

HBase Programming

Compiled by Amit S Khedkar

Training kickoff



Talentum Global Technologies

Course Structure

- ▶ Ability to use the command line

Pre-requisites

- ▶ Ability to use the command line
- ▶ Some knowledge of Java, or programming in general (We are going to use Java 8)
- ▶ Linux and Mac are strongly preferred
- ▶ Willingness to learn an awesome technology



Who is this course for?

- ▶ You could be a **developer** and you want to learn how to write an application using Kafka
- ▶ You may be an **architect** who understand the role of Kafka in the Enterprise pipeline, some different architectures
- ▶ Or finally, you may be a **devops** who wants to understand how Kafka works with regards to topics, partitions, and multi broker setup

Teaching Philosophy

- ▶ Clear coverage of concepts & fundamentals
- ▶ API: Enough to clearly understand how it works
 - ▶ But not so much that it obscures everything else – it's not a reference manual
- ▶ Highly interactive (questions, discussions, etc. are welcome)
- ▶ Hands-on (learn by doing)

About You And Me

► About you

- ▶ Your Name
- ▶ Your background (developer, admin, manager ...etc)
- ▶ Technologies you are familiar with
- ▶ Familiarity with Kafka (scale of 1 - 4 ; 1 - new, 4 - expert)
- ▶ **Something non-technical about you!**
(favorite ice cream flavor / hobby...etc)



HBase Introduction



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HBase

Many technological
innovations are inspired
by nature

HBase

Take **ants** for example



HBase

Take **ants** for example



**Ants are fascinating
in many ways**

HBase

Individually,
each ant is
seemingly
inconsequential



HBase

Collectively, they work together to accomplish complicated things

They rarely come alone. They march single file through minuscule cracks around windows or under doors, looking for crumbs, water or a warm place to make a new home. Often you'll see them trooping up your walls or across your counter, organized and on a mission. You have an ant invasion.

MARY JO DILONARDO, "What kind of ants are in my house?", *Mother Nature Network*, August 10, 2015

HBase

Together, ants behave
like a single entity

In pursuit of a
common goal

HBase

a single entity
common goal

Take one ant down;
Another comes up to
take it's place!

Distributed computing

is the idea of putting
many small and cheap
computers together

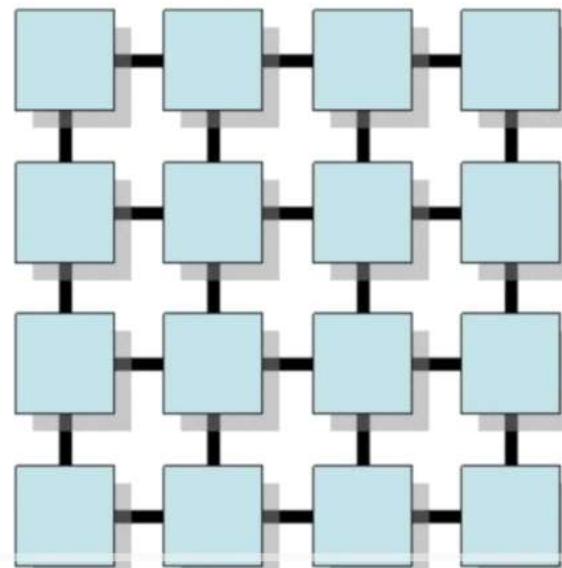
HBase

problem with distributed computing

Distributed computing

is the idea of putting many small
and cheap computers together

to accomplish
really complex
tasks

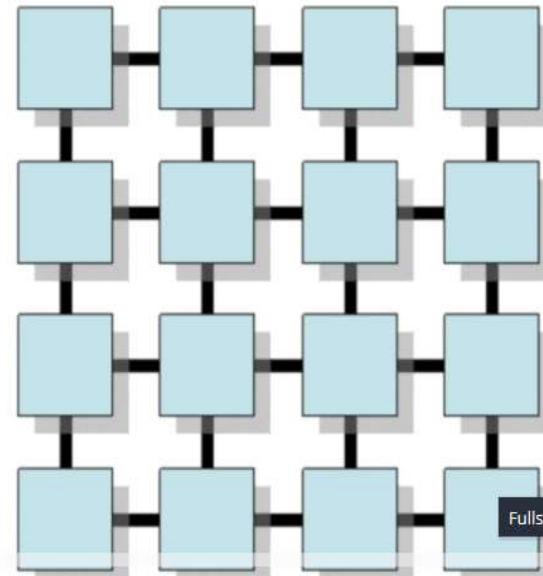


HBase

A problem with distributed computing

Distributed computing

Each individual computer is called a node



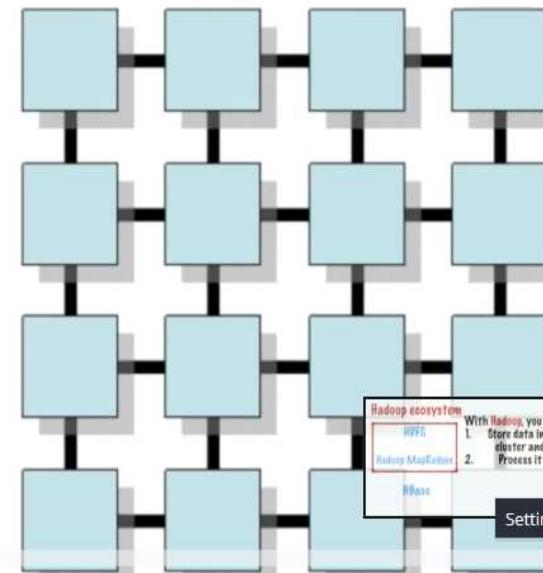
18

HBase

problem with distributed computing

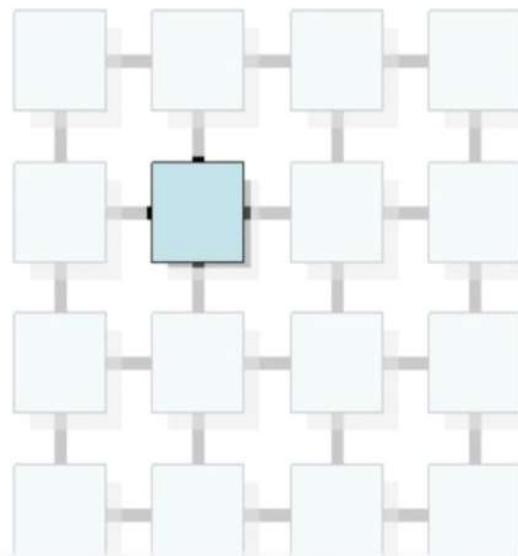
Distributed computing

Together, all the nodes form a cluster



Distributed computing

Like ants,
Each **individual**
node is pretty
inconsequential



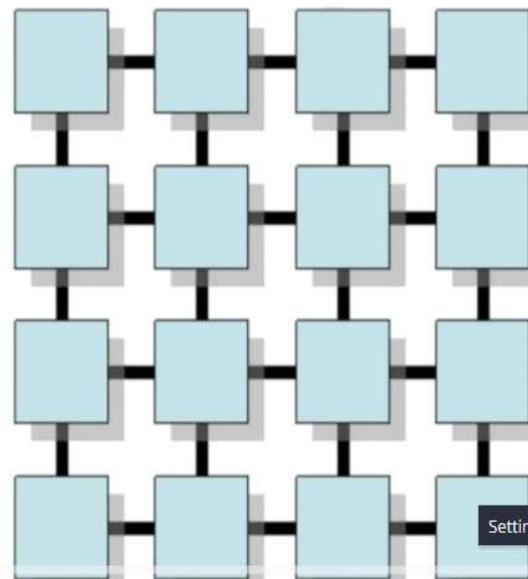
20

HBase

The problem with distributed computing

Distributed computing

Like ants,
Together these
nodes act like a
single entity with
a common goal



HBase

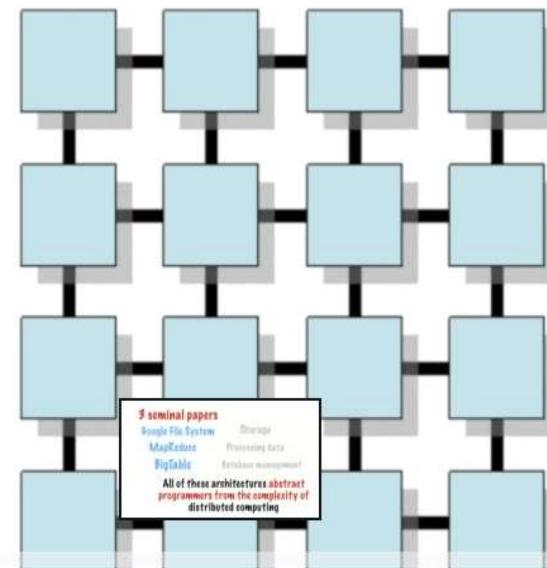
The problem with distributed computing

Distributed computing

Why is this so cool?

Find 5s

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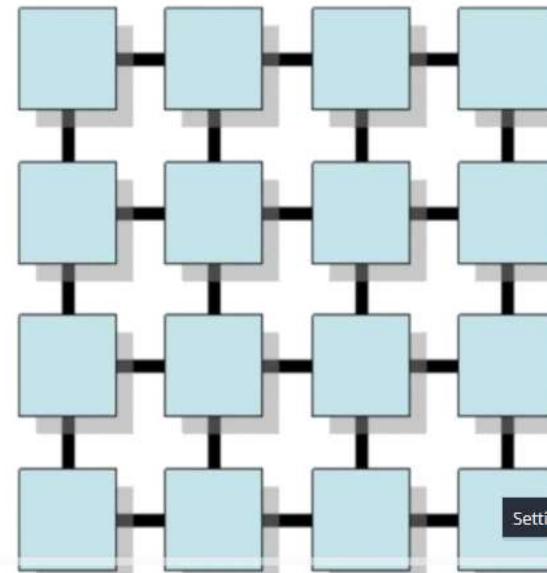


HBase

A problem with distributed computing

Distributed computing

The performance
of this system
scales linearly



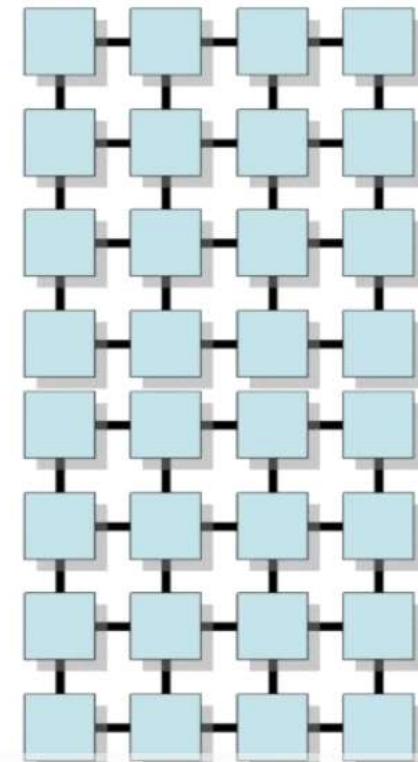
23

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problem with distributed computing

Distributed computing

To double the performance, just double the number of nodes



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a problem with distributed computing

Distributed computing

This is not true
of individual
computers



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problem with distributed computing

Distributed computing

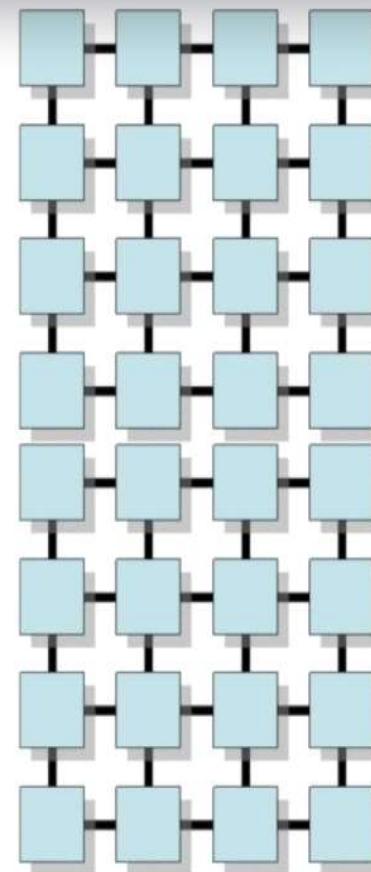
A computer that's
twice as expensive,
will not necessarily
give you twice the
performance



HBase

The problem with distributed computing

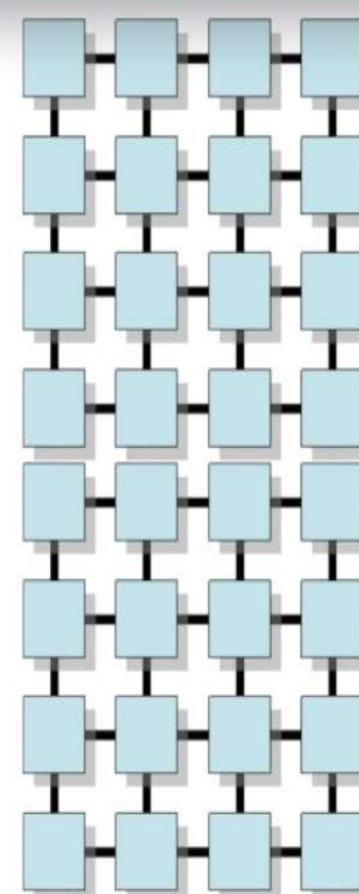
Distributed computing
can get **very complicated**



HBase

Distributed computing can get **very complicated**

1. You have to **manage resources and memory across multiple nodes**

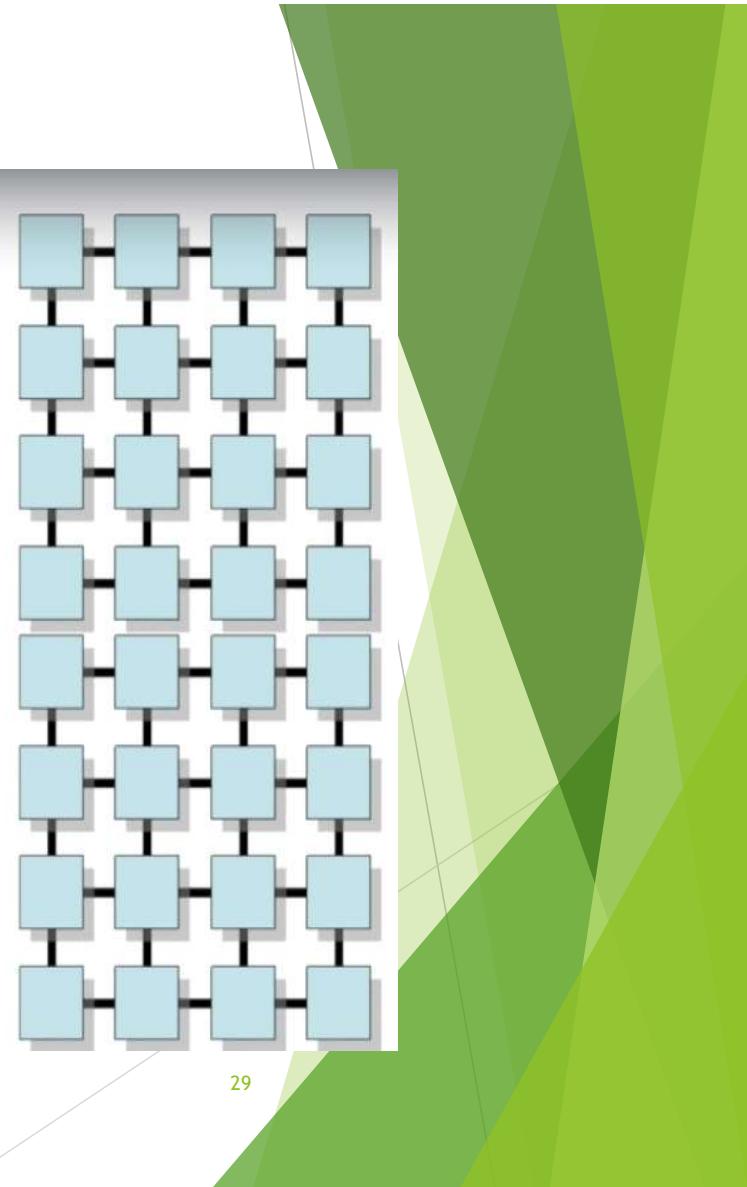


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HBase

Distributed computing can get **very complicated**
manage resources and memory

**2. You have to co-ordinate
and schedule tasks**

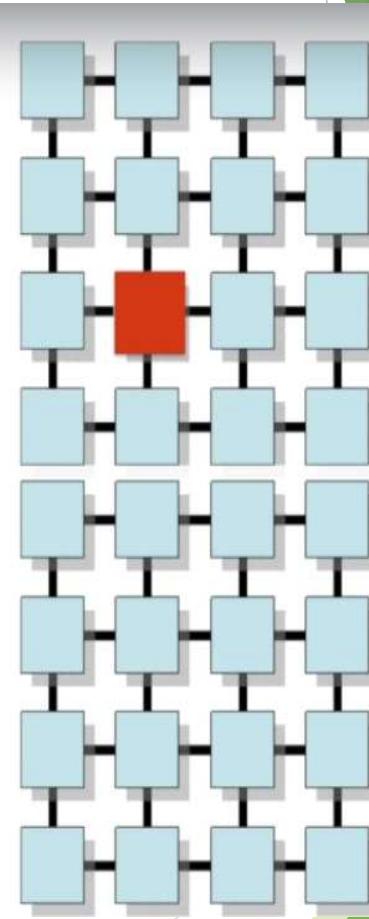


HBase

Distributed computing can get **very complicated**

manage resources and memory
co-ordinate and schedule tasks

**3. If one node goes down, the system should not be affected
(Just like with ants)**



HBase

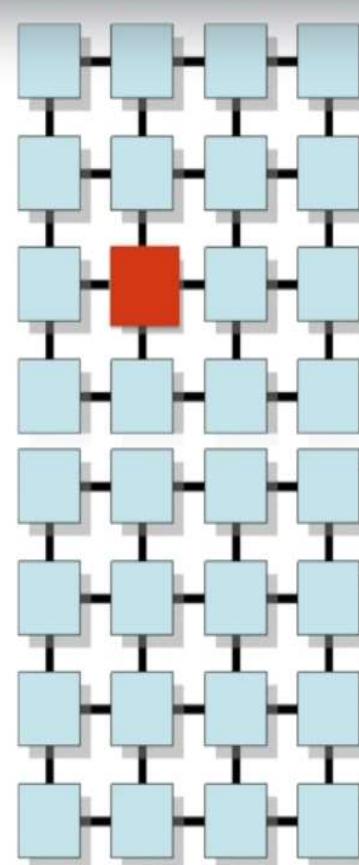
Distributed computing can get **very complicated**

manage resources and memory

co-ordinate and schedule tasks

Fault Tolerance

3. If one node goes down, the system should not be affected
(Just like with ants)



HBase

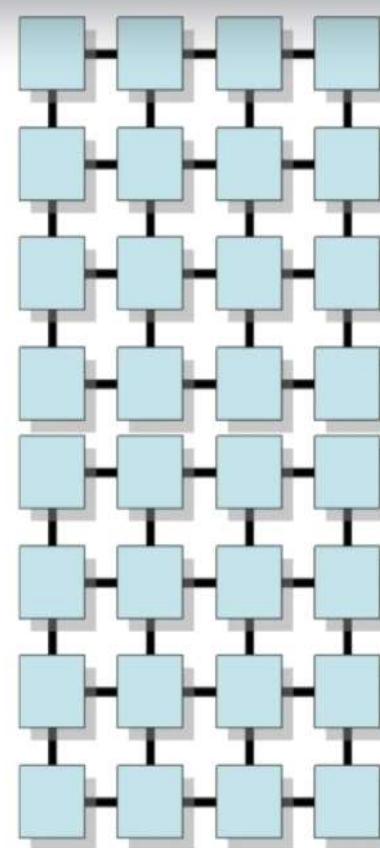
Distributed computing can get **very complicated**

manage resources and memory

co-ordinate and schedule tasks

Fault tolerance

Before the 2000s, all of these problems had to be taken care of by the programmer



HBase

Between 2003 and 2006

Google published 3 seminal papers

that completely changed the
world of distributed computing

HBase

3 seminal papers

Google File System

MapReduce

BigTable

HBase

The paper was presented at the conference

3 seminal papers

Google File System

MapReduce

BigTable

These are all
technologies
built to power
Google Search

HBase

3 seminal papers

Google File System

MapReduce

BigTable

Each of these papers
proposed an
architecture for an
important distributed
computing problem

HBase

3 seminal papers

Google File System

proposed an architecture for

Storage

MapReduce

BigTable

HBase

3 seminal papers

Google File System

MapReduce

BigTable

proposed an architecture for

Storage

Processing data

HBase

3 seminal papers

Google File System

proposed an architecture for

Storage

MapReduce

Processing data

BigTable

Database management

HBase

3 seminal papers

Google File System

MapReduce

BigTable

Storage

Processing data

Database management

All of these architectures abstract
programmers from the complexity of
distributed computing

HBase

Google File System

MapReduce

BigTable

Storage

Processing data

Database management

Hadoop ecosystem

An ecosystem of Open source softwares
based on these architectures

HBase

The problem with distributed computing

9 seminal papers

Hadoop ecosystem

Google File System
Storage



HDFS

MapReduce
Processing data

BigTable
Database management

HBase

5. The problem with distributed computing

→ **3 seminal papers**

Hadoop ecosystem

Google File System
Storage



HDFS

MapReduce
Processing data



Hadoop MapReduce

BigTable
Database management

HBase

The problem with distributed computing

9 seminal papers

Hadoop ecosystem

Google File System
Storage



HDFS

MapReduce
Processing data



Hadoop MapReduce

BigTable
Database management



HBase

HBase

The problem with distributed computing

Hadoop ecosystem

HDFS

Hadoop MapReduce

HBase

HADOOP

HBase

3. The problem with distributed computing

Hadoop ecosystem

HDFS

Hadoop MapReduce

HBase

With Hadoop, you can

1. Store data in a cluster and
2. Process it

HBase

6. The problem with distributed computing

Hadoop ecosystem

HDFS

Hadoop MapReduce

HBase

Why then, do you need a
separate architecture for
database management?

Hbase - Installation

- ▶ Please refer HBaseInstall.txt for Hbase installation

HBase

5. The Hadoop ecosystem

Hadoop ecosystem

HDFS

Hadoop MapReduce

HBase

HADOOP

HBase

HADOOP

is a distributed computing framework
developed and maintained by

THE APACHE SOFTWARE FOUNDATION

HBase

HADOOP

is a distributed computing framework
developed and maintained by

THE APACHE SOFTWARE FOUNDATION

written in Java

HBase

HADOOP

A file system to
manage the
storage of data

HBase

HADOOP

A file system to
manage the
storage of data

A framework to
process data across
multiple servers

HBase

HADOOP

HDFS

A file system to
manage the
storage of data

MapReduce

A framework to
process data across
multiple servers

HBase

HDFS****

The Hadoop Distributed File System

Hadoop uses this to **store**
data across multiple disks

HBase

part of the Hadoop ecosystem

HDFS

Name node

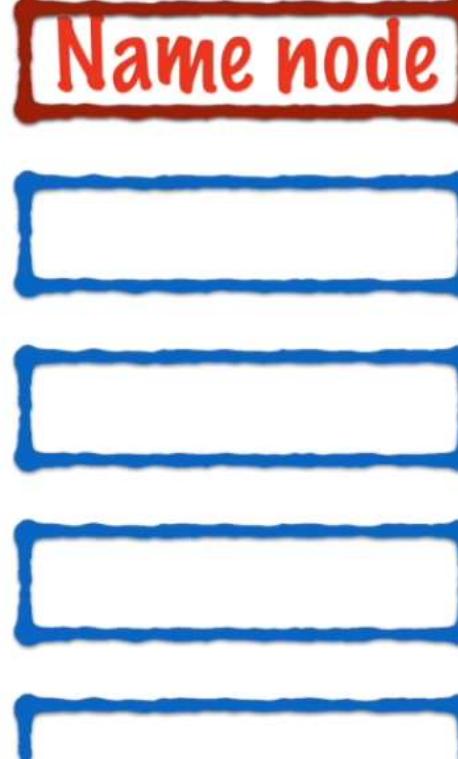


One of the nodes acts as the master node

HBase

Hadoop ecosystem

HDFS



One of the nodes acts as the **master node**

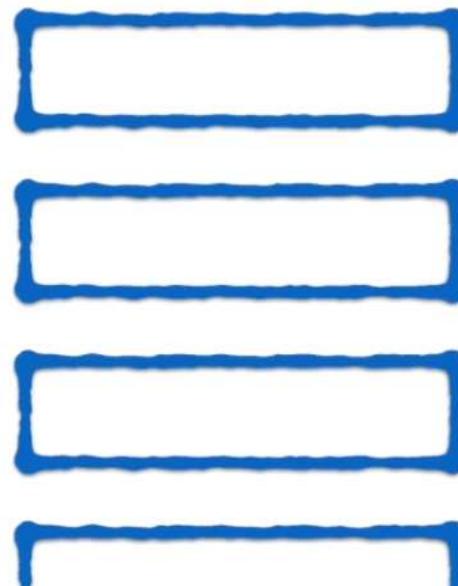
This node
manages the
overall file system

HBase

The Hadoop ecosystem

HD**FS**

Name node



The **name node** stores

1. The directory structure
2. Metadata for all the files

d 5s

HBase

The Hadoop ecosystem

Name node

Data node 1

Data node 2

Data node 3

Data node 4

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HDFS

Other nodes are called **data nodes**

The data is **physically stored** on these nodes

HBase

5. The Hadoop ecosystem

HDFS

Here is a large text file

Next up previous contents index
Next: Dynamic indexing Previous: Single-pass in-memory indexing Contents Index

Distributed indexing

Collections are often so large that we cannot perform index construction efficiently on a single machine. This is particularly true of the World Wide Web for which we need large computer clusters [+] to construct any reasonably sized web index. Web search engines, therefore, use distributed indexing algorithms for index construction. The result of the construction process is a distributed index that is partitioned across several machines – either according to term or according to document. In this section, we describe distributed indexing for a term-partitioned index. Most large search engines prefer a document-partitioned index (which can be easily generated from a term-partitioned index). We discuss this topic further in Section 29.3 (page [+]).

The distributed index construction method we describe in this section is an application of MapReduce , a general architecture for distributed computing. MapReduce is designed for large computer clusters. The point of a cluster is to solve large computing problems on cheap commodity machines or nodes that are built from standard parts (processor, memory, disk) as opposed to on a supercomputer with specialized hardware. Although hundreds or thousands of machines are available in such clusters, individual machines can fail at any time. One requirement for robust distributed indexing is, therefore, that we divide the work up into chunks that we can easily assign and – in case of failure – reassign. A master node directs the process of assigning and reassigning tasks to individual worker nodes.

The map and reduce phases of MapReduce split up the computing job into chunks that standard machines can process in a short time. The various steps of MapReduce are shown in Figure 4.5 and an example on a collection consisting of 100 documents is shown in Figure 4.6 . First, the input data, in our case a collection of web pages, are split into s_{ns} splits where the size of the split is chosen to ensure that the work can be distributed evenly (chunks should not be too large) and efficiently (the total number of chunks we need to manage should not be too large; 16 or 64 MB are good sizes in distributed indexing). Splits are not preassigned to machines, but are instead assigned by the master node on an ongoing basis: As a machine finishes processing one split, it is assigned the next one. If a machine dies or becomes a laggard due to hardware problems, the split it is working on is simply reassigned to another machine.

Figure 4.5: An example of distributed indexing with MapReduce. Adapted from Dean and Ghemawat (2004).
\\includegraphics[width=11.5cm]{art/mapreduce.pdf}

In general, MapReduce breaks a large computing problem into smaller parts by recasting it in terms of manipulation of key-value pairs . For indexing, a key-value pair is of the form $(termID, docID)$. In distributed indexing, the mapping from terms to termIDs is also distributed and therefore more complex than in single-machine indexing. A simple solution is to maintain a (perhaps precomputed) mapping for frequent terms that is copied to all nodes and to use terms directly (instead of termIDs) for infrequent terms. We do not address this problem here and assume that all nodes share a consistent term \rightarrow termID mapping.

The map phase of MapReduce consists of mapping splits of the input data to key-value pairs. This is the same parsing task we also encountered in BSBI and SPAMI, and we therefore call the machines that execute the map phase parsers . Each parser writes its output to local intermediate files, the segment files (shown as \backslash hbox{a-f}\medstrut \backslash\hbox{g-h}\medstrut \backslash\hbox{i-q-z}\medstrut in Figure 4.5).

For the reduce phase , we want all values for a given key to be stored close together, so that they can be read and processed quickly. This is achieved by partitioning the keys into s_{rs} term partitions and having the parsers write key-value pairs for each term partition into a separate segment file. In Figure 4.5 , the term partitions are according to first letter: a-f, g-p, q-r, and s-j-3s . (We chose these key ranges for ease of exposition. In general, key ranges need not correspond to contiguous terms or termIDs.) The term partitions are defined by the person who operates the indexing system (Exercise 4.6). The parsers then write corresponding segment files, one for each term partition. Each term partition thus corresponds to s_{rs} segment files, where s_{rs} is the number of parsers. For instance, Figure 4.5 shows three a-f segment files of the a-f partition, corresponding to the three parsers shown in the figure.

Let's see how this file is stored in HDFS

HBase

5. The Hadoop ecosystem

The screenshot shows a web page titled "HDFS" with the sub-section "distributed indexing". The page discusses the challenges of indexing large web pages and introduces the MapReduce framework for distributed indexing. It shows a file named "indexing2.txt" which has been split into 8 blocks of size 128 MB each. The blocks are labeled Block 1 through Block 8. The page also mentions the MapReduce process, including the map and reduce phases, and how it handles splits and failures.

Next: Dynamic indexing | Up: Index construction | Previous: Single-pass in-memory indexing | Contents | Index

Block 1

World Wide Web for which we need large computer clusters. To construct any reasonably sized web index, web search engines, therefore, use distributed indexing algorithms for index construction. The result of the construction process is a distributed index that is partitioned across several machines – either according to the document or to the document. In this section, we describe distributed indexing for a term-partitioned index. Most large search engines prefer a document-partitioned index (which can be easily generated from a term-

Block 2

The distributed index construction method we describe in this section is an application of MapReduce, a general architecture for distributed computing. MapReduce is designed for large computation on cheap commodity machines or nodes that are built from standard hardware (CPU, memory, disk) as opposed to a supercomputer with specialized hardware. Although hundreds or thousands of machines are available in such clusters, individual machines can fail at any time.

Block 3

The map and reduce phases of MapReduce split up the computation into smaller tasks that standard machines can process in a short time. The various steps of MapReduce are shown in Figure 4.5 and an example of a file consisting of two documents is shown in Figure 4.6. First, the input data, in our case a collection of web pages, is split into various splits where the size of the split is chosen to ensure that the work can be distributed evenly. Chunks should not be too large and efficiently (the total number of chunks we need to manage

Block 4

should be small). The next step is the map phase, where each split is processed by one or more mappers. If a mapper fails or becomes a laggard due to hardware problems, the split it was in charge of is simply reassigned to another machine.

Figure 4.5: An example of distributed indexing with MapReduce. (Courtesy of Dean and Ghemawat, (2004). [MapReduce: Simplified Data Processing on Large Clusters](#))

Block 5

MapReduce needs to turn complex problems into smaller parts by partitioning it in terms of manipulation of key-value pairs.

Block 6

and therefore more complex than single-machine indexing. A simple solution is to maintain a (term, precomputed) mapping for frequent terms that is copied to all nodes and to use terms directly as keys (or groups) for infrequent terms. We do not address this problem here and assume that all nodes share a consistent term mapping.

Block 7

The map phase of MapReduce consists of mapping splits of the input data to key-value pairs. This is the same parsing task we also

Block 8

For the reduce phase, we want all values for a given key to be read together, so that they can be read and processed quickly. This is achieved by partitioning the keys into SRB term partitions and writing the parsers write key-value pairs for each term partition into a separate segment file. In Figure 4.5, the term partitioning corresponds to first letters: a-f, g-p, q-z, and \$|-\$. We chose these terms for ease of illustration. In general, the output need not be restricted to contiguous terms or term\$|-\$. The term partitioning can

each partition. Each term partition thus corresponds to SRB segment files, where SRB is the number of parsers. For instance, Figure 4.5 shows three a-f segment files of the a-f partition, corresponding to the three parsers shown in the figure.

Collecting all values (here: docID) for a given key (here: a-f) is the task of the inverters in the reduce phase. The

First the file is
broken into
blocks of size
128 MB

HBase

5. The Hadoop ecosystem

The screenshot shows the HDFS interface with a file named 'index' split into 8 blocks. The blocks are labeled Block 1 through Block 8. The interface includes navigation links like 'Next', 'Dynamic indexing up', 'Index construction Previous: Statistics in memory indexing', 'Contents', and 'Index'. A large red watermark 'HDFS' is visible across the interface.

Block 1

Block 2

Block 3

Block 4

Block 5

Block 6

Block 7

Block 8

First the file is broken into blocks of size 128 MB

This size is chosen to minimize the time to seek to the block on the disk

HBase

. The Hadoop ecosystem

HDFS

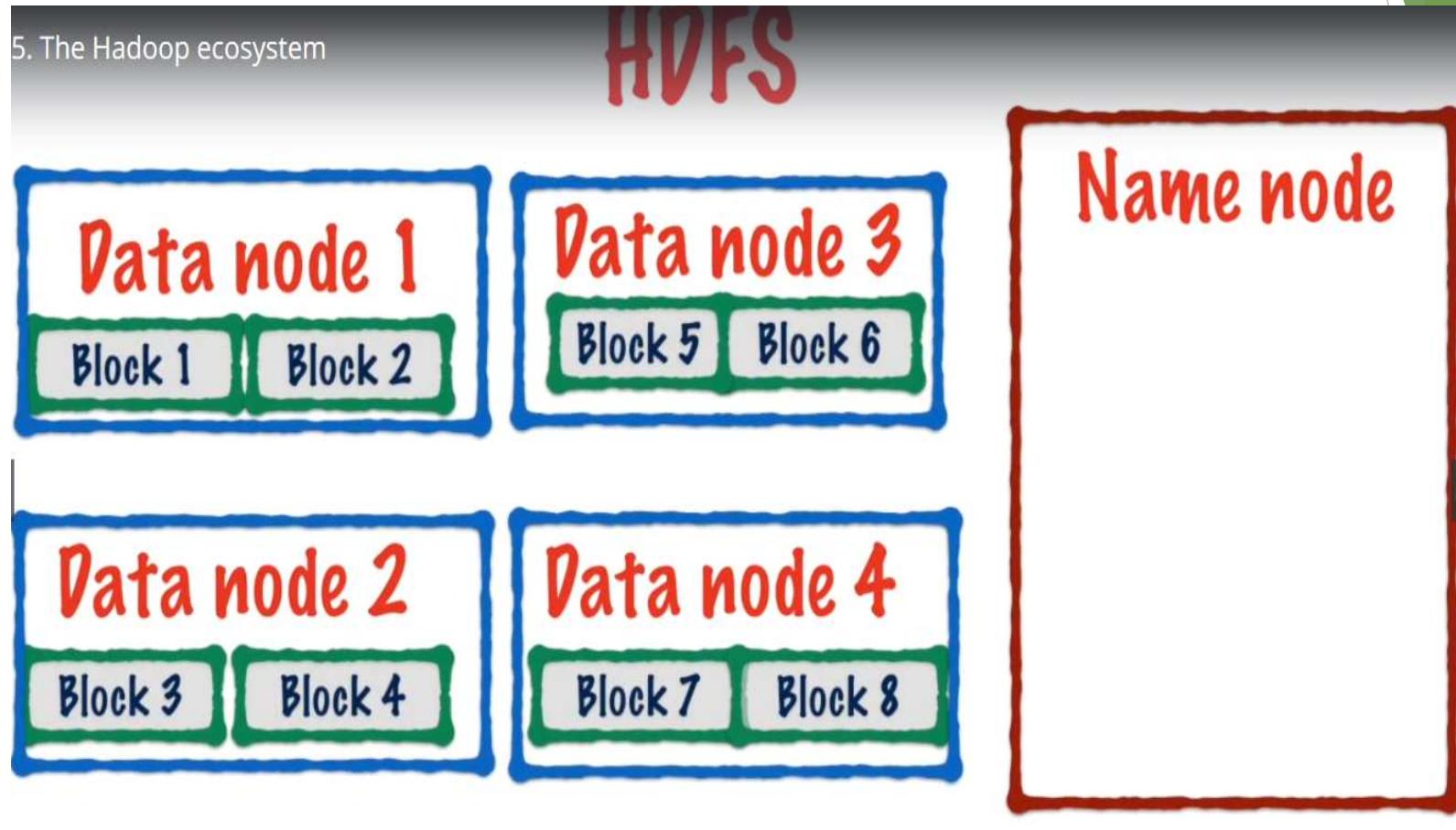
The screenshot shows a web page with a large red header 'HDFS'. Below the header, there is a list of eight items, each labeled 'Block 1' through 'Block 8'. Each item has a small thumbnail image and some descriptive text. The text for each block is as follows:

- Block 1:** A brief introduction to distributed indexing.
- Block 2:** A detailed explanation of distributed indexing for large clusters.
- Block 3:** An overview of MapReduce, highlighting its use for distributed computing on commodity hardware.
- Block 4:** A discussion of the map and reduce phases of MapReduce, mentioning the minimization of key-value pairs.
- Block 5:** A note about the map phase, stating it is typically the bottleneck.
- Block 6:** A note about the reduce phase, mentioning the need to maintain a mapping for frequent terms.
- Block 7:** A note about the reduce phase, mentioning the task of inverters.
- Block 8:** A note about the reduce phase, mentioning the task of collecting all values.

These blocks are
then stored
across the data
nodes

HBase

5. The Hadoop ecosystem



HBase

5. The Hadoop ecosystem

HDFS

Data node 1

Block 1

Block 2

Data node 3

Block 5

Block 6

Data node 2

Block 3

Block 4

Data node 4

Block 7

Block 8

Name node

The name
node stores
metadata

HBase

The Hadoop ecosystem

HDFS

Block locations
for each file are
stored in the
name node

Name node		
File 1	Block 1	DN 1
File 1	Block 2	DN 1
File 1	Block 3	DN 2
File 1	Block 4	DN 2
File 1	Block 5	DN 3

HBase

5. The Hadoop ecosystem

HD**FS**

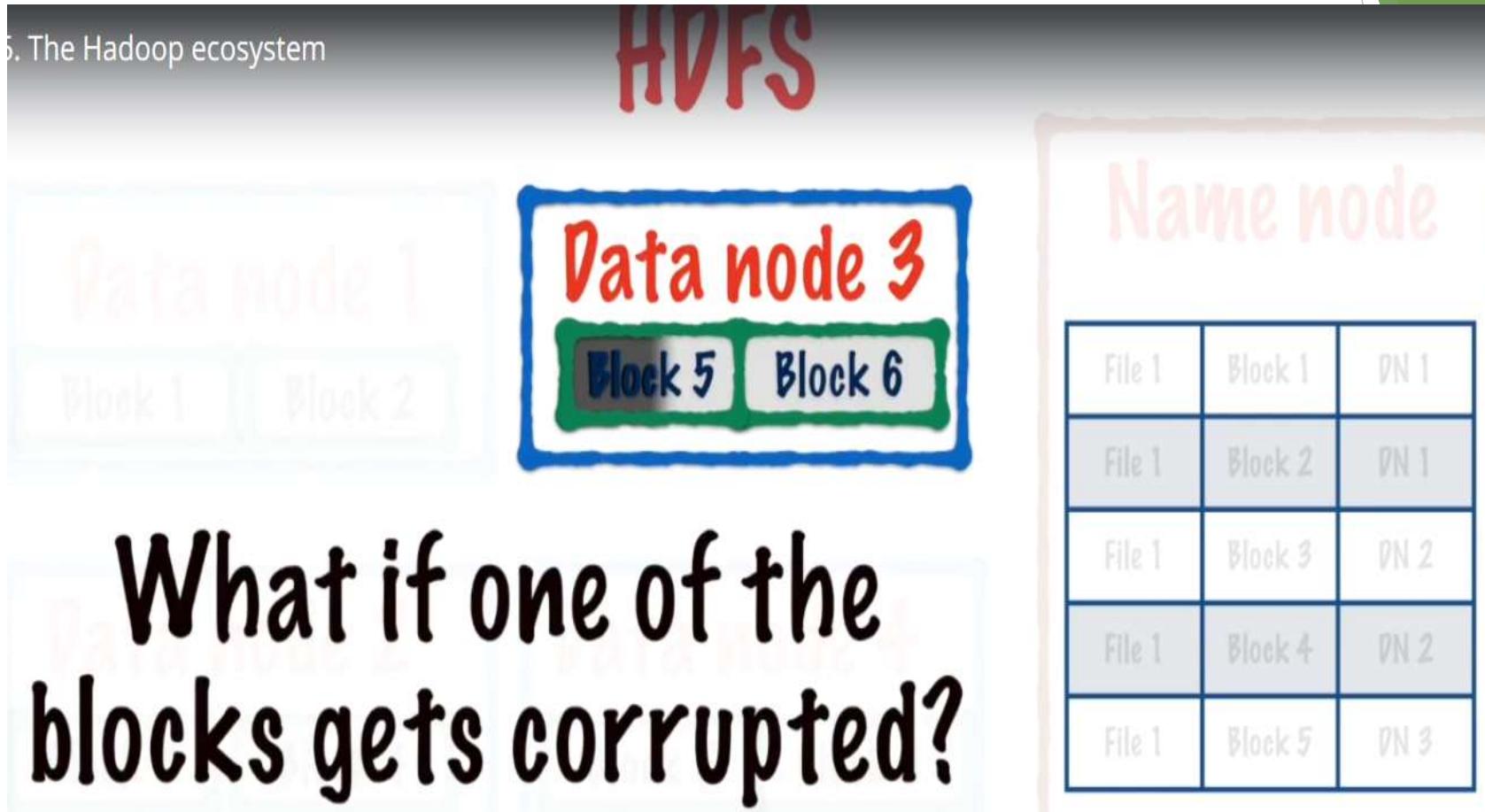
A file is read using

1. The **metadata** in name node
2. The **blocks** in the data nodes

File 1	Block 1	DN 1
File 1	Block 2	DN 1
File 1	Block 3	DN 2
File 1	Block 4	DN 2
File 1	Block 5	DN 3

HBase

6. The Hadoop ecosystem



HBase

The Hadoop ecosystem

HD**F**S

Data node 1

Block 1

Block 2

Data node 3

Block 5

Block 6

Or one of the data nodes crashes?

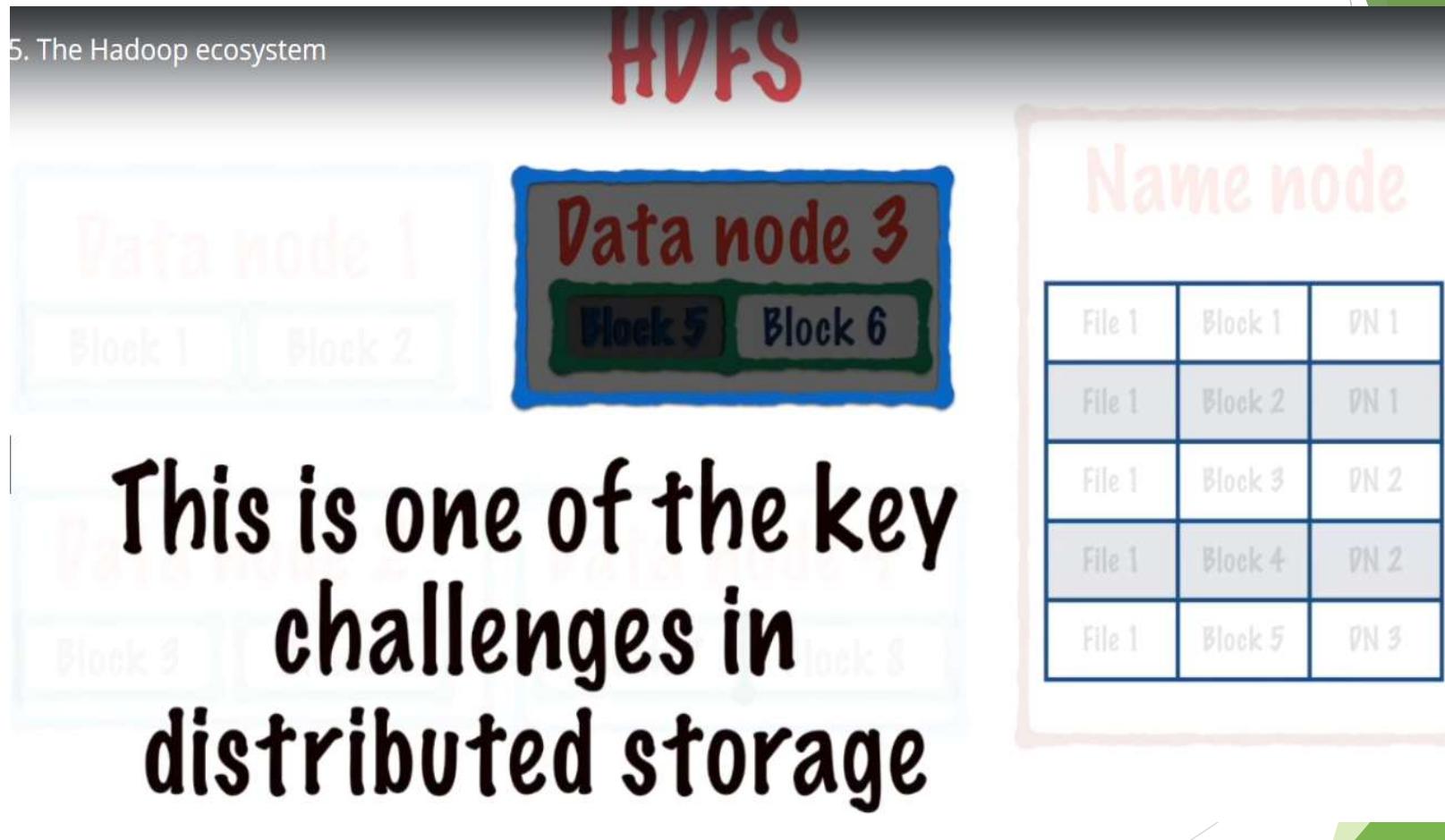
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Name node

File 1	Block 1	DN 1
File 1	Block 2	DN 1
File 1	Block 3	DN 2
File 1	Block 4	DN 2
File 1	Block 5	DN 3

HBase

5. The Hadoop ecosystem



HBase

. The Hadoop ecosystem

HDFS

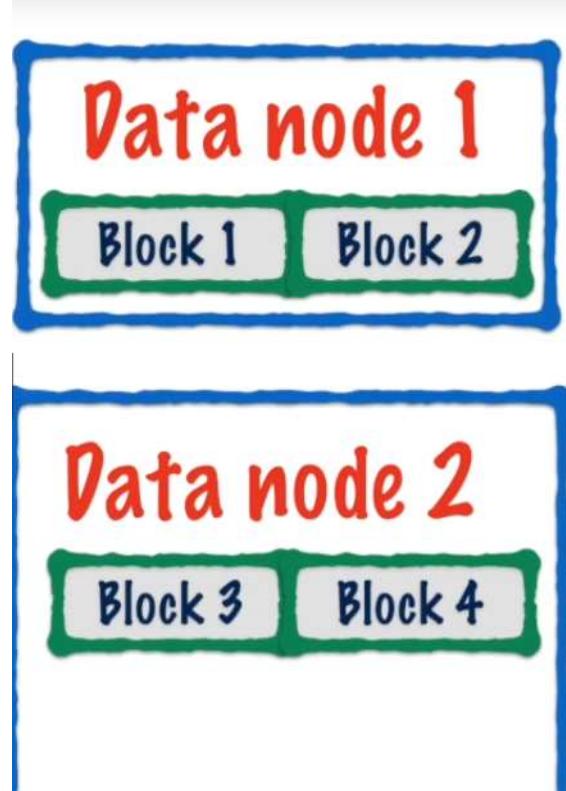
You can define a
replication factor in
HDFS

Name node

File 1	Block 1	DN 1
File 1	Block 2	DN 1
File 1	Block 3	DN 2
File 1	Block 4	DN 2
File 1	Block 5	DN 3

HBase

5. The Hadoop ecosystem



HDFS

Data node 3

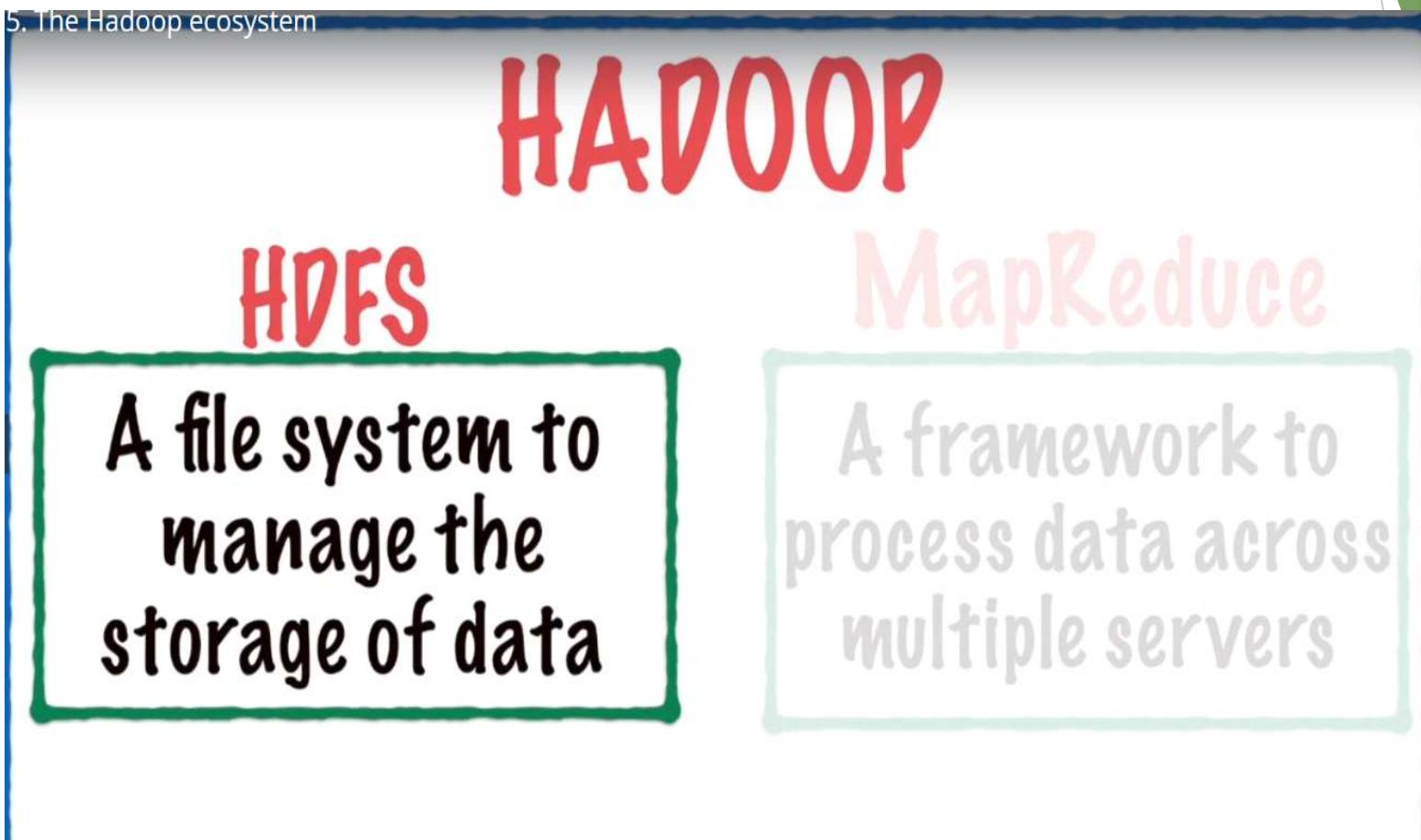
Block 5 Block 6

Name node

Each block is replicated,
and the replicas are
stored in different data
nodes

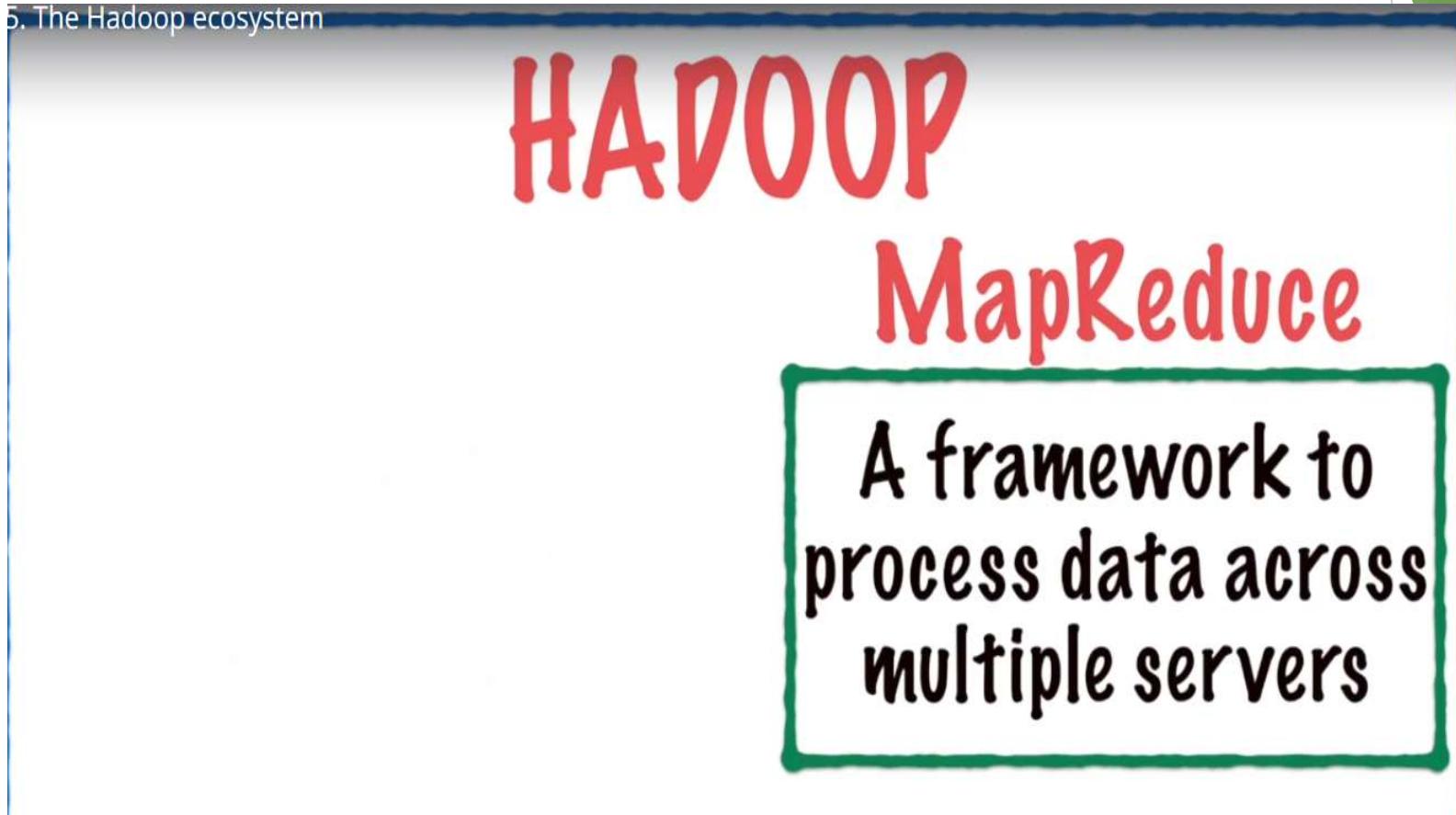
HBase

5. The Hadoop ecosystem



HBase

5. The Hadoop ecosystem



HBase

Hadoop ecosystem

MapReduce

**MapReduce is a way
to parallelize a data
processing task**

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The Hadoop ecosystem

MapReduce

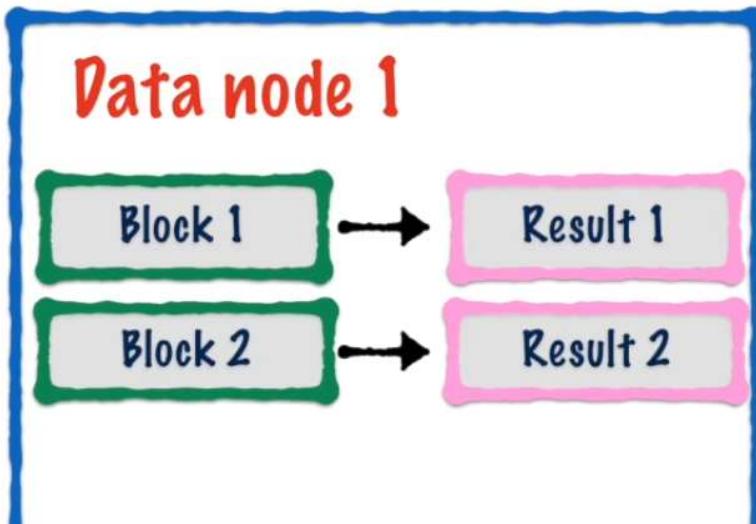
**MapReduce tasks
have 2 phases**

HBase

The Hadoop ecosystem

MapReduce

1. Process each block in the node it is stored in



Map phase

HBase

The Hadoop ecosystem

MapReduce

2. Take all the results to one node and combine them



nd 5s

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. The Hadoop ecosystem

MapReduce

2. Take all the results to one node and combine them

Reduce phase



Name node
The name node stores metadata

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The Hadoop ecosystem

MapReduce

Any data processing task can
be expressed as a chain of map
reduce operations

MapReduce

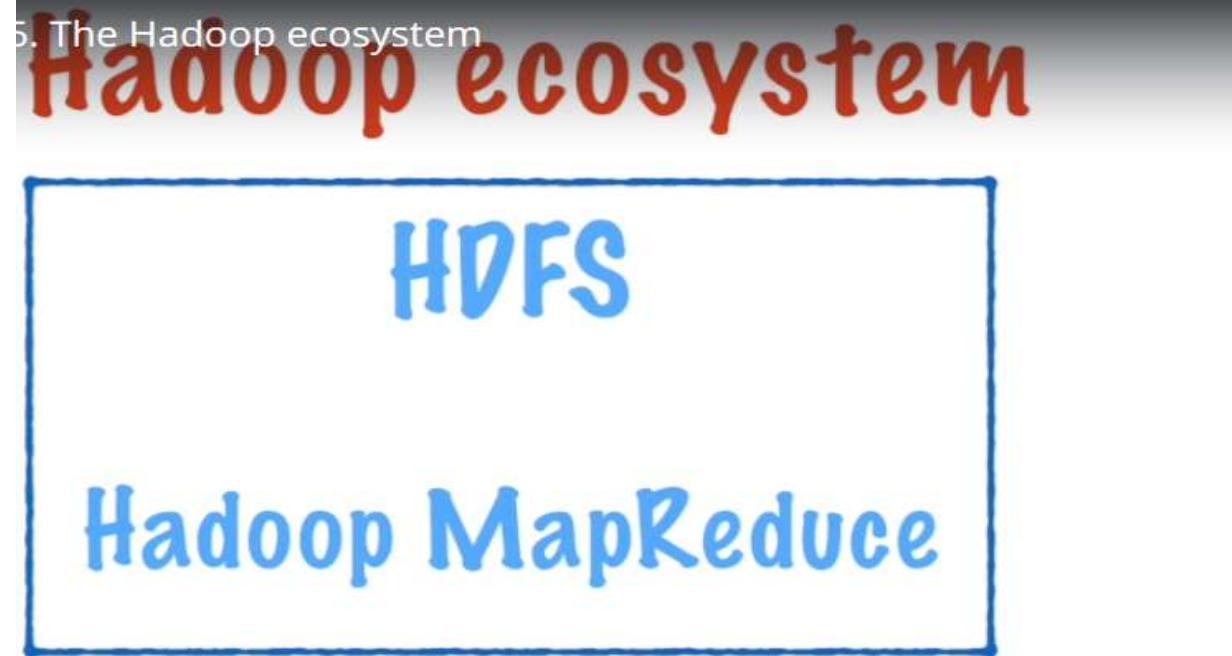
The programmer just specifies
the logic to be implemented the
map and reduce phases

MapReduce

The programmer just specifies
the logic to be implemented the
map and reduce phases

The rest is taken care
of by Hadoop

HBase



HBase

HBase

role of HBase in the Hadoop ecosystem

Hadoop vs Databases

Databases are at the heart of most applications

HBase

The role of HBase in the Hadoop ecosystem

Hadoop vs Databases

Databases are at **the heart of most** applications

e-mails

Sales

Bank accounts

Payroll

HBase

6. The role of HBase in the Hadoop ecosystem

Hadoop vs Databases

e-mails
Sales
Bank accounts
Payroll

Databases that serve such applications do something called **Transaction processing**

HBase

6. The role of HBase in the Hadoop ecosystem

Hadoop vs Databases

e-mails

Sales

Bank accounts

Payroll

They store data
in the form of
**tables, rows,
columns**

HBase

6. The role of HBase in the Hadoop ecosystem

Hadoop vs Databases

e-mails
Sales
Bank accounts
Payroll

A transaction involves
Inserting, updating,
deleting data (or a
combination of these)

HBase

6. The role of HBase in the Hadoop ecosystem

Hadoop vs Databases

e-mails
Sales
Bank accounts
Payroll

Transaction processing has certain requirements

HBase

of HBase in the Hadoop ecosystem

Hadoop vs Databases

Hadoop has a **few limitations** which make it unsuited for transaction processing

HBase

6. The role of HBase in the Hadoop ecosystem

Hadoop vs Databases

Hadoop limitations

1. Unstructured data
2. No random access
3. High latency
4. Not ACID compliant

HBase

The role of HBase in the Hadoop ecosystem

Hadoop vs Databases

1. Unstructured data

Hadoop stores
data in HDFS

HBase

The role of HBase in the Hadoop ecosystem

Hadoop vs Databases

1. Unstructured data

The data in HDFS is
Unstructured

HBase

The role of HBase in the Hadoop ecosystem

Hadoop vs Databases

1. Unstructured data

Unlike databases, HDFS
data doesn't have any
schema

HBase

The role of HBase in the Hadoop ecosystem

Hadoop vs Databases

1. Unstructured data

It's basically in the form of files

Text files

Log files

Video/Audio files

wind 5s

Talentum Global Technologies

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HBase

6. The role of HBase in the Hadoop ecosystem

Hadoop vs Databases

1. Unstructured data

There's no concept of rows/columns

There are no tables

HBase

The role of HBase in the Hadoop ecosystem

Hadoop vs Databases

1. Unstructured data

This is not to say that
Hadoop can't be used to
store structured data

HBase

The role of HBase in the Hadoop ecosystem

Hadoop vs Databases

1. Unstructured data

You could store your data in a structured format even in Hadoop

csv files

xml files

jsons

HBase

The role of HBase in the Hadoop ecosystem

Hadoop Vs Databases

Each record
in these files
could be 1
row in a table

1. Unstructured data

csv files
xml files
jsons

HBase

The role of HBase in the Hadoop ecosystem

Hadoop Vs Databases

1. Unstructured data

But unlike databases,
Hadoop **will not**
enforce the schema
or any constraints
on these rows/tables

csv files
xml files
jsons

HBase

The role of HBase in the Hadoop ecosystem

Hadoop vs Databases

Hadoop limitations

1. Unstructured data

2. No random access

HBase

The role of HBase in the Hadoop ecosystem

Hadoop vs Databases 2. No random access

Applications that use databases
require **random access**

ie. the ability to create, access and
modify **individual rows of a table**

HBase

The role of HBase in the Hadoop ecosystem

Hadoop vs Databases

2. No random access

HDFS is optimal for storing large files

MapReduce is optimal for processing these files as a **whole**

HBase

5. The role of HBase in the Hadoop ecosystem

Hadoop vs Databases

2. No random access

If an HDFS file consists of many rows in a table

There is no provision to access or modify a specific row without processing the entire file

HBase

. The role of HBase in the Hadoop ecosystem

Hadoop vs Databases

Hadoop limitations

1. Unstructured data

2. No random access

3. High latency

HBase

The role of HBase in the Hadoop ecosystem

Hadoop vs Databases

3. High latency

Applications also require **low latency**

Any operations like inserting,
updating or deleting data should
occur **as fast as possible**

HBase

The role of HBase in the Hadoop ecosystem

Hadoop Vs Databases

3. High latency

All processing in Hadoop occurs via
MapReduce tasks on complete files

Even on large clusters, these tasks
might take **minutes or hours** at times

HBase

6. The role of HBase in the Hadoop ecosystem

Hadoop vs Databases

Hadoop limitations

1 Unstructured data

| 2 No random access

3 High latency

4 Not ACID compliant

HBase

6. The role of HBase in the Hadoop ecosystem

Hadoop Vs Databases

4. Not ACID compliant

Databases are **the**
source of truth for the
data that they store

HBase

The role of HBase in the Hadoop ecosystem

Hadoop vs Databases

4. Not ACID compliant

Databases guarantee ACID properties to maintain the integrity of their data

HBase

The role of HBase in the Hadoop ecosystem

Hadoop Vs Databases

4. Not ACID compliant

ACID
properties

Atomicity
Consistency
Isolation
Durability

HBase

. The role of HBase in the Hadoop ecosystem

Hadoop vs Databases

4. Not ACID compliant

Atomicity

Operations (aka transactions) must be
all-or-nothing

HBase

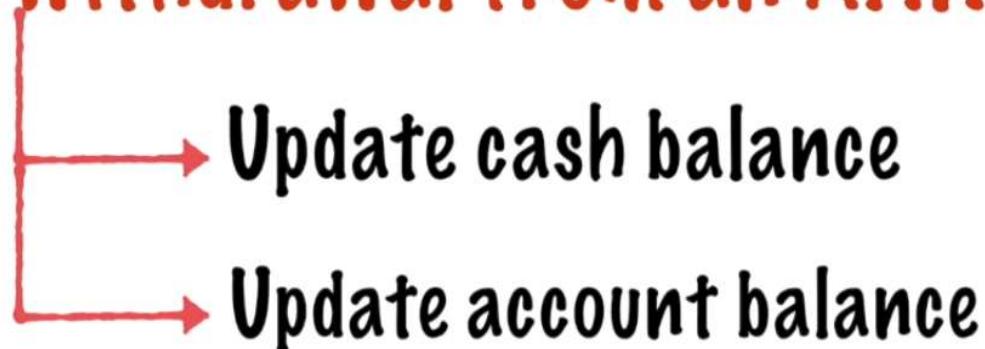
6. The role of HBase in the Hadoop ecosystem

Hadoop vs Databases

4. Not ACID compliant

Atomicity

Example of a transaction :
Cash withdrawal from an ATM



HBase

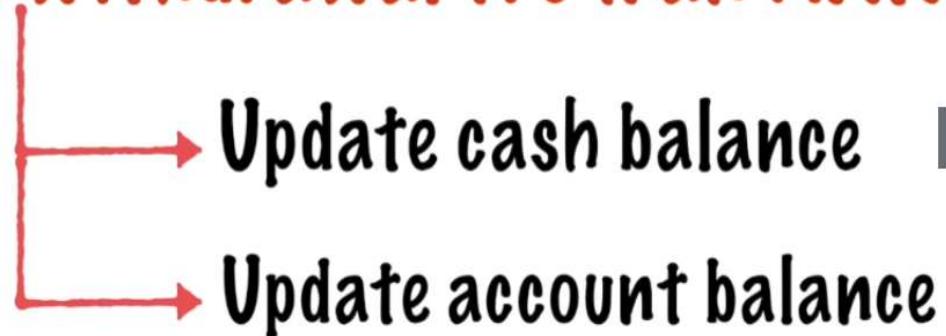
. The role of HBase in the Hadoop ecosystem

Hadoop vs Databases

4. Not ACID compliant

Atomicity

Cash withdrawal from an ATM



If one of these fails, the whole transaction should fail

HBase

. The role of HBase in the Hadoop ecosystem

Hadoop Vs Databases

4. Not ACID compliant

Atomicity

Consistency

Isolation

Durability

Any changes to the database **must not violate** any specified database constraints

HBase

The role of HBase in the Hadoop ecosystem

Hadoop vs Databases

4. Not ACID compliant

Atomicity
Consistency

Isolation

Durability

If multiple/concurrent operations occur, the result is as if these operations are applied in sequence

HBase

The role of HBase in the Hadoop ecosystem

Hadoop Vs Databases

4. Not ACID compliant

Atomicity
Consistency
Isolation
Durability

Once a transaction
is executed, the
changes are
permanent

HBase

6. The role of HBase in the Hadoop ecosystem

Hadoop vs Databases

4. Not ACID compliant

Atomicity
Consistency
Isolation
Durability

Traditional databases are designed to guarantee all of these properties

HBase

. The role of HBase in the Hadoop ecosystem

Hadoop vs Databases

4. Not ACID compliant

ACID guarantees require that
the database management
system is aware of the structure
and contents of the data

HBase

6. The role of HBase in the Hadoop ecosystem

Hadoop Vs Databases

4. Not ACID compliant

ACID guarantees require that the database management system **is aware of the structure and contents of the data**

HDFS** being just a file storage system, has no such awareness**

HBase

6. The role of HBase in the Hadoop ecosystem

Hadoop vs Databases

Hadoop limitations

1. Unstructured data
2. No random access
3. High latency
4. Not ACID compliant

HBase

6. The role of HBase in the Hadoop ecosystem

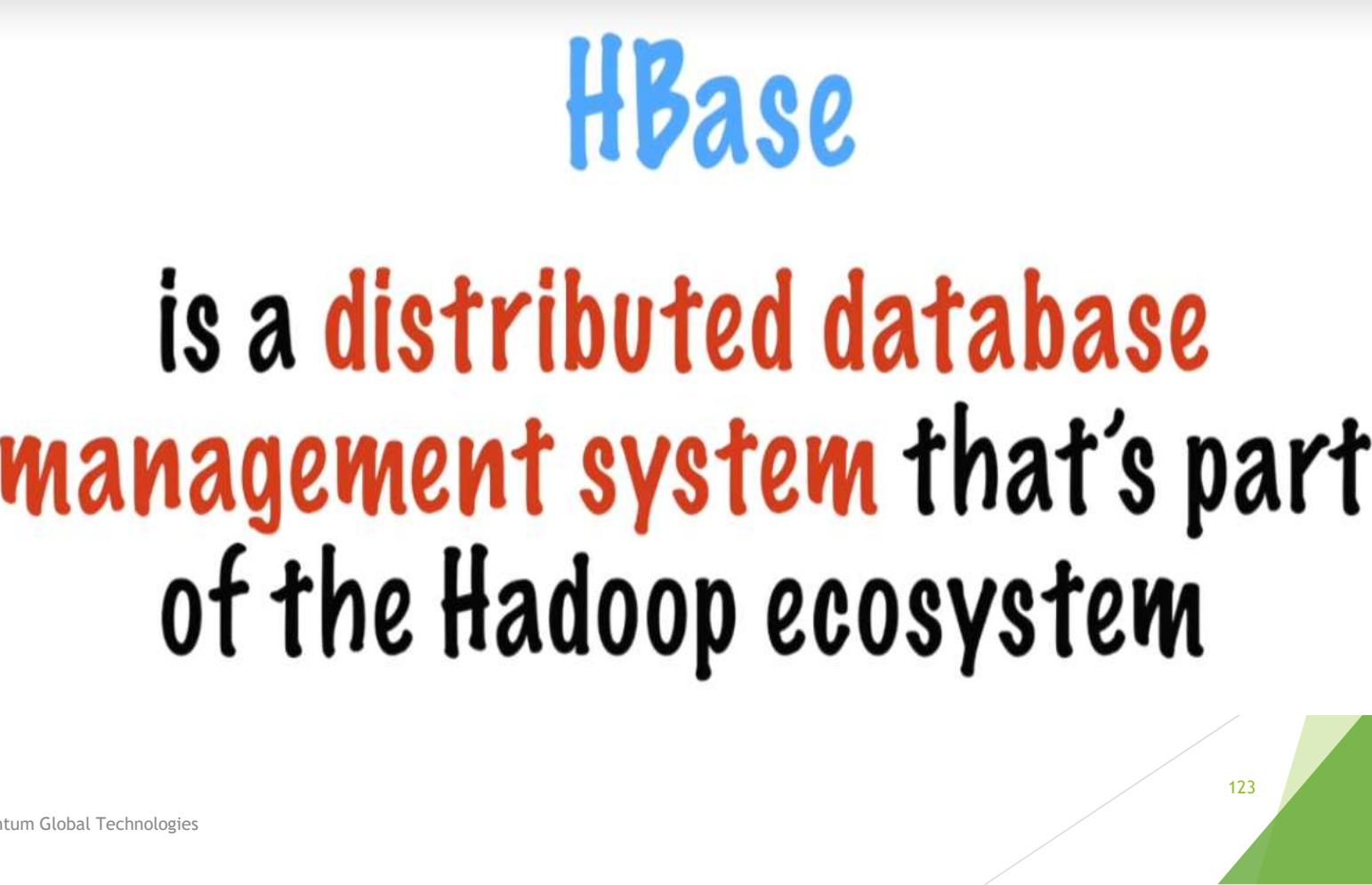
Hadoop vs Databases

Hadoop limitations

1. Unstructured data
2. No random access
3. High latency
4. Not ACID compliant

All these
limitations make
Hadoop unsuited
for transaction
processing

HBase



HBase
is a **distributed database management system** that's part of the Hadoop ecosystem

HBase

6. The role of HBase in the Hadoop ecosystem

HBase

**HBase uses HDFS to store
it's underlying data**

HBase

6. The role of HBase in the Hadoop ecosystem



**HBase has the architecture
benefits of HDFS**

1. **Distributed storage**
2. **Fault tolerance**

HBase

6. The role of HBase in the Hadoop ecosystem

HBase

It also has many of the properties required for **transaction processing**

- 1. Awareness of the structure of data
- 2. Low latency
- 3. Random access
- 4. ACID compliant at some levels

HBase

HBase

To understand HBase
it's helpful understand how it's
different from a traditional
RDBMS

HBase

How is HBase different from RDBMS?

HBase vs RDBMS

NoSQL

HBase does not support SQL

HBase

- . How is HBase different from RDBMS?

HBase vs RDBMS

In a traditional RDBMS, all operations like creating, inserting, updating rows are done using SQL

HBase does not support SQL

HBase

. How is HBase different from RDBMS?

HBase vs RDBMS

Only CRUD operations

HBase only supports a basic set of operations (Create-Read-Update-Delete)

HBase

- . How is HBase different from RDBMS?

HBase vs RDBMS

(Create-Read-Update-Delete)

Only CRUD operations

All these operations have to
be applied at a row level

HBase

- . How is HBase different from RDBMS?

HBase vs RDBMS

(Create-Read-Update-Delete)

Only CRUD operations

HBase does not support any operations across rows (or) across tables

HBase

- . How is HBase different from RDBMS?

HBase vs RDBMS

(Create-Read-Update-Delete)

Only CRUD operations

This means that you cannot
perform operations like
Joins, Group by etc

HBase

7. How is HBase different from RDBMS?

HBase vs RDBMS

Only **CRUD** operations

Denormalized

HBase tables are **not designed using a relational data model**

HBase

- How is HBase different from RDBMS?

HBase vs RDBMS

Only CRUD operations

Denormalized

**All the data pertaining to
an entity is stored in 1 row
(ie tables are denormalized)**

HBase

. How is HBase different from RDBMS?

HBase vs RDBMS

Distributed operations

Denormalized

Column oriented storage

HBase has a special kind of
data model

HBase

- . How is HBase different from RDBMS?

HBase vs RDBMS

Only CRUD operations
Denormalized
Column oriented storage

ACID at a row level

HBase is ACID compliant for limited kinds of transactions

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HBase

- . How is HBase different from RDBMS?

HBase vs RDBMS

Column oriented storage

Denormalized

Only CRUD operations

ACID at a row level

HBase

. HBase Data Model

HBase vs RDBMS

Column oriented storage

Denormalized

Only CRUD operations

ACID at a row level

Let's
understand the
implications of
each of these

HBase

8. HBase Data Model

HBase vs RDBMS

Column oriented storage

Say we have an application that manages notifications to the users of a social network



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3. HBase Data Model

Hbase vs RDBMS

Search

Notifications

Jessica accepted your friend request. Since she's new to Facebook, you should suggest people she knows.

 Jessica is new on Facebook. To welcome her:
Suggest people that she knows
Write on her wall
34 minutes ago

Jon Dugan commented on your photo. about an hour ago

Daniel J. Adams commented on your link. 2 hours ago

Chaz Yoon commented on your photo. 2 hours ago

Brendan McLaughlin commented on your link. 3 hours ago

Brendan McLaughlin likes your link. 3 hours ago

Bruce Robert Abbott commented on your photo. 3 hours ago

Chaz Yoon commented on your link. 3 hours ago

Column oriented storage

Here is a table that stores some notification related data

id	type	for user	from user	timestamp
1	Friend request status	Ryan	Jessica	146710201
2	Comment	Chaz	Daniel	146711200
3	Comment	Rick	Brendan	1467112205
4	Like	Rick	Brendan	1467112213

HBase vs RDBMS

Column oriented storage

This is how data is stored
in traditional databases

id	type	for user	from user	timestamp
1	Friend request status	Ryan	Jessica	146710201
2	Comment	Chaz	Daniel	146711200
3	Comment	Rick	Brendan	1467112205
4	Like	Rick	Brendan	1467112213

A table with a fixed schema is defined

id	type	for user	from user	timestamp
1	Friend request status	Ryan	Jessica	146710201
2	Comment	Chaz	Daniel	146711200
3	Comment	Rick	Brendan	1467112205
4	Like	Rick	Brendan	1467112213

Each row represents a data point

id	type	for user	from user	timestamp
1	Friend request status	Ryan	Jessica	146710201
2	Comment	Chaz	Daniel	146711200
3	Comment	Rick	Brendan	1467112205
4	Like	Rick	Brendan	1467112213

In a column oriented store, each cell represents a datapoint

id	type	for user	from user	timestamp
1	Friend request status	Ryan	Jessica	146710201
2	Comment	Chaz	Daniel	146711200
3	Comment	Rick	Brendan	1467112205
4	Like	Rick	Brendan	1467112213

HBase

. HBase Data Model

HBase vs RDBMS

Column oriented storage

id	type	for user	from user	timestamp
1	Friend request status	Ryan	Jessica	146710201
2	Comment	Chaz	Daniel	146711200
3	Comment	Rick	Brendan	1467112205
4	Like	Rick	Brendan	1467112213

Data is stored
in a map

8. HBase Data Model

HBase vs RDBMS

Column oriented storage

id	type	for user	from user	timestamp
1	Friend request status	Rick	Jessica	146710201
2	Comment	Chaz	Daniel	146711200
3	Comment	Rick	Brendan	1467112205
4	Like	Rick	Brendan	1467112213

Data is stored
in a map

Key = <Row id, Col id>

Value = <data>

HBase vs RDBMS

id	type	for user	from user	timestamp
1	Friend request status	Ryan	Jessica	146710201
2	Comment	Chaz	Daniel	146711200
3	Comment	Rick	Brendan	1467112205
4	Like	Rick	Brendan	1467112213

Key = 2, for_user
 Value = Chaz

Column oriented storage

Data is stored
 in a map

8. HBase Data Model

HBase vs RDBMS**Column oriented storage**

id	type	for user	from user	timestamp
1	Friend request status	Ryan	Jessica	146710201
2	Comment	Chaz	Daniel	146711200
3	Comment	Rick	Brendan	1467112205
4	Like	Rick	Brendan	1467112213



row	column	value
1	type	Friend request status
1	for user	Ryan
1	from user	Jessica
1	timestamp	146710201
2	type	Comment
2	for user	Chaz
2	from user	Daniel
2	timestamp	146711200
3	type	Comment
3	for user	Rick
3	from user	Brendan
3	timestamp	1467112205

Fullscreen

An HBase table
is in fact a
sorted map

Keys Values

row	column	value
1	type	Friend request status
	for user	Ryan
	from user	Jessica
	timestamp	146710201
2	type	Comment
	for user	Chaz
	from user	Daniel
	timestamp	146711200
3	type	Comment
	for user	Rick
	from user	Brendan

3. HBase Data Model

Hbase vs RDBMS

A screenshot of a Facebook notifications feed. At the top, there's a search bar and a globe icon. Below it, a section titled "Notifications" shows a message from Jessica about a friend request. Below that, several other notifications are listed:

- Jon Dugan commented on your photo, about an hour ago
- Daniel J. Adams commented on your link, 2 hours ago
- [REDACTED] commented on [REDACTED]'s photo, 2 hours ago
- Brendan McLaughlin commented on your link, 3 hours ago
- Brendan McLaughlin likes your link, 3 hours ago
- Bruce Robert Abbott commented on your photo, 3 hours ago
- Craig Yoon commented on your link, 3 hours ago

At the bottom left, there's a "Rewind 5s" button.

Column oriented storage

Let's say some notifications have **special attributes** depending on their type

8. HBase Data Model

Jessica is new on Facebook. To welcome her:
Suggest people that she knows
Write on her wall

34 minutes ago

Jon Dugan commented on your photo, about an hour ago

Daniel J. Adams commented on your link, 2 hours ago

[REDACTED] commented on [REDACTED]'s photo.
2 hours ago

Brendan McLaughlin commented on your link, 3 hours ago

Brendan McLaughlin likes your link, 3 hours ago

Bruce Robert Abbott commented on your photo, 3 hours ago

Chaz Yoon commented on your link, 3 hours ago

Column oriented storage

Friend request notifications might have information about the friend

HBase

8. HBase Data Model

Jessica is new on Facebook. To welcome her:
Suggest people that she knows
Write on her wall

34 minutes ago

-  Jon Dugan commented on your photo, about an hour ago
-  Daniel J. Adams commented on your link, 2 hours ago
-  [REDACTED] commented on [REDACTED]'s photo.
2 hours ago
-  Brendan McLaughlin commented on your link, 3 hours ago
-  Brendan McLaughlin likes your link, 3 hours ago
-  Bruce Robert Abbott commented on your photo, 3 hours ago
-  Chaz Yoon commented on your link, 3 hours ago

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Column oriented storage

Comments and likes have information about a link or photo that prompted them

HBase

HBase Data Model

HBase vs RDBMS

Column oriented storage

id	type	for user	from user	timestamp	friend type
1	Friend request	Ryan	Jessica	146710201	new
2	Comment	Chaz	Daniel	146711200	-
3	Comment	Rick	Brendan	1467112205	-
4	Like	Rick	Brendan	1467112213	-

HBase

8. HBase Data Model

HBase vs RDBMS

Column oriented storage

id	type	for user	from user	timestamp	friend type	commented on
1	Friend request	Ryan	Jessica	146710201	new	-
2	Comment	Chaz	Daniel	146711200	-	link
3	Comment	Rick	Brendan	1467112205	-	photo
4	Like	Rick	Brendan	1467112213	-	-

HBase vs RDBMS

Column oriented storage

id	type	for user	from user	timestamp	friend type	commented on
1	Friend request	Ryan	Jessica	146710201	new	-
2	Comment	Chaz	Daniel	146711200	-	link
3	Comment	Rick	Brendan	1467112205	-	photo
4	Like	Rick	Brendan	1467112213	-	-

In the **RDBMS table**, each of these attributes **becomes a new column**

HBase vs RDBMS

Column oriented storage

id	type	for user	from user	timestamp	friend type	commented on
1	Friend request	Ryan	Jessica	146710201	new	-
2	Comment	Chaz	Daniel	146711200	-	link
3	Comment	Rick	Brendan	1467112205	-	photo
4	Like	Rick	Brendan	1467112213	-	-

This results in tables that
are **very sparse**

HBase vs RDBMS

Column oriented storage

id	type	for user	from user	timestamp	friend type	commented on
1	Friend request	Ryan	Jessica	146710201	new	-
2	Comment	Chaz	Daniel	146711200	-	link
3	Comment	Rick	Brendan	1467112205	-	photo
4	Like	Rick	Brendan	1467112213	-	-

In an RDBMS, Sparse tables **utilize disk space even for these empty cells**

HBase vs RDBMS

Column oriented storage

id	type	for user	from user	timestamp	friend type	commented on
1	Friend request	Ryan	Jessica	146710201	new	-
2	Comment	Chaz	Daniel	146711200	-	link
3	Comment	Rick	Brendan	1467112205	-	photo
4	Like	Rick	Brendan	1467112213	-	-

In a column-oriented store, these cells can be skipped completely

HBase vs RDBMS

Column oriented storage

id	type	for user	from user	timestamp	friend type	commented on
1	Friend request status	Ryan	Jessica	146710201	new	
2	Comment	Chaz	Daniel	146711200	-	link
3	Comment	Rick	Brendan	1467112205	-	photo
4	Like	Rick	Brendan	1467112213	-	-

row id	column	value
1	type	Friend request status
1	for user	Ryan
1	from user	Jessica
1	timestamp	146710201
1	friend type	new

8. HBase Data Model

HBase vs RDBMS**Column oriented storage**

id	type	for user	from user	timestamp	friend type	commented on
1	Friend request status	Ryan	Jessica	146710201	new	link
2	Comment	Chaz	Daniel	146711200	link	link
3	Comment	Rick	Brendan	1467112205	-	photo
4	Like	Rick	Brendan	1467112213	-	-

row id	column	value
1	type	Friend request status
1	for user	Ryan
1	from user	Jessica
1	timestamp	146710201
1	friend type	new
2	type	Friend request status
2	for user	Ryan
2	from user	Jessica
2	timestamp	146710201
2	commented on	link

HBase vs RDBMS

Column oriented storage

Column oriented storage has some
powerful advantages

Column oriented storage has some powerful advantages

1. You can store **really sparse** tables very efficiently

Column oriented storage has some powerful advantages

1. You can store **really sparse** tables very efficiently
2. You can accommodate **dynamically changing attributes**

Each row id can have a different set of col ids

1. You can store really sparse tables very efficiently
2. You can accommodate dynamically changing attributes

HBase vs RDBMS

Column oriented storage

The schema for a row id is not fixed, you can keep changing it

ie, Add or remove new col ids

2. You can accommodate dynamically changing attributes

HBase

. HBase Data Model

HBase vs RDBMS

Column oriented storage ✓

Denormalized

Only CRUD operations

ACID at a row level

HBase

3. HBase Data Model

HBase vs RDBMS

Denormalized

LET'S SAY WE HAVE AN EMPLOYEES DATABASE

WE WANT TO CAPTURE EMPLOYEE NAME,
ADDRESS, SUBORDINATES

HBase vs RDBMS

Denormalized

A TRADITIONAL RDBMS WOULD MODEL IT AS 3 TABLES

EmplID	EmpName	AddressId
1	Vitthal	1

AddressId	Street	City
1	Bellandur	Bangalore

EmplID	SubordinateEmplID
1	3
1	4
1	8

HBase vs RDBMS

Denormalized

A TRADITIONAL RDBMS WOULD MODEL IT AS 3 TABLES

EmpID	EmpName	AddressId
1	Vitthal	1

AddressId	Street	City
1	Bellandur	Bangalore

EmpID	SubordinateEmpID
1	3
1	4
1	8

THIS KIND OF DESIGN
MINIMIZES REDUNDANT
STORAGE OF DATA

HBase vs RDBMS

Denormalized

EmpID	EmpName	AddressId
1	Vitthal	1

AddressId	Street	City
1	Bellandur	Bangalore

EmpID	SubordinateEmpID
1	3
1	4
1	8

THESE STREET AND CITY NAMES
ARE ONLY STORED ONCE
AND REFERRED TO BY AN
INTEGER ID THEREAFTER

. HBase Data Model

HBase vs RDBMS

EmpID	EmpName	AddressId
1	Vitthal	1

AddressId	Street	City
1	Bellandur	Bangalore

EmpID	SubordinateEmpID
1	3
1	4
1	8

Denormalized

NORMALIZATION
OPTIMIZES FOR
STORAGE

. HBase Data Model

HBase vs RDBMS

EmpID	EmpName	AddressId
1	Vitthal	1

AddressId	Street	City
1	Bellandur	Bangalore

EmpID	SubordinateEmpID
1	3
1	4
1	8

Denormalized

**IN A DISTRIBUTED SYSTEM,
STORAGE IS CHEAP**

HBase Data Model

HBase vs RDBMS

EmpID	EmpName	AddressId
1	Vitthal	1

AddressId	Street	City
1	Bellandur	Bangalore

EmpID	SubordinateEmpID
1	3
1	4
1	8

Denormalized

IN A DISTRIBUTED SYSTEM,
STORAGE IS CHEAP

INSTEAD YOU NEED TO
OPTIMIZE DISK SEEKS

HBase vs RDBMS

Denormalized

EmpID	EmpName	AddressId
1	Vitthal	1

AddressId	Street	City
1	Bellandur	Bangalore

EmpID	SubordinateEmpID
1	3
1	4
1	8

IF YOU STORE DATA
ACROSS DIFFERENT TABLES
YOU HAVE TO PERFORM
DISK SEEKS FOR EACH TABLE

HBase vs RDBMS

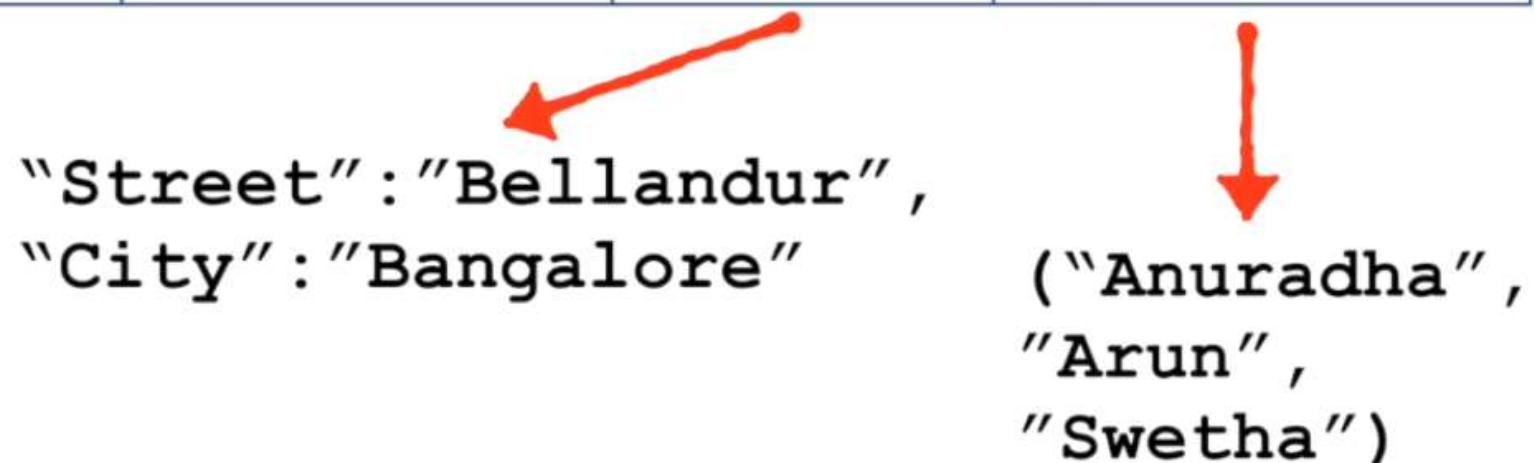
Denormalized

INSTEAD WE CAN EMBED ALL 3 TABLES INTO A SINGLE TABLE

EmplID	EmpName	Address	Subordinates
1	Vitthal	<STRUCT>	<ARRAY>

“Street”: “Bellandur”,
“City”: “Bangalore”

“Anuradha”,
“Arun”,
“Swetha”)



HBase vs RDBMS

Denormalized

EmpID	EmpName	Address	Subordinates
1	Vitthal	<STRUCT>	<ARRAY>

THIS IS A
DENORMALIZED
DESIGN

HBase vs RDBMS

Denormalized

EmplID	EmpName	Address	Subordinates
1	Vitthal	<STRUCT>	<ARRAY>

ALL THE DATA
CORRESPONDING TO AN
EMPLOYEE IS STORED
IN A SINGLE TABLE

HBase

. HBase Data Model

HBase vs RDBMS

Column oriented storage ✓

Denormalized ✓

Only CRUD operations

ACID at a row level

HBase

HBase vs RDBMS Only **CRUD** operations

**HBase architecture is
designed such that you can
get random read-write
access to a specific row**

HBase

1. Introducing CRUD operations

HBase vs RDBMS

Only CRUD operations

Unlike, traditional
RDBMS, HBase does
not support SQL

HBase

Introducing CRUD operations

HBase vs RDBMS

Only CRUD operations

**Unlike, traditional
RDBMS, HBase does
not support SQL**

NoSQL

HBase

. Introducing CRUD operations

HBase vs KVDBMS

Only CRUD operations

HBase only supports a limited set of operations

. Introducing CRUD operations

HBase vs KVDBMS

Only CRUD operations

HBase only supports a limited set of operations

Create

Read

Update

Delete

HBase vs KVDBMS

Only CRUD operations

HBase only supports a limited set of operations

Create

Add a new value to the table

Read

Update

Delete

HBase vs KVMS

Only CRUD operations

HBase only supports a limited set of operations

Create

Add a new value to the table

Read

Read the value for a specific row id, col id

Update

Delete

HBase vs KVDBMS Only CRUD operations

HBase only supports a limited set of operations

Create

Add a new value to the table

Read

Read the value for a specific row id, col id

Update

Update the value for a specific row id, col id

Delete

HBase vs KDBMS

Only CRUD operations

HBase only supports a limited set of operations

Create

Add a new value to the table

Read

Read the value for a specific row id, col id

Update

Update the value for a specific row id, col id

Delete

Delete the value for a specific row id, col id

HBase vs KVDBMS

Only CRUD operations

Create
Read
Update
Delete

All HBase operations
deal with a specific
row

. Introducing CRUD operations

HBase vs KVDBMS

Create
Read
Update
Delete

Only CRUD operations

HBase does not support
any operations across
tables

No Joins

HBase vs KVDBMS

Create
Read
Update
Delete

Only CRUD operations

HBase does not support
any operations across
row ids

No Grouping/Aggregation

HBase vs KVDBMS

Only CRUD operations

Create
Read
Update
Delete

This is another reason
why **denormalization**
is important in HBase

HBase vs KVDBMS

Only CRUD operations

Create
Read
Update
Delete

All the data needed to
describe an entity
should be self-contained
within its row id

HBase vs RDBMS Only CRUD operations

LET'S GO BACK TO THE EMPLOYEE EXAMPLE

A TRADITIONAL RDBMS WOULD MODEL IT AS 3 TABLES

EmplID	EmpName	AddressId
1	Vitthal	1

AddressId	Street	City
1	Bellandur	Bangalore

EmplID	SubordinateEmplID
1	3
1	4
1	8

Introducing CRUD operations

HBase vs KVDBMS Only CRUD operations

WHEN AN APPLICATION ASKS FOR AN EMPLOYEE'S DETAILS

EmplID	EmpName	AddressId
1	Vitthal	1

AddressId	Street	City
1	Bellandur	Bangalore

YOU WOULD NEED TO JOIN 2 TABLES
TO FETCH THE ADDRESS

WHEN AN APPLICATION ASKS FOR AN EMPLOYEE'S DETAILS

EmplID	EmpName	AddressId
1	Vitthal	1

EmplID	SubordinateEmplID
1	3
1	4
1	8

YOU WOULD NEED TO
JOIN THESE 2 TABLES
TWICE TO GET THE
LIST OF SUBORDINATES
FOR AN EMPLOYEE

HBase

Introducing CRUD operations

HBase vs RDBMS

Only CRUD operations

IN AN RDBMS THESE JOINS CAN
BE MADE EFFICIENT WITH THE
ADDITION OF INDICES

HBase

Introducing CRUD operations

HBase vs KVDBMS Only CRUD operations

**IN HBASE, THERE IS NO SUPPORT FOR
JOINING TABLES ON THE FLY WHILE
FETCHING THE DETAILS FOR 1 ROW**

HBase

. Introducing CRUD operations
HBase vs KVDBMS Only **CRUD** operations

**YOU COULD USE AN EXTERNAL
APPLICATION LIKE MAPREDUCE
TO PERFORM JOINS**

10. HBase is different from Hive

HBase vs KVDBMS

Only CRUD operations

YOU COULD USE AN EXTERNAL
APPLICATION LIKE MAPREDUCE
TO PERFORM JOINS

WHILE THIS IS FINE FOR ANALYTICAL
QUERIES, IT WOULD NOT BE SUITABLE
FOR TRANSACTION PROCESSING

Only CRUD operations

IN A DENORMALIZED DESIGN

EmplID	EmpName	Address	Subordinates
1	Vitthal	<STRUCT>	<ARRAY>

**YOU CAN USE THE HBASE SUPPORTED
READ OPERATION TO READ THE
ROW AND FETCH ALL THE DATA**

HBase

9. Introducing CRUD operations

HBase vs KVDBMS

Column oriented storage ✓

Denormalized ✓

Only CRUD operations ✓

ACID at a row level

HBase

. Introducing CRUD operations HBase vs KVDBMS ACID at a row level

HBase is ACID compliant, but
only at a row id level

HBase is ACID compliant, but
only **at a row id level**

For example, let's look at
Atomicity

HBase vs KVDBMS

ACID at a row level

Atomic

Transaction 1:
Update values
for **2 col ids**
within **1 row**

Atomicity

Transaction 2:
If one col id update
fails, the entire
transaction fails

. Introducing CRUD operations

HBase vs KVDBMS

ACID at a row level
Atomicity

Not Atomic

Transaction 2:

**Update values
for 2 col ids
for 10 row ids**

HBase vs RDBMS

ACID at a row level

Atomicity

If the operation fails after 5 row ids are updated,
the row ids which are updated remain updated

Not Atomic

Transaction 2:
Update values
for 2 col ids
for 10 row ids

HBase

. Introducing CRUD operations

HBase vs RDBMS

Column oriented storage ✓

Denormalized ✓

Only CRUD operations ✓

ACID at a row level. ✓

HBase

If you are familiar with the Hadoop ecosystem, you might know of other technologies **which seem similar to HBase**

HIVE FOR INSTANCE

HBase

HBase is a database
management system

HIVE IS A DATA
WAREHOUSE

HBase

HBase is a database management system

Used for both transaction processing and analytical processing

HIVE IS A DATA WAREHOUSE

HBase

HBase is a database management system

Used for both transaction processing and analytical processing

HIVE IS A DATA WAREHOUSE

Used only for analytical processing

HBase

HBase is a database management system

Provides low latency and random access for some supported operations

HIVE IS A DATA WAREHOUSE

HBase

HBase is a **database management system**

Provides low latency and random access for some supported operations

HIVE IS A DATA WAREHOUSE

Only suitable for batch processing jobs that can tolerate high latency

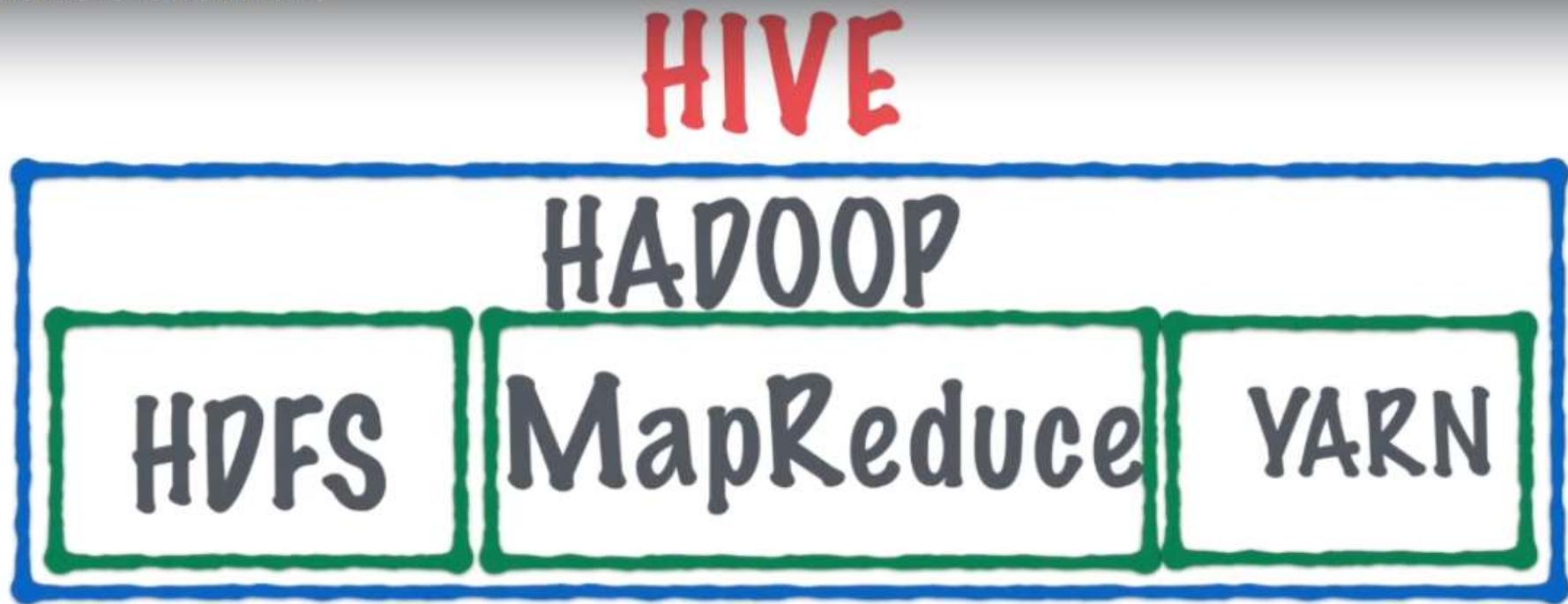
HBase

**HBase does not provide
any SQL interface**

Hive does!

HBase

HBase is different from Hadoop



HBase

HIVE

HADOOP

HDFS

MapReduce

YARN

HIVE IS A DATAWAREHOUSE
BUILT ON TOP OF HADOOP

HIVE

HDFS

HADOOP

MapReduce

YARN

HIVE STORES IT'S DATA
AS FILES IN HDFS

different from Hive

HIVE

HADOOP

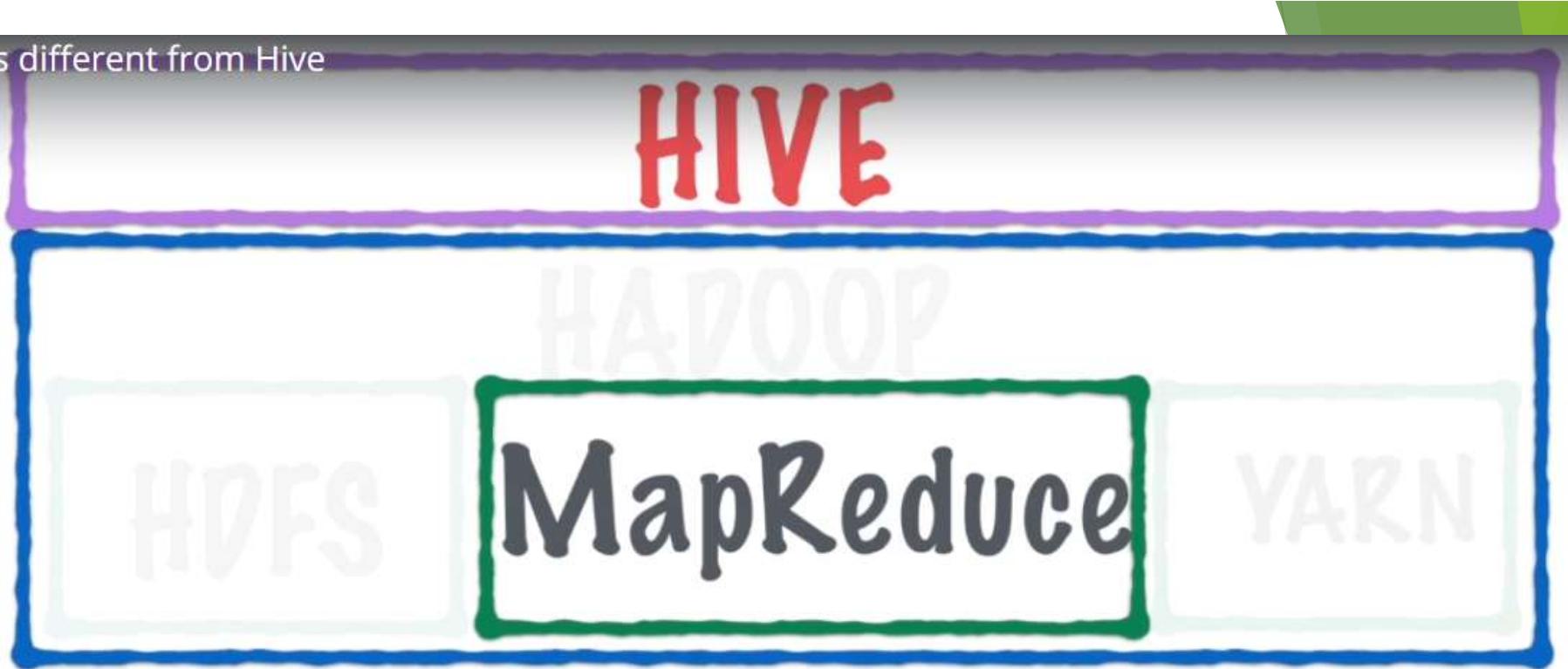
HDFS

MapReduce

YARN

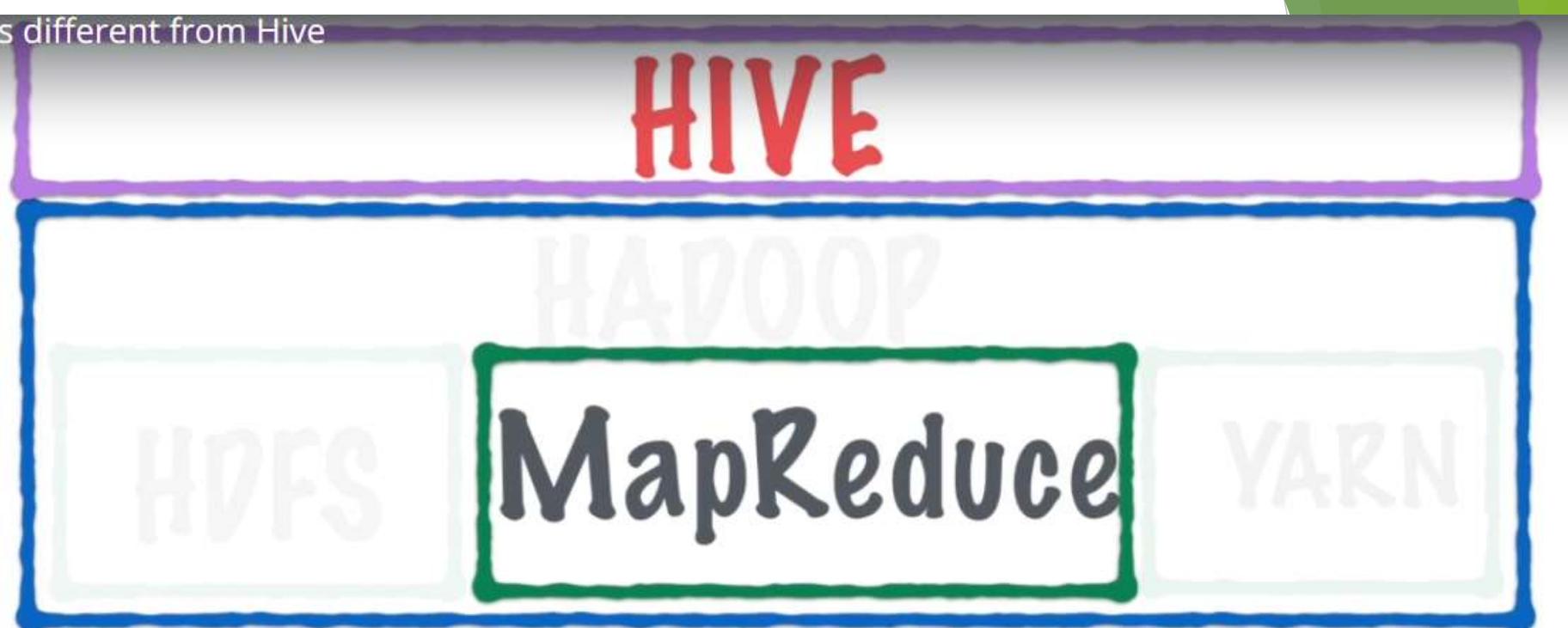
All processing tasks in Hadoop
are run using MapReduce tasks

is different from Hive



MapReduce tasks are usually
written using a Java Framework

s different from Hive



Writing these MapReduce
tasks can be pretty daunting

HIVE

HADOOP

HDFS

MapReduce

YARN

HIVE PROVIDES AN SQL LIKE
INTERFACE TO DATA IN HDFS

HDFS

HIVE

HADOOP

HDFS

MapReduce

YARN

THE FILES IN HDFS ARE EXPOSED TO
THE USER IN THE FORM OF TABLES

se is different from Hive

HIVE

HADOOP

HDFS

MapReduce

YARN

THE USER CAN WRITE SQL-LIKE
QUERIES TO WORK WITH THESE TABLES

HBase

SQL-LIKE QUERY



HIVE



HDFS

MapReduce

YARN

HIVE WILL
TRANSLATE THE
QUERY INTO 1/MORE
MAPREDUCE TASKS

HBase

HBase is different from Hive

HIVE

USED FOR BATCH
PROCESSING

HBASE

USED FOR BOTH
BATCH AND
TRANSACTION
PROCESSING

HBase

HIVE

USED FOR BATCH PROCESSING

**PROVIDES AN SQL
SKIN FOR HADOOP**

HBASE

USED FOR BOTH BATCH AND
TRANSACTION PROCESSING

**NO SQL
INTERFACE**

HBase

HIVE

USED FOR BATCH PROCESSING
PROVIDES AN **SQL SKIN** FOR
HADOOP

**USES BOTH HDFS
AND THE
MAPREDUCE ENGINE**

HBASE

USED FOR BOTH BATCH AND
TRANSACTION PROCESSING
NO SQL INTERFACE

**USES HDFS BUT
HAS IT'S OWN
ARCHITECTURE**

HBase

HIVE

USED FOR BATCH PROCESSING
PROVIDES AN SQL SKIN FOR
HADOOP
USES BOTH HDFS AND THE
MAPREDUCE ENGINE

DATA MODEL IS
SIMILAR TO
DATABASES (TABLES
WITH FIXED SCHEMA)

Talentum Global Technologies

HBASE

USED FOR BOTH BATCH AND
TRANSACTION PROCESSING
NO SQL INTERFACE
USES HDFS BUT HAS IT'S OWN
ARCHITECTURE

DATA MODEL IS
COLUMN ORIENTED
STORAGE

Hbase Architecture

Hbase Architecture

**Hbase's Architecture
is inspired by**

**Google™
BigTable**

Hbase Architecture

Recap

HBase vs RDBMS

This is how data is stored
in traditional databases

id	type	for user	from user	timestamp
1	Friend request status	Ryan	Jessica	146710201
2	Comment	Chaz	Daniel	146711200
3	Comment	Rick	Brendan	1467112205
4	Like	Rick	Brendan	1467112213

Hbase Architecture

Recap

Column oriented storage

id	type	for user	from user	timestamp
1	Friend request status	Ryan	Jessica	146710201
2	Comment	Chaz	Daniel	146711200
3	Comment	Rick	Brendan	1467112205
4	Like	Rick	Brendan	1467112213

Data is stored
in a map

Key = <Row id, Col id>

Value = <data>

Hbase Architecture

Recap

id	type	for user	from user	timestamp
1	Friend request status	Ryan	Jessica	146710201
2	Comment	Chaz	Daniel	146711200
3	Comment	Rick	Brendan	1467112205
4	Like	Rick	Brendan	1467112213

Column oriented storage

Data is stored
in a map

Key = 2, for_user

Value = Chaz

Hbase Architecture

Recap

Column oriented storage

id	type	for user	from user	timestamp
1	Friend request status	Ryan	Jessica	146710201
2	Comment	Chaz	Daniel	146711200
3	Comment	Rick	Brendan	1467112205
4	Like	Rick	Brendan	1467112213



row	column	value
1	type	Friend request status
1	for user	Ryan
1	from user	Jessica
1	timestamp	146710201
2	type	Comment
2	for user	Chaz
2	from user	Daniel
2	timestamp	146711200
3	type	Comment
3	for user	Rick
3	from user	Brendan
3	timestamp	1467112205

Hbase Architecture

Recap

An HBase table
is in fact a
sorted map

Column oriented storage

Keys Values

row	column	value
1	type	Friend request status
	for user	Ryan
	from user	Jessica
	timestamp	146710201
2	type	Comment
	for user	Chaz
	from user	Daniel
	timestamp	146711200
3	type	Comment
	for user	Rick
	from user	Brendan

Hbase Architecture

A sorted nested map

<Row id,
ColumnFamily,
<Column,
<Timestamp,Value>>>

Hbase Architecture

<Row id,

A sorted nested
map

When you read data
from HBase, it
performs a lookup for
the specified row id

Hbase Architecture

<Row id,

A sorted nested map

When you write data to HBase, it needs to insert the row id in the right place, so the rows are sorted

Hbase Architecture

<Row id,

A sorted nested
map

HBase does this
using Region Servers

Hbase Architecture

row id
1
2
3
4
5
6
7
8
9
10
11
12

Region 1

Region 2

Region 3

Region Servers

Row ids in a table are divided into ranges called regions

Hbase Architecture

row id
1
2
3
4
5
6
7
8
9
10
11
12

Region 1

Region 2

Region 3

Region Servers

Each region is
handled by a
Region Server

Hbase Architecture

Region Server 1

Region 1
Region 3

Region Server 2

Region 2

Region Servers

Regions serve as an index to perform fast lookup for where a row key belongs

Hbase Architecture

Region Server 1

Region 1
Region 3

Region Server 2

Region 2

Region Servers

A region server handles all read-write operations to Regions that are allotted to it

Hbase Architecture

Region Server

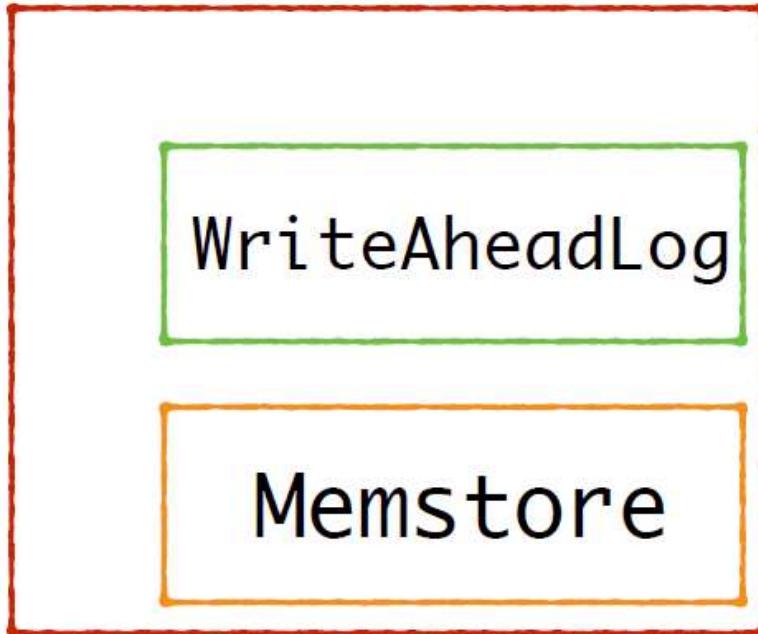


Region Servers

Initially all writes are stored in memory

Hbase Architecture

Region Server



Region Servers

Whenever there is a new change, the data is updated in the Memstore and a change log is written to disk

Hbase Architecture

Region Server

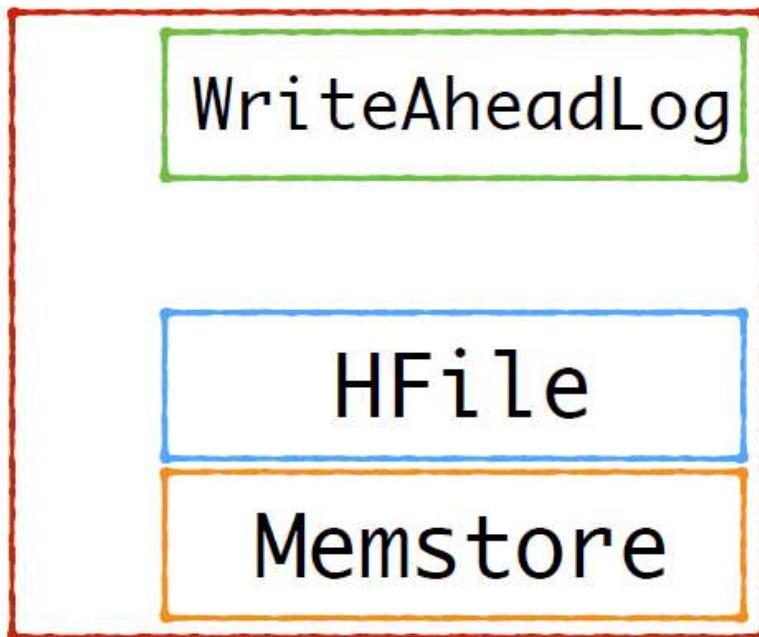


Region Servers

The WriteAheadLog
is created for
recovery in case
the Region Server
crashes

Hbase Architecture

Region Server

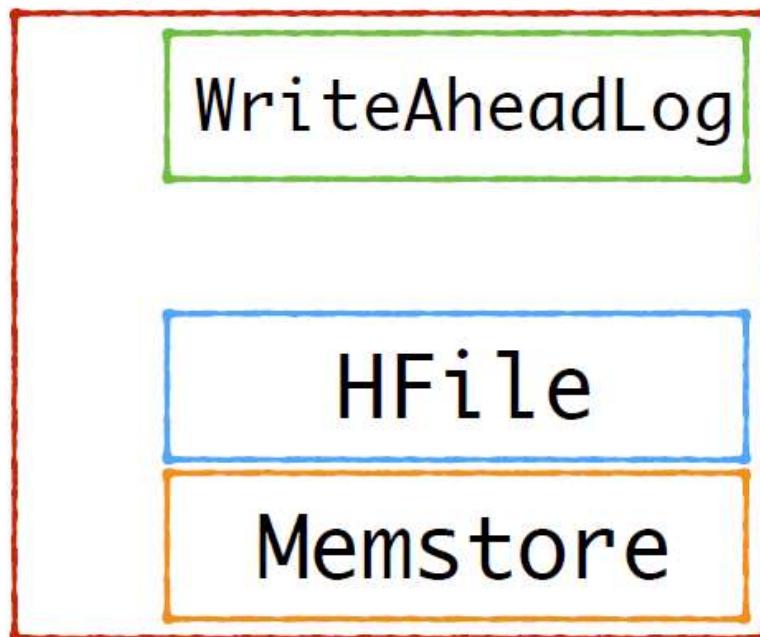


Region Servers

Periodically the Memstore gets full, and the data in Memstore is flushed to disk

Hbase Architecture

Region Server

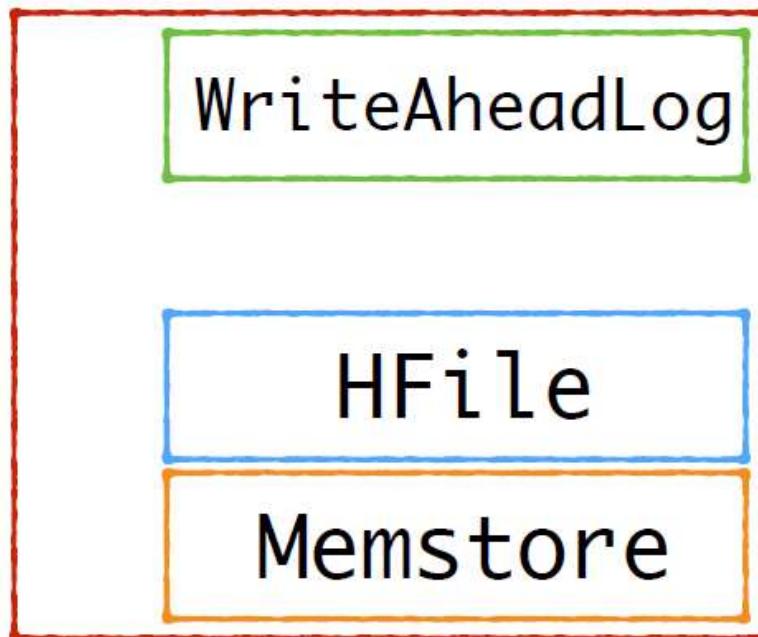


Region Servers

The data for a row key is either in the Memstore or in a HFile

Hbase Architecture

Region Server



Region Servers

HFiles are stored in HDFS

Hbase Architecture

Region Server



Region Servers

HDFS will break up the HFile into blocks and store it on different nodes

Hbase Architecture

Region Server

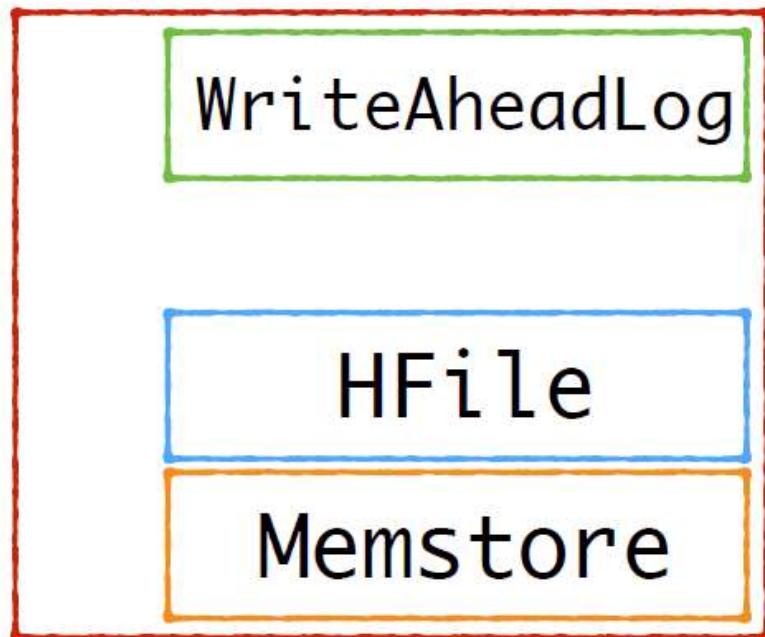


Region Servers

To minimize disk seeks, the region server **keeps an index of row key to HFile block in memory**

Hbase Architecture

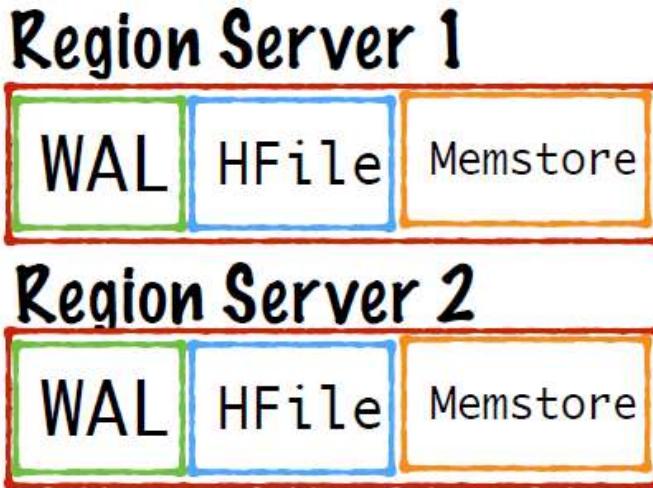
Region Server



Region Servers

It only performs
1 disk seek for
finding a row key

Hbase Architecture

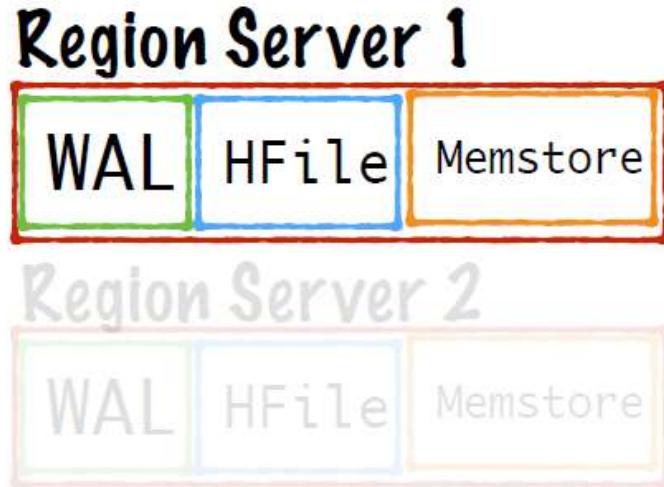


Region Servers

When you try to
read/insert data

1. The region server containing the row key is identified

Hbase Architecture



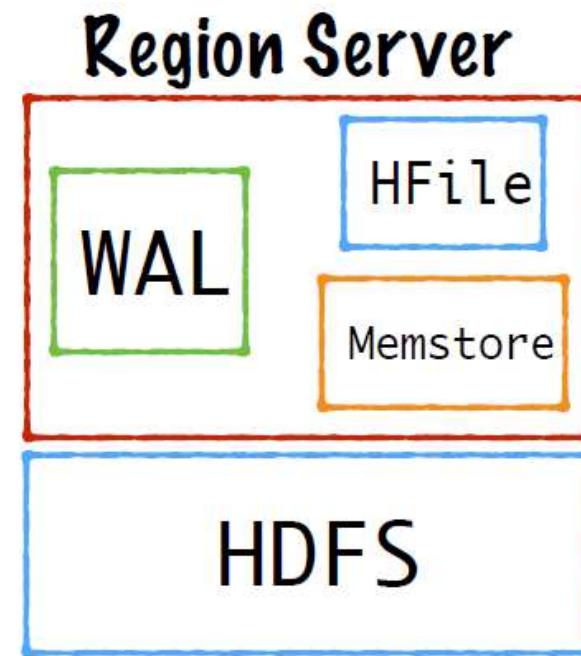
Region Servers

When you try to read/
insert data

1. The region server containing the row key is identified
2. The region server will lookup the Memstore or the HFile and do the needful

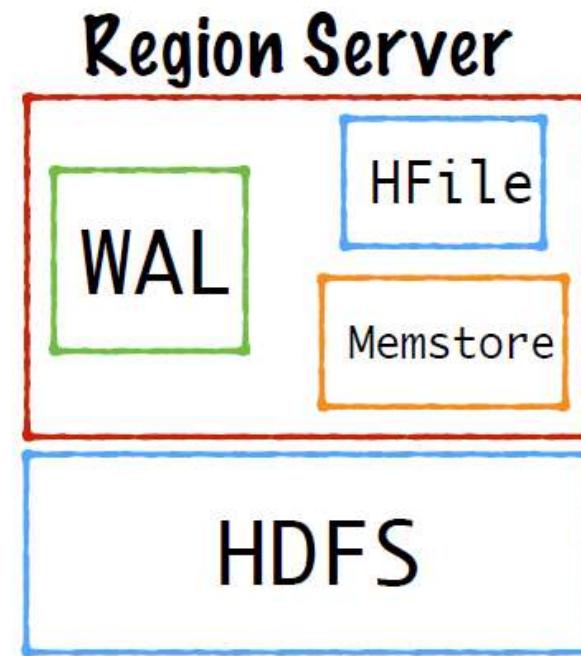
Hbase Architecture

Clients interact directly with a Region server handling the relevant row keys



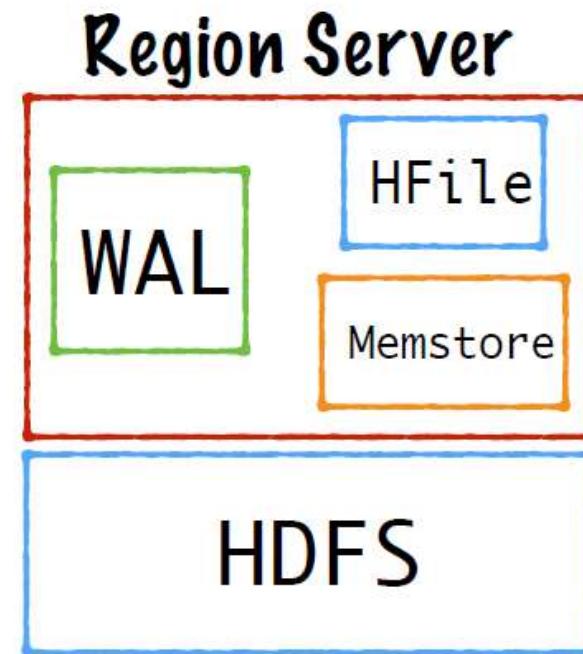
Hbase Architecture

They need to know which region server their row key is being handled by

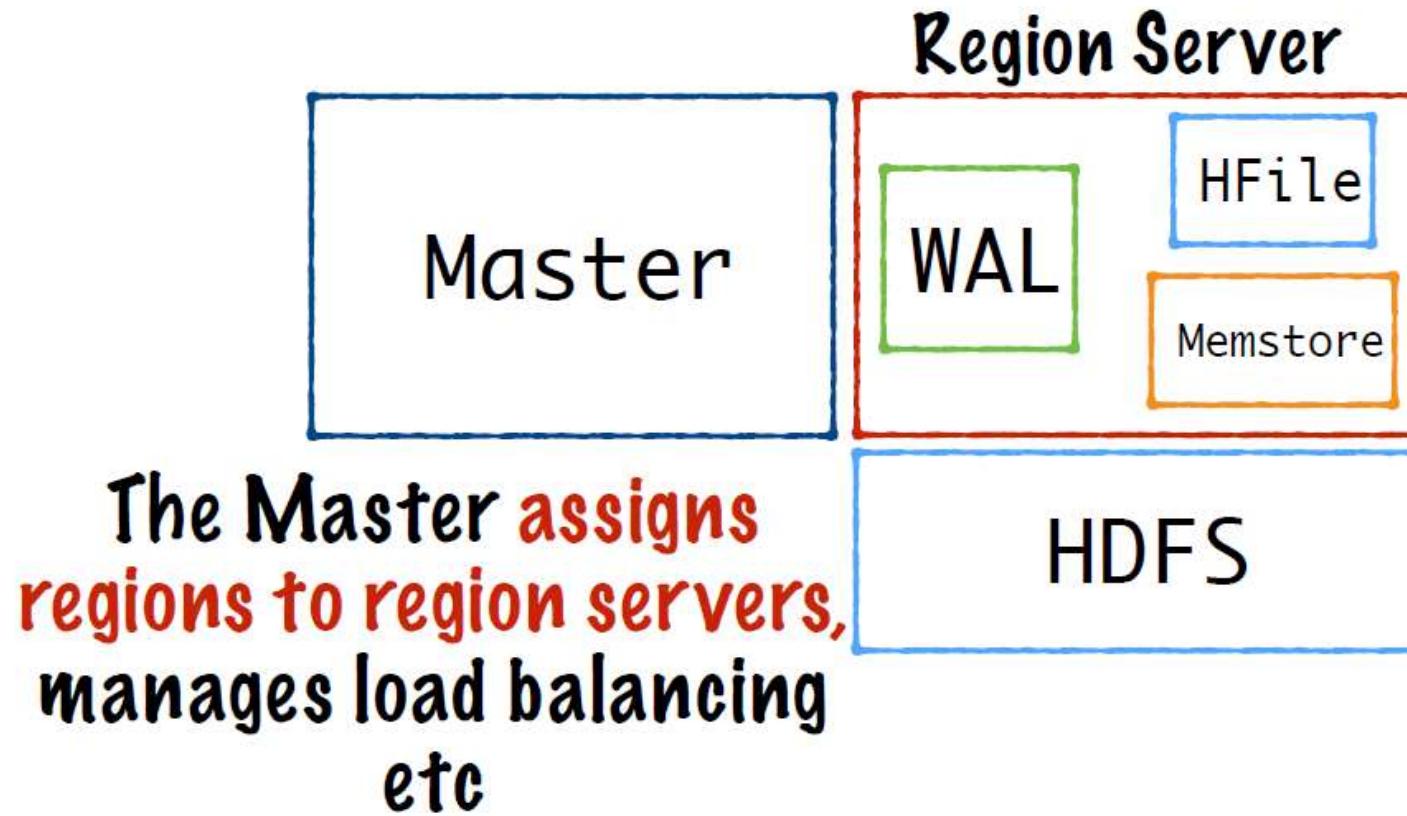


Hbase Architecture

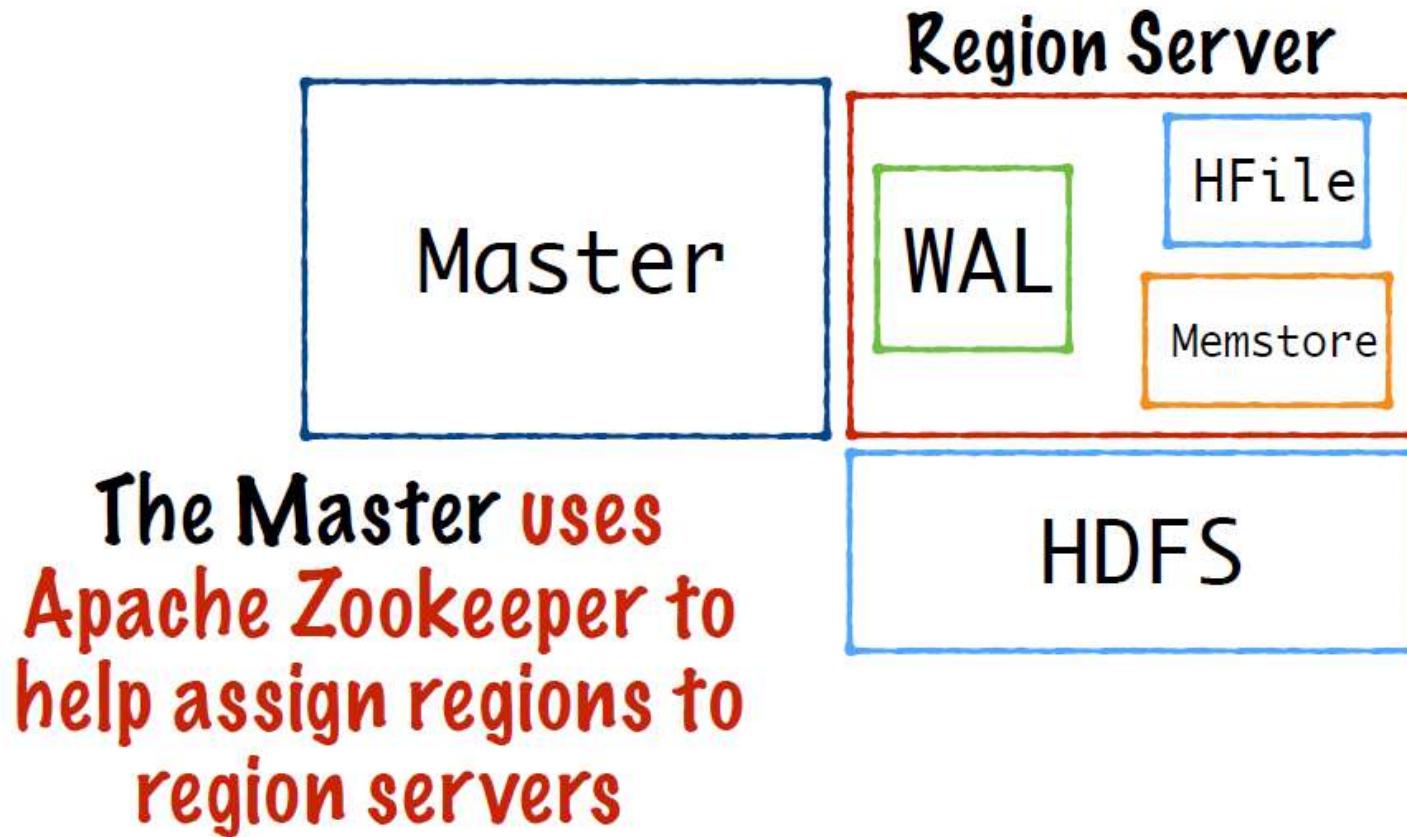
HBase uses a Master server to manage Regions and RegionServers



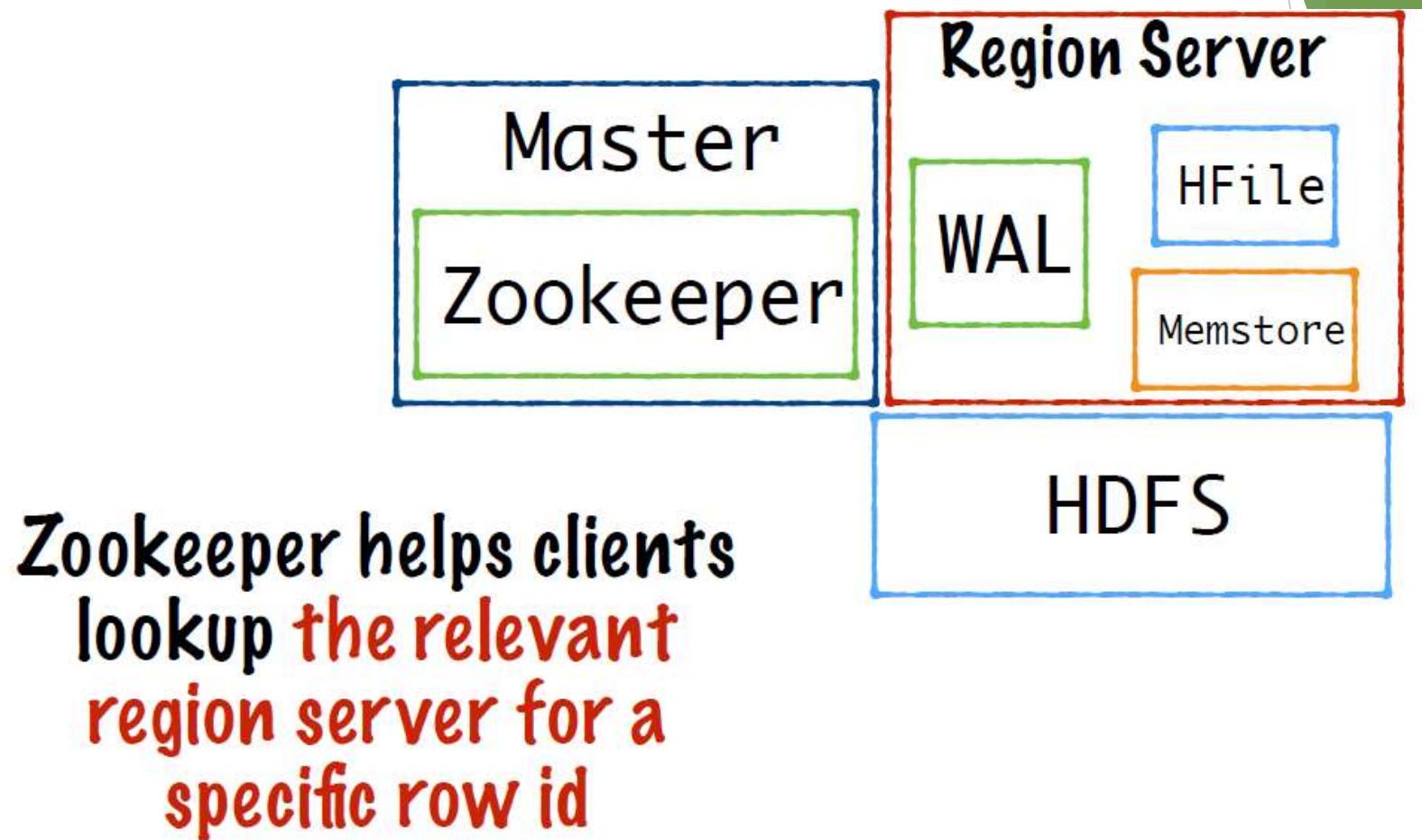
Hbase Architecture



Hbase Architecture



Hbase Architecture



Hbase Architecture

