Big data: Apache Hadoop ecosystem

Introduction to Hadoop framework tools

HDFS, HBASE, Spark, Impala, Hive and Pig

TE: 18/12/17

Layout

- HDFS: Hadoop distributed storage system
- HBASE: family oriented key-value store
- MapReduce processing alternatives
    - Spark, Impala, Pig, Hive
- Site Reliability Engineering in Google datacenter context

HDFS

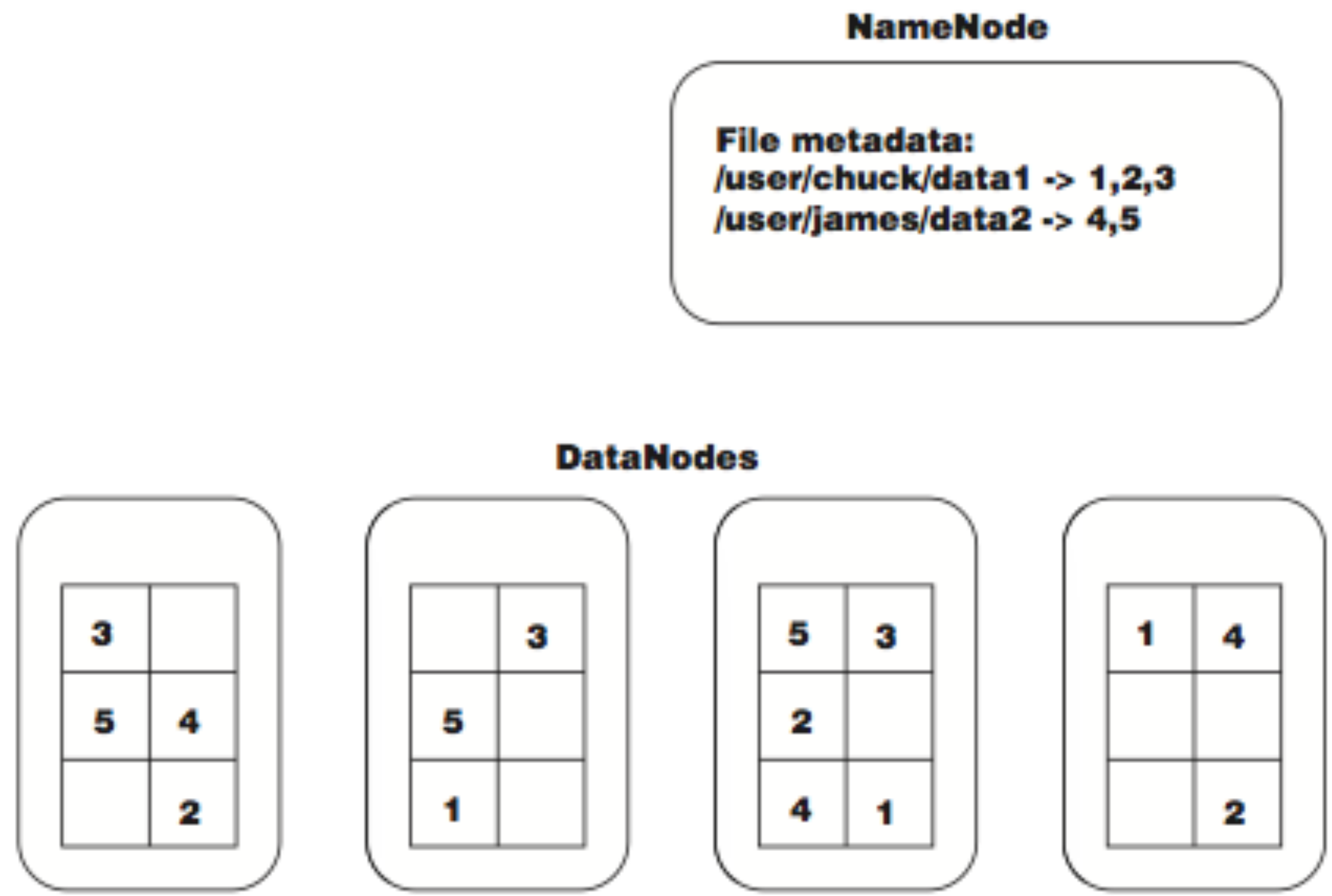
- Distributed file store for low cost hardware
- Tolerance for hardware failure: detection and automatic recovery of nodes
- Simple coherency: append content to end of files, updates are not supported
- Large data sets
- Streaming data access: focus on throughput, not latency

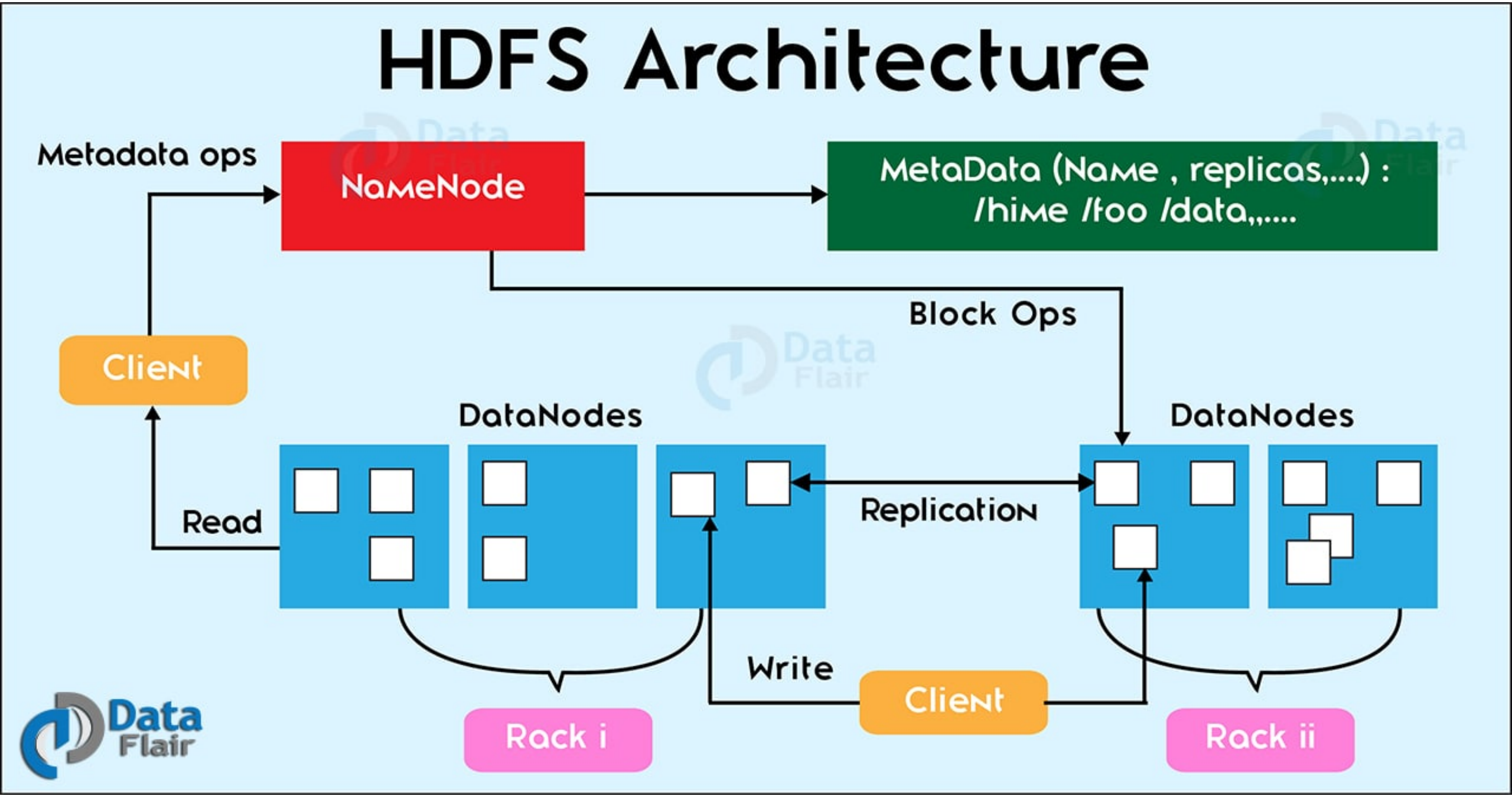
Move computation is cheaper than moving data

- Do not move data to workers: <u>move workers to data</u>
  - Store data on the local disks of nodes in the cluster
  - Start up workers on available slots with local data
- Disk access (latency) is slow but aggregated throughput is reasonable

HDFS architecture

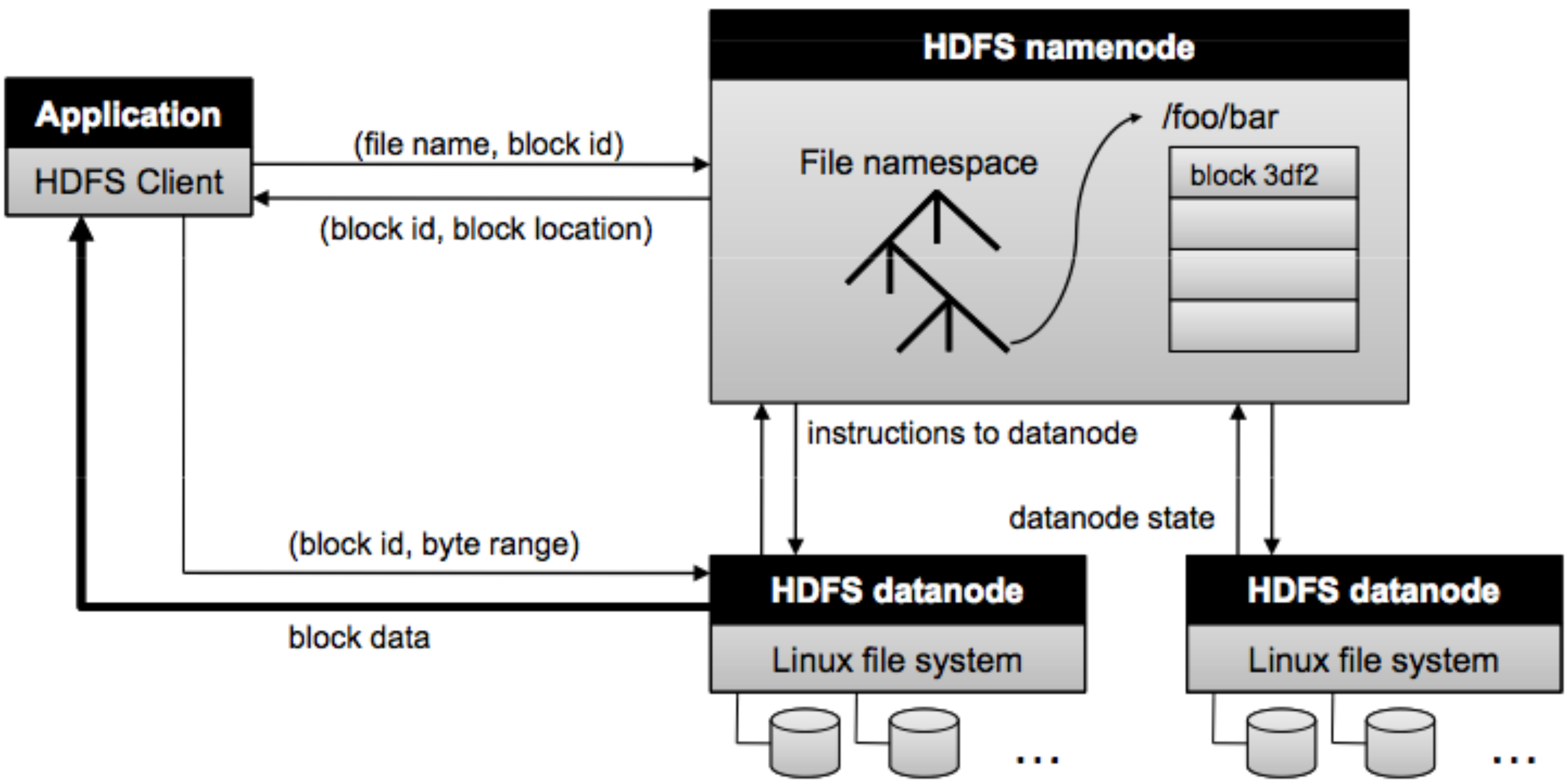
- Master/worker
- NameNode: file namespace manager
- DataNodes: manage local storage system
- Each file is a list of blocks
- Blocks are stored in a set of DataNodes





HDFS Architecture
Metadata ops
NameNode
MetaData (Name , replicas,....) :
/hime /foo /data,,....
Block Ops
Client
DataNodes
DataNodes
Read
Replication
Write
Client
Rack i
Rack ii
Data Flair

HDFS



HDFS namenode
Application
HDFS Client
(file name, block id)
(block id, block location)
File namespace
/foo/bar
block 3df2
instructions to datanode
datanode state
(block id, byte range)
block data
HDFS datanode
Linux file system
HDFS datanode
Linux file system

Data replication

- Each file is a sequence of blocks
- All blocks of a file have the same size except the last
- Blocks of a file are replicated for fault tolerace
- Namenode keeps control of DataNodes' health and applies replication rules
- Algorithm to minimize read latency: get data from replica closest to the user

HDFS operations with files: FS shell

`hadoop dfs -fs` `<command> <directory>`

- Create folder: `hadoop dfs -fs mkdir /user/hadoop/data`
- List files in HDFS: `-ls /user/hadoop/data`
- Copy a file to HDFS: `-put local.txt /user/hadoop/data`
- Get a file from HDFS: `-get /user/hadoop/data/part-00000 d1.txt`
- Cat a file in HDFS: `-cat /user/hadoop/data/part-00000`

HBASE

Family oriented DB

HBase

- map: key-value based
- persistent
- distributed
- sorted
- multidimensional
- sparse

HBase is a Map

Associative array (PHP), dictionary (Python), Hash (Ruby), or Object (JavaScript)

```
{
  "Smith" : "John",
  "Fernandez" : "Laura",
  "Kent" : "Clark",
  "Parker" : "Peter",
  "Richards" : "Rich"
}
```

HBase is distributed

- HBase and BigTable are built on distributed filesystems so that the underlying file storage can be spread out among an array of independent machines
- HBase sits atop either Hadoop's Distributed File System (HDFS)
- Data is replicated across a number of participating nodes

HBase is sorted

- HBase key/value pairs are kept in strict alphabetical order by key
- That is to say that the row for the key "aaaaa" should be right next to the row with key "aaaab" and very far from the row with key "zzzzz"
- Consider a table whose keys are domain names. It makes the most sense to list them in reverse notation (so "com.mydomain.www" rather than "www.mydomain.com") so that rows about a subdomain will be near the parent domain row.

HBase is multidimensional

```
{
  "1" : {
    "A" : "x",
    "B" : "z"
  },
  "aaaaa" : {
    "A" : "y",
    "B" : "w"
  },
  "aaaab" : {
    "A" : "world",
    "B" : "ocean"
  },
  "xyz" : {
    "A" : "hello",
    "B" : "there"
```

Row

Column family A

Column family B

HBase is multidimensional

- Column families are specified when the table is created
- A column family may have any number of columns, denoted by a column "qualifier" or "label"

```
{
  "com.cnn.www" : {
    "contents" : {
      "html" : "",
      "txt" : "data"
    },
    "anchor" : {
      "" : "data"
    }
 },
```

Each row of the table has
- family contents, qualifiers “html” and “txt”
- family anchor, qualifier empty: “”

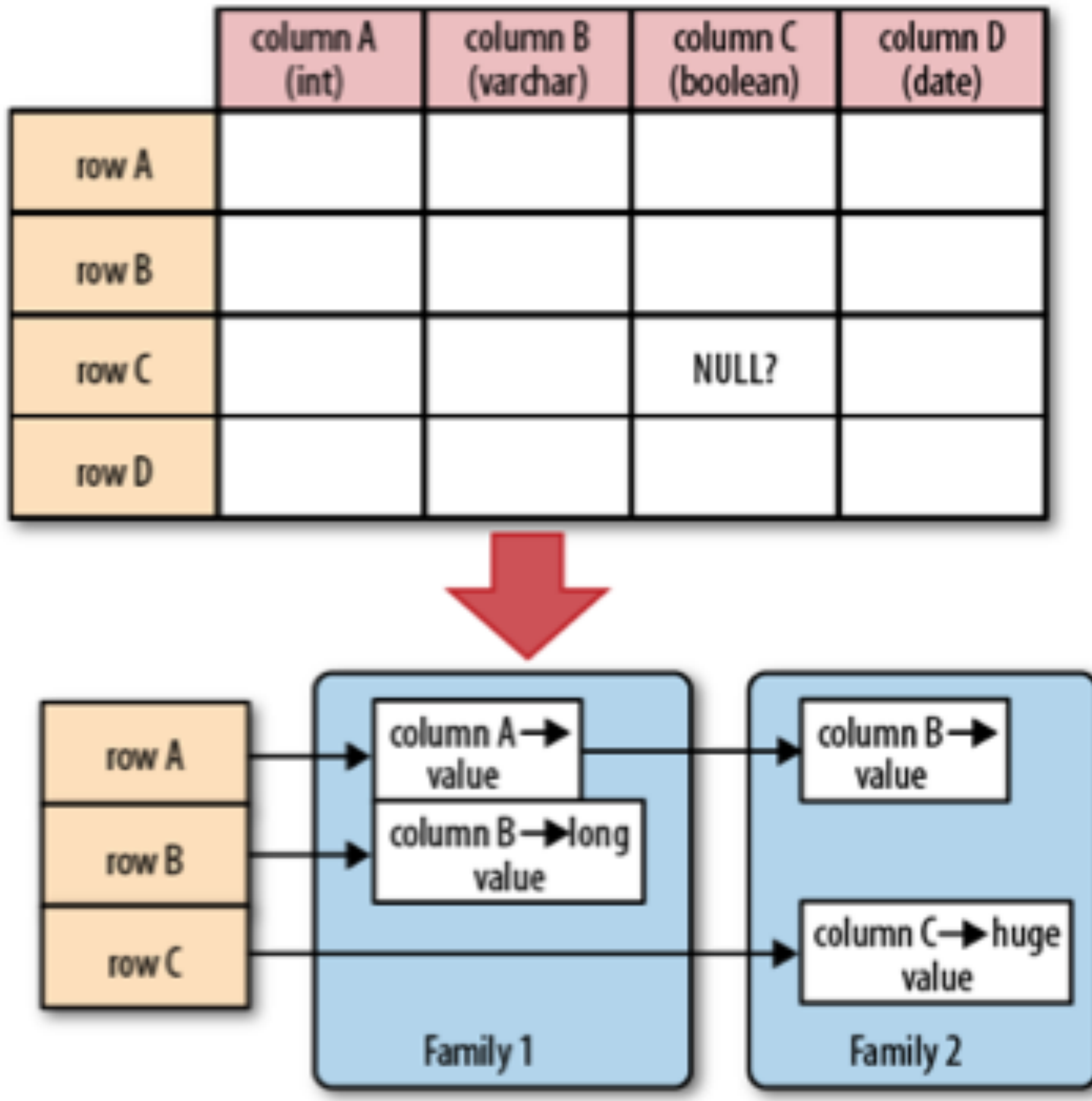
HBase is multidimensional

- When asking HBase for data, you must provide the full column name in the form "<family>:<qualifier>"

- So for example, both rows in the above example have three columns: "content:html", "content:txt" and "anchor:"

- All data is versioned either using an integer timestamp

Sparse: DBMS vs HBASE



Example: rows, families, qualifiers and time

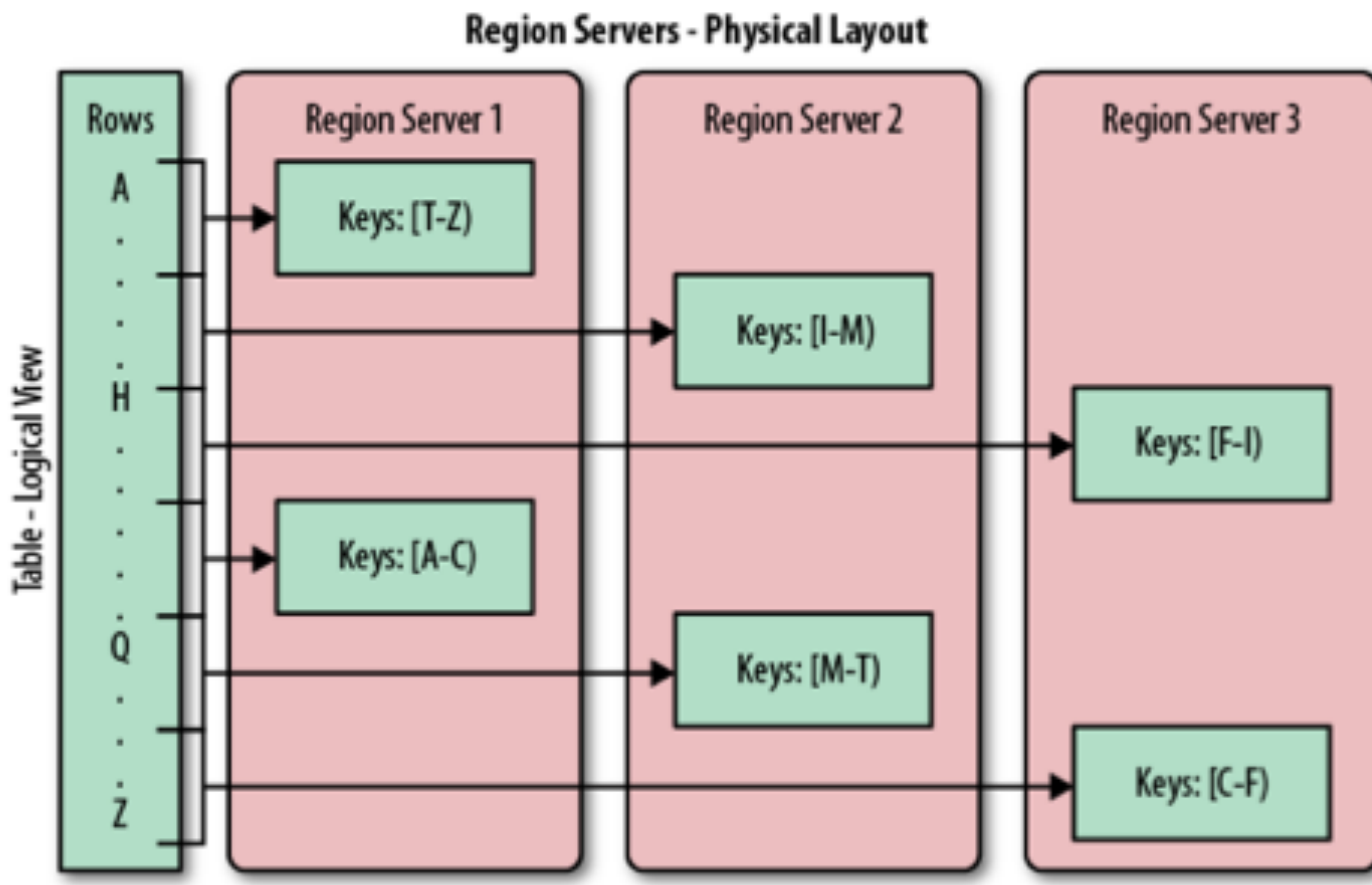
Row Key	Time stamp	Family contents:	Family anchor:
com.cnn.www	t9		anchor:**cnnsi.com** = "CNN"
com.cnn.www	t8		anchor:**my.look.ca** = "CNN.com"
com.cnn.www	t6	contents:**html** = "<html>..."	
com.cnn.www	t5	contents:html = "<html>..."	
com.cnn.www	t3	contents:html = "<html>..."	

qualifiers

Auto-sharding

- Regions: contiguous ranges of rows stored together
- Basic unit of scalability and load balancing
- When regions exceed size limit: they are split in equal halves
- Each region server stores many regions

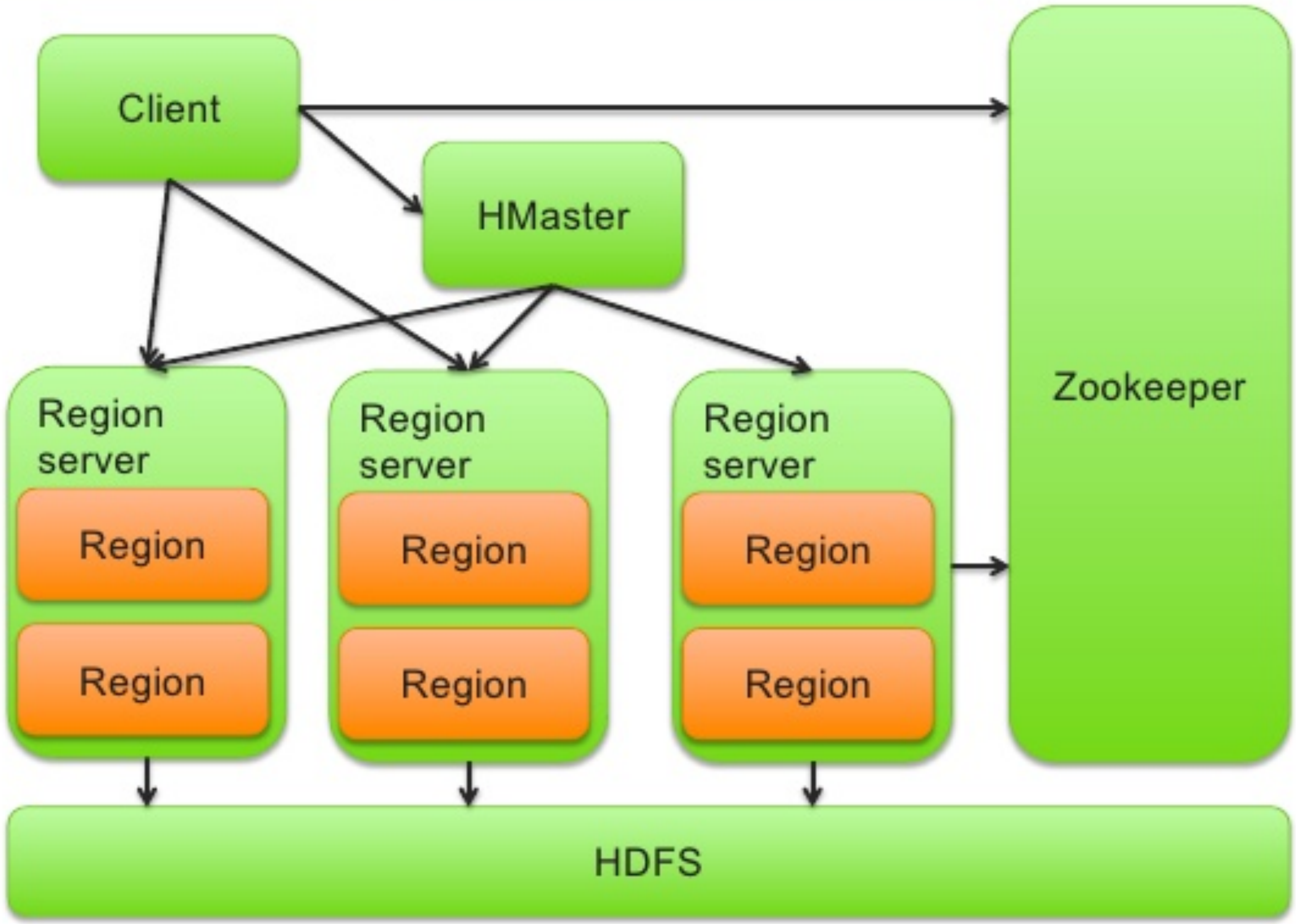
Region servers



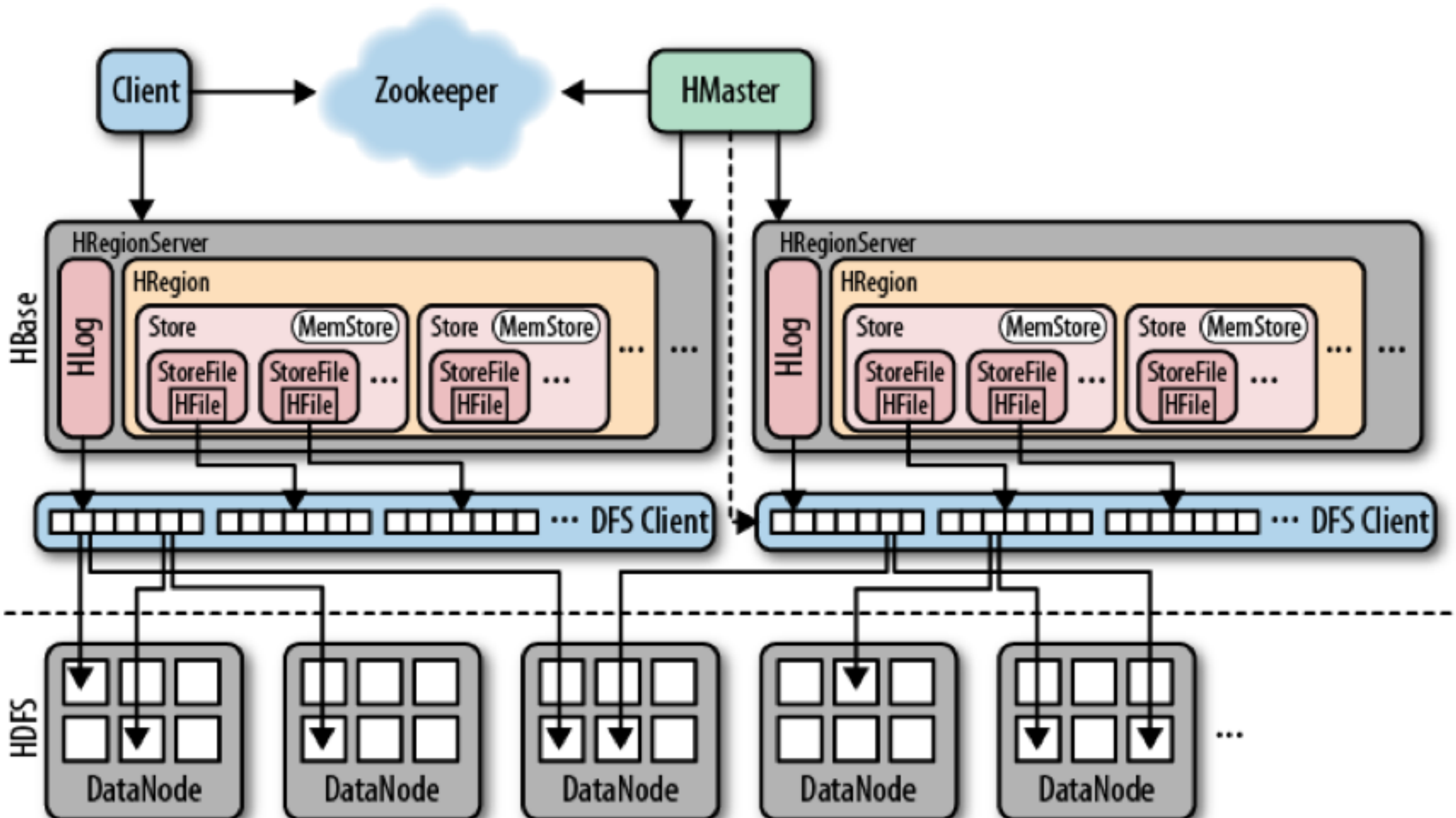
Region counts

- Region count: 10 - 1000 per server
- Each region: 1 - 2 GB
- Autosharding: automatic processes of splitting and serving regions

Apache HBase Architecture



HBASE Architecture



Read process (client)

- new client retrieves server with ROOT region
- gets server name with .META. table region
- get server name with row key
- gets row data (atomic) from server

Read process (server)

- *HRegionServer* opens a region and creates new *HRegion*
- Sets up a *Store* instance for each *HColumnFamily* for the table
- Store has one or more *StoreFiles* to access actual storage file *HFile*

Basic API: Put

```
Configuration conf = HBaseConfiguration.create();
HTable table = new HTable(conf, "testtable");
Put put = new Put(Bytes.toBytes("row1"));
put.add(Bytes.toBytes("colfam1"),
        Bytes.toBytes("qual1"),
        Bytes.toBytes("val1"));
put.add(Bytes.toBytes("colfam1"),
        Bytes.toBytes("qual2"),
        Bytes.toBytes("val2"));
table.put(put);
```

Basic API functions: get

```
Configuration conf = HBaseConfiguration.create();
HTable table = new HTable(conf, "testtable");
Get get = new Get(Bytes.toBytes("row1"));
get.addColumn(Bytes.toBytes("colfam1"),
              Bytes.toBytes("qual1"));
Result result = table.get(get);
byte[] val = result.getValue(Bytes.toBytes("colfam1"),
                             Bytes.toBytes("qual1"));
System.out.println("Value: " + Bytes.toString(val));
```

Scan: get data from HBASE

```
Scan scan = new Scan();
scan.addFamily(Bytes.toBytes("colfamily1"));
ResultScanner scanner = table.getScanner(scan);
for (Result res : scanner) {
  System.out.println(res);
}
scanner.close();
```

Hadoop ecosystem of Data Analysis tools

Other tools for MapReduce programming

- **Impala**
- **Spark**
- Abstractions: **Pig, Hive**

Apache Impala

Impala: low latency query engine

- not based on the MapReduce processing engine.
- *Designed to optimize latency* rather than scale and throughput, its architecture is similar to that of traditional massively parallel data warehouses such as Netezza, Greenplum and Teradata
- Data is read from the disk when the tables are initially scanned, and then remains in memory as it goes through multiple phases of processing.

Impala requirements

- Most of the data set has to fit into memory
- In general Impala requires significantly more memory per node than **MapReduce** based processing. 128GB of RAM are recommended, or large queries may fail when they run out of memory.
- **Impala** query can't recover from the loss of a node like MapReduce. If you lose a node your query will fail.
- **Impala** is recommended for queries that run quickly enough that restarting the entire query in case of a failure is not a major event.

Impala requirements

- **Long running daemons**: Impala daemons always stay on. There is no need for a start up cost and no moving of jar over the network or loading class files. Impala is just always ready.

- **Execution Engine in C++**

- **Use of LLVM**: use of LLVM to compile the query and all the functions used in this query into optimized machine code

Impala broadcast join execution plan

- **Impala** takes the smaller dataset distributes this dataset to all the Impala daemons involved with the query plan, where it will be stored as an in-memory hash table.

- Then each Impala daemon will read the parts of the larger dataset that are local to its node and use the in-memory hash table to find the rows that match between both tables, i.e. perform a hash-join.

- There is no need to read the entire large data set into memory, so Impala uses a 1GB buffer to read the large table and perform the joining part by part.

Impala example

```
select
       *
from
      Huge f JOIN small b on (f.fooBarId = b.barId)
where
      f.fooVal < 500 and
      f.fooVal + b.barVal < 1000;
```

When to use Impala

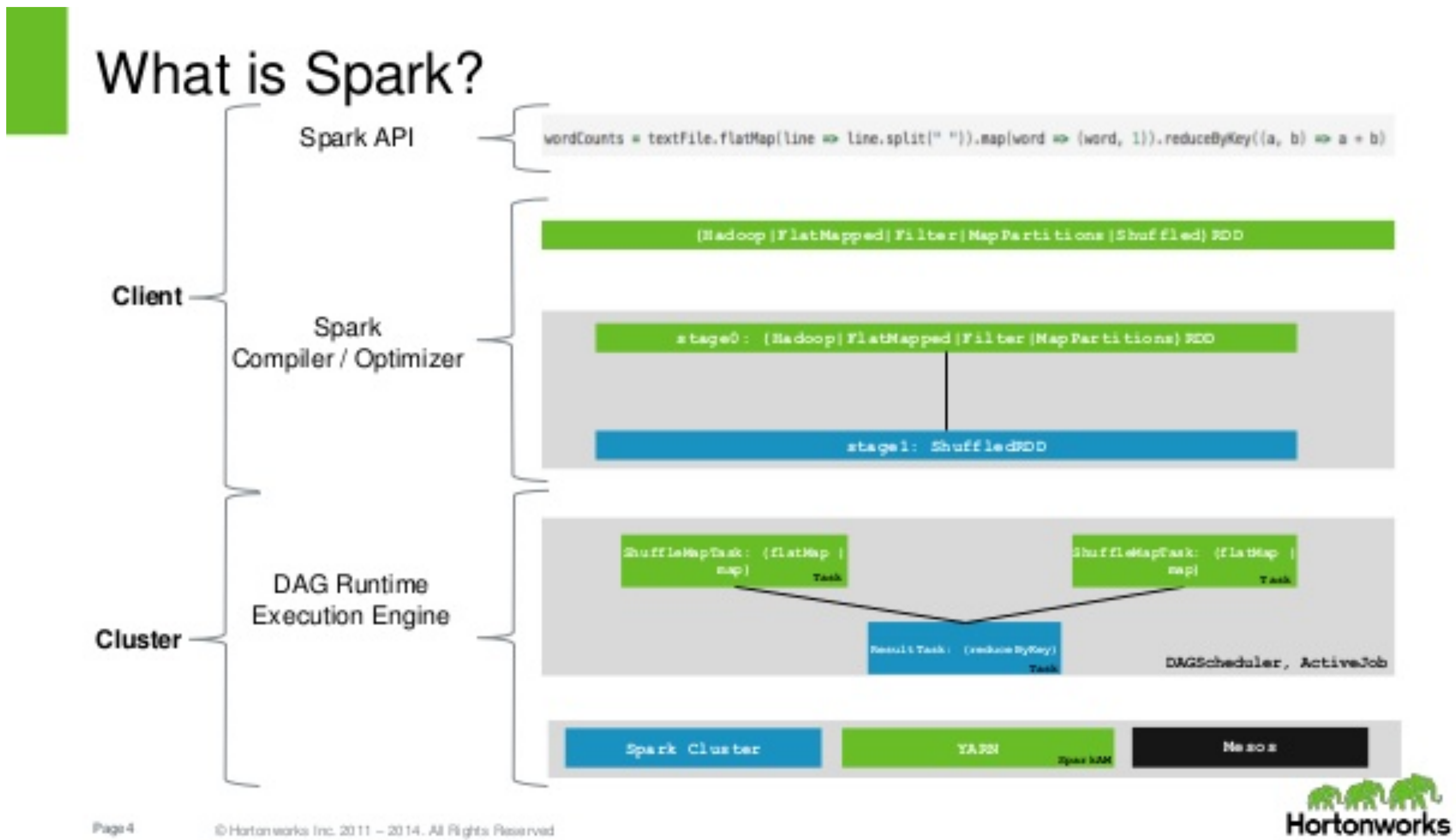
- Given its performance, Impala should be the first choice when using SQL on Hadoop.
- high-concurrency SQL access is a requirement.
- For many users who running SQL queries within Hadoop

Apache Spark

Apache Spark: iterative MapReduce data analysis

- Why **Spark**?
- MapReduce framework is limited to a very rigid data flow model that is unsuitable for many applications.
- reuse a dataset cached in memory for multiple processing tasks
- For example, applications such as iterative machine learning or interactive data analysis

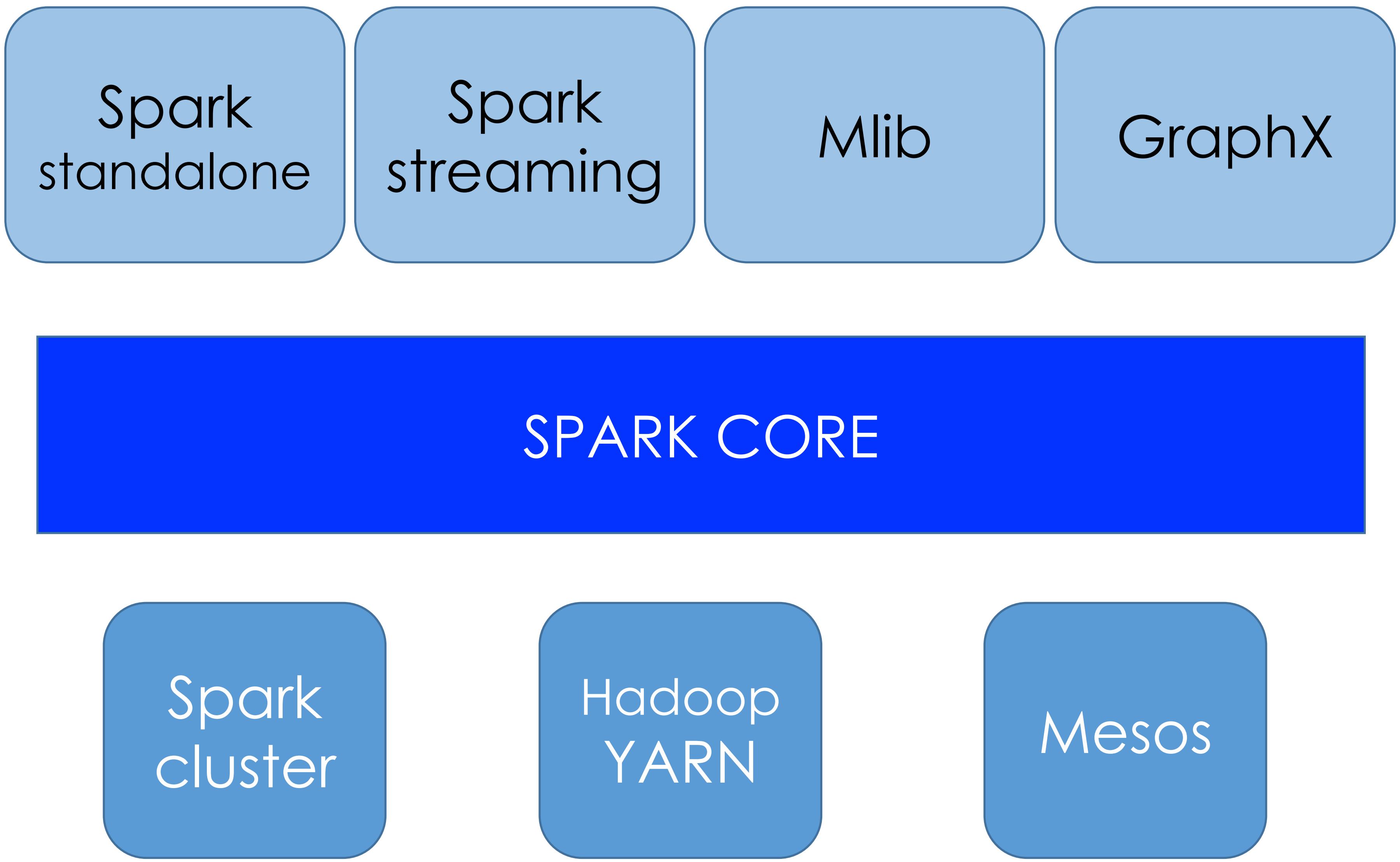
Apache Spark: iterative MapReduce data analysis



Spark overview

- **Support of DAG**: What Spark adds is the fact that the engine itself supports creating those complex chains of steps
- Complex algorithms and data processing pipelines within the same job and allows the framework to optimize the job as a whole
- **Simple**: Spark APIs are significantly cleaner and simpler than those of MapReduce.
- **Versatile:** Spark was built from the ground up to be an extensible, general purpose, parallel processing framework: stream processing engine: **Spark Streaming**, a graph processing engine called **GraphX**, and a machine learning framework called **MILib**.

Spark architecture



Reduced I/O: Resilient Distributed Datasets

- **Resilient Distributed Datasets (RDD)** to reduce IO and maintaining the processed dataset in memory
- RDDs are collections of serializable elements. The collection may be partitioned, in which case it is stored on multiple nodes
- RDDs are typically created from an Hadoop InputFormat (file on HDFS for example), or by applying transformations on existing RDDs.
- When creating an RDD from InputFormat, the number of partitions is determined by the InputFormat, very similar to the way splits are determined in MapReduce jobs.

Spark data transformations

- **map**: Applies a function on every element of an RDD to produce a new RDD
  - For example: lines.map(s⇒s.length) takes an RDD of Strings (“lines”) and returns an RDD with the length of the strings.

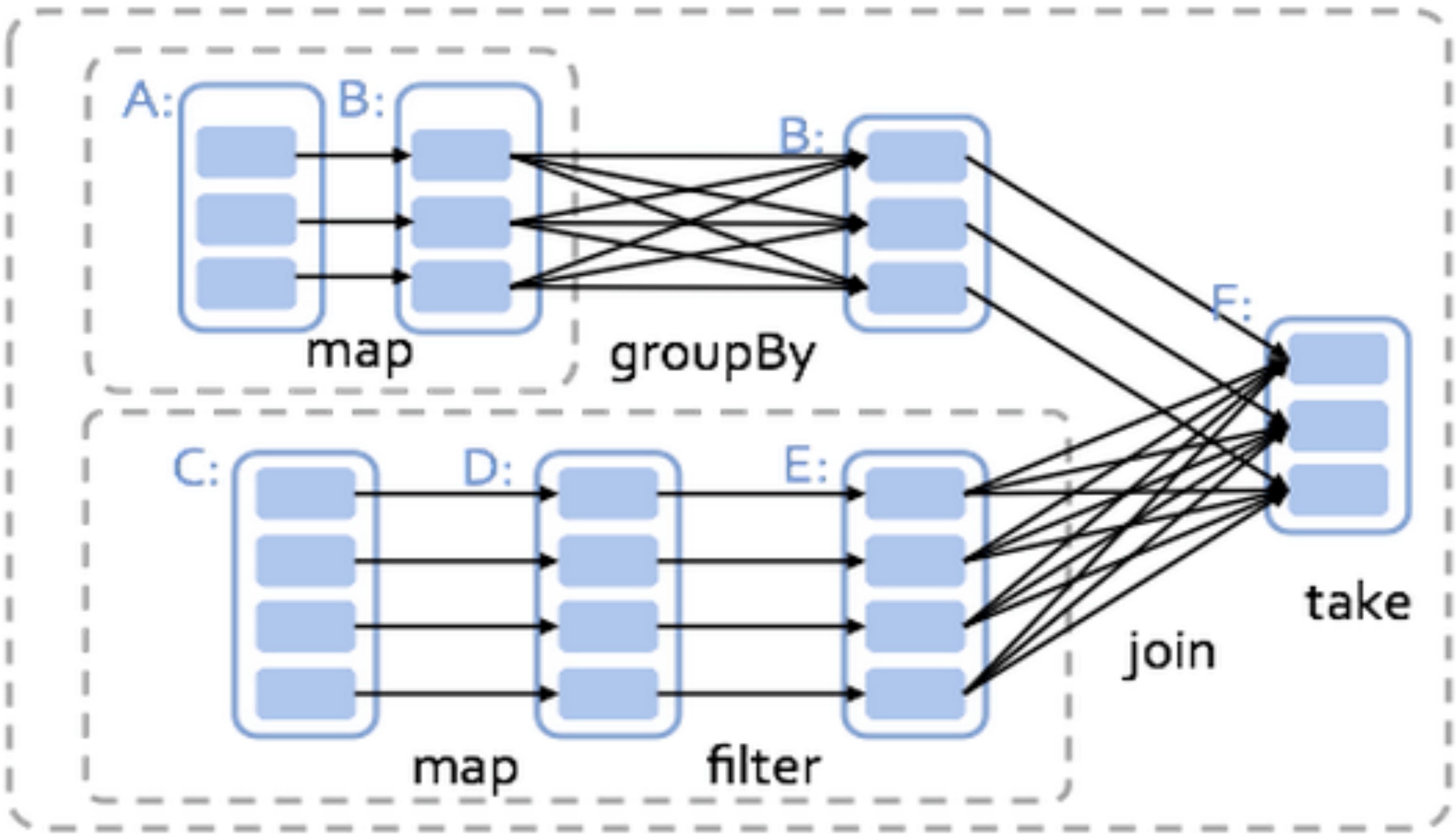
- **filter**: Takes a boolean function as a parameter, executes this function on every element of the RDD, and return a new RDD containing only the elements for which the function returned true.
  - For example lines.filter(s⇒(s.length>50)) returns an RDD containing only the lines with more than 50 characters

- **join**: Joins two key/value RDDs by their keys.
  - For example, lets assume we have two RDDs: lines and more_lines. Each entry in both RDDs containing the line length as the key and the line as the value. lines.join(more_lines) will return for each line length a pair of Strings, one from “lines” RDD and one from “more lines”. Each resulting element looks like: <length,<line,more_line>>

Spark simple example: top 10

```
rdd1.map(lines).filter(”data”)

rdd2.map(lines).groupBy(key)

rdd2.join(rdd1, key).take(10)
```

Spark simple example: top 10



Spark features

- **Storage:** Spark gives the developers a lot of flexibility regarding how RDDs are stored. This includes: In-memory on a single node, in-memory but replicated to multiple nodes, or persisted to disk.
- Developer controls the persistence: RDD can go multiple stages of transformation without storing anything to disk
- **Multi Language** While Spark itself is developed in Scala, Spark APIs are implemented for **Java**, **Scala**, **Python and R**
- **Interactive shell (REPL)** Spark includes a shell (also called REPL). This allows for fast interactive experimentation with the data and easy validation of ideas

Spark two-set join example

- Load “foo” and “bar” data sets into two RDDs

```
var fooTable = sc.textFile("hdfs:///user/root/foo")
var barTable = sc.textFile("hdfs:///user/root/bar”)
```

- Split each row of “foo” into a collection of separate cells

```
var fooSplit = fooTable.map(line => line.split("\\|"))
```

- Filter the splitted “foo” dataset and keep only the elements where the second column is smaller than 500

```
var fooFiltered = fooSplit.filter(cells => cells(1).toInt <= 500)
```

- Convert the results into key/value pairs using the ID column as the key

```
var fooKeyed = fooFiltered.keyBy(cells => cells(2))
```

- Split the columns in “bar” in the same way we splitted “foo” and again convert into key/value pairs with the ID as the key

```
var barSplit = barTable.map(line => line.split("\\|"))
var barKeyed = barSplit.keyBy(cells => cells(0))
```

Spark join example

- Join “bar” and “foo”

```
var joinedValues = fooKeyed.join(barKeyed)
```

- Filter the joined results - The filter function here takes the value of joinedVal RDD, which contains a pair of a “foo” and a “bar” rows. We take the first column from each row and check if their sum is lower than 1000

```
var joinedFiltered =joinedValues.filter(joinedVal =>
            joinedVal._2._1(1).toInt +
            joinedVal._2._2(1).toInt <= 1000)
```

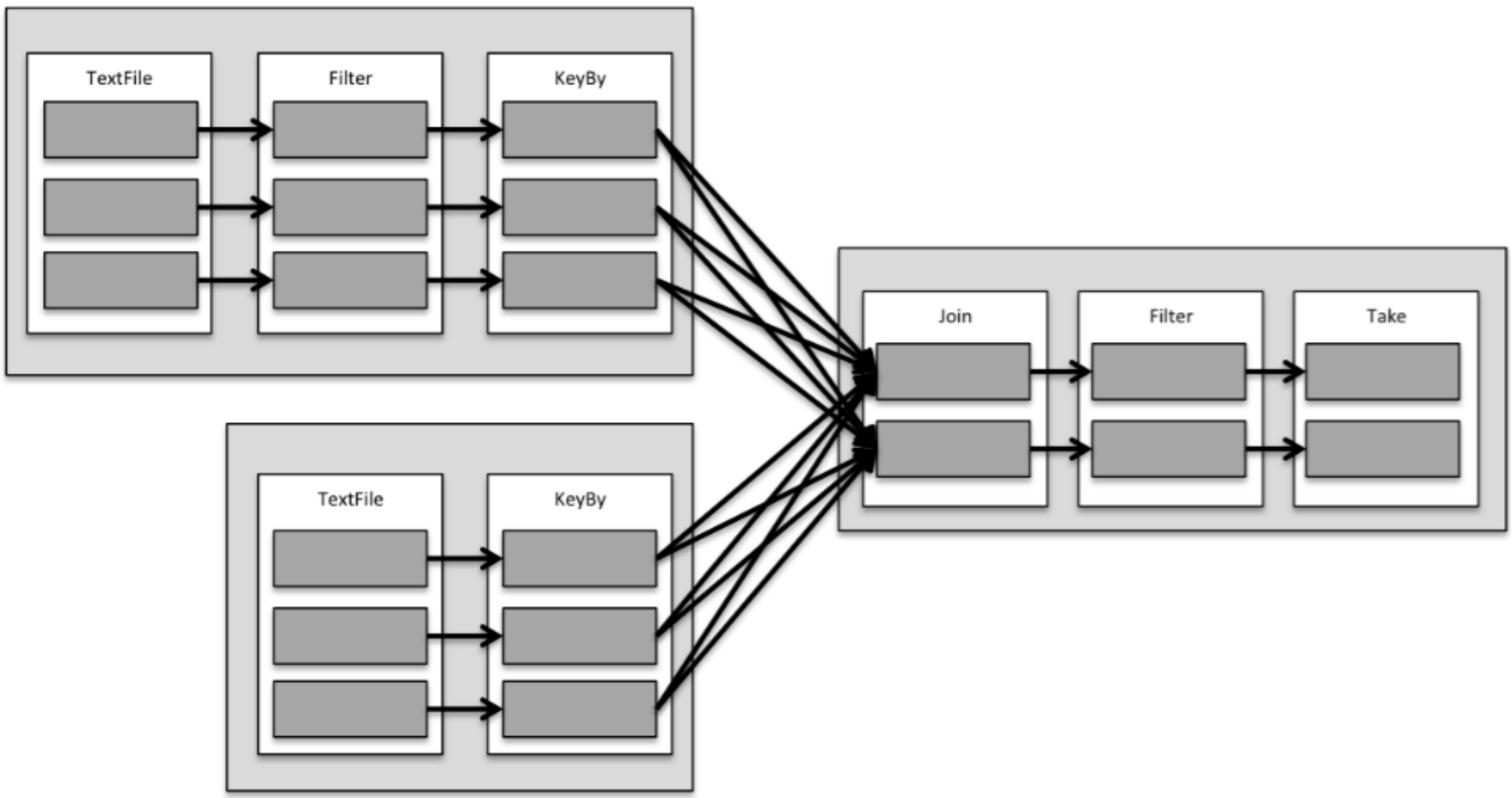
- Show the first 10 results - note that this is the only action in the code, therefore the entire chain of transformations we defined here will only be triggered at this point.

```
joinedFiltered.take(10)
```

Spark example: joining two sets

```
var fooTable = sc.textFile("hdfs:///user/root/foo")
var barTable = sc.textFile("hdfs:///user/root/bar")
var fooSplit = fooTable.map(line => line.split("\\|"))
var fooFiltered = fooSplit.filter(cells => cells(1).toInt
<= 500)
var fooKeyed = fooFiltered.keyBy(cells => cells(2))
var barSplit = barTable.map(line => line.split("\\|"))
var barKeyed = barSplit.keyBy(cells => cells(0))
var joinedValues = fooKeyed.join(barKeyed)
var joinedFiltered =joinedValues.filter(joinedVal =>
           joinedVal._2._1(1).toInt +
           joinedVal._2._2(1).toInt <= 1000)
joinedFiltered.take(10)
```

Example execution plan



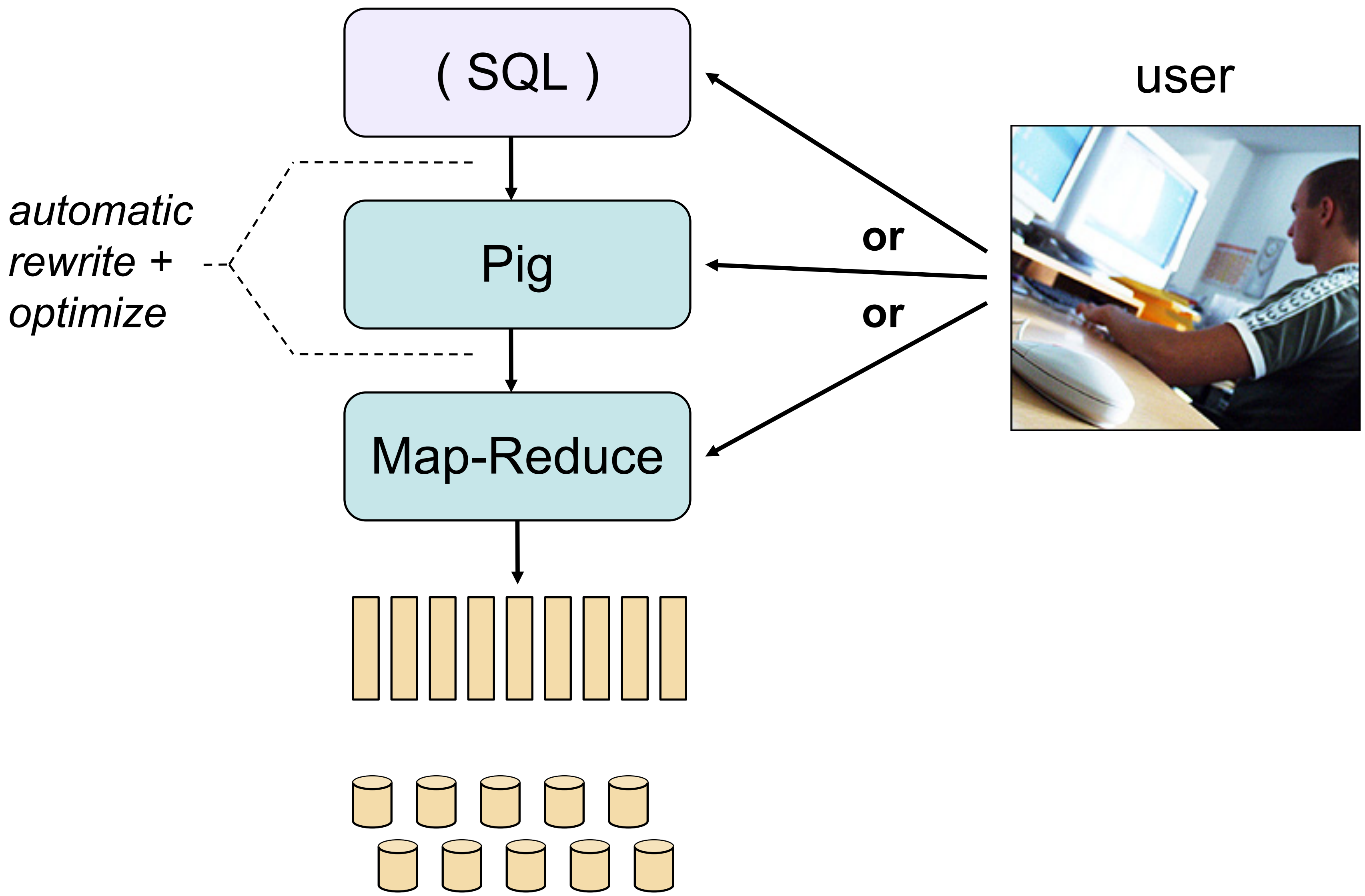
Spark conclusions

- Good implementation for large datasets
- Flexible: selection of high level languages and libraries
- Oriented to DAG processing: data pipelines
- More popular than hadoop map reduce now

MapReduce abstractions

- Since MapReduce was introduced there have been many projects trying to make it easier to use
- **ETL(Extract, Transform and Load)** are optimized to take a given dataset and do a bunch of operations on it to produce a set of outcomes.
  - **Pig** (Yahoo), Crunch, Cascading
- **Query(SQL)** are oriented to use SQL language to ask a question of the data to get an answer.
  - **Hive** (Facebook)

Pig: high level ETL queries

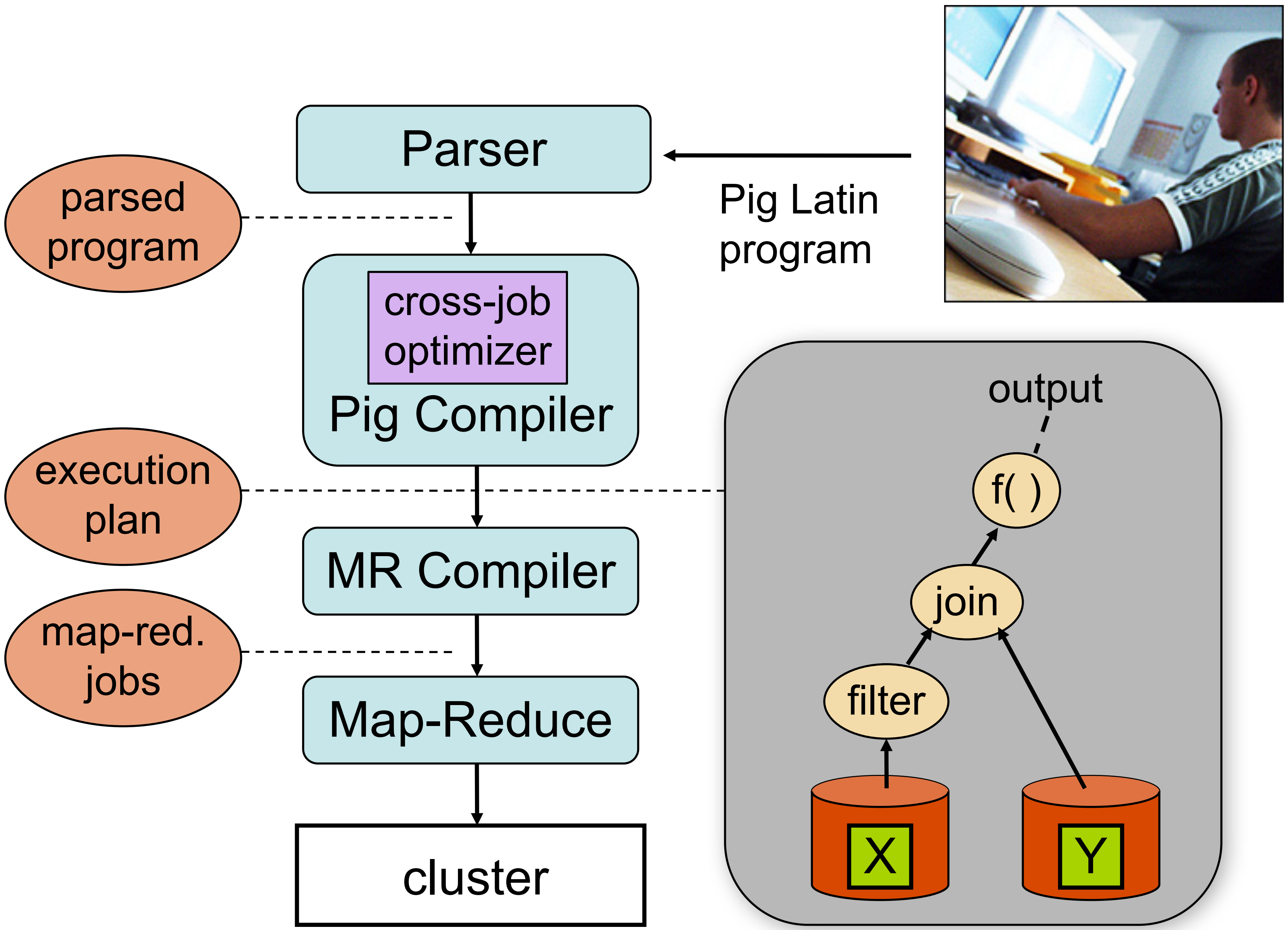


Pig “explicits” MR

- Map-reduce encapsulates three primitives:
  - record processing -> group creation -> group processing
- Pig: three operations:
  - a=FOREACH input GENERATE flatten(Map(*))
  - b=GROUP a BY $0
  - c=FOREACH b GENERATE Reduce(*)
- Operations: filtering, projection, combine tables

Pig vs SQL

- SQL is declarative: what data to get, not how
- Pig: how to get data step by step
  - Longer queries
  - Sequence order is semantic
  - Incremental build using intermediate data: error prone

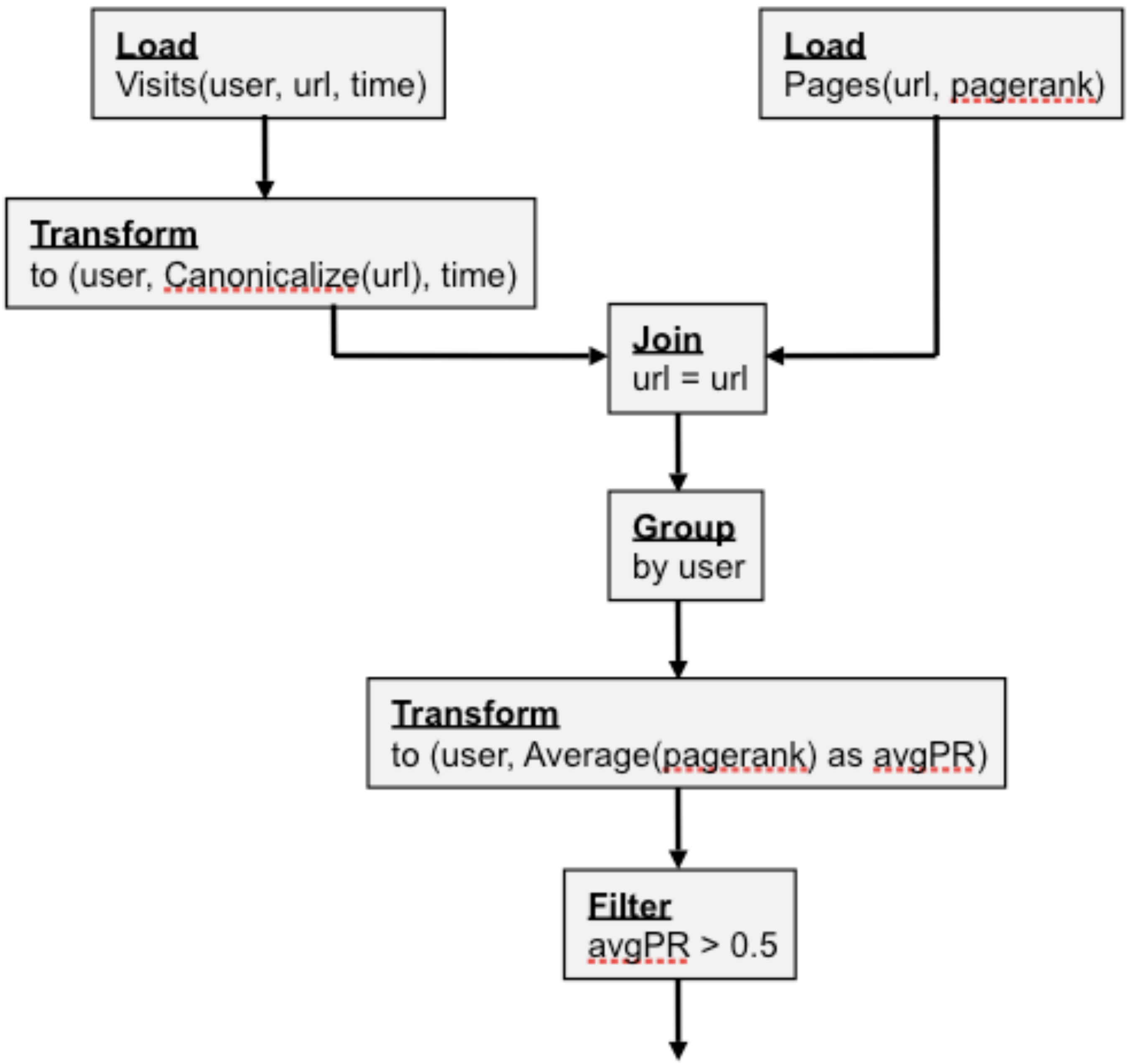

Parser
Pig Latin
program
parsed
program
cross-job
optimizer
Pig Compiler
execution
plan
output
f( )
join
filter
X
Y
MR Compiler
map-red.
jobs
Map-Reduce
cluster

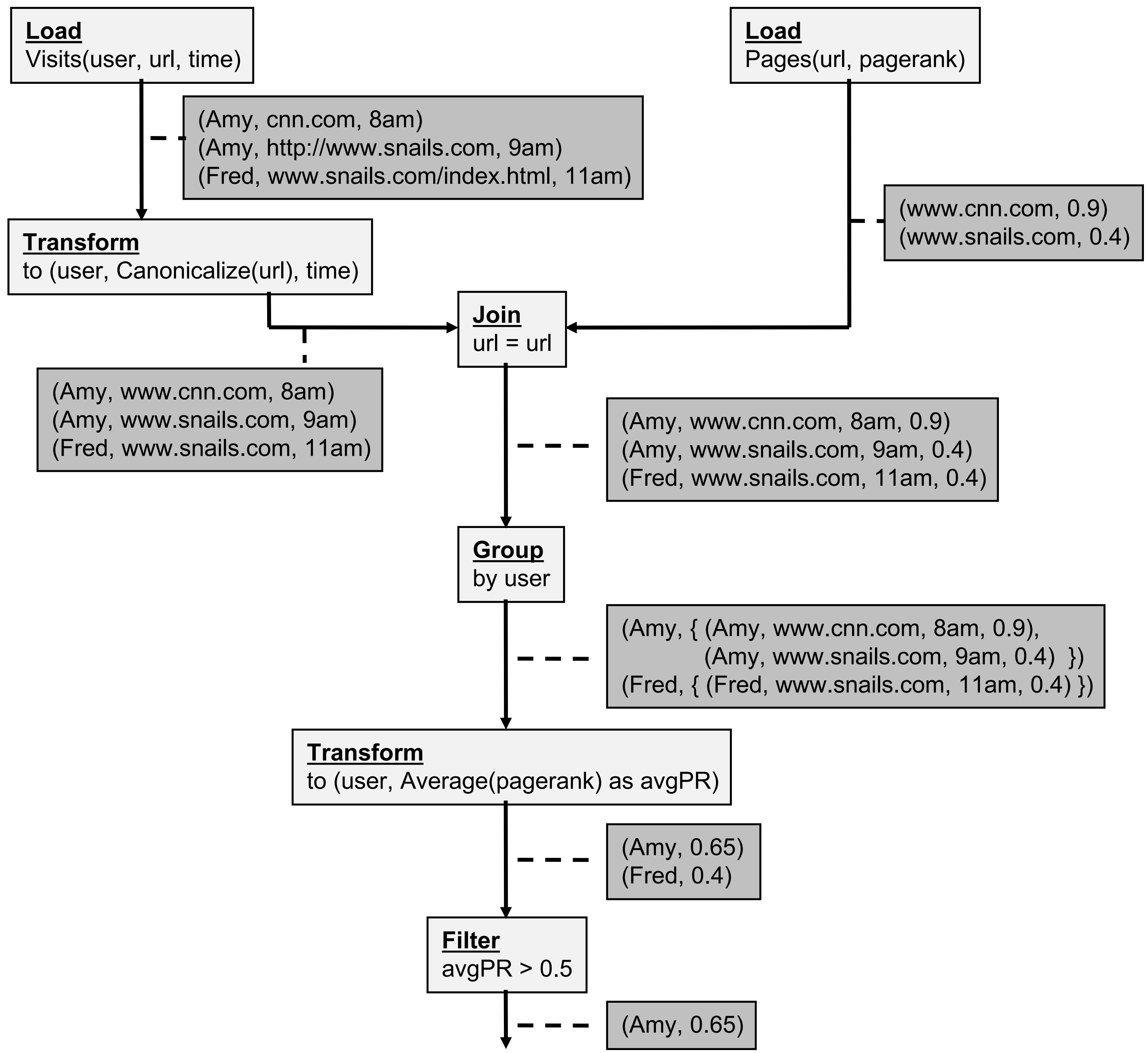
Pig count

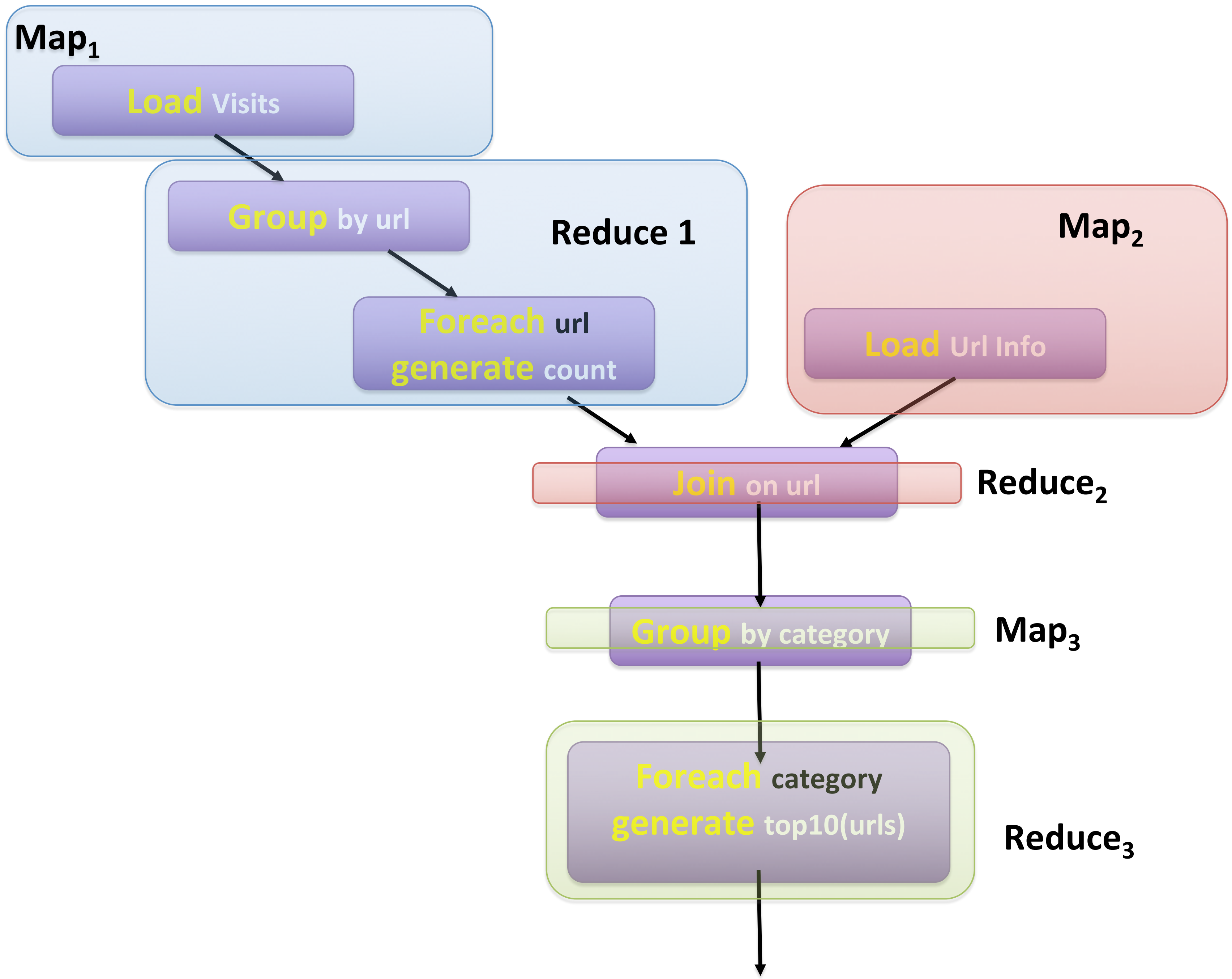
```
input = LOAD ‘input-dir’ USING TextLoader();

words = FOREACH input GENERATE FLATTEN(TOKENIZE(*));

grouped = GROUP words BY $0;

counts = FOREACH grouped GENERATE group, COUNT(words);

STORE counts INTO ‘out-dir’;
```

visual structure

Find users who tend to visit “good” pages.




Load
Visits(user, url, time)
Load
Pages(url, pagerank)
(Amy, cnn.com, 8am)
(Amy, http://www.snails.com, 9am)
(Fred, www.snails.com/index.html, 11am)
(www.cnn.com, 0.9)
(www.snails.com, 0.4)
Transform
to (user, Canonicalize(url), time)
Join
url = url
(Amy, www.cnn.com, 8am)
(Amy, www.snails.com, 9am)
(Fred, www.snails.com, 11am)
(Amy, www.cnn.com, 8am, 0.9)
(Amy, www.snails.com, 9am, 0.4)
(Fred, www.snails.com, 11am, 0.4)
Group
by user
(Amy, { (Amy, www.cnn.com, 8am, 0.9),
(Amy, www.snails.com, 9am, 0.4) })
(Fred, { (Fred, www.snails.com, 11am, 0.4) })
Transform
to (user, Average(pagerank) as avgPR)
(Amy, 0.65)
(Fred, 0.4)
Filter
avgPR > 0.5
(Amy, 0.65)



Map$_1$
Load Visits
Group by url
Reduce 1
Foreach url
generate count
Map$_2$
Load Url Info
Join on url
Reduce$_2$
Group by category
Map$_3$
Foreach category
generate top10(urls)
Reduce$_3$

Hive: data warehousing and analytics on Hadoop

Why create Hive?

- Problem: Data, 2+ TB raw data per day
- Hadoop
  - better scalability/availability than DBs
  - Map-reduce is hard to program to sql users
- HIVE: a SQL language for hadoop

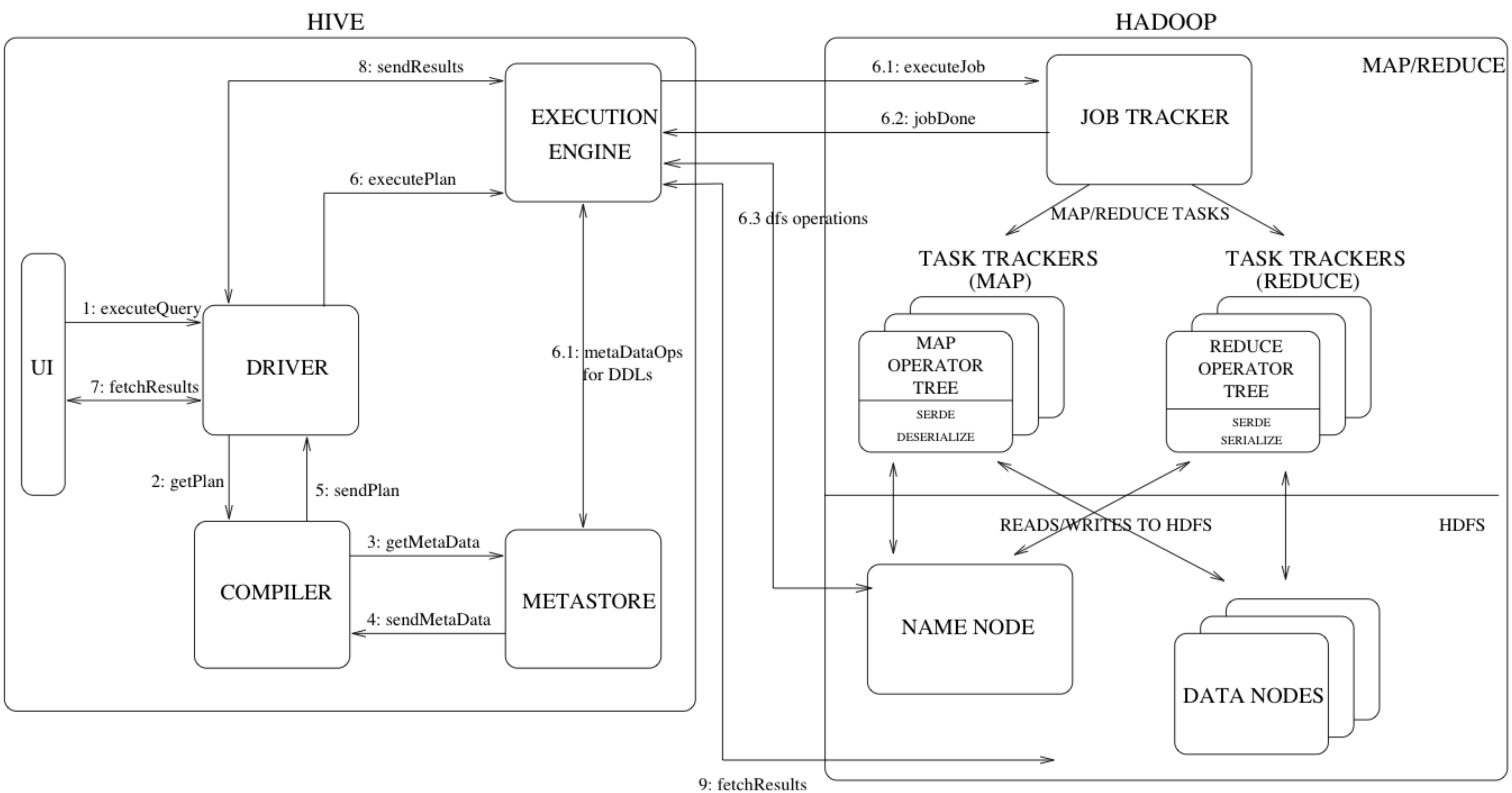
What is Apache HIVE?

- Open source data warehouse system
- Rich data types: structs, lists, maps
- SQL programming tool
- Rich meta data to allow data discovery and for optimization
- For large dataset batch queries
- Support for data partitioning

Applications

- Summaries: daily aggregation of click counts
- Data mining (assembling training data): user engagement as a function of user attributes
- Spam detection: anomalous usage patterns of APIs
- Ad hoc analysis: how many group admins broken down by state/country

System overview



Daily data statistics

- 3200 jobs/day with 800K map reduce tasks
- 55TB compressed data scanned
- 15TB of compressed output data to hdfs
- 80 M compute minutes

Database creation and data import

- Create database

```
create database customers;
```

- Create invoices table

```
create table invoices(id INT, customer INT, product STRING,
cost DOUBLE) row format delimited fields terminated by ‘,’
stored as textfile;
```

- Insertar data from HDFS file

```
LOAD DATA INPATH ‘invoices.txt’  OVERWRITE INTO TABLE
invoices;
```

Using Hive partitions

```
CREATE TABLE web_url(url STRING, website STRING, date
DATETIME)

PARTITIONED BY (country STRING)

STORED AS TEXTFILE;
```

- Each partition corresponds to a particular country value
- It is stored in a separated HDFS folder

Using Hive partitions

```
SELECT *

FROM web_url

WHERE date >=‘2017-12-24’ AND country= ‘UK’ AND

web_url.site like ‘%example.com’
```

The Data center computational environment

Introduction: the Toyota Camry case

In September 2007, Jean Bookout, 76, was driving her Toyota Camry down an unfamiliar road in Oklahoma, with her friend Barbara Schwarz seated next to her on the passenger side. Suddenly, the Camry began to accelerate on its own. Bookout tried hitting the brakes, applying the emergency brake, but the car continued to accelerate. The car eventually collided with an embankment, injuring Bookout and killing Schwarz.

In a subsequent legal case, lawyers for Toyota pointed to the most common of culprits in these types of accidents: human error. “Sometimes people make mistakes while driving their cars,” one of the lawyers claimed. Bookout was old, the road was unfamiliar, these tragic things happen.

The after case: consequences of software errors

However, a recently concluded product liability case against Toyota has turned up a very different cause: **a stack overflow error in Toyota's software for the Camry**.

1. human error proved not to be the cause

2. we have definitively crossed a threshold from software failures causing minor annoyances or (potentially large) corporate revenue losses into the realm of human safety.

Responsibility

- But what happens if a failure that's completely out of the car's control occurs?
- What if the data feed that's helping the car to recognize stop lights fails?
- What if Google Maps tells it to do something stupid that turns out to be dangerous?

Current software systems development

We have reached a point in software development where we can no longer understand, see, or control all the component parts, both technical and social/organizational—they are increasingly complex and distributed.

The **business of software itself has become a distributed, complex system**.

How do we develop and manage systems that are too large to understand, too complex to control, and that fail in unpredictable ways?

Understanding complexity

No one single thing or approach could prevent something like the Toyota incident from happening again. In fact, it’s almost a given that something like that will happen again.

The answer is to **embrace that failures of an unthinkable variety are possible** and to change how we think about the systems we are building

When you’re in a distributed environment and most of the failure modes are things you can’t predict in advance and can’t test for, **monitoring is the only way to understand your application’s behavior**.

Site Reliability Engineering (SRE)

"How should a complex computing system that operates at a large scale be run?" The term "DevOps" emerged in industry in late 2008. Core principles:

- Involvement of the IT function in each phase of a system's design and development
- Heavy reliance on automation versus human effort
- The application of engineering practices and tools to operations tasks

Production environment at Google

- Machine: a piece of hardware (or perhaps a VM)

- Server: a piece of software that implements a service

Machines can run any server, so we don't dedicate specific machines to specific server programs.

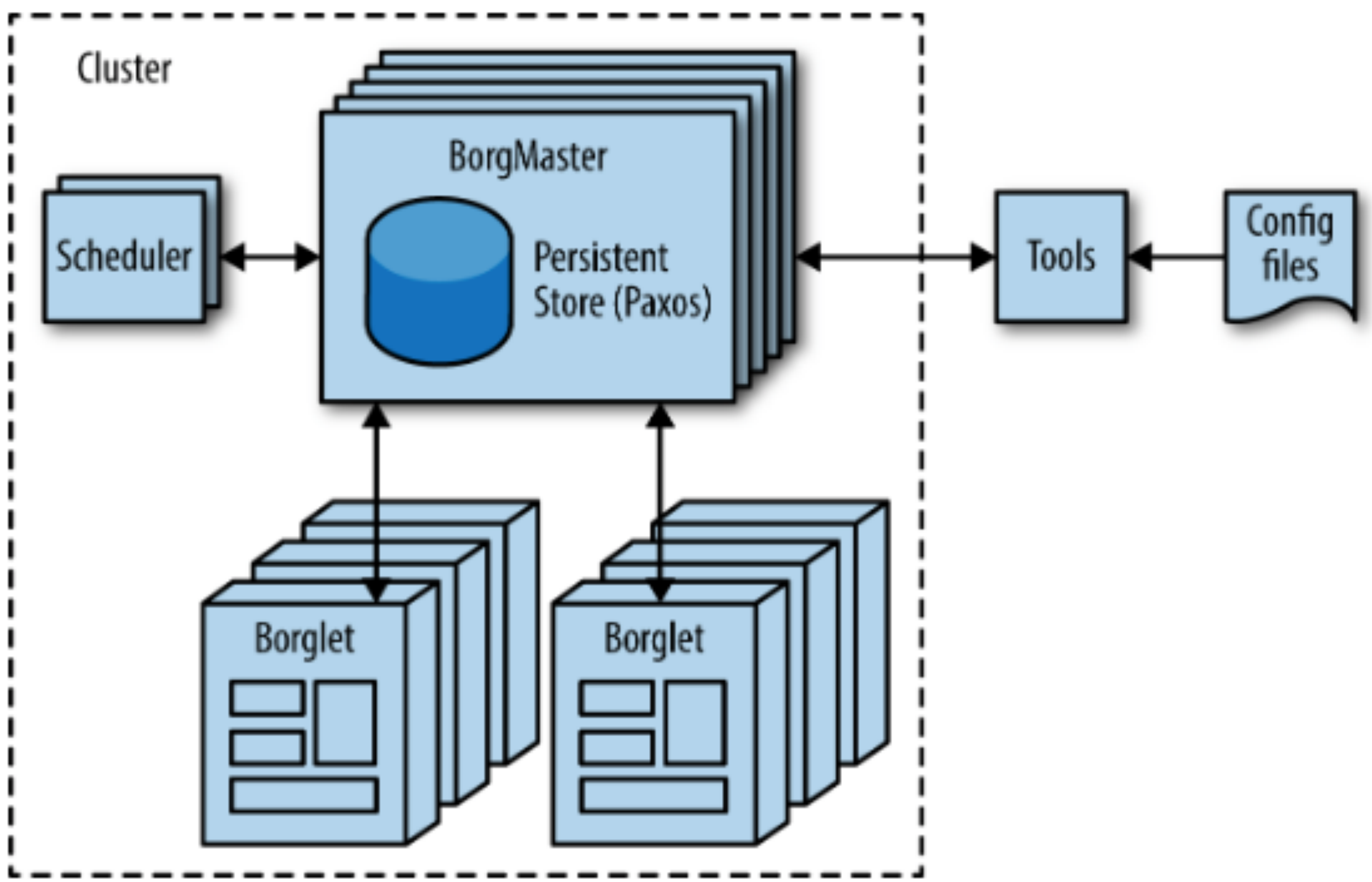
There's no specific machine that runs our mail server, for example. Instead, resource allocation is handled by a cluster operating system: **Borg**

System view of a Google datacenter

Tens of machines are placed in a rack.
Racks stand in a row.

Borg: distributed operating system

- Borg is a distributed cluster operating system similar to Apache Mesos
- Borg manages jobs at the cluster level



Borg jobs

- Borg is responsible for running users' jobs, which can either be indefinitely running servers or batch processes like **MapReduce**

- Jobs can consist of more than one (and sometimes thousands) of identical tasks, both for reasons of reliability and because a single process can't usually handle all cluster traffic.

- When Borg starts a job, it finds machines for the tasks and tells the machines to start the server program.

- Borg then continually monitors these tasks. If a task malfunctions, it is killed and restarted, possibly on a different machine.

Borg job management

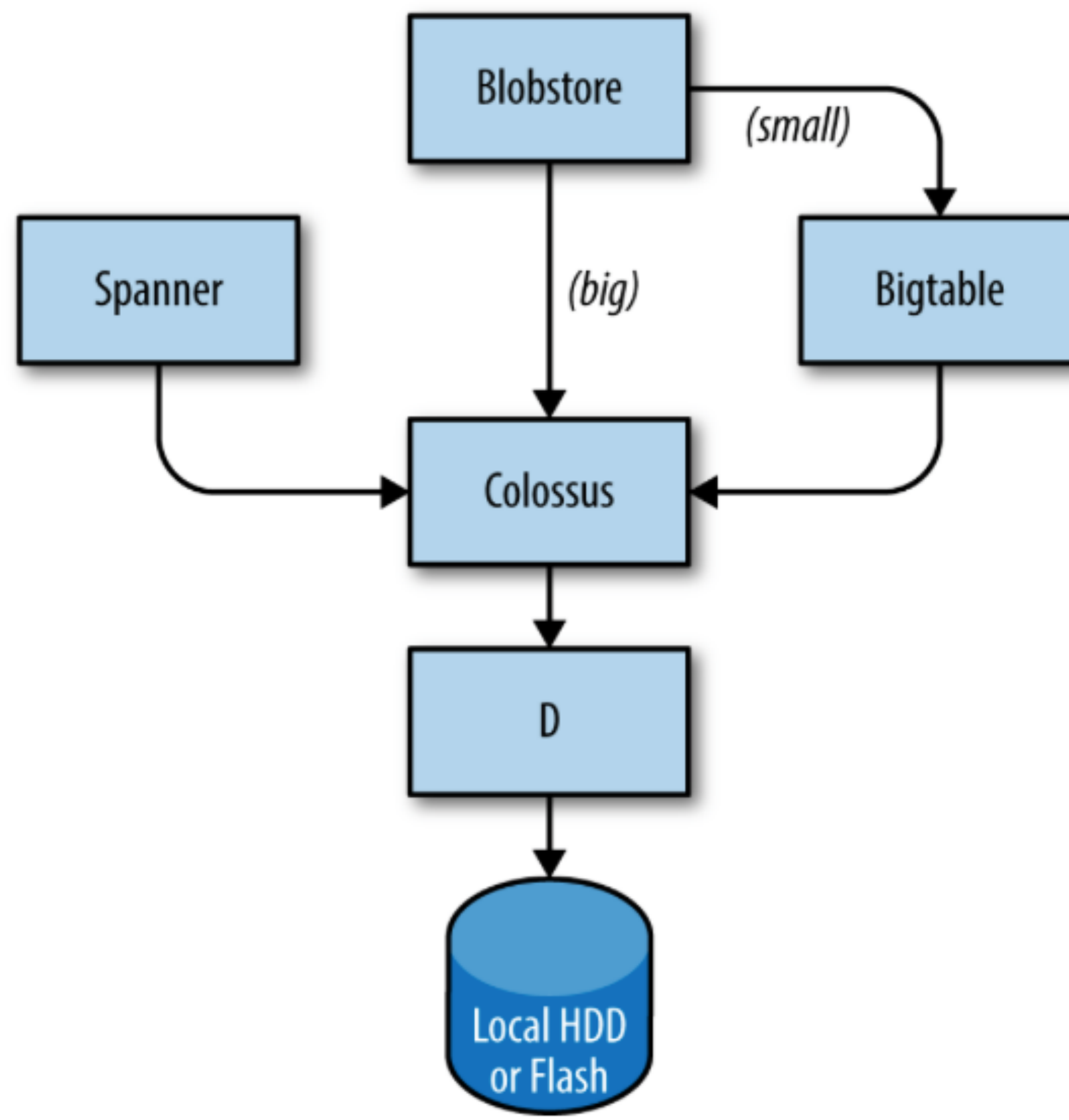
- Borg is also responsible for the allocation of resources to jobs. Every job needs to specify its required resources like CPU cores or RAM
- Using the list of requirements for all jobs, Borg can binpack the tasks over the machines in an optimal way that also accounts for failure domains
- Example: Borg won't run all of a job's tasks on the same rack, as doing so means that the top of rack switch is a single point of failure for that job

Storage system

- Tasks can use the local disk on machines as a scratch pad, but we have several cluster storage options for permanent storage
- These are comparable to **Lustre** and the **Hadoop Distributed File System (HDFS)**, which are both open source cluster file systems

Storage system layers

- The lowest layer is called **D**: fileserver running on almost all machines in a cluster.
- However, users who want to access their data don't want to have to remember which machine is storing their data
- A layer on top of **D** called **Colossus** creates a cluster-wide file system that offers usual file system semantics, as well as replication and encryption.



Database-like services on top of Colossus

- **Bigtable** is a NoSQL database system that can handle databases that are petabytes in size.
- **Bigtable** is a sparse, distributed, persistent multidimensional sorted map that is indexed by row key, column key, and timestamp; each value in the map is an uninterpreted array of bytes.
- **Bigtable** supports eventually consistent, cross-datacenter replication.

Network management

- Some services have jobs running in multiple clusters, which are distributed across the world.
- In order to minimize latency for globally distributed services, we want to direct users to the closest datacenter with available capacity.
- **Global Software Load Balancer (GSLB)** performs load balancing on three levels:
  - Geographic load balancing for DNS requests (www.google.com)
  - Load balancing at a user service level (YouTube or Google Maps)
  - Load balancing at the Remote Procedure Call (RPC) level

General references

- Hadoop, the definitive guide. Tom White. O'Reilly. 2015
- Big data principles. Nathan Marz. Manning. 2014
- Site Reliability Engineering. Betsy Beyer, Chris Jones, Jennifer Petoff, and Niall Richard Murphy. O'Reilly, 2016.