MapReduce & Hadoop

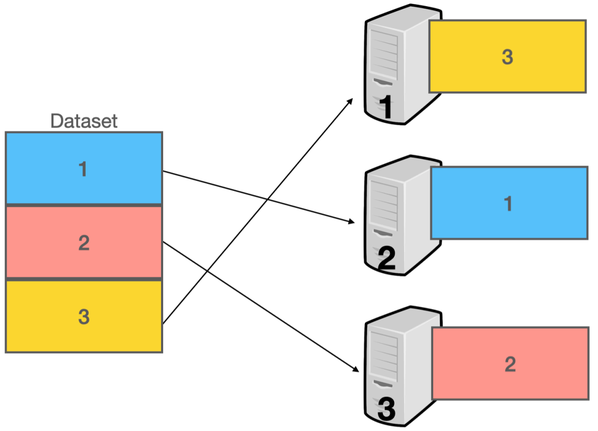
Big Data Management

19-09-2025

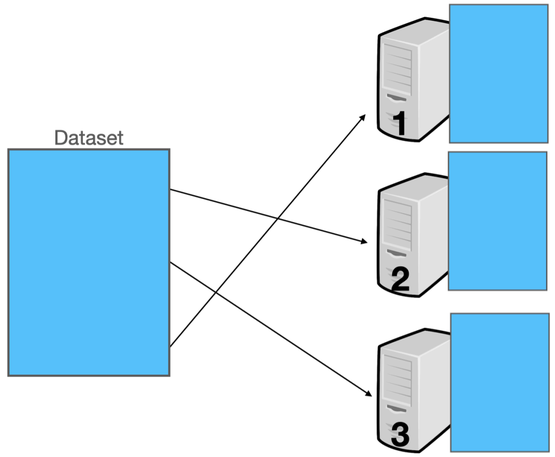
photo: https://www.bmvg.de/de/service/open-data

Previously…

- **Partitioning**
  - Splitting data into (typically disjoint) subsets —> **partitions**
    - hash vs. range partitioning
  - Each partition is assigned to a different node (aka sharding)
  - **Rebalancing** partitions when nodes are added



- **Replication**
  - Keeping a **replica** (i.e., copy) of the same data on different nodes
  - Most common strategy: **leader-follower**
  - **Synchronous** vs. **asynchronous**
  - Different consistency models for handling **replication lag**



From distributed systems to big data systems

- Working with distributed systems: totally different from writing software on a single computer
- Problems with distributed systems
  - Nondeterministic behaviour
  - Partial failures
  - Debugging becomes very hard
  - High probability of large variance in runtime/throughput performance

Need for new tools

Google cluster idea (2003)

- **Failures are the norm**
  - 1 server→may stay up 3 years (1,000 days)
  - 10,000 servers→expect to lose 10 per day
  - Ultra-reliable hardware doesn't really help (at large scales, even most reliable hardware fails, albeit less often)
  - Software still needs to be fault-tolerant
- **Data is growing**: either large files or billions of small files
- **Append-only** instead of overwriting
  - Random writes are practically inexistent

Use of commodity machines!

Goal: throughput and not peak performance

Need for new tools

- Distributed File Systems (DFS)
  - Store petabytes of data in a cluster
  - Transparently handle fault-tolerance and replication
- Parallel Processing Platforms
  - Offer a programming model to allow developers to easily write distributed applications
  - Alleviate developer from handling concurrency, network communication, and machine failures
  - Move computation to data, not data to computation

In this lecture…

- ✦ Distributed file systems (DFS)
- ✦ The MapReduce distributed data processing paradigm
- ✦ Hadoop/MapReduce under the hood

In this lecture…

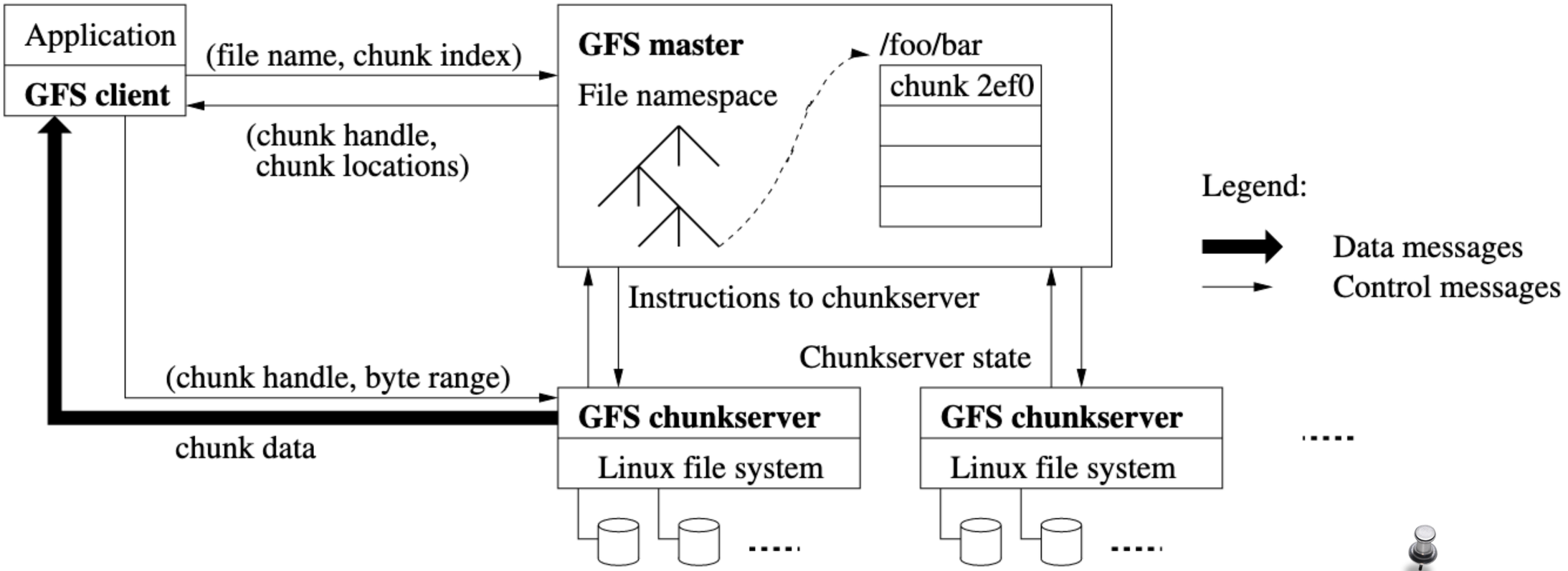
- ✦ **Distributed file systems (DFS)**
- ✦ The MapReduce distributed data processing paradigm
- ✦ Hadoop/MapReduce under the hood

Distributed File System (DFS)

- Files should be:
  - Enormous
  - Rarely updated
- Stores very large data files **efficiently** and **reliably**
- Files partitioned into **fixed-sized chunks** (eg., 64MB)
  - Stored as Linux files
- Chunks are replicated (typically 3 times)

Google File System (GFS) architecture

- Single master, multiple chunk servers



Master is potential **single point of failure / scalability bottleneck** —> Use **shadow** masters

Hadoop Distributed File System (HDFS)

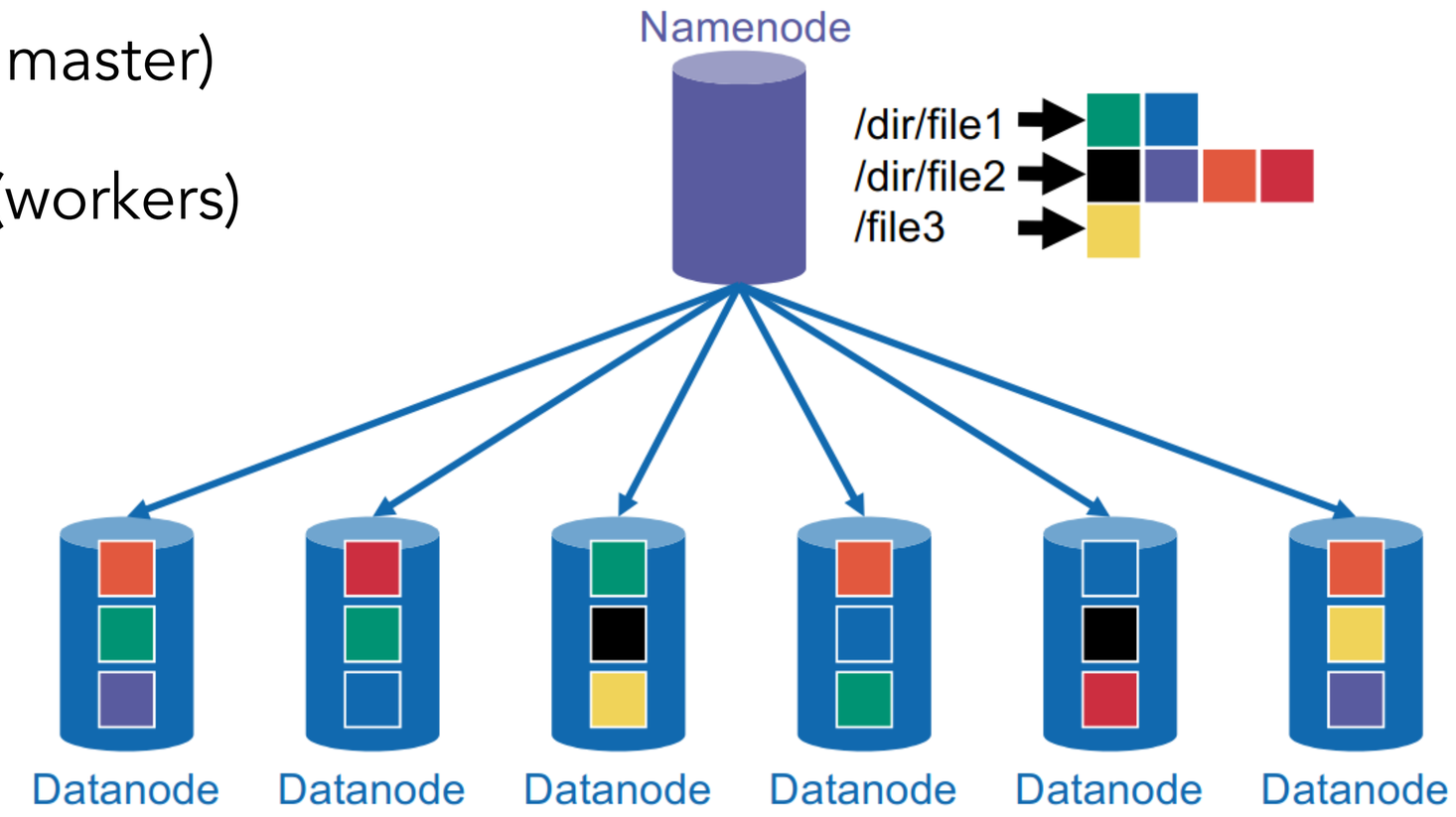
- Distributed file systems manage the storage across a network of machines
- HDFS is Hadoop's flagship filesystem

HDFS Block

- HDFS stores very large files
- Files are **split** into block-sized chunks (by default 64MB)
- With this block abstraction:
  - A file can be larger than a single disk in the network
  - HDFS blocks are larger than disk blocks
  - Storage system is simplified (metadata for blocks)
  - **Replication** for fault-tolerance and availability

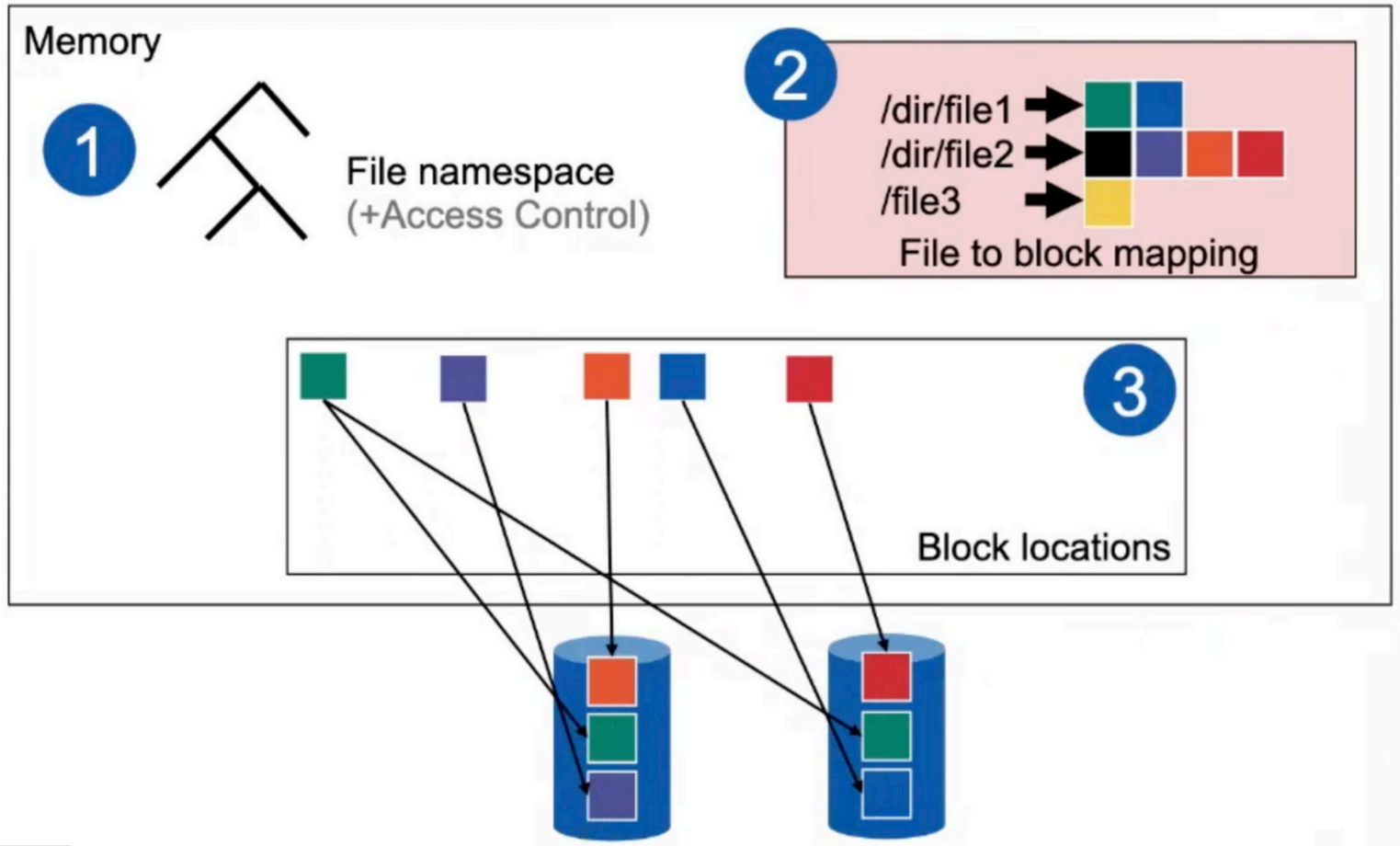
HDFS architecture

- Two types of HDFS nodes
  - One **namenode** (the master)
  - Multiple **datanodes** (workers)



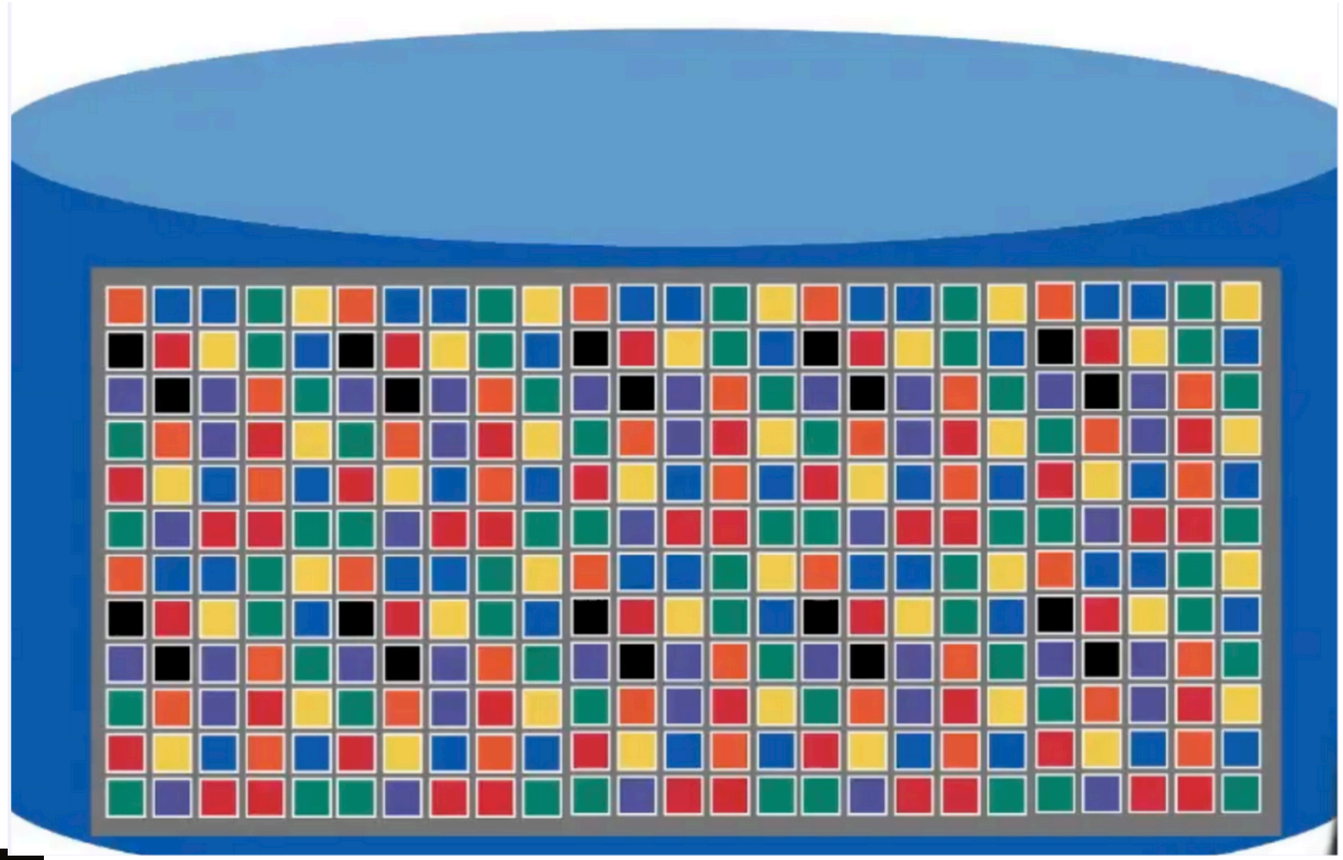
Namenode

- Namenode manages the filesystem namespace
  - File system tree and metadata, stored persistently
  - Block locations, stored transiently

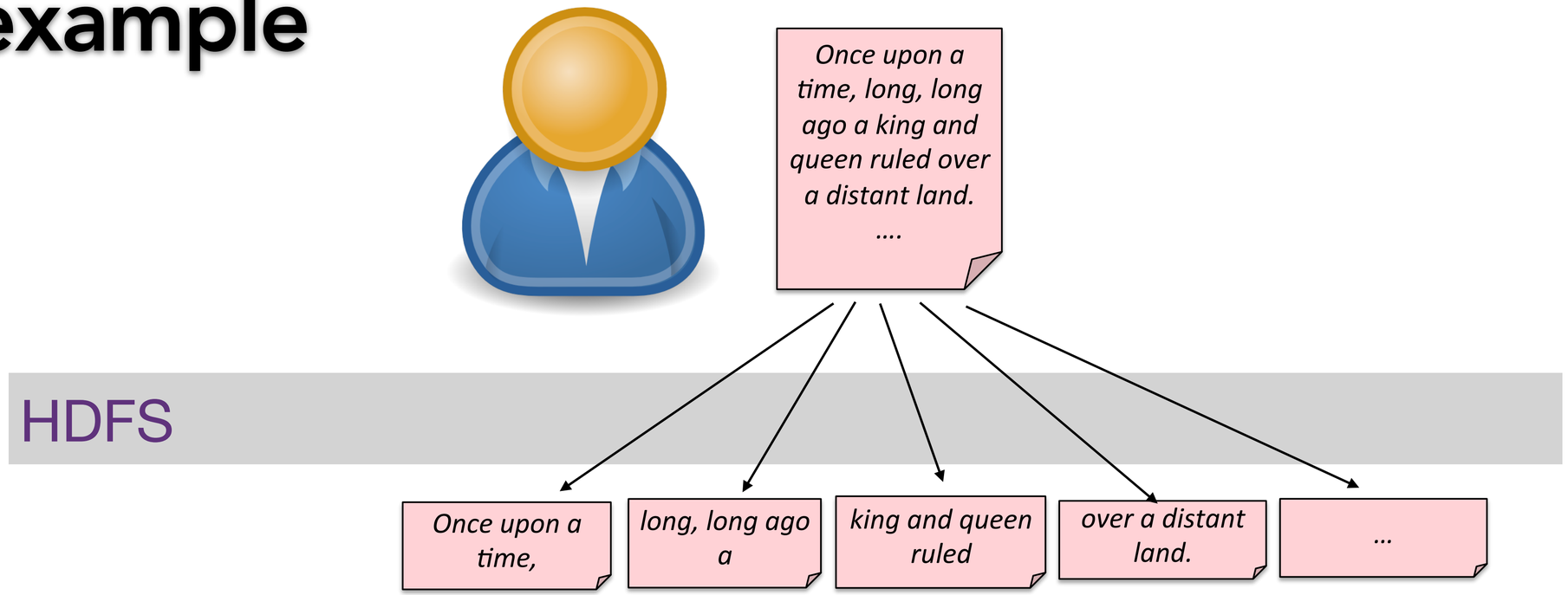


Datanode

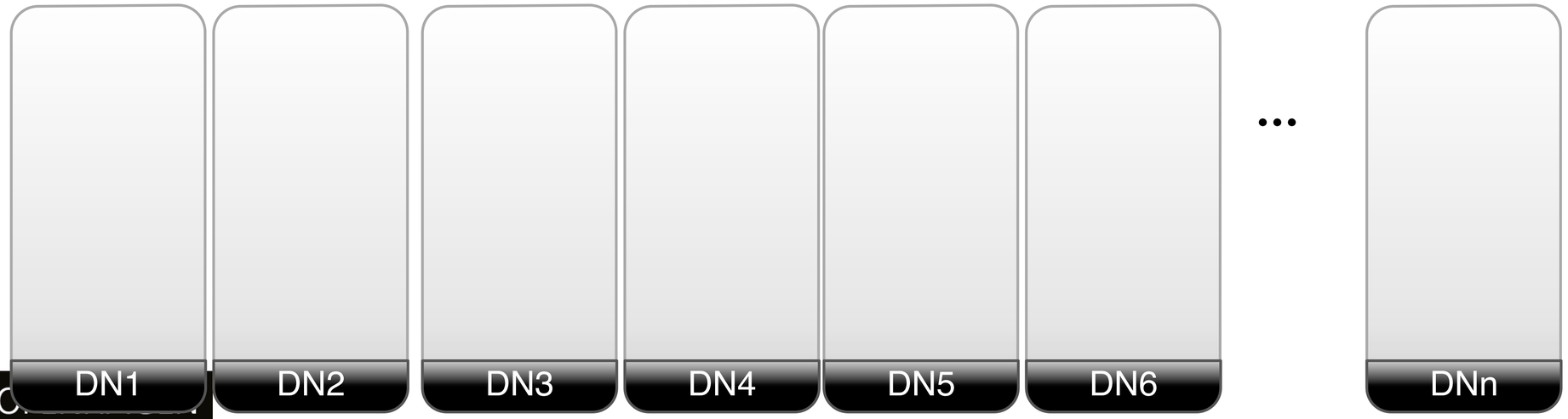
- Datanodes store and retrieve data blocks
  - When requested from clients or namenode
  - Also send list of stored blocks periodically to namenode



HDFS example



horizontal partitions

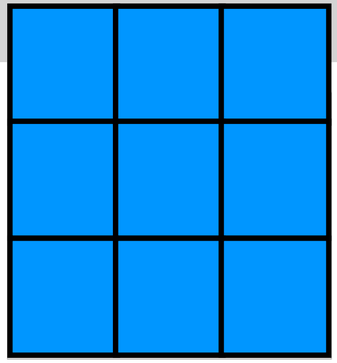


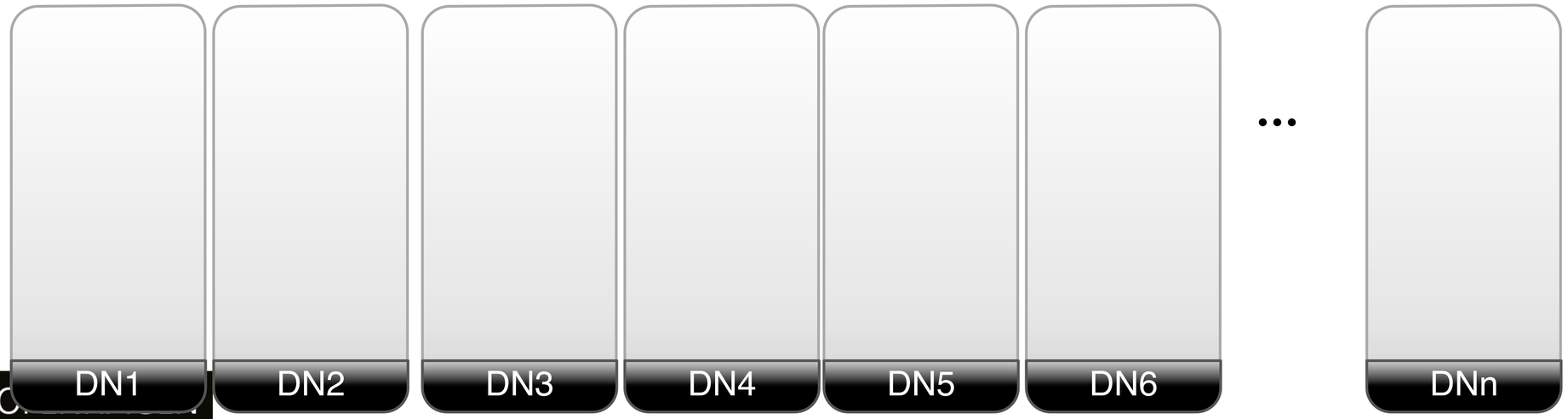
HDFS example

Once upon a time, long, long ago a king and queen ruled over a distant land. ….

HDFS

horizontal partitions

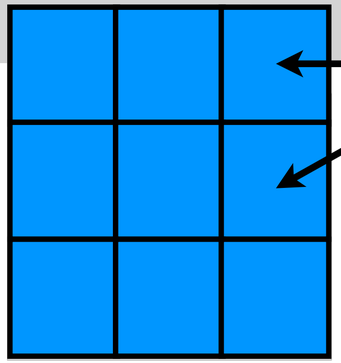




HDFS example

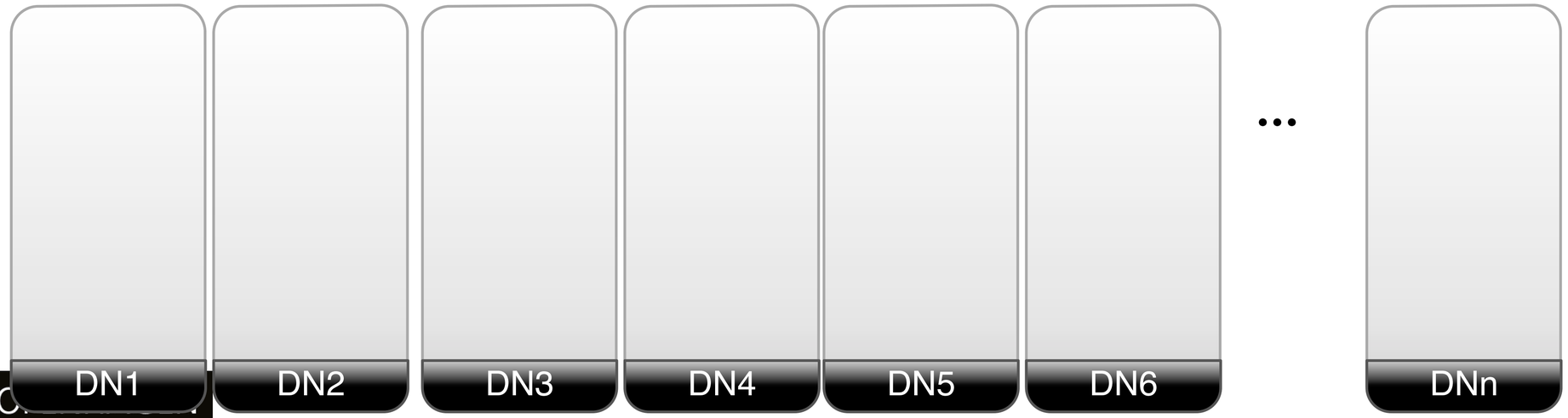
Once upon a time, long, long ago a king and queen ruled over a distant land. ….

HDFS



HDFS blocks
64MB (default)

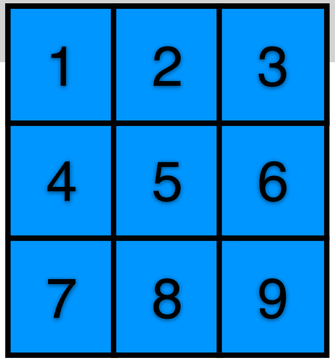
horizontal partitions

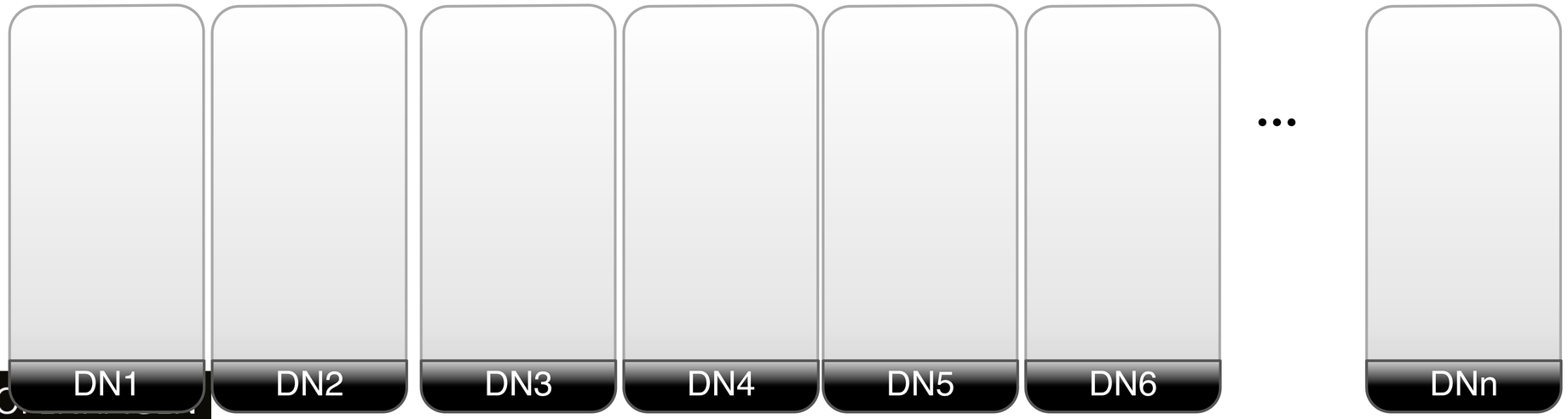


HDFS example

Once upon a time, long, long ago a king and queen ruled over a distant land. ….

HDFS

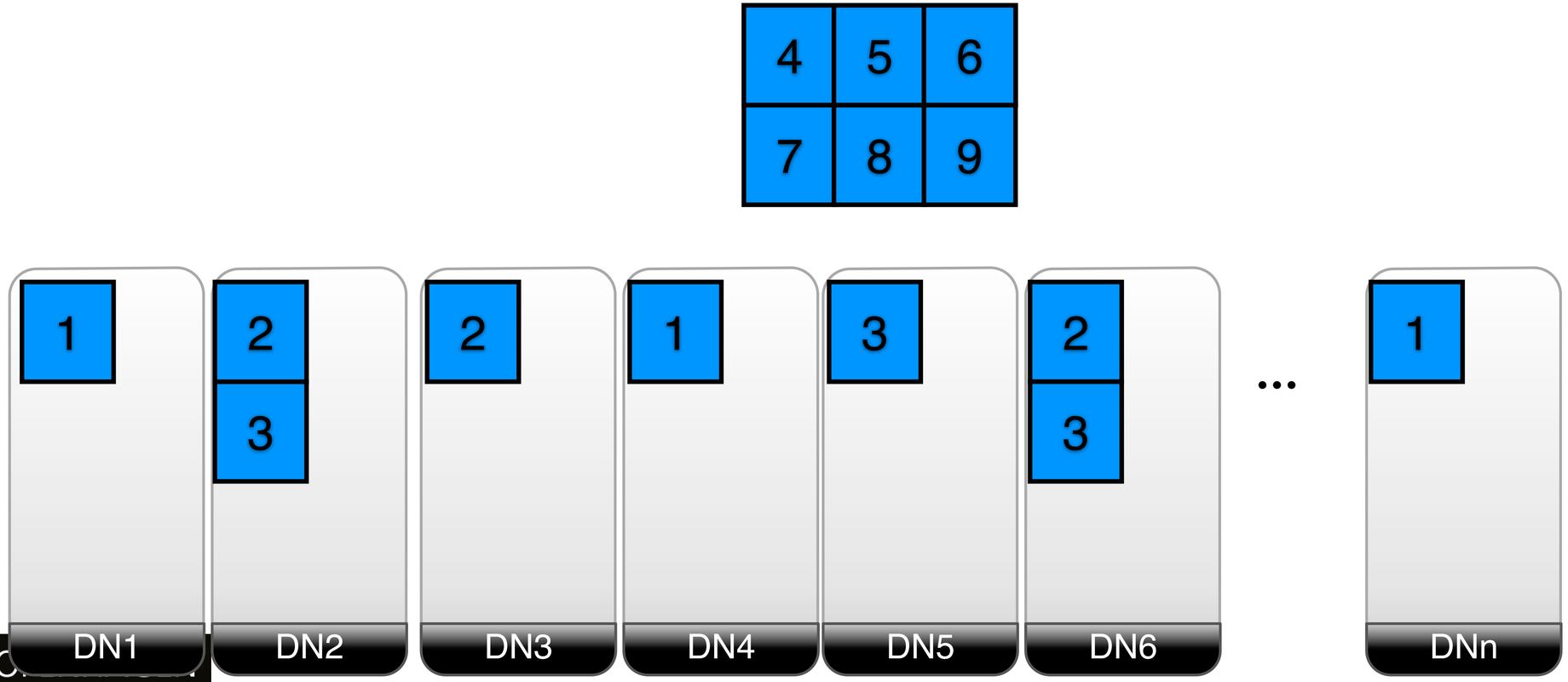




HDFS example

Once upon a time, long, long ago a king and queen ruled over a distant land. ….

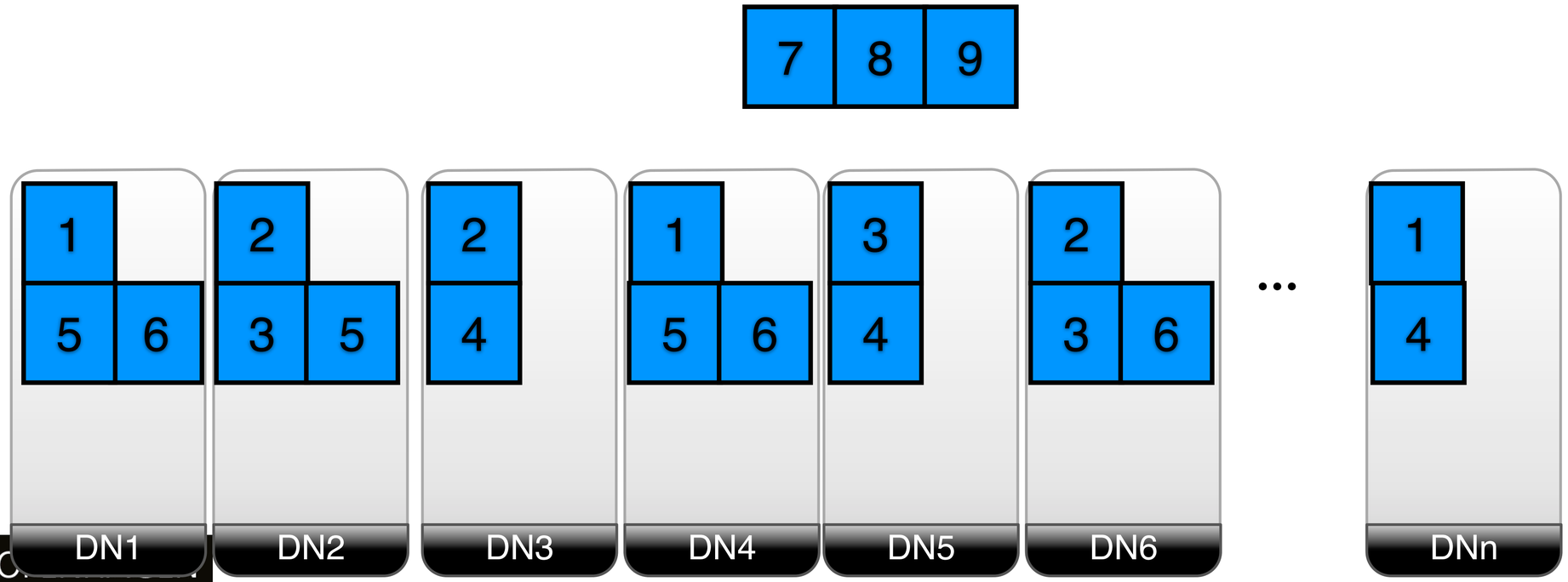
HDFS



HDFS example

Once upon a time, long, long ago a king and queen ruled over a distant land. ….

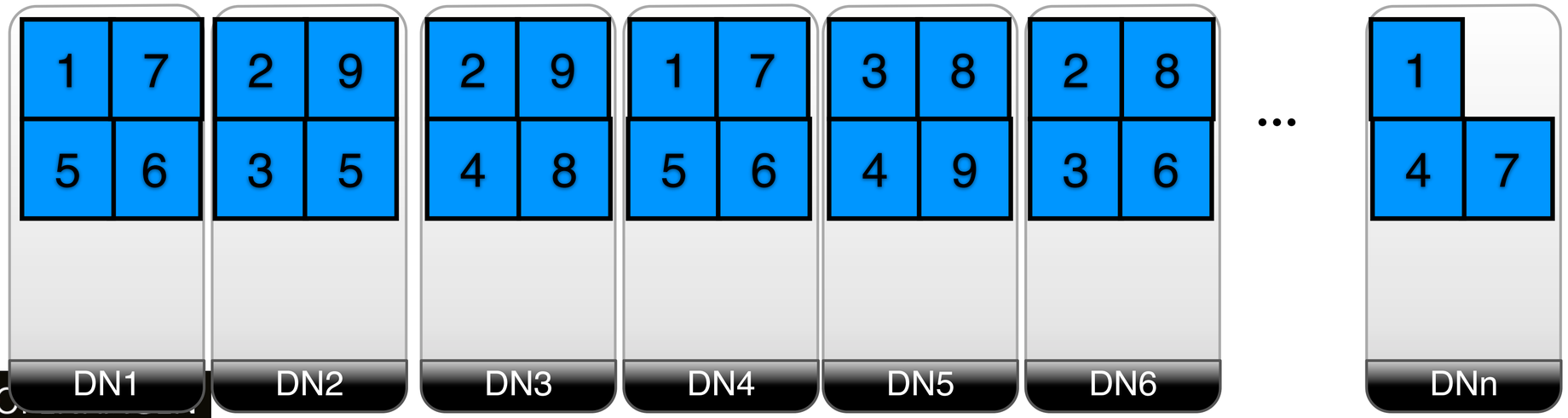
HDFS



HDFS example

Once upon a time, long, long ago a king and queen ruled over a distant land. ….

HDFS



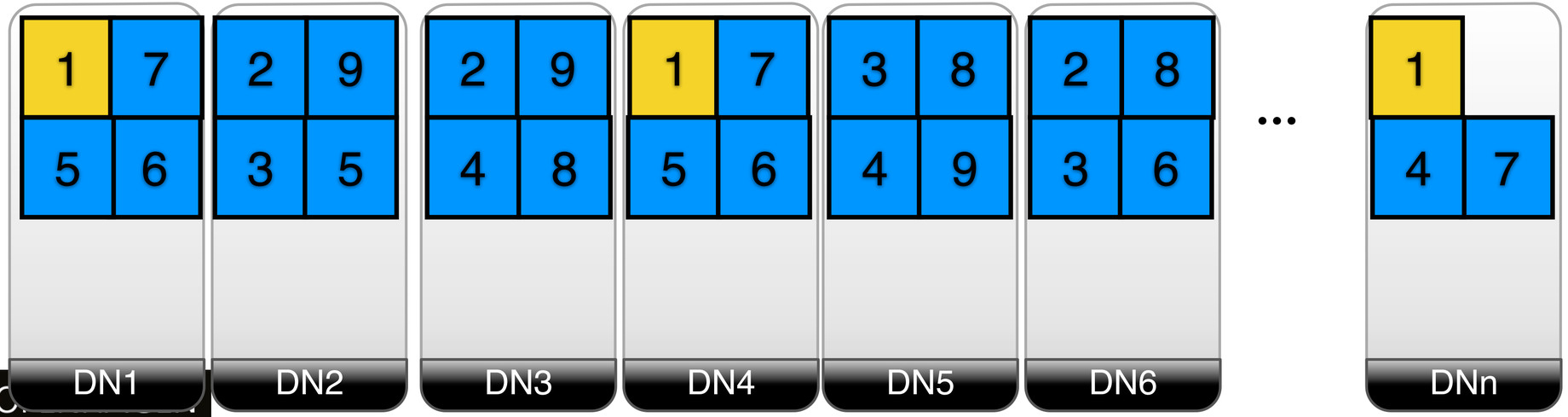
HDFS example

Once upon a time, long, long ago a king and queen ruled over a distant land. ….

HDFS

partitioning

replication (by default factor 3)

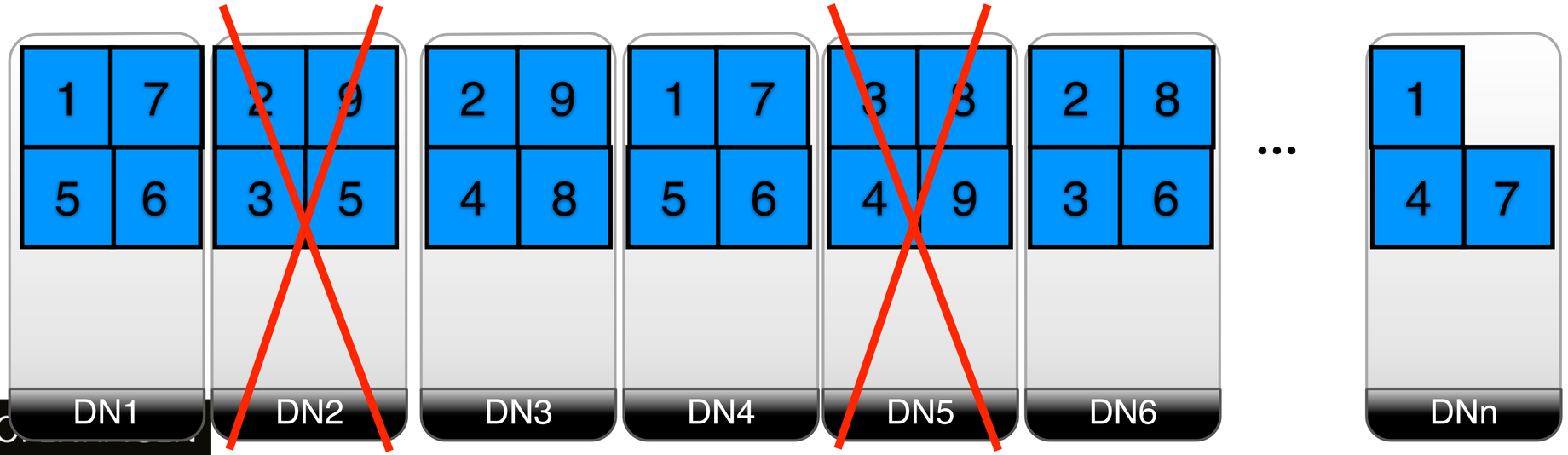


HDFS example

Fault-tolerance

Once upon a time, long, long ago a king and queen ruled over a distant land. ....

HDFS

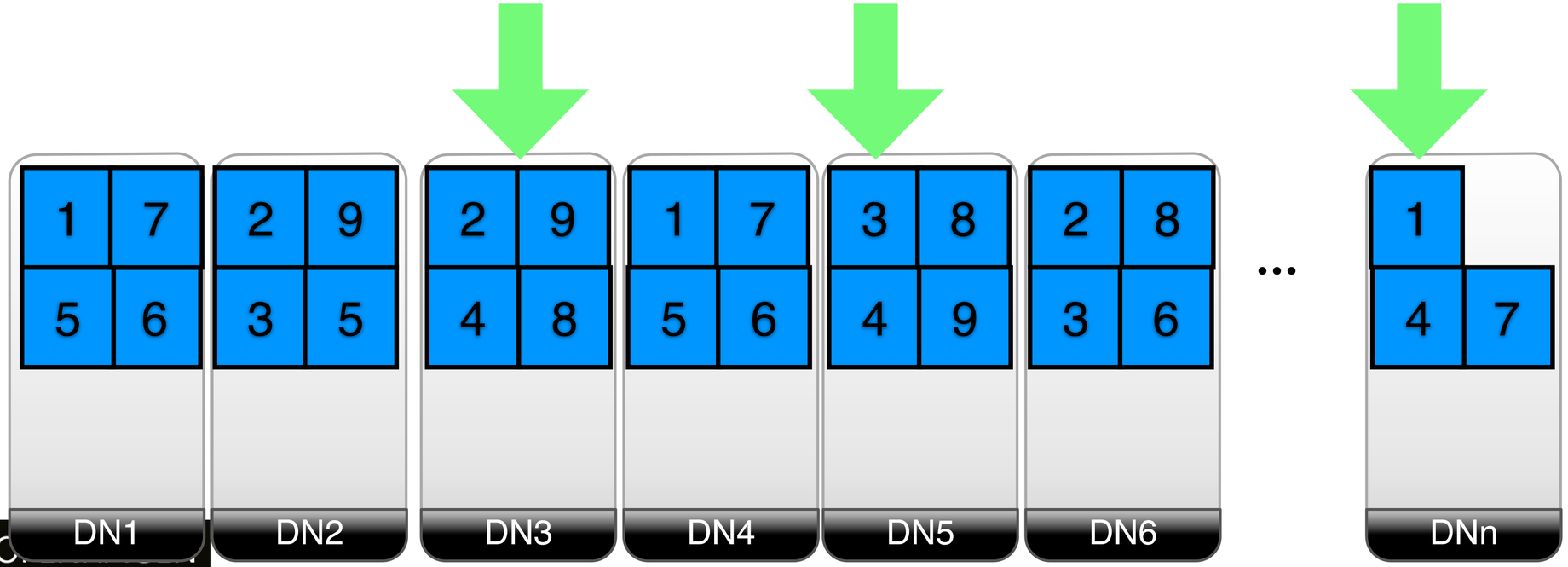


HDFS example

Load balancing

I would like to have block 4!

HDFS

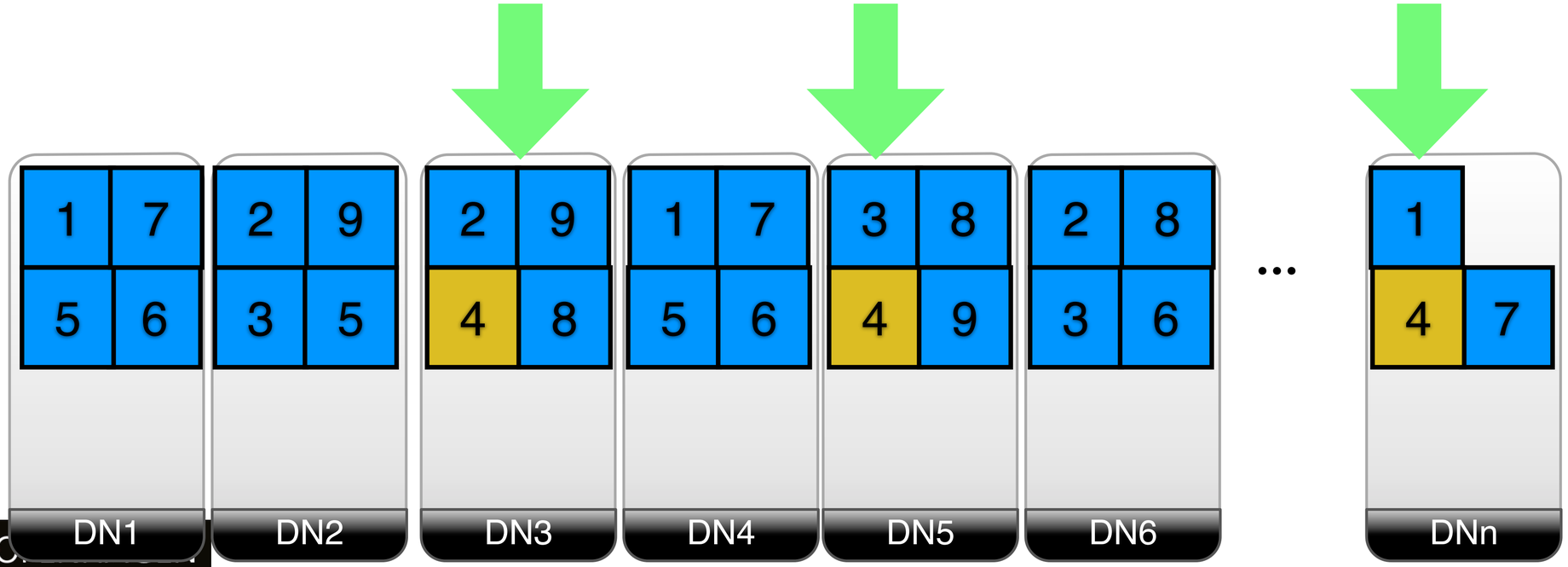


HDFS example

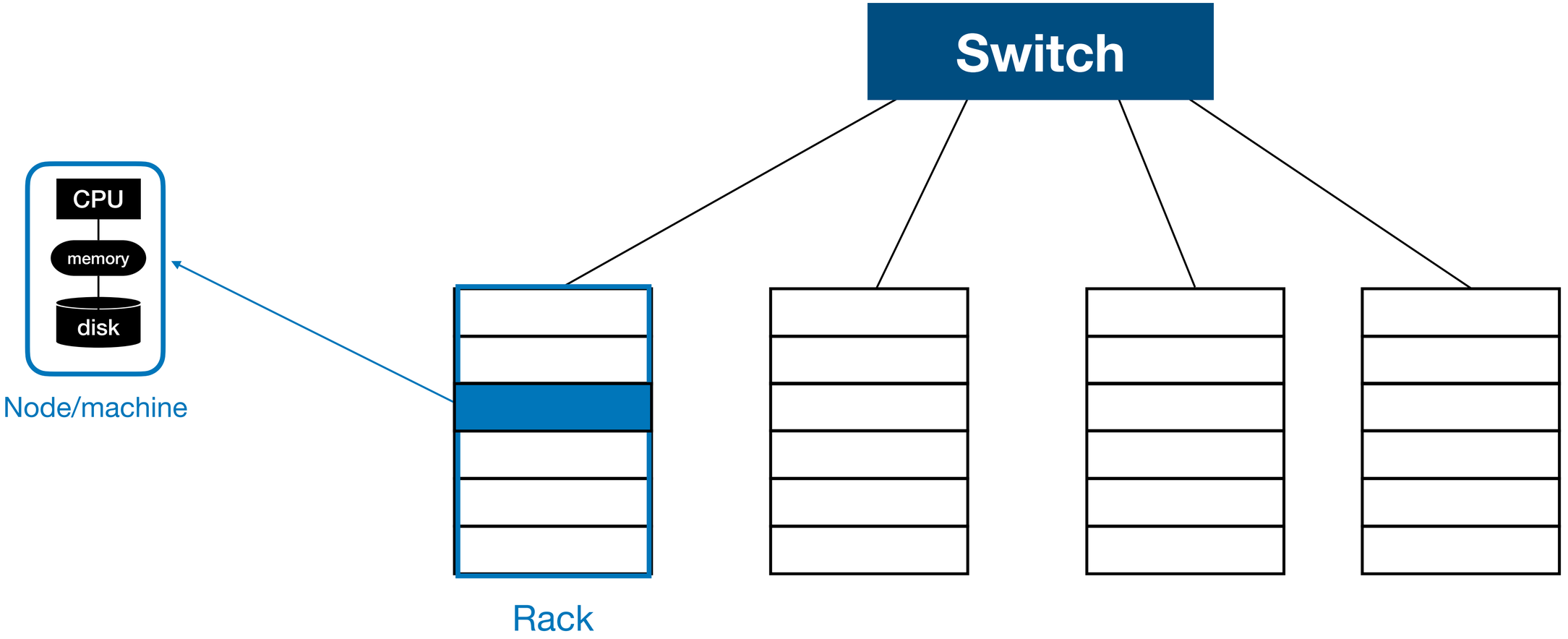
Load balancing

I would like to have block 4!

HDFS

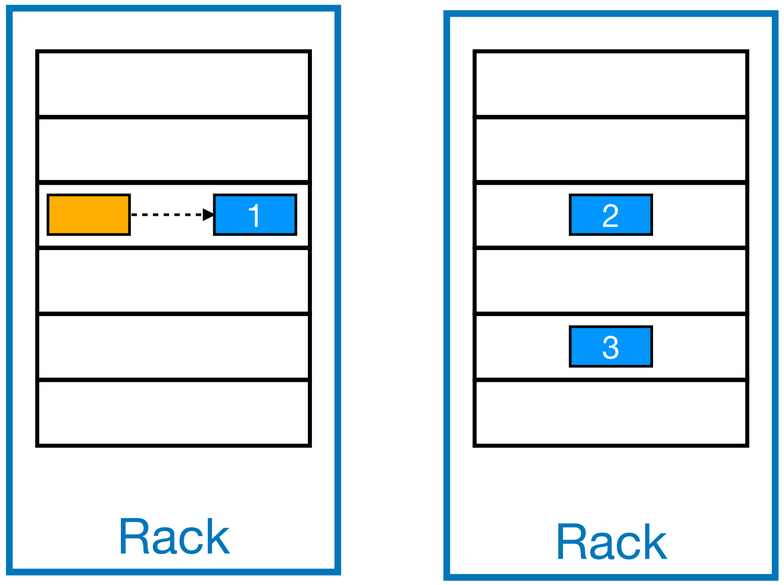


Recall: Typical cluster configuration



Replicas placement

- Goal
  - Reliability
  - Write and read bandwidth
  - Block distribution
- Default strategy
  - First replica: on the client node
  - Second: random, off rack
  - Third: same rack as second, different node
  - More: random



Today's lecture

- Distributed file systems (HDFS)
- **The MapReduce distributed data processing paradigm**
- Hadoop/MapReduce under the hood

What is MapReduce and Hadoop?

- **MapReduce**: A programming model
  - Functional style
  - Users specify Map and Reduce functions
  - Expressive

- **Hadoop**: An associated implementation
  - Automatically parallelized
  - Automatic partitioning, execution, failure handling, load balancing, communication
  - Can handle very large datasets in clusters of commodity computers

MapReduce in a nutshell (I)

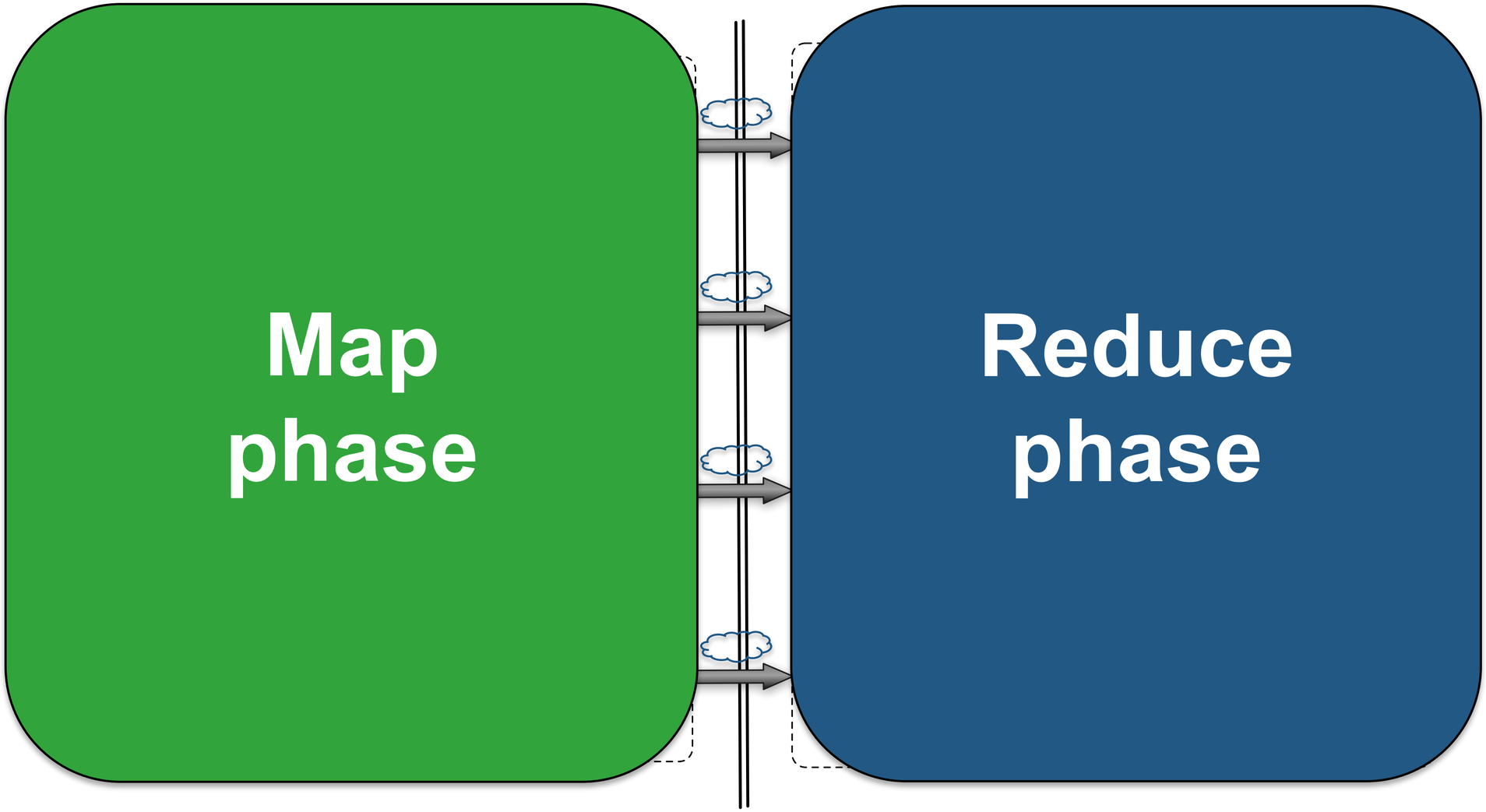
- Framework
  - Read lots of data
  - **Map**: process a data item / record
  - **Sort and shuffle**
  - **Reduce**: aggregate, summarize, filter, transform
  - Write results

- Map and Reduce are **user-specified** → used to model a given problem
  - Input is a **user-defined function**
- Sort and shuffle is taken care by the system itself

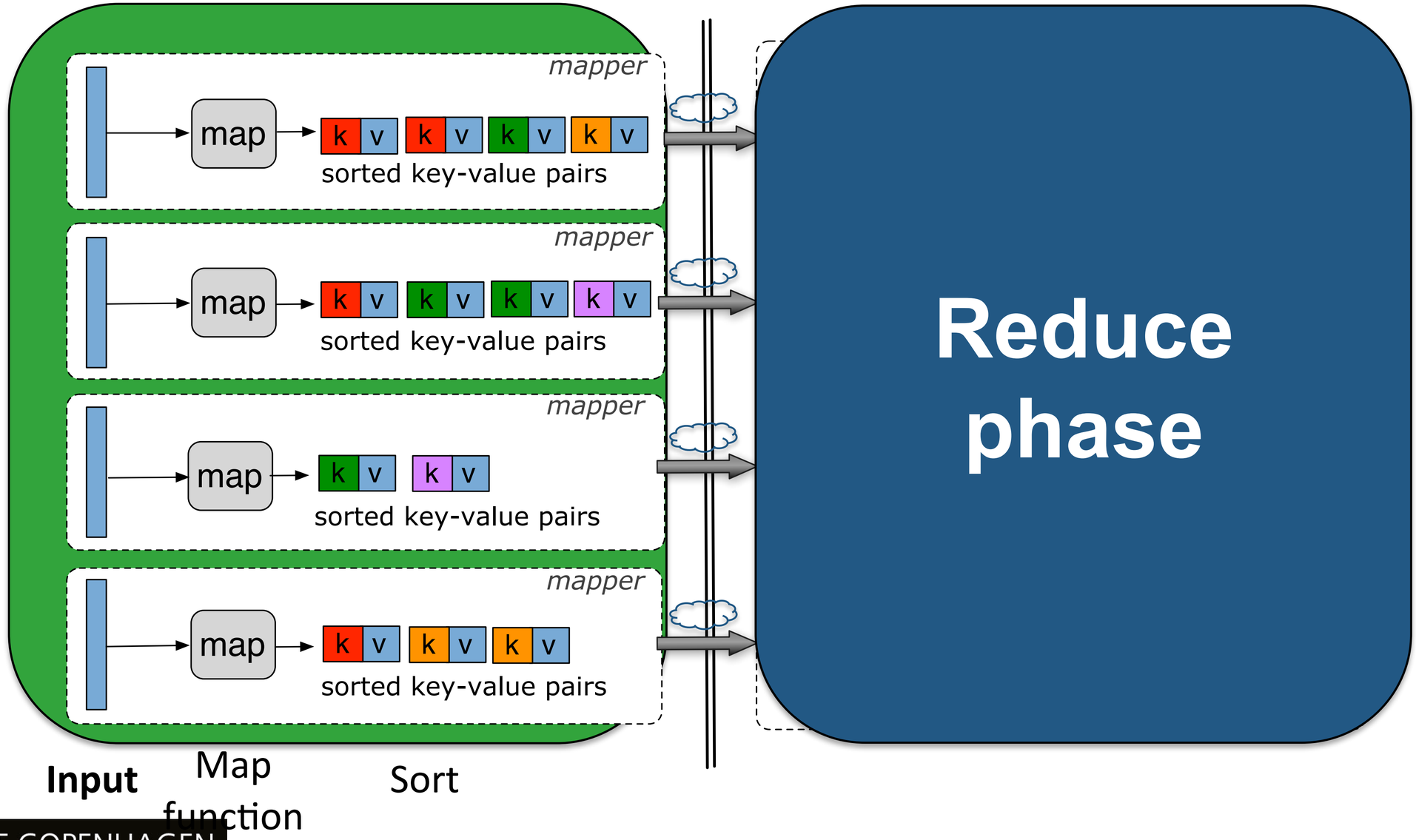
MapReduce in a nutshell (II)

- Simple API
  - **Map** (*key*, *value*) —> {*ikey*, *ivalue*}
  - **Reduce** (*ikey*, {*ivalues*}) —> (*key'*, *value'*)
- **Map** phase: independent processes (mappers) which run in parallel
  - operate on the chunks (blocks) of input data
  - output intermediate results
- **Shuffle** phase: Intermediate results are shuffled through the network
- **Reduce** phase: independent processes (reducers) which run in parallel
  - group intermediate results of the map phase
  - operate on the groups
  - output final results

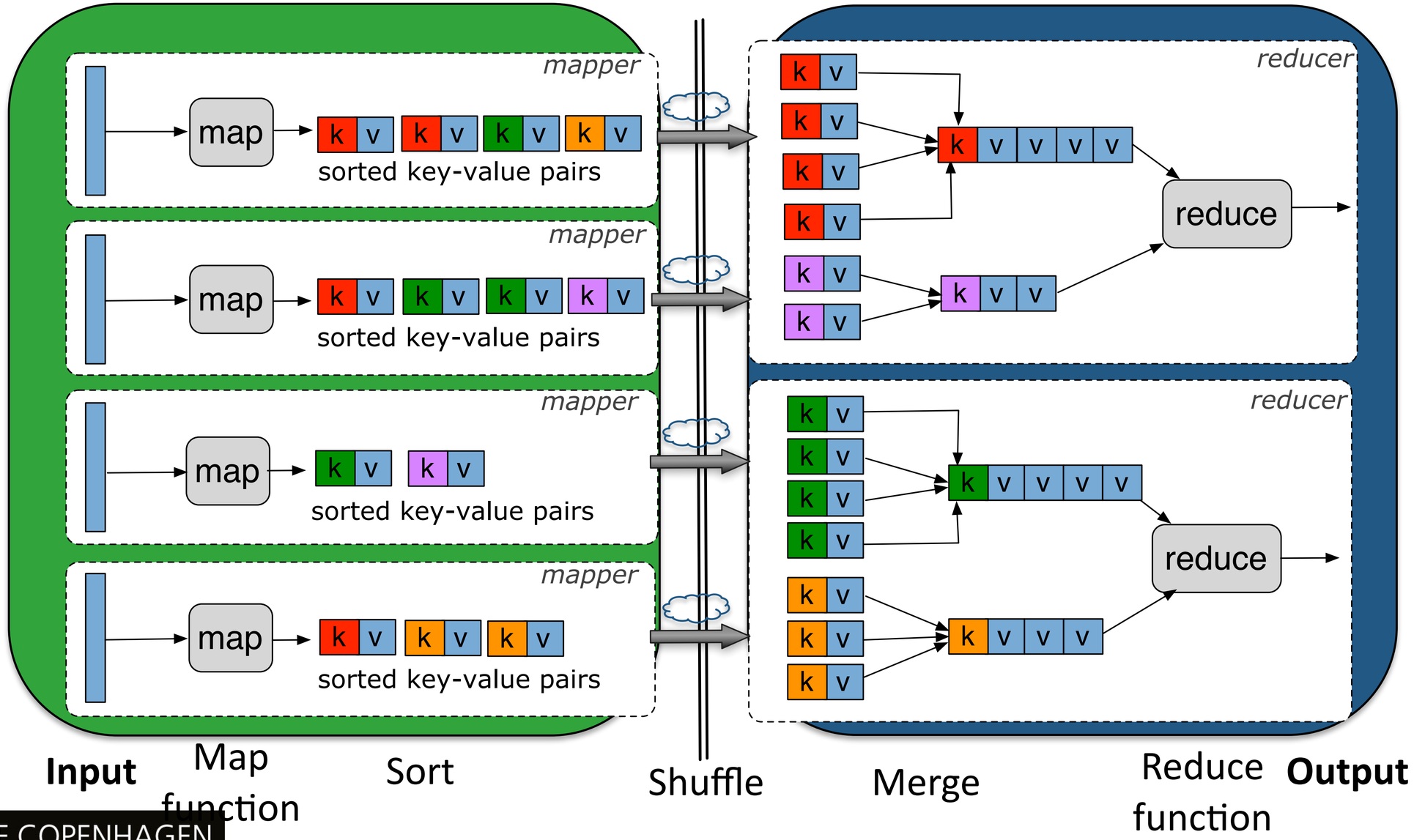
MapReduce illustration



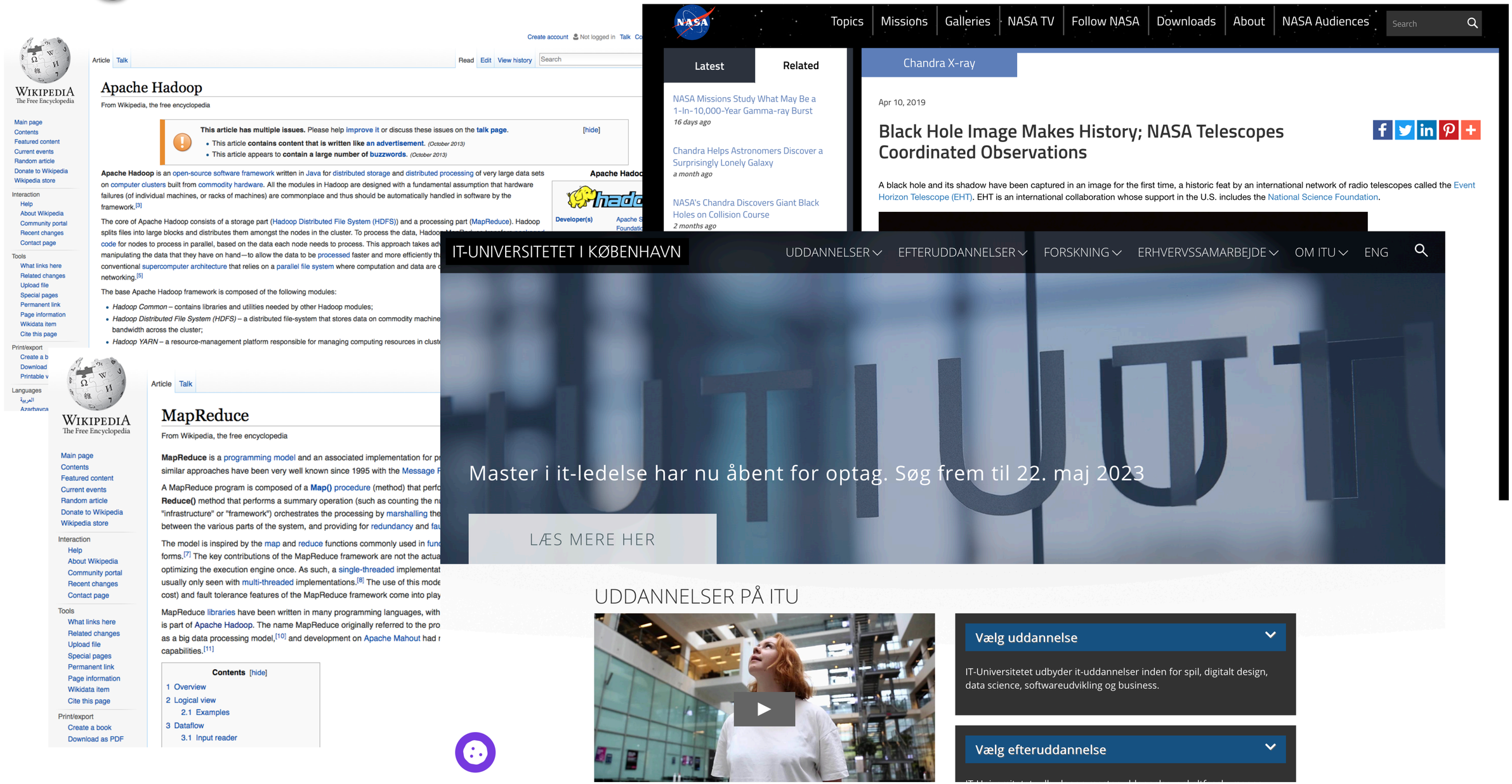
MapReduce illustration



MapReduce illustration



Google Use Case: Web Index



Google Use Case: Web Index

Google

big data

All Images News Videos Books More Tools

About 18.300.000 results (0,45 seconds)

The Stack

The birth of “Big Code” and how to deliver it with remote ex…

Big Data is big, obviously. But we only use the expression because it is intended to convey the now the mostly-forgotten notion that some...

18 hours ago

Forbes

From Big Data To Smart Data: How Manufacturers Can Dri… Value From Industrial Data

Heiko Claussen is SVP of AI at AspenTech, responsible for the company's industry 4.0 strategy, industrial AI research and data science.

21 hours ago

menafn

Big Data Analytics In Energy Market To Reach $ 36.76 Bn …

Big Data Analytics in Energy Market Size The big data analytics in energy market forecast is offered along with information related to ke.

1 day ago

Google Use Case: Web Index

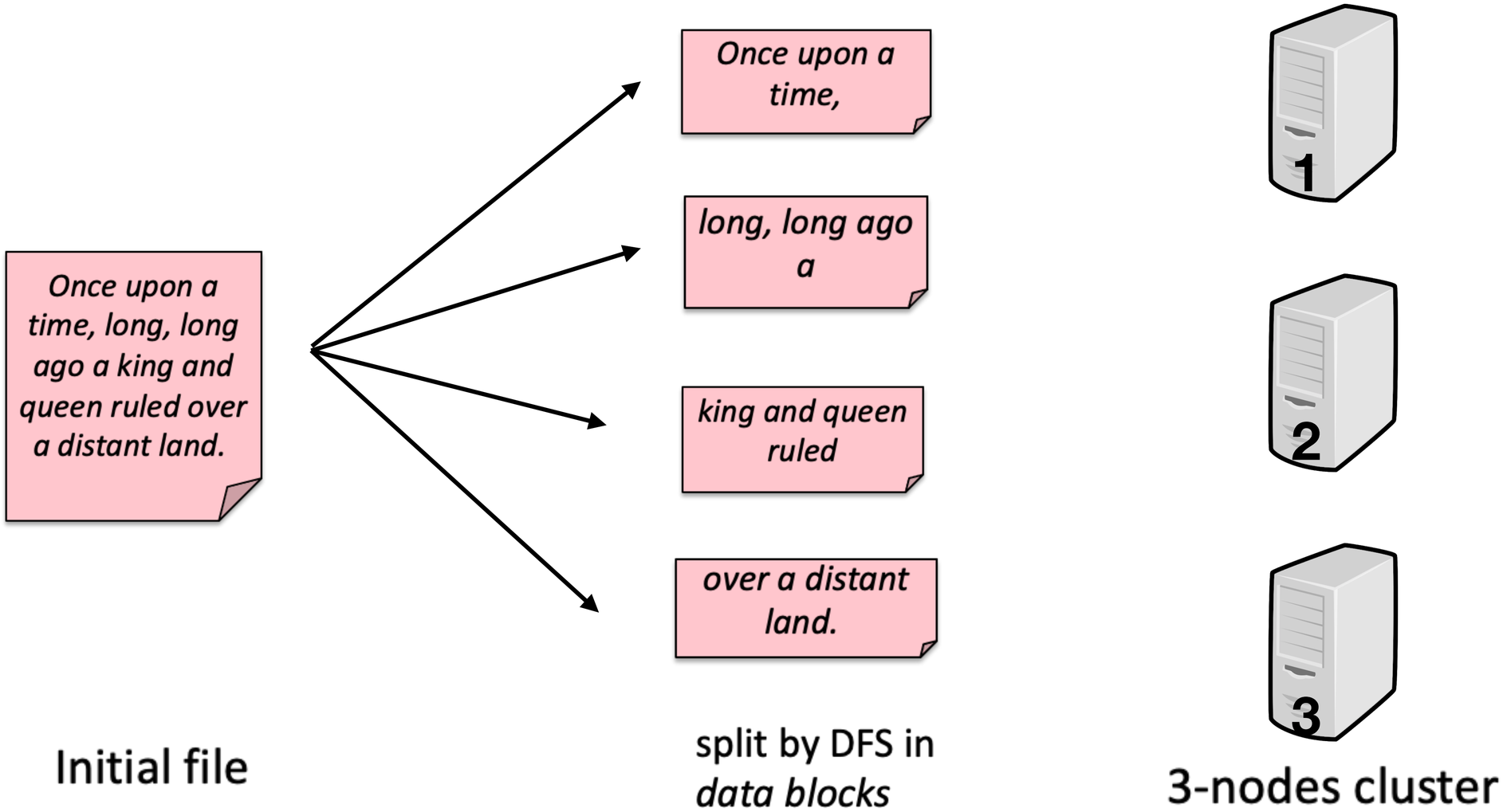
Term	<DocumentIDs, Count>
Big data	<32,10> <45, 7> <59, 3>
….	….
MapReduce	<12, 50> <3, 20>
….	….

Wordcount example

Map (*key*, *value*) —> {*ikey*, *ivalue*}
Reduce (*ikey*, {*ivalues*}) —> (*key'*, *value'*)

Map (*docID*, *text*) —> {*word*, *1*}
Reduce (*word*, {*1, 1, …*}) —> (*word*, count)

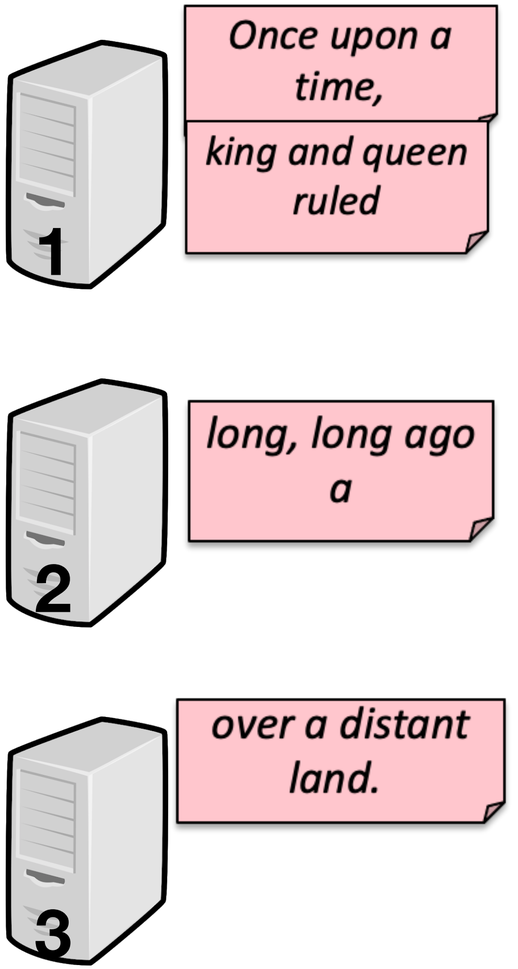
Wordcount example



Wordcount example

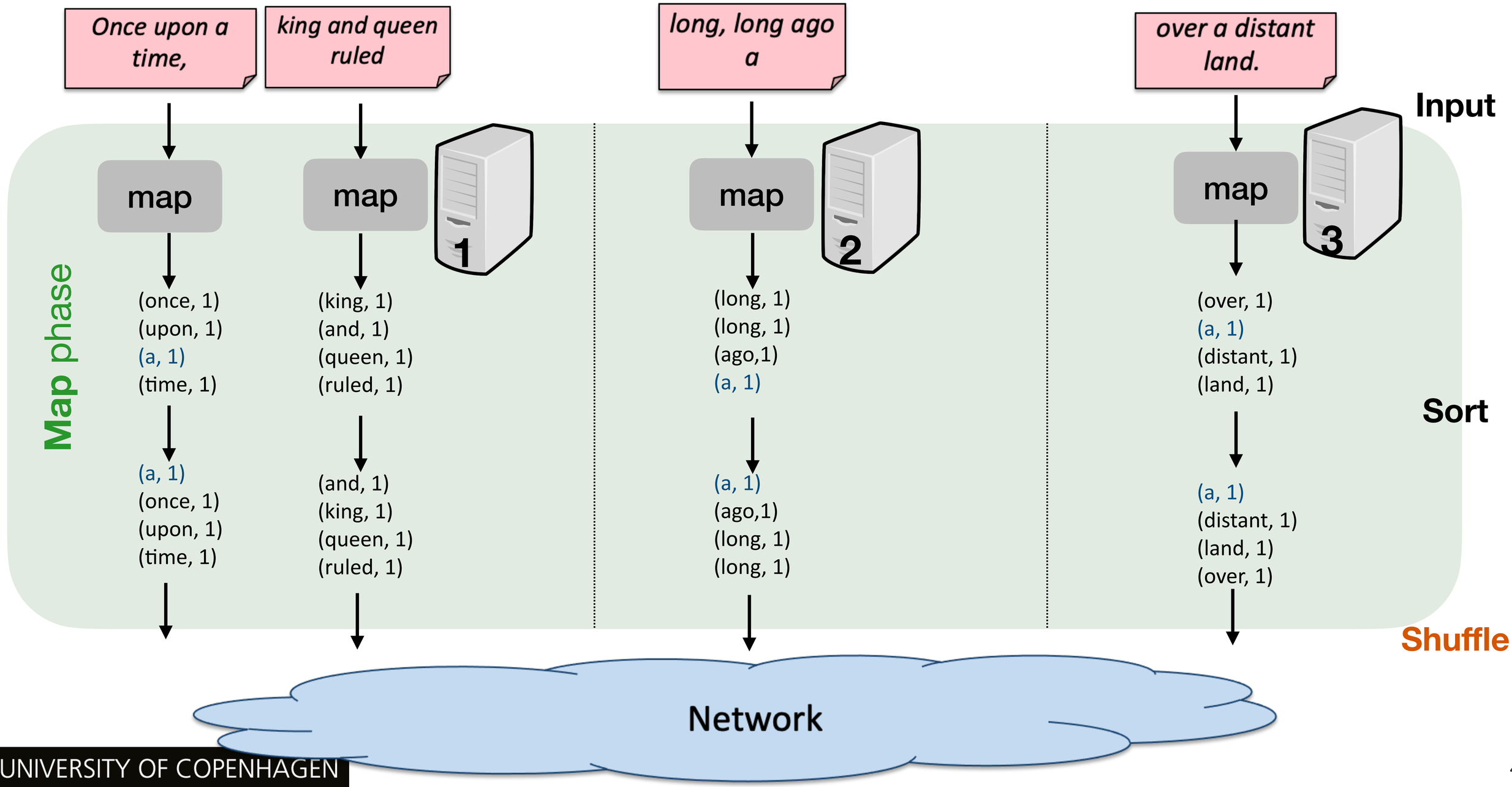
Once upon a time, long, long ago a king and queen ruled over a distant land.

Initial file

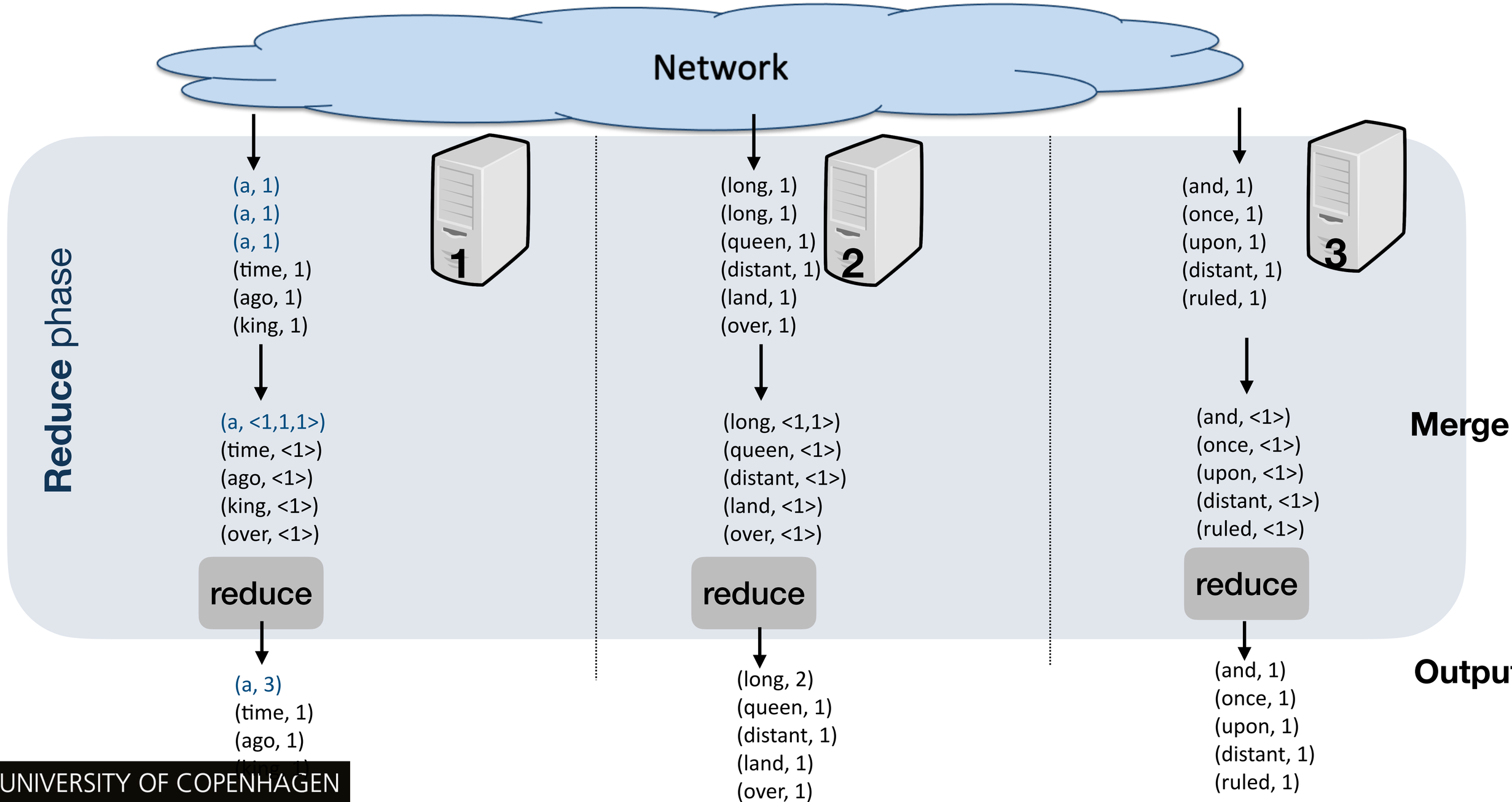


3-nodes cluster

Wordcount example (Map phase)



Wordcount example (Reduce phase)



WordCount example: pseudocode

```
Map(Integer key, String text)
   foreach word w in text:
      emit (w, 1)
```

```
Reduce(String word, Iterator<Integer> counts)
   int result = 0
   foreach count in counts:
      result += count
      emit (word, result)
```

Hadoop/MapReduce Wordcount code :)

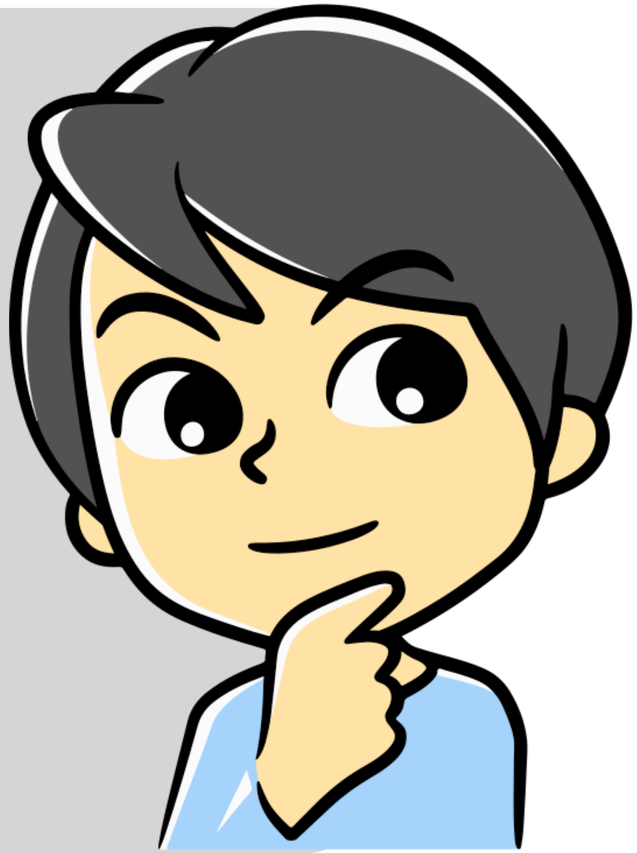
```
 1 package org.myorg;
 2
 3 import java.io.IOException;
 4 import java.util.*;
 5
 6 import org.apache.hadoop.fs.Path;
 7 import org.apache.hadoop.conf.*;
 8 import org.apache.hadoop.io.*;
 9 import org.apache.hadoop.mapreduce.*;
10 import org.apache.hadoop.mapreduce.lib.input.FileInputFormat;
11 import org.apache.hadoop.mapreduce.lib.input.TextInputFormat;
12 import org.apache.hadoop.mapreduce.lib.output.FileOutputFormat;
13 import org.apache.hadoop.mapreduce.lib.output.TextOutputFormat;
14
15 public class WordCount {
16
17  public static class Map extends Mapper<LongWritable, Text, Text, IntWritable> {
18    private final static IntWritable one = new IntWritable(1);
19    private Text word = new Text();
20
21    public void map(LongWritable key, Text value, Context context) throws IOException, InterruptedException {
22      String line = value.toString();
23      StringTokenizer tokenizer = new StringTokenizer(line);
24      while (tokenizer.hasMoreTokens()) {
25        word.set(tokenizer.nextToken());
26        context.write(word, one);
27      }
28    }
29  }
30
31  public static class Reduce extends Reducer<Text, IntWritable, Text, IntWritable> {
32
33    public void reduce(Text key, Iterable<IntWritable> values, Context context)
34      throws IOException, InterruptedException {
35      int sum = 0;
36      for (IntWritable val : values) {
37        sum += val.get();
38      }
39      context.write(key, new IntWritable(sum));
40    }
41  }
42
43  public static void main(String[] args) throws Exception {
44    Configuration conf = new Configuration();
45
46      Job job = new Job(conf, "wordcount");
47
48    job.setOutputKeyClass(Text.class);
49    job.setOutputValueClass(IntWritable.class);
50
51    job.setMapperClass(Map.class);
52    job.setReducerClass(Reduce.class);
53
54    job.setInputFormatClass(TextInputFormat.class);
55    job.setOutputFormatClass(TextOutputFormat.class);
56
57    FileInputFormat.addInputPath(job, new Path(args[0]));
58    FileOutputFormat.setOutputPath(job, new Path(args[1]));
59
60    job.waitForCompletion(true);
61  }
62
63 }
```

Only **63** lines for a distributed/ parallel application!

Reflection time

- MapReduce is powerful enough to run basic SQL queries
  - Although that's not its original intention

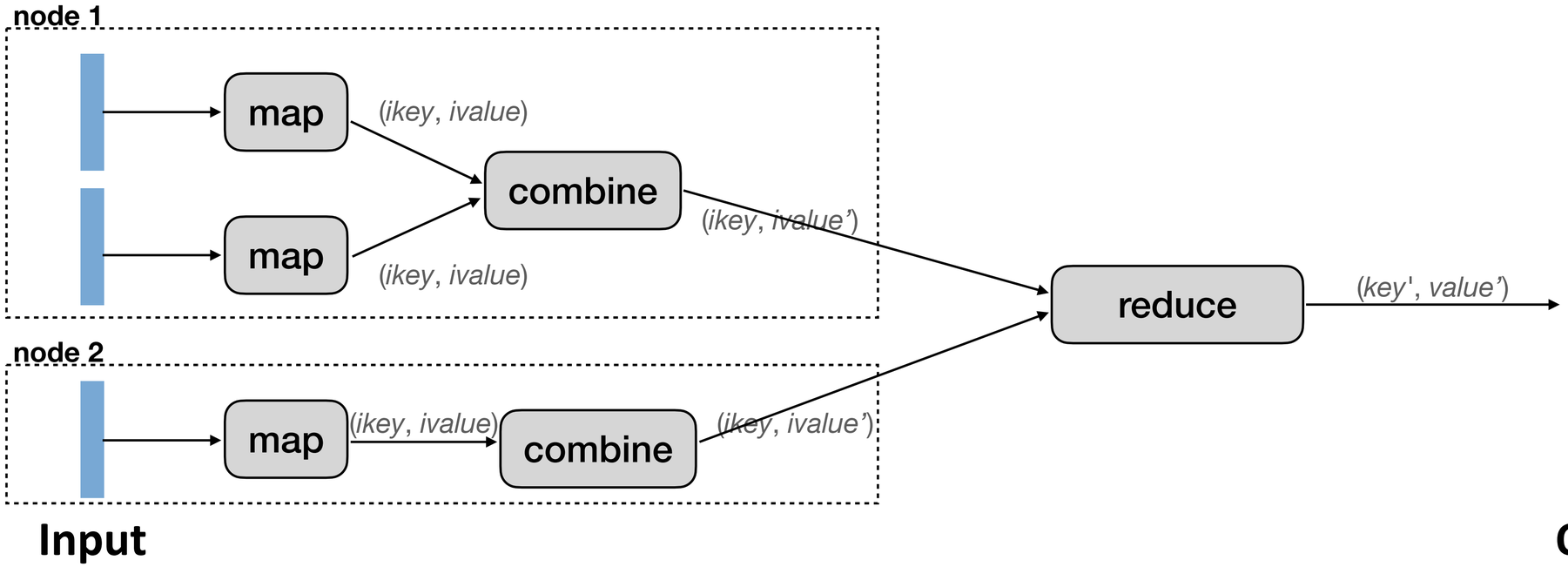
- Compute the total price of the products for each product type available in store 10.
  - `prodId, prodName, prodType, price, storeId`
  -
```
select prodType, sum(price)
from products
where storeId = 10
groupby prodType
```
- How you would implement it in MapReduce?



Combiner

Local reducer

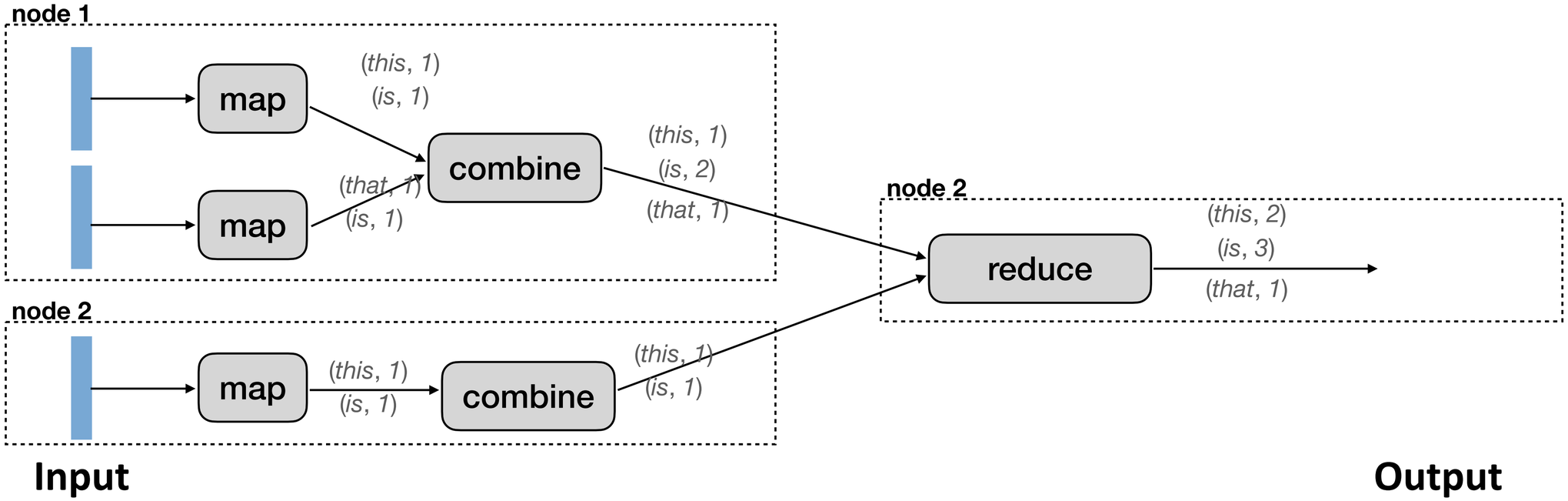
- Pre-aggregate in Map phase
  - Reduces network bandwidth
  - Reduces work on Reduce phase
  - Reduce functions needs to be associative and commutative



Combiner

Local reducer

- Pre-aggregate in Map phase
  - Reduces network bandwidth
  - Reduces work on Reduce phase
  - Reduce functions needs to be associative and commutative



SQL in MapReduce

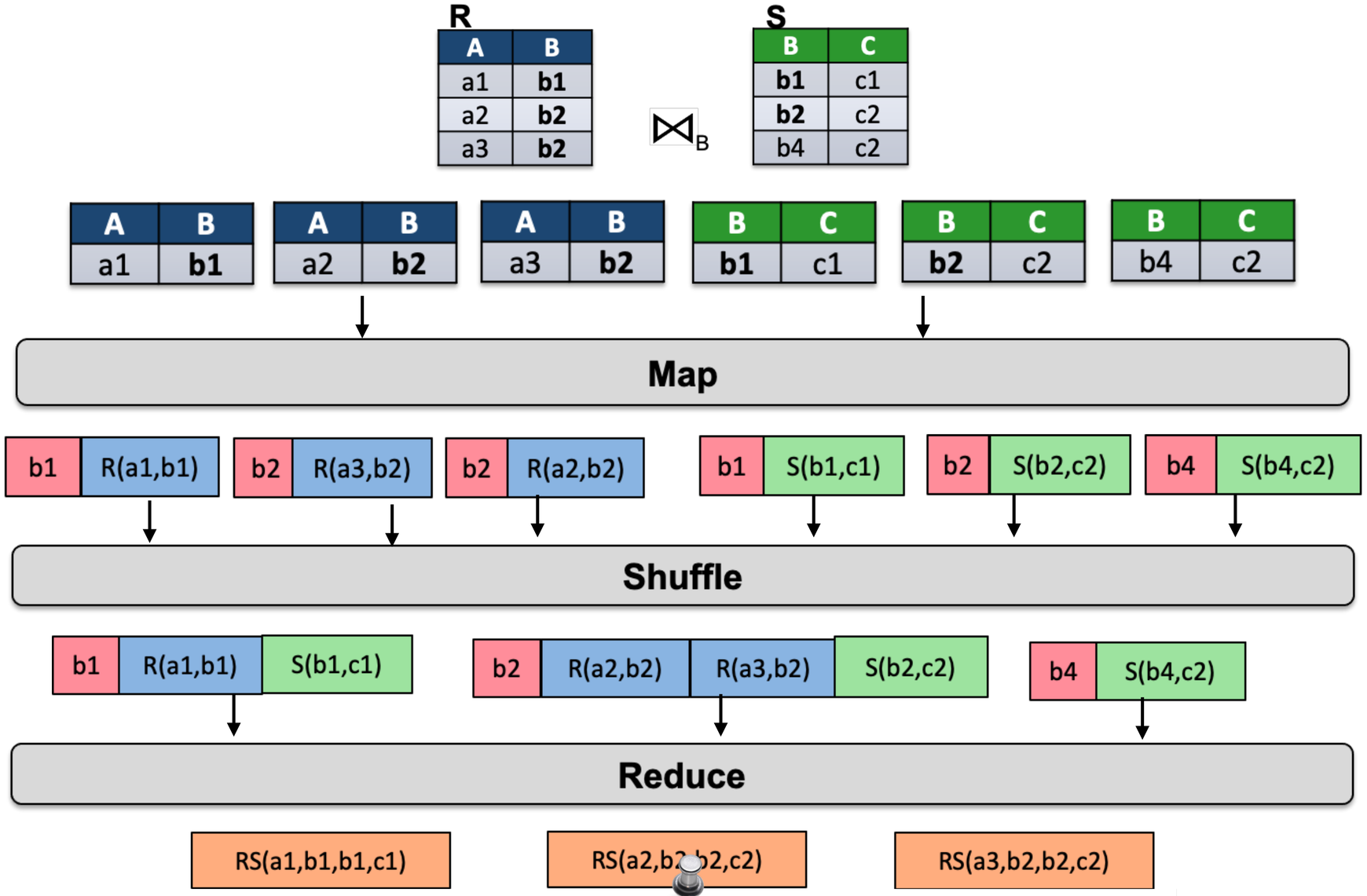
- MapReduce is powerful enough to run basic SQL queries
  - Although that's not its original intention

- Easy case: single table, no sorting
  - Map: selection, projection w/o duplicate elimination
  - MapReduce framework: grouping
  - Reduce: aggregation, having, duplicate elimination

Joins in MapReduce

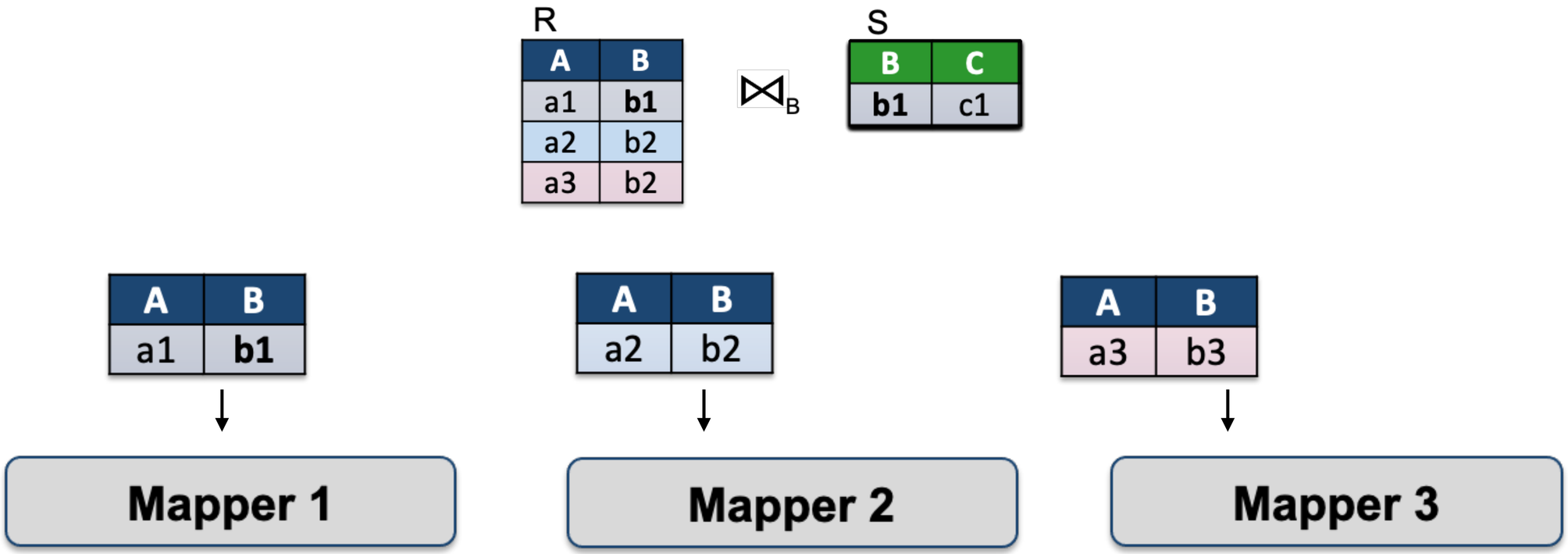
- Two main strategies:
  - **symmetric hash join** (**repartition** join)
  - **replicated join** (**broadcast** join)

Repartition join

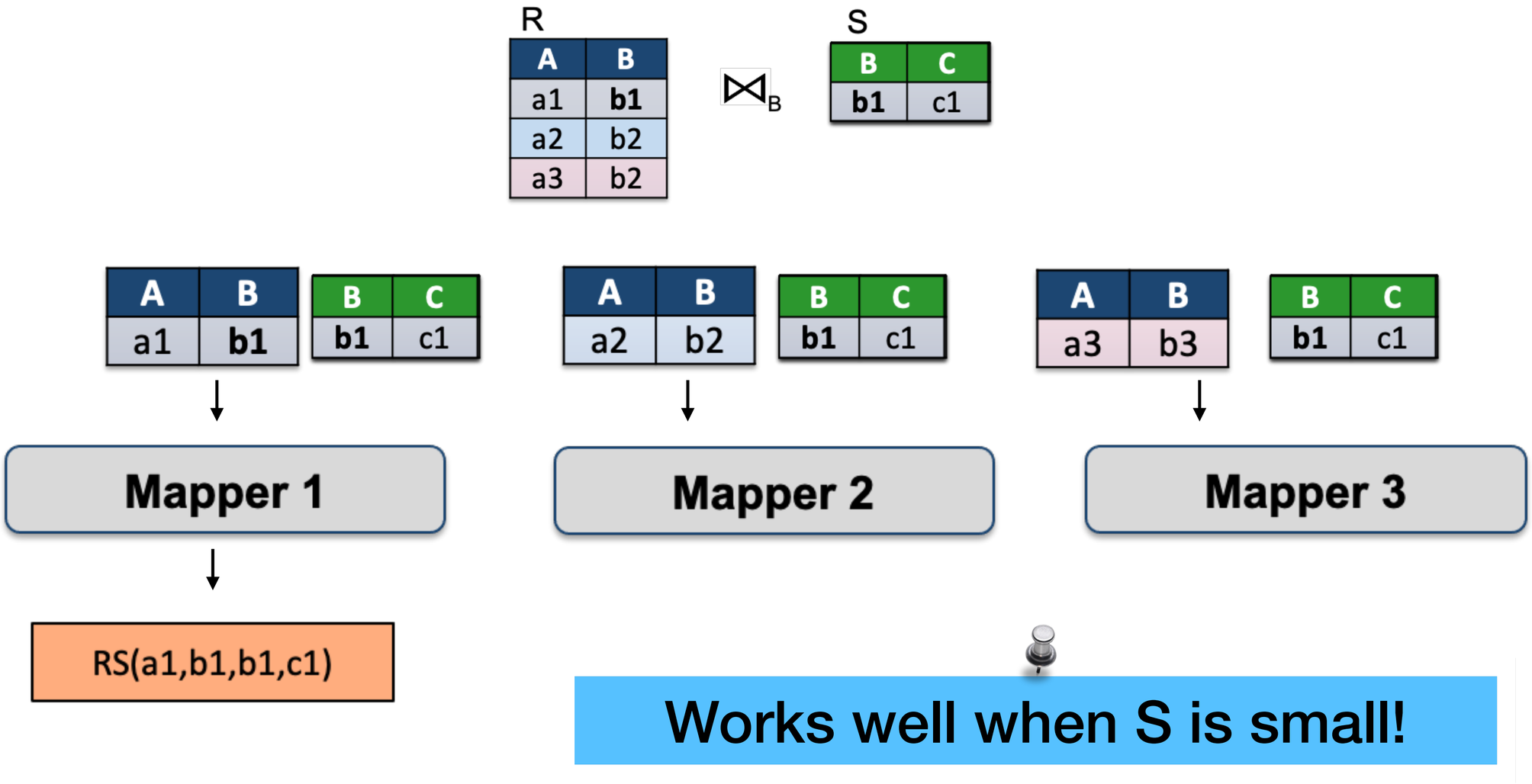


That's a parallel hash join!

Broadcast join



Broadcast join



Today's lecture

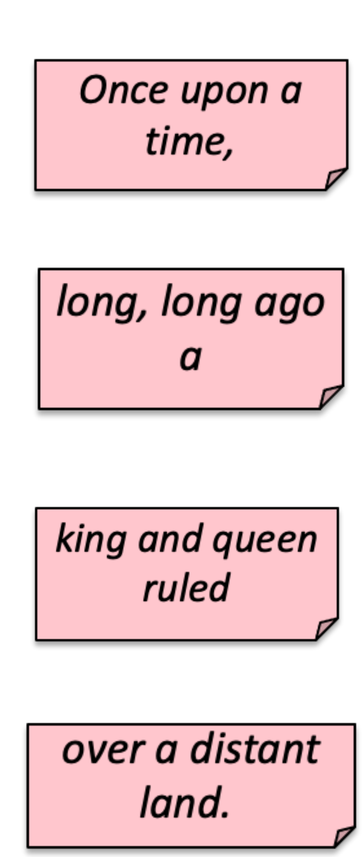
- ✦ Distributed file systems (HDFS)
- ✦ The MapReduce distributed data processing paradigm
- ✦ **Hadoop/MapReduce under the hood**

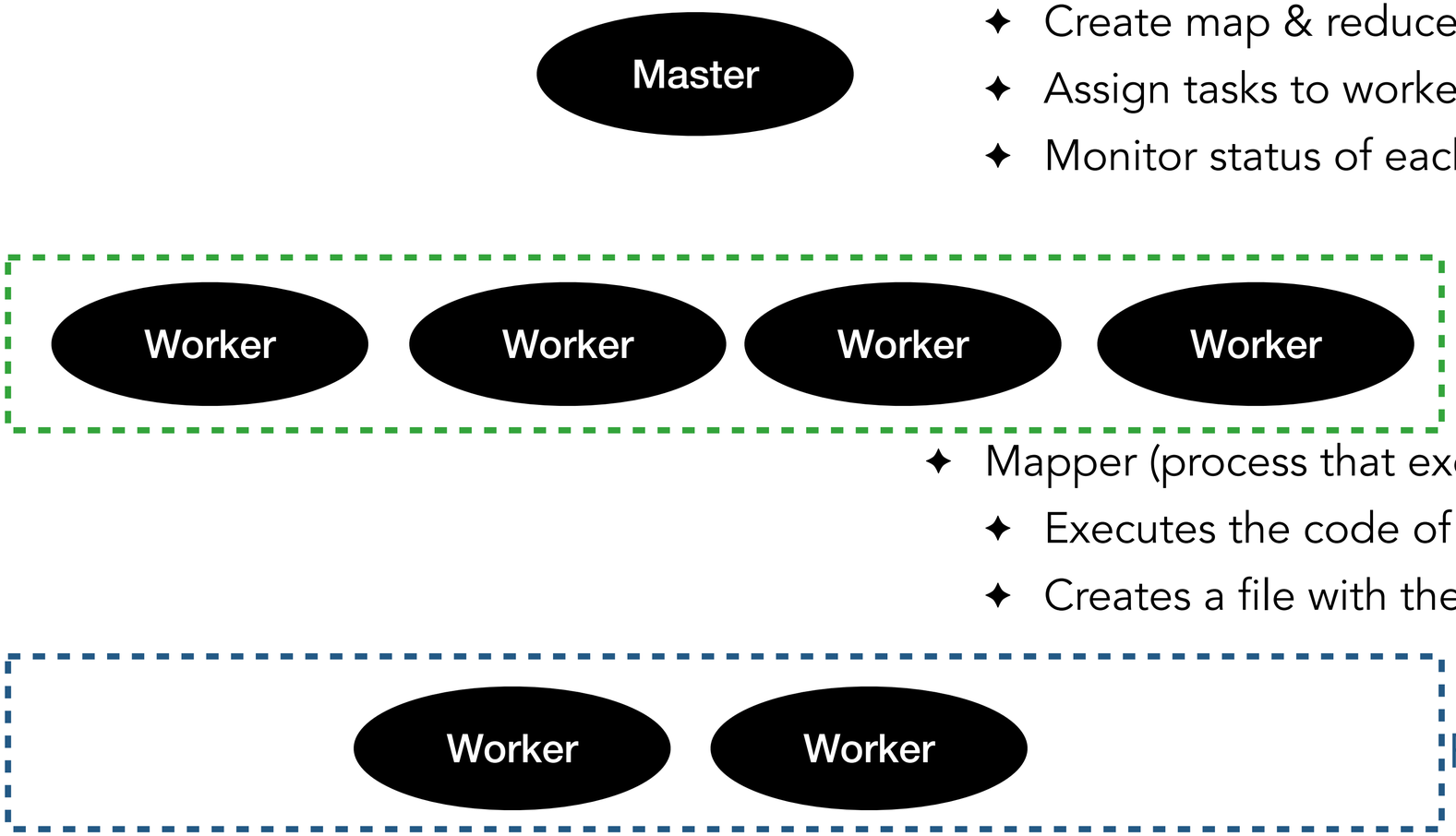
Parallelization in MapReduce

- Application of user-defined function (UDF) f in map() on a data item often not influenced by computations on other data items
  - **Embarrassingly parallel**
  - Implies that we can re-order or parallelize the execution
  - Note: not true when f has side-effects or state

This property forms the basis for MapReduce!

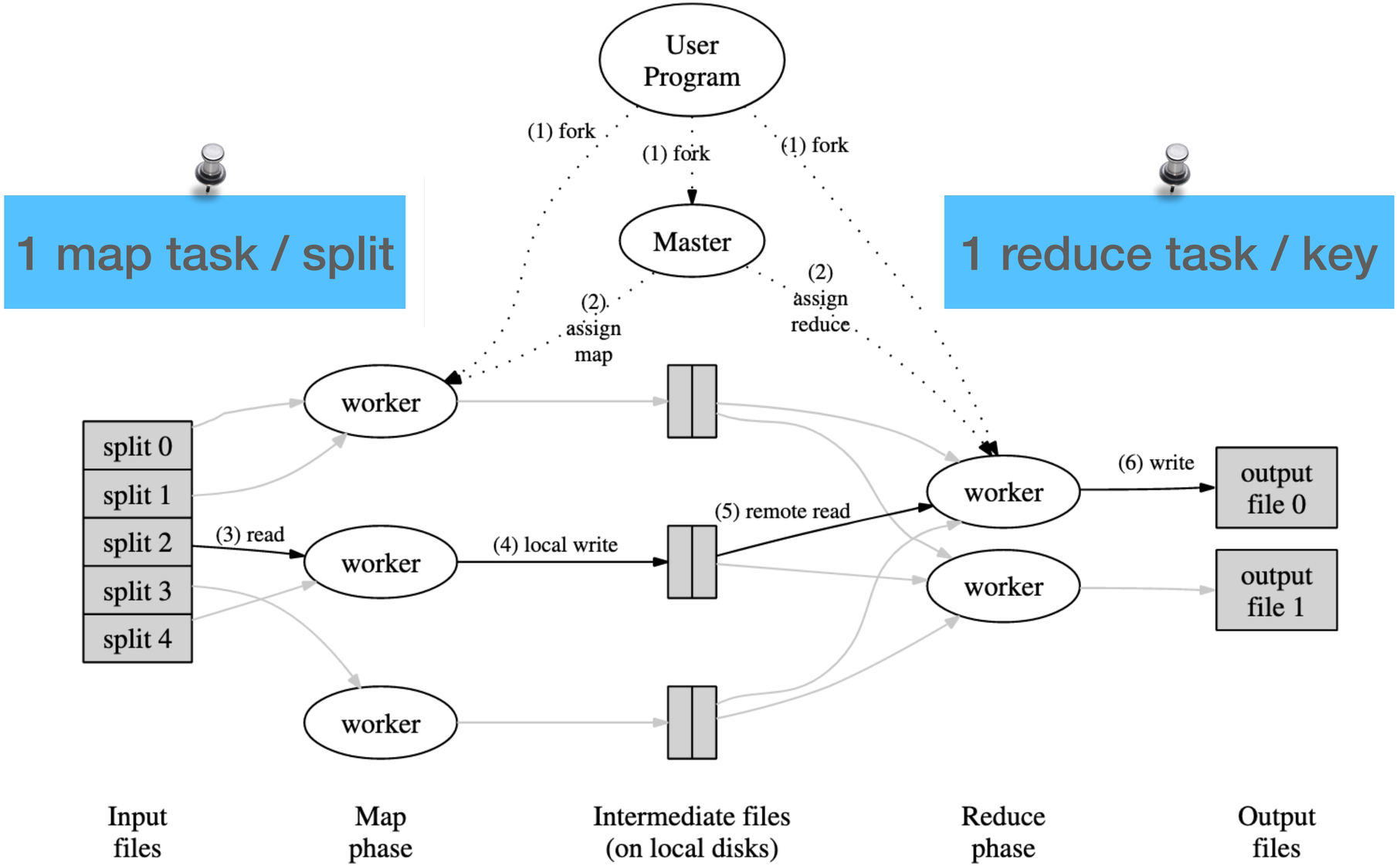
Hadoop/MapReduce under the hood





- Master:
  - Create map & reduce **tasks**
  - Assign tasks to workers
  - Monitor status of each task
- Mapper (process that executes a map task):
  - Executes the code of the map() function
  - Creates a file with the intermediate results
- Reducer (process that executes a reduce task):
  - Executes the code of the reduce() function
  - Writes output in DFS

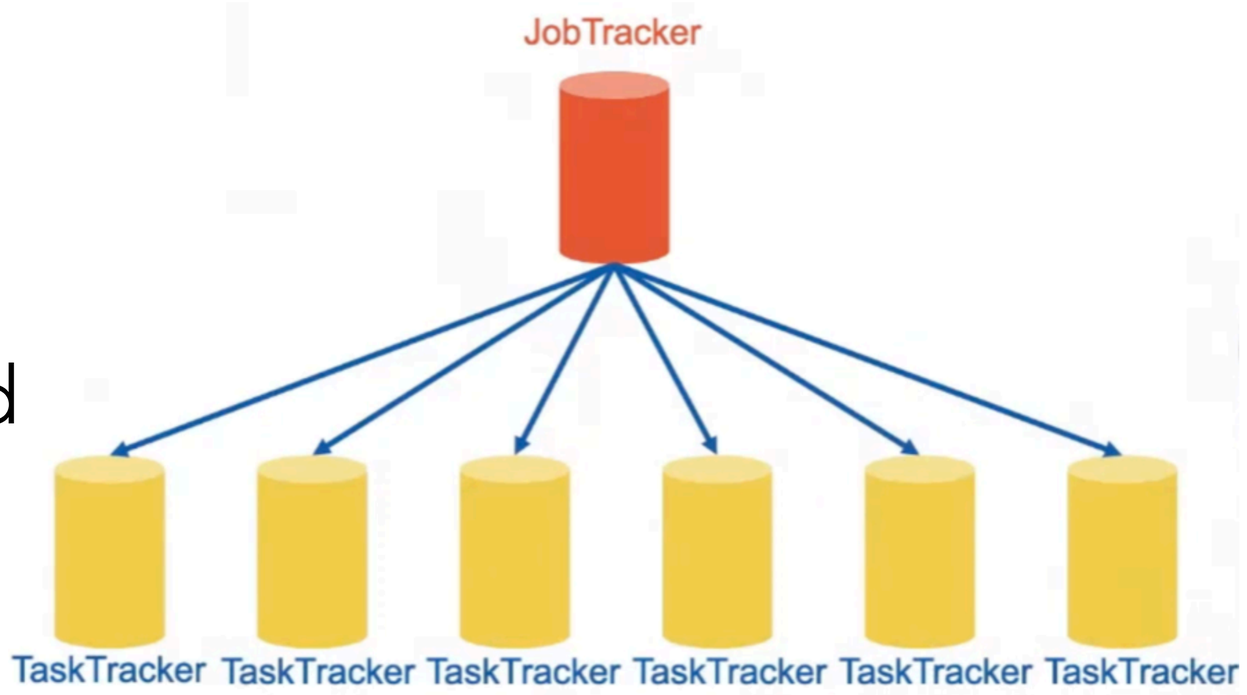
Google MapReduce execution overview



Hadoop architecture

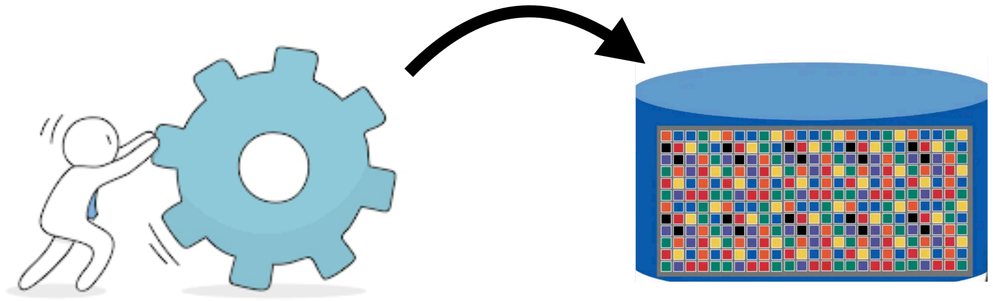
- **Jobtracker**: client communication, job scheduling, resource management, lifecycle coordination

- **Tasktracker**: task execution and management



Data locality

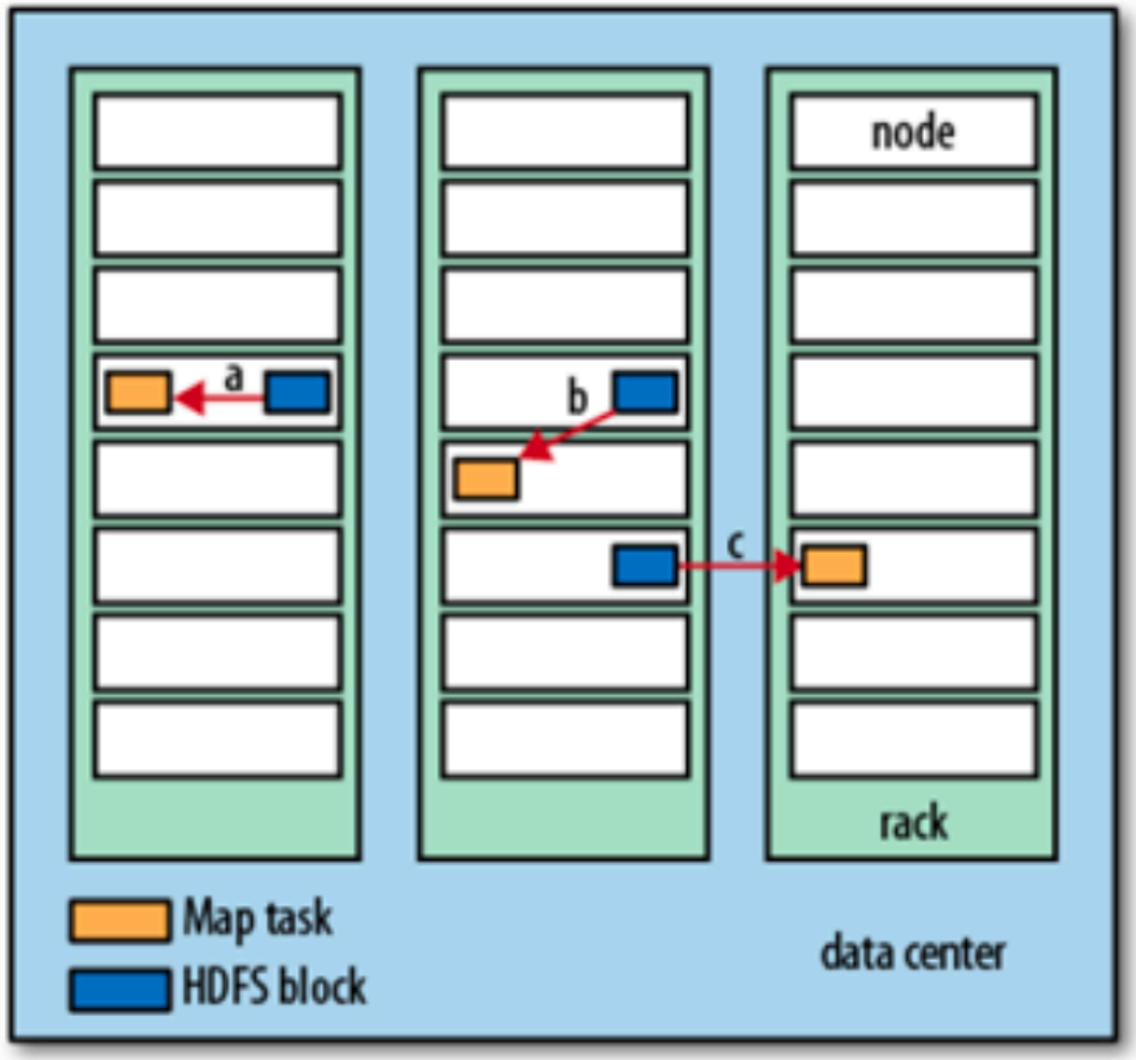
- Move **computation to data**
  - Small code, large data
  - Reduces network bandwidth



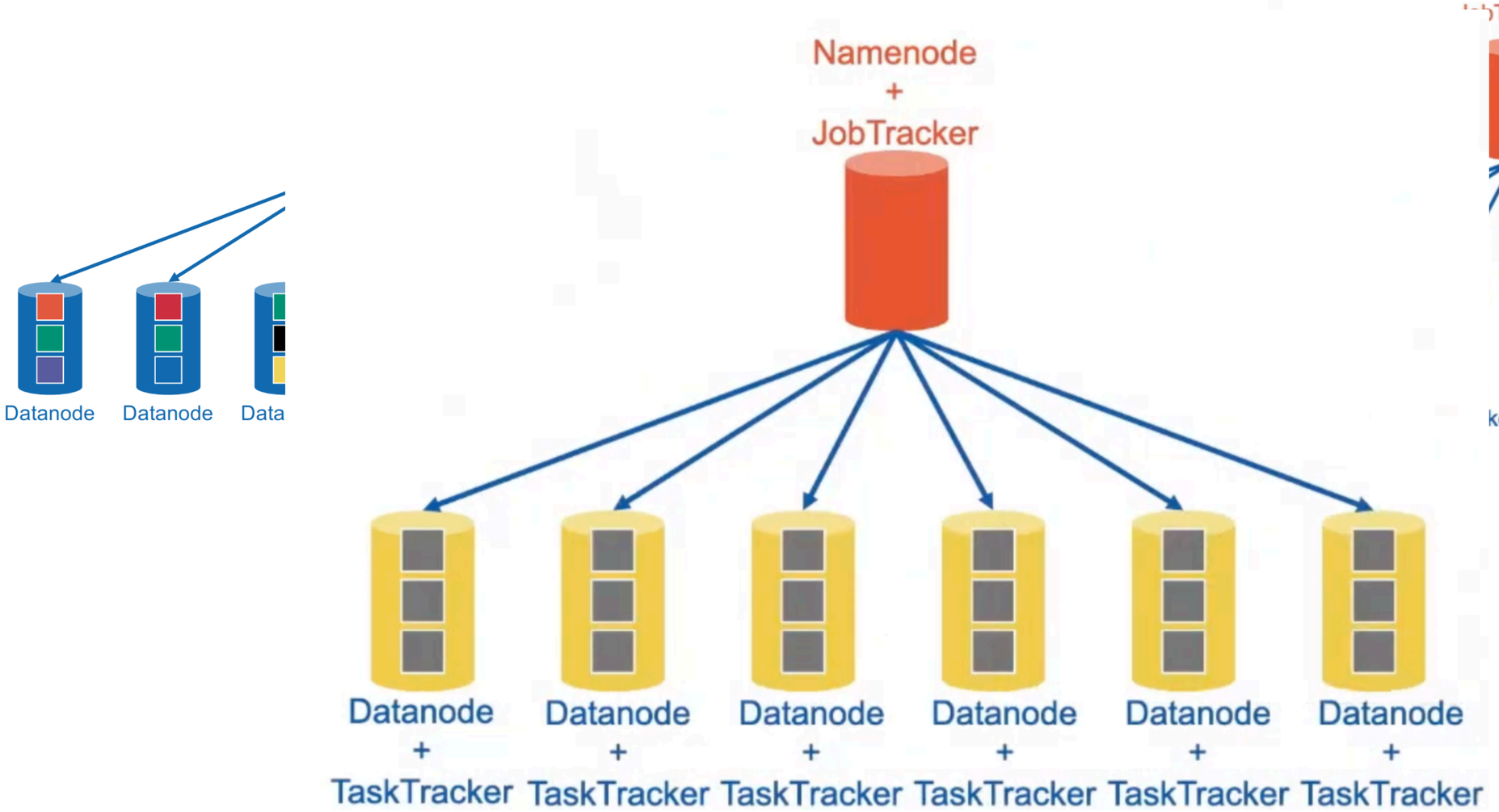
- Goal: run map task on machine that stores input chunk
  - Then map task reads data locally (**local fetch**)
  - Thousands of machines can read at local disk speed; read rate not limited by network

Different types of map tasks based on locality

- (a) Local map task
- (b) rack-local map task
- (c) off-rack map task



Hadoop infrastructure



Hadoop/MapReduce Summary

- **Distributed File System**:
  - Large files split into fixed-size (large) chunks
  - Chunks replicated 3 times
- **MapReduce**: programming model for distributed computation
  - Users code map() and reduce() functions
- **Hadoop**: Open-source implementation of MapReduce
  - Parallelizes map and reduce functions
  - Handles nodes failures

In the next lecture …

- ✦ Dataflow engines paradigm
- ✦ Introduction to Apache Spark

Readings

- Chapter 2 from “Mining of Massive Datasets” book
- GFS paper:
  - Sanjay Ghemawat et al.: The Google file system. SOSP 2003: 29-43 [pdf]
- MapReduce paper:
  - Jeffrey Dean, Sanjay Ghemawat: MapReduce: Simplified Data Processing on Large Clusters. OSDI 2004: 137-150 [pdf]