Distributed RDF Datastores

Dimitrios Tsoumakos

Some slides taken from :

- Distributed Big Graph Management Methods and Systems, N. Papailiou
- Hexastore: Sextuple Indexing for Semantic Web Data Management, C. Weiss, P. Karras, et al
- Matrix “Bit” loaded: A Scalable Lightweight Join Query Processor for RDF Data, Medha Atre, et al

BIG DATA, MODERN DISTRIBUTED COMPUTE ENGINES AND NOSQL DATABASES OVERVIEW

Processes 20 PB a day (2008)
Crawls 20B web pages a day (2012)
Search index is 100+ PB (5/2014)
Bigtable serves 2+ EB, 600M QPS (5/2014)

400B pages, 10+ PB (2/2014)

Hadoop: 365 PB, 330K nodes (6/2014)

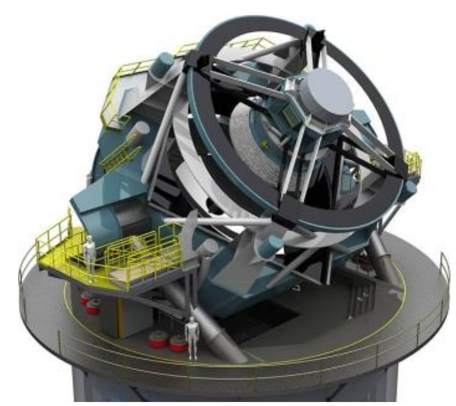
150 PB on 50k+ servers running 15k apps (6/2011)

Hadoop: 10K nodes, 150K cores, 150 PB (4/2014)

300 PB data in Hive + 600 TB/day (4/2014)

LHC: ~15 PB a year

S3: 2T objects, 1.1M request/second (4/2013)



LSST: 6-10 PB a year (~2020)

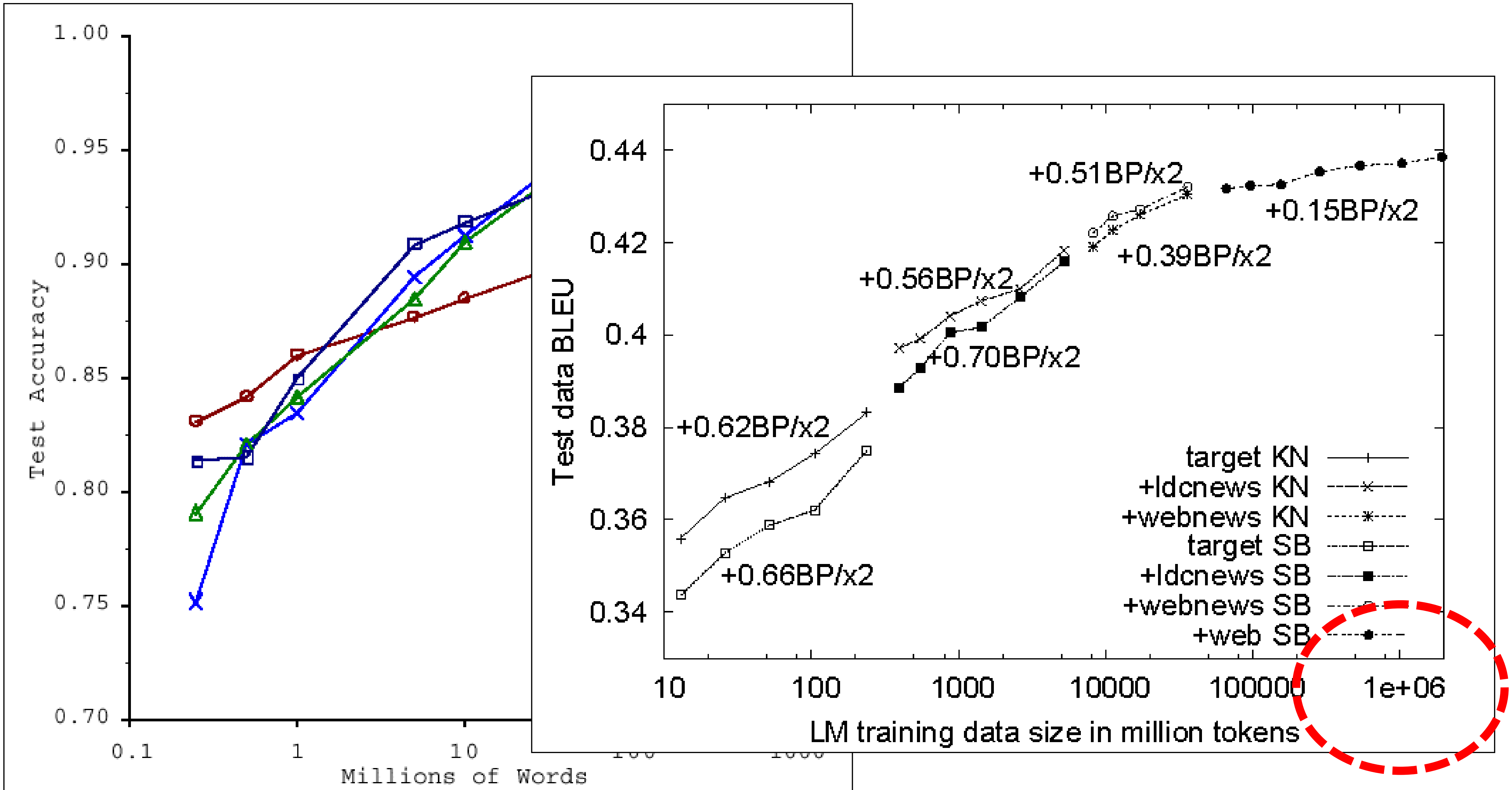
640K ought to be enough for anybody.

SKA: 0.3 – 1.5 EB per year (~2020)

How much data?

No data like more data!

s/knowledge/data/g;



How do we get here if we're not Google?

(Banko and Brill, ACL 2001)
(Brants et al., EMNLP 2007)

What is cloud computing?

Just a buzzword?

- Before clouds…
  - P2P computing
  - Grids
  - HPC
  - …
- Cloud computing means many different things:
  - Large-data processing
  - Rebranding of web 2.0
  - Utility computing
  - Everything as a service

Rebranding of web 2.0

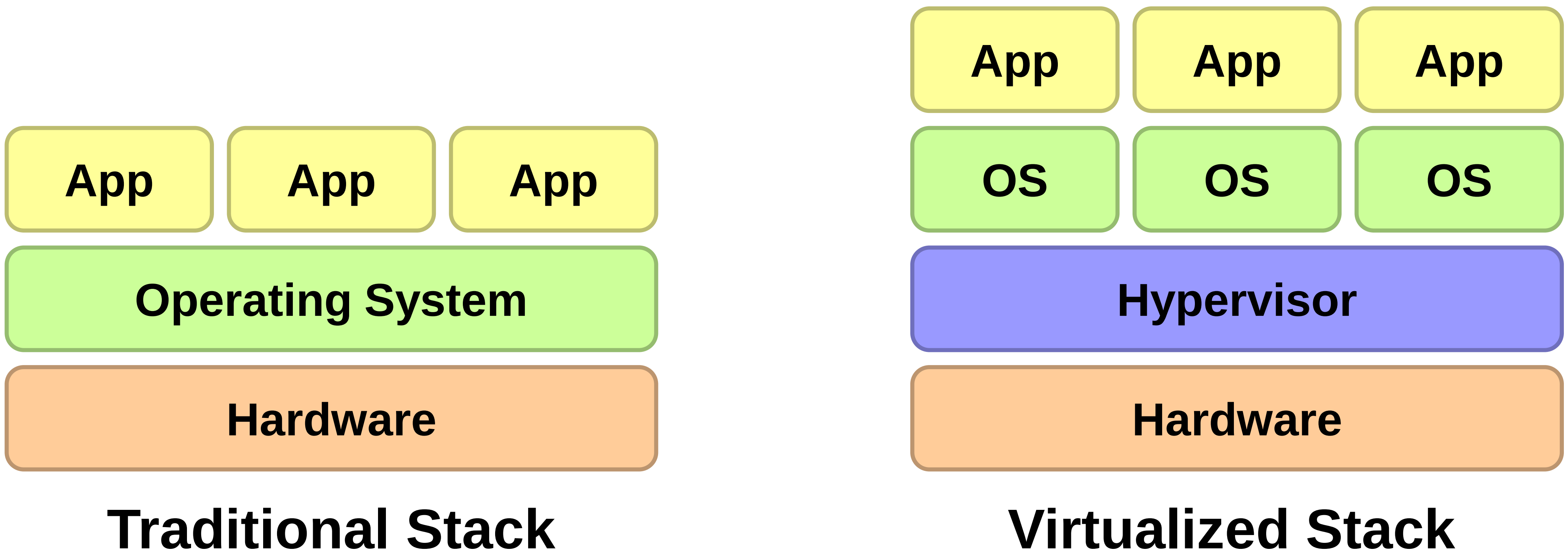
- Rich, interactive web applications
  - Clouds refer to the servers that run them
  - AJAX as the de facto standard (for better or worse)
  - Examples: Facebook, YouTube, Gmail, …
- "The network is the computer": take two
  - User data is stored "in the clouds"
  - Rise of the netbook, smartphones, etc.
  - Browser *is* the OS

Utility Computing

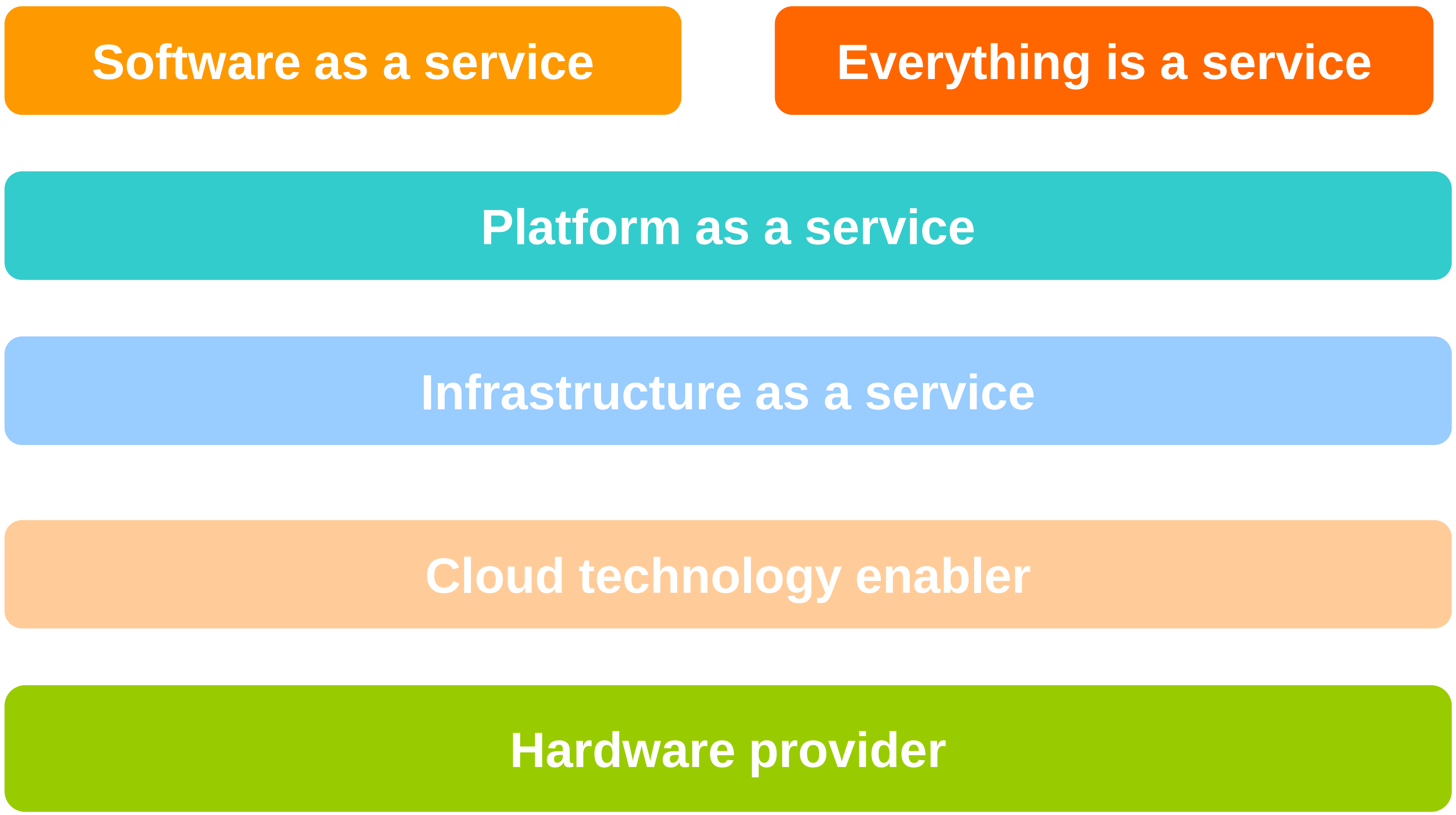
- What?
  - Computing resources as a metered service ("pay as you go")
  - Ability to dynamically provision virtual machines
- Why?
  - Cost: capital vs. operating expenses
  - Scalability: "infinite" capacity
  - Elasticity: scale up or down on demand
- Does it make sense?
  - Benefits to cloud users
  - Business case for cloud providers

I think there is a world market for about five computers.

Enabling Technology: Virtualization



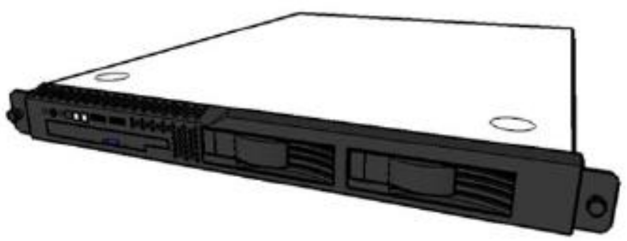
Cloud computing market

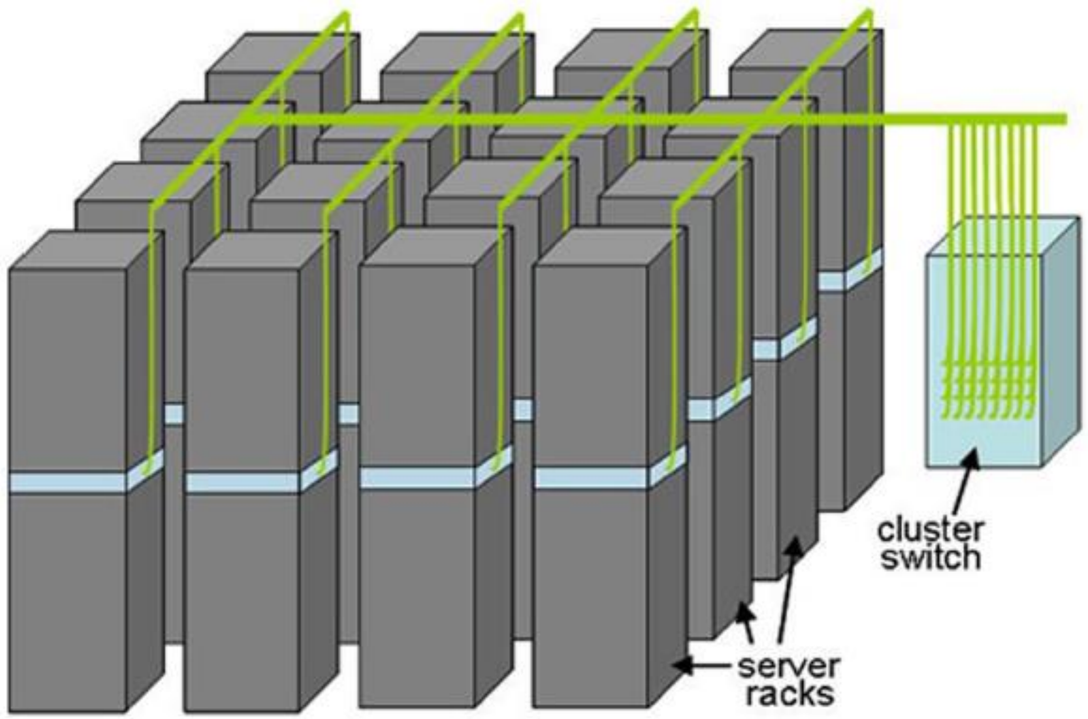


Everything as a Service

- Utility computing = Infrastructure as a Service (IaaS)
  - Why buy machines when you can rent cycles?
  - Examples: Amazon’s EC2, Rackspace
- Platform as a Service (PaaS)
  - Give me nice API and take care of the maintenance, upgrades, …
  - Example: Google App Engine
- Software as a Service (SaaS)
  - Just run it for me!
  - Example: Gmail, Salesforce

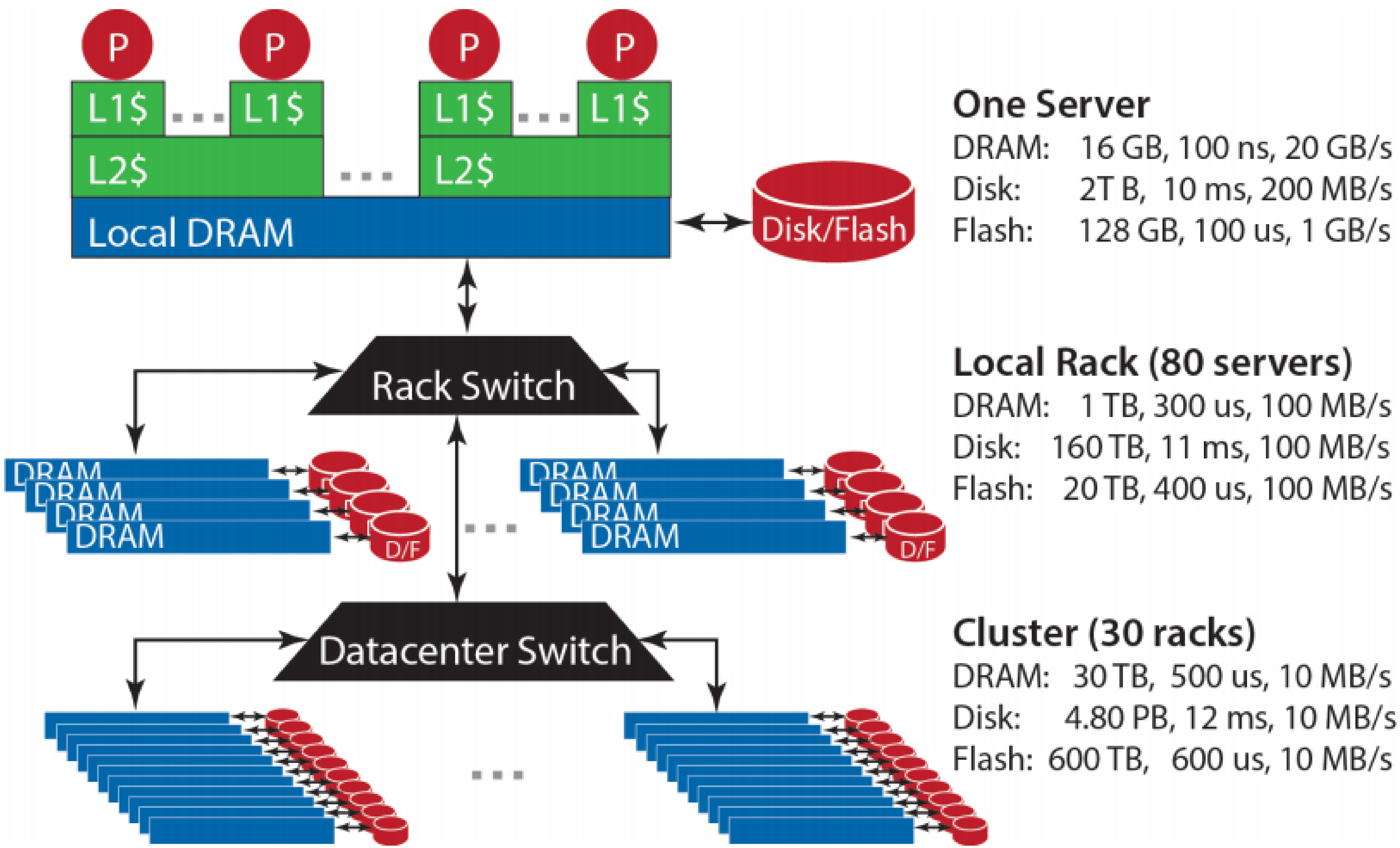
Building Blocks





Source: Barroso and Urs Hölzle (2009)

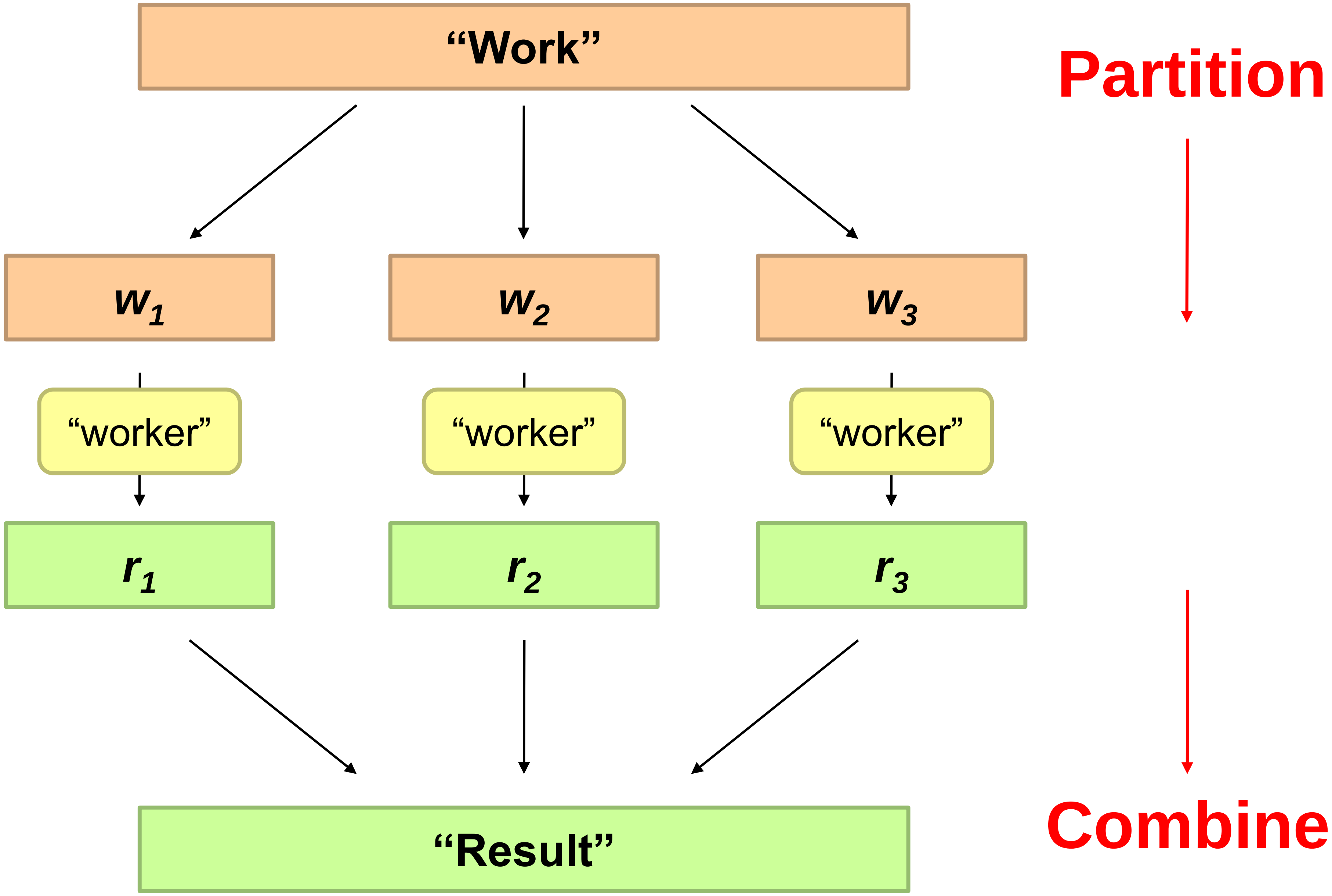
Storage Hierarchy



Source: Barroso and Urs Hölzle (2013)

How do we scale up?

Divide and Conquer



Parallelization Challenges

- How do we assign work units to workers?
- What if we have more work units than workers?
- What if workers need to share partial results?
- How do we aggregate partial results?
- How do we know all the workers have finished?
- What if workers die?

What is the common theme of all of these problems?

Synchronization!

- Parallelization problems arise from:
  - Communication between workers (e.g., to exchange state)
  - Access to shared resources (e.g., data)
- Thus, we need a synchronization mechanism

Managing Multiple Workers

- Difficult because
  - We don’t know the order in which workers run
  - We don’t know when workers interrupt each other
  - We don’t know the order in which workers access shared data
- Thus, we need:
  - Semaphores (lock, unlock)
  - Conditional variables (wait, notify, broadcast)
  - Barriers
- Still, lots of problems:
  - Deadlock, livelock, race conditions...
  - Dining philosophers, sleeping barbers, cigarette smokers...
- Moral of the story: be careful!

“Big Ideas”

- Scale “out”, not “up”
  - Limits of SMP and large shared-memory machines
- Move processing to the data
  - Cluster have limited bandwidth
- Process data sequentially, avoid random access
  - Seeks are expensive, disk throughput is reasonable
- Seamless scalability
  - From the mythical man-month to the tradable machine-hour

MapReduce

What is MapReduce?

- Programming model for expressing distributed computations at a massive scale
- Execution framework for organizing and performing such computations
- Open-source implementation called Hadoop

Typical Large-Data Problem

- Iterate over a large number of records
- Extract something of interest from each
- Shuffle and sort intermediate results
- Aggregate intermediate results
- Generate final output

Map

Reduce

Key idea: provide a functional abstraction for these two operations

(Dean and Ghemawat, OSDI 2004)

Challenges

1. **Cheap nodes fail, especially if you have many**
   - Mean time between failures for 1 node = 3 years
   - Mean time between failures for 1000 nodes = 1 day
   - <u>Solution:</u> Build fault-tolerance into system

2. **Commodity network = low bandwidth**
   - <u>Solution:</u> Push computation to the data

3. **Programming distributed systems is hard**
   - <u>Solution:</u> Data-parallel programming model: users write "map" & "reduce" functions, system distributes work and handles faults

MapReduce

- Programmers specify two functions:

  map (k, v) → <k’, v’>*

  reduce (k’, v’) → <k’’, v’’>*

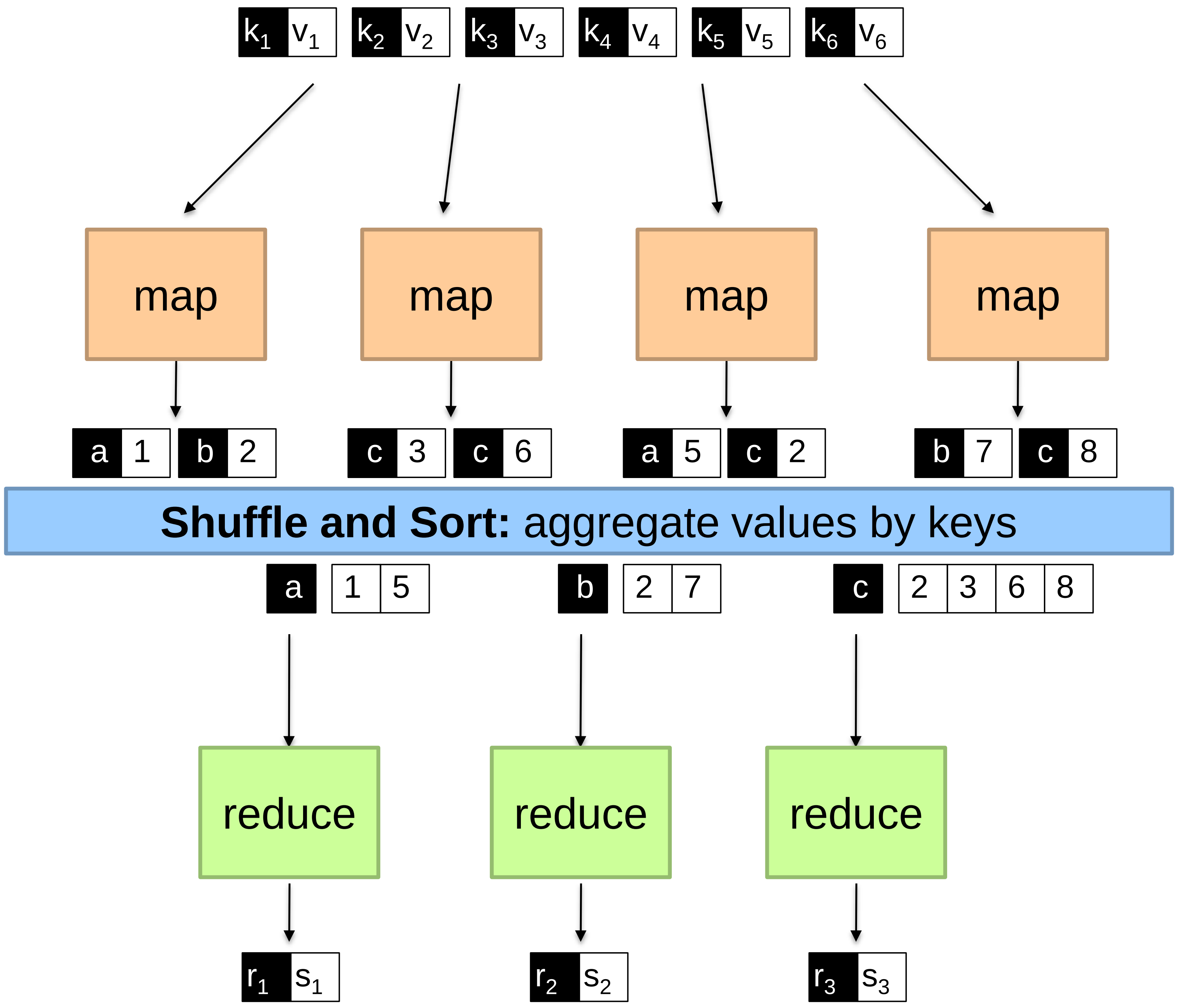
  - All values with the same key are reduced together
- The execution framework handles everything else…
- Not quite…usually, programmers also specify:

  partition (k’, number of partitions) → partition for k’

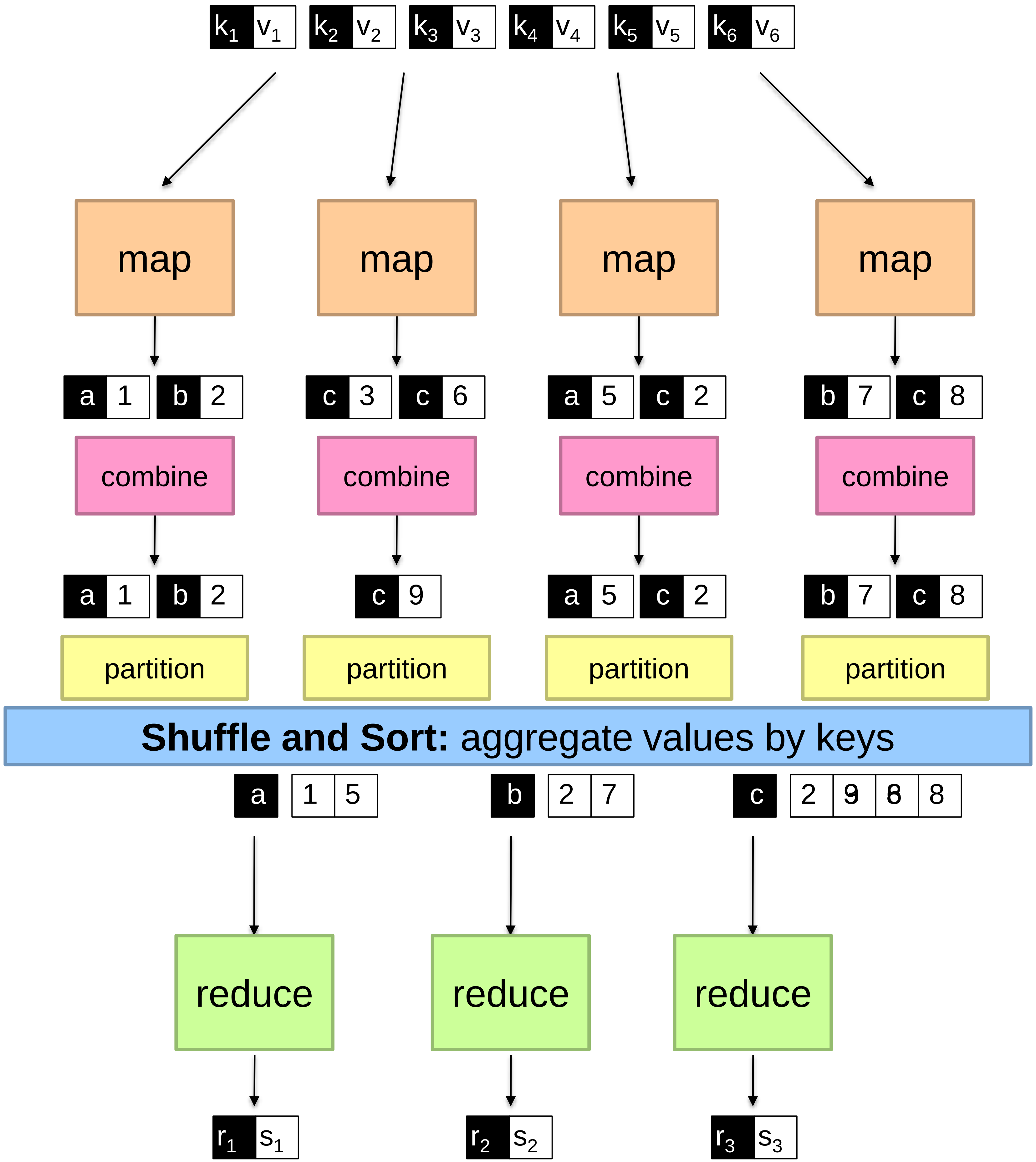
  - Often a simple hash of the key, e.g., hash(k’) mod n
  - Divides up key space for parallel reduce operations

  combine (k’, v’) → <k’, v’>*

  - Mini-reducers that run in memory after the map phase
  - Used as an optimization to reduce network traffic



k1 v1
k2 v2
k3 v3
k4 v4
k5 v5
k6 v6
map
map
map
map
a 1
b 2
c 3
c 6
a 5
c 2
b 7
c 8
Shuffle and Sort: aggregate values by keys
a 1 5
b 2 7
c 2 3 6 8
reduce
reduce
reduce
r1 s1
r2 s2
r3 s3



k1 v1
k2 v2
k3 v3
k4 v4
k5 v5
k6 v6
map
map
map
map
a 1
b 2
c 3
c 6
a 5
c 2
b 7
c 8
combine
combine
combine
combine
a 1
b 2
c 9
a 5
c 2
b 7
c 8
partition
partition
partition
partition
Shuffle and Sort: aggregate values by keys
a 1 5
b 2 7
c 2
8
reduce
reduce
reduce
r1 s1
r2 s2
r3 s3

MapReduce “Runtime”

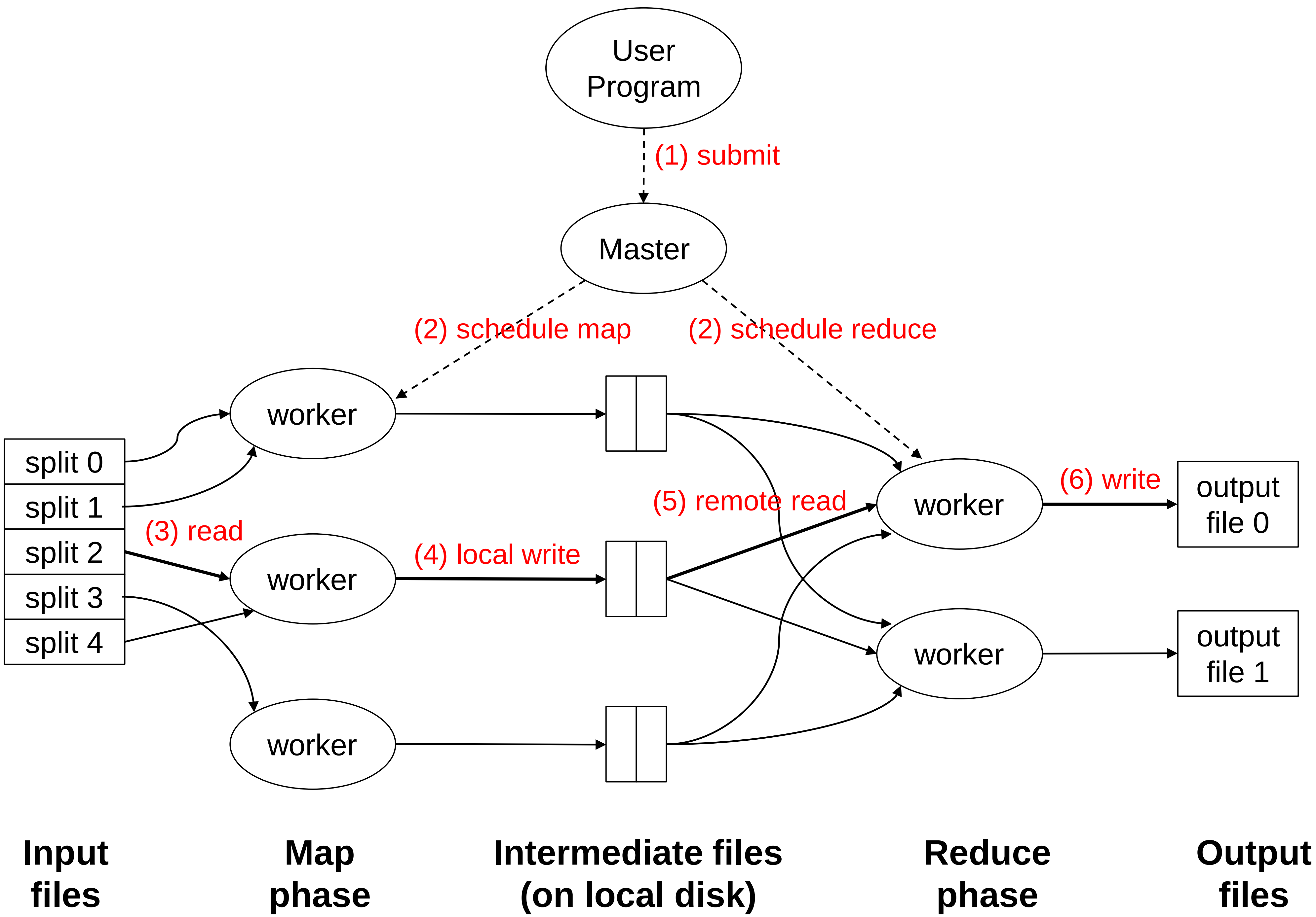
- Handles scheduling
  - Assigns workers to map and reduce tasks
- Handles “data distribution”
  - Moves processes to data
- Handles synchronization
  - Gathers, sorts, and shuffles intermediate data
- Handles errors and faults
  - Detects worker failures and restarts
- Everything happens on top of a distributed FS

Two more details…

- Barrier between map and reduce phases
  - But we can begin copying intermediate data earlier
- Keys arrive at each reducer in sorted order
  - No enforced ordering *across* reducers

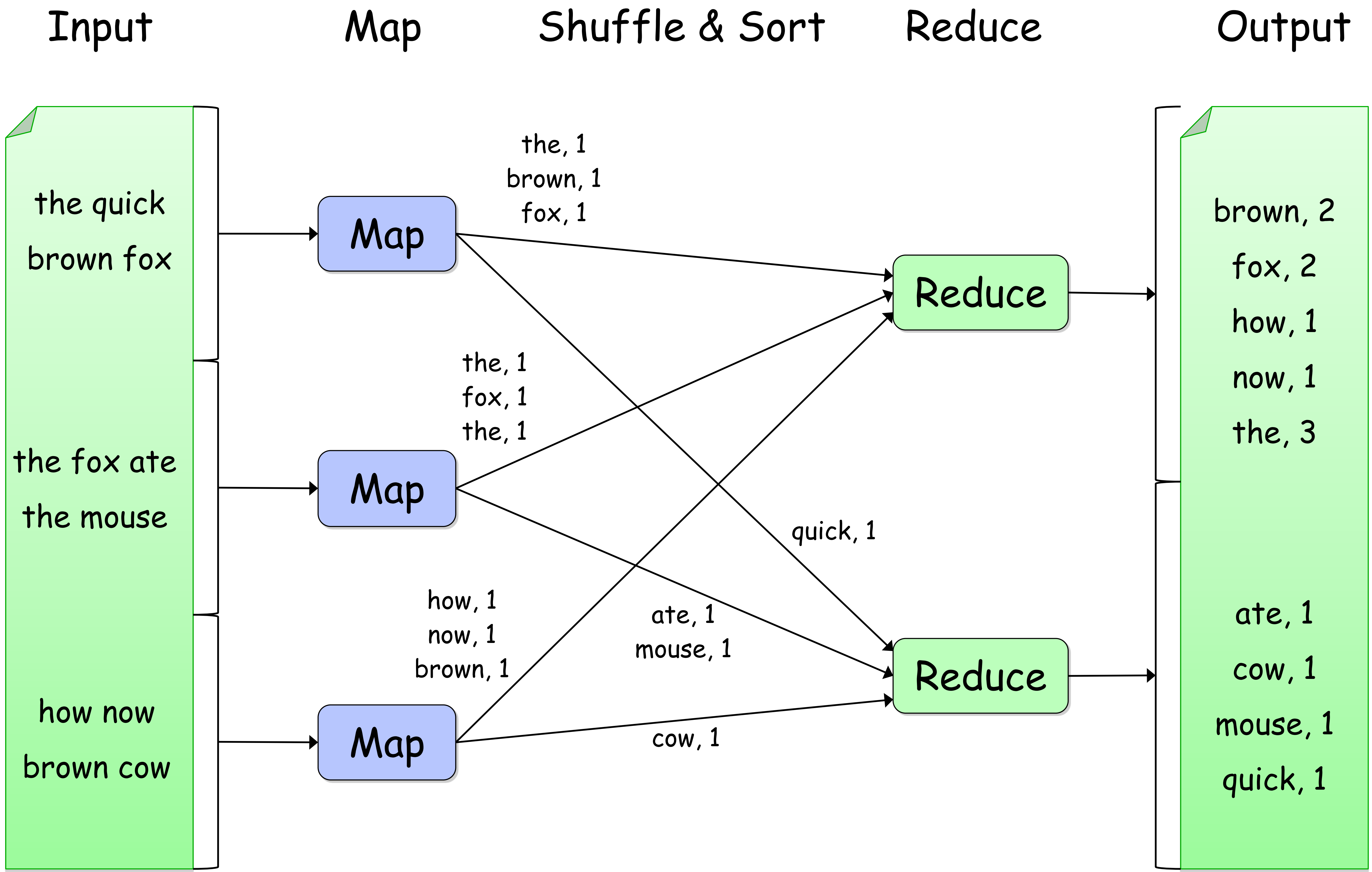
MapReduce Execution

- Single *master* controls job execution on multiple *slaves*
- Mappers preferentially placed on same node or same rack as their input block
  - Minimizes network usage
- Mappers save outputs to local disk before serving them to reducers
  - Allows recovery if a reducer crashes
  - Allows having more reducers than nodes

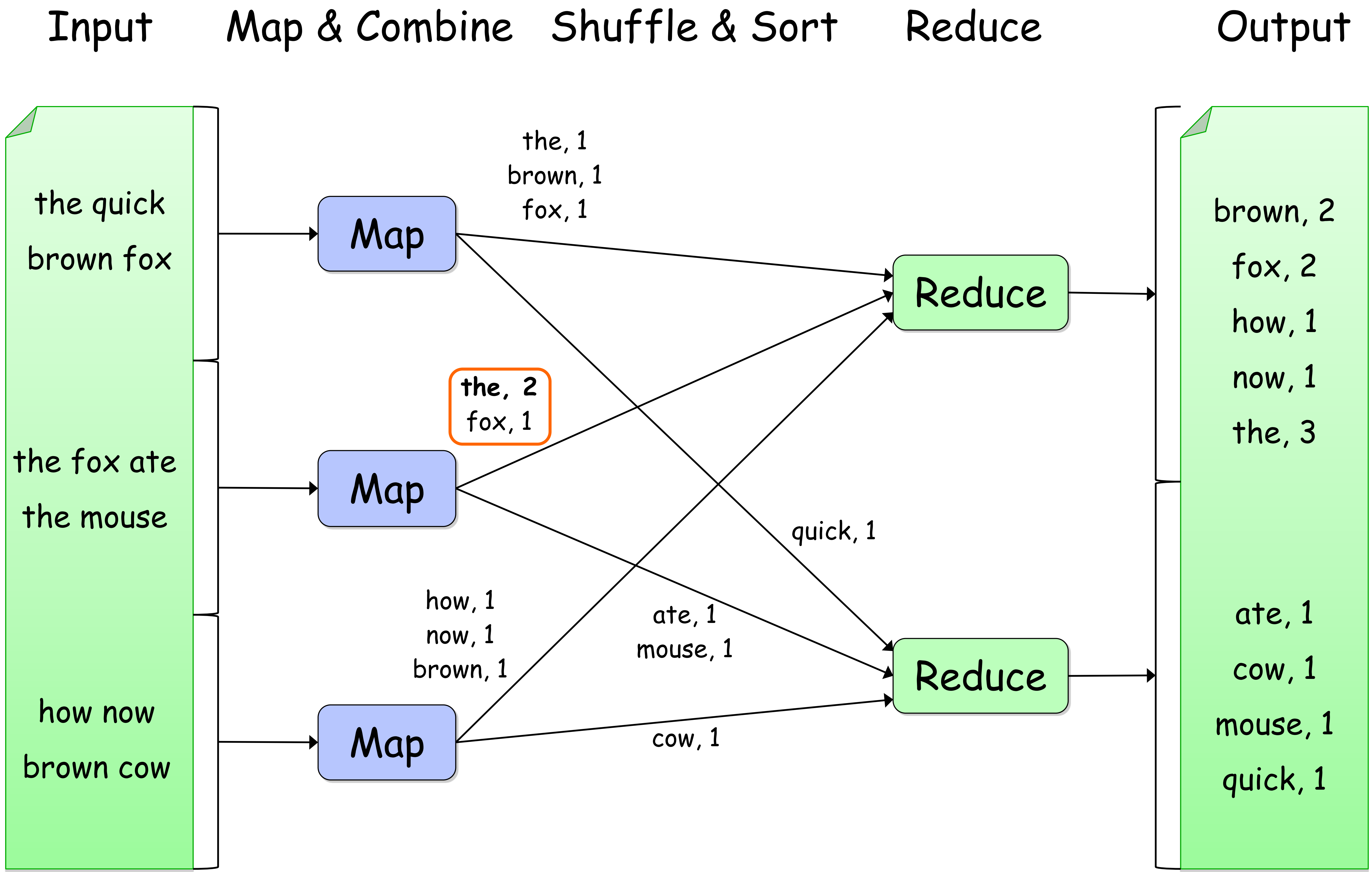


Adapted from (Dean and Ghemawat, OSDI 2004)

Word Count Execution



Word Count with Combiner



Inverted Index Example

- **Input:** (filename, text) records
- **Output:** list of files containing each word

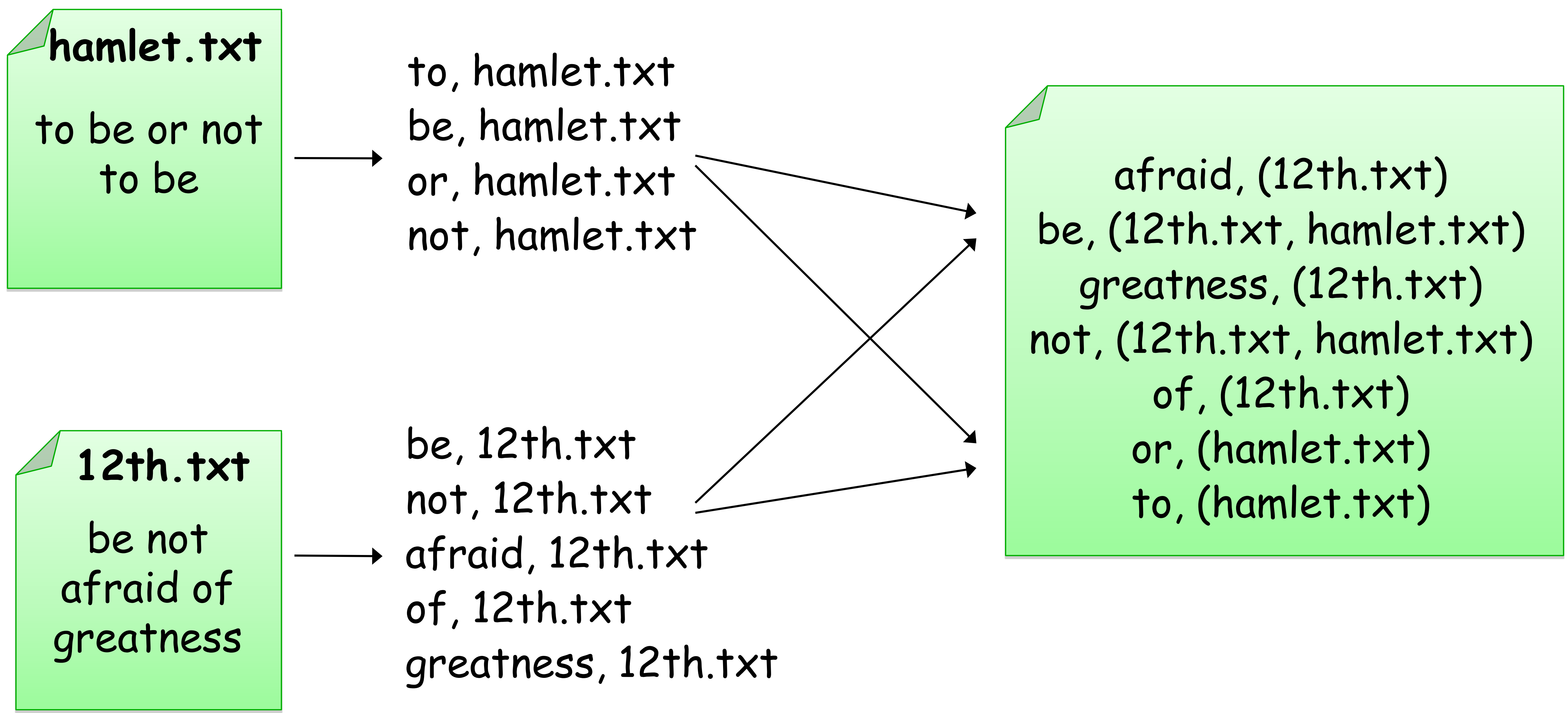
- **Map:**

```
foreach word in text.split():
    output(word, filename)
```

- **Combine:** uniquify filenames for each word
- **Reduce:**

```
def reduce(word, filenames):
    output(word, sort(filenames))
```

Inverted Index Example



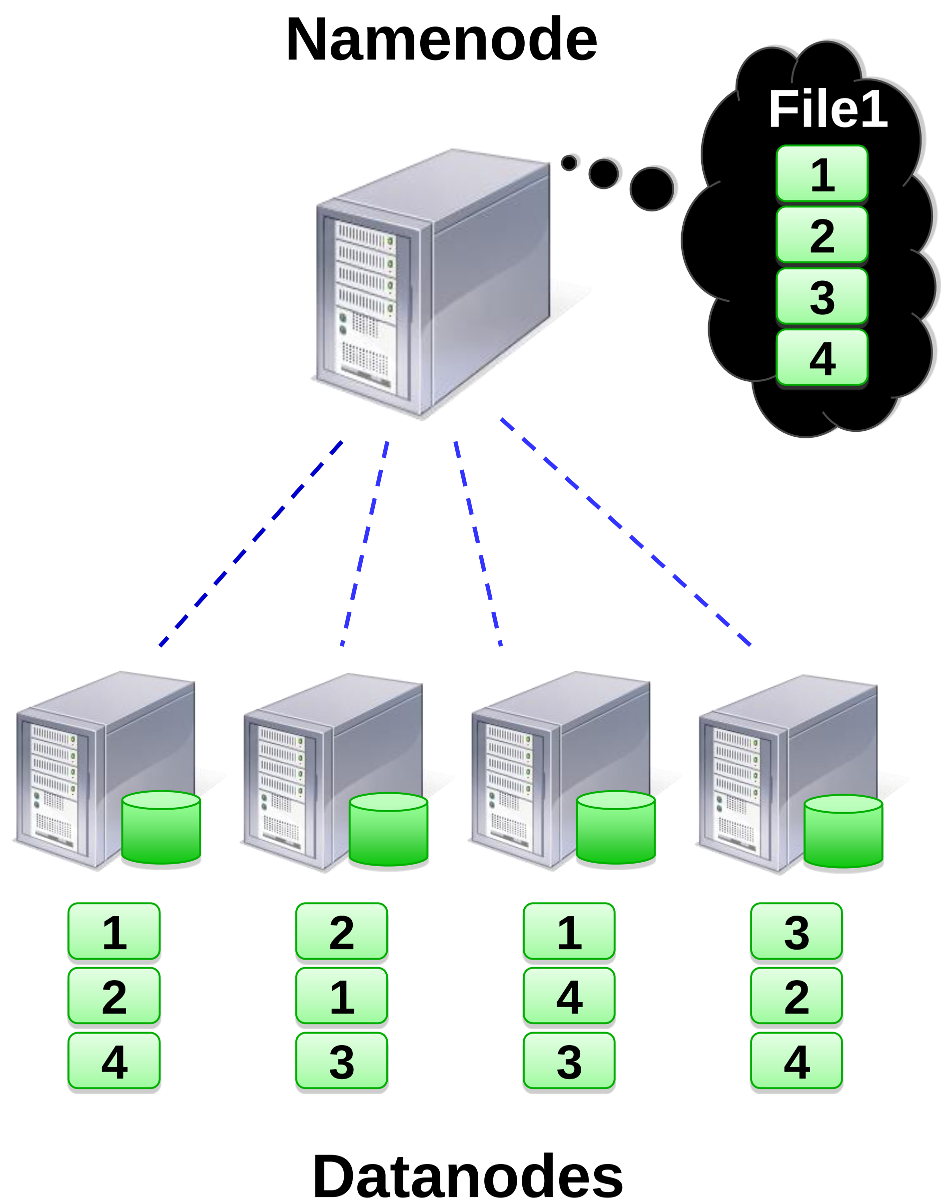
Hadoop Components

- **Distributed file system (HDFS)**
  - Single namespace for entire cluster
  - Replicates data 3x for fault-tolerance

- **MapReduce framework**
  - Executes user jobs specified as “map” and “reduce” functions
  - Manages work distribution & fault-tolerance

Hadoop Distributed File System

- Files split into 64MB *blocks*
- Blocks replicated across several *datanodes* (usually 3)
- Single *namenode* stores metadata (file names, block locations, etc)
- Optimized for large files, sequential reads
- Files are append-only



Sequoia

16.32 PFLOPS
98,304 nodes with 1,572,864 million cores
1.6 petabytes of memory
7.9 MWatts total power

Introduction to NoSQL, HBase

Material adapted from slides by :

Perry Hoekstra and *Gary Dusbabek(Rackspace)*

CS 525 ***Indranil Gupta***

SQL

- Specialized data structures (think B-trees)
  - Shines with complicated queries
- Focus on fast query & analysis
  - Not necessarily on large datasets

Scaling Up

- Issues with scaling up when the dataset is just too big
- RDBMS were not designed to be distributed
- Began to look at multi-node database solutions
- Known as ‘scaling out’ or ‘horizontal scaling’
- Different approaches include:
  - Master-slave
  - Sharding

What is NoSQL?

- Stands for **N**ot **O**nly **SQL**
- Class of non-relational data storage systems
- Usually do not require a fixed table schema nor do they use the concept of joins
- All NoSQL offerings relax one or more of the ACID properties (will talk about the CAP theorem)

How did we get here?

- Explosion of social media sites (Facebook, Twitter) with large data needs
- Rise of cloud-based solutions such as Amazon S3 (simple storage solution)
- Just as moving to dynamically-typed languages (Ruby/Groovy), a shift to dynamically-typed data with frequent schema changes
- Open-source community

More Programming and Less Database Design

Alternative to traditional relational DBMS

- + Flexible schema
- + Quicker/cheaper to set up
- + Massive scalability
- + Relaxed consistency $\rightarrow$ higher performance & availability

- – No declarative query language $\rightarrow$ more programming
- – Relaxed consistency $\rightarrow$ fewer guarantees

Challenge: Coordination

- The solution to availability and scalability is to decentralize and replicate functions and data…but how do we coordinate the nodes?
  - data consistency
  - update propagation
  - mutual exclusion
  - consistent global states
  - group membership
  - group communication
  - event ordering
  - distributed consensus
  - quorum consensus

Dynamo and BigTable

- Three major papers were the seeds of the NoSQL movement
  - BigTable (Google)
  - Dynamo (Amazon)
    - Gossip protocol (discovery and error detection)
    - Distributed key-value data store
    - Eventual consistency
  - CAP Theorem

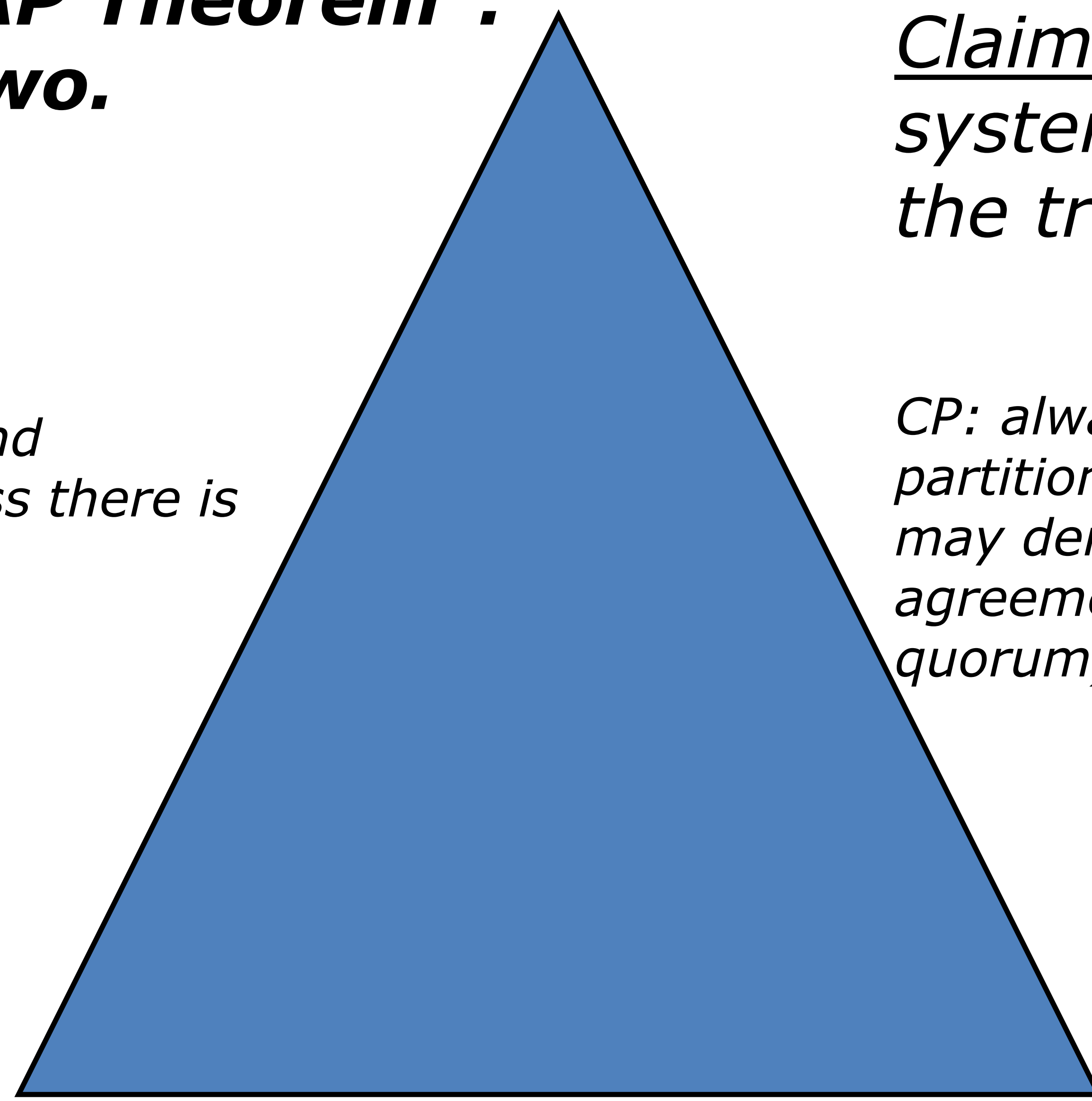
CAP Theorem

- Proposed by Eric Brewer (Berkeley)
- Subsequently proved by Gilbert and Lynch
- In a distributed system you can satisfy at most 2 out of the 3 guarantees
  1. **Consistency**: all nodes have same data at any time
  2. **Availability**: the system allows operations all the time
  3. **Partition-tolerance**: the system continues to work in spite of network partitions

Fox&Brewer "CAP Theorem": C-A-P: choose two.

Consistency

C



Claim: every distributed system is on one side of the triangle.

CA: available, and consistent, unless there is a partition.

CP: always consistent, even in a partition, but a reachable replica may deny service without agreement of the others (e.g., quorum).

A

Availability

AP: a reachable replica provides service even in a partition, but may be inconsistent if there is a failure.

P

Partition-resilience

Availability

- Traditionally, thought of as the server/process available five 9's (99.999 %).
- However, for large node system, at almost any point in time there's a good chance that a node is either down or there is a network disruption among the nodes.
  - Want a system that is resilient in the face of network disruption

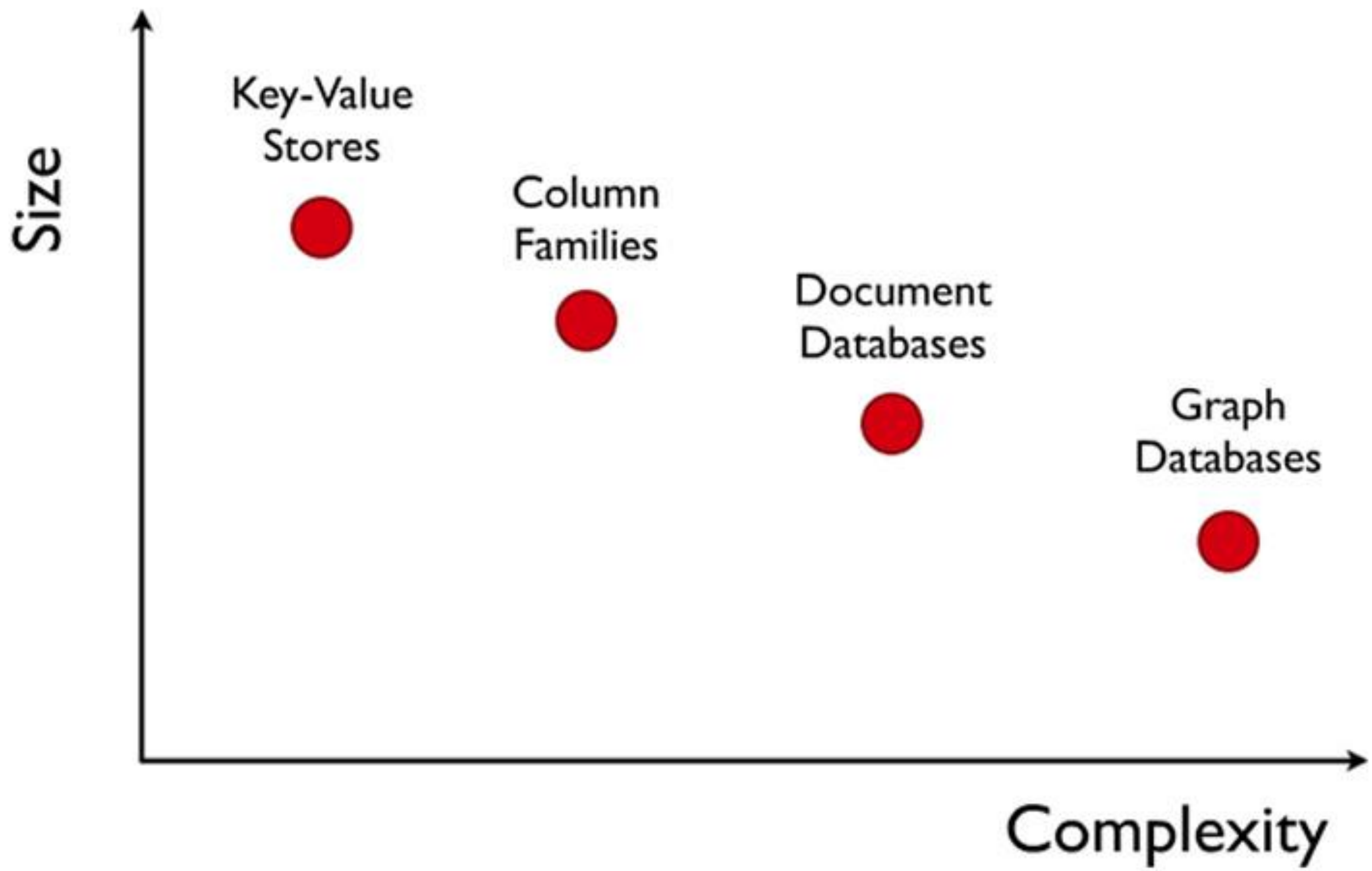
Consistency Model

- A consistency model determines rules for visibility and apparent order of updates.
- For example:
  - Row X is replicated on nodes M and N
  - Client A writes row X to node N
  - Some period of time t elapses.
  - Client B reads row X from node M
  - Does client B see the write from client A?
  - Consistency is a continuum with tradeoffs
  - For NoSQL, the answer would be: maybe
  - CAP Theorem states: Strict Consistency can't be achieved at the same time as availability and partition-tolerance.

Eventual Consistency

- When no updates occur for a long period of time, eventually all updates will propagate through the system and all the nodes will be consistent
- For a given accepted update and a given node, eventually either the update reaches the node or the node is removed from service
- Known as BASE (**B**asically **A**vailable, **S**oft state, **E**ventual consistency), as opposed to ACID
  - Soft state: copies of a data item may be inconsistent
  - Eventually Consistent – copies becomes consistent at some later time if there are no more updates to that data item
  - Basically Available – possibilities of faults but not a fault of the whole system

NoSQL Categories



Categories of NoSQL databases

- Key-value stores
- Column NoSQL databases
- Document-based
- Graph database (neo4j, InfoGrid)
- XML databases (myXMLDB, Tamino, Sedna)

Key/Value

Pros:

– very fast
– very scalable
– simple model
– able to distribute horizontally

Cons:

- many data structures (objects) can't be easily modeled as key value pairs

Schema-Less

Pros:

- Schema-less data model is richer than key/value pairs
- eventual consistency
- many are distributed
- still provide excellent performance and scalability

Cons:

- typically no ACID transactions or joins

Common Advantages

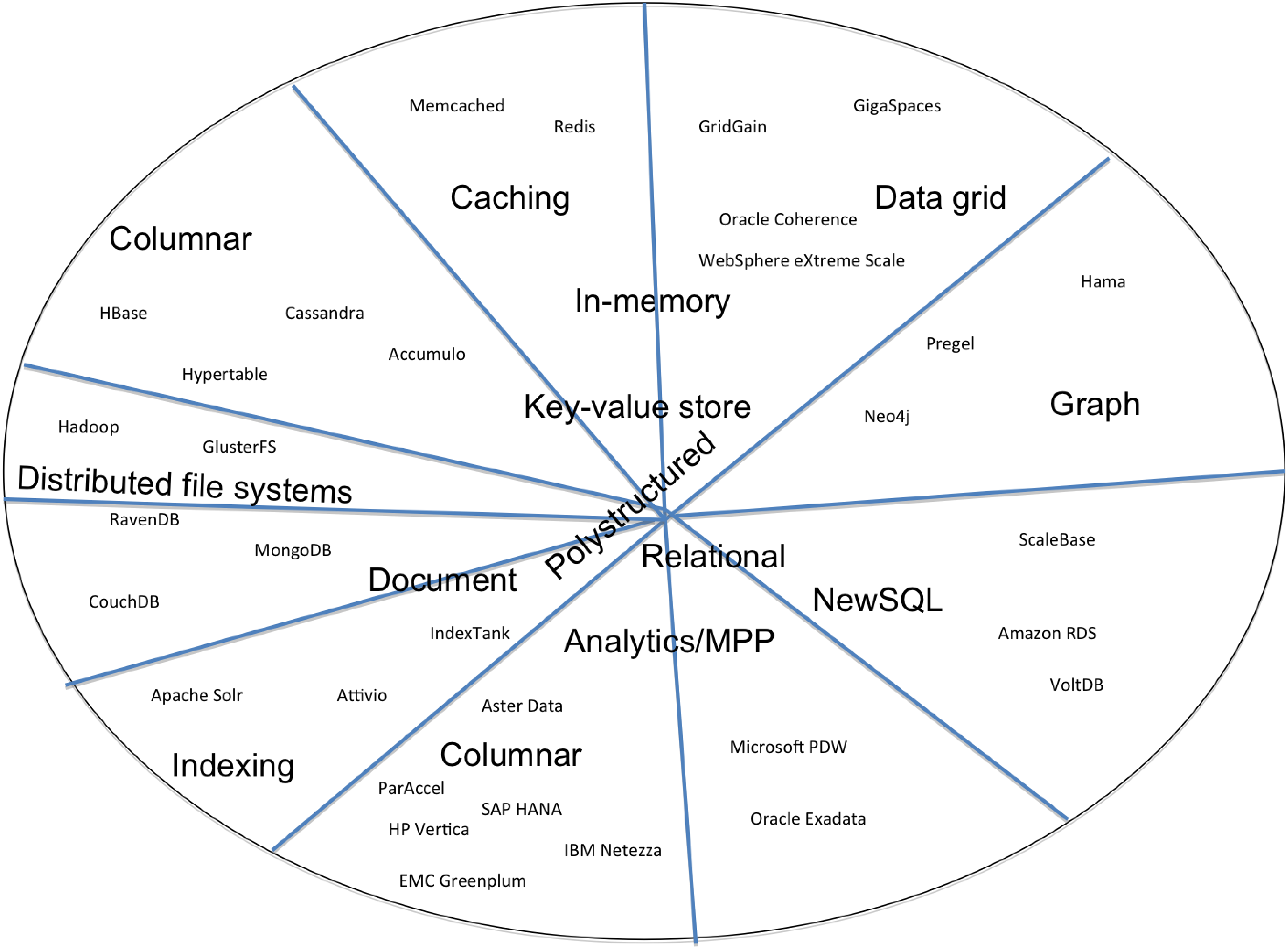
- Cheap, easy to implement (open source)
- Data are replicated to multiple nodes (therefore identical and fault-tolerant) and can be partitioned
  - Down nodes easily replaced
  - No single point of failure
- Easy to distribute
- Don't require a schema
- Can scale up and down
- Relax the data consistency requirement (CAP)

Typical NoSQL API

- Basic API access:
  - get(key) -- Extract the value given a key
  - put(key, value) -- Create or update the value given its key
  - delete(key) -- Remove the key and its associated value
  - execute(key, operation, parameters) -- Invoke an operation to the value (given its key) which is a special data structure (e.g. List, Set, Map .... etc).

What am I giving up?

- joins
- group by
- order by
- ACID transactions
- SQL as a sometimes frustrating but still powerful query language
- easy integration with other applications that support SQL



Memcached
Redis
GridGain
GigaSpaces
Caching
Data grid
Oracle Coherence
WebSphere eXtreme Scale
Columnar
In-memory
Hama
HBase
Cassandra
Accumulo
Pregel
Hypertable
Key-value store
Graph
Neo4j
Hadoop
GlusterFS
Polystructured
Distributed file systems
RavenDB
ScaleBase
MongoDB
Relational
Document
NewSQL
CouchDB
IndexTank
Amazon RDS
Analytics/MPP
VoltDB
Apache Solr
Attivio
Aster Data
Microsoft PDW
Indexing
Columnar
ParAccel
SAP HANA
Oracle Exadata
HP Vertica
IBM Netezza
EMC Greenplum

An Introduction to Hadoop HBase

HBase is …

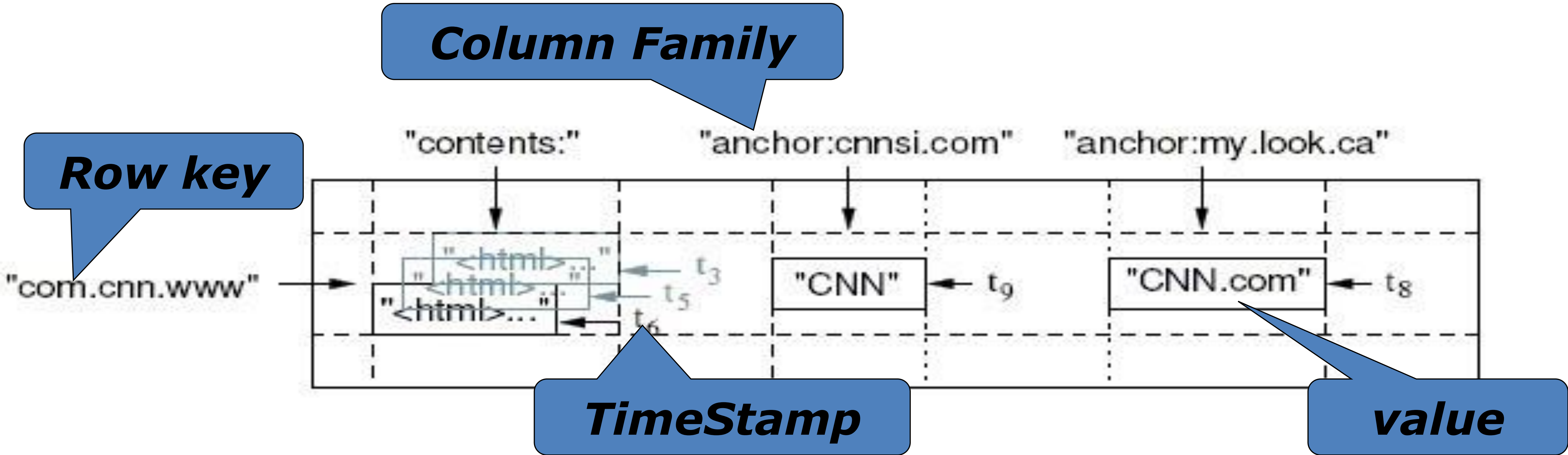
- A distributed data store that can scale horizontally to 1,000s of commodity servers and petabytes of indexed storage.
- Designed to operate on top of the Hadoop distributed file system (HDFS) or Kosmos File System (KFS, aka Cloudstore) for scalability, fault tolerance, and high availability.

Benefits

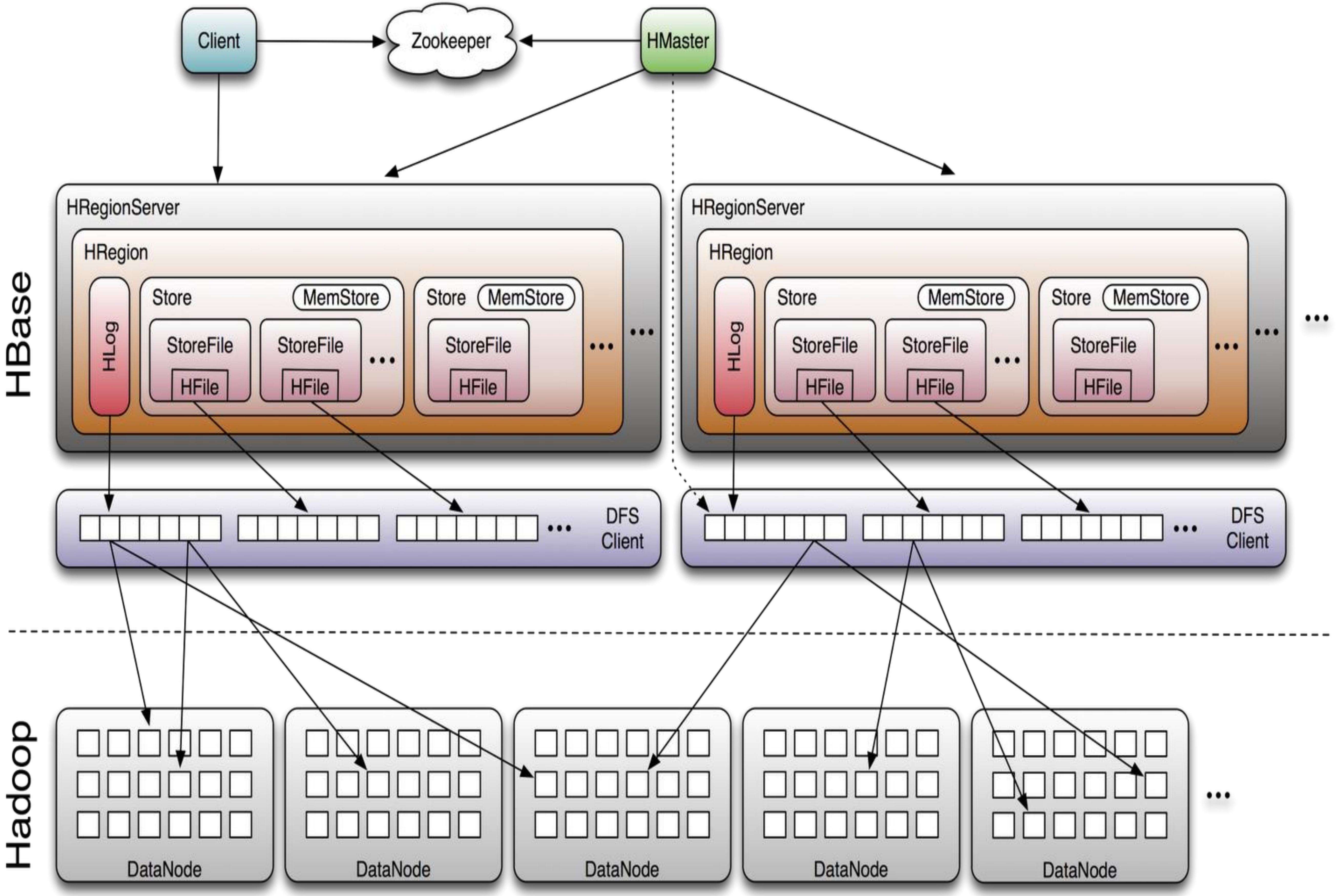
- Distributed storage
- Table-like in data structure
  - multi-dimensional map
- High scalability
- High availability
- High performance

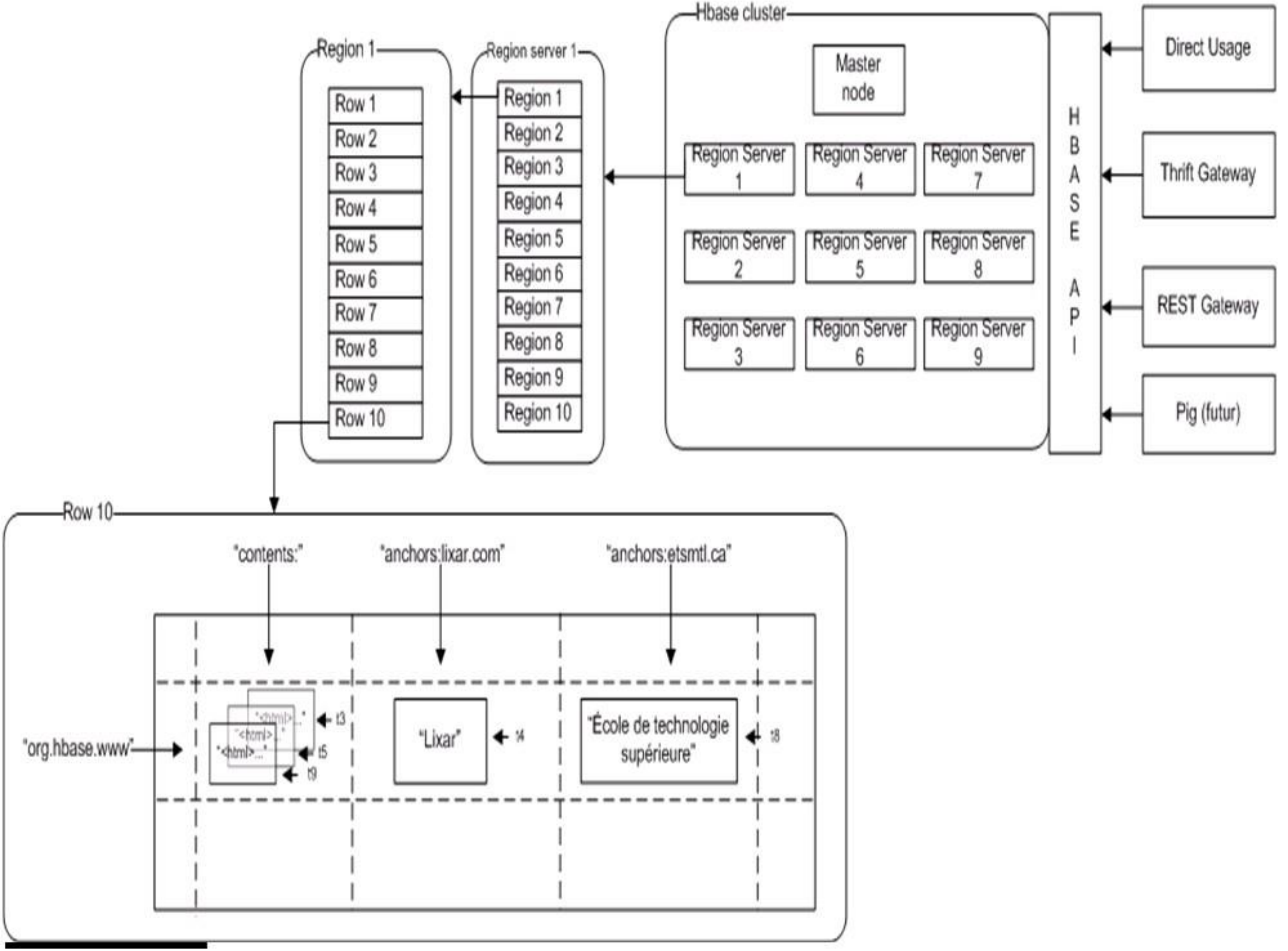
Data Model

- Tables are sorted by Row
- Table schema: *column families*
  - Each family consists of any number of columns
  - Each column consists of any number of versions
  - Columns only exist when inserted, NULLs are free.
  - Columns within a family are sorted and stored together
- Everything except table names are byte[]
- (Row, Family: Column, Timestamp) → Value

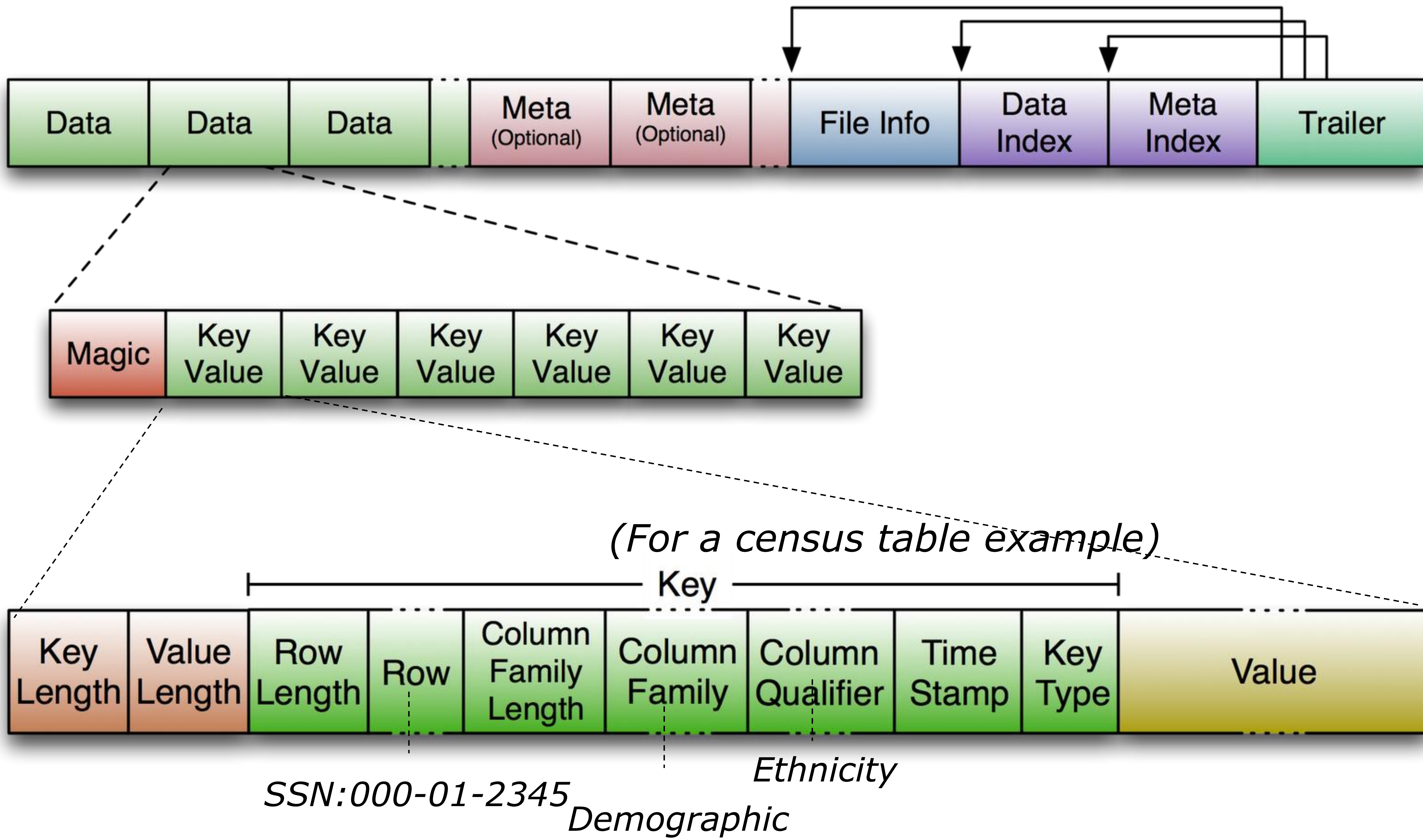


Architecture




Hbase cluster
Master node
Region Server 1
Region Server 2
Region Server 3
Region Server 4
Region Server 5
Region Server 6
Region Server 7
Region Server 8
Region Server 9
HBASE API
Direct Usage
Thrift Gateway
REST Gateway
Pig (futur)
Region server 1
Region 1
Region 2
Region 3
Region 4
Region 5
Region 6
Region 7
Region 8
Region 9
Region 10
Region 1
Row 1
Row 2
Row 3
Row 4
Row 5
Row 6
Row 7
Row 8
Row 9
Row 10
Row 10
"contents:"
"anchors:lixar.com"
"anchors:etsmtl.ca"
"org.hbase.www"
"Lixar"
"École de technologie supérieure"
t3
t5
t9
t4
t8

HFile



Source: http://blog.cloudera.com/blog/2012/06/hbase-io-hfile-input-output/