

- **Store files are implemented by the `HFile` class**
  - Efficient data storage is the goal

- **`HFiles` consist of a variable number of blocks**
  - Two fixed blocks: *info* and *trailer*
  - *index* block: records the offsets of the `data` and meta `blocks`
  - Block size: *large* $\rightarrow$ sequential access; *small* $\rightarrow$ random access

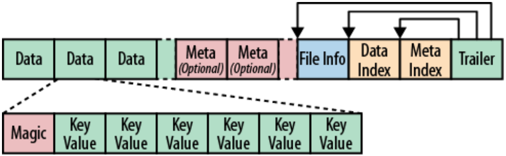


Figure: The HFile structure

Storage

HFile size and HDFS block size

- **HBase uses any underlying filesystem**
- **In case HDFS is used**
  - HDFS block size is generally 64MB
  - This is 1,024 times the default `HFile` block size (64 KB)
  - → There is no correlation between HDFS block and HFile sizes

Storage

The KeyValue Format

- **Each KeyValue in the HFile is a low-level byte array**
  - It allows for *zero-copy* access to the data

- **Format**
  - Fixed-length preambule indicates the length of the key and value
    - This is useful to offset into the array to get direct access to the value, ignoring the key
  - Key format
    - Contains row key, column family name, column qualifier...
    - `[TIP]`: consider small keys to avoid overhead when storing small data

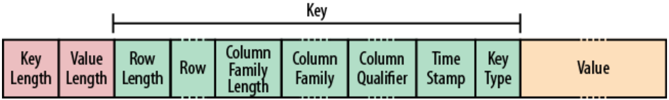


Figure: The KeyValue Format

The Write-Ahead Log

- **Main tool to ensure resiliency to failures**
  - Region servers keep data in-memory until enough is collected to warrant a flush
  - What if the server crashes or power is lost?
- **WAL is a common approach to address fault-tolerance**
  - Every data update is first written to a log
  - Log is persisted (and replicated, since it resides on HDFS)
  - Only when log is written, client is notified a successful operation on data

The Write-Ahead Log

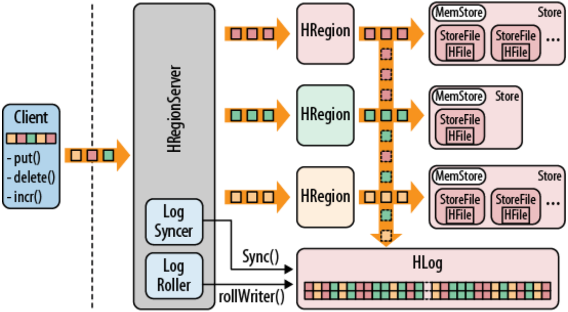
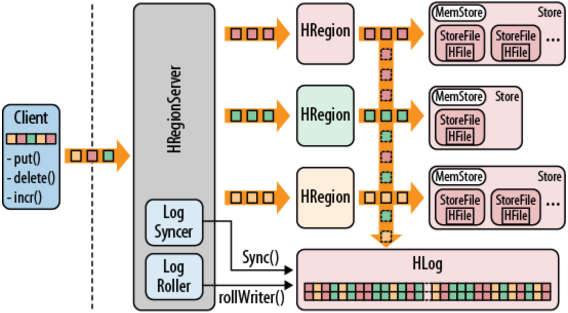


Figure: The write path of HBase

- **WAL records all changes to data**
  - Can be replayed in case of server failure
  - If write to WAL fails, the whole operations has to fail

The Write-Ahead Log



- **Write Path**
  - Client modifies data (`put()`, `delete()`, `increment()`)
  - Modifications are wrapped into a KeyValue object
  - Objects are batched to the corresponding `HRegionServer`
  - Objects are routed to the corresponding `HRegion`
  - Objects are written to WAL and in the `MemStore`

Read Path

- **HBase uses multiple store files per column family**
  - These can be either in-memory and/or materialized on disk
  - Compactions and clean-up background processes take care of store files maintenance
  - Store files are immutable, so deletion is handled in a special way

- **The anatomy of a `get` command**
  - HBase uses a `QueryMatcher` in combination with a `ColumnTracker`
  - First, an exclusion check is performed to filter skip files (and eventually tombstone labelled data)
  - Scanning data is implemented by a `RegionScanner` class which retrieves a `StoreScanner`
  - `StoreScanner` includes both the `MemStore` and `HFiles`
  - Read/Scans happen in the same order as data is saved

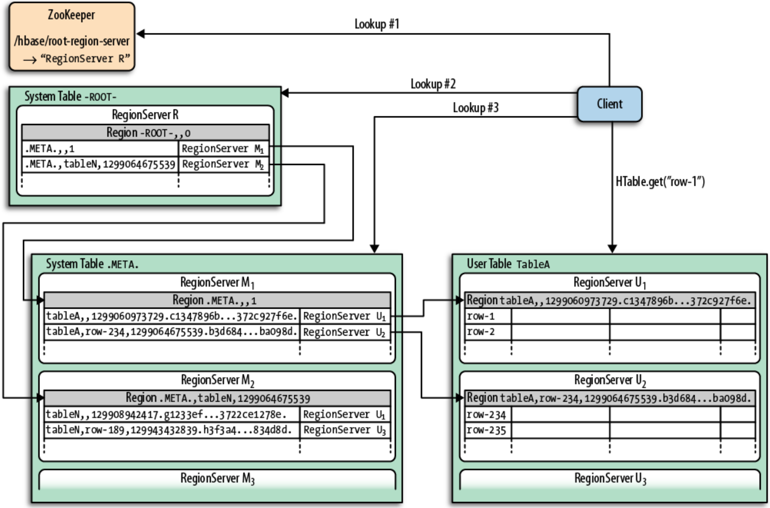
Region Lookups

- **How does a client find the region server hosting a specific row key range?**
  - HBase uses two special catalog tables, `-ROOT-` and `.META.`
  - The `-ROOT-` table is used to refer to all regions in the `.META.` table
- **Three-level B+ Tree -like operation**
  - Level 1: a node stored in ZooKeeper, containing the location (region server) of the `-ROOT-` table
  - Level 2: Lookup in the -ROOT- table to find a matching meta region
  - Level 3: Retrieve the table region from the `.META.` table

Region Lookups

- **Where to send requests when looking for a specific row key?**
  - This information is cached, but the first time or when the cache is stale or when there is a miss due to compaction, the following procedure applies
- **Recursive discovery process**
  - Ask the region server hosting the matching `.META.` table to retrieve the row key address
  - If the information is invalid, it backs out: asks the `-ROOT-` table where the relevant `.META.` region is
  - If this fails, ask ZooKeeper where the `-ROOT-` table is

Region Lookups



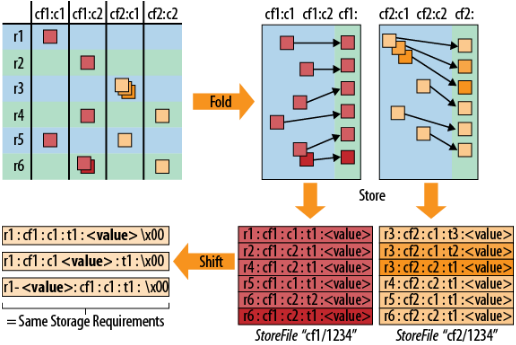
Key Design

Concepts

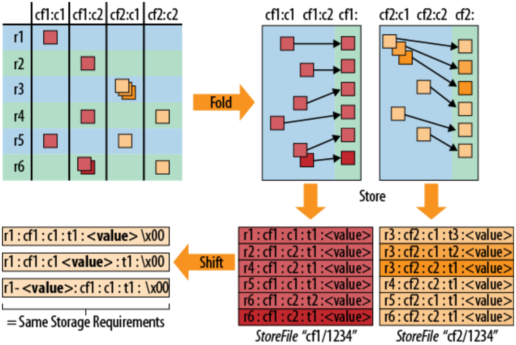
- **HBase has two fundamental key structures**
  - Row key
  - Column key
- **Both can be used to convey meaning**
  - Because they store particularly meaningful data
  - Because their sorting order is important

Concepts

- **Logical vs. on-disk layout of a table**
  - Main unit of separation within a table is the *column family*
  - The actual columns (as opposed to other column-oriented DB) are not used to separate data
  - Although cells are stored logically in a table format, rows are stored as linear sets of the cells
  - Cells contain all the vital information inside them



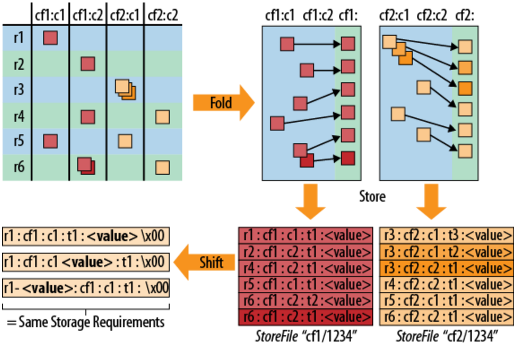
Concepts



- **Logical Layout (Top-Left)**
  - Table consists of rows and columns
  - Columns are the combination of a column family name and a column qualifier

  → `<cf name: qualifier>` is the **column key**
  - Rows have a **row key** to address all columns of a single logical row

Concepts



- **Folding the Logical Layout (Top-Right)**
  - The cells of each row are stored one after the other
  - Each column family are stored separately
  - → On disk all cells of one family reside on an individual `StoreFile`
  - HBase does not store unset cells
  - → **Row and column key is required to address every cell**

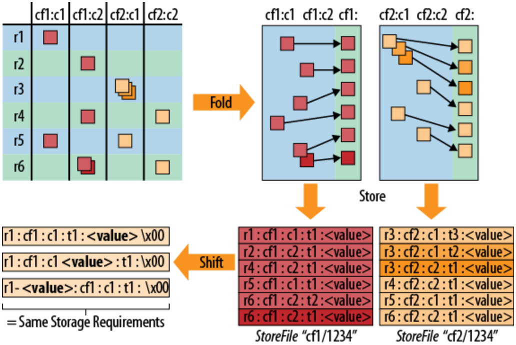
Concepts

- **Versioning**
  - Multiple versions of the same cell stored consecutively, together with the *timestamp*
  - Cells are sorted in descending order of timestamp

  $\rightarrow$ Newest value first

- **`KeyValue` object**
  - The entire cell, with all the structural information, is a `KeyValue` object
  - Contains: `row key`, `<column family: qualifier>` $\rightarrow$ `column key`, `timestamp` and `value`
  - Sorted by row key first, then by column key

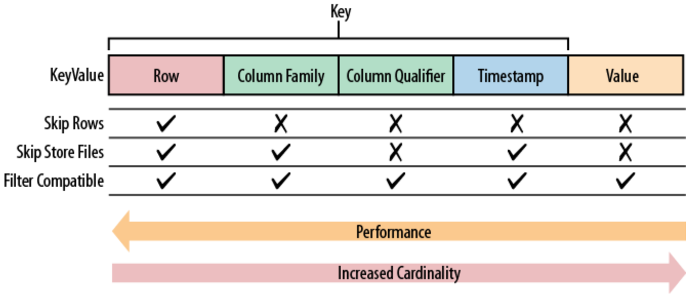
Concepts



- **Physical Layout (Lower-Right)**
  - Select data by row key
    - This reduces the amount of data to scan for a row or a range of rows
  - Select data by row key and column key
    - This focuses the system on an individual storage file
  - Select data by column qualifier
    - Exact lookups, including filters to omit useless data

Concepts

- **Summary of key lookup properties**



Tall-Narrow vs. Flat-Wide Tables

- **Tall-Narrow Tables**
  - Few columns
  - Many rows

- **Flat-Wide Tables**
  - Many columns
  - Few rows

- **Given the query granularity explained before**
  - $\rightarrow$ Store parts of the cell data in the row key
  - Furthermore, HBase splits at row boundaries
  - $\rightarrow$ It is recommended to go for Tall-Narrow Tables

Tall-Narrow vs. Flat-Wide Tables

- **Example: email data - version 1**
  - You have all emails of a user in a single row (e.g. `userID` is the row key)
  - There will be some outliers with orders of magnitude more emails than others

  → A single row could outgrow the maximum file/region size and work against split facility

- **Example: email data - version 2**
  - Each email of a user is stored in a separate row (e.g. `userID:messageID` is the row key)
  - On disk this makes no difference (see the disk layout figure)
    - ★ If the `messageID` is in the column qualifier or the row key, each cell still contains a single email message

  → The table can be split easily and the query granularity is more fine-grained

Partial Key Scans

- **Partial Key Scans reinforce the concept of Tall-Narrow Tables**
  - From the email example: assume you have a separate row per message, across all users
  - If you don't have an exact combination of user and message ID you cannot access a particular message

- **Partial Key Scan solves the problems**
  - Specify a *start* and *end* key
  - The start key is set to the exact `userID` only, with the end key set at `userID+1`

  → This triggers the internal lexicographic comparison mechanism
    - ⋆ Since the table does not have an exact match, it positions the scan at: `<userID>:<lowest-messageID>`
  - The scan will then iterate over all the messages of an exact user, parse the row key and get the `messageID`

Partial Key Scans

- **Composite keys and atomicity**
  - Following the email example: a single user inbox now spans many rows
  - It is no longer possible to modify a single user inbox in one atomic operation
- **If this is acceptable or not, depends on the application at hand**

Time Series Data

- **Stream processing of events**
  - E.g. data coming from a sensor, stock exchange, monitoring system ...
  - Such data is a time series $\rightarrow$ **The row key represents the event time**

  $\rightarrow$ HBase will store all rows sorted in a distinct range, namely regions with specific start and stop keys

- **Sequential monotonously increasing nature of time series data**
  - All incoming data is written to the same region (and hence the same server)

  $\rightarrow$ **Regions become HOT!**
  - Performance of the whole cluster is bound to that of a single machine

Time Series Data

- **Solution to achieve load balancing: Salting**
  - We want data to be spread over all region servers
  - This can be done, e.g., by prefixing the row key with a non-sequential number

Salting example

```
byte prefix = (byte) (Long.hashCode(timestamp) % <number of
region servers>);
byte[] rowkey = Bytes.add(Bytes.toBytes(prefix),
Bytes.toBytes(timestamp));
```

\- Data access needs to be *fanned out* across many servers

\+ Use multiple threads to read for I/O performance: e.g. use the Map phase of MapReduce

Time Series Data

- **Solution to achieve load balancing: Field swap/promotion**
  - Move the timestamp filed of the row key or prefix it with another field
    - If you already have a composite row key, simply *swap* elements
    - Otherwise if you only have the timestamp, you need to *promote* another field
  - The sequential, monotonously increasing timestamp is moved to a secondary position in the row key

\- You can only access data (especially time ranges) for a given swapped or promoted field (but this could be a feature)

\+ You achieve load balancing

Time Series Data

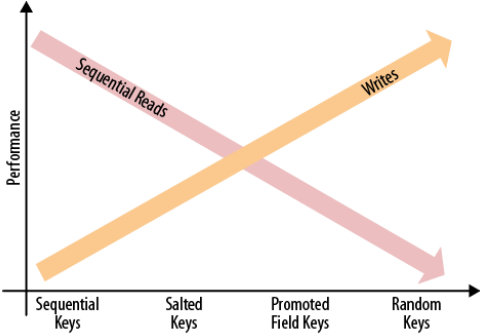
- **Solution to achieve load balancing: Randomization**
  - `byte[] rowkey = MD5(timestamp)`
  - This gives you a random distribution of the row key across all available region servers

- Less than ideal for range scans

+ Since you can re-hash the timestamp, this solution is good for **random access**

Time Series Data

- **Summary**



Cassandra

Cassandra: Overview (1)

- **Distributed key value store**
  - Stores large amounts of data
  - Lienar scalability, high availability, no SPF
- **Tunable consistency**
  - Often eventually consistent, hence in AP
  - Can guarantee strong consistency, shifting it to CP
- **Column-oriented data model**
  - One key per row

Cassandra: Overview (2)

- **Combines techniques from Amazon Dynamo and HBase**
  - HBase data model
    - One key per row
    - Columns, column families
  - Dynamo-like architecture
    - Partitioning, placement (using consistent hashing)
    - Replication, gossip-based membership, anti-entropy

- **Some key differences**
  - Many of them recentyl added

Data Partitioning

- **Uses consistent hashing**
  - Random Partitioner
  - ByteOrdered Partitioner

- **Partitioning strategy can be changed on-the-fly**
  - All data needs to be reshuffled
  - Needs to be chosen carefully

Random Partitioner

- **Hash-based identifiers for keys (data) and storage nodes**
  - Supports virtual nodes
- **Consistent hashing + load monitoring per ring**
  - Lightly loaded nodes move on the ring to alleviate heavily loaded ones
  - Make deterministic choices about load balancing, e.g., divides the hash-ring evenly w.r.t. to number of nodes
- **Node addition / suppression**
  - Requires re-balancing the cluster if no virtual nodes

ByteOrdered Partitioner

- **Supports range queries**
  - Ensures row keys to be stored in sorted order
  - Very different from consistent hashing
- **Key partitioning**
  - There is still a ring
  - Keys are ordered lexicographically along the ring by their value[2]
- **Precautions**
  - Might be bad for load balancing
  - Range scan can be obtained by using column family indexes

[2] The key value is different from the value associated to a key

Data Replication

- **Asynchronous replication**
  - Walk down the ring and choose $N - 1$ successor nodes as replicas
  - Builds a preference list

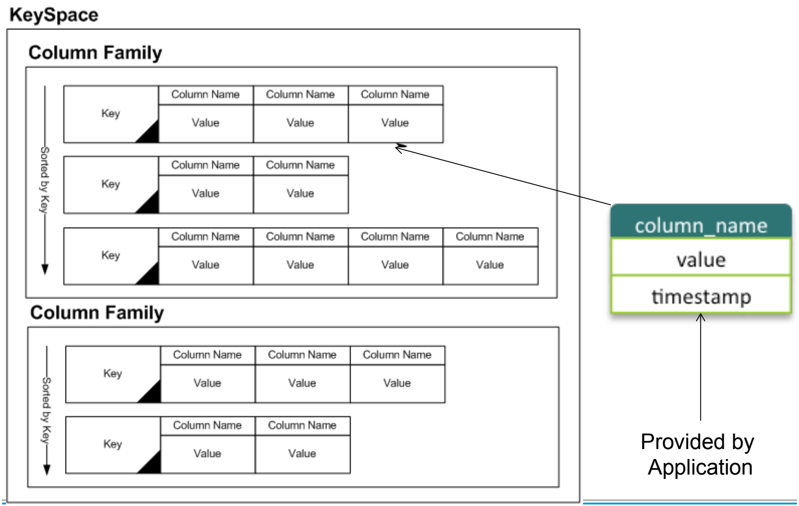
- **Replication strategies**
  - Simple Strategy:
    - Main replica = node responsible for a key
    - Additional $N - 1$ replicas placed on successor nodes, clockwise in the ring, w/o rack or datacenter information
  - NetworkTopology Strategy
    - Allows better performance when knowledge of the datacenter layout is available
    - Reads served locally
    - Replica placement is independent in each datacenter
    - Rack-aware placement like in HDFS

Data Replication Strategies: Implications

- **Focus on the NetworkTopology strategy**
  - Requires Snitches[3] and optionally Zookeeper
  - Mechanism to discover the underlying cluster configuration
- **Potential problems**
  - Unbalanced load across datacenter
  - Consider datacenter-specific key rings

[3] We don't cover the details here: refer to the official documentation or the additional slides provided in the lecture notes.

Data Model



KeySpace
Column Family
Sorted by Key
Key
Column Name
Value
Column Family
column_name
value
timestamp
Provided by Application

Data Model: Special Columns

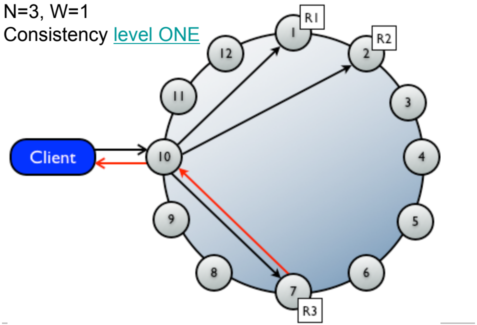
- **Counter columns**
  - Store counters
  - Timestamp information automatically generated (use NTP!)
- **Expiring columns**
  - Specify a TTL value after which, data is removed
  - Tombstone marker, as for HBase
- **Super columns**
  - Additional nesting levels
  - Group multiple columns on a common lookup value
    - E.g.: “home address” super column, grouping “street”, “city”, “ZIP” columns
  - No timestamps

Anatomy of Read/Write Operations

- **Request routing**
  - Proxy-based mechanism (coordinator, in Cassandra terms)
  - Proxy route request to any replica
- **Proxy nodes**
  - Handle interaction between a client and Cassandra
  - First, determine replicas for a given key
  - Zookeeper may by useful here

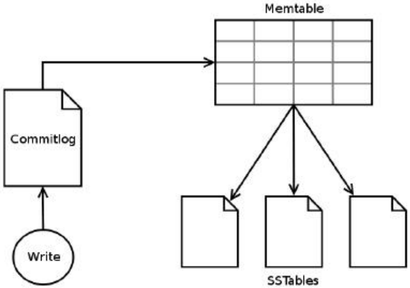
Write Requests (1)

- **Proxy nodes forward write requests**
  - Request routed to all N replicas
  - This is true, regardless of consistency configuration



Write Requests (2)

- **Write request**: similar mechanism to HBase
  - Write to the commit log
  - Write to in-memory data structure (`memtable`)
  - → Write is considered successful now
  - Writes are batched and periodically flushed to a persistent data structure called a sorted string table (`SSTable`)



Write Requests (3)

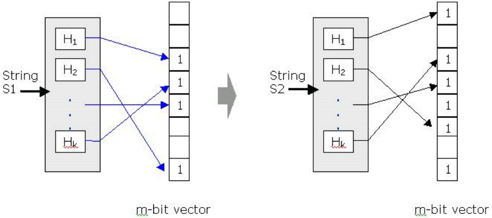
- **Memtables**
  - Organized in sorted order by row key
  - Flushed to SSTables sequentially, no random seeks

- **SSTables**
  - Immutable (no rewrite after flushing)
  - A single row can be stored in many SSTables

  → At read time, rows must be combined from all SSTables (on disk or from memtables) to produce the requested data
  - Use Bloom Filters to optimize the process

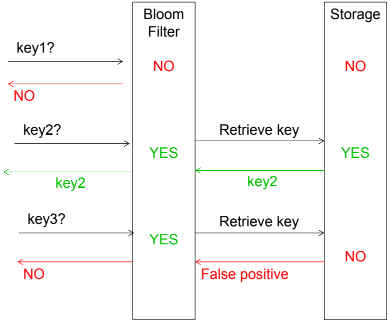
Bloom Filters (1)

- **Bloom Filters in a nutshell**
  - Used to check for set membership
  - *k* hash functions hashing into the same *m*-bit space



Bloom Filters (1)

- **One bloom filter per SSTable**
  - Used in combining from row data from multiple “sources”
  - Check if a requested row key exists in the SSTables, before doing any disk seeks



Read Requests (1)

- **Similar mechanism to Dynamo**
  - Proxy initiates a read repair (a.k.a. writeback) if it detects inconsistent replicas
  - This is done in the background, after the read has been served to the client

- **The number of replicas contacted upon a read request depend on the consistency level**
  - Proxy routes the requests to the closest replica
  - Proxy routes requests to all replicas and wait for a quorum

Read Requests (2)

- **When a node receives a read request**
  - Row must be combined from all SSTables on that node
  - Data not yet flushed to SSTables, i.e. stored in memtables, must be considered as well

  → This produces the requested data

- **Key techniques to achieve high performance**
  - Row-level column index
  - Bloom filters

- **Cutting read latency**
  - Combining data before serving it can be slow
  - Read cache (in memory)
  - Advanced topics: cache invalidation, consistency...

Consistency

- **Consistency in Cassandra is tunable**
  - Hence is availability, as per CAP
  - Read and Write consistency levels can be independent

- **Given N replicas in the preference list**
  - Write request: all N replicas are contacted
    - Ends when W respond (i.e. acknowledgment)
  - Read request: only R replicas are contacted
    - This is optimistic, may need to contact all N replicas

- **Choices of W and R define consistency level**
  - Dynamo: $W + R > N$ (recall extended preference list + sloppy quorum)
  - Cassandra: $W + R > N$ not mandatory

Consistency Levels: ONE

- $W = 1$
  - One replica must write to commit log and memtable
- $R = 1$
  - Returns a response from the closest replica (as determined by the snitch)
  - By default, a read repair runs in the background to make the other replicas consistent
- **This is true regardless of the replication factor N**

Consistency Levels: QUORUM

- **QUORUM**
  - $W = \text{floor}(N/2 + 1)$: a majority
    - A write is written to the commit log and memtable on a quorum of W replicas
  - $R = \text{floor}(N/2 + 1)$: a majority
    - Read returns the record with the most recent timestamp, once a quorum of size R has responded
    - Timestamp = application timestamp

- **LOCAL_QUORUM**
  - Restricted to a local datacenter

- **EACH_QUORUM**
  - QUORUM invariant must be satisfied across datacenters

Consistency Levels: ALL, ANY

- **ALL**
  - $W = N$: all replica nodes must acknowledge
  - $R = N$: returns the record with the most recent timestamp across all replicas

- **ANY**
  - Additional consistency for writes
  - Allow writes to complete even if all N replicas are down
  - Hinted handowff mechanism

Lightweight Transactions

- **Simple mechanism at the single key level**
  - Single object transactions
  - No support for multi-key transactions
  - "Consistency" level: SERIAL

- **Compare and Swap (CAS) mechanism**
  - Enhancements available in Cassandra 2.0
  - Paxos based mechanism
  - Address the problem of solving the agreement for 2 processes, that requires using locks

References I

[1] B+ tree.
http://en.wikipedia.org/wiki/B%2B_tree.

[2] Eric Brewer.
Lessons from giant-scale services.
In *In IEEE Internet Computing*, 2001.

[3] Fay Chang, Jeffrey Dean, Sanjay Ghemawat, Wilson C. Hsieh, Deborah A. Wallach, Mike Burrows, Tushar Chandra, Andrew Fikes, and Robert E. Gruber.
Bigtable: A distributed storage system for structured data.
In *Proc. od USENIX OSDI*, 2006.

[4] Jeffrey Dean and Sanjay Ghemawat.
Mapreduce: Simplified data processing on large clusters.
In *Proc. of ACM OSDI*, 2004.

References II

[5] Lars George.
HBase, The Definitive Guide.
O'Reilly, 2011.

[6] Sanjay Ghemawat, Howard Gobioff, and Shun-Tak Leung.
The google file system.
In *Proc. of ACM OSDI*, 2003.

[7] Patrick O'Neil, Edward Cheng, Dieter Gawlick, and Elizabeth O'Neil.
The log-structured merge-tree (lsm-tree).
1996.

References III

[8] D. Salmen.
Cloud data structure diagramming techniques and design patterns.
https://www.data-tactics-corp.com/index.php/component/jdownloads/finish/22-white-papers/68-cloud-data-structure-diagramming, 2009.