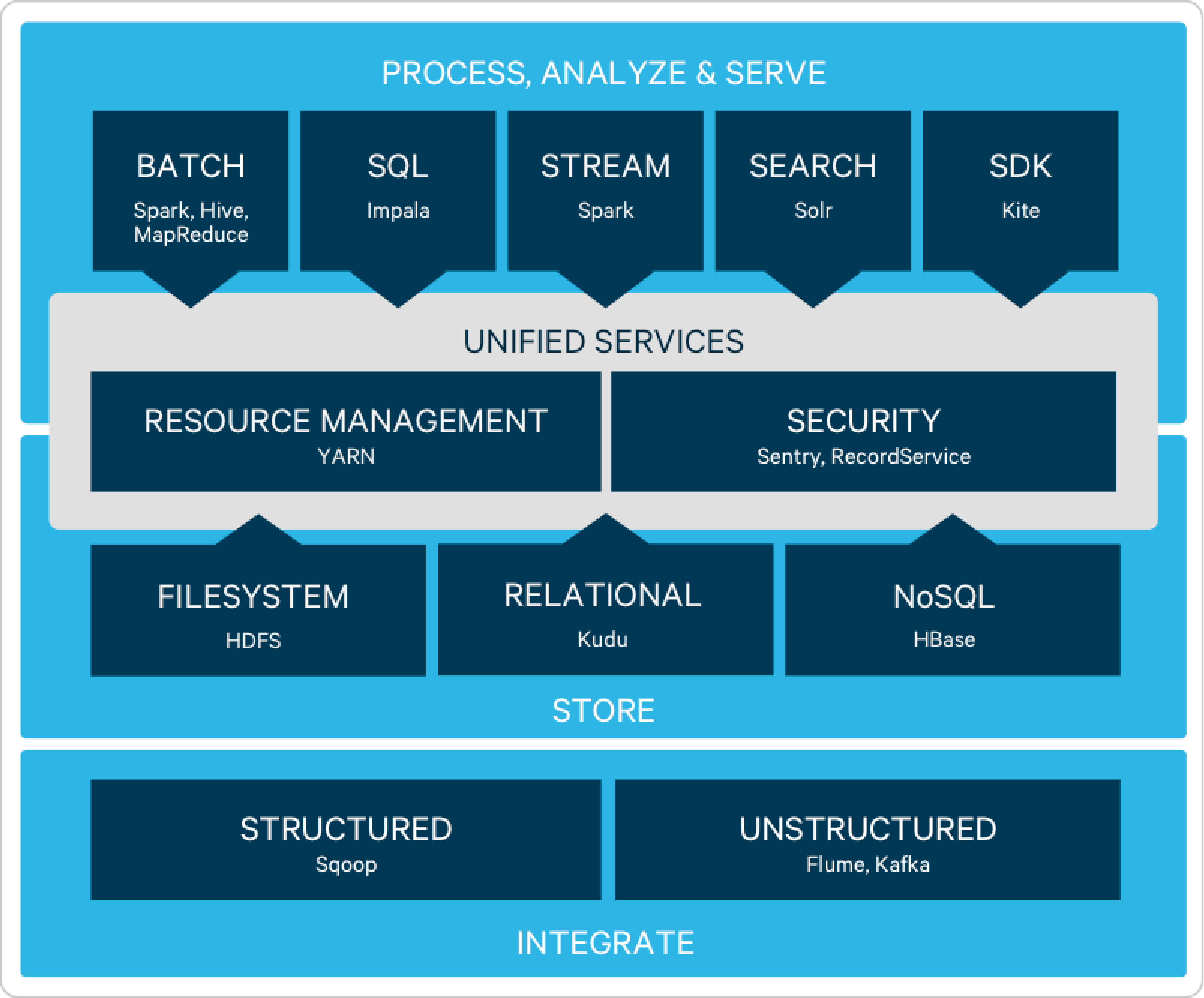
How is big data analyzed?

One of the best-known methods for turning raw data into useful information is by what is known as MapReduce. MapReduce is a method for taking a large data set and performing computations on it across multiple computers, in parallel. It serves as a model for how to program, and is often used to refer to the actual implementation of this model.

- Components
- How to Hadoop
- Examples/Patterns
- Homework

- Google File System, 2003: http://research.google.com/archive/gfs.html
- Map Reduce, 2004: http://research.google.com/archive/mapreduce.html
- Doug Cutting, Yahoo: 2004. Now with Cloudera

Hadoop



https://www.cloudera.com/products/open-source/apache-hadoop.html

What is Hadoop/MapReduce?

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

MapReduce can refer to…

Usage is usually clear from context!

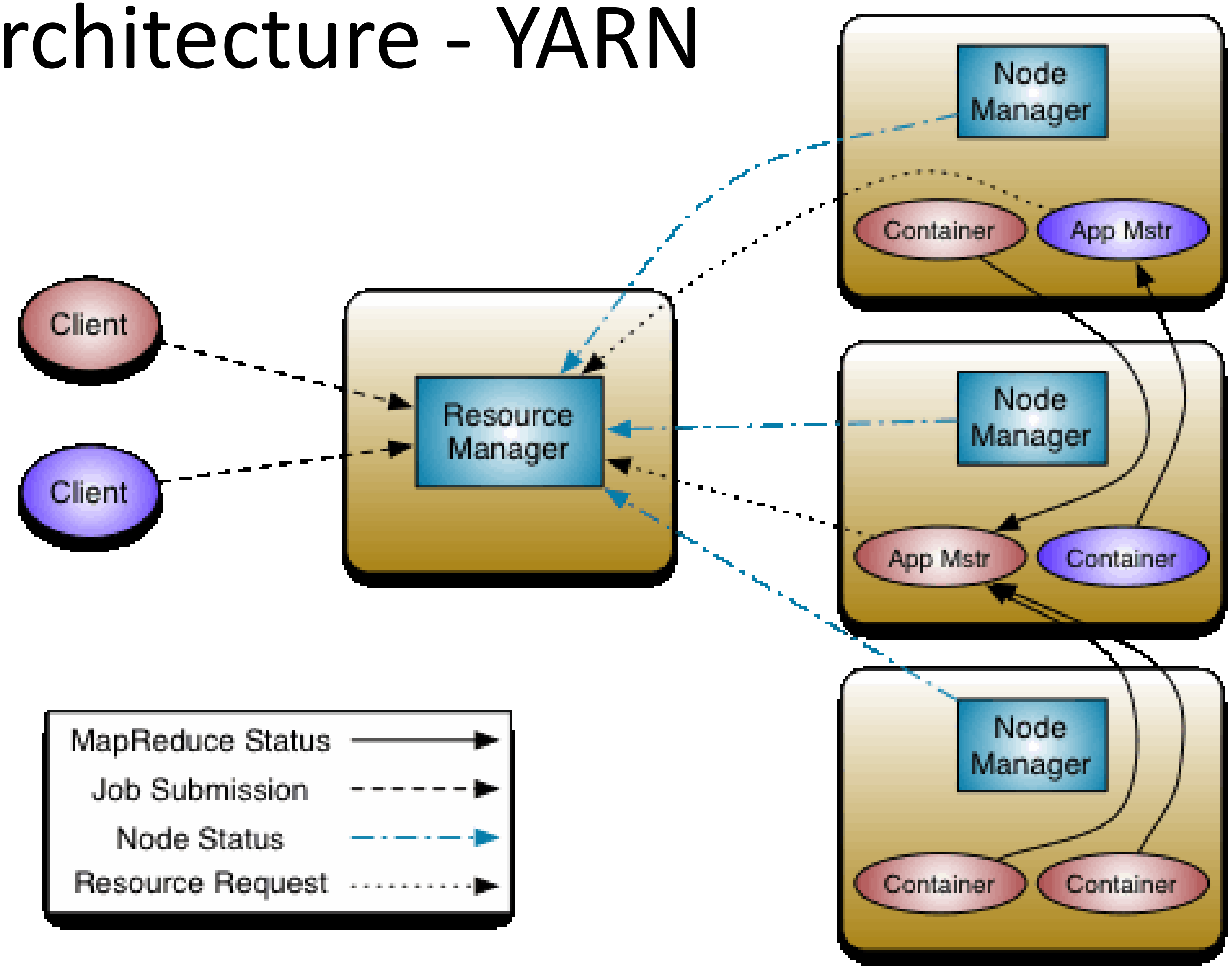
The programming model
The execution framework (aka “runtime”)
The specific implementation

Apache Hadoop

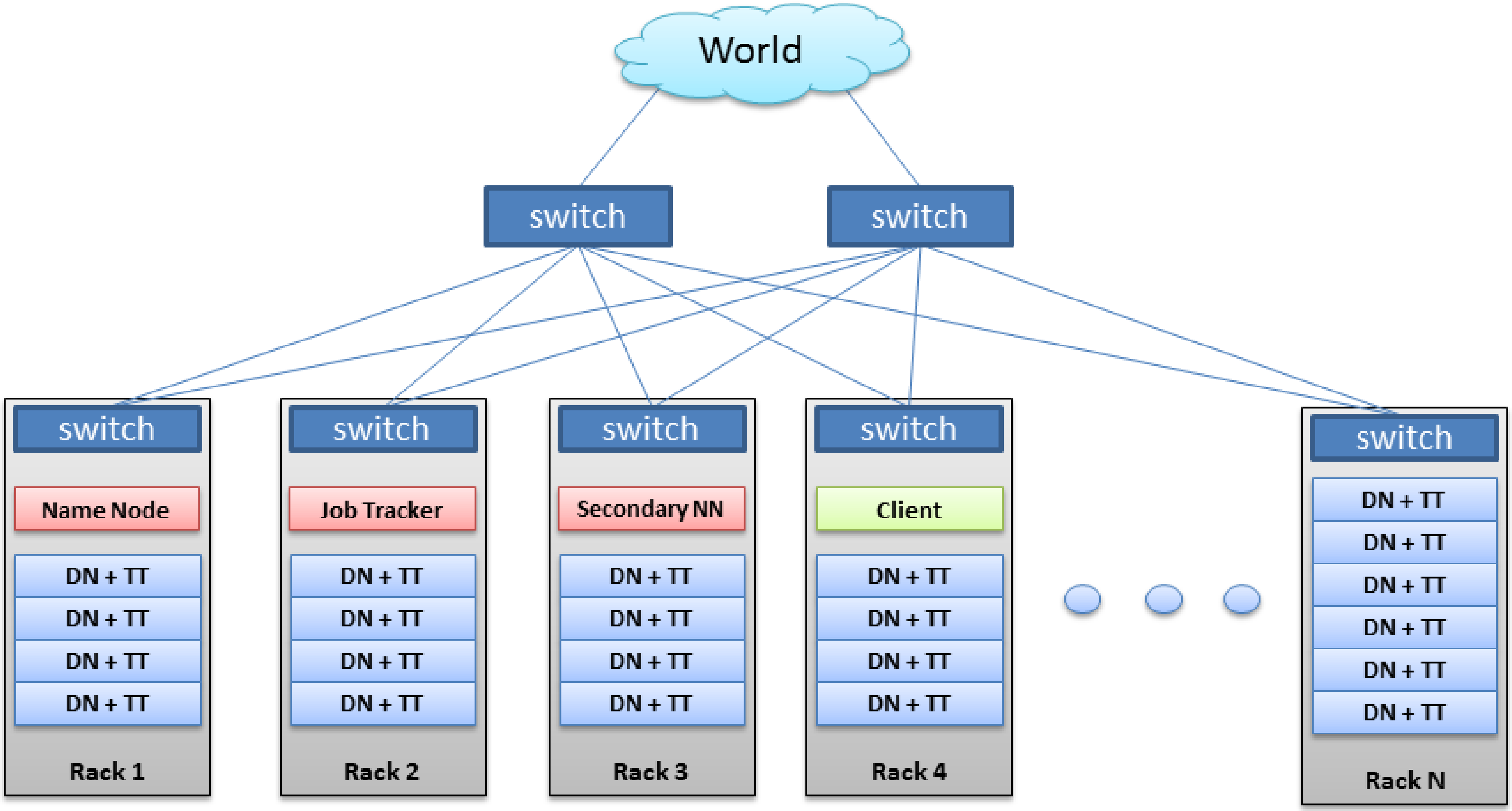
- Apache Hadoop Project : http://hadoop.apache.org/docs/current/

  A software stack for reliable, scalable, distributed computing
- Core components
  - Hadoop Common
  - Hadoop Distributed File System - HDFS
  - Hadoop YARN
  - Hadoop MapReduce
- Hadoop Related projects: Ambari, Avro, Cassandra, HBase, Hive, Mahout, Pig, Spark, Tez, ZooKeeper, Hue, …?

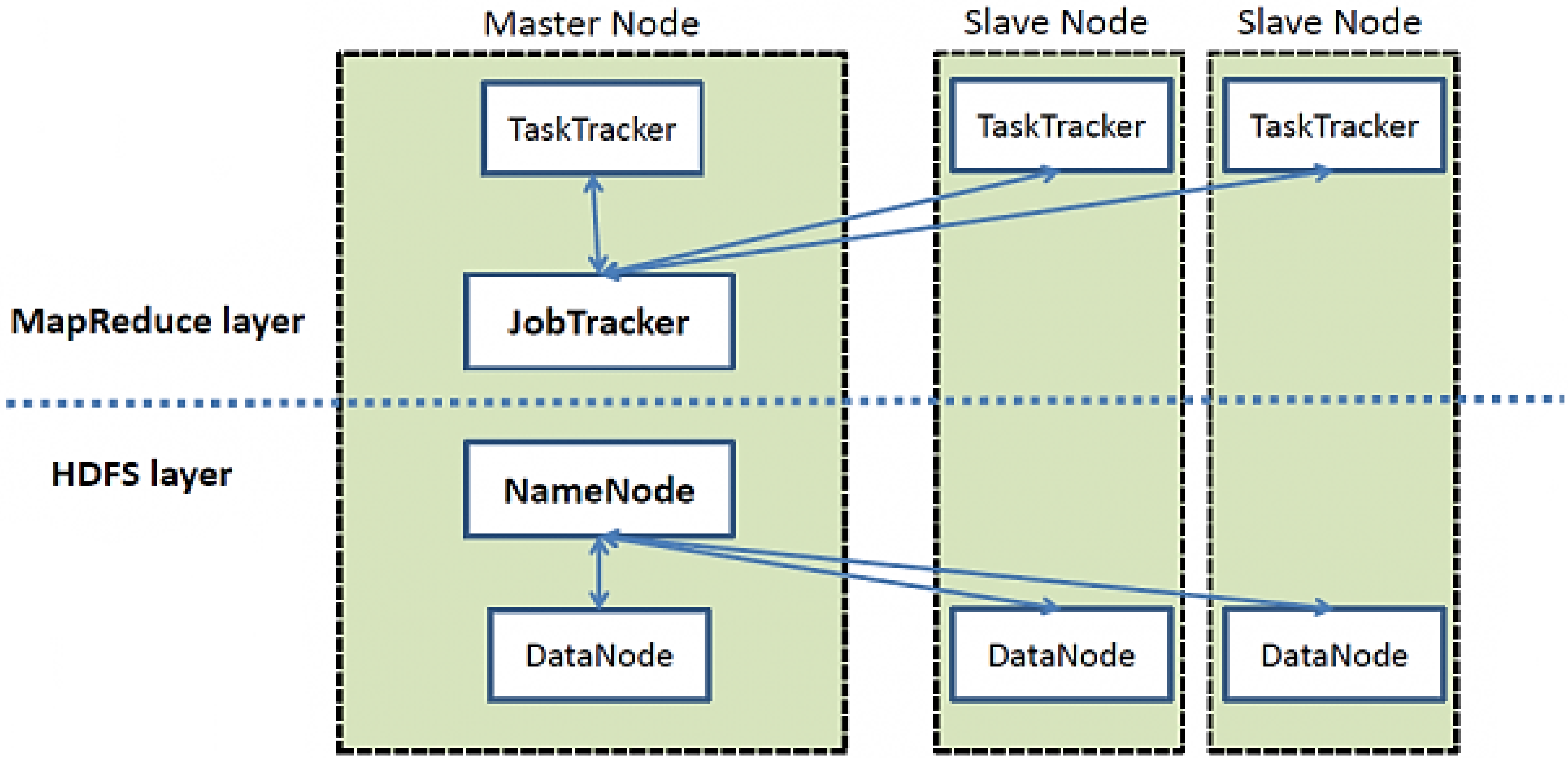
Hadoop Architecture - YARN



Hadoop Architecture/ YARN



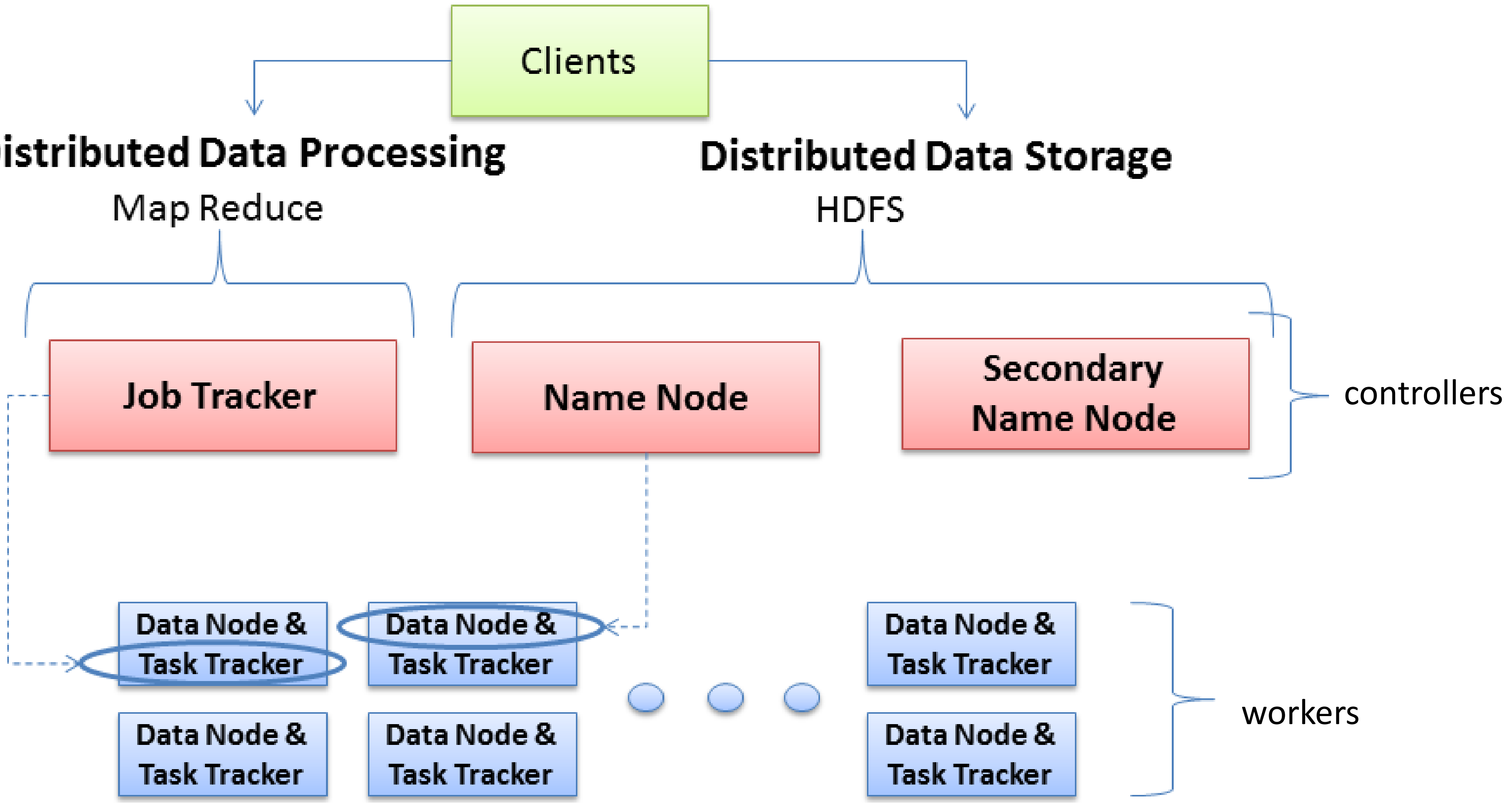
Hadoop Architecture/HDFS, MapReduce



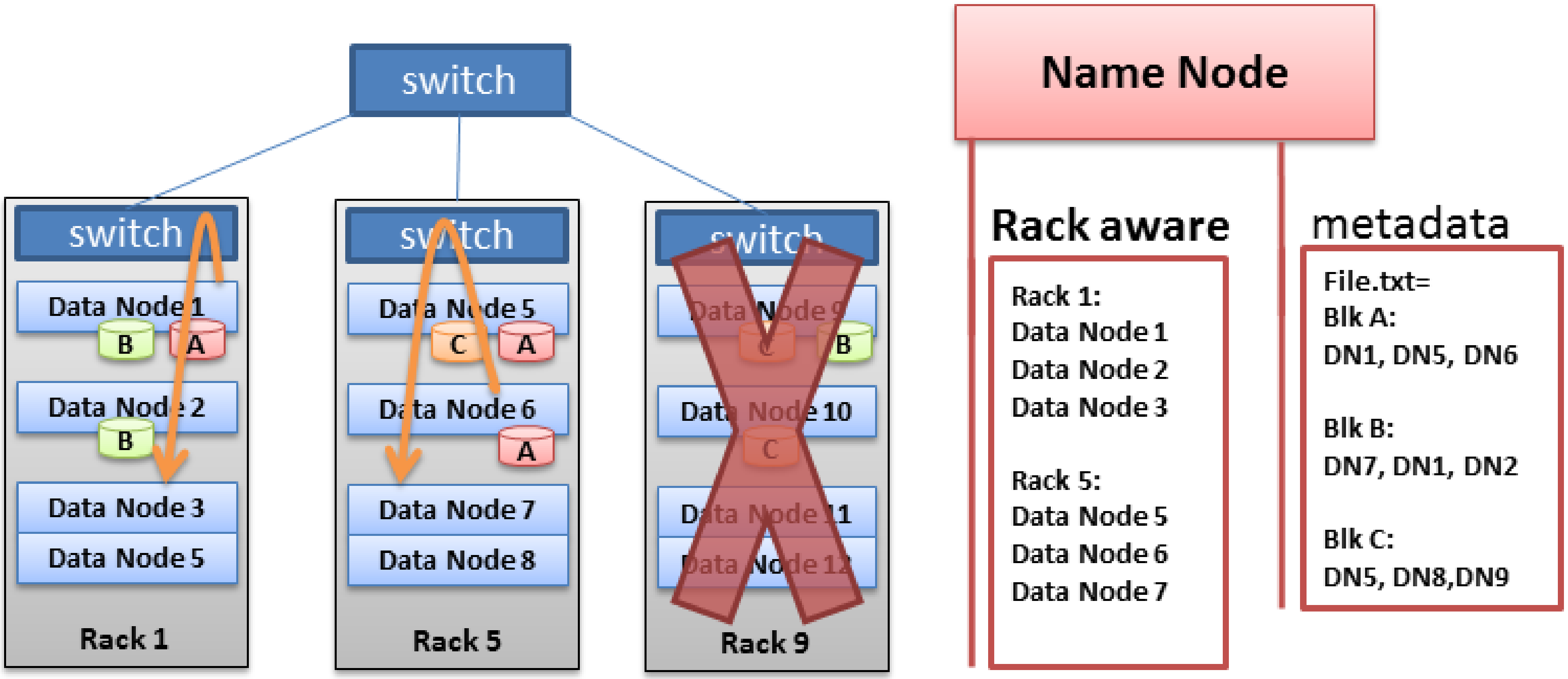
NYU

HDFS

Hadoop Architecture / HDFS



Hadoop Architecture / HDFS



Distributed File System

- Don’t move data to workers… move workers to the data!
  - Store data on the local disks of nodes in the cluster
  - Start up the workers on the node that has the data local
- Why?
  - Not enough RAM to hold all the data in memory
  - Disk access is slow, but disk throughput is reasonable
- A distributed file system is the answer
  - GFS (Google File System) for Google’s MapReduce
  - HDFS (Hadoop Distributed File System) for Hadoop

GFS: Assumptions

- Commodity hardware over “exotic” hardware
  - Scale “out”, not “up”
- High component failure rates
  - Inexpensive commodity components fail all the time
- “Modest” number of huge files
  - Multi-gigabyte files are common, if not encouraged
- Files are write-once, mostly appended to
  - Perhaps concurrently
- Large streaming reads over random access
  - High sustained throughput over low latency

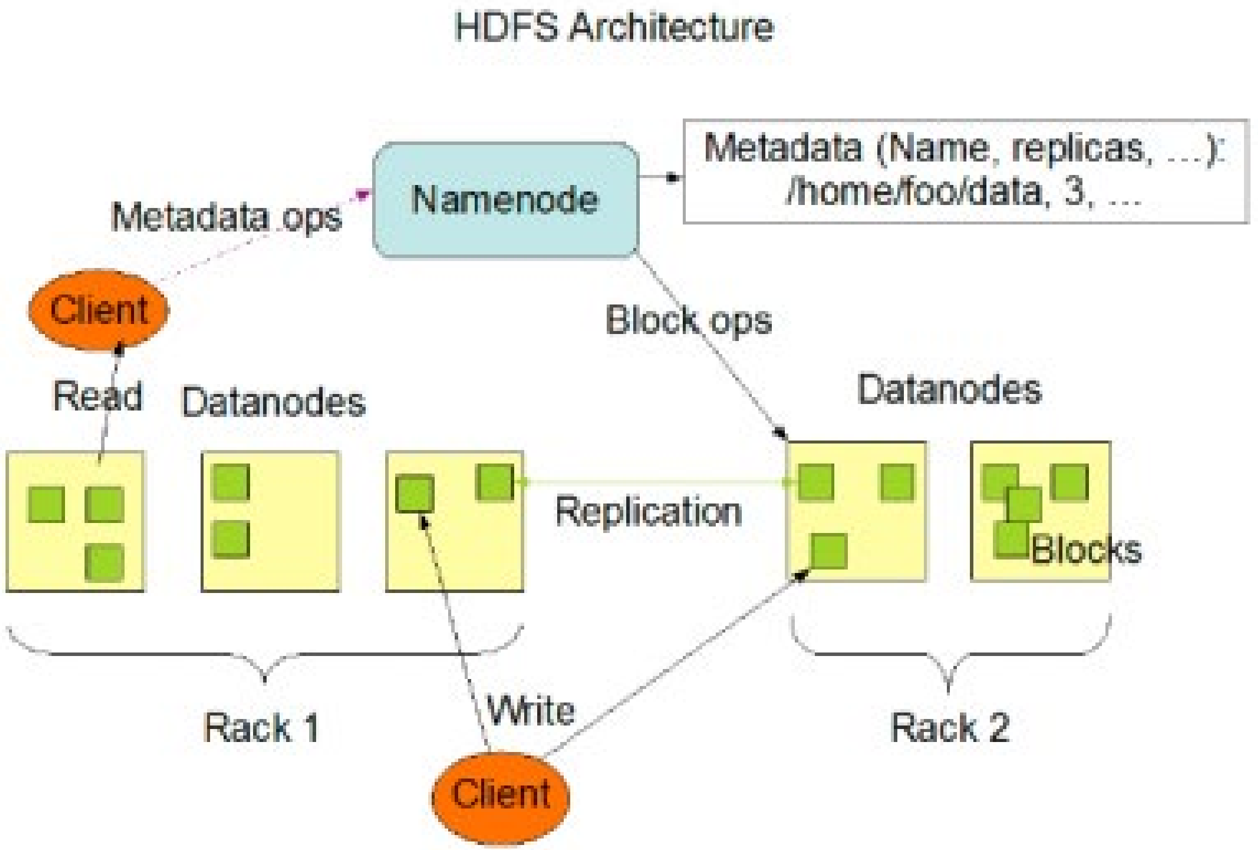
GFS slides adapted from material by (Ghemawat et al., SOSP 2003)

GFS: Design Decisions

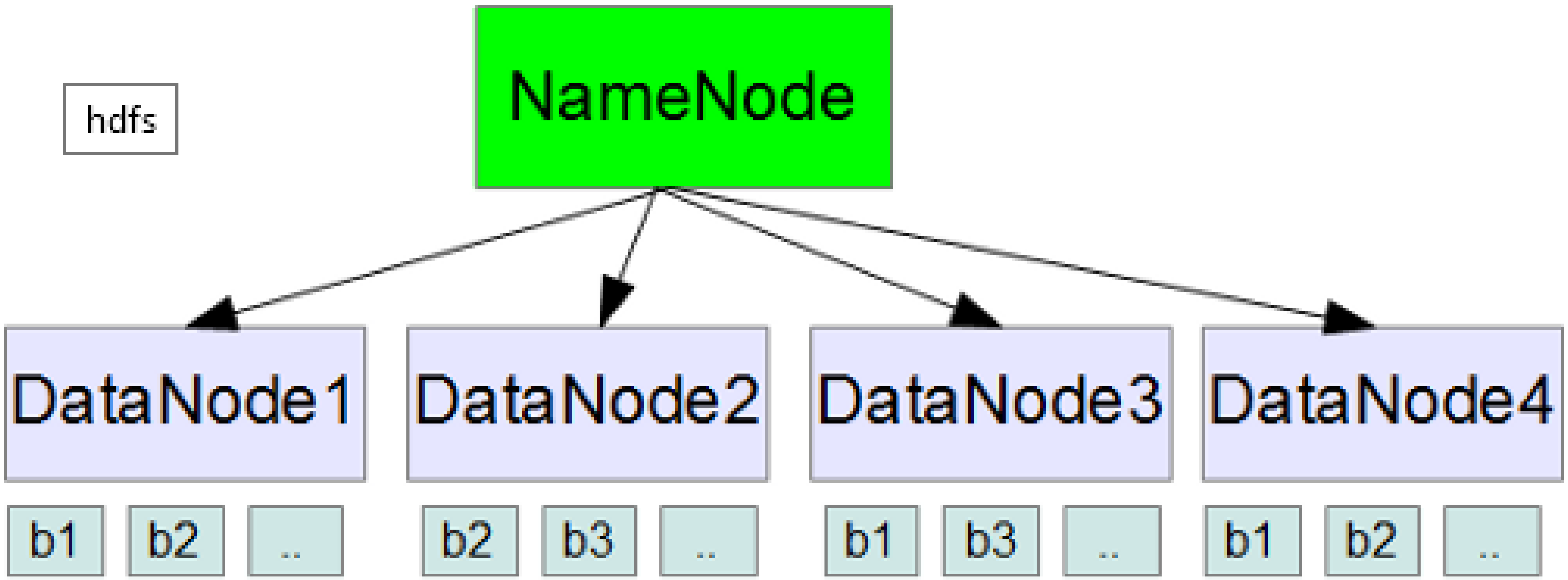
- Files stored as chunks
  - Fixed size (64MB)
- Reliability through replication
  - Each chunk replicated across 3+ chunkservers
- Single controller to coordinate access, keep metadata
  - Simple centralized management
- No data caching
  - Little benefit due to large datasets, streaming reads
- Simplify the API
  - Push some of the issues onto the client (e.g., data layout)

HDFS Terminology

- Namenode
- Datanode
- DFS Client
- Files/Directories
- Replication
- Blocks
- Rack-awareness

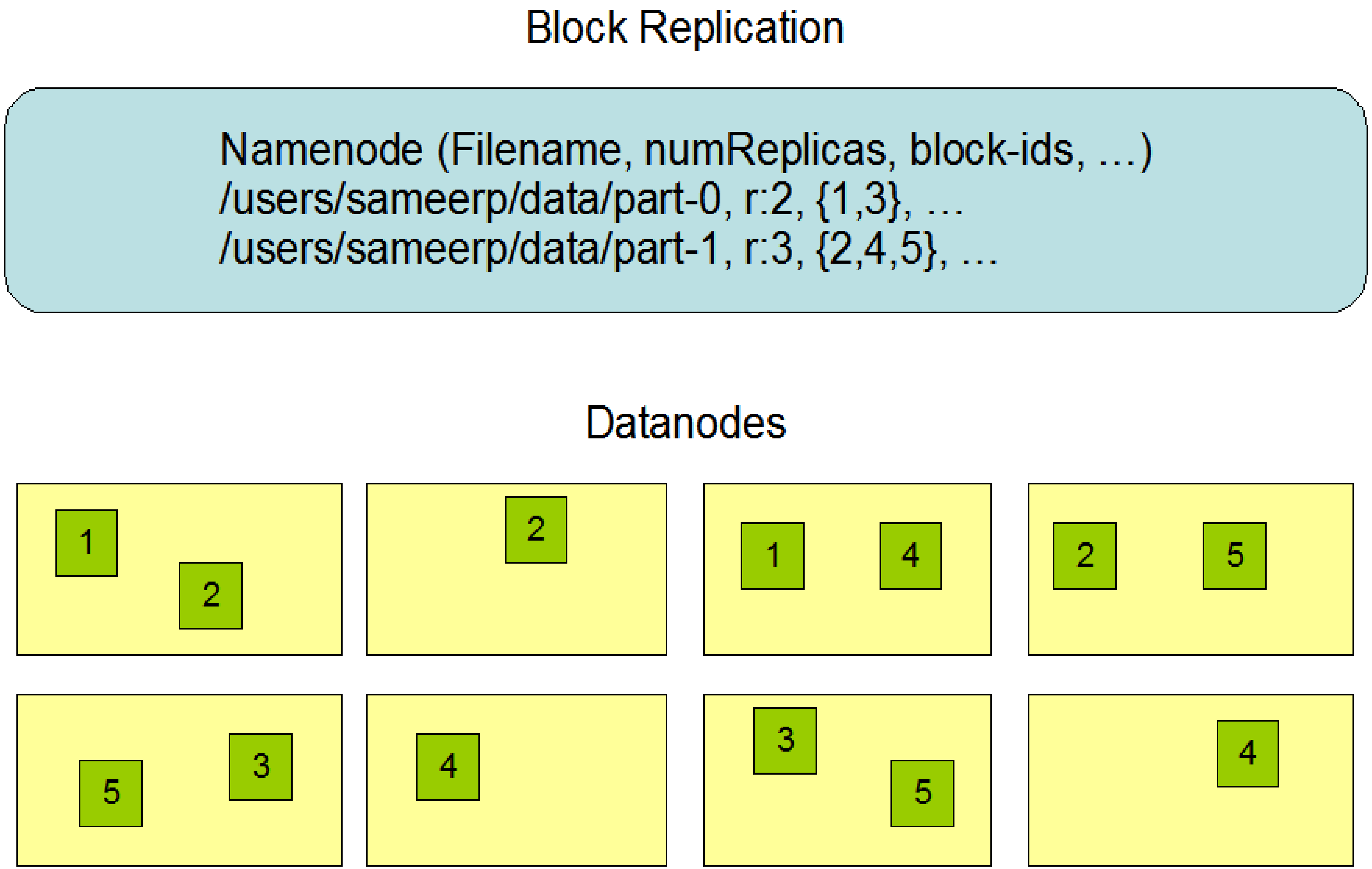


Hadoop Architecture / HDFS



* Google File System, 2003 http://research.google.com/archive/gfs.html

Hadoop - HDFS


Block Replication
Namenode (Filename, numReplicas, block-ids, …)
/users/sameerp/data/part-0, r:2, {1,3}, …
/users/sameerp/data/part-1, r:3, {2,4,5}, …
Datanodes
1
2
2
1
4
2
5
5
3
4
3
5
4

Exploring HDFS command line

- Attempt to re-create new dir :
  - $ hadoop dfs -mkdir /user/foo
- Create a destination directory using implicit path:
  - $ hadoop dfs -mkdir bar
- Auto-create nested destination directories:
  - $ hadoop dfs -mkdir dir1/dir2/dir3
- Remove dir:
  - $ hadoop dfs -rmr /user/foo
- Remove dir:
  - $ hadoop dfs -rmr bar dir1

HDFS Example: Import access log data

- Load access log into hdfs:
  - $ hadoop dfs -put /var/log/apache2/access.log input/access.log
- Verify it's in there:
  - $ hadoop dfs -ls input/access.log
- View the contents:
  - $ hadoop dfs -cat input/access.log

Browse HDFS using web UI

- Open http://<hadoopIP>:50070

MapReduce

Hadoop Programming

- “strong Java programming” as pre-requisite?
  - Hadoop Streaming: ability to use an arbitrary language to define a job’s map and reduce processes
- this class is *not* about programming!
  - Focus on “thinking at scale” and algorithm design
  - We expect you to pick up Hadoop (quickly)
- How do I learn Hadoop?
  - This session: brief overview
  - White’s book
  - Read the docs

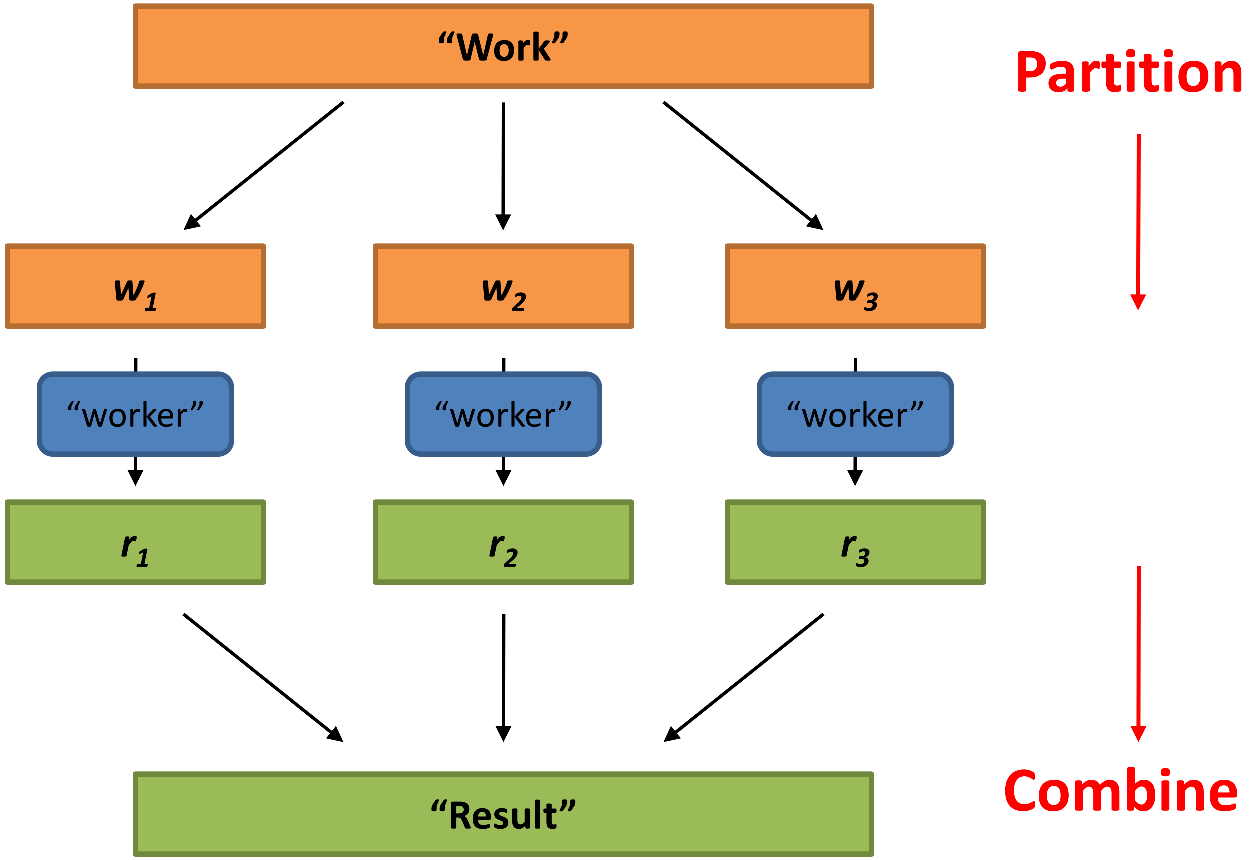
Next…

- Map Reduce
  - Functional Programming
  - Map Reduce / Components
  - I/O

- Creating/Running MR Programs
  - Java
  - Streaming / Command Line

- Patterns
  - Word Count
  - Filtering
  - Joins
  - Top K
  - Binning
  - Bloom Filters
  - Page Rank

Hadoop/MapReduce
Divide and Conquer



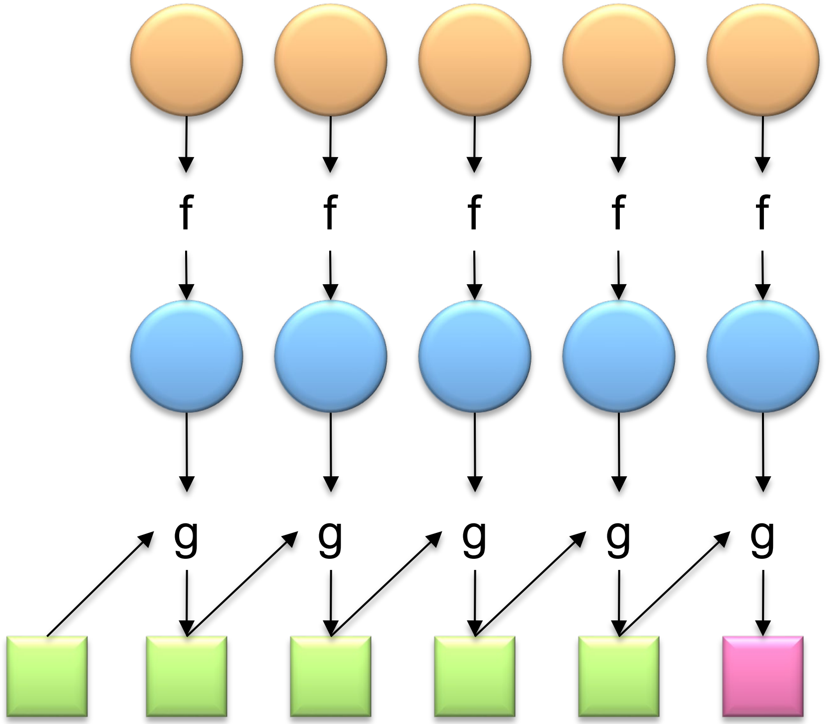
MapReduce

- 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 file system (HDFS)

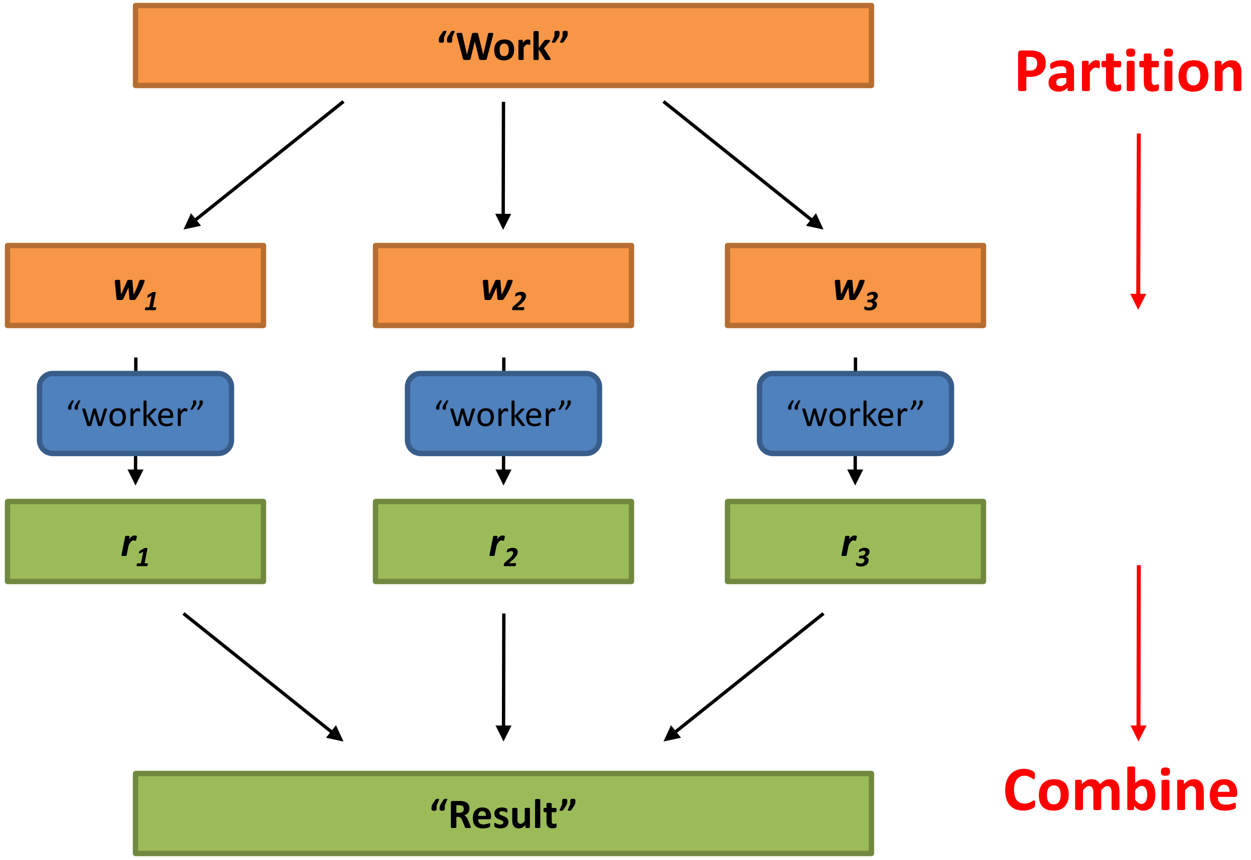
Roots in Functional Programming

Map

Fold



Map Reduce Framework



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)

Data Types in Hadoop

Writable	Defines a de/serialization protocol. Every data type in Hadoop is a Writable.
WritableComparable	Defines a sort order. All keys must be of this type (but not values).
IntWritable LongWritable Text …	Concrete classes for different data types.
SequenceFiles	Binary encoded of a sequence of key/value pairs

Complex Data Types in Hadoop

- How do you implement complex data types?
- The easiest way:
  - Encoded it as Text, e.g., (a, b) = “a:b”
  - Use regular expressions to parse and extract data
  - Works, but pretty hack-ish
- The hard way:
  - Define a custom implementation of WritableComprable
  - Must implement: readFields, write, compareTo
  - Computationally efficient, but slow for rapid prototyping
- Alternatives:
  - Cloud[9] offers two other choices: Tuple and JSON
  - (Actually, not that useful in practice)

MapReduce

- Programmers specify two functions:

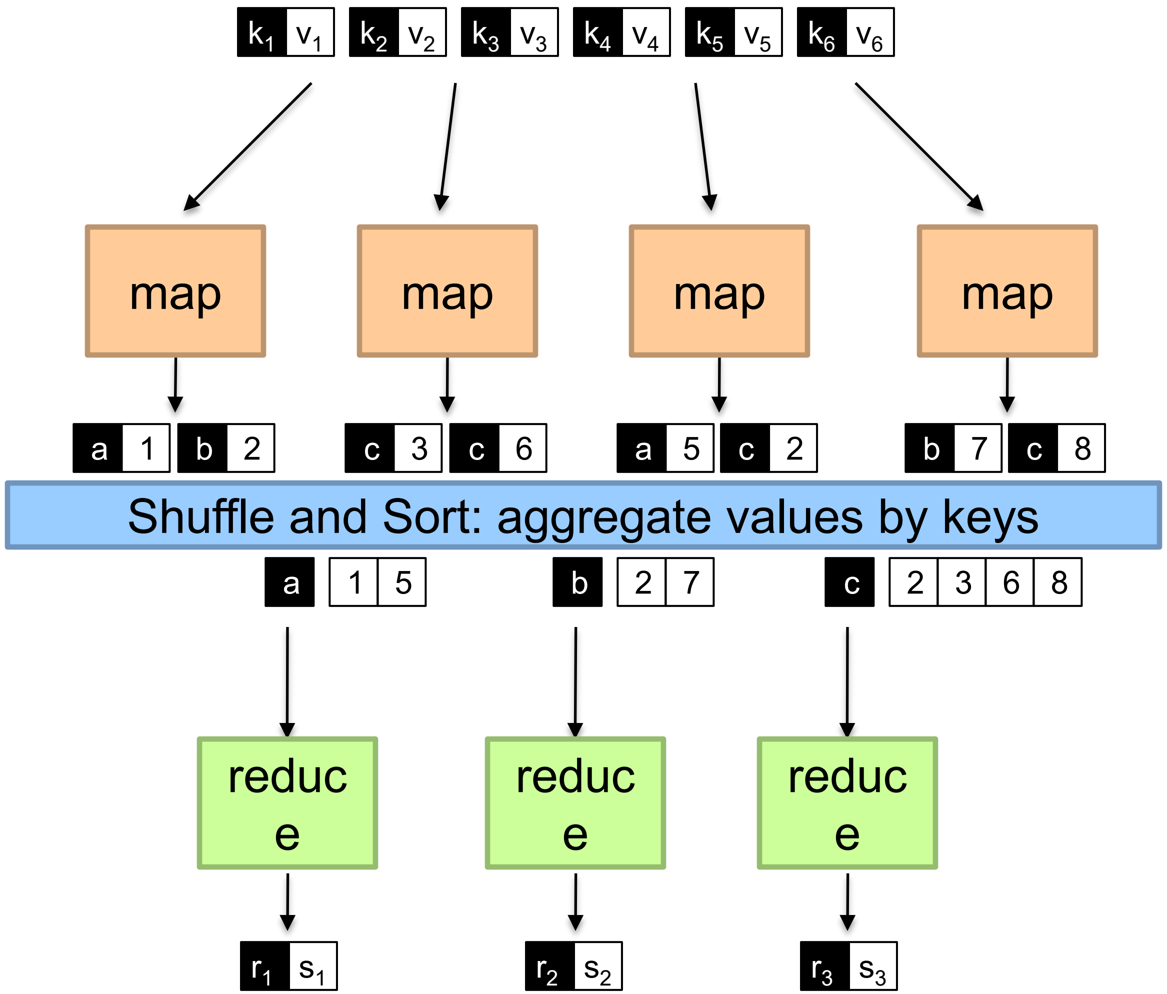
  map (k, v) → <k’, v’>*

  reduce (k’, v’) → <k’’, v’’>*

  - All values with the same key are sent to the same reducer

- The execution framework handles everything else…

  What’s “everything else”?



k_1 v_1 k_2 v_2 k_3 v_3 k_4 v_4 k_5 v_5 k_6 v_6
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
reduc e
reduc e
reduc e
r_1 s_1
r_2 s_2
r_3 s_3

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 (later)

MapReduce

- Programmers specify two functions:

  map (k, v) → <k’, v’>*

  reduce (k’, v’) → <k’’, v’’>*

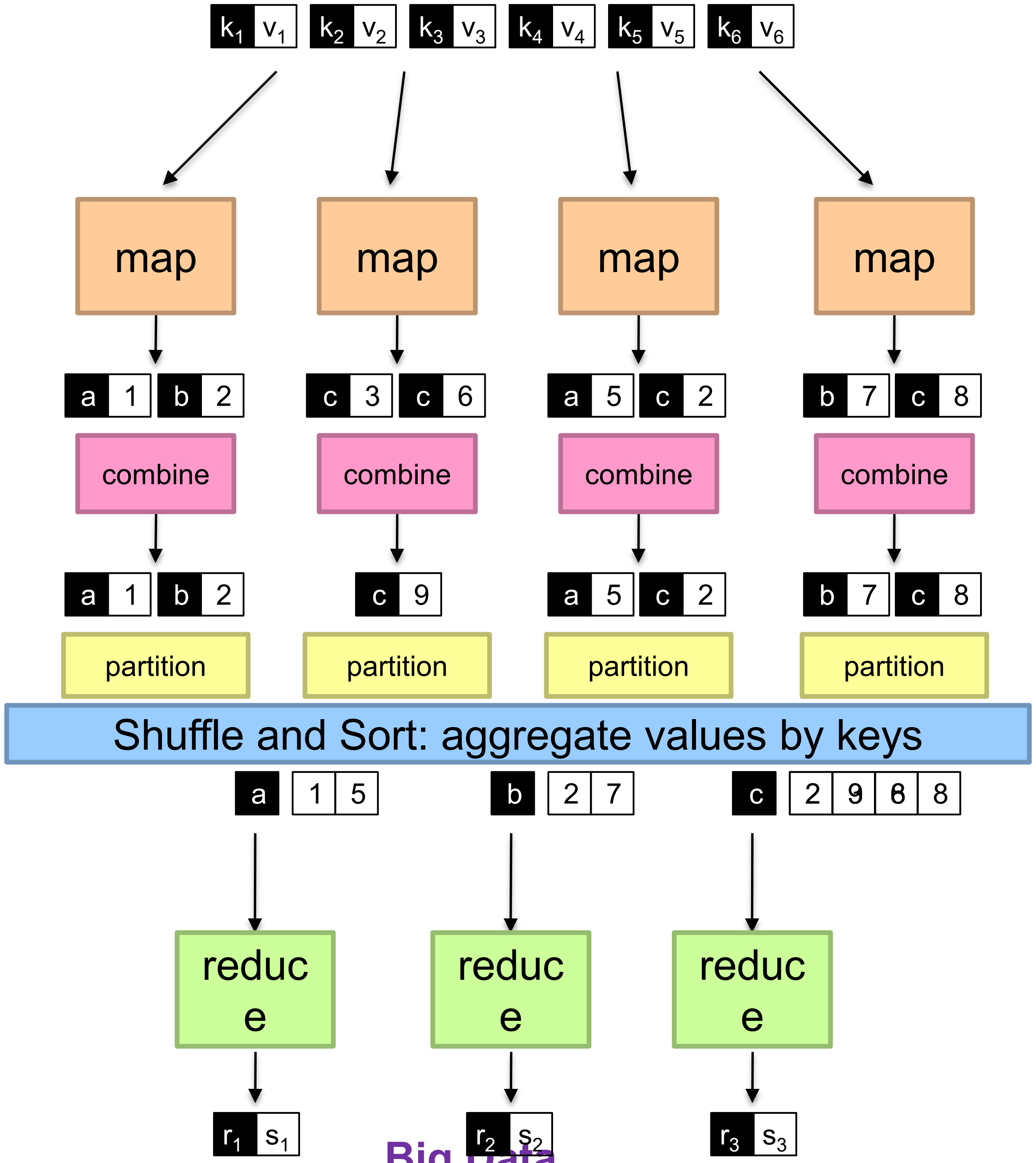
  - All values with the same key are reduced together
- The execution framework handles everything else…
- Not quite…usually, programmers also specify:

  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
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 9 6 8
reduce
reduce
reduce
r1 s1
r2 s2
r3 s3

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 Implementations

- Google has a proprietary implementation in C++
  - Bindings in Java, Python
- Hadoop is an open-source implementation in Java
  - Development led by Yahoo, used in production
  - Now an Apache project
  - Rapidly expanding software ecosystem
- Lots of custom research implementations
  - For GPUs, cell processors, etc.

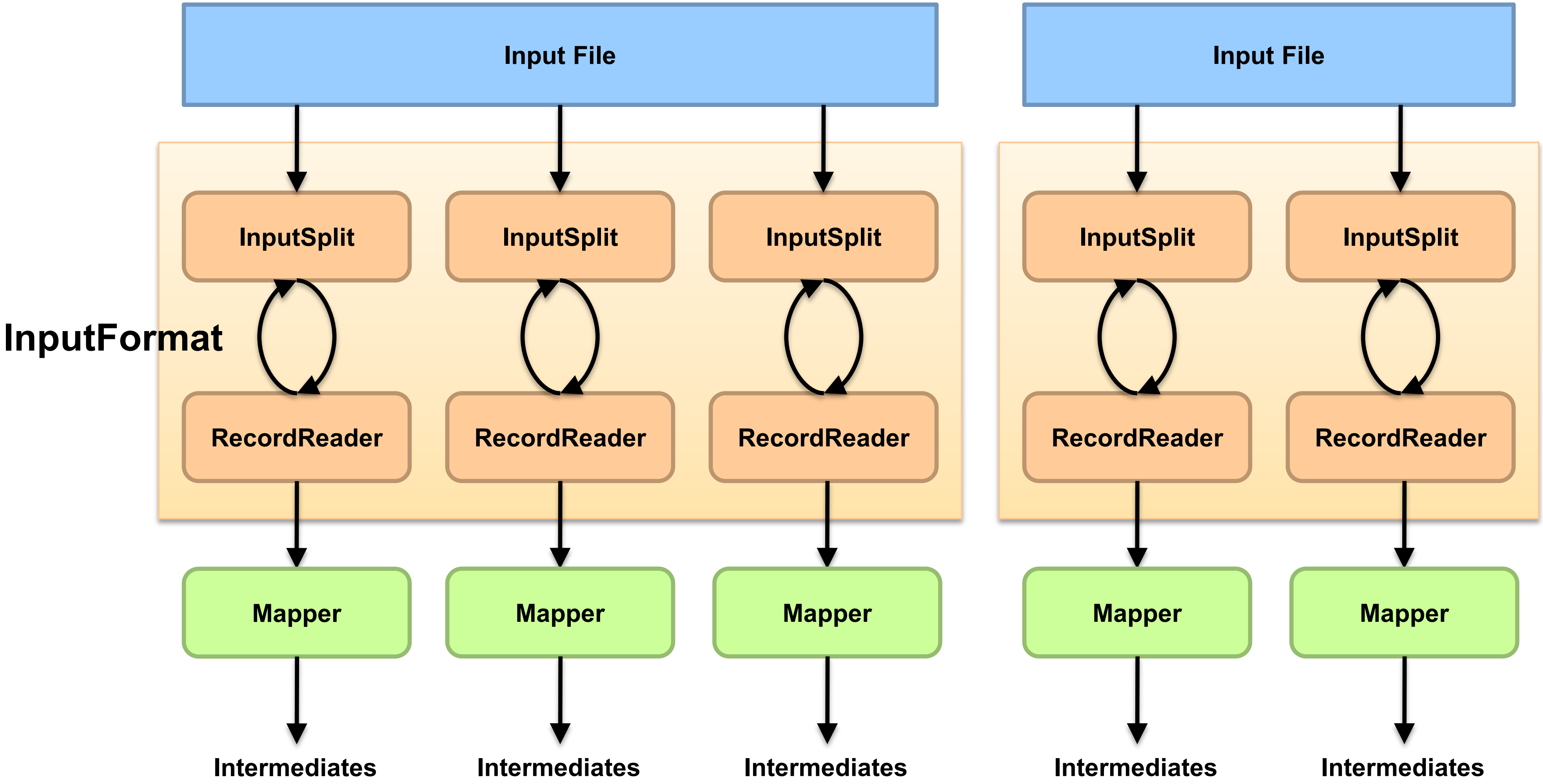
“Hello World”: Word Count

```
Map(String docid, String text):
    for each word w in text:
        Emit(w, 1);

Reduce(String term, Iterator<Int> values):
    int sum = 0;
    for each v in values:
        sum += v;
        Emit(term, value);
```

Anatomy of a Job

- MapReduce program in Hadoop = Hadoop job
  - Jobs are divided into map and reduce tasks
  - An instance of running a task is called a task attempt
  - Multiple jobs can be composed into a workflow
- Job submission process
  - Client (i.e., driver program) creates a job, configures it, and submits it to job tracker
  - JobClient computes input splits (on client end)
  - Job data (jar, configuration XML) are sent to JobTracker
  - JobTracker puts job data in shared location, enqueues tasks
  - TaskTrackers poll for tasks
  - Off to the races…



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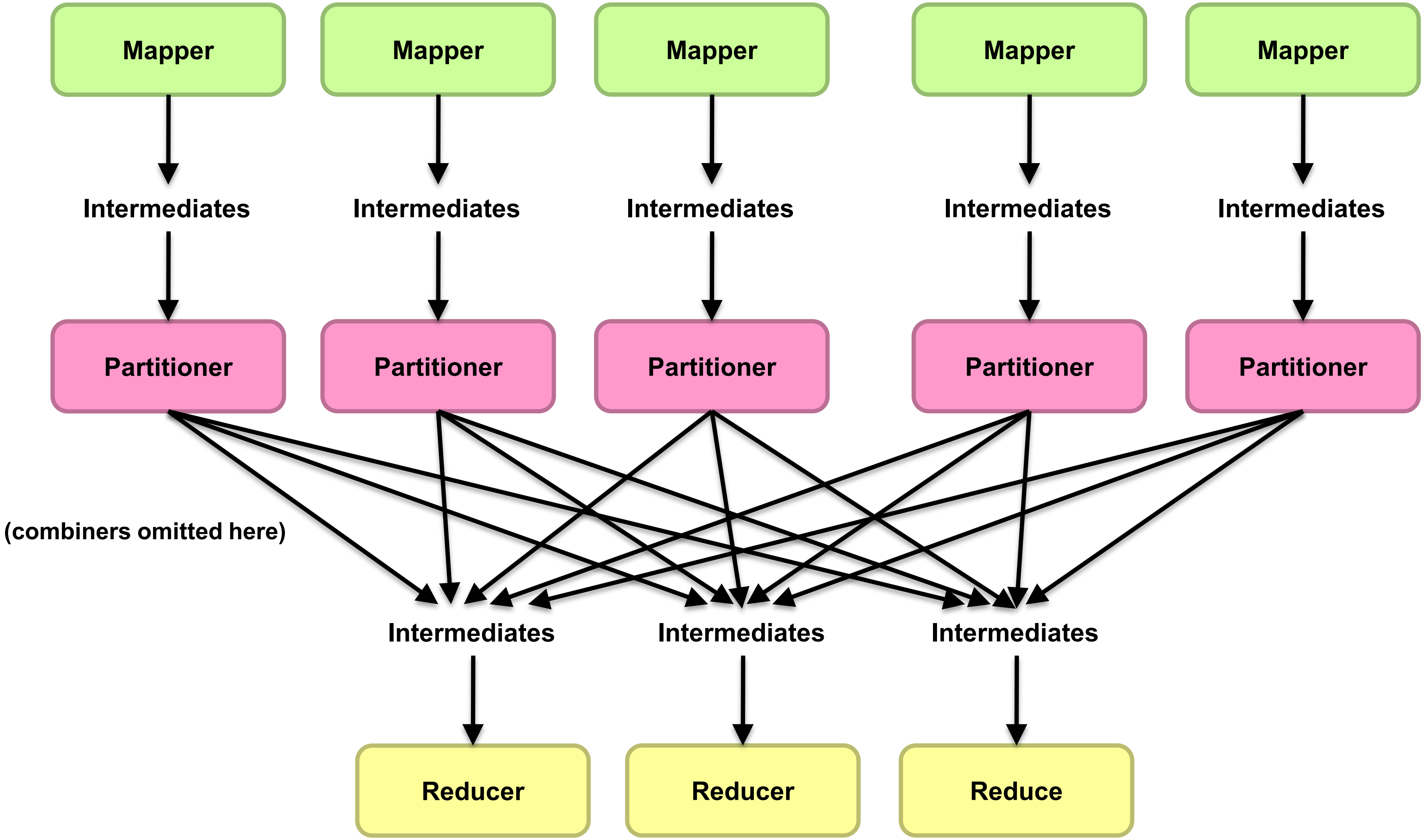

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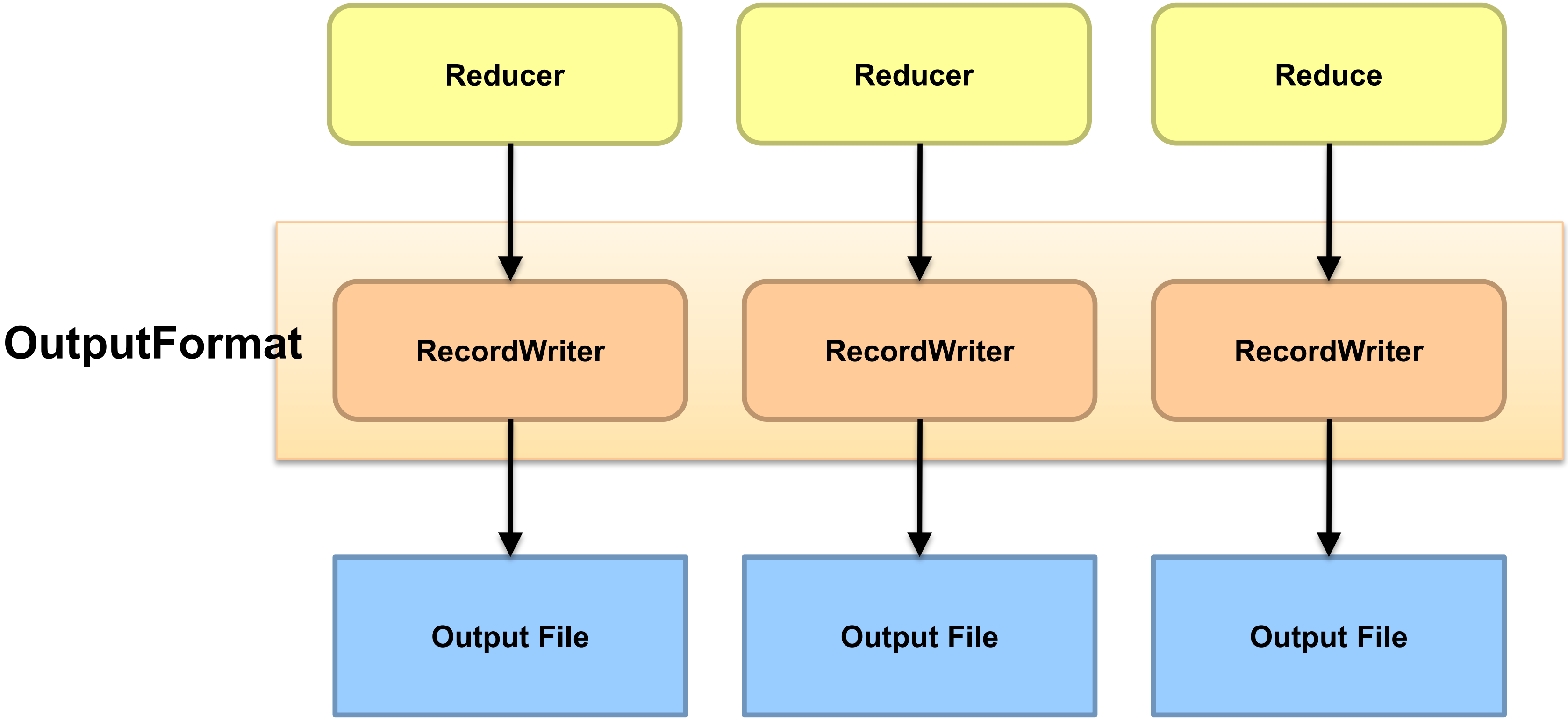

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Basic Hadoop API*

- Mapper
  - void map(K1 key, V1 value, OutputCollector<K2, V2> output, Reporter reporter)
  - void configure(JobConf job)
  - void close() throws IOException
- Reducer/Combiner
  - void reduce(K2 key, Iterator<V2> values, OutputCollector<K3,V3> output, Reporter reporter)
  - void configure(JobConf job)
  - void close() throws IOException
- Partitioner
  - void getPartition(K2 key, V2 value, int numPartitions)

*Note: forthcoming API changes…

“Hello World”: Word Count

```
Map(String docid, String text):
    for each word w in text:
        Emit(w, 1);

Reduce(String term, Iterator<Int> values):
    int sum = 0;
    for each v in values:
        sum += v;
        Emit(term, value);
```

Three Gotchas

- Avoid object creation, at all costs
- Execution framework reuses value in reducer
- Passing parameters into mappers and reducers
  - DistributedCache for larger (static) data

Input and Output

- InputFormat:
  - TextInputFormat
  - KeyValueTextInputFormat
  - SequenceFileInputFormat
  - …
- OutputFormat:
  - TextOutputFormat
  - SequenceFileOutputFormat
  - …

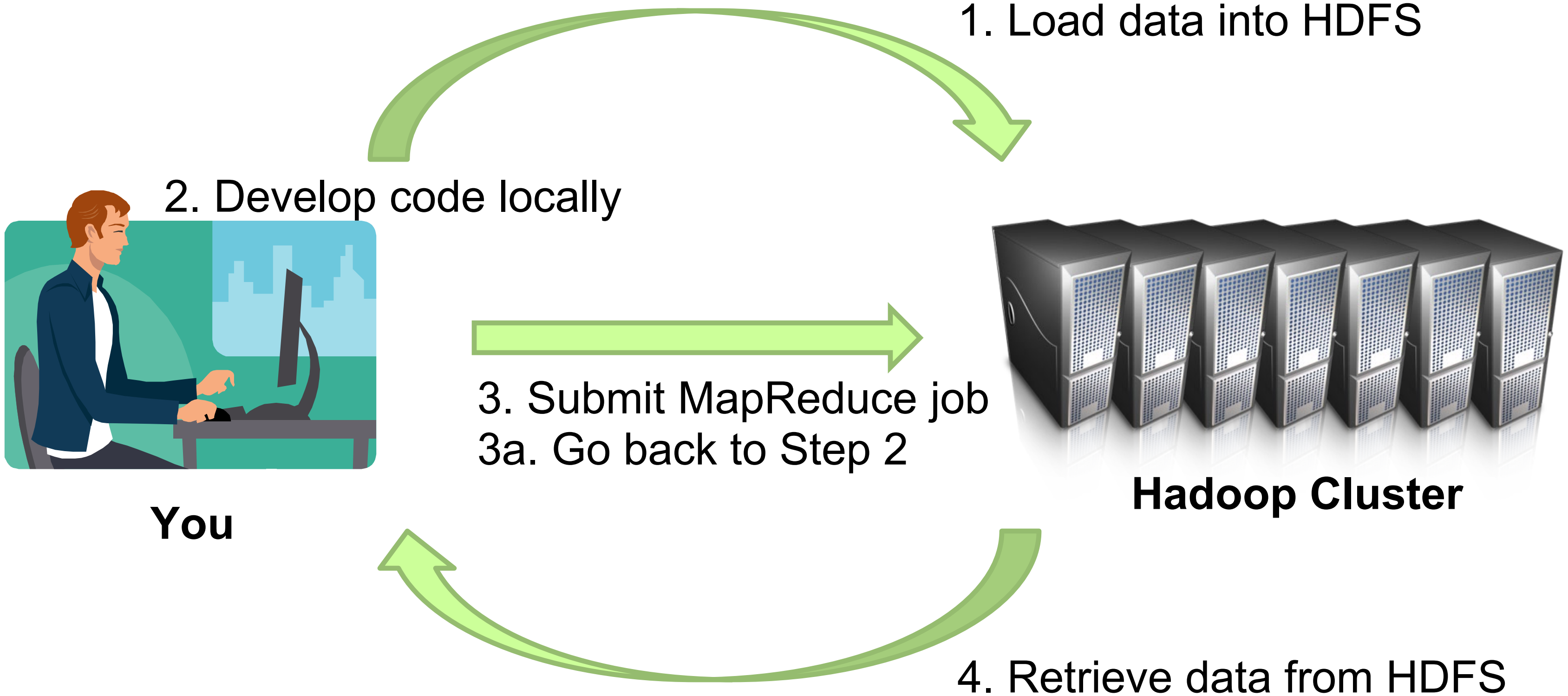
Recap

- Why large data?
- Cloud computing and MapReduce
- Large-data processing: “big ideas”
- What is MapReduce?
- Importance of the underlying distributed file system

Shuffle and Sort in Hadoop

- Probably the most complex aspect of MapReduce!
- Map side
  - Map outputs are buffered in memory in a circular buffer
  - When buffer reaches threshold, contents are “spilled” to disk
  - Spills merged in a single, partitioned file (sorted within each partition): combiner runs here
- Reduce side
  - First, map outputs are copied over to reducer machine
  - “Sort” is a multi-pass merge of map outputs (happens in memory and on disk): combiner runs here
  - Final merge pass goes directly into reducer

Hadoop Workflow



Debugging Hadoop

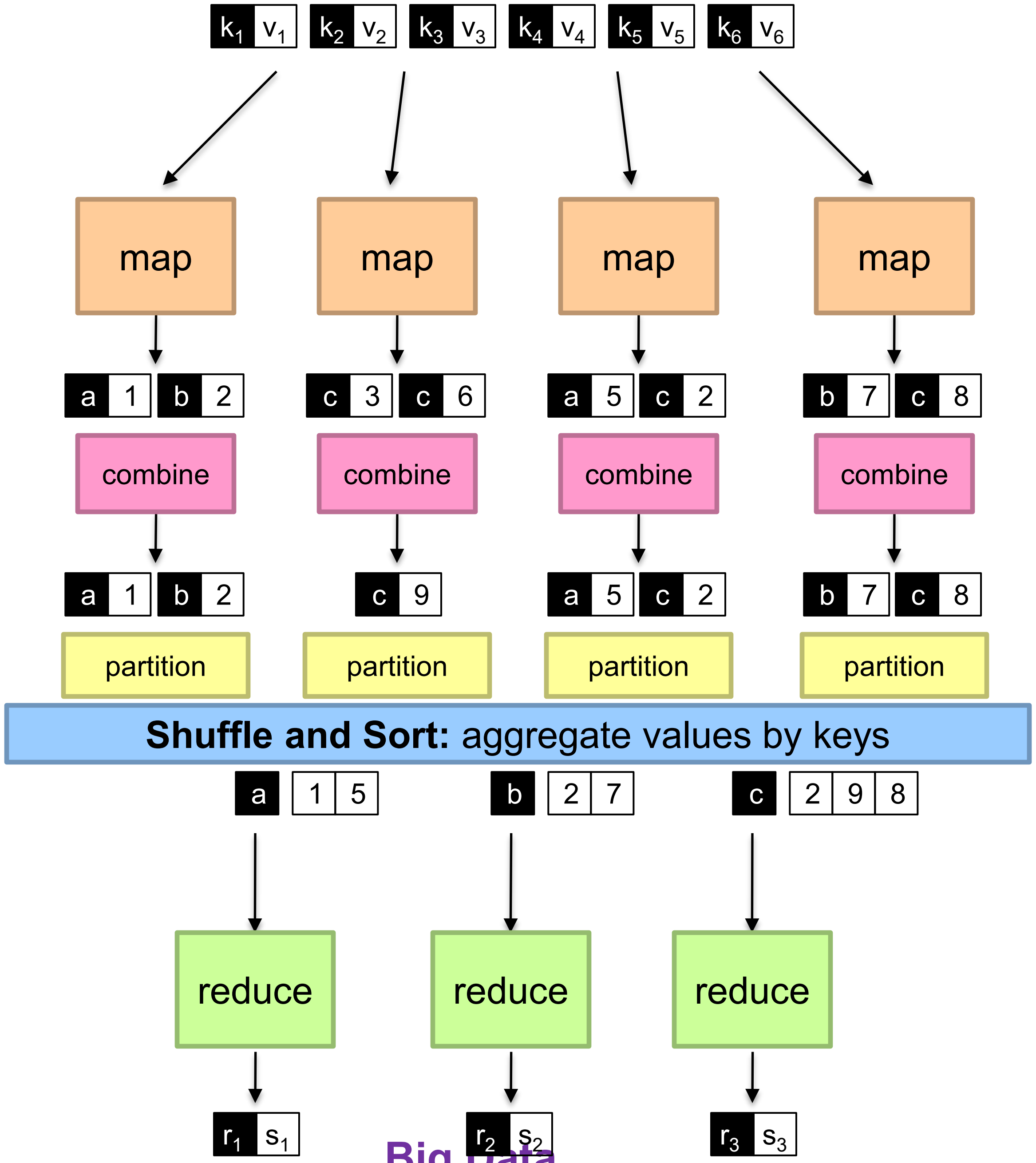
- First, take a deep breath
- Start small, start locally
- Strategies
  - Learn to use the webapp
  - Where does println go?
  - Don’t use println, use logging
  - Throw RuntimeExceptions

Recap

- Hadoop data types
- Anatomy of a Hadoop job
- Hadoop jobs, end to end
- Software development workflow

MapReduce: Recap

- Programmers must specify:
  - **map** (k, v) → <k’, v’>*
  - **reduce** (k’, v’) → <k’, v’>*
  - All values with the same key are reduced together
- Optionally, also:
  - **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
- The execution framework handles everything else…



k_1 v_1
k_2 v_2
k_3 v_3
k_4 v_4
k_5 v_5
k_6 v_6
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 9 8
reduce
reduce
reduce
r_1 s_1
r_2 s_2
r_3 s_3

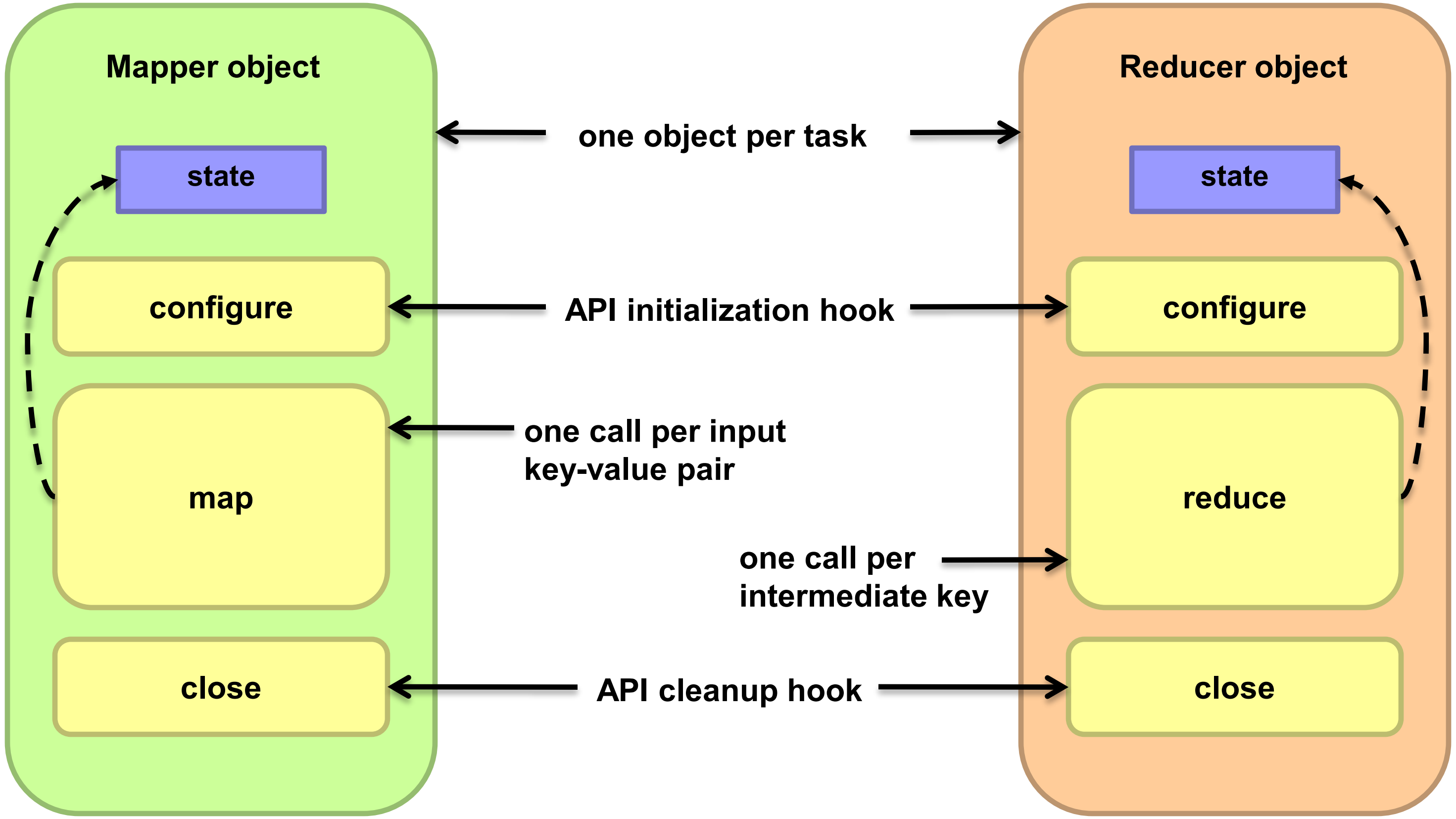
“Everything Else”

- The execution framework handles everything else…
  - Scheduling: assigns workers to map and reduce tasks
  - “Data distribution”: moves processes to data
  - Synchronization: gathers, sorts, and shuffles intermediate data
  - Errors and faults: detects worker failures and restarts
- Limited control over data and execution flow
  - All algorithms must expressed in m, r, c, p
- You don’t know:
  - Where mappers and reducers run
  - When a mapper or reducer begins or finishes
  - Which input a particular mapper is processing
  - Which intermediate key a particular reducer is processing

Tools for Synchronization

- Cleverly-constructed data structures
  - Bring partial results together
- Sort order of intermediate keys
  - Control order in which reducers process keys
- Partitioner
  - Control which reducer processes which keys
- Preserving state in mappers and reducers
  - Capture dependencies across multiple keys and values

Special Topics - Preserving State



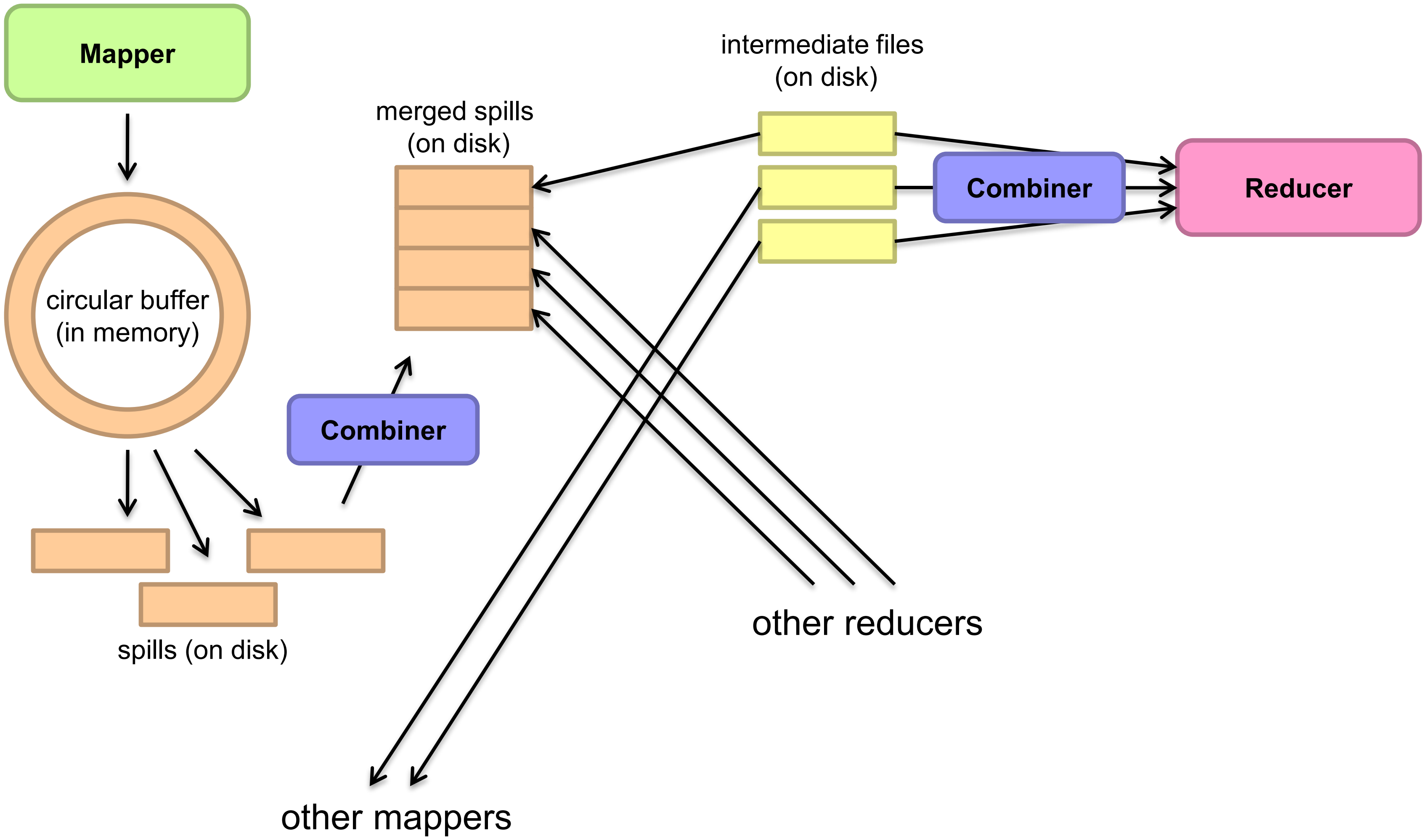
Scalable Hadoop Algorithms: Themes

- Avoid object creation
  - Inherently costly operation
  - Garbage collection
- Avoid buffering
  - Limited heap size
  - Works for small datasets, but won't scale!

Importance of Local Aggregation

- Ideal scaling characteristics:
  - Twice the data, twice the running time
  - Twice the resources, half the running time
- Why can’t we achieve this?
  - Synchronization requires communication
  - Communication kills performance
- Thus… avoid communication!
  - Reduce intermediate data via local aggregation
  - Combiners can help

Shuffle and Sort



Design Pattern for Local Aggregation

- "In-mapper combining"
  - Fold the functionality of the combiner into the mapper by preserving state across multiple map calls
- Advantages
  - Speed
  - Why is this faster than actual combiners?
- Disadvantages
  - Explicit memory management required
  - Potential for order-dependent bugs

Combiner Design

- Combiners and reducers share same method signature
  - Sometimes, reducers can serve as combiners
  - Often, not…
- Remember: combiner are optional optimizations
  - Should not affect algorithm correctness
  - May be run 0, 1, or multiple times
- Example: find average of all integers associated with the same key

Recap: Tools for Synchronization

- Cleverly-constructed data structures
  - Bring data together
- Sort order of intermediate keys
  - Control order in which reducers process keys
- Partitioner
  - Control which reducer processes which keys
- Preserving state in mappers and reducers
  - Capture dependencies across multiple keys and values

Issues and Tradeoffs

- Number of key-value pairs
  - Object creation overhead
  - Time for sorting and shuffling pairs across the network
- Size of each key-value pair
  - De/serialization overhead
- Local aggregation
  - Opportunities to perform local aggregation varies
  - Combiners make a big difference
  - Combiners vs. in-mapper combining
  - RAM vs. disk vs. network

Debugging at Scale

- Works on small datasets, won’t scale… why?
  - Memory management issues (buffering and object creation)
  - Too much intermediate data
  - Mangled input records
- Real-world data is messy!
  - Word count: how many unique words in Wikipedia?
  - There’s no such thing as “consistent data”
  - Watch out for corner cases
  - Isolate unexpected behavior, bring local