CS60021: Scalable Data Mining

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Hadoop Map Reduce

- Provides:
  - Automatic parallelization and Distribution
  - Fault Tolerance
  - Methods for interfacing with HDFS for colocation of computation and storage of output.
  - Status and Monitoring tools
  - API in Java
  - Ability to define the mapper and reducer in many languages through Hadoop streaming.

HDFS

- Outline:
  - HDFS – Motivation
  - HDFS – User commands
  - HDFS – System architecture
  - HDFS – Implementation details

What's HDFS

- HDFS is a distributed file system that is fault tolerant, scalable and extremely easy to expand.
- HDFS is the primary distributed storage for Hadoop applications.
- HDFS provides interfaces for applications to move themselves closer to data.
- HDFS is designed to 'just work', however a working knowledge helps in diagnostics and improvements.

HDFS

- Design Assumptions
  - Hardware failure is the norm.
  - Streaming data access.
  - Write once, read many times.
  - High throughput, not low latency.
  - Large datasets.
- Characteristics:
  - Performs best with modest number of large files
  - Optimized for streaming reads
  - Layer on top of native file system.

HDFS

- Data is organized into file and directories.
- Files are divided into blocks and distributed to nodes.
- Block placement is known at the time of read
  - Computation moved to same node.
- Replication is used for:
  - Speed
  - Fault tolerance
  - Self healing.

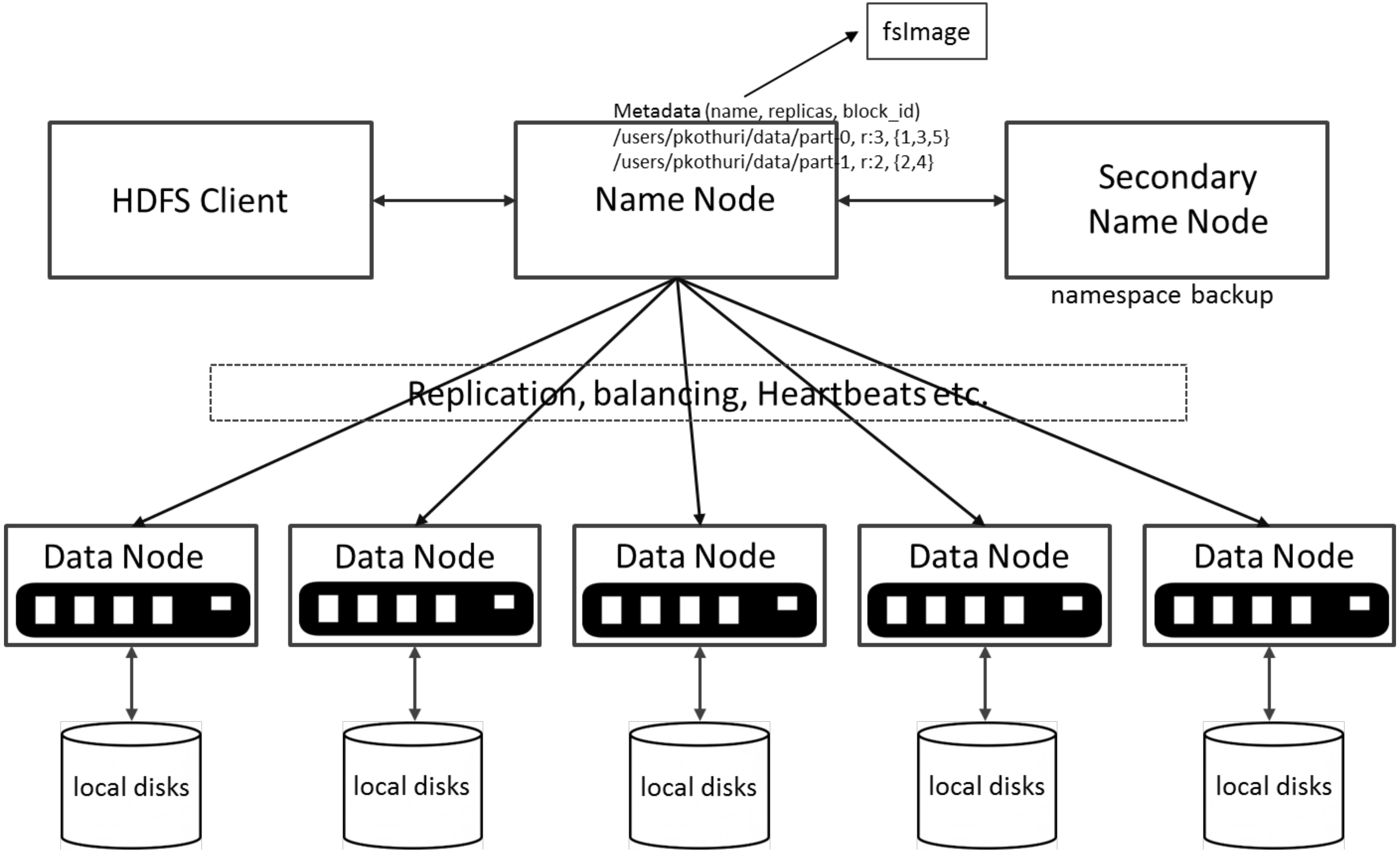
Components of HDFS

There are two (*and a half*) types of machines in a HDFS cluster

- <u>NameNode</u> :– is the heart of an HDFS filesystem, it maintains and manages the file system metadata. E.g; what blocks make up a file, and on which datanodes those blocks are stored.

- <u>DataNode</u> :- where HDFS stores the actual data, there are usually quite a few of these.

HDFS Architecture



HDFS – User Commands (dfs)

List directory contents

```
hdfs dfs –ls
hdfs dfs -ls /
hdfs dfs -ls -R /var
```

Display the disk space used by files

```
hdfs dfs -du /hbase/data/hbase/namespace/
hdfs dfs -du -h /hbase/data/hbase/namespace/
hdfs dfs -du -s /hbase/data/hbase/namespace/
```

HDFS – User Commands (dfs)

Copy data to HDFS

```
hdfs dfs -mkdir tdata
hdfs dfs -ls
hdfs dfs -copyFromLocal tutorials/data/geneva.csv tdata
hdfs dfs -ls –R
```

Copy the file back to local filesystem

```
cd tutorials/data/
hdfs dfs –copyToLocal tdata/geneva.csv geneva.csv.hdfs
md5sum geneva.csv geneva.csv.hdfs
```

HDFS – User Commands (acls)

List acl for a file

```
hdfs dfs -getfacl tdata/geneva.csv
```

List the file statistics – (%r – replication factor)

```
hdfs dfs -stat "%r" tdata/geneva.csv
```

Write to hdfs reading from stdin

```
echo "blah blah blah" | hdfs dfs -put - tdataset/tfile.txt
hdfs dfs -ls –R
hdfs dfs -cat tdataset/tfile.txt
```

Goals of HDFS

- **Very Large Distributed File System**
  – 10K nodes, 100 million files, 10 PB
- **Assumes Commodity Hardware**
  – Files are replicated to handle hardware failure
  – Detect failures and recovers from them
- **Optimized for Batch Processing**
  – Data locations exposed so that computations can move to where data resides
  – Provides very high aggregate bandwidth
- **User Space, runs on heterogeneous OS**

Distributed File System

- **Single Namespace for entire cluster**
- **Data Coherency**
  - Write-once-read-many access model
  - Client can only append to existing files
- **Files are broken up into blocks**
  - Typically 128 MB block size
  - Each block replicated on multiple DataNodes
- **Intelligent Client**
  - Client can find location of blocks
  - Client accesses data directly from DataNode

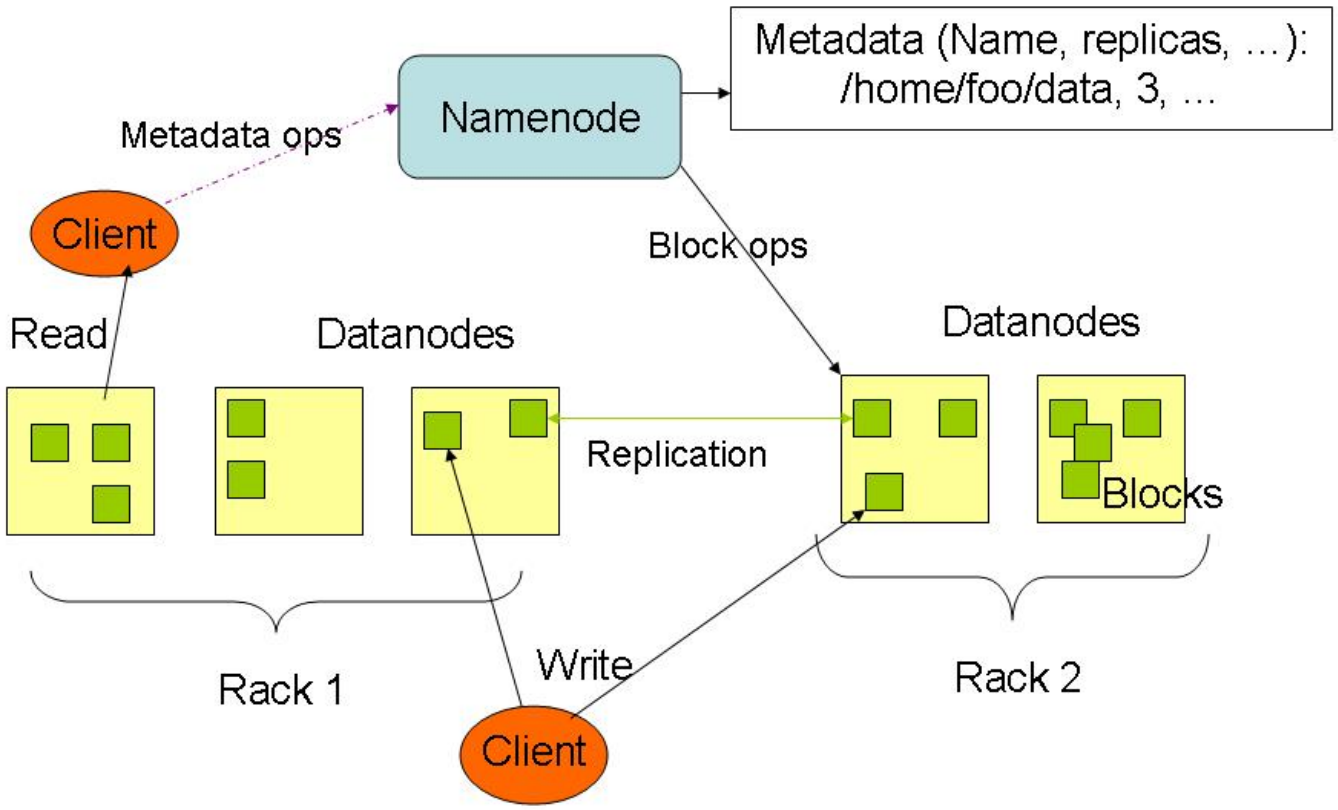
NameNode Metadata

- **Meta-data in Memory**
  - The entire metadata is in main memory
  - No demand paging of meta-data
- **Types of Metadata**
  - List of files
  - List of Blocks for each file
  - List of DataNodes for each block
  - File attributes, e.g creation time, replication factor
- **A Transaction Log**
  - Records file creations, file deletions. etc

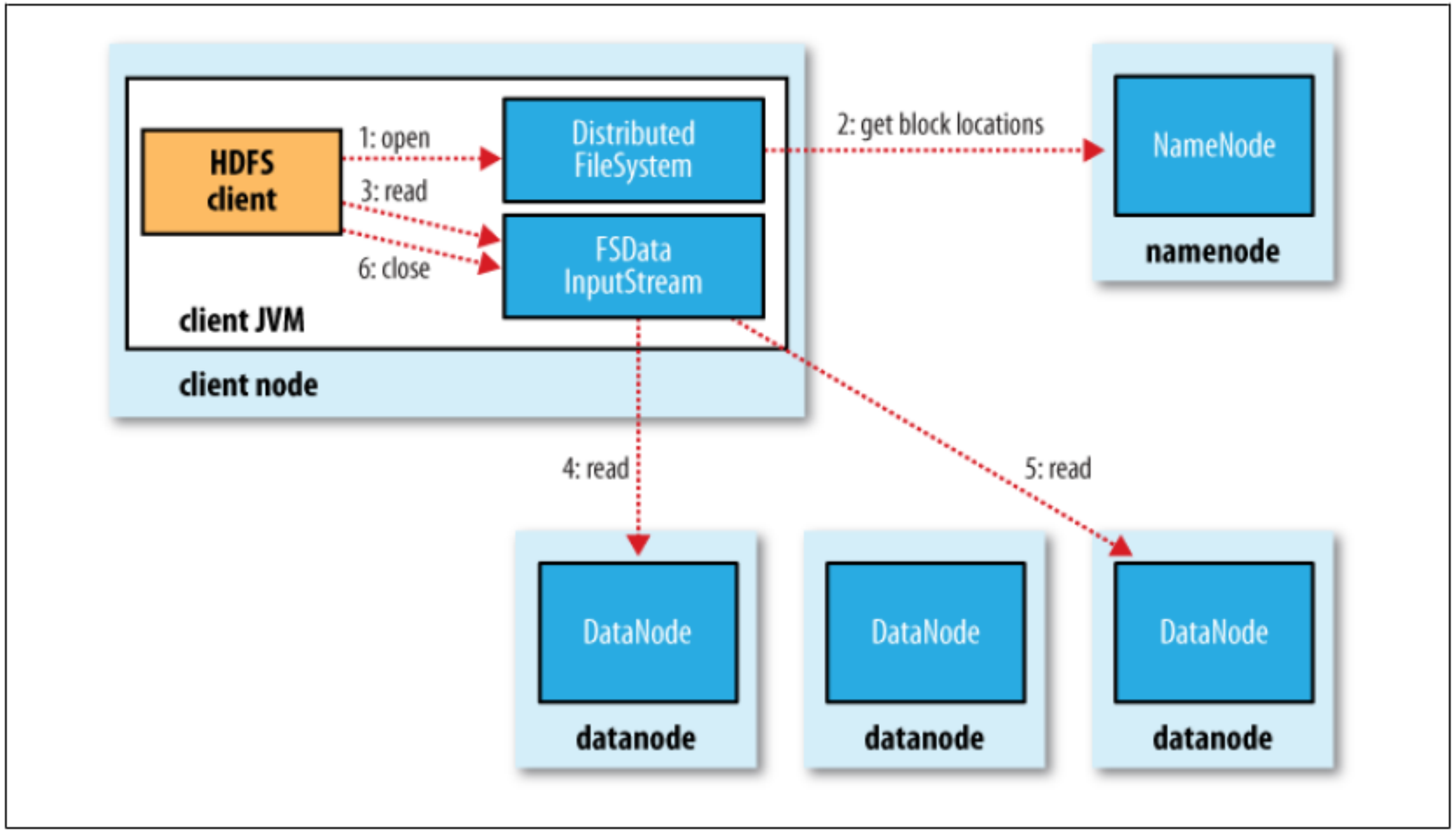
DataNode

- **A Block Server**
  – Stores data in the local file system (e.g. ext3)
  – Stores meta-data of a block (e.g. CRC)
  – Serves data and meta-data to Clients
- **Block Report**
  – Periodically sends a report of all existing blocks to the NameNode
- **Facilitates Pipelining of Data**
  – Forwards data to other specified DataNodes

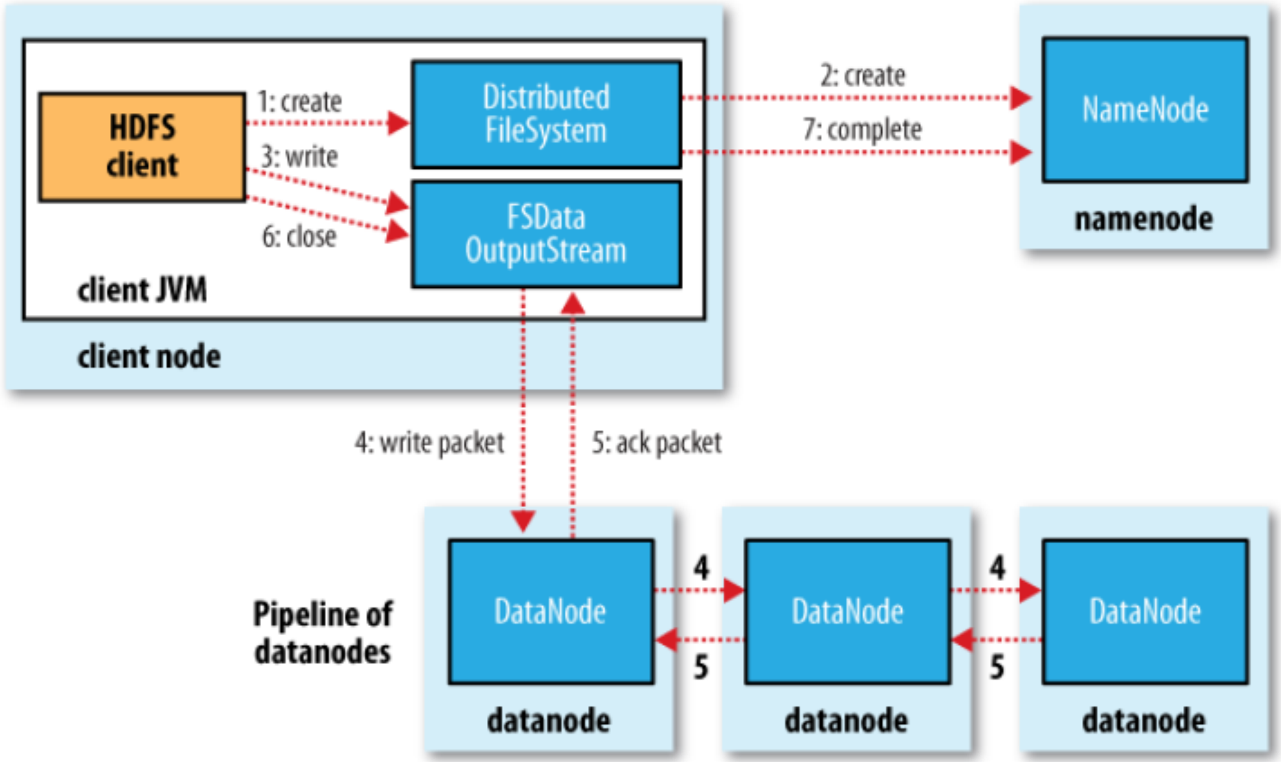
HDFS Architecture



HDFS read client



HDFS write Client



Block Placement

- **Current Strategy**

  -- One replica on local node

  -- Second replica on a remote rack

  -- Third replica on same remote rack

  -- Additional replicas are randomly placed

- **Clients read from nearest replica**

- **Would like to make this policy pluggable**

NameNode Failure

- **A single point of failure**
- **Transaction Log stored in multiple directories**
  - A directory on the local file system
  - A directory on a remote file system (NFS/CIFS)

Data Pipelining

- Client retrieves a list of DataNodes on which to place replicas of a block
- Client writes block to the first DataNode
- The first DataNode forwards the data to the next DataNode in the Pipeline
- Usually, when all replicas are written, the Client moves on to write the next block in file

Conclusion:

- We have seen:
  - The structure of HDFS.
  - The shell commands.
  - The architecture of HDFS system.
  - Internal functioning of HDFS.

MAPREDUCE INTERNALS

Wordcount program

```
import java.io.IOException;
import java.util.StringTokenizer;

import org.apache.hadoop.conf.Configuration;
import org.apache.hadoop.fs.Path;
import org.apache.hadoop.io.IntWritable;
import org.apache.hadoop.io.Text;
import org.apache.hadoop.mapreduce.Job;
import org.apache.hadoop.mapreduce.Mapper;
import org.apache.hadoop.mapreduce.Reducer;
import org.apache.hadoop.mapreduce.lib.input.FileInputFormat;
import org.apache.hadoop.mapreduce.lib.output.FileOutputFormat;
```

Wordcount program - Main

```
public class WordCount {

public static void main(String[] args) throws Exception {
Configuration conf = new Configuration();
Job job = Job.getInstance(conf, "word count");
job.setJarByClass(WordCount.class);
job.setMapperClass(TokenizerMapper.class);
job.setCombinerClass(IntSumReducer.class);
job.setReducerClass(IntSumReducer.class);
job.setOutputKeyClass(Text.class);
job.setOutputValueClass(IntWritable.class);
FileInputFormat.addInputPath(job, new Path(args[0]));
FileOutputFormat.setOutputPath(job, new Path(args[1]));
System.exit(job.waitForCompletion(true) ? 0 : 1);
} }
```

Wordcount program - Mapper

```
public static class TokenizerMapper extends Mapper<Object, Text, Text,
IntWritable>{
private final static IntWritable one = new IntWritable(1);
private Text word = new Text();

public void map(Object key, Text value, Context context )
throws IOException, InterruptedException {
   StringTokenizer itr = new StringTokenizer(value.toString());
   while (itr.hasMoreTokens()) {
      word.set(itr.nextToken()); context.write(word, one);
   }
}
}
```

Wordcount program - Reducer

```
public static class IntSumReducer extends
Reducer<Text,IntWritable,Text,IntWritable> {
private IntWritable result = new IntWritable();

public void reduce(Text key, Iterable<IntWritable> values, Context
context )
throws IOException, InterruptedException {
   int sum = 0;
   for (IntWritable val : values) {
      sum += val.get();
   }
   result.set(sum);
   context.write(key, result);
}
}
```

Wordcount program - running

```
export JAVA_HOME=[ Java home directory ]

bin/hadoop com.sun.tools.javac.Main WordCount.java

jar cf wc.jar WordCount*.class

bin/hadoop jar wc.jar WordCount [Input path] [Output path]
```

Wordcount in python

Mapper.py

```
#!/usr/bin/env python

import sys

# input comes from STDIN (standard input)
for line in sys.stdin:
    # remove leading and trailing whitespace
    line = line.strip()
    # split the line into words
    words = line.split()
    # increase counters
    for word in words:
        # write the results to STDOUT (standard output);
        # what we output here will be the input for the
        # Reduce step, i.e. the input for reducer.py
        #
        # tab-delimited; the trivial word count is 1
        print '%s\t%s' % (word, 1)
```

Wordcount in python

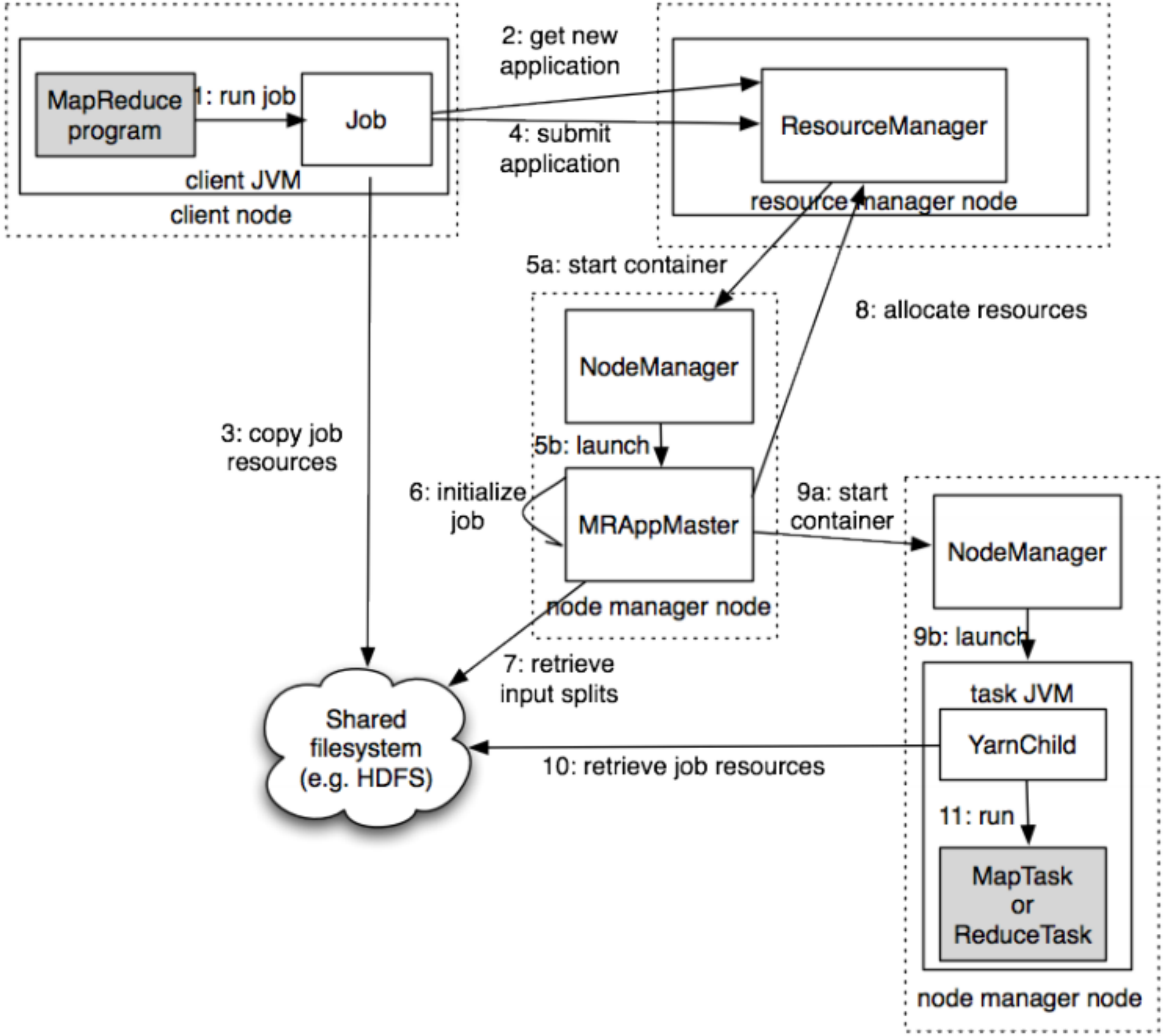
Reducer.py

```
#!/usr/bin/env python

from operator import itemgetter
import sys

# maps words to their counts
word2count = {}

# input comes from STDIN
for line in sys.stdin:
    # remove leading and trailing whitespace
    line = line.strip()

    # parse the input we got from mapper.py
    word, count = line.split('\t', 1)
    # convert count (currently a string) to int
    try:
        count = int(count)
        word2count[word] = word2count.get(word, 0) + count
    except ValueError:
        # count was not a number, so silently
        # ignore/discard this line
        pass

# sort the words lexigraphically;
#
# this step is NOT required, we just do it so that our
# final output will look more like the official Hadoop
# word count examples
sorted_word2count = sorted(word2count.items(), key=itemgetter(0))

# write the results to STDOUT (standard output)
for word, count in sorted_word2count:
    print '%s\t%s'% (word, count)
```

Execution code

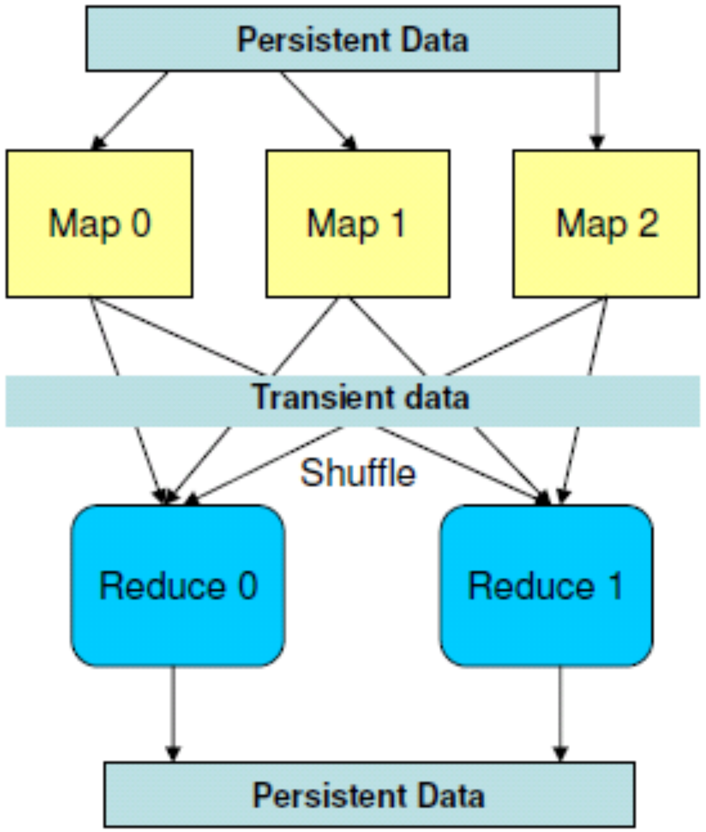
```
bin/hadoop dfs -ls

bin/hadoop dfs –copyFromLocal example example

bin/mapred streaming -input example   -output java-output  -mapper
mapper.py  -reducer reducer.py  -file mapper.py  -file reducer.py

bin/hadoop dfs -cat java-output/part-00000

bin/hadoop dfs -copyToLocal java-output/part-00000 java-output-local
```

Hadoop(v2) MR job

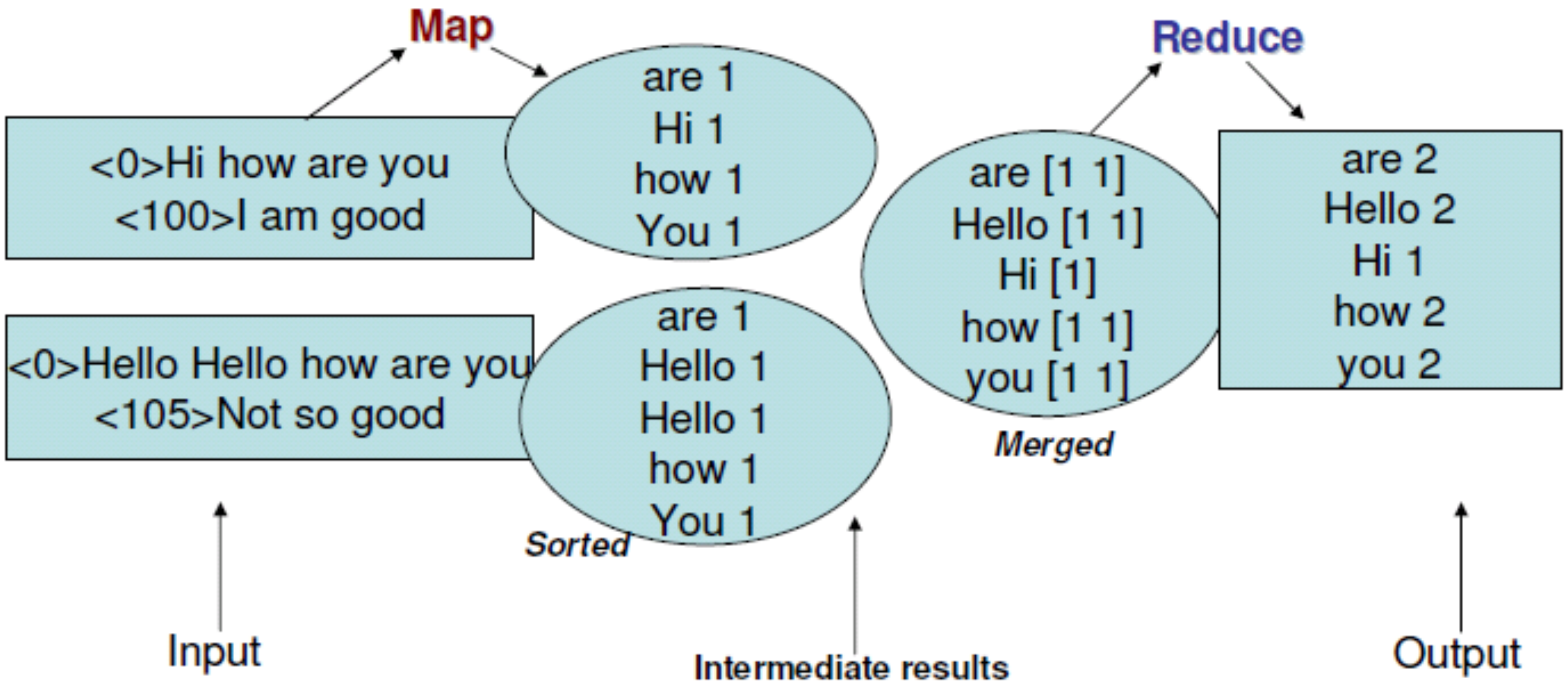


Source: Hadoop: The Definitive Guide

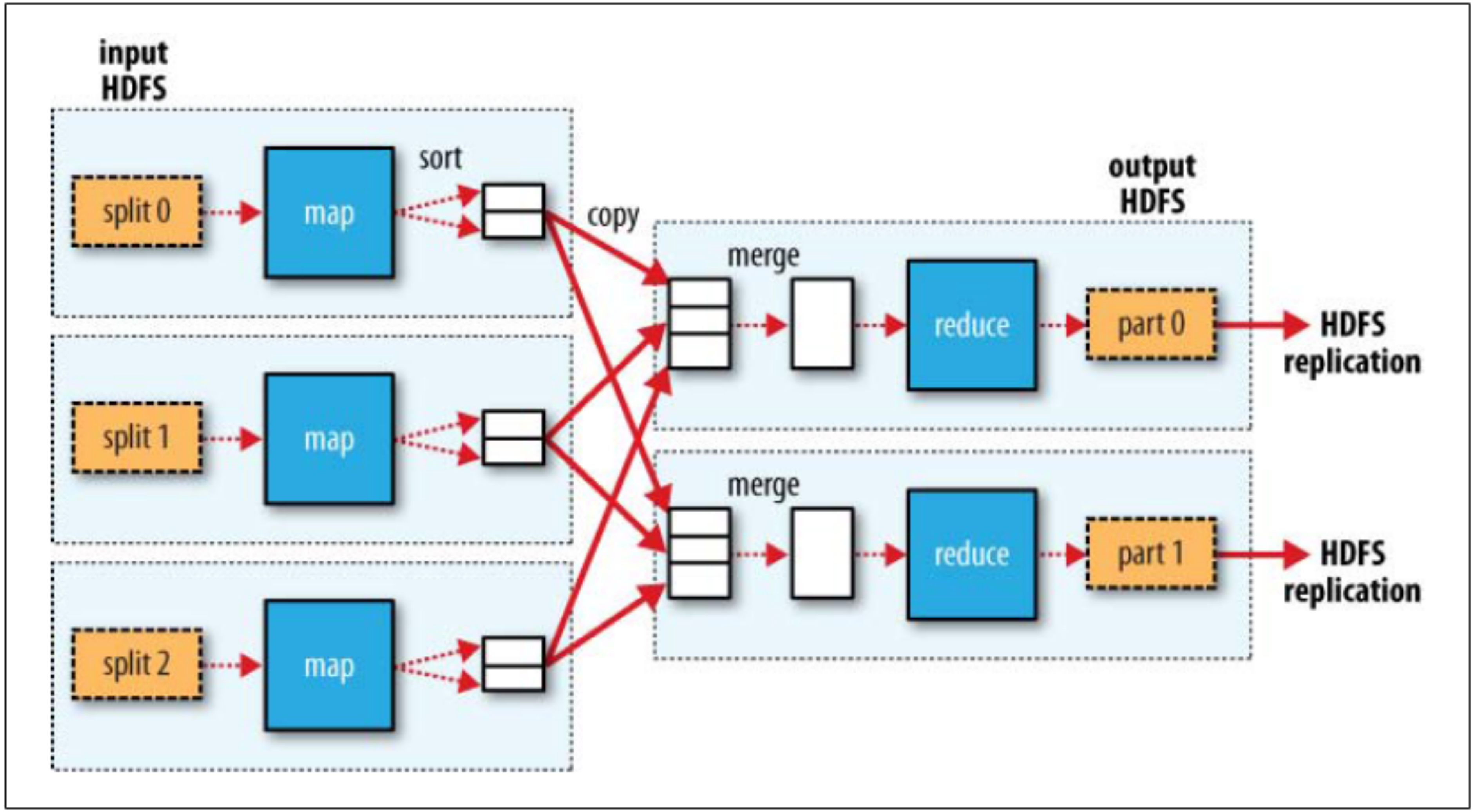
Map Reduce Data Flow



Data: Stream of keys and values

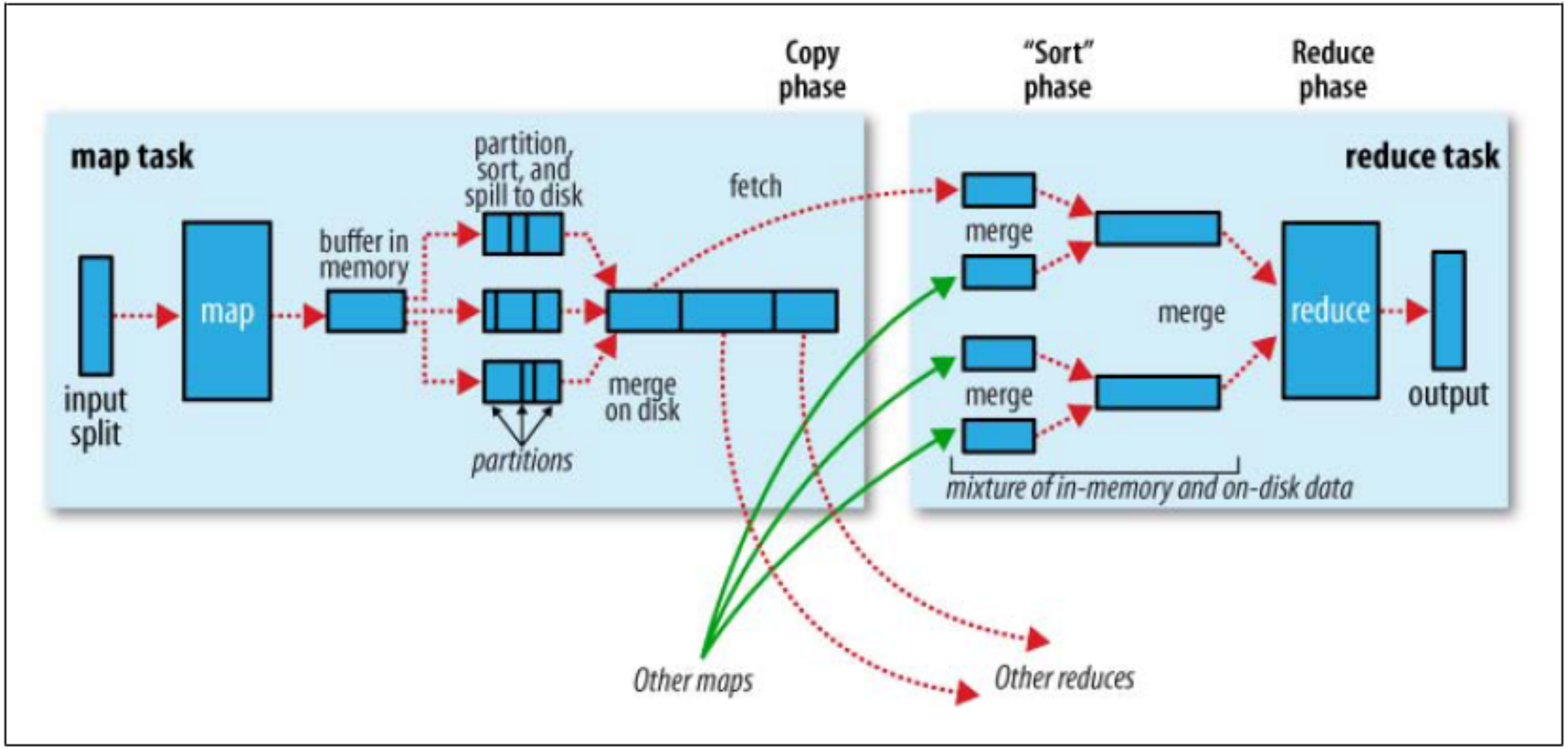


Hadoop MR Data Flow



Source: Hadoop: The Definitive Guide

Shuffle and sort



Source: Hadoop: The Definitive Guide

Data Flow

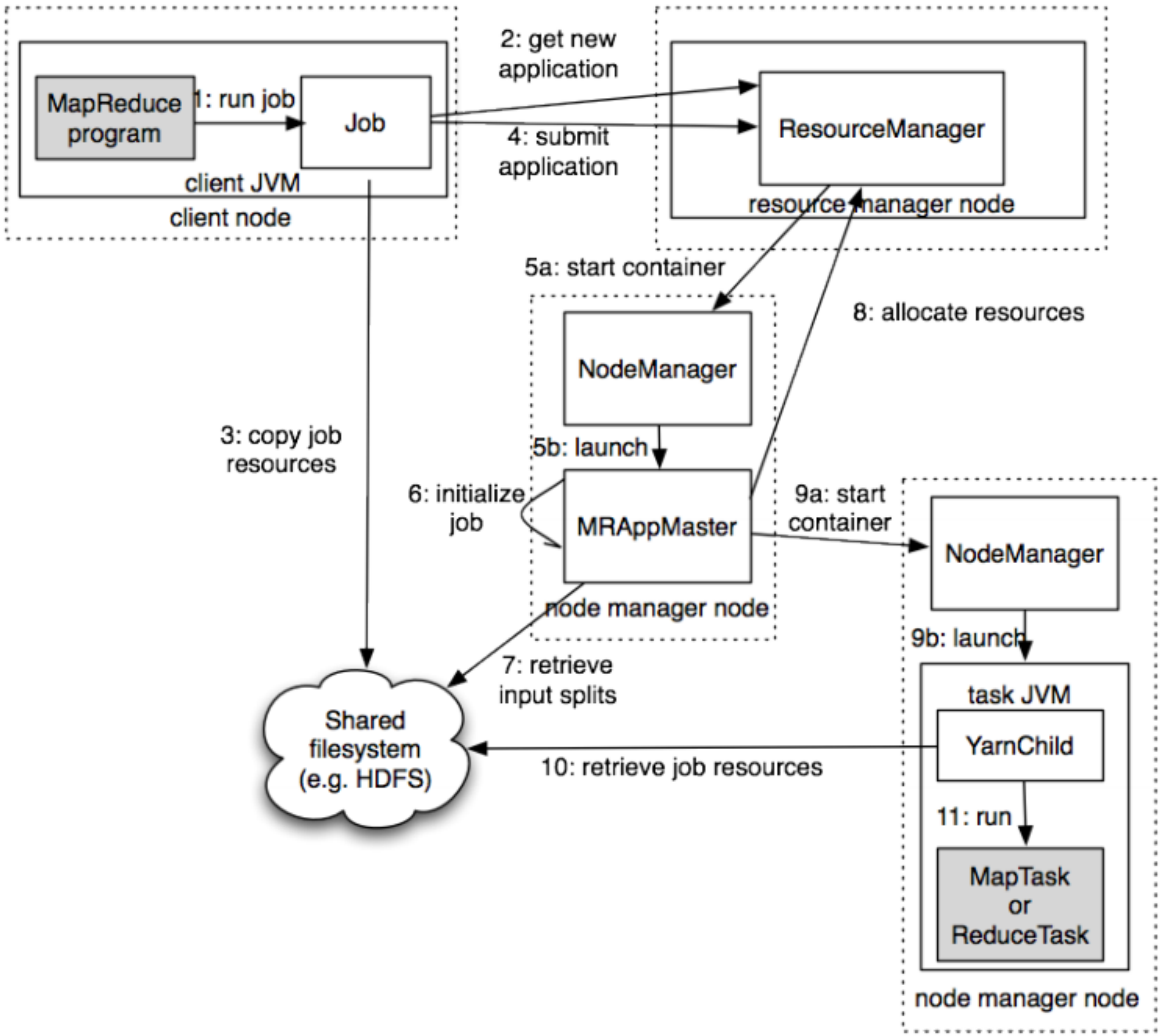
- **Input and final output are stored on a distributed file system (FS):**
  - Scheduler tries to schedule map tasks “close” to physical storage location of input data

- **Intermediate results are stored on local FS of Map workers.**

- **Output** of **Reduce** workers are stored on a **distributed file system**.

- **Output is often input to another MapReduce task**

Hadoop(v2) MR job



Source: Hadoop: The Definitive Guide

Fault tolerance

- Comes from scalability and cost effectiveness

- HDFS:
  - Replication

- Map Reduce
  - Restarting failed tasks: map and reduce
  - Writing map output to FS
  - Minimizes re-computation

Coordination: Master

- Master node takes care of coordination:
  - **Task status:** (idle, in-progress, completed)
  - **Idle tasks** get scheduled as workers become available
  - When a map task completes, it sends the master the location and sizes of its *R* intermediate files, one for each reducer
  - Master pushes this info to reducers
- Master pings workers periodically to detect failures

Failures

- Task failure
  - Task has failed – report error to node manager, appmaster, client.
  - Task not responsive, JVM failure – Node manager restarts tasks.
- Application Master failure
  - Application master sends heartbeats to resource manager.
  - If not received, the resource manager retrieves job history of the run tasks.
- Node manager failure

Dealing with Failures

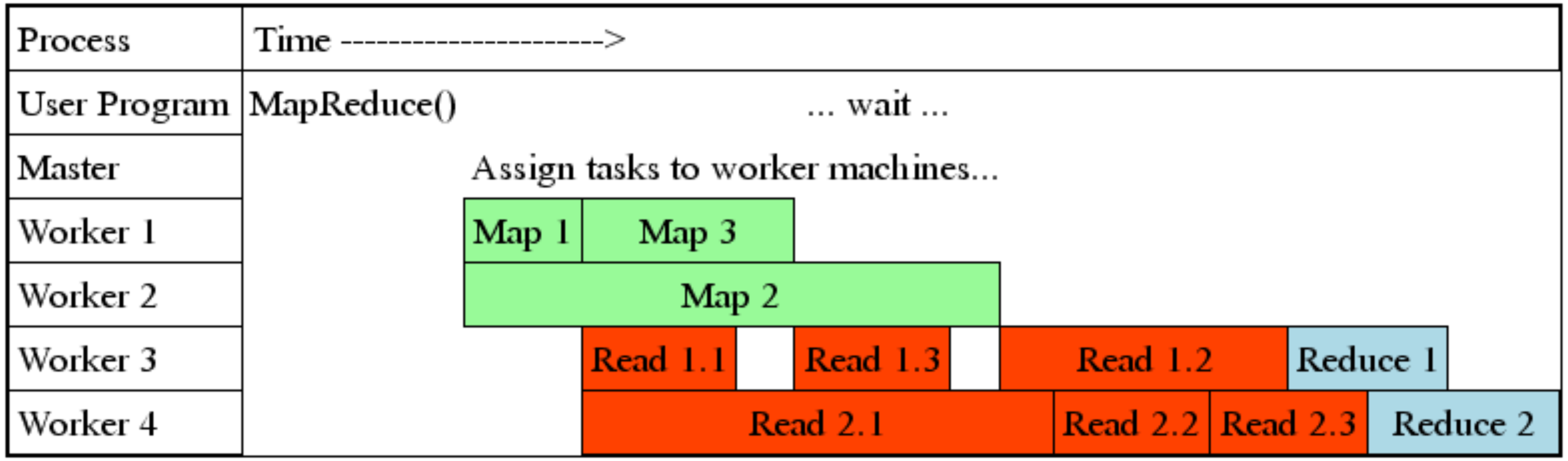
- **Map worker failure**
  - Map tasks completed or in-progress at worker are reset to idle
  - Reduce workers are notified when task is rescheduled on another worker
- **Reduce worker failure**
  - Only in-progress tasks are reset to idle
  - Reduce task is restarted
- **Master failure**
  - MapReduce task is aborted and client is notified

How many Map and Reduce jobs?

- *M* map tasks, *R* reduce tasks
- **Rule of a thumb:**
  - Make *M* much larger than the number of nodes in the cluster
  - One DFS chunk per map is common
  - Improves dynamic load balancing and speeds up recovery from worker failures
- **Usually *R* is smaller than *M***
  - Because output is spread across *R* files

Task Granularity & Pipelining

- **Fine granularity tasks:** map tasks >> machines
  - Minimizes time for fault recovery
  - Can do pipeline shuffling with map execution
  - Better dynamic load balancing



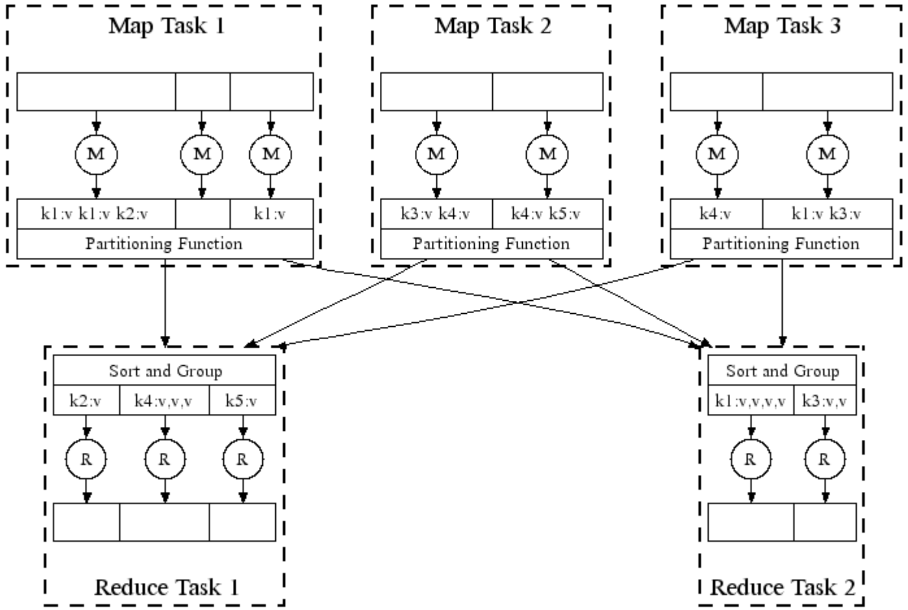
Refinements: Backup Tasks

- **Problem**
  - Slow workers significantly lengthen the job completion time:
    - Other jobs on the machine
    - Bad disks
    - Weird things
- **Solution**
  - Near end of phase, spawn backup copies of tasks
    - Whichever one finishes first “wins”
- **Effect**
  - Dramatically shortens job completion time

Refinement: Combiners

- Often a Map task will produce many pairs of the form (k,v_1), (k,v_2), … for the same key k
  - E.g., popular words in the word count example

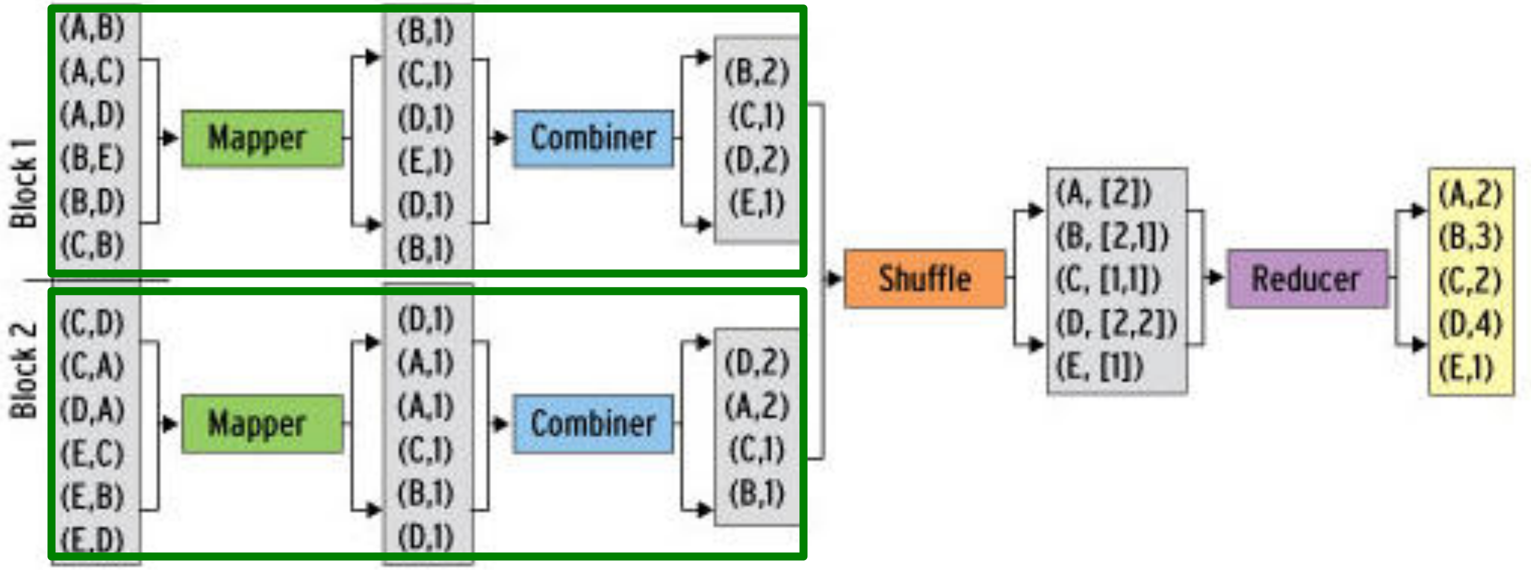
- **Can save network time by pre-aggregating values in the mapper:**
  - combine(k, list(v_1)) → v_2
  - Combiner is usually same as the reduce function



- Works only if reduce function is commutative and associative

Refinement: Combiners

- **Back to our word counting example:**
  - Combiner combines the values of all keys of a single mapper (single machine):



  - Much less data needs to be copied and shuffled!

Refinement: Partition Function

- **Want to control how keys get partitioned**
  - Inputs to map tasks are created by contiguous splits of input file
  - Reduce needs to ensure that records with the same intermediate key end up at the same worker

- **System uses a default partition function:**
  - **hash(key) mod *R***

- **Sometimes useful to override the hash function:**
  - E.g., **hash(hostname(URL)) mod *R*** ensures URLs from a host end up in the same output file

Example: Join By Map-Reduce

- **Compute the natural join *R(A,B)* ⋈ *S(B,C)***
- *R* and *S* are each stored in files
- Tuples are pairs *(a,b)* or *(b,c)*

A	B
a_1	b_1
a_2	b_1
a_3	b_2
a_4	b_3

R

⋈

B	C
b_2	c_1
b_2	c_2
b_3	c_3

S

=

A	C
a_3	c_1
a_3	c_2
a_4	c_3

Map-Reduce Join

- **Use a hash function *h* from B-values to *1...k***
- **A Map process turns:**
  - Each input tuple *R(a,b)* into key-value pair *(b,(a,R))*
  - Each input tuple *S(b,c)* into *(b,(c,S))*

- **Map processes** send each key-value pair with key *b* to Reduce process *h(b)*
  - Hadoop does this automatically; just tell it what *k* is.
- Each **Reduce process** matches all the pairs *(b,(a,R))* with all *(b,(c,S))* and outputs *(a,b,c)*.

Cost Measures for Algorithms

- **In MapReduce we quantify the cost of an algorithm using**

1. *Communication cost* = total I/O of all processes
2. *Elapsed communication cost* = max of I/O along any path
3. (*Elapsed*) *computation cost* analogous, but count only running time of processes

Note that here the big-O notation is not the most useful
(adding more machines is always an option)

Example: Cost Measures

- **For a map-reduce algorithm:**
  - **Communication cost =** input file size + 2 × (sum of the sizes of all files passed from Map processes to Reduce processes) + the sum of the output sizes of the Reduce processes.
  - **Elapsed communication cost** is the sum of the largest input + output for any map process, plus the same for any reduce process

What Cost Measures Mean

- Either the I/O (communication) or processing (computation) cost dominates
  - Ignore one or the other
- Total cost tells what you pay in rent from your friendly neighborhood cloud
- Elapsed cost is wall-clock time using parallelism

Cost of Map-Reduce Join

- **Total communication cost** $= O(|R|+|S|+|R \bowtie S|)$
- **Elapsed communication cost** = O(s)
  - We're going to pick ***k*** and the number of Map processes so that the I/O limit ***s*** is respected
  - We put a limit ***s*** on the amount of input or output that any one process can have. ***s* could be:**
    - What fits in main memory
    - What fits on local disk
- With proper indexes, computation cost is linear in the input + output size
  - So computation cost is like comm. cost

References:

- Jure Leskovec, Anand Rajaraman, Jeff Ullman. **Mining of Massive Datasets.** *2nd edition. - Cambridge University Press.* http://www.mmds.org/

- Tom White. **Hadoop: The definitive Guide.** Oreilly Press.