Tutorial: HBase

Theory and Practice of a Distributed Data Store

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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

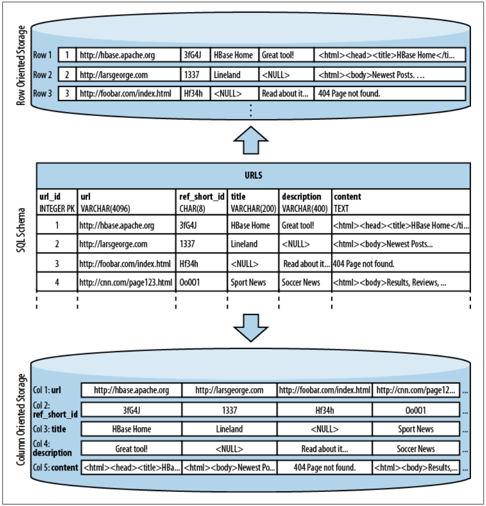

Figure: Example of Storage Layouts

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

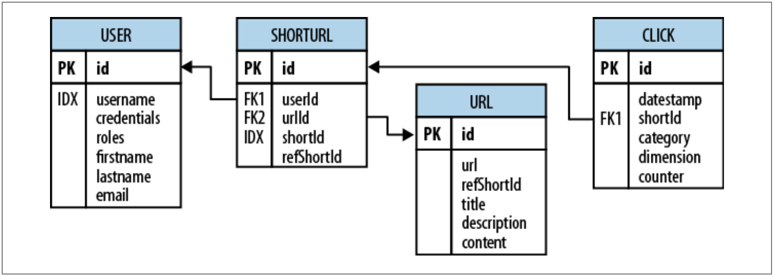

Figure: The Hush Schema expressed as an ERD

The Problem with RDBMS

- **Find all short URLs for a given user**
  - `JOIN` `user` and `shorturl` tables
- **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
  - → 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 time 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.

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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

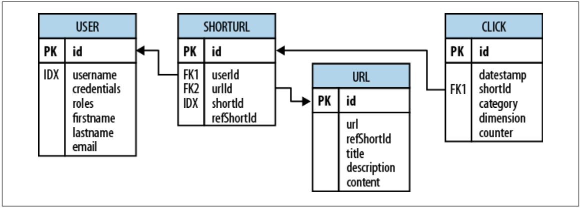


Figure: The Hush Schema expressed as an ERD

- `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

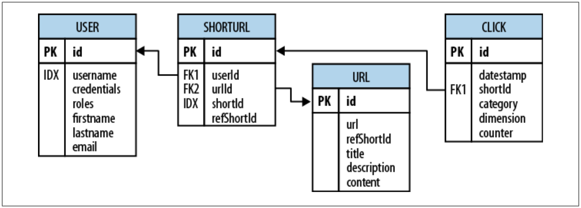


Figure: The Hush Schema expressed as an ERD

- `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

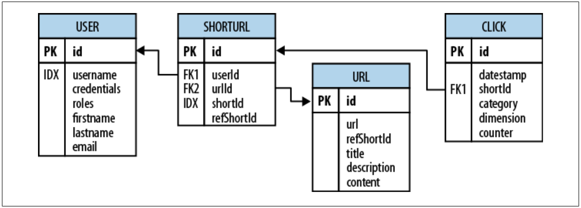


Figure: The Hush Schema expressed as an ERD

- `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*
  - $\rightarrow$ 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`

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»»`

  - 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

- **Which means:**
  - 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

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
  - 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

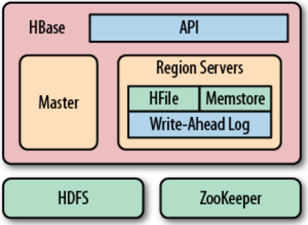
- **Compactions**
  - Flushing data from `memstores` to disk implies the creation of new `HFiles` each time
  - → We end up with many (possibly small) files
  - → We need to do housekeeping [WHY?]

- **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

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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

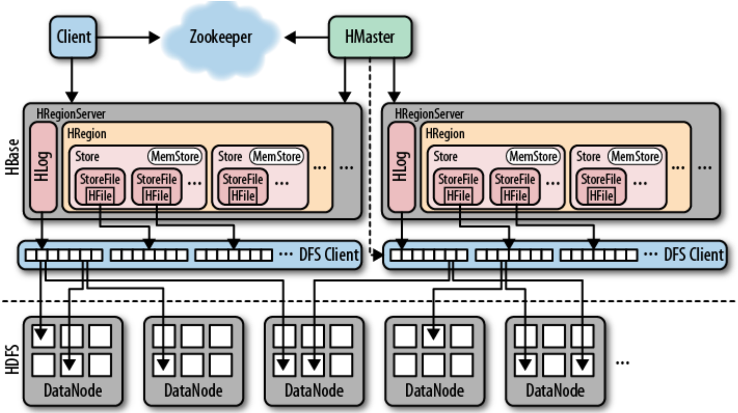


Figure: Overview of how HBase handles files in the filesystem

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
    - Assign region servers to key space
    - Keep metadata
    - Talk 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 contain 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

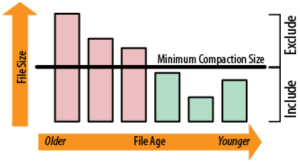


Figure: A set of store files showing the minimum compaction threshold

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* → sequential access; *small* → random access

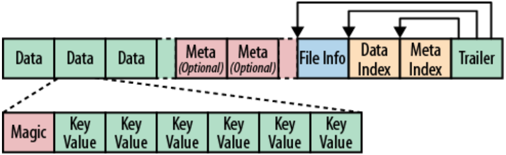


Figure: The HFile structure

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 indicated 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

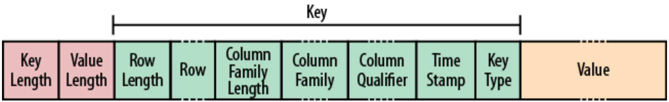


Figure: The KeyValue Format

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

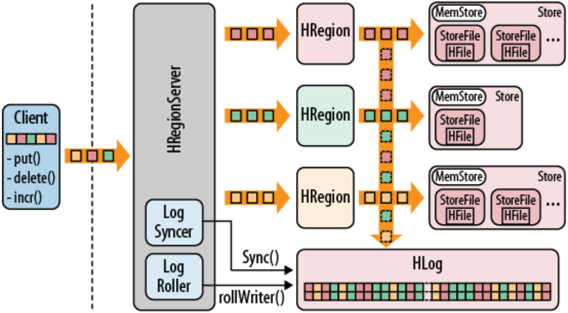
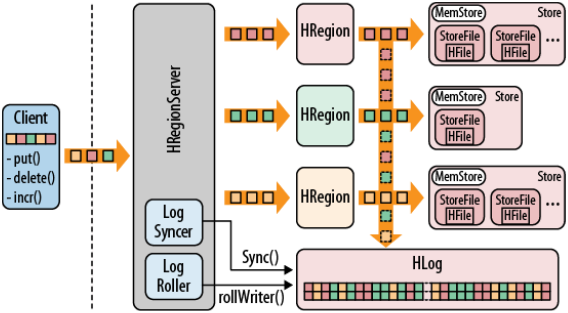


Figure: The write path of HBase

- **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

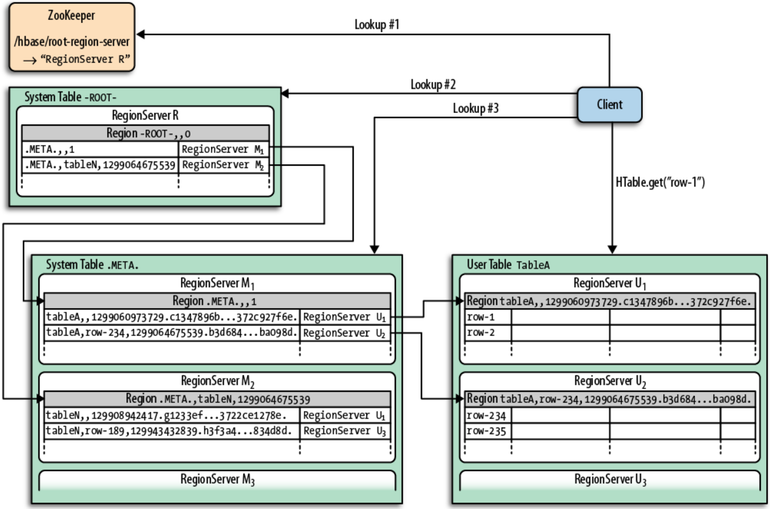
- **How does a client find the region server hosting a specific row key range?**
  - HBase uses two special catalog tables, `-ROOT-` and `.META.`
  - The `-ROOT-` table is used to refer to all regions in the `.META.` table

- **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



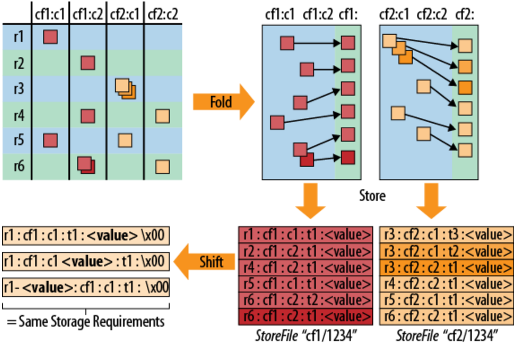
Key Design

Concepts

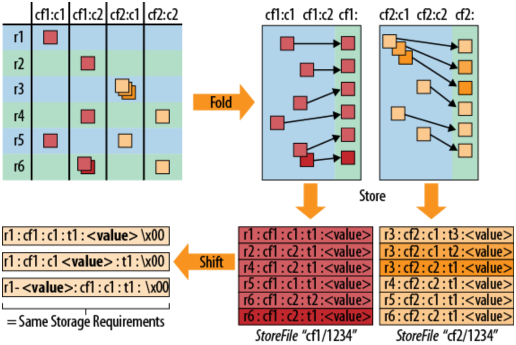
- **HBase has two fundamental key structures**
  - Row key
  - Column key
- **Both can be used to convey meaning**
  - Because they store particularly meaningful data
  - Because their sorting order is important

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

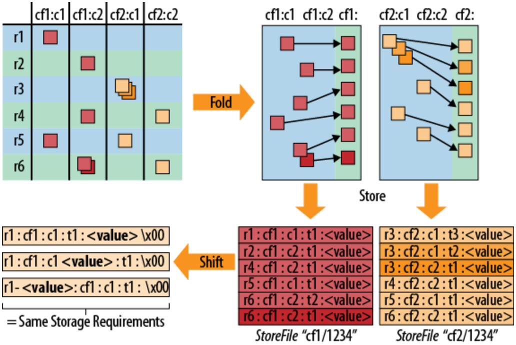


Concepts



- **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



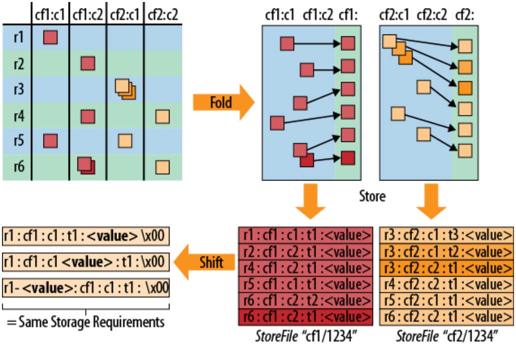
- **Folding the Logical Layout (Top-Right)**
  - The cells of each row are stored one after the other
  - Each column family are stored separately
  - → On disk all cells of one family reside on an individual `StoreFile`
  - HBase does not store unset cells
  - → **Row and column key is required to address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

Concepts

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

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

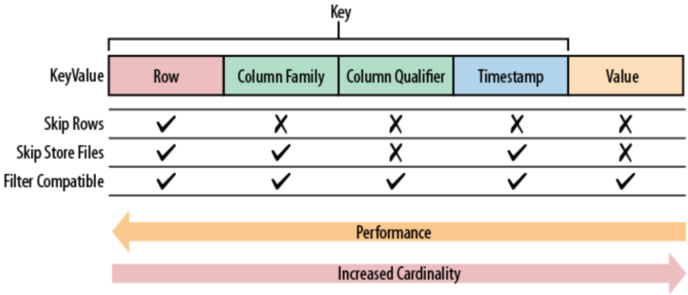
Concepts



- **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**
  - → Store parts of the cell data in the row key
  - Furthermore, HBase splits at row boundaries
  - → 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

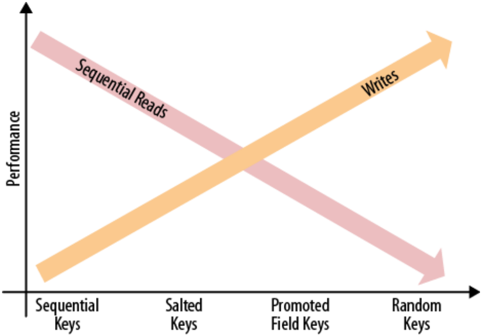
- **Solution to achieve load balancing: Randomization**
  - `byte[] rowkey = MD5(timestamp)`
  - This gives you a random distribution of the row key across all available region servers

\- Less than ideal for range scans

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

Time Series Data

- **Summary**



MapReduce Integration

Introduction

- **In the following we review the main classes involved in reading and writing data from/to an underlying data store**
- **For MapReduce to work with HBase, some more practical issues have to be addressed**
  - E.g.: creating an appropriate JAR file inclusive of all required libraries
- Refer to [5], Chapter 7 for an in-depth treatment of this subject

Main classes involved in MapReduce

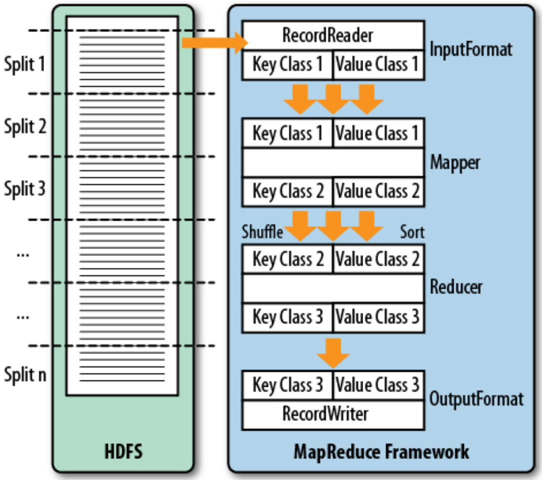


Figure: Main MapReduce Classes

Main classes involved in MapReduce

`InputFormat`

- **It is responsible for two things**
  - Splits input data
  - Returns a `RecordReader` instance
    - Defines a *key* and a *value* object
    - Provides a `next()` method to iterate over input records

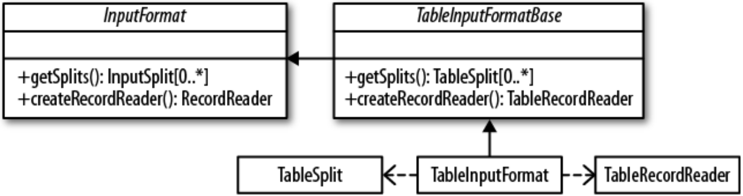


Figure: InputFormat hierarchy

Main classes involved in MapReduce

`InputFormat` → `TableInputFormatBase`

- **Implement a full turnkey solution to scan an HBase table**
  - Splits the table into proper blocks and hand them to the MapReduce process
- **Must supply a `Scan` instance to interact with a table**
  - Specify start and stop keys for the scan
  - Add filters (optional)
  - Specify the number of versions

Main classes involved in MapReduce

`Mapper`

- **Each record read using the `RecordReader` is processed using the `map()` method**
- **The `Mapper` reads specific types of input key/value pairs, but emit possibly another type**

Figure: The Mapper hierarchy

Main classes involved in MapReduce

`Mapper` → `TableMapper`

- **`TableMapper` class enforces:**
  - The input key to the mapper to be an `ImmutableBytesWritable` type
  - The input value to be a `Result` type
- **A handy implementation is the `IdentityTableMapper`**
  - This is the equivalent of an identity mapper

Main classes involved in MapReduce

OutputFormat

- **Used to persist data**
  - Output written to files
  - Output written to HBase tables
    - This is done using a `TableRecordWriter`

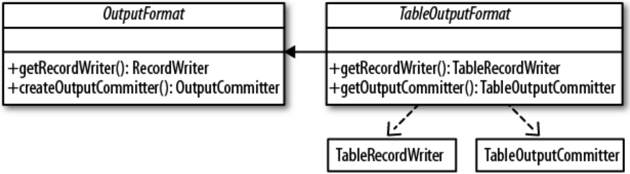


Figure: The OutputFormat hierarchy

Main classes involved in MapReduce

`OutputFormat` $\rightarrow$ `TableOutputFormat`

- **This is the class that handles the key/valu pairs and writes them to their final destination**
  - Single instance that takes the output record from each reducer subsequently
- **Details**
  - Must specify the table name when the MR job is created
  - Handles buffer flushing implicitly (*autoflush* option is set to false)

MapReduce Locality

- **How does the system make sure data is placed close to where it is needed?**
  - This is done implicitly by MapReduce when using HDFS
  - When MapReduce uses HBase things are a bit different

- **How HBase handles data locality**
  - Shared vs. non-shared cluster
  - HBase store its files on HDFS (`HFiles` and WAL)
  - HBase servers are not restarted frequently and they perform compactions regularly

  → HDFS is smart enough to ensure data locality
    - ★ There is a block placement policy that enforces local writes
    - ★ The data node compares the server name of the writer with its own
    - ★ If they match, the block is written to the local filesystem
  - Just be careful about region movements during load balancing or server failures

Table Splits

- **When running a MapReduce job that reads from an HBase table you use the `TableInputFormat`**
  - Overrides `getSplits()` and `createRecordReader()`
- **Before a job is run, the framework calls getSplit() to determine how the data is to be separated into chunks**
  - `TableInputFormat`, given the `Scan` instance you define, divide the table at region boundaries
  - → The number of input splits is equal to all regions between the start and stop keys

Table Splits

- **When a job starts, the framework calls `createRecordReader()` for each input split**
  - It iterates over the splits and create a new `TableRecordReader` with the current split
  - Each `TableRecordReader` handles exactly one region, reading and mapping every row from the region's start and end keys
- **Data locality**
  - Each split contains the server name hosting the region
  - The framework checks the server name and if the `TaskTracker` is running on the same machine, it will run it on that server
  - The `RegionServer` is colocated with the HDFS `DataNode`, hence data is read from the local filesystem
- **TIP: Turn off speculative execution!**

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