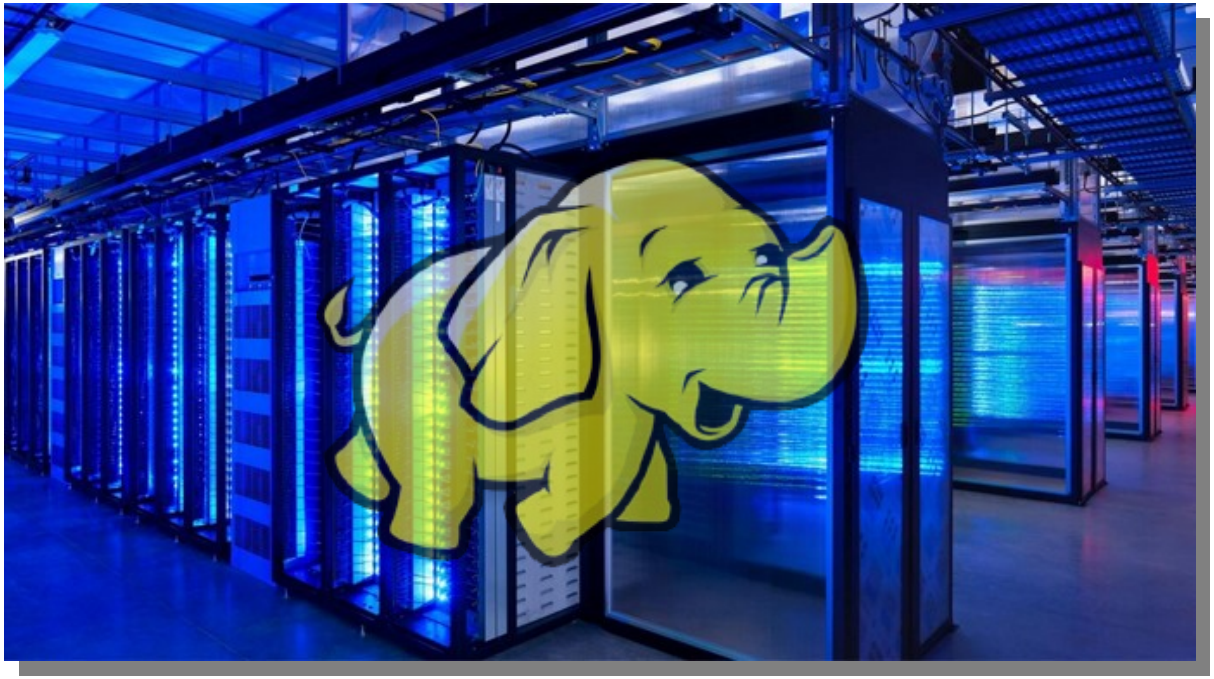
Big Data Analytics and Cluster Computing
with Apache Hadoop



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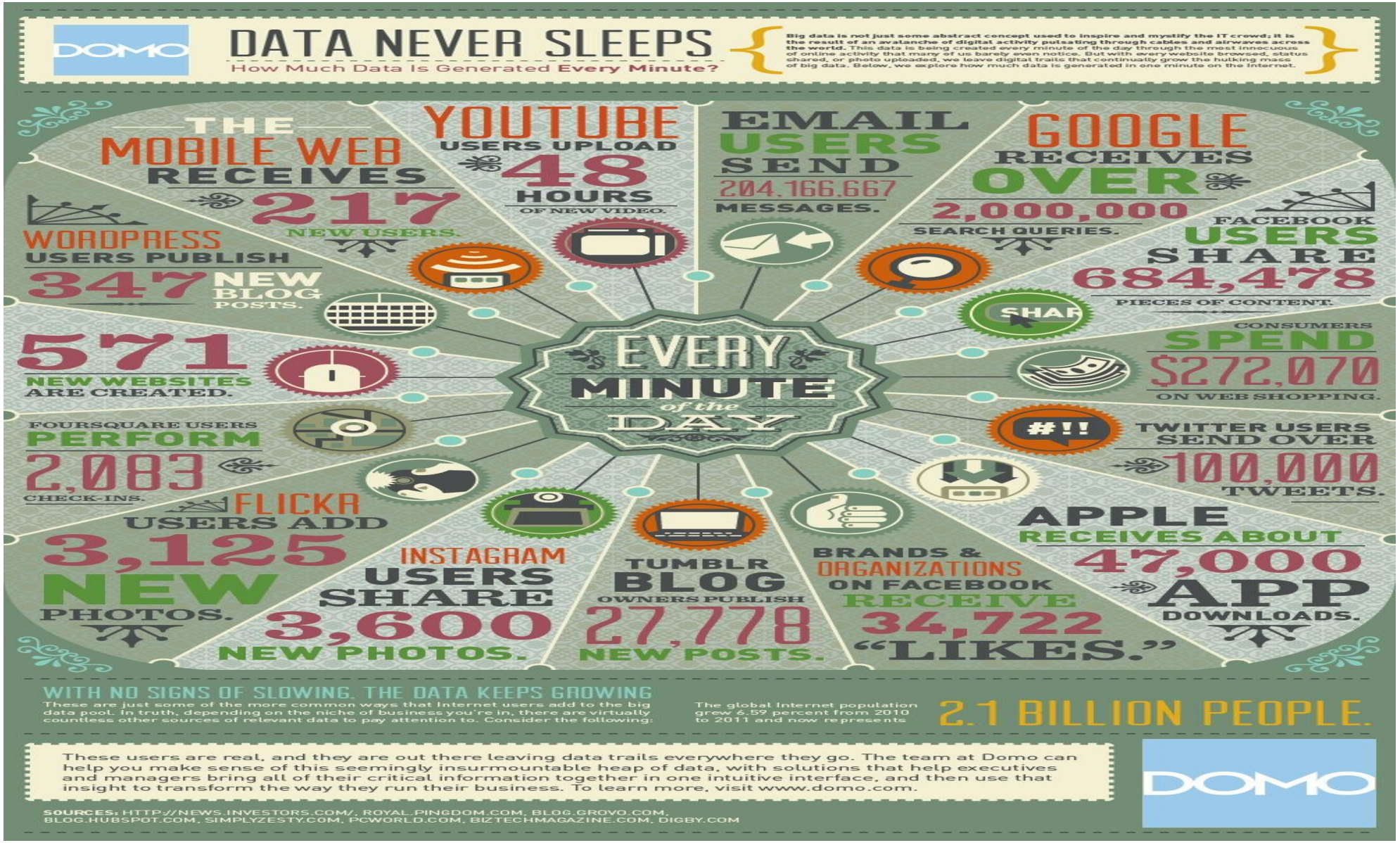
Outline

- Big Data everywhere
- Why one machine is not enough ?
- Parallel architectures
- Important issues in cluster computing
- Hadoop MapReduce
- Architecture of HDFS
- Architecture of YARN cluster manager
- MapReduce limitations

Big Data Everywhere



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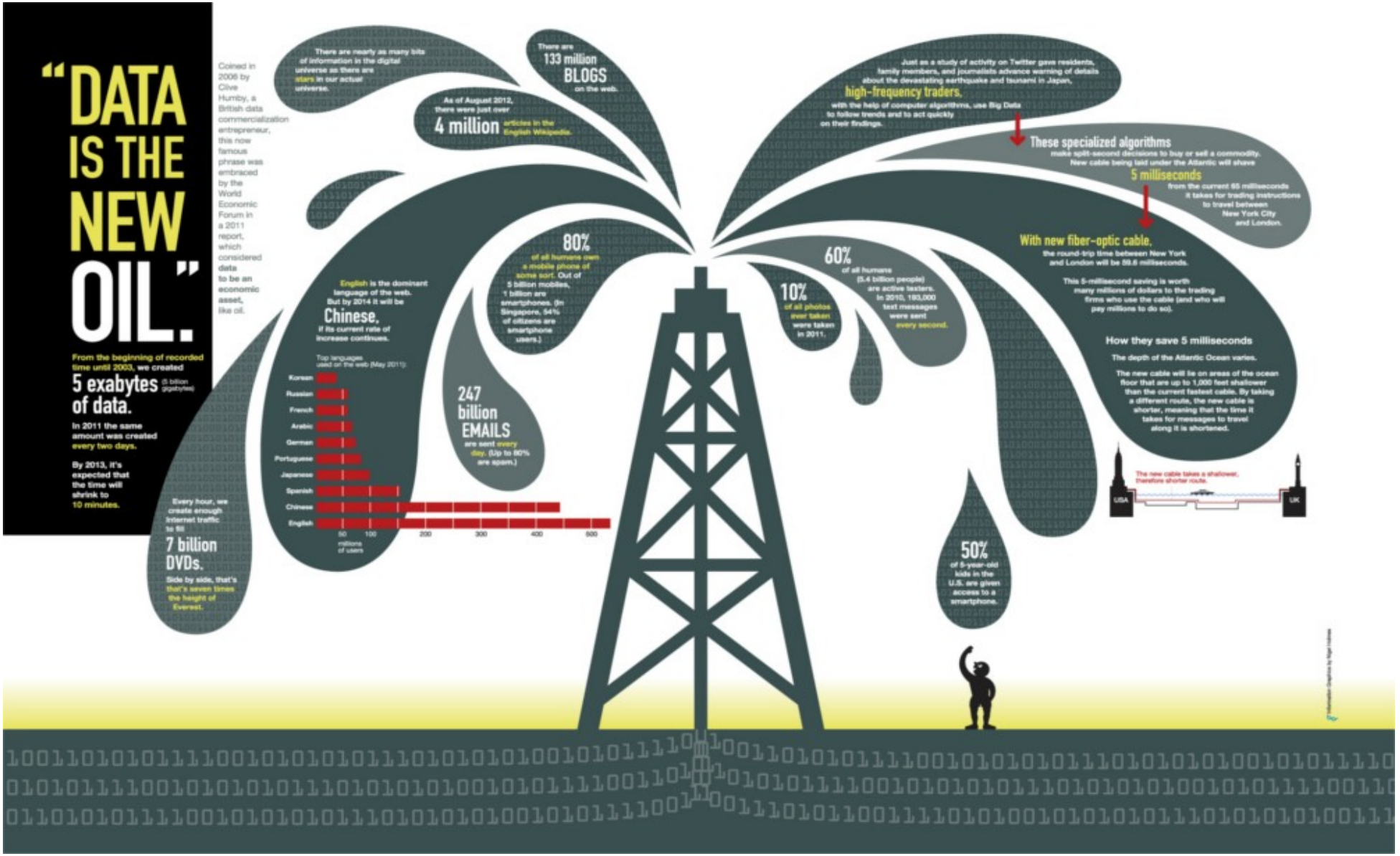
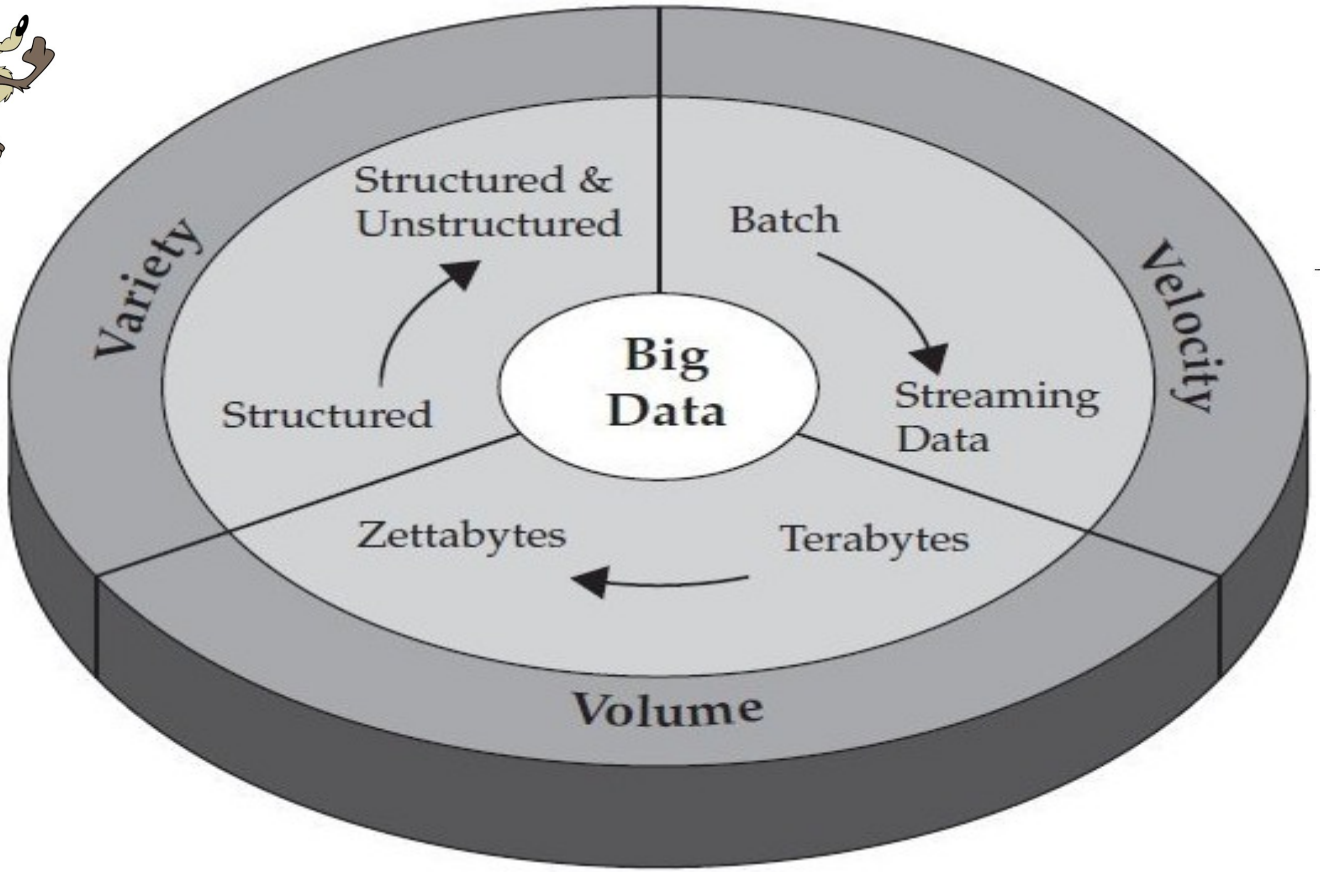
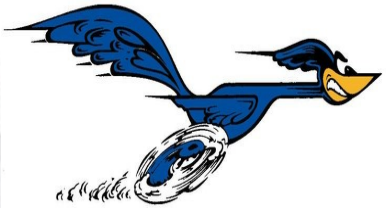
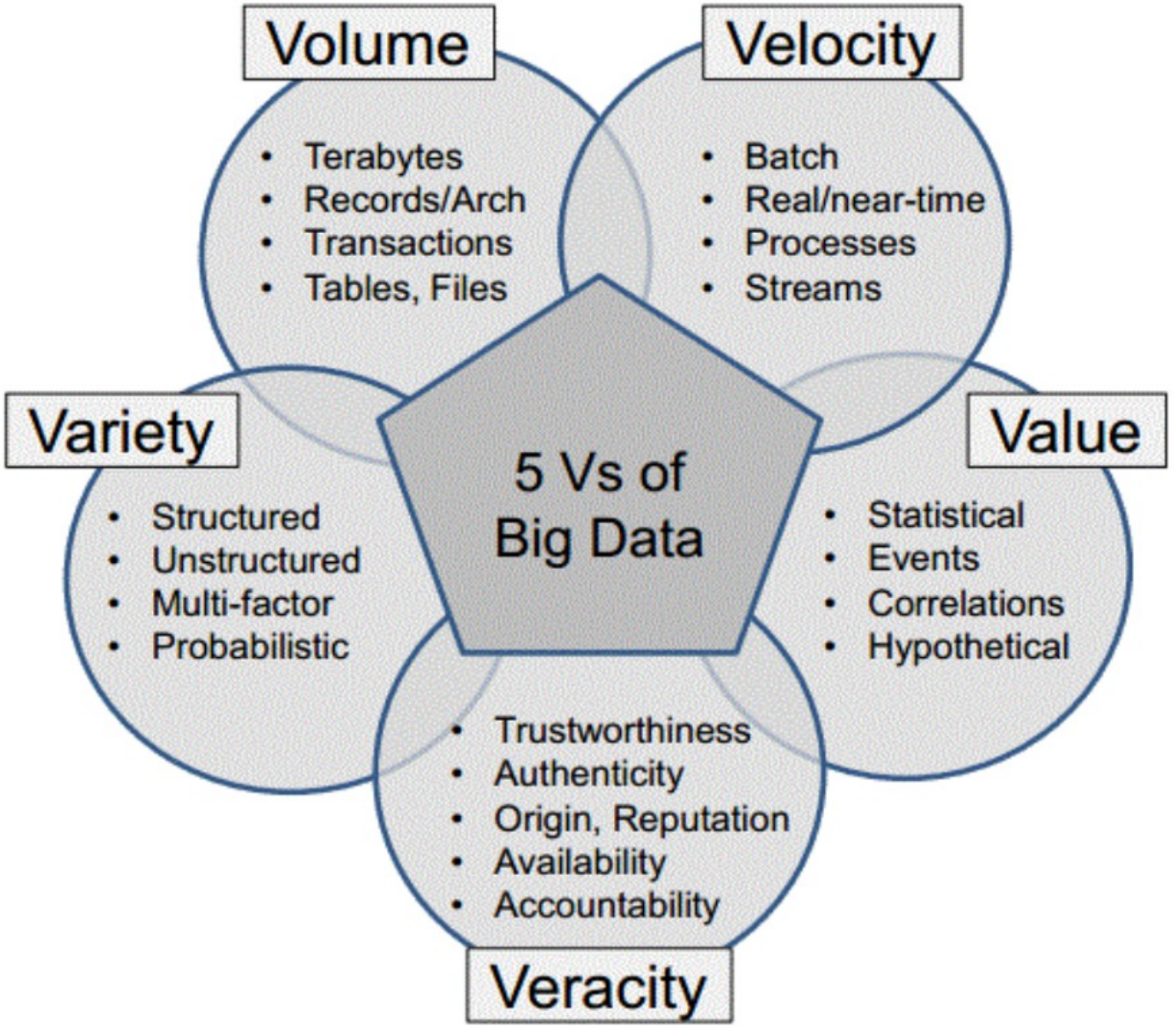


The 3 V's of Big Data

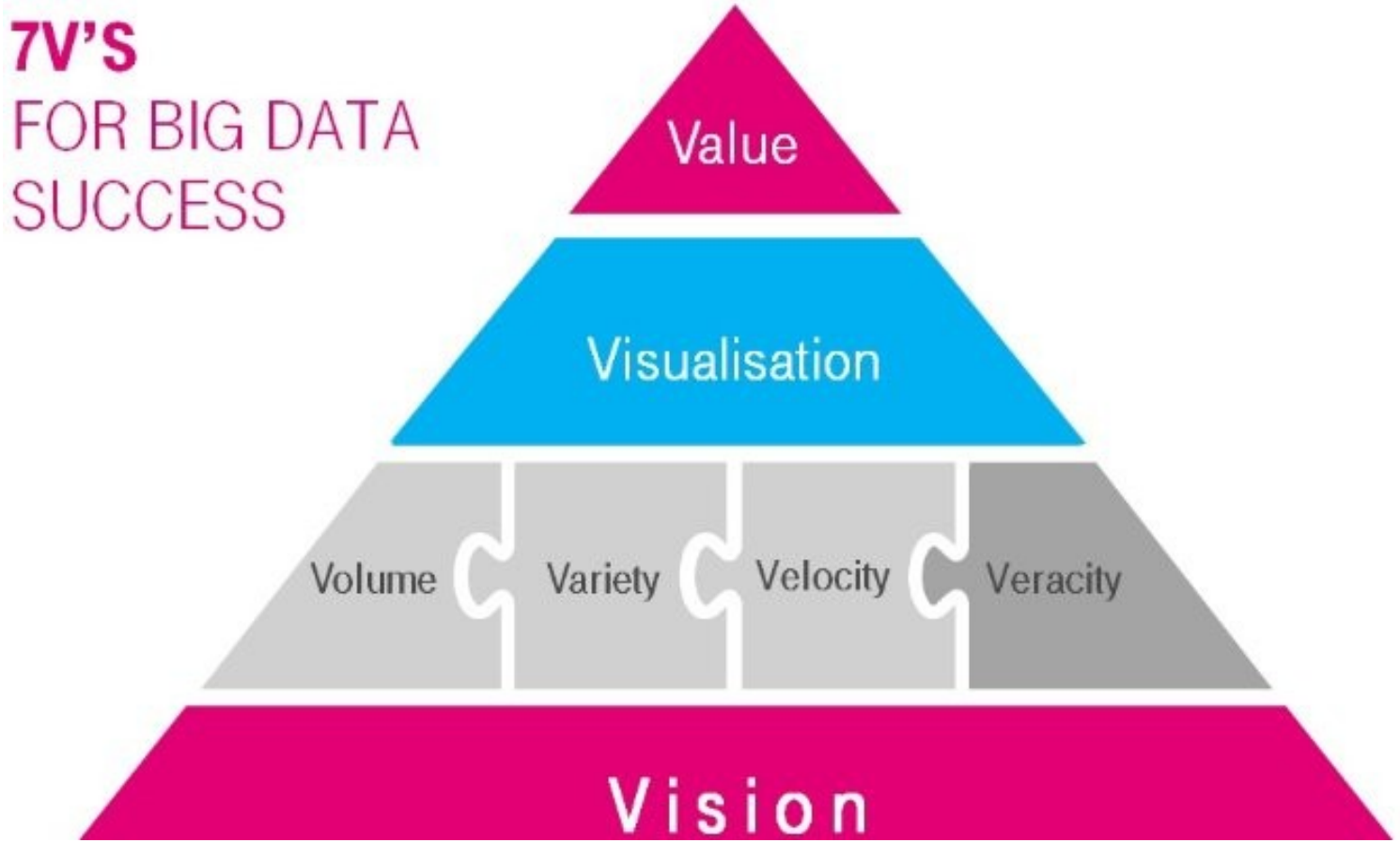




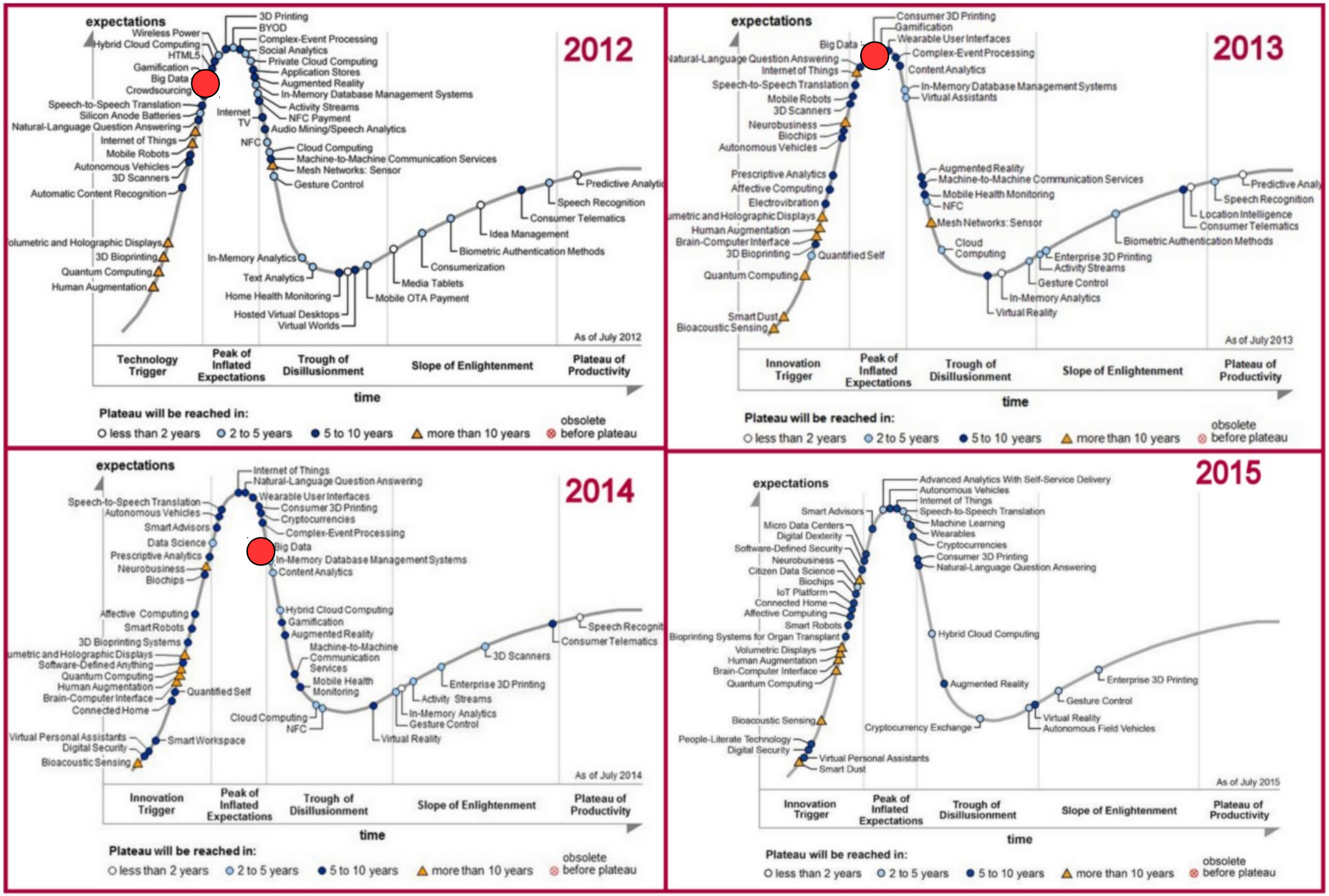
The 5 V's of Big Data



The 7 V's of Big Data



Big Data is not a Hype



Motivation

We need **more CPUs** because:

- we can run programs faster

We need **more disks** because:

- modern applications require huge amounts of data
- with many disks we can perform I/O in parallel

Assume that we are able to build a single disk with **500 TB** capacity. This is enough to store more than **20 billion webpages** (assuming an average size per page of **20KB**).

However, **just to scan** these 500 TB we need **more than 4 months** if the disk can bring **40 MB/sec**. Imagine the time required to process the data !

In the Near Future

"***IBM Research*** *and Dutch astronomy agency* ***Astron*** *work on new technology to handle*

one exabyte of raw data per day

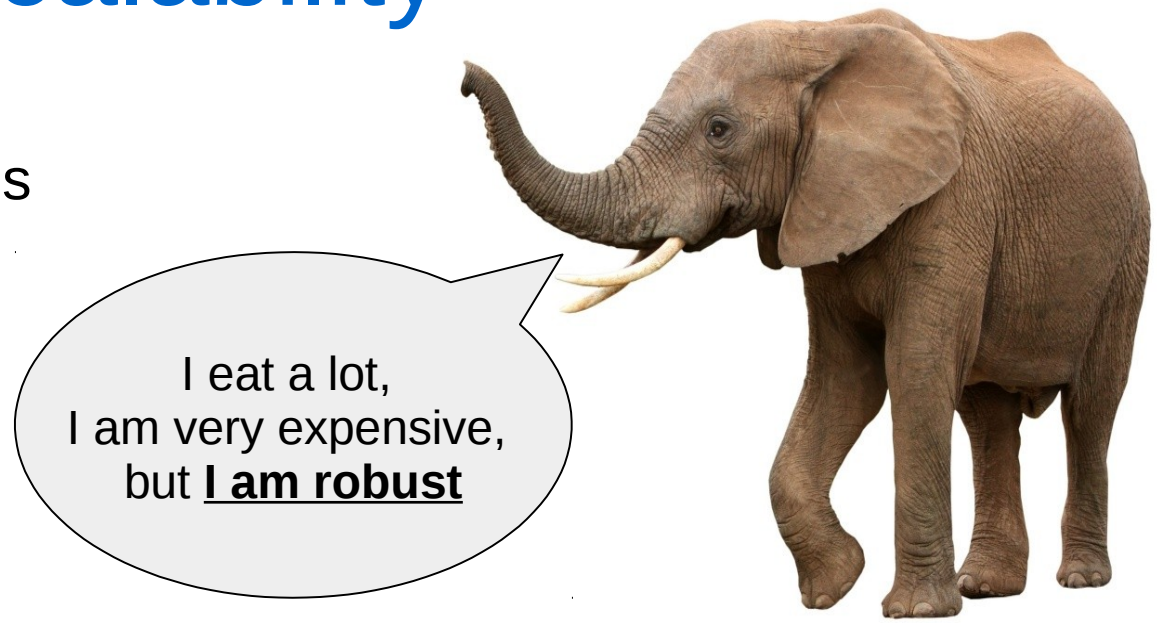
that will be gathered by the world largest radio telescope, the ***Square Kilometer Array****, when activated in* ***2024***."

Some Challenges

- Scalability
- Load balancing
- Fault Tolerance
- Efficiency
- Data Stream processing
- Support for complex objects
- Accuracy/Speed tradeoffs (with performance guarantees)

Scalability

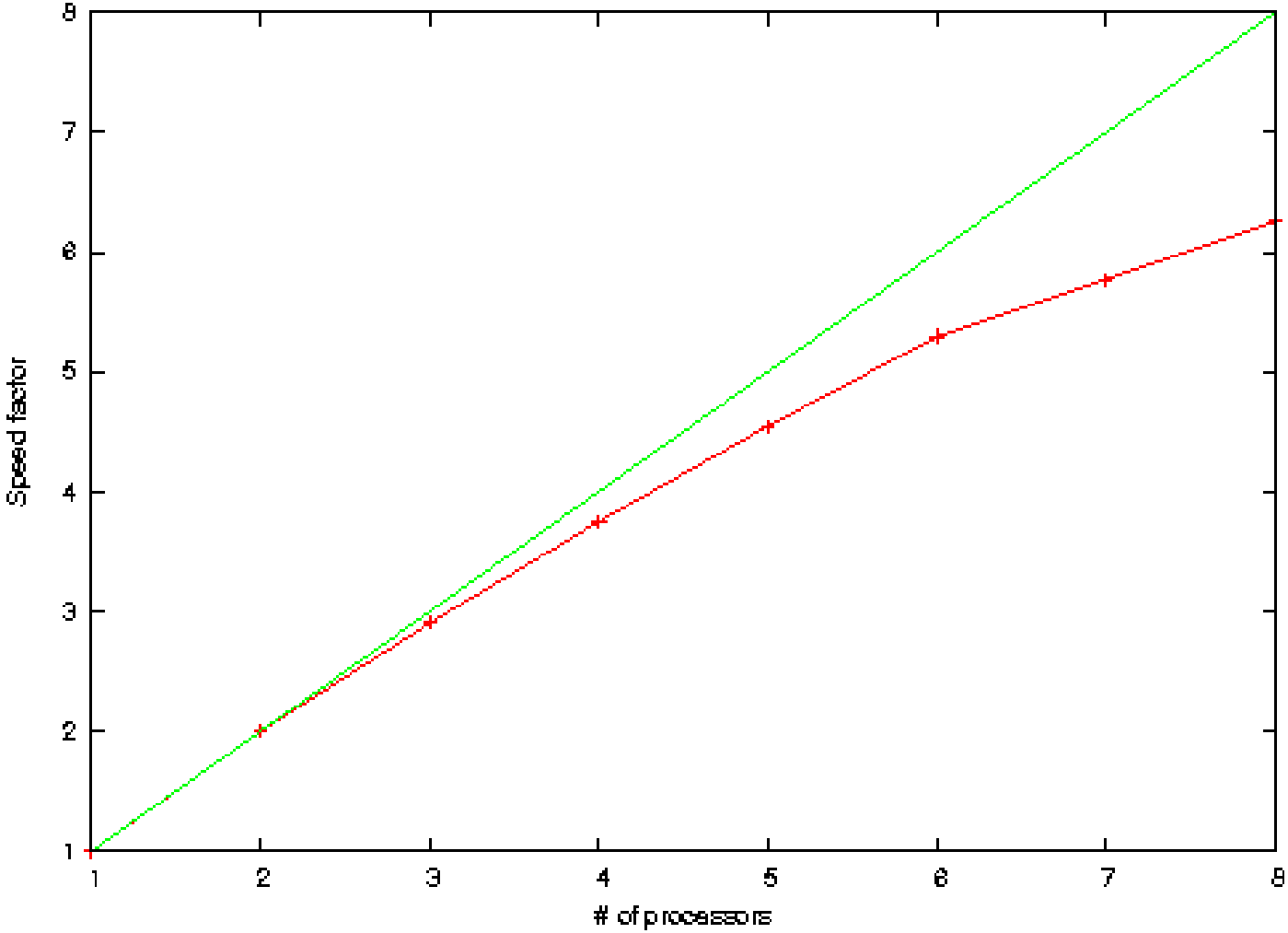
Scale-Up: put more resources into the system to make it bigger and more powerful



Scale-Out: connect a large number of “ordinary” machines and create a cluster

Scale-Out is **more powerful** than Scale-Up, and also **less expensive**

The Speedup Curve



Real Curves are Non-Linear

Why ?

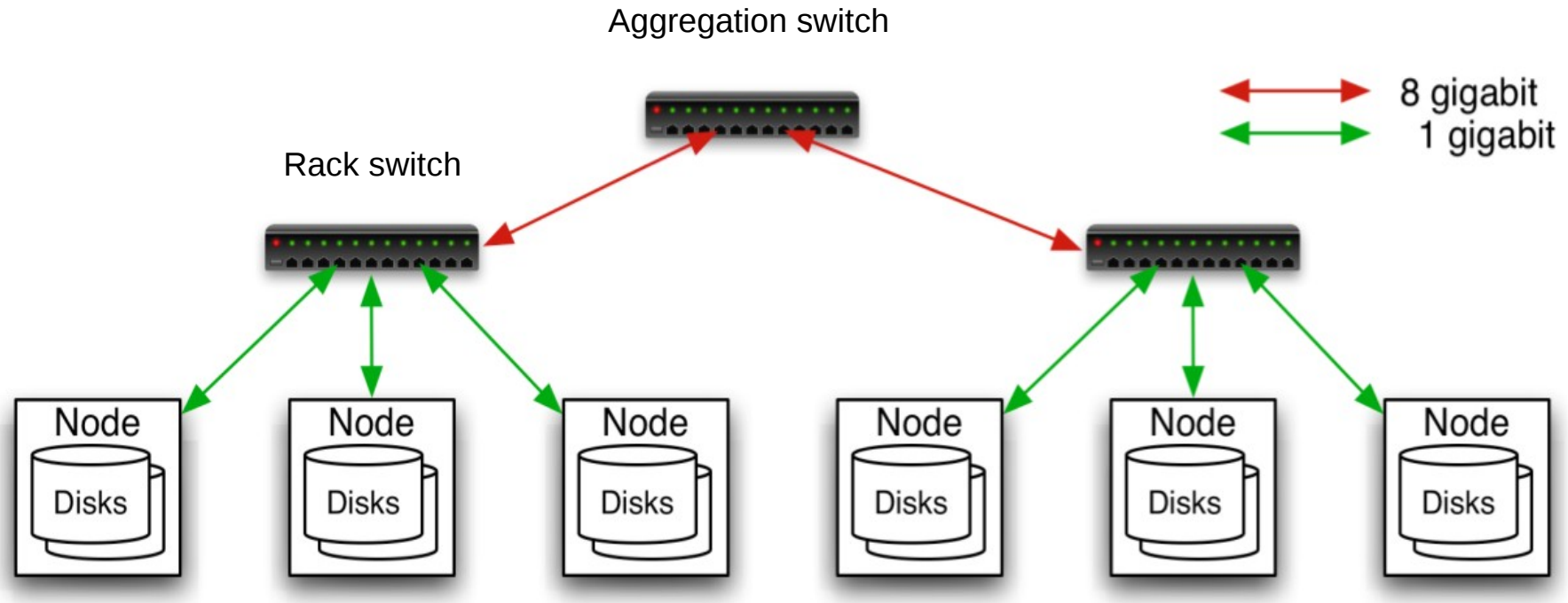
Start-up costs: cost for starting an operation in a processor

Interference: cost for communication among processors and resource congestion

Skew: either in data or tasks → the slowest processor becomes the bottleneck

Result formation: partial results from each processor must be combined to provide the final result.

Cluster Configuration Example



- 40 nodes/rack, 1000-4000 nodes in cluster
- 1 Gbps bandwidth within rack, 8 Gbps out of rack
- 8 x 2GHz cores, 8 GB RAM, 4 disks (= 4 TB?)

Source: Matei Zaharia

Fault Tolerance

Failures are very common in massively parallel systems

Let *P* the probability that a disk will fail in the next month. If we have *D* disks in total, the probability that at least one disk will fail is given by:

$$Prob\{at\_least\_one\_disk\_failure\} = 1 - (1 - P)^D$$

e.g., *D* = 10000, *P* = 0.0001

Prob {*at least one disk failure*} = 0.63

Fault Tolerance

Failures may happen because of:

Hardware not working properly

- Disk failure
- Memory failure (8% of DIMMs have problems)
- Inadequate cooling (CPU overheating)

Resource unavailability

- Due to overload

We must provide fault tolerance in the cluster!

Fault Tolerance

Simplest protocol: if there is a failure, restart the job.

Assume a job that requires 1 week of processing. If there is a failure once per week, the job will never finish!

Fault Tolerance

A better protocol:

Replicate the data and also split the job in parts and replicate them as well. As an alternative, submit a smaller job (task) and if it fails then start another one.

A large job must be decomposed to simpler ones.

Meet Hadoop

A very successful platform to run jobs in massively parallel systems (thousands of processors and disks).

It contains **many different components**. We will focus on:

- the Hadoop MapReduce layer
- the YARN resource manager
- the Hadoop Distributed File System (HDFS)

Hadoop is the open-source alternative of MapReduce and Google File System (GFS) invented by Google. It has been used in Google's data centers mainly for:

- constructing and maintaining the **Inverted Index** and
- executing the **PageRank** algorithm.

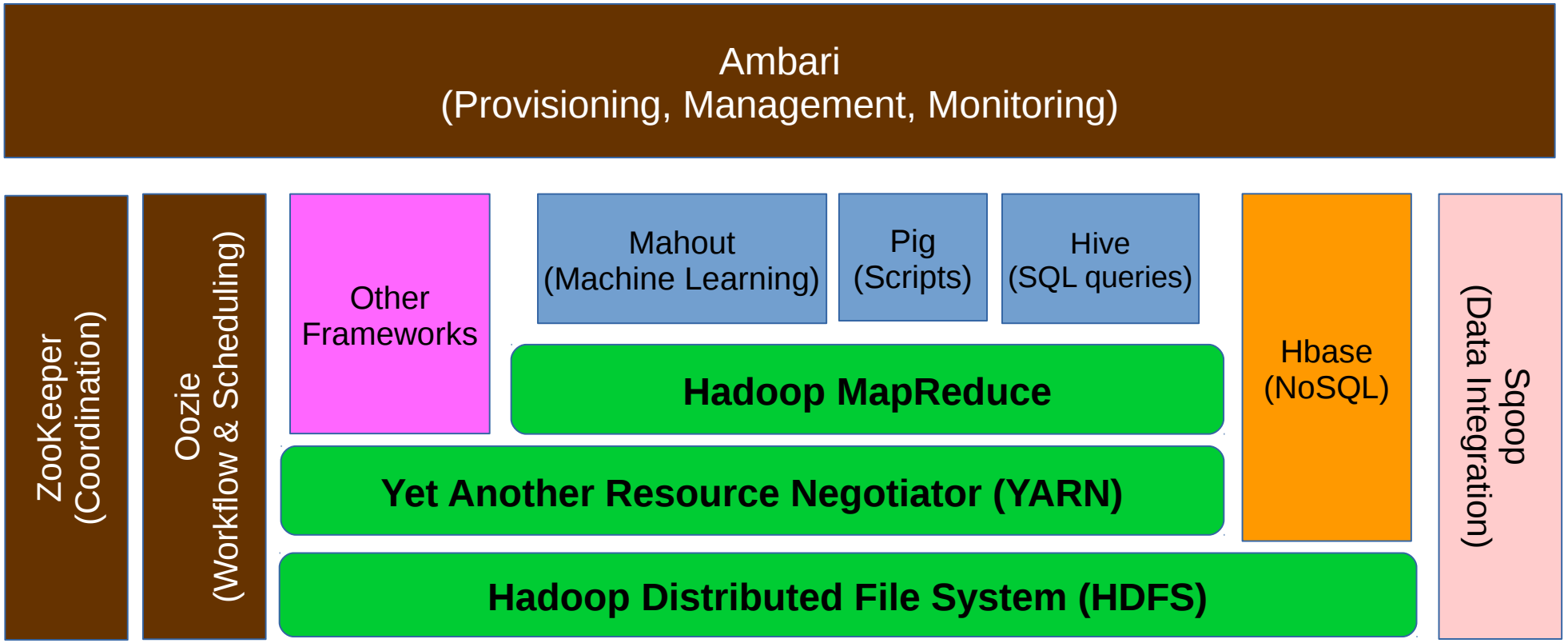
Meet Hadoop

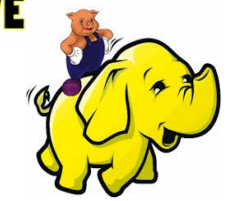
Doug Cutting, explains how the name came about

From Wikipedia: *Douglass Read "Doug" Cutting is an advocate and creator of open-source search technology. He originated* ***Lucene*** *and, with Mike Cafarella,* ***Nutch****, both open-source search technology projects which are now managed through the Apache Software Foundation. He is also the creator of* ***Hadoop*** *(Yahoo!, Cloudera).*

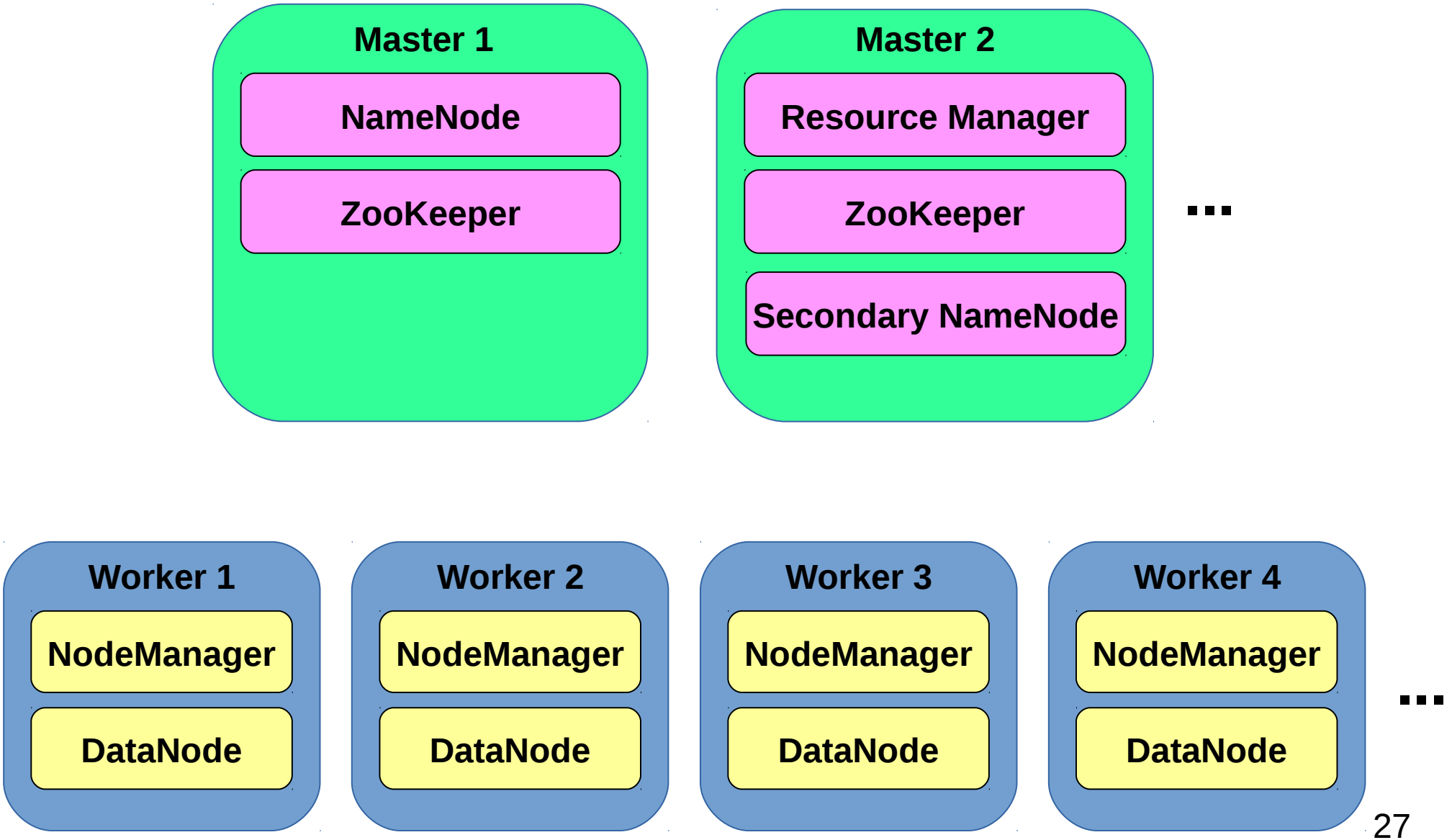
"The name my kid gave a **stuffed yellow elephant**. Short, relatively easy to spell and pronounce, meaningless, and not used elsewhere: those are my naming criteria. Kids are good at generating such. Googol is a kid's term"

The Hadoop Ecosystem





Hadoop Cluster Architecture



HDFS Architecture

HDFS stands for **Hadoop Distributed File System**

It is a File System that lives across the nodes of a cluster. It stores files, each file has a filename and is located in a specific directory.

It supports most of the operations supported by an ordinary File System.

Every HDFS cluster is comprised of:

- one or two **NameNodes** and
- many **DataNodes**

HDFS Architecture

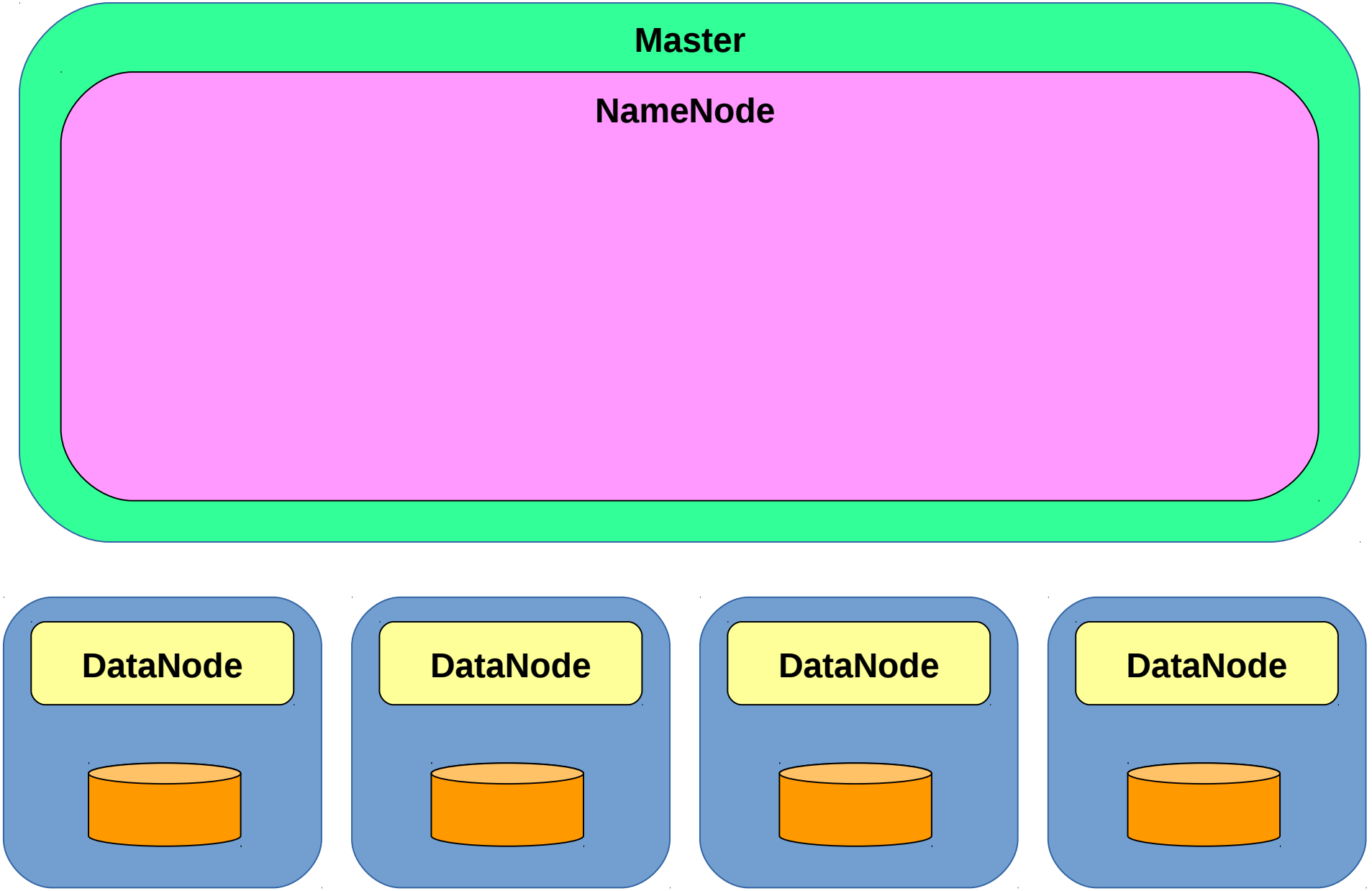
NameNode (one or two per cluster)

- Represents a single filesystem namespace rooted at /
- Is the master service of HDFS
- Determines and maintains how the chunks of data are distributed across the DataNodes
- Actual data never resides here, only metadata (e.g., maps of where blocks are distributed).

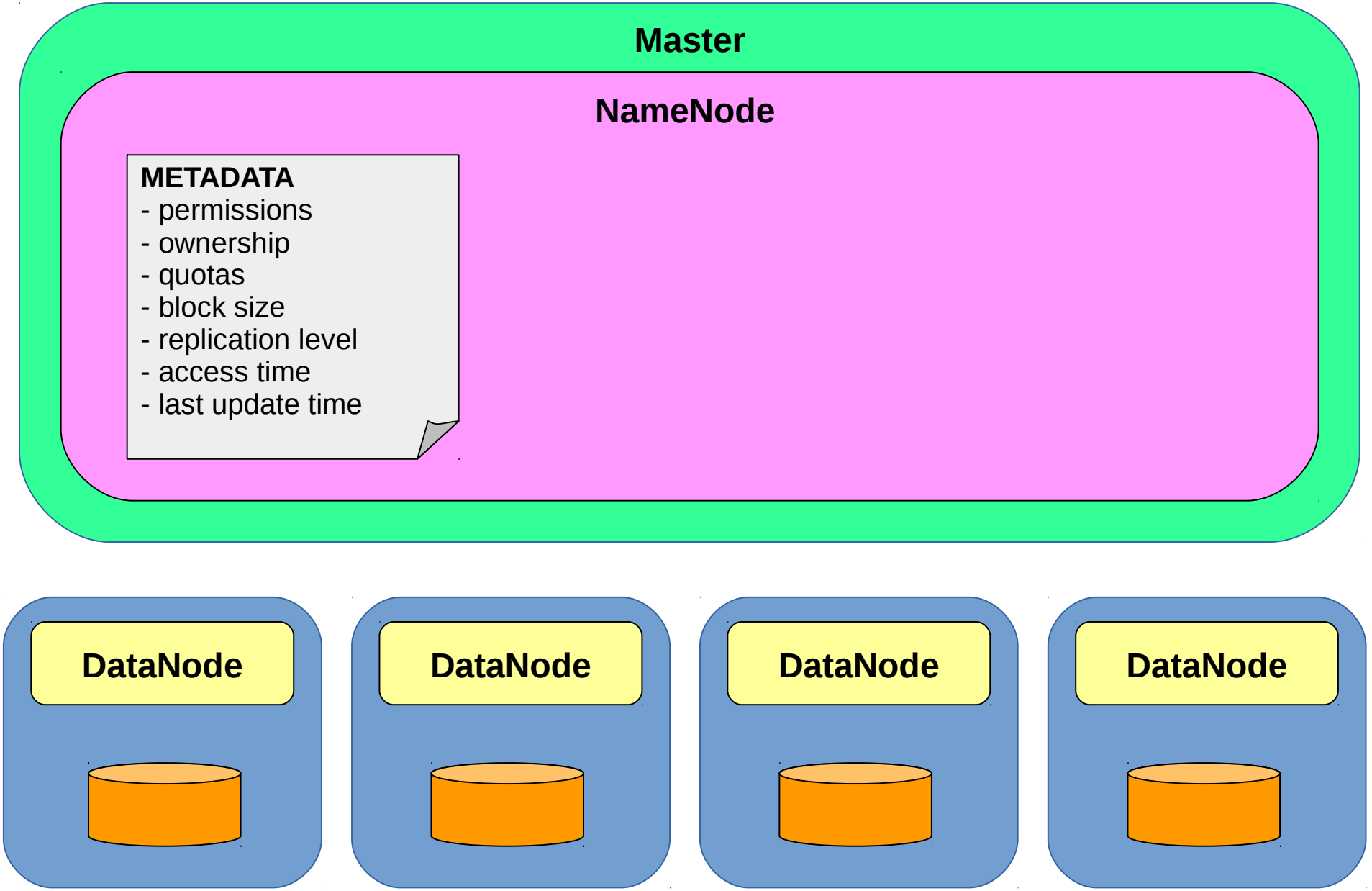
DataNode (as many as you want per cluster)

- Stores the chunks of data, and is responsible for **replicating** the chunks across other DataNodes
- Default number of replicas on most clusters is 3 (but it can be changed on a per-file basis)
- Default block size on most clusters is 128MB.

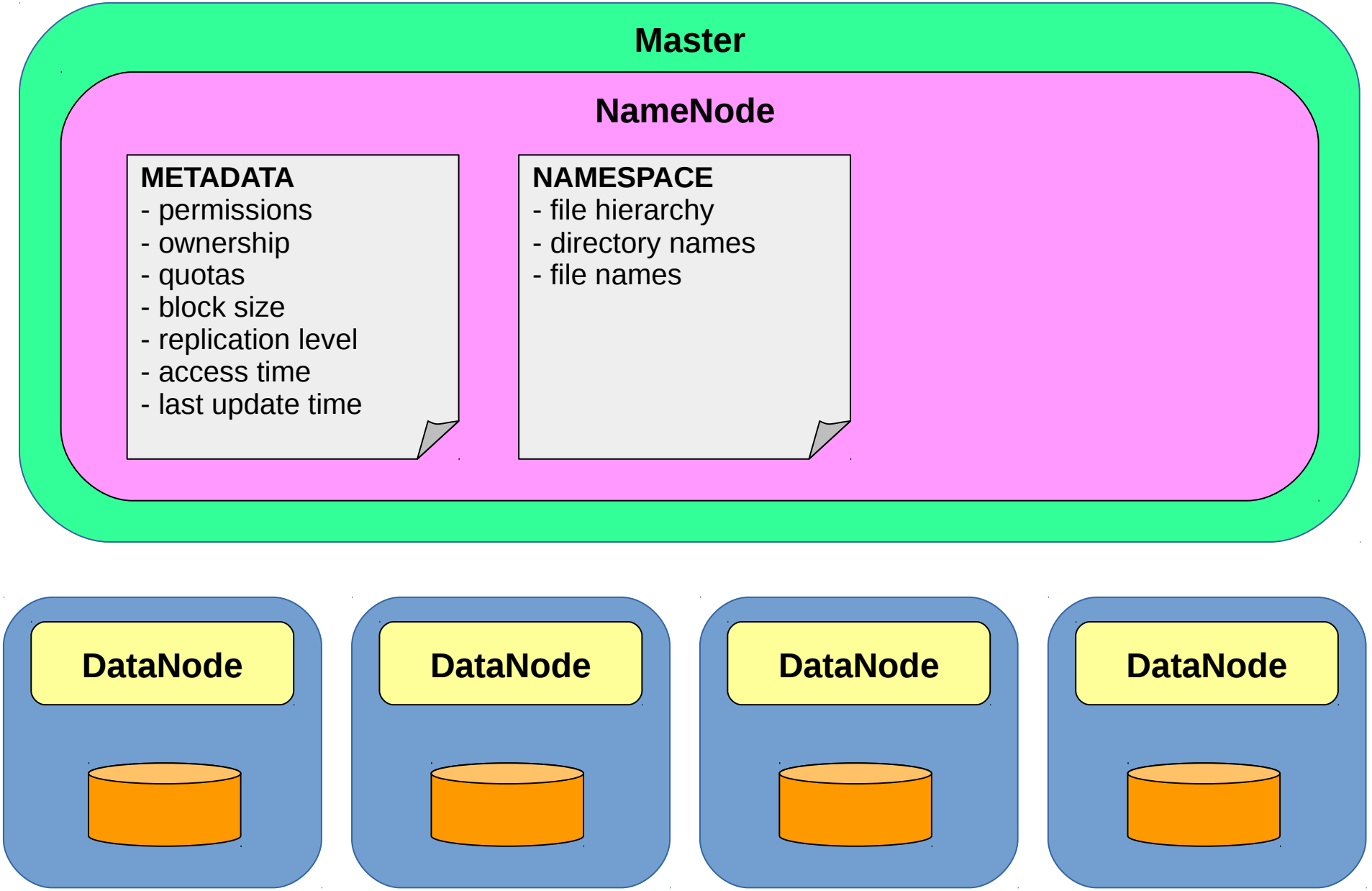
HDFS Architecture: NameNode



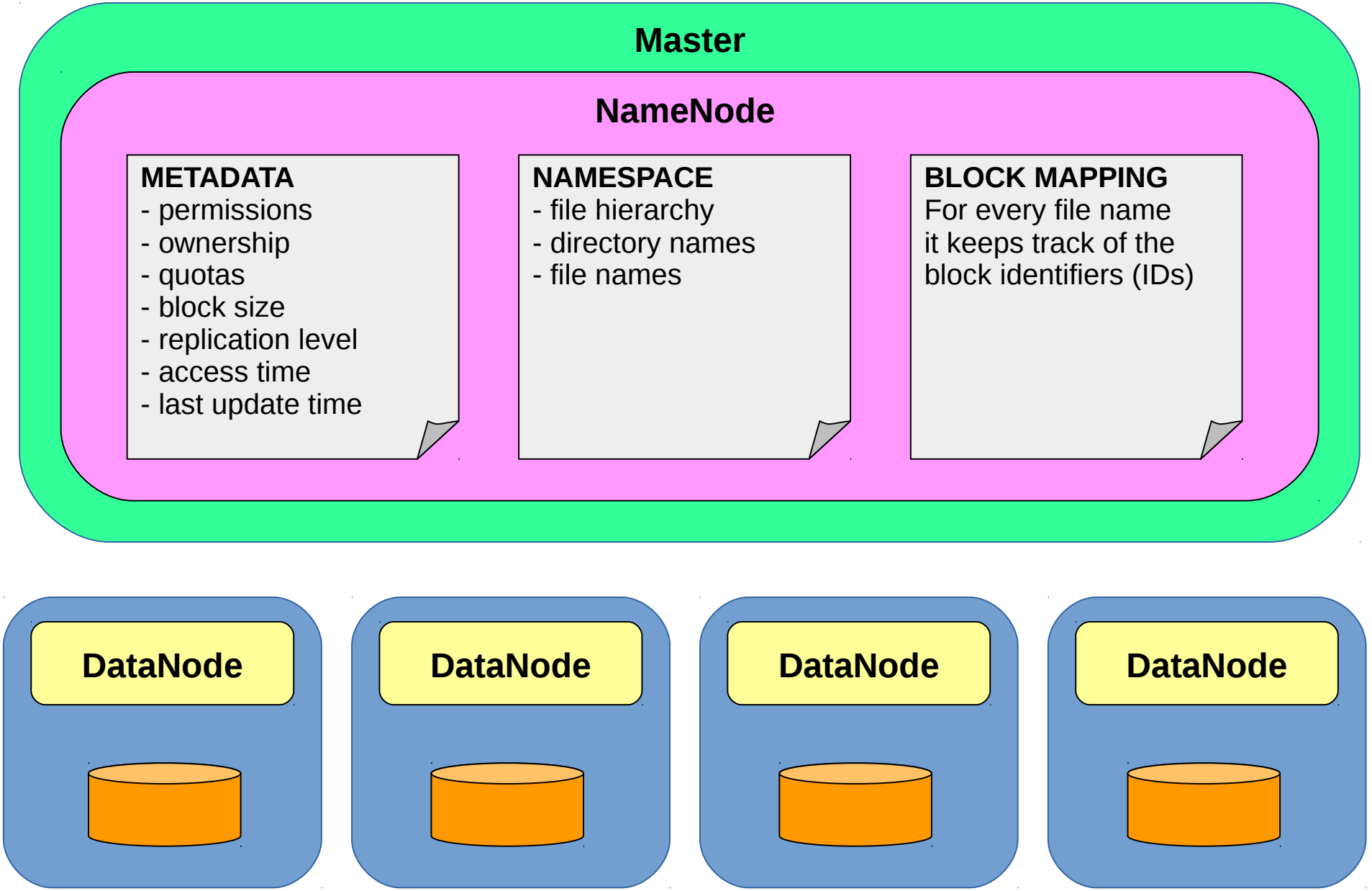
HDFS Architecture: NameNode



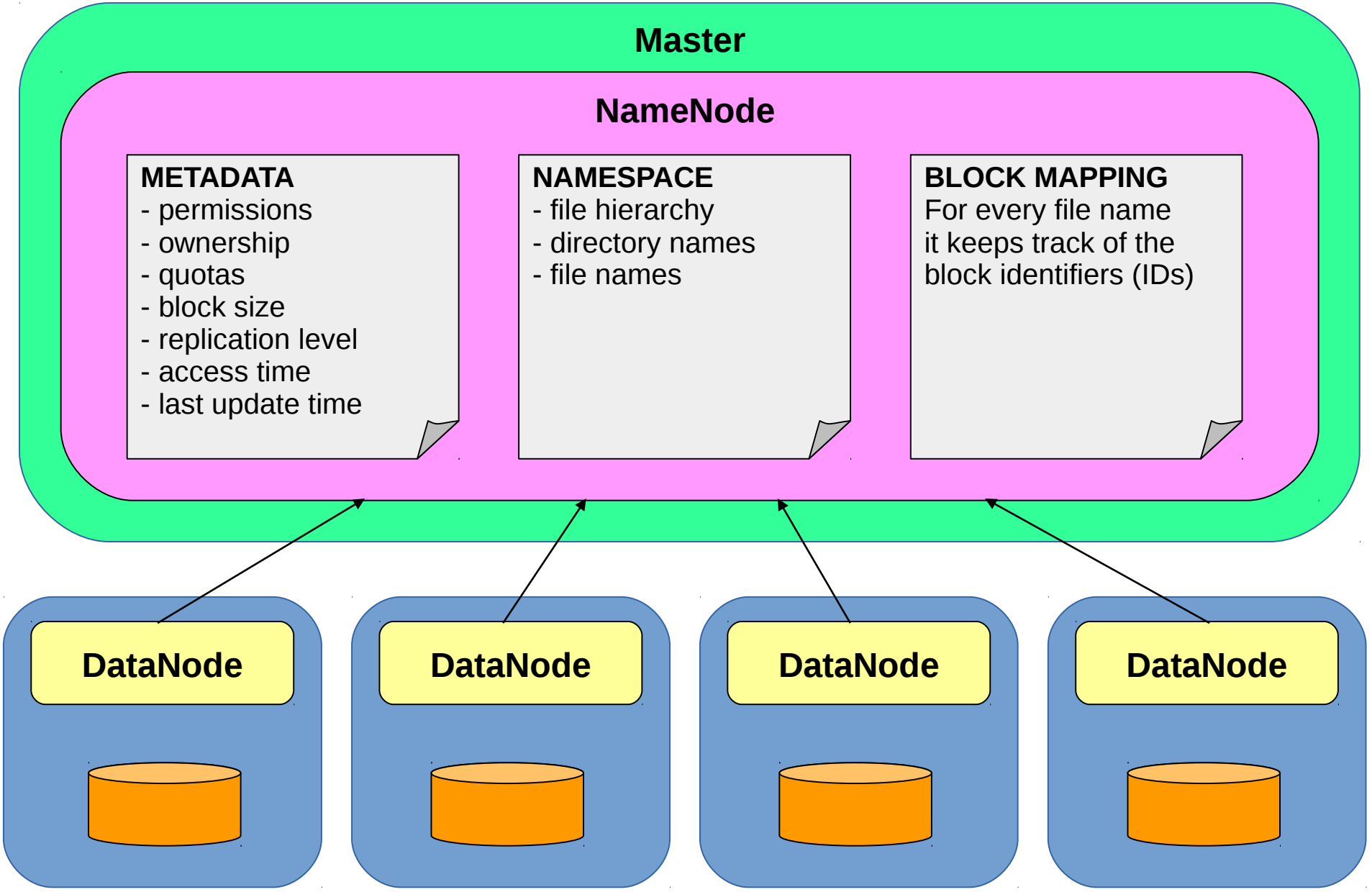
HDFS Architecture: NameNode



HDFS Architecture: NameNode



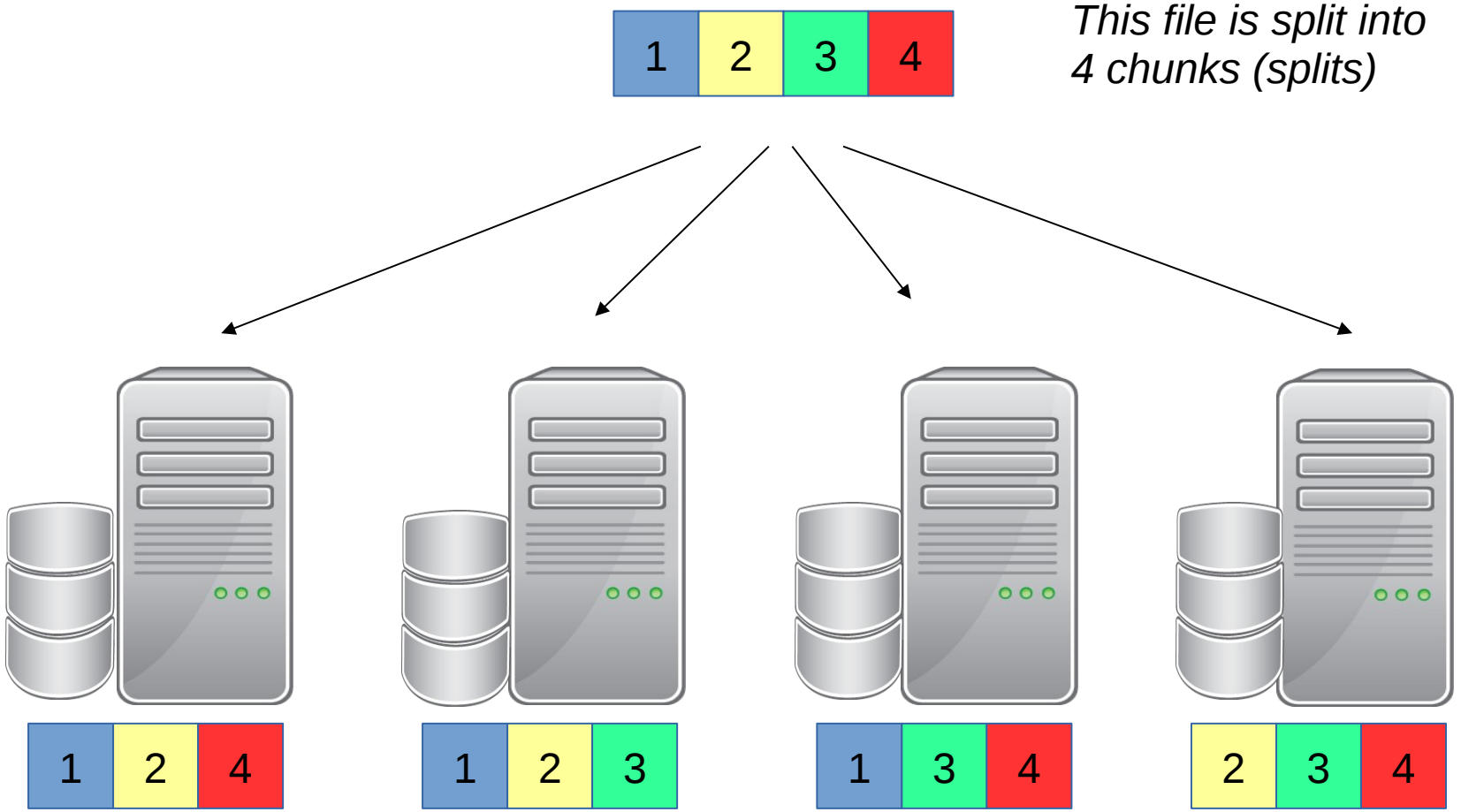
HDFS Architecture: NameNode



Important: DataNodes initiate connections to the NameNode (not vice versa)

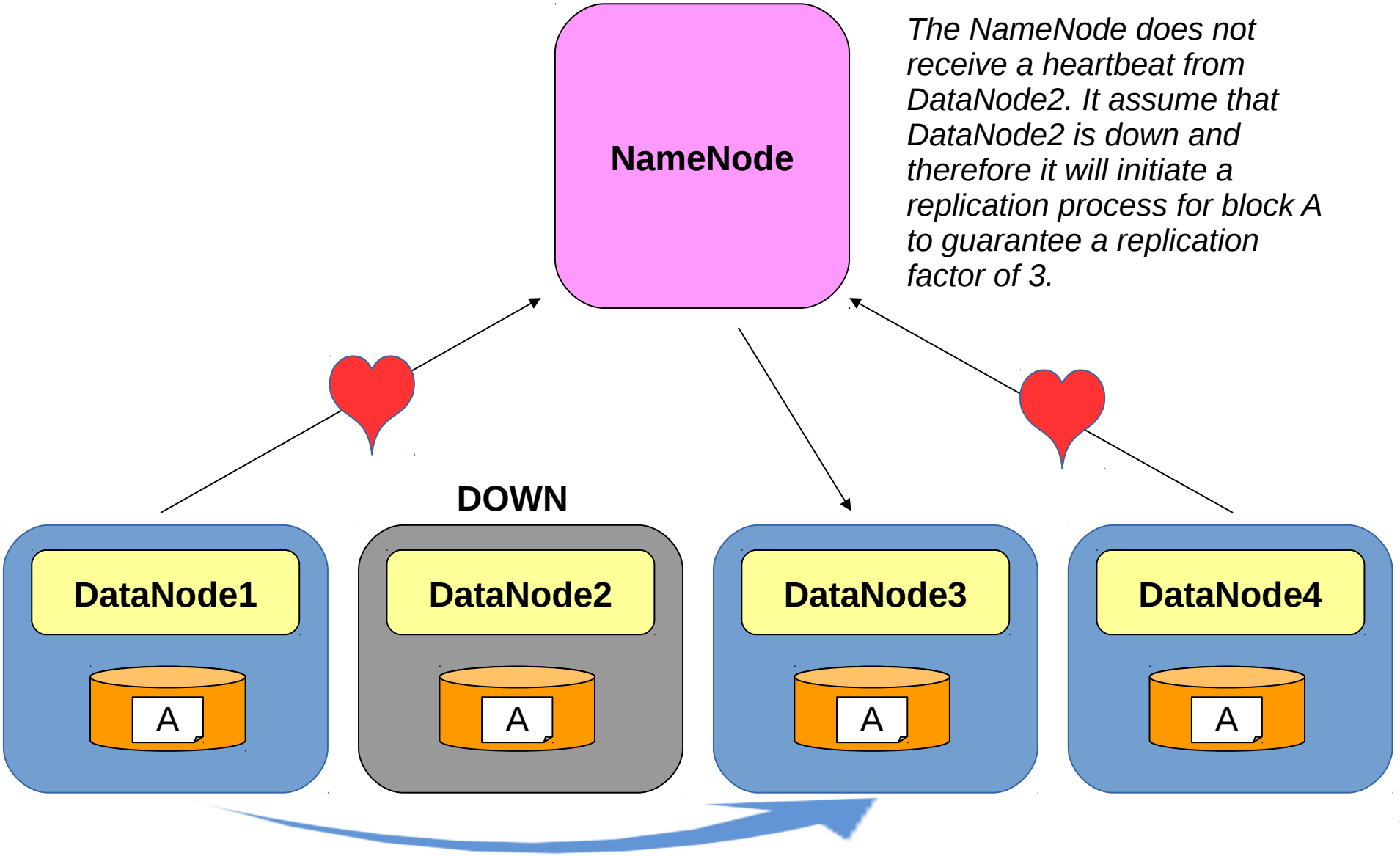
HDFS Architecture: replication

Replication in HDFS

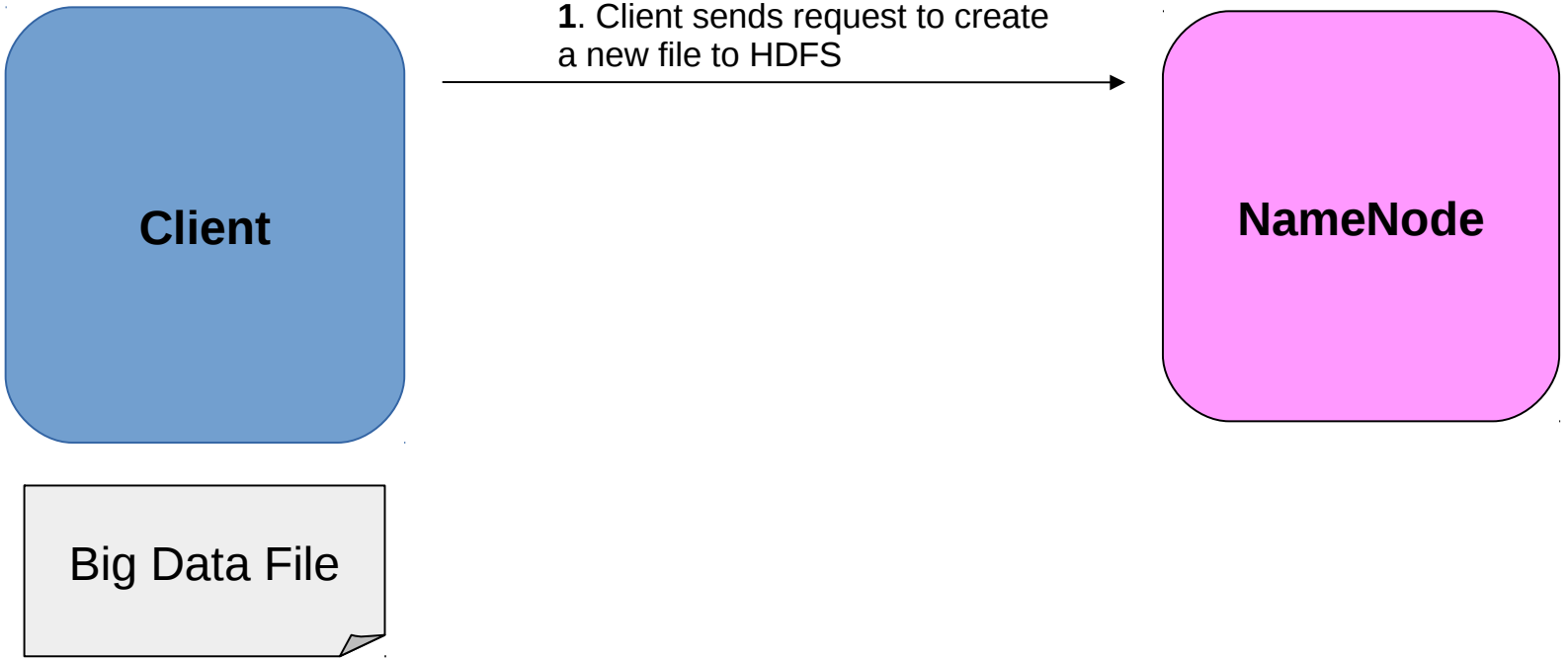


The the file is split in chunks. Each is replicated three times in this example. One of the chunk is located at a different rack for increased fault tolerance.

HDFS Architecture: replication



HDFS Architecture: writing a file



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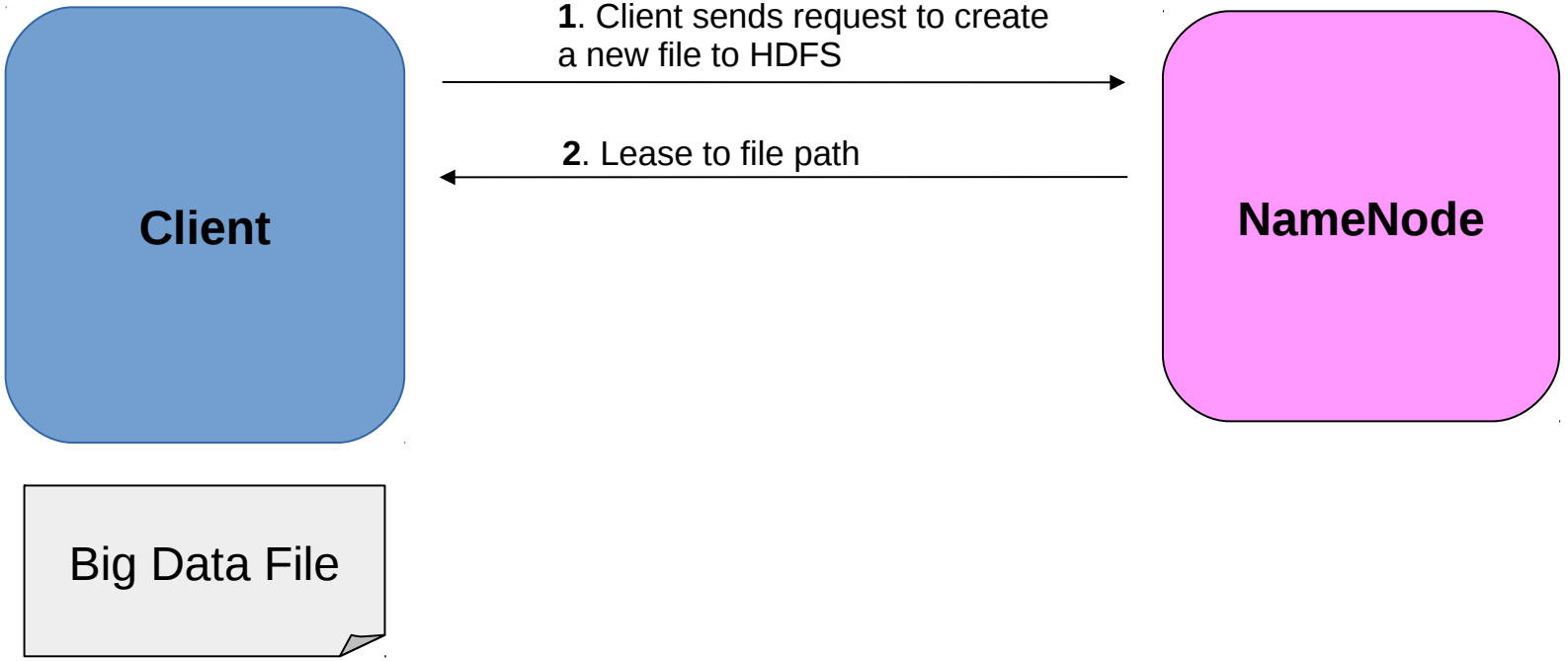

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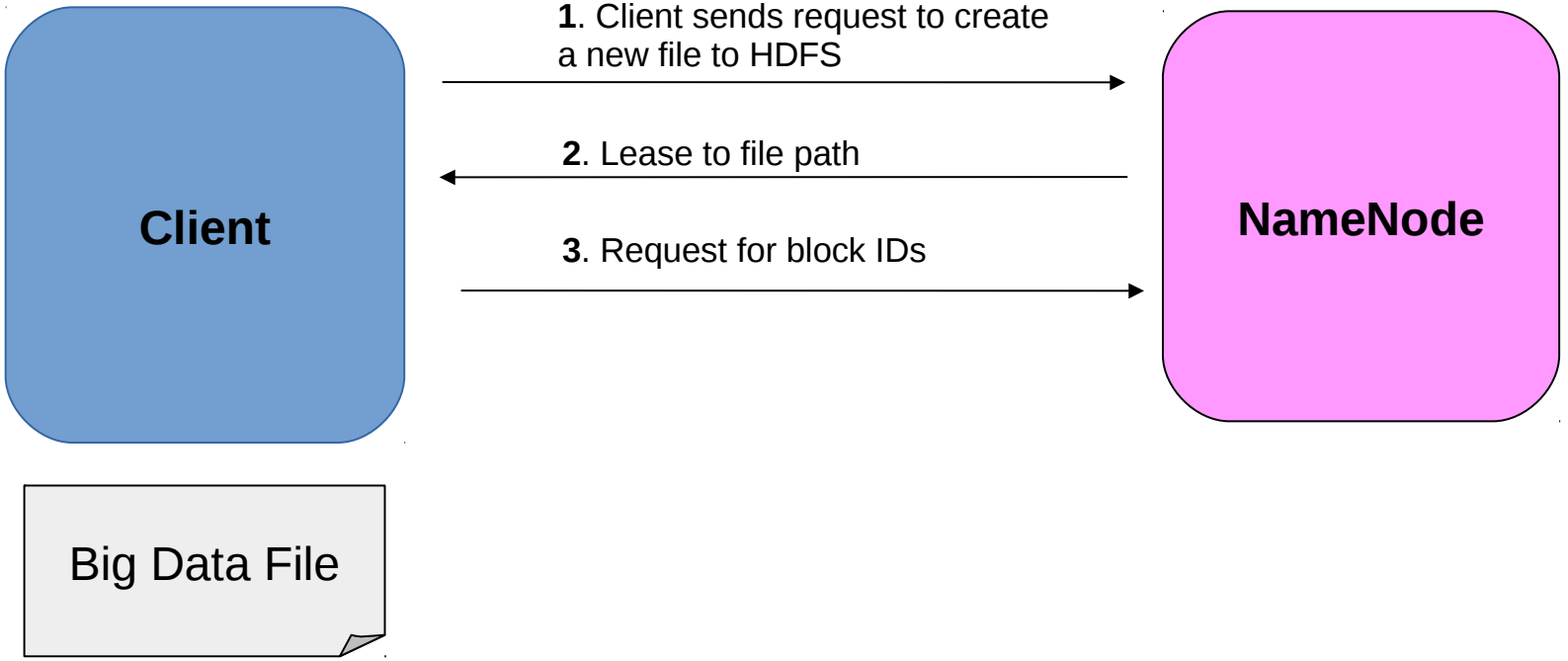

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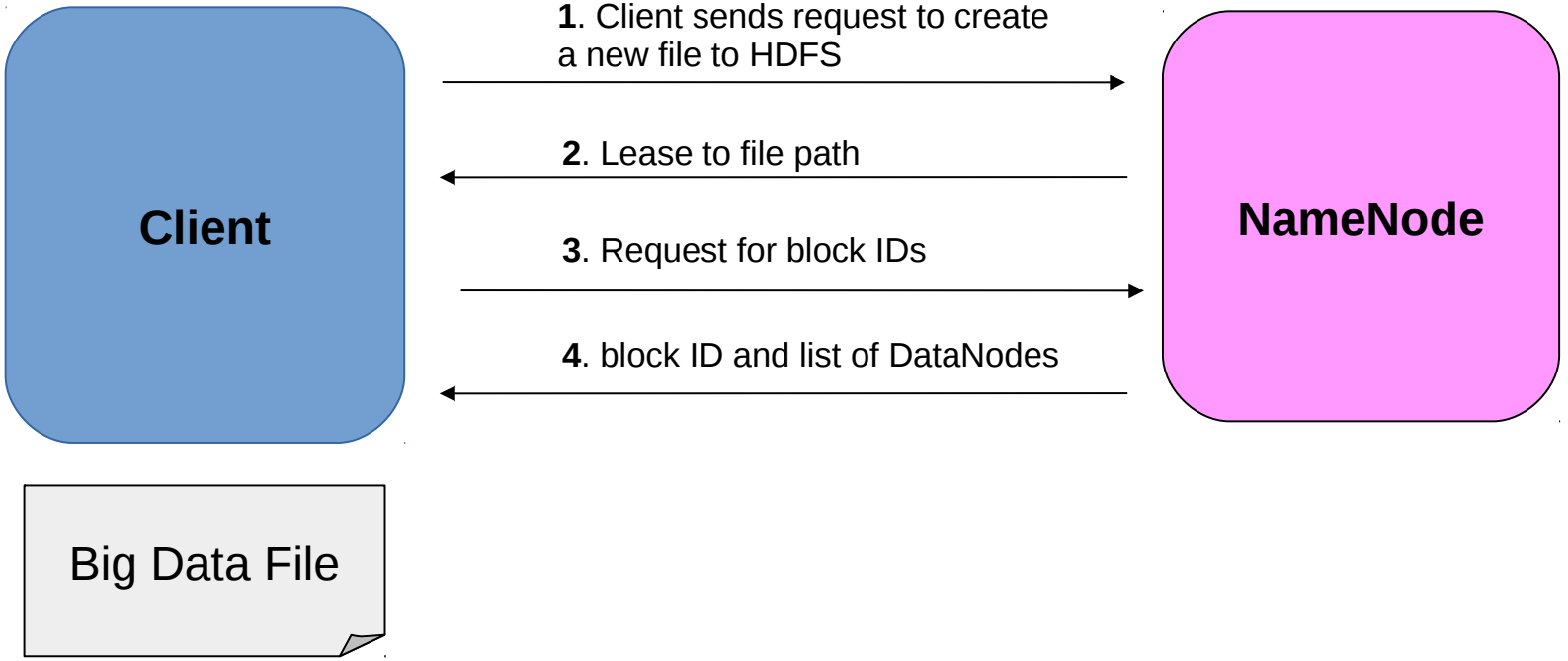

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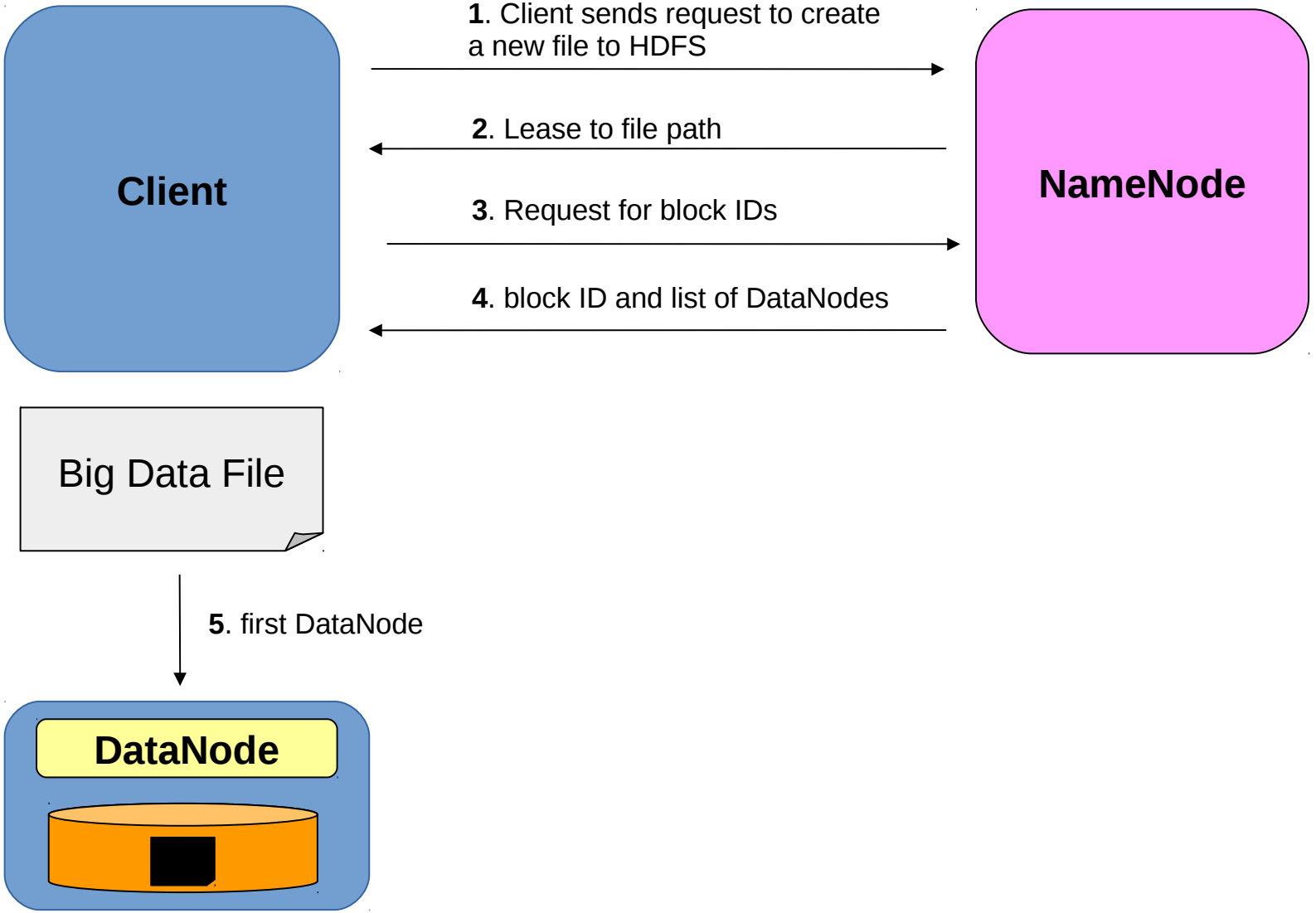

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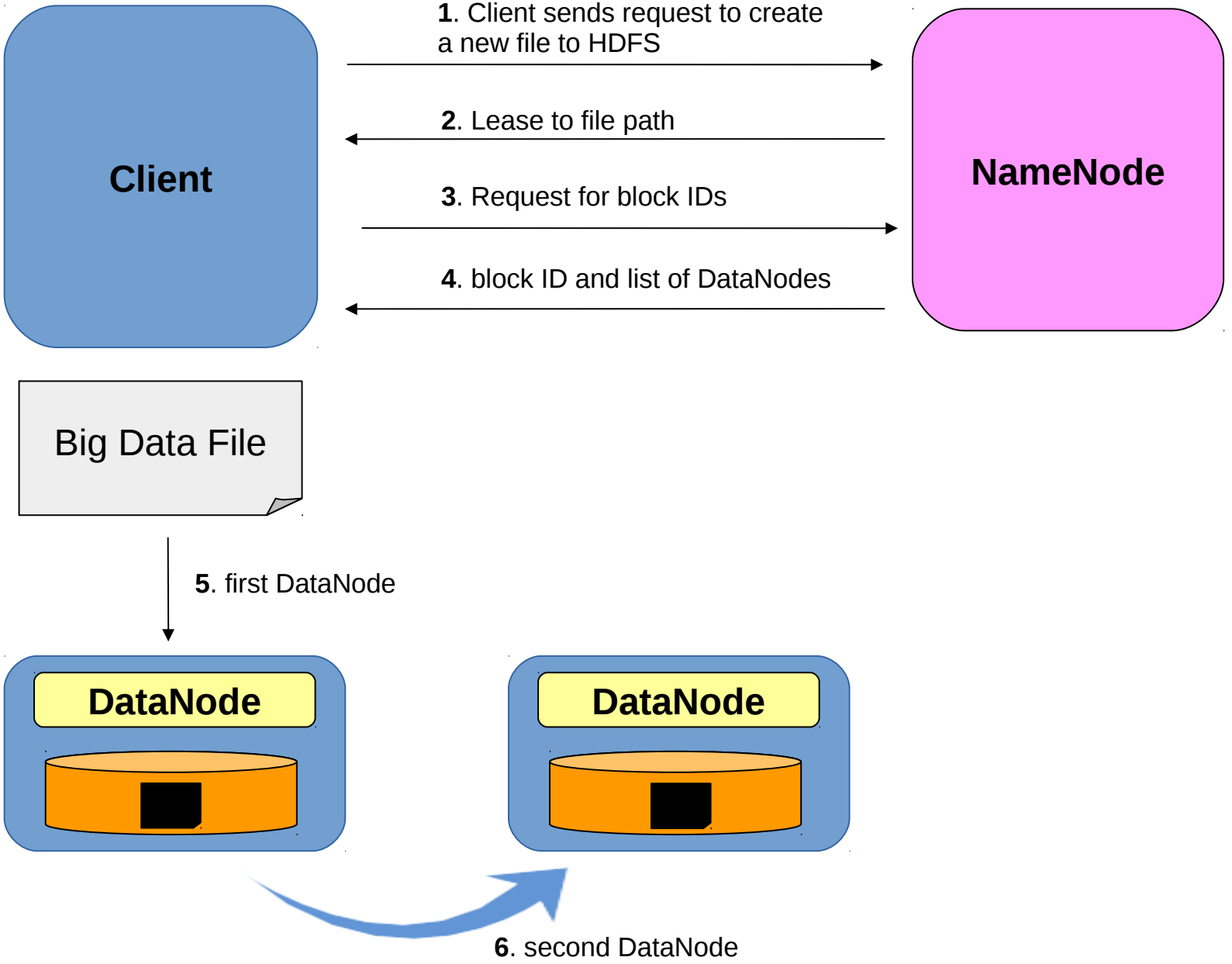

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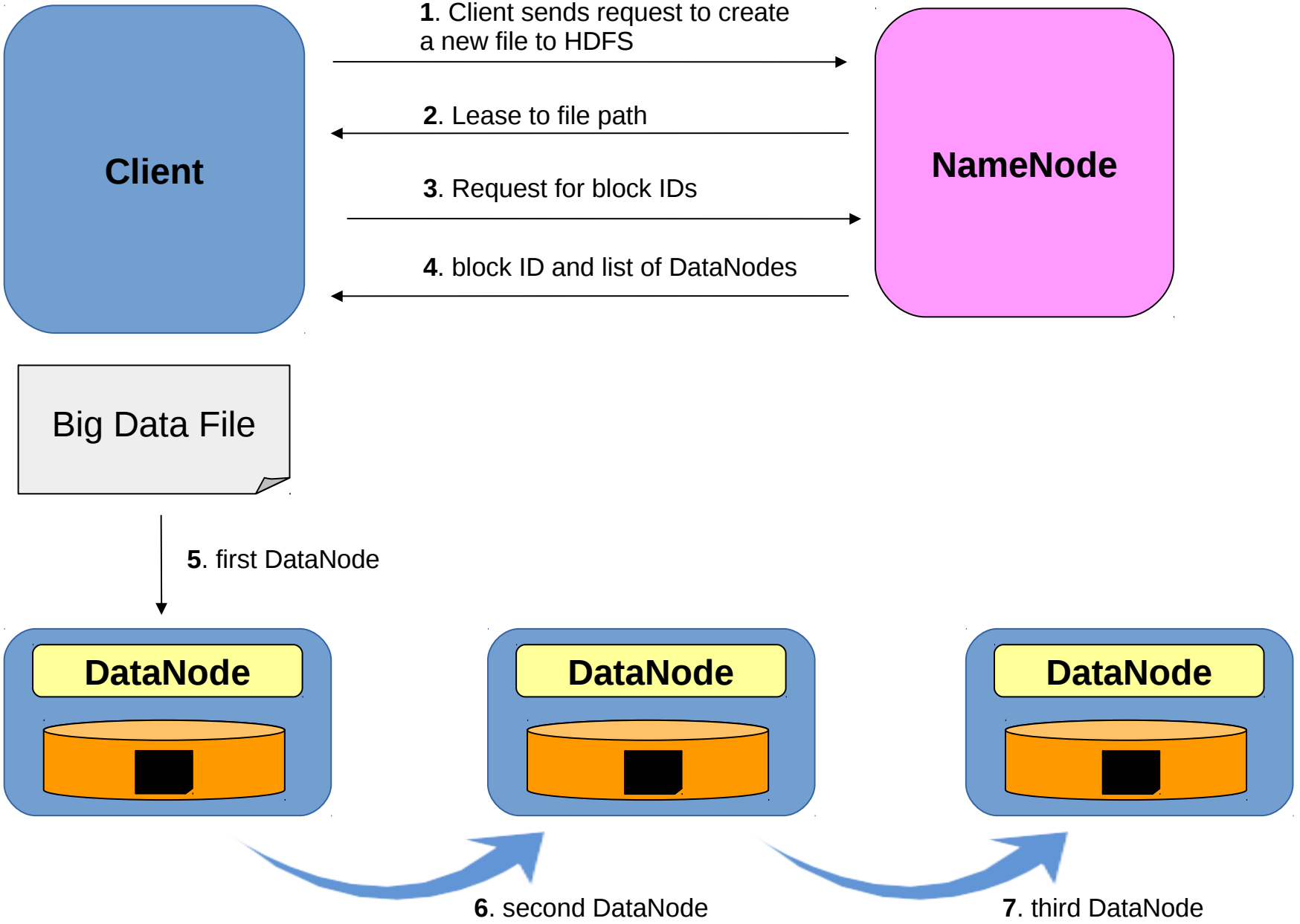
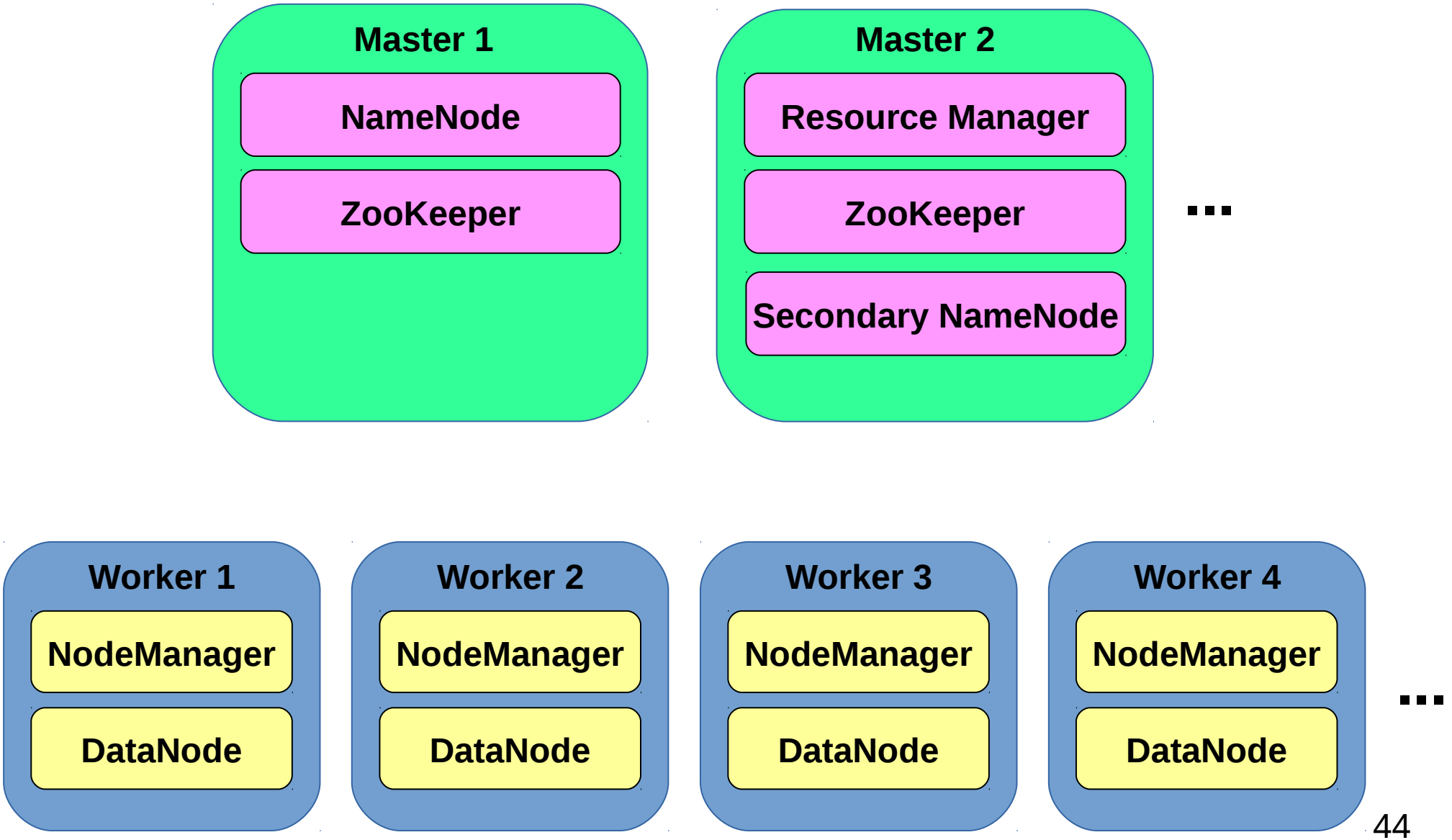
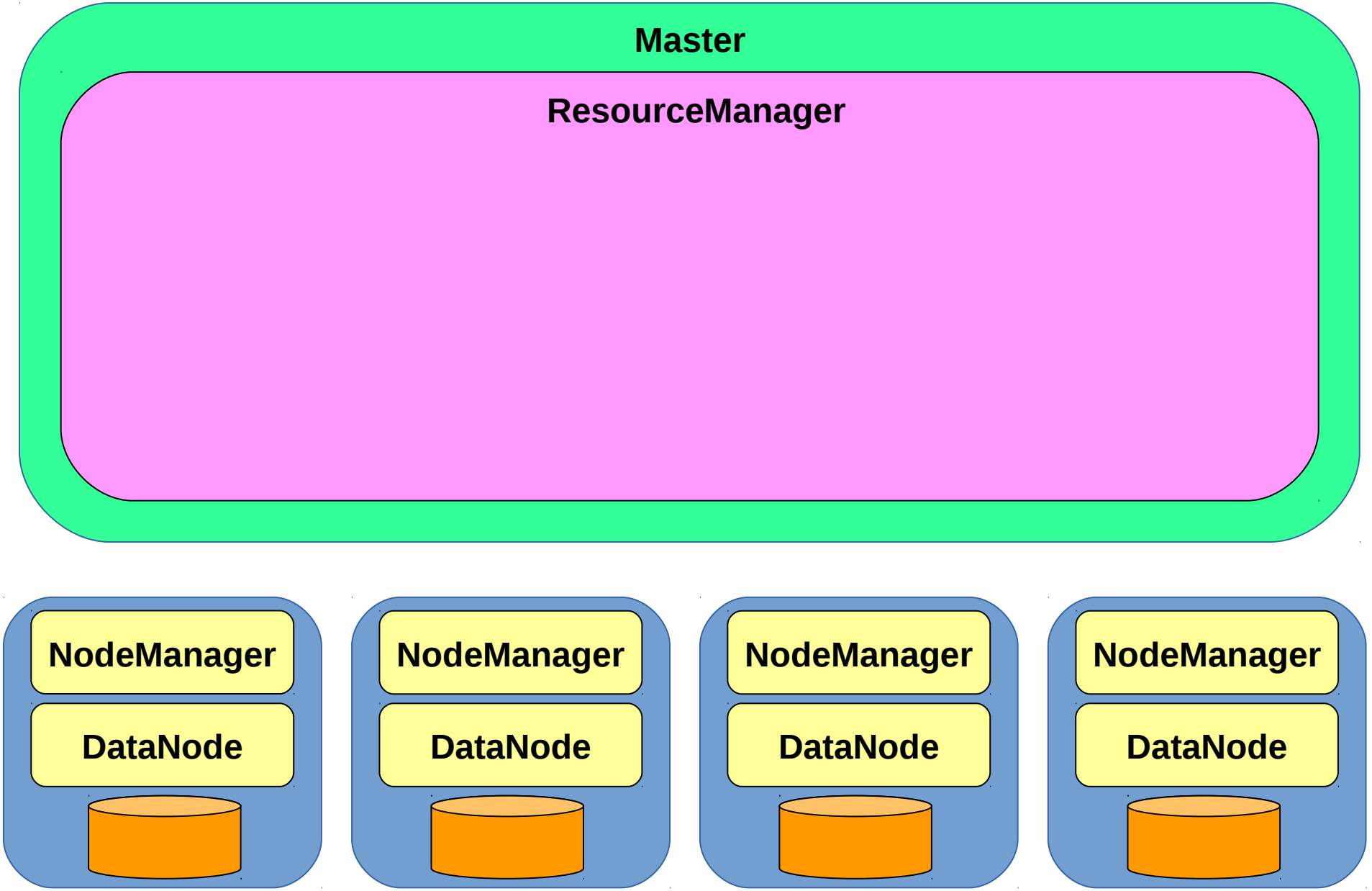


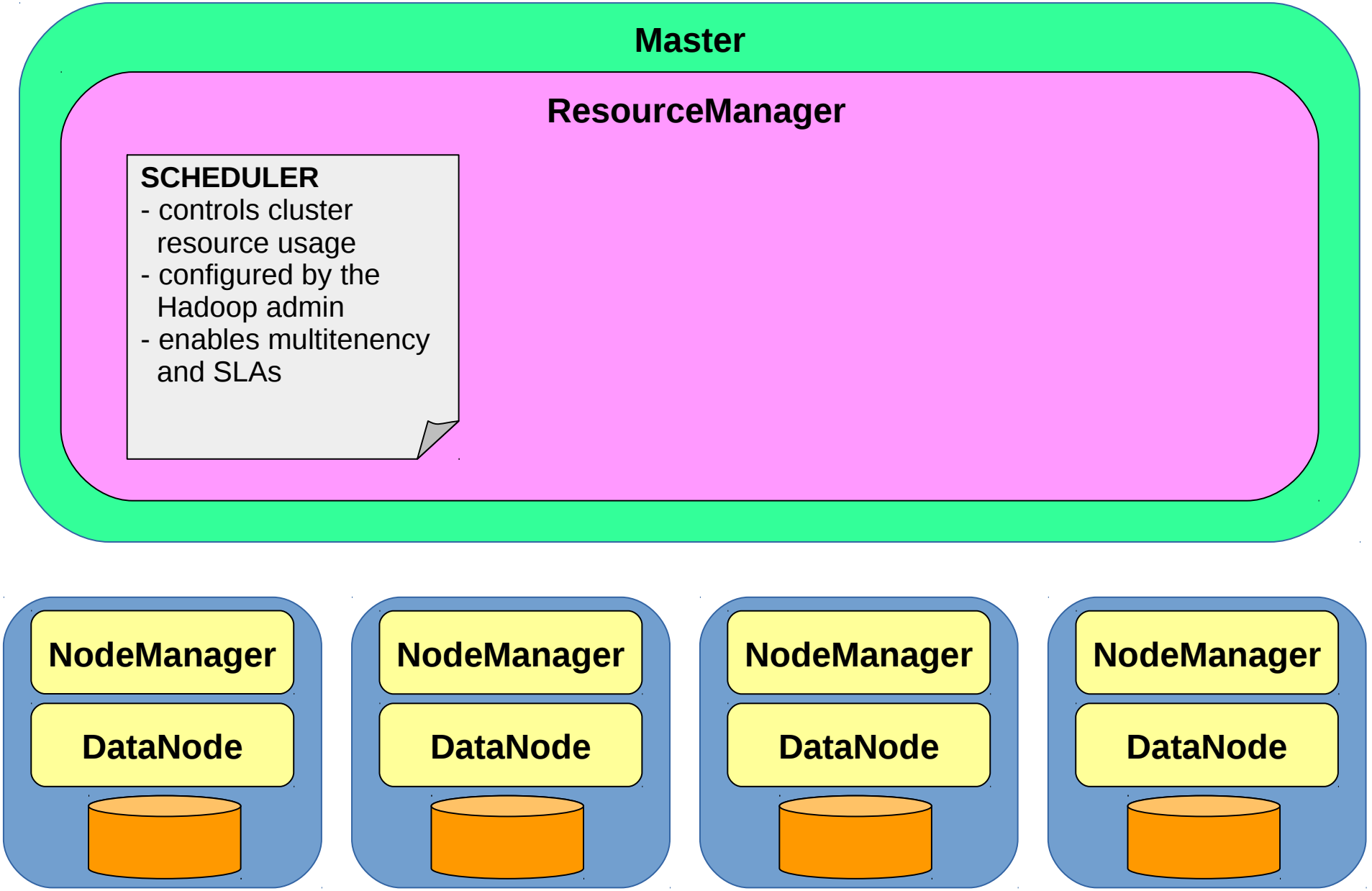
Hadoop Cluster Architecture



YARN Architecture: ResourceManager



YARN Architecture: ResourceManager



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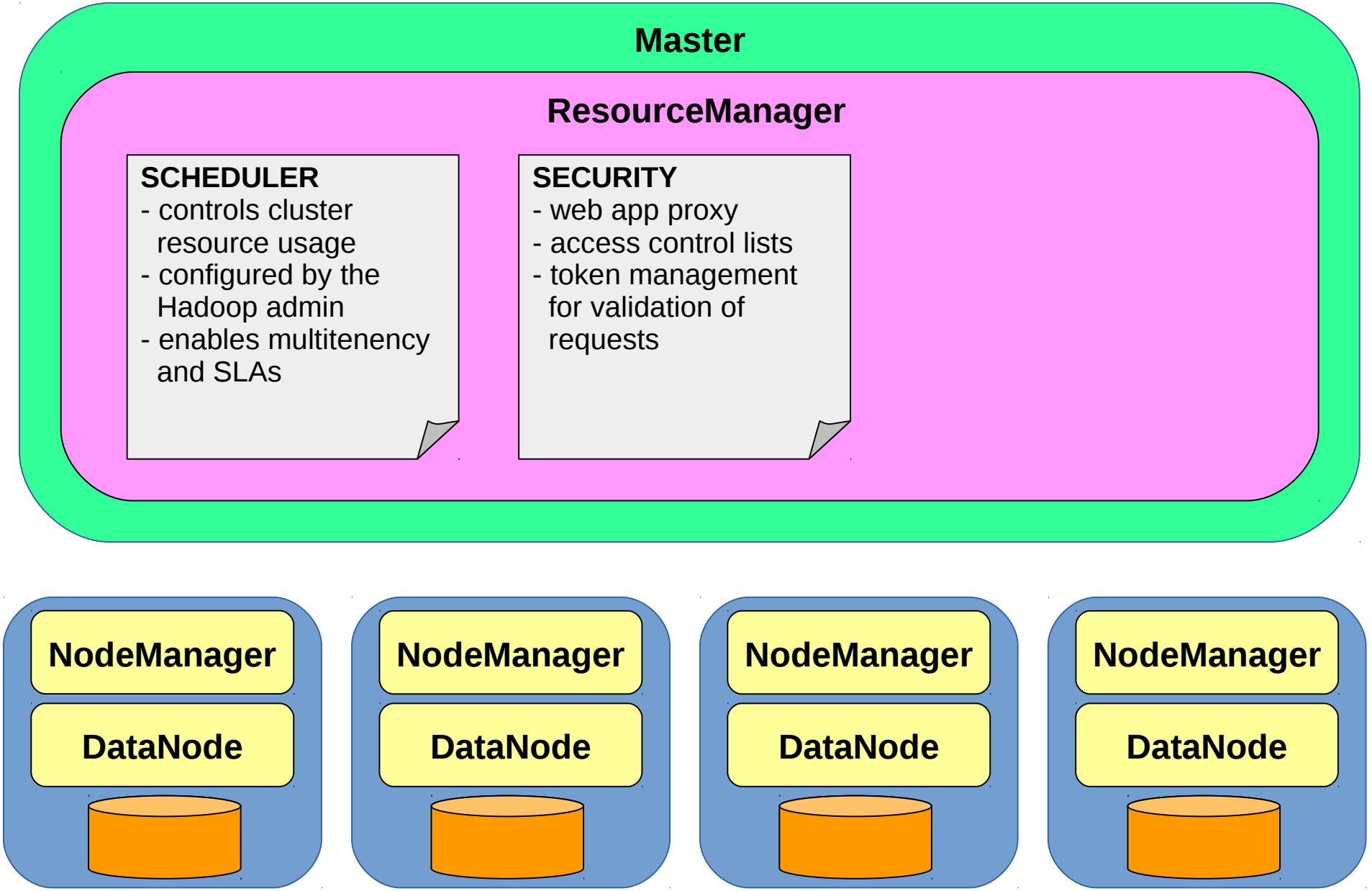
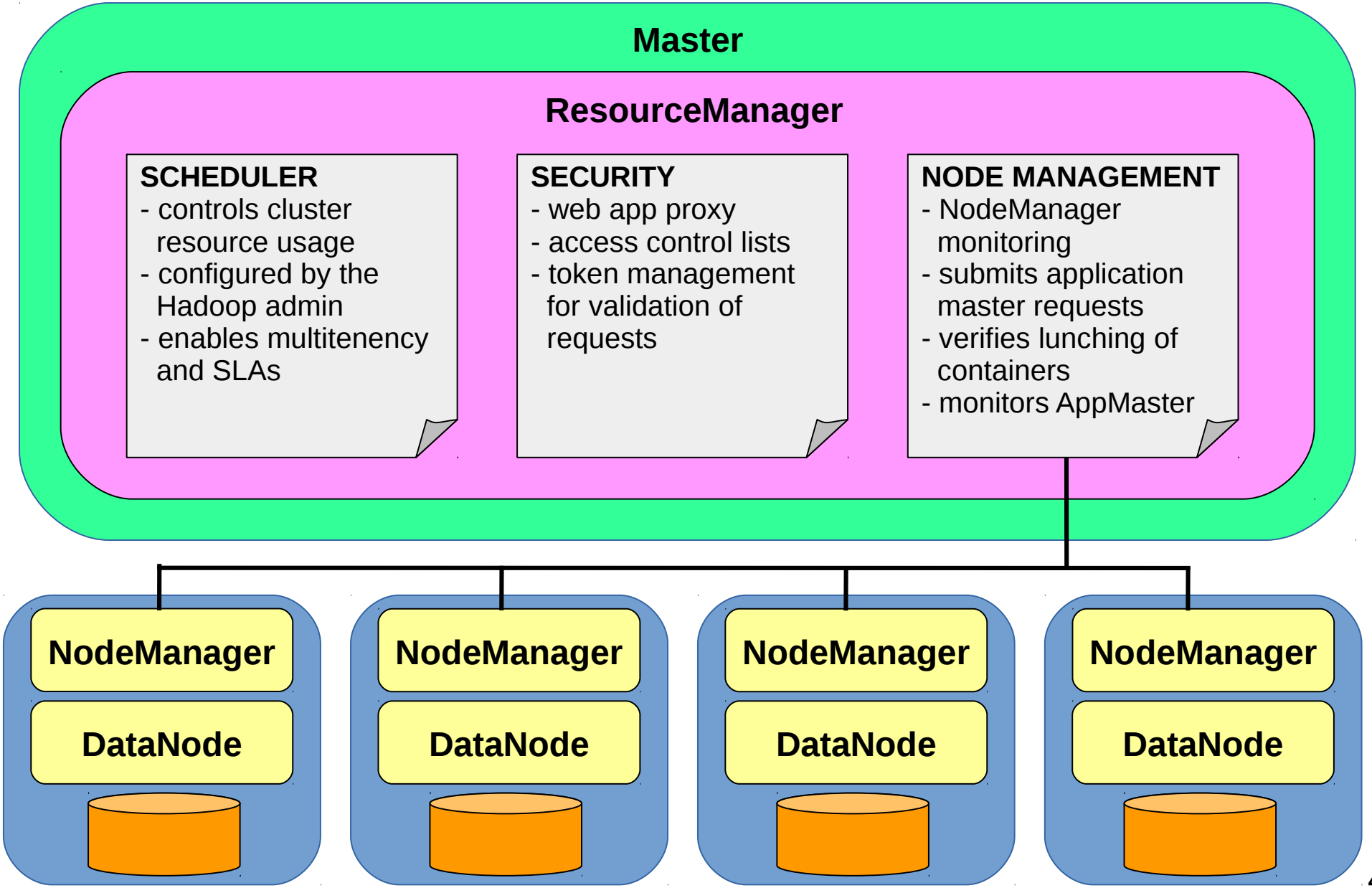


YARN Architecture: ResourceManager



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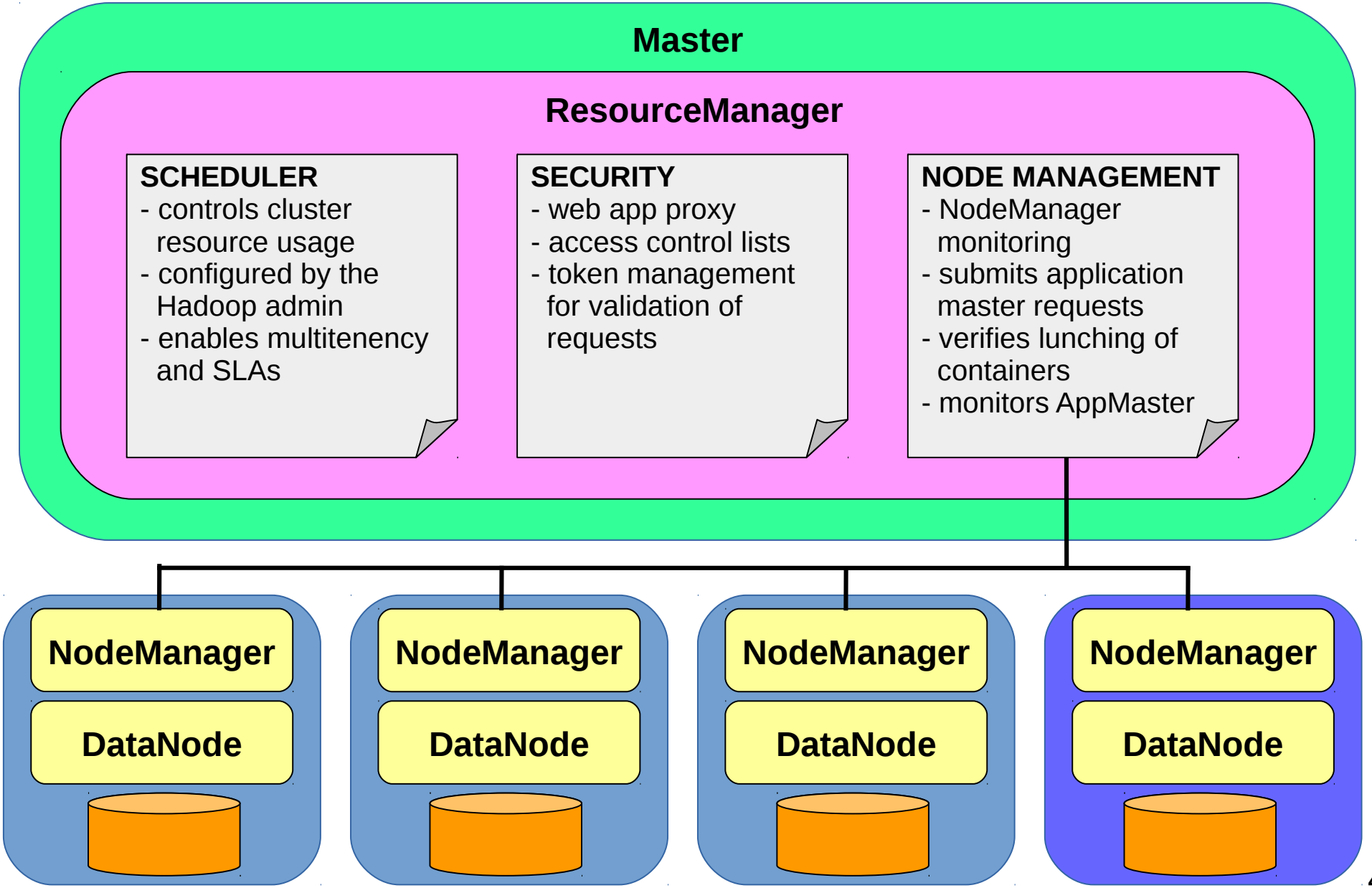
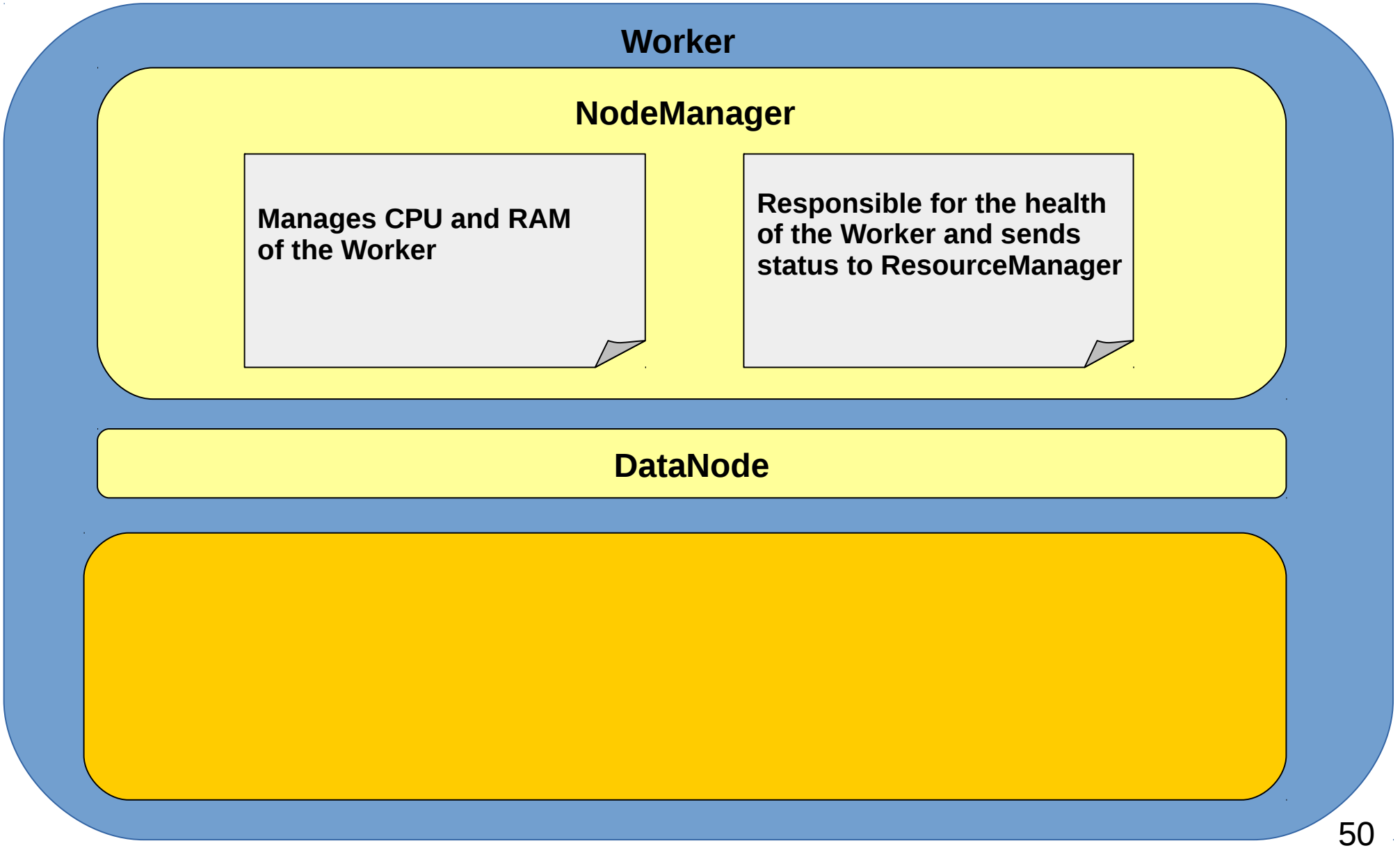
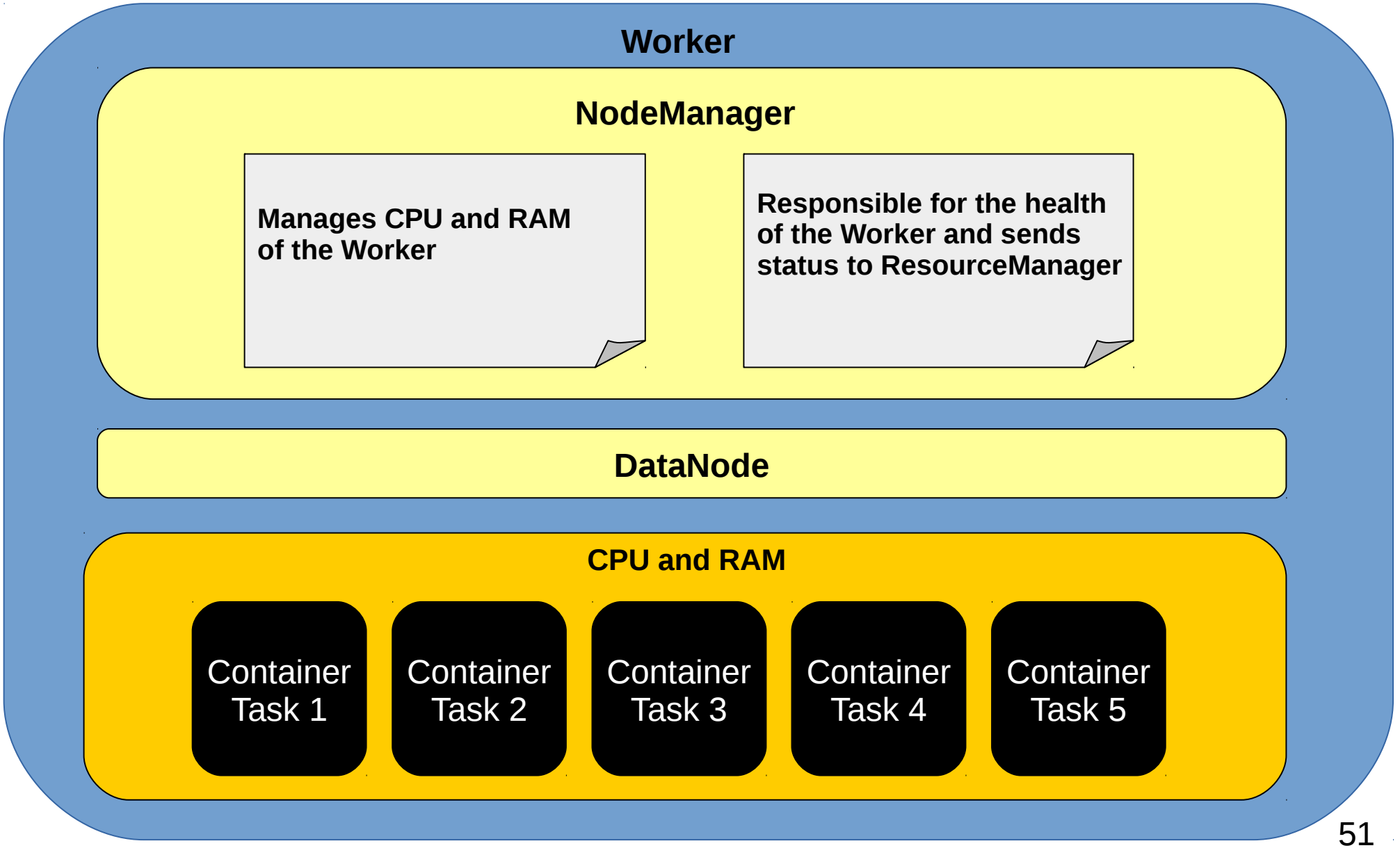


YARN Architecture: NodeManager



YARN Architecture: NodeManager



Writing a MapReduce Program

Based on key-value pairs

Each job is composed of one or more MR stages

Each MR stage comprises:

- the **map** phase
- the **shuffle-and-sort** phase
- the **reduce** phase

The programmer **focuses on the problem**. Replication, fault tolerance, scheduling, re-scheduling and other low level procedures are handled by HDFS or YARN.

Complete MapReduce API

The programmer must implement the following functions:

map(): accepts a set of key-value pairs and generates another list of key-value pairs.

combine(): performs an aggregation before sending the data to reducers (reduces network traffic).

partition(): uses a hash function to distribute data to reducers (load balancing, avoids hotspots).

reduce(): accepts a key and a list of values for this specific key and performs an aggregation.

Note: combine() and partition() are optional

Simple Example: WordCount

Given a potentially massive txt file, compute the number of occurrences of every word. For every word, output a pair

(**word**, **#occurrences**)

The number of pairs in the output equals the number of unique words in the file.

E.g.,

input: **can you** see the real me? **can you**? **can you**?

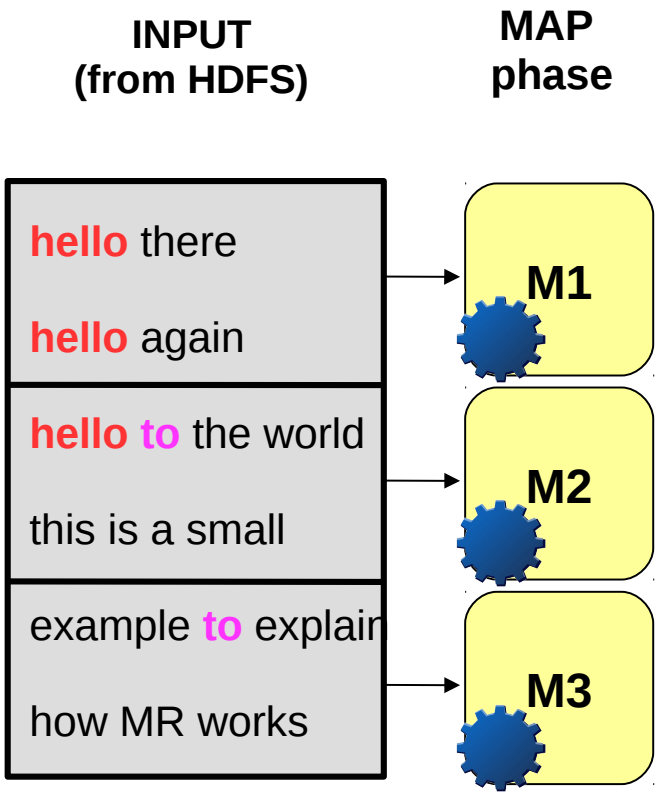
output: (**can**,3), (**you**,3), (see,1), (the,1), (real,1), (me,1)

WordCount Example

INPUT
(from HDFS)

3 splits
(HDFS)

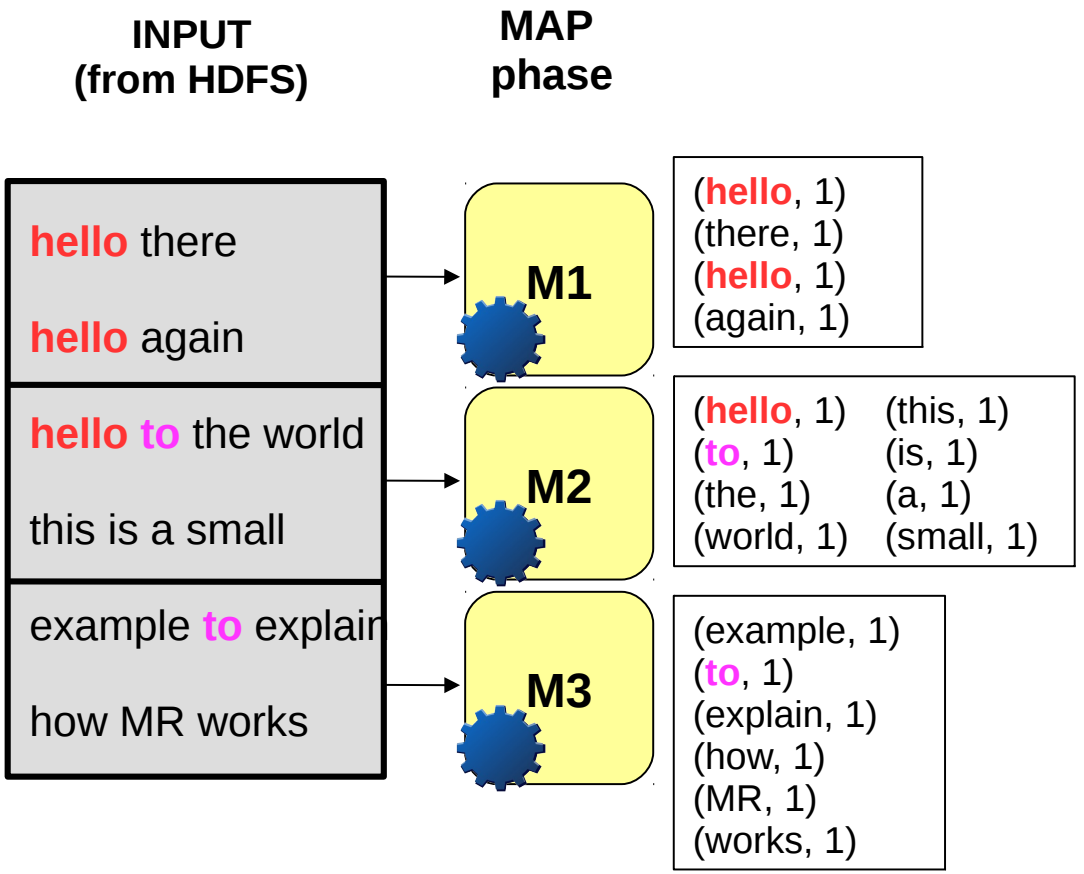
WordCount Example



3 splits (HDFS)

3 mappers

WordCount Example

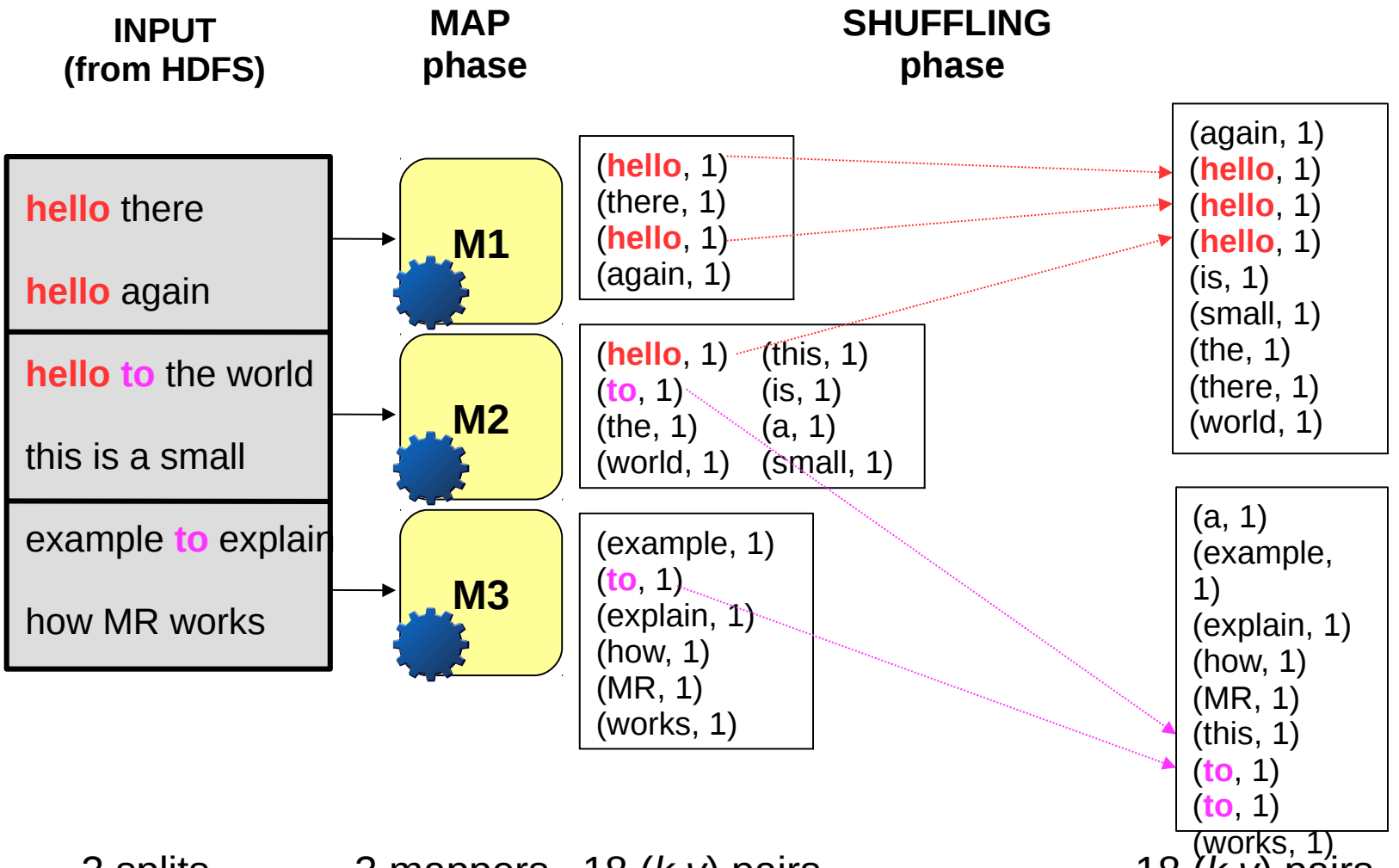


3 splits (HDFS)

3 mappers

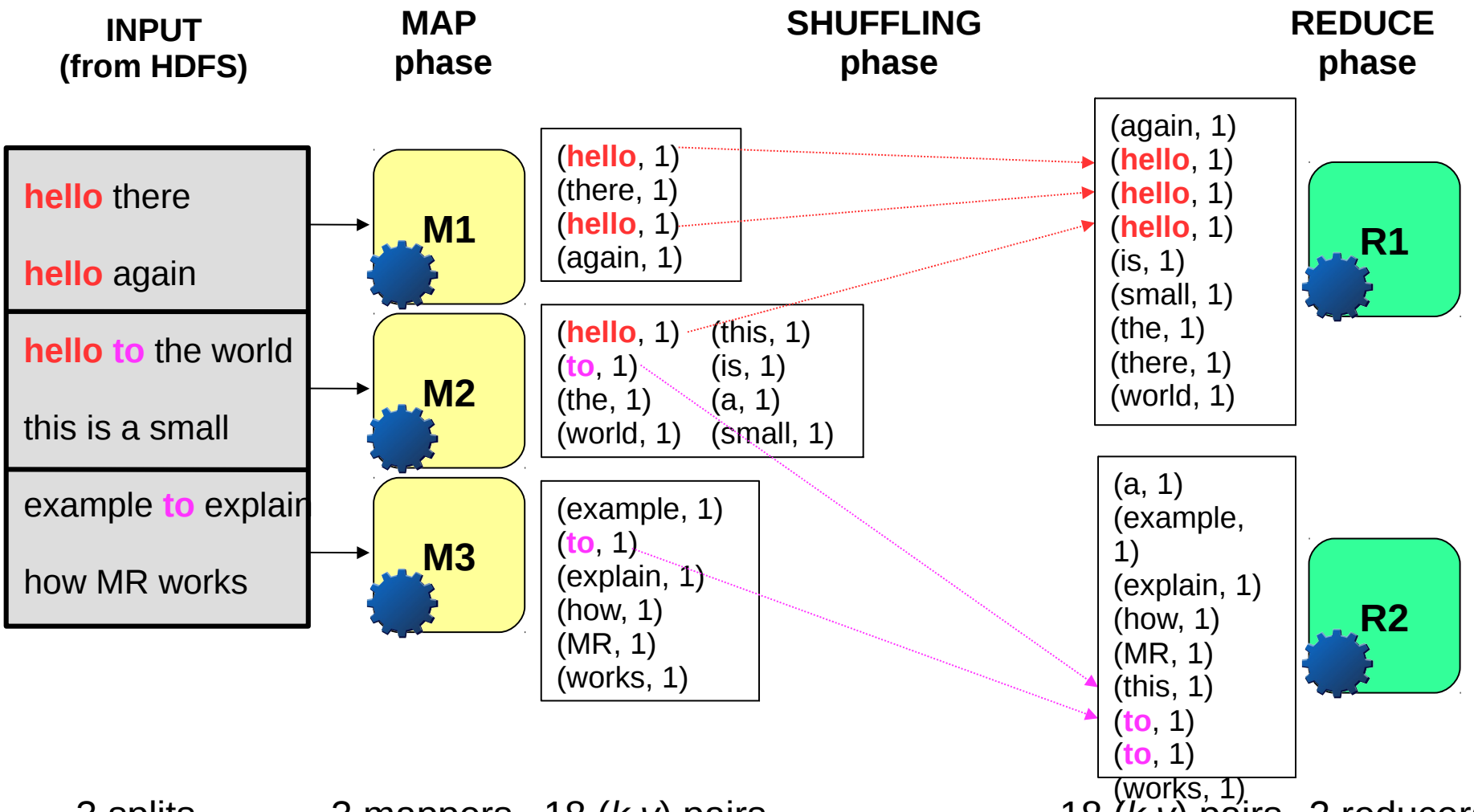
18 (*k*,*v*) pairs (local FS)

WordCount Example

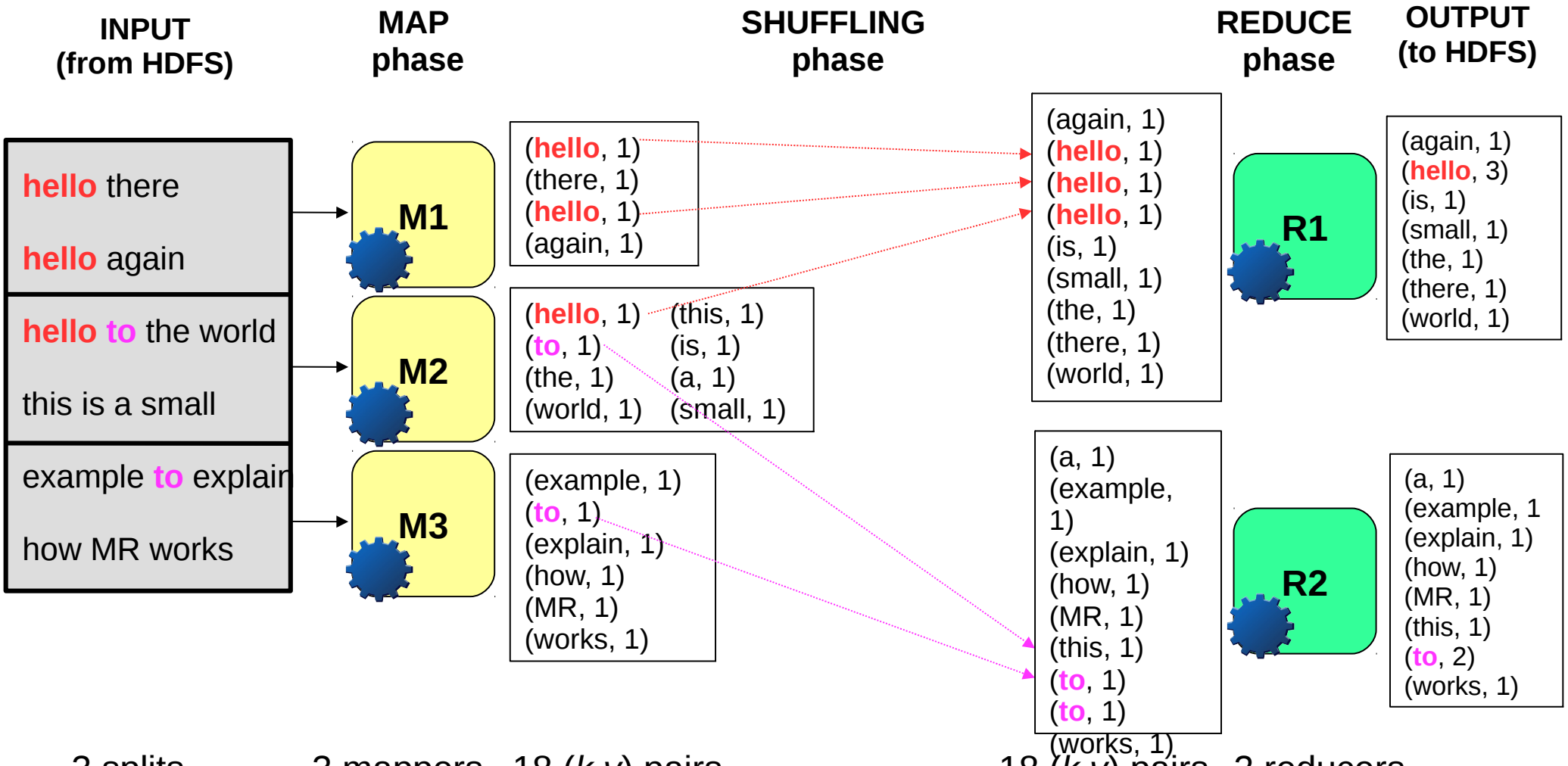


3 splits (HDFS) | 3 mappers | 18 (*k*,*v*) pairs (local FS) | 18 (*k*,*v*) pairs

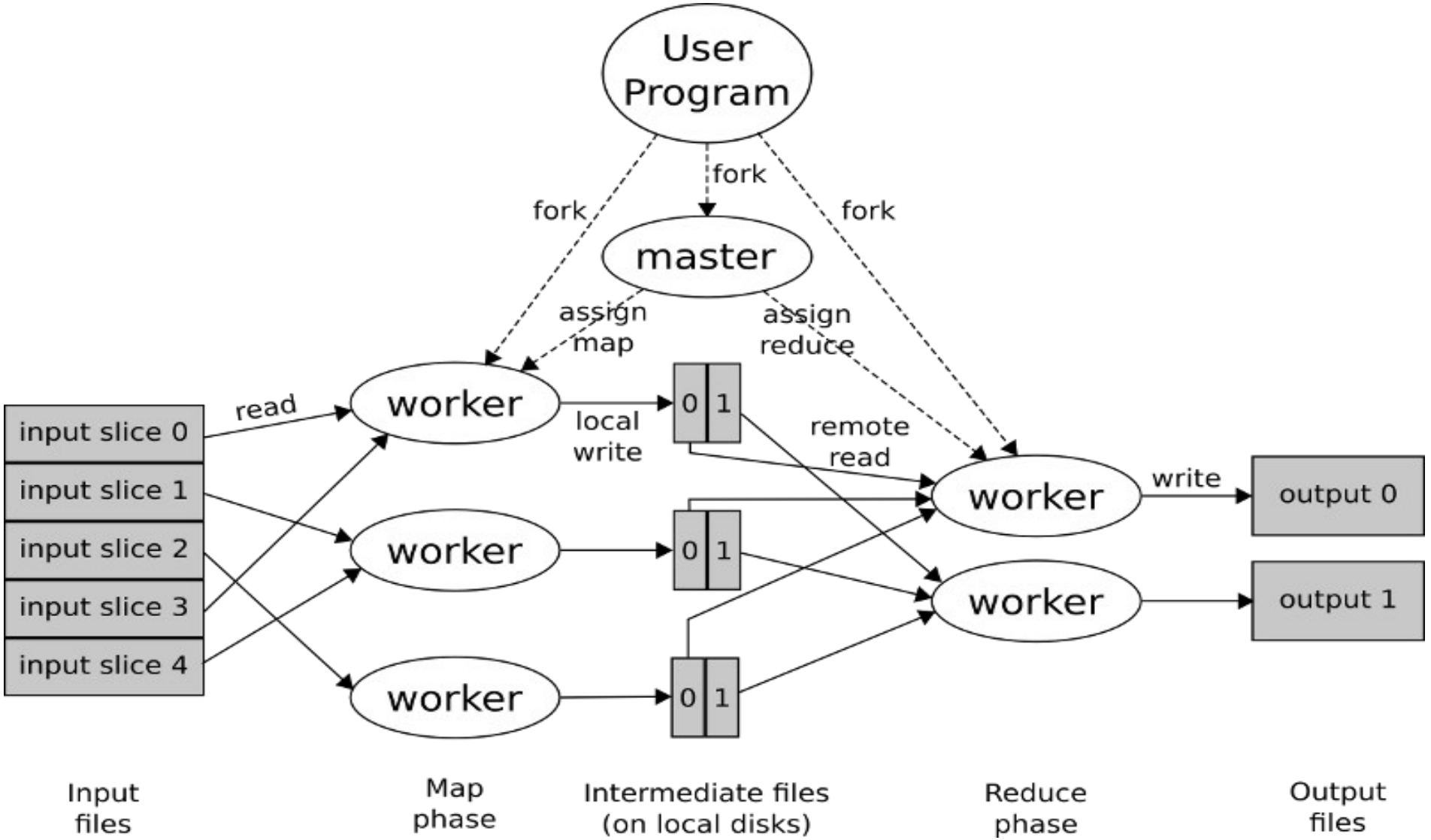
WordCount Example



WordCount Example



Workflow in Hadoop



WordCount Source Code

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

import org.apache.hadoop.fs.Path;
import org.apache.hadoop.conf.*;
import org.apache.hadoop.io.*;
import org.apache.hadoop.mapreduce.*;
import org.apache.hadoop.mapreduce.lib.input.FileInputFormat;
import org.apache.hadoop.mapreduce.lib.input.TextInputFormat;
import org.apache.hadoop.mapreduce.lib.output.FileOutputFormat;
import org.apache.hadoop.mapreduce.lib.output.TextOutputFormat;

public class WordCount {

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

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

 public static class Reduce extends Reducer<Text, IntWritable, Text,
 IntWritable> {

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

    public static void main(String[] args) throws Exception {

      Configuration conf = new Configuration();

      Job job = new Job(conf, "wordcount");

      job.setOutputKeyClass(Text.class);

      job.setOutputValueClass(IntWritable.class);

      job.setMapperClass(Map.class);

      job.setReducerClass(Reduce.class);

      job.setInputFormatClass(TextInputFormat.class);

      job.setOutputFormatClass(TextOutputFormat.class);

      FileInputFormat.addInputPath(job, new Path(args[0]));

      FileOutputFormat.setOutputPath(job, new Path(args[1]));

      job.waitForCompletion(true);

    }


}
```

WordCount: the **driver** program

```
public static void main(String[] args) throws Exception {
      Configuration conf = new Configuration();
      Job job = new Job(conf, "wordcount");
      job.setOutputKeyClass(Text.class);
      job.setOutputValueClass(IntWritable.class);
      job.setMapperClass(Map.class);
      job.setReducerClass(Reduce.class);
      job.setInputFormatClass(TextInputFormat.class);
      job.setOutputFormatClass(TextOutputFormat.class);
      FileInputFormat.addInputPath(job, new Path(args[0]));
      FileOutputFormat.setOutputPath(job, new Path(args[1]));
      job.waitForCompletion(true);
   }
```

WordCount: the **map()** function

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

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

WordCount: the **reduce()** function

```
public static class Reduce extends Reducer<Text, IntWritable, Text,
 IntWritable> {


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

Theoretical Issues in MapReduce

Paper titles:

- “On the Computational Complexity of MapReduce”
- “A new Computation Model for Cluster Computing”
- “Fast Greedy Algorithms in MapReduce and Streaming”
- “Minimal MapReduce Algorithms”
- “Filtering: A Method for Solving Graph Problems in MapReduce”
- “A Model of Computation for MapReduce” (**SODA 2010**)

MapReduce Limitations

- Difficult to design efficient/optimal algorithms (everything must be expressed in key-value pairs)
- A lot of disk I/Os (mappers reading HDFS and writing local data)
- A lot of network traffic (shuffling is expensive)
- Difficult to handle data skew (the curse of the last reducer!)
- Not very good for iterative processing (requires many MR rounds, memory contents are not available across rounds)
- Not very good for **streaming applications**

Case Studies

Nokia

Nokia collects and analyzes vast amounts of data from mobile phones

Problem:

(1) Dealing with 100TB of structured data and 500TB+ of semi-structured data

(2) 10s of PB across Nokia, 1TB / day

Solution: HDFS data warehouse allows storing all the semi/multi structured data and offers processing data at peta byte scale

Hadoop Vendor: Cloudera

Cluster/Data size:

(1) 500TB of data

(2) 10s of PB across Nokia, 1TB / day

Links:

(1) Cloudera case study (Published Apr 2012)
(http://hadoopilluminated.com/hadoop_illuminated/cached_reports/Cloudera_Nokia_Case_Study_Hadoop.pdf)

(2) strata NY 2012 presentation slides (http://hadoopilluminated.com/hadoop_illuminated/cached_reports/Nokia_Bigdata.pdf)

Strata NY 2012 presentation

Case Studies

China Mobil Guangdong

Problem: Storing billions of mobile call records and providing real time access to the call records and billing information to customers. Traditional storage/database systems couldn't scale to the loads and provide a cost effective solution

Solution: HBase is used to store billions of rows of call record details. 30TB of data is added monthly

Hadoop vendor: Intel

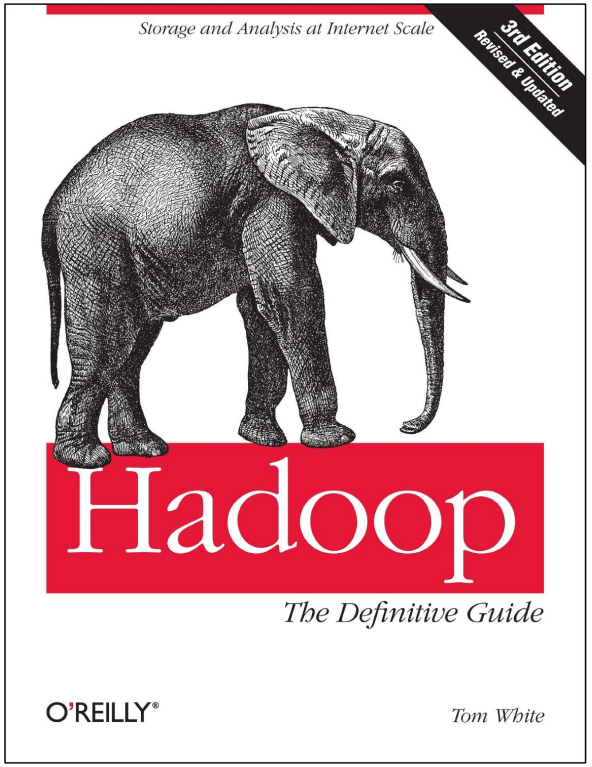
Hadoop cluster size: 100+ nodes

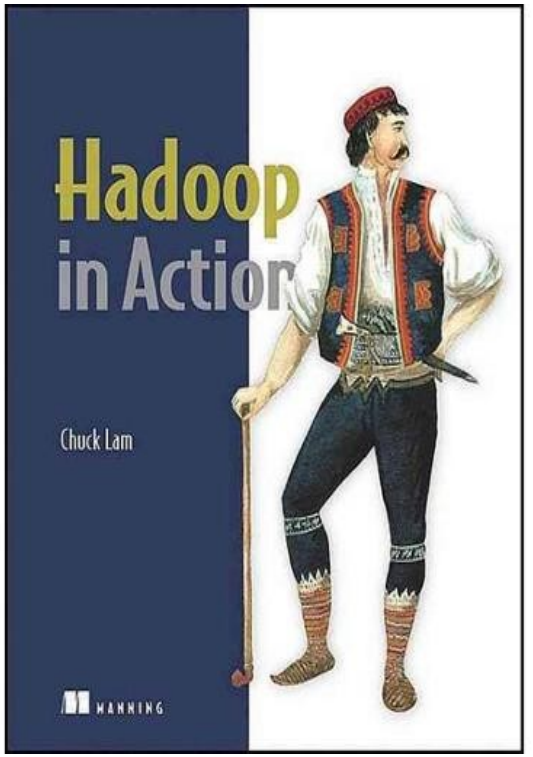
Links:

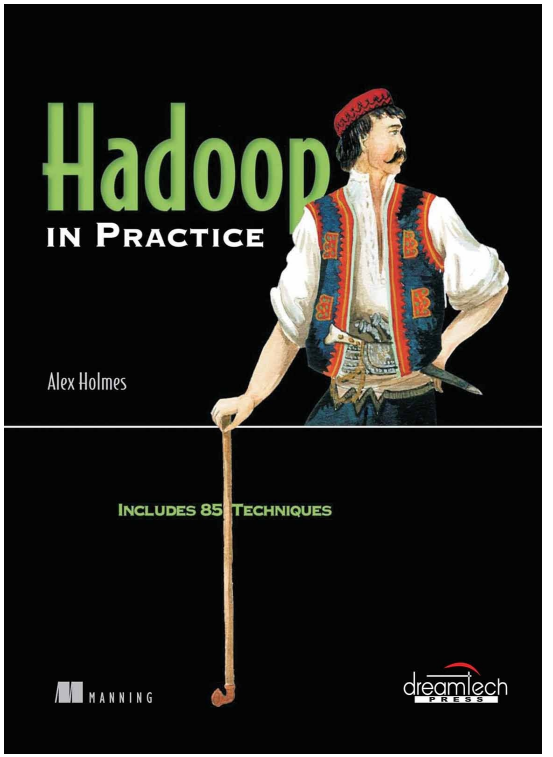
China Mobil Quangdong (http://gd.10086.cn/)

Intel APAC presentation (http://www.slideshare.net/IntelAPAC/apac-big-data-dc-strategy-update-for-idh-launch-rk)

Related Books







Related MOOCs

Introduction to Apache Hadoop (edX)

https://www.edx.org/course/introduction-apache-hadoop-linuxfoundationx-lfs103x

Hadoop platform and application framework (Coursera)

https://www.coursera.org/learn/hadoop

Introduction to Big Data (Coursera)

https://www.coursera.org/learn/big-data-introduction

Thank You

Questions ?