CS 4440 A

Emerging Database Technologies

Lecture 19

03/30/26

Announcements

Start Assignment 4 if you haven't already!

- Due Apr 8

Guest lecture this Wednesday (Apr 1)

- Attendance required
- Please email staff if you can not make it to lecture.

So far:

One query/update
One machine

Multiple query/updates
One machine

Transactions

One query/update
Multiple machines

Parallel and Distributed query processing

Agenda

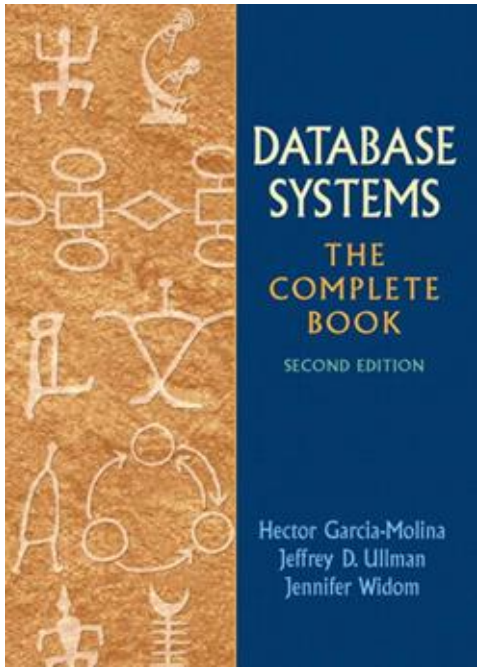
1. Distributed File System

2. Map Reduce

Reading Materials

Database Systems: The Complete Book (2nd edition)

- Chapter 20 – Parallel and Distributed Databases



Research Papers:

- The Google File System
- MapReduce

Historical Context

Early 2000s, people wants to scale up systems

- Non SQL or Non relational (nowadays, Not only SQL)

Triggered by needs of Web 2.0 companies (e.g., Facebook, Amazon, Google)

Trades off consistency requirements of RDBMS for speed

Image source: https://www.geeksforgeeks.org/what-is-internet-definition-uses-working-advantages-and-disadvantages/

Goal: managing large amounts of data quickly

Ranking Web pages by importance

- Iterated matrix-vector multiplication where dimension is many billions

Search friends in social networks

- Graphs with hundreds of millions of nodes and many billions of edges

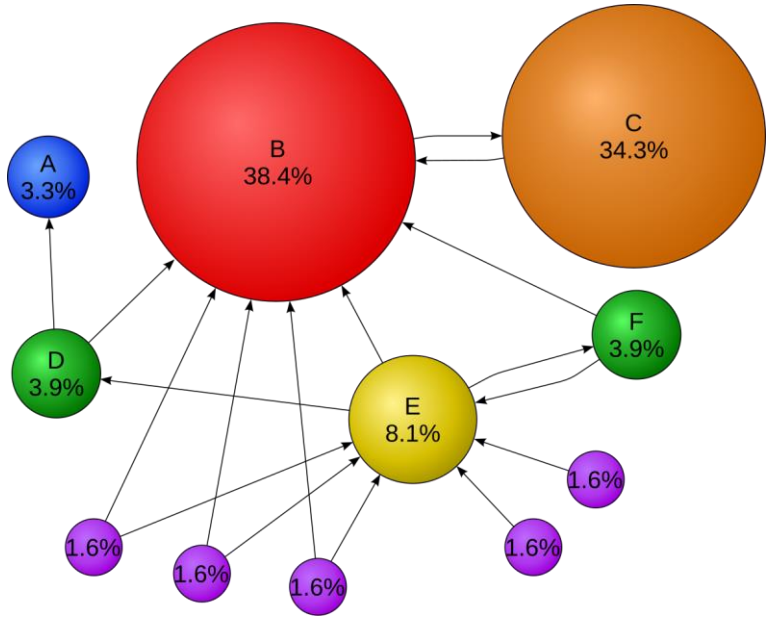


Image source: https://en.wikipedia.org/wiki/PageRank

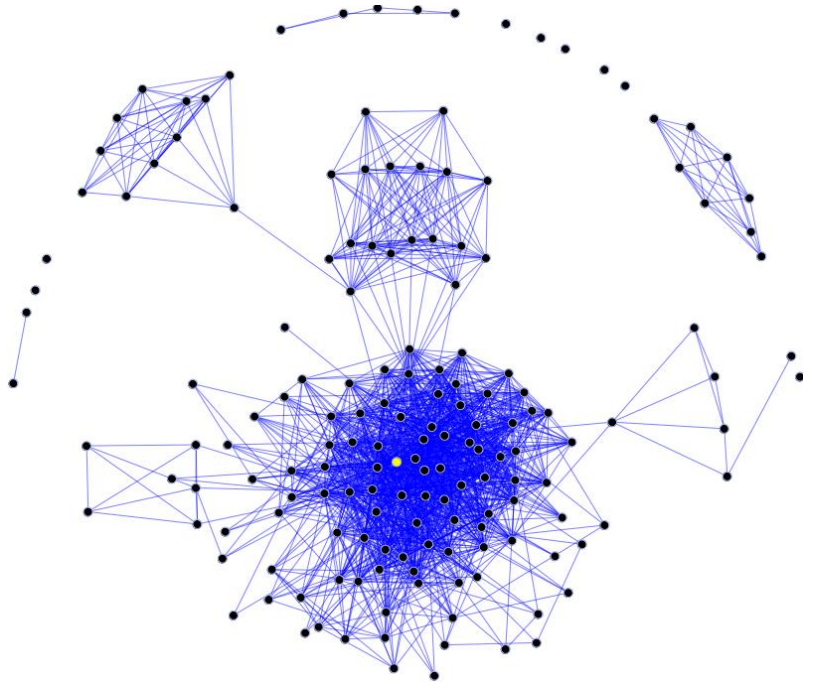


Image source: https://en.wikipedia.org/wiki/Social_graph

Horizontal vs Vertical Scaling

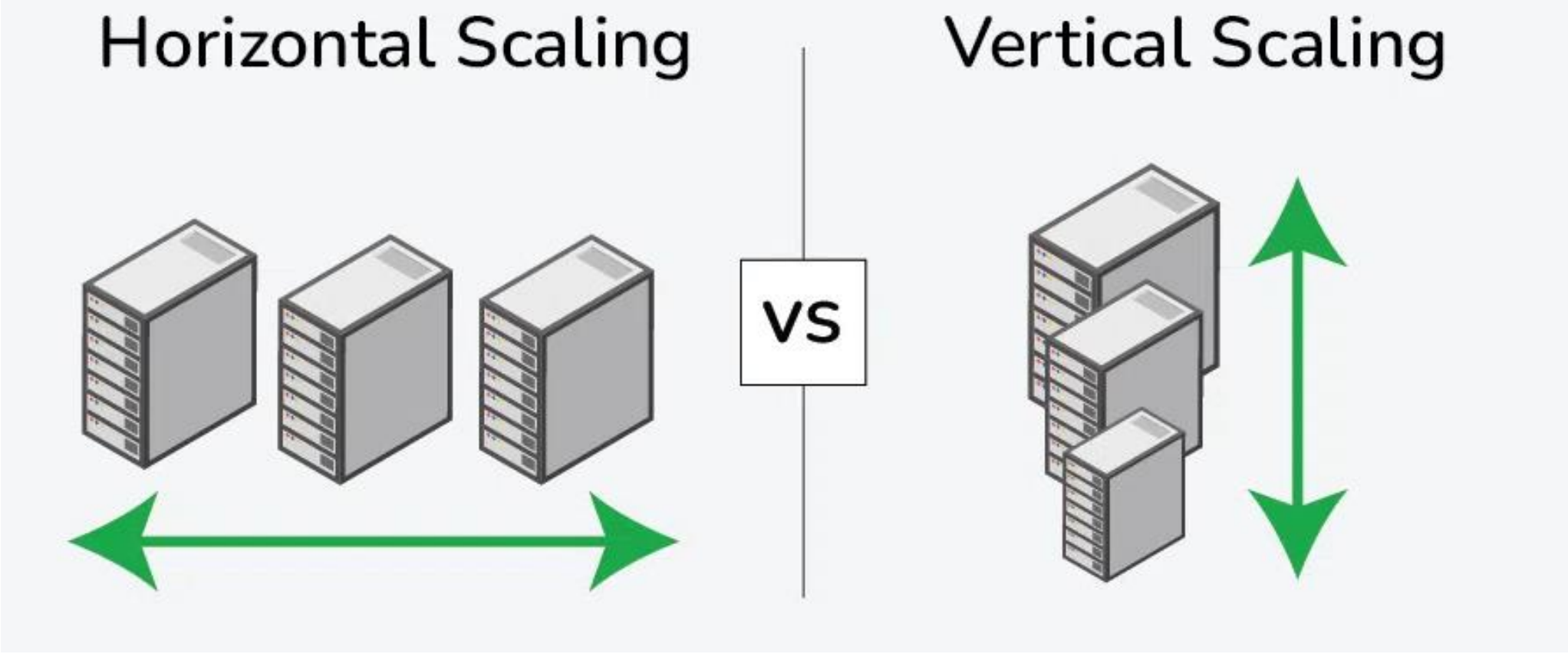


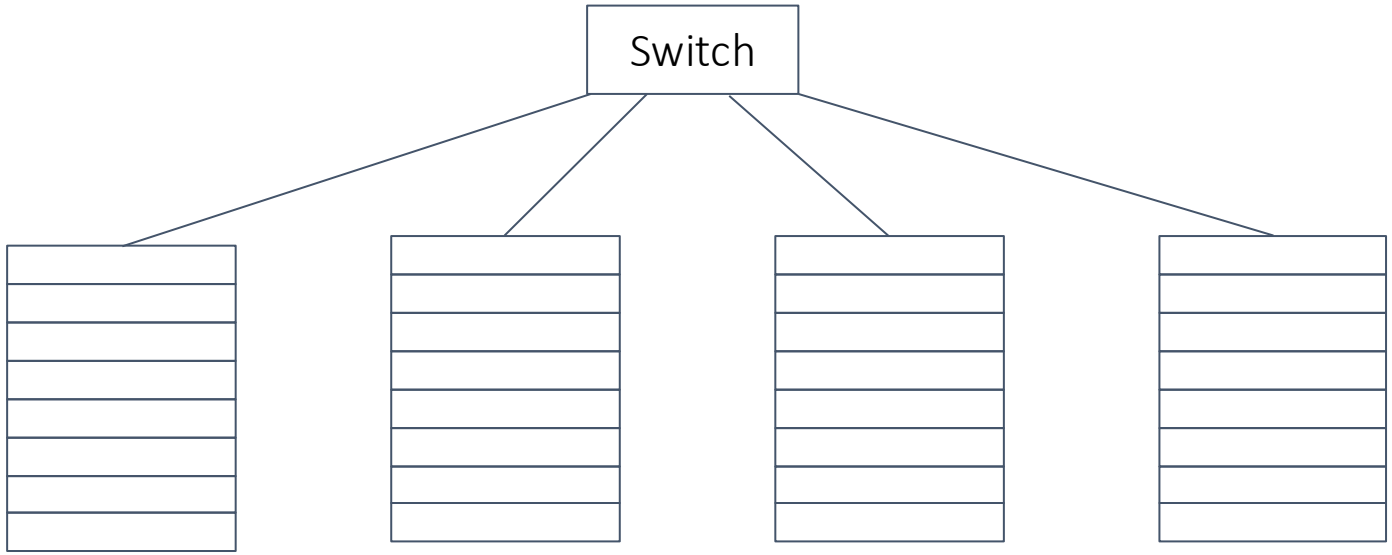
Image source: https://www.geeksforgeeks.org/system-design-horizontal-and-vertical-scaling/

Horizontal scaling

- Instead of a supercomputer (aka vertical scaling), we have large collections of commodity hardware connected by Ethernet cables or inexpensive switches

Physical organization of compute nodes

- Compute nodes are stored on racks (perhaps 8-64 on a rack)
- The nodes on a single rack are connected by a network, typically gigabit Ethernet
- There can be many racks of compute nodes connected by another level of network or a switch



Racks of compute nodes

New Challenges

How do you distribute computation?

How can we make it easy to write distributed programs?

It is a fact of life that components fail:

- One server may stay up 3 years (1,000 days)
- If you have 1,000 servers, expect to lose 1/day
- With 1M machines, 1,000 machines fail every day!

Need solutions for recovering data and computation during failure!

A new software stack

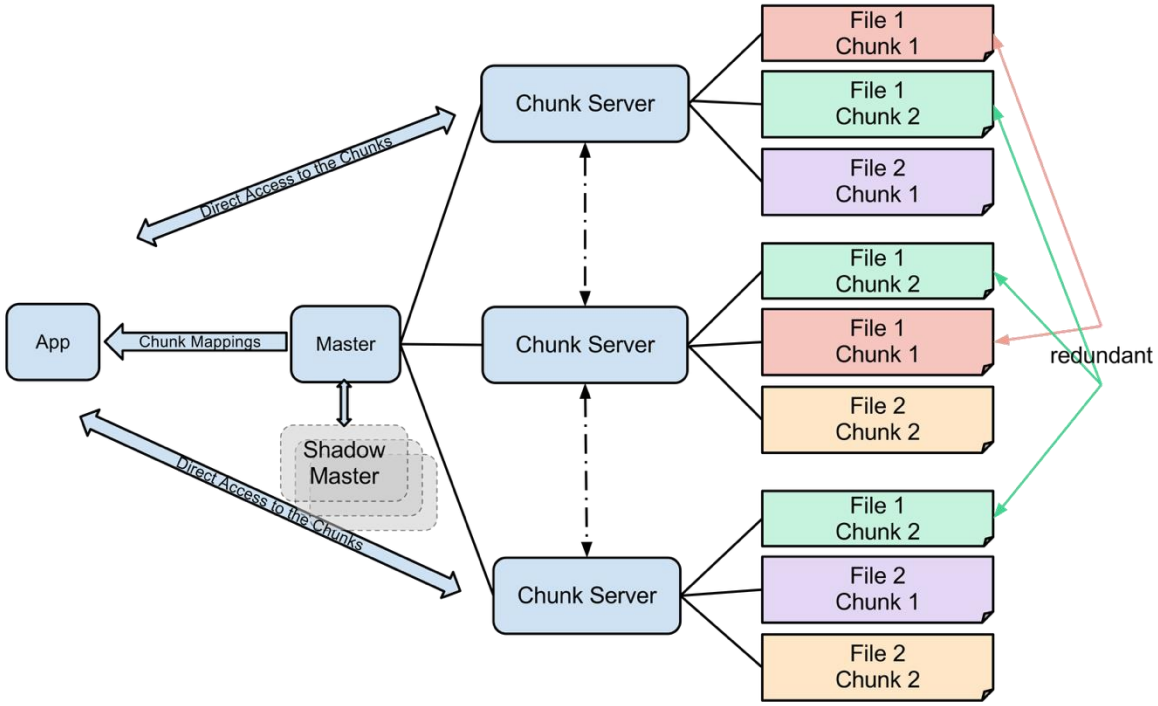
Distributed file system

- Example: Google File System
- Large blocks and data replication to protect against media failures

Programming abstraction

- Example: Map Reduce
- Enables common calculations on large-scale data to be performed on computing clusters efficiently
- Tolerant to hardware failures

1. Distributed File System



The Google File System

Sanjay Ghemawat, Howard Gobioff, and Shun-Tak Leung

SOSP'03

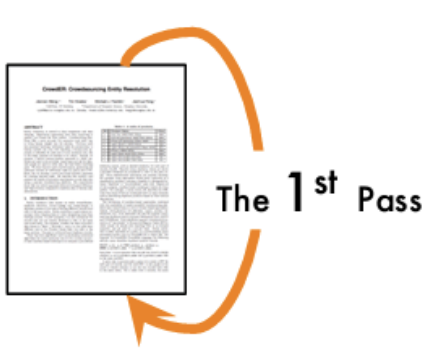
How to read a paper in depth

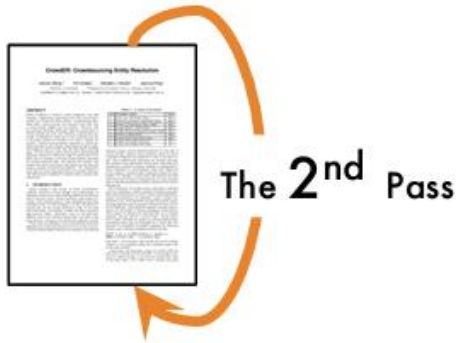
The "three-pass" approach [1]

first pass: a quick scan

second pass: with greater care, but ignore the details

third pass: re-implementing the paper





[1] S. Keshav. How to read a paper? http://blizzard.cs.uwaterloo.ca/keshav/home/Papers/data/07/paper-reading.pdf

The first pass: a quick scan

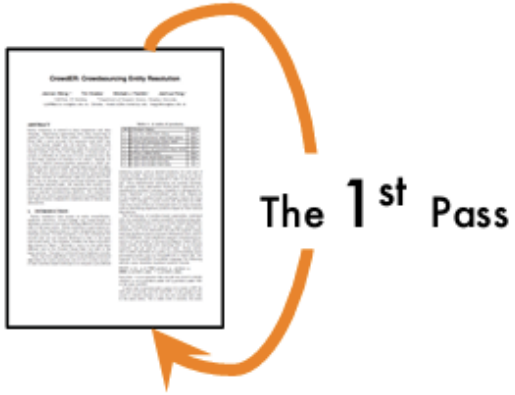
Goal: get bird's-eye view of the paper (5~10 min)

What to read:

- Title, abstract, introduction and conclusion
- Section and sub-section headings
- Main figures
- Scan of bibliography

You should be able to answer:

- What type of paper is this?
- What are the main contributions?



The second pass: grasp the content

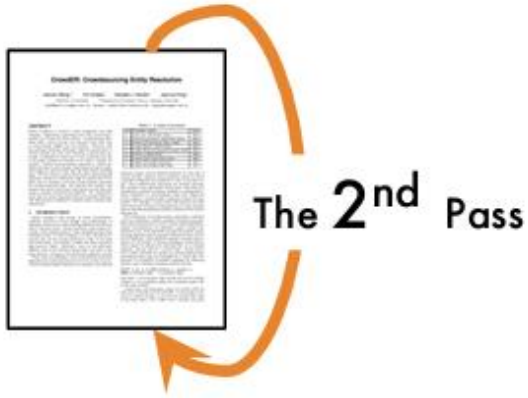
Goal: get a good understanding of the ”meat” of the paper

How to read:

- Look carefully at figures, diagrams and examples
- Take notes of questions, unread references etc.
- Ignore proofs, appendix, extensions etc.

You should be able to:

- Summarize main thrusts of the paper, with supporting evidence, to someone else



The third pass: all about the details

Goal: think about what you would have done if you were to re-implement such an idea

How to read:

- Challenge every assumption
- Compare your version with the actual paper
  - Often leads to questions like: why not do it this way?

You should be able to:

- Identify hidden assumptions/potential design flaws
- Get ideas for future work

Let’s try the first pass!

1. **Category**: What type of paper is this? A measurement paper? An analysis of an existing system? A description of a research prototype?
2. **Context**: Which other papers is it related to?
3. **Correctness**: Do the assumptions appear to be valid?
4. **Contributions**: What are the paper’s main contributions?
5. **Clarity**: Is the paper well written?

Large-scale file system organization

To exploit cluster computing, files must look and behave differently from conventional file systems on single computers

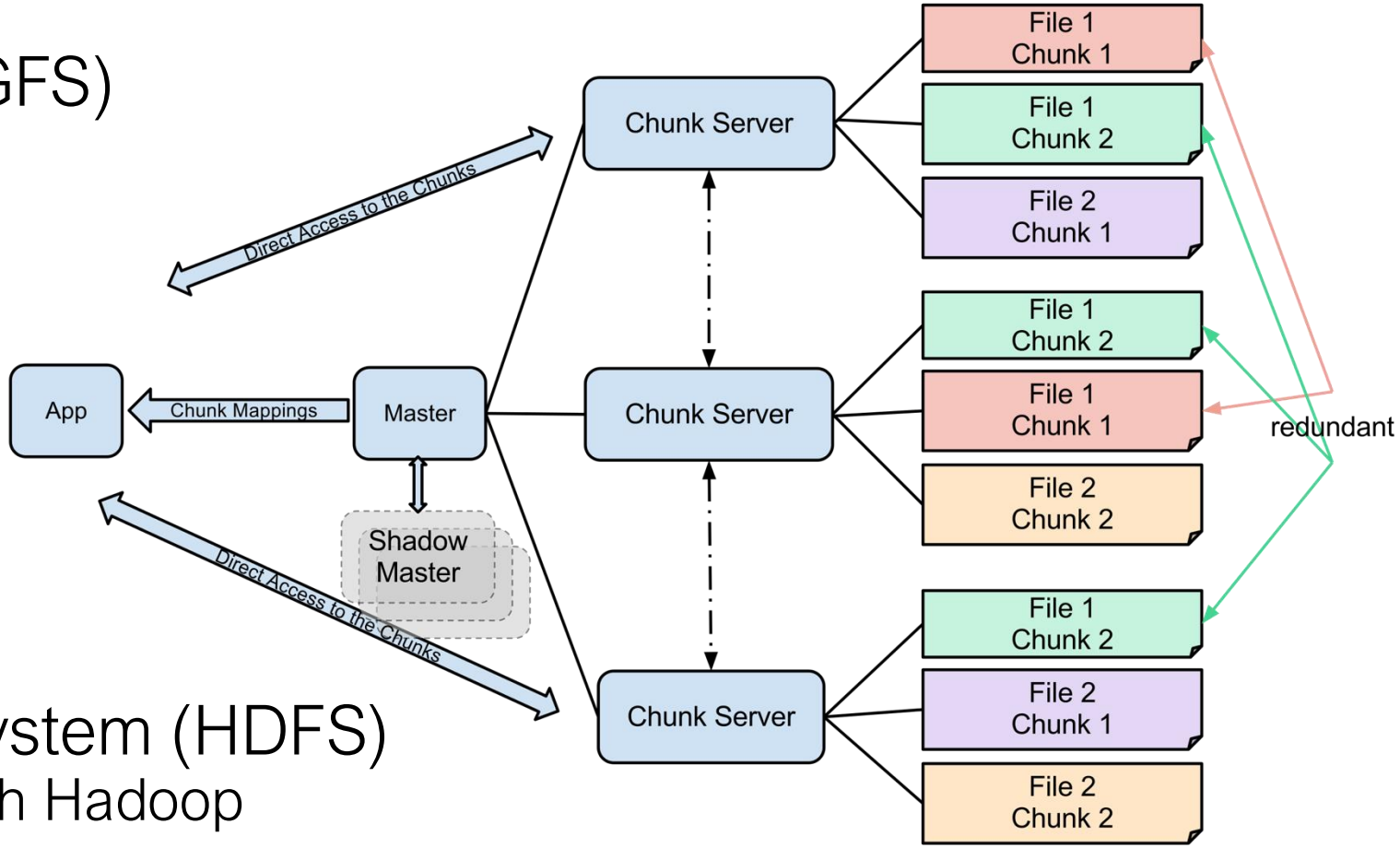
A Distributed File System (DFS) can be used when:

- For very large files: TBs, PBs
- Files are rarely updated and usually read or appended with data
- Mostly sequential reads
- Not useful for OLTP

Distributed File System implementations

The Google File System (GFS)

- Previously used in Google
- Proprietary



Hadoop Distributed File System (HDFS)

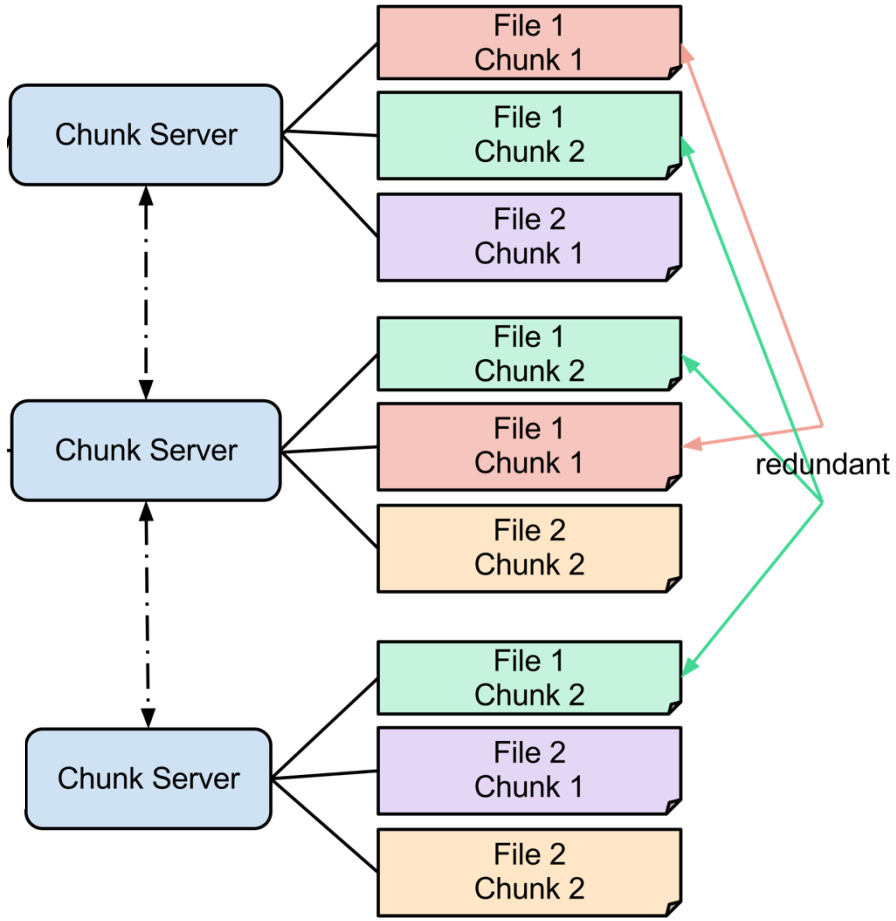
- Open-source DFS used with Hadoop

Image source: https://en.wikipedia.org/wiki/Google_File_System#/media/File:GoogleFileSystemGFS.svg

The Google File System (GFS)

Files are divided into chunks, which are typically 64 MBs

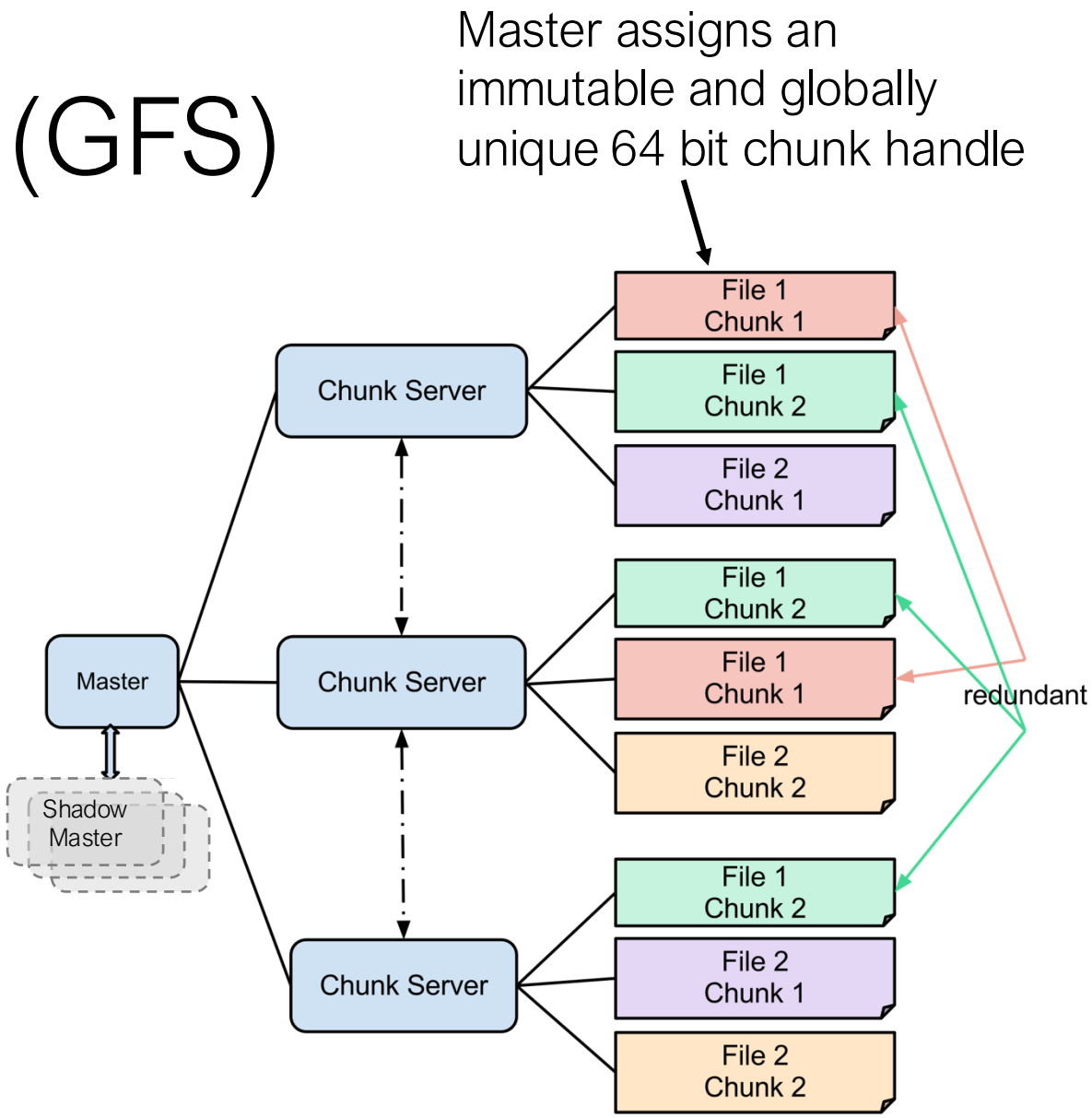
- Chunks are replicated (say 3 times) at different compute nodes (called chunks servers)
- The compute nodes should be located on different racks
- Chunk size and degree of replication decided by the user



The Google File System (GFS)

Master node

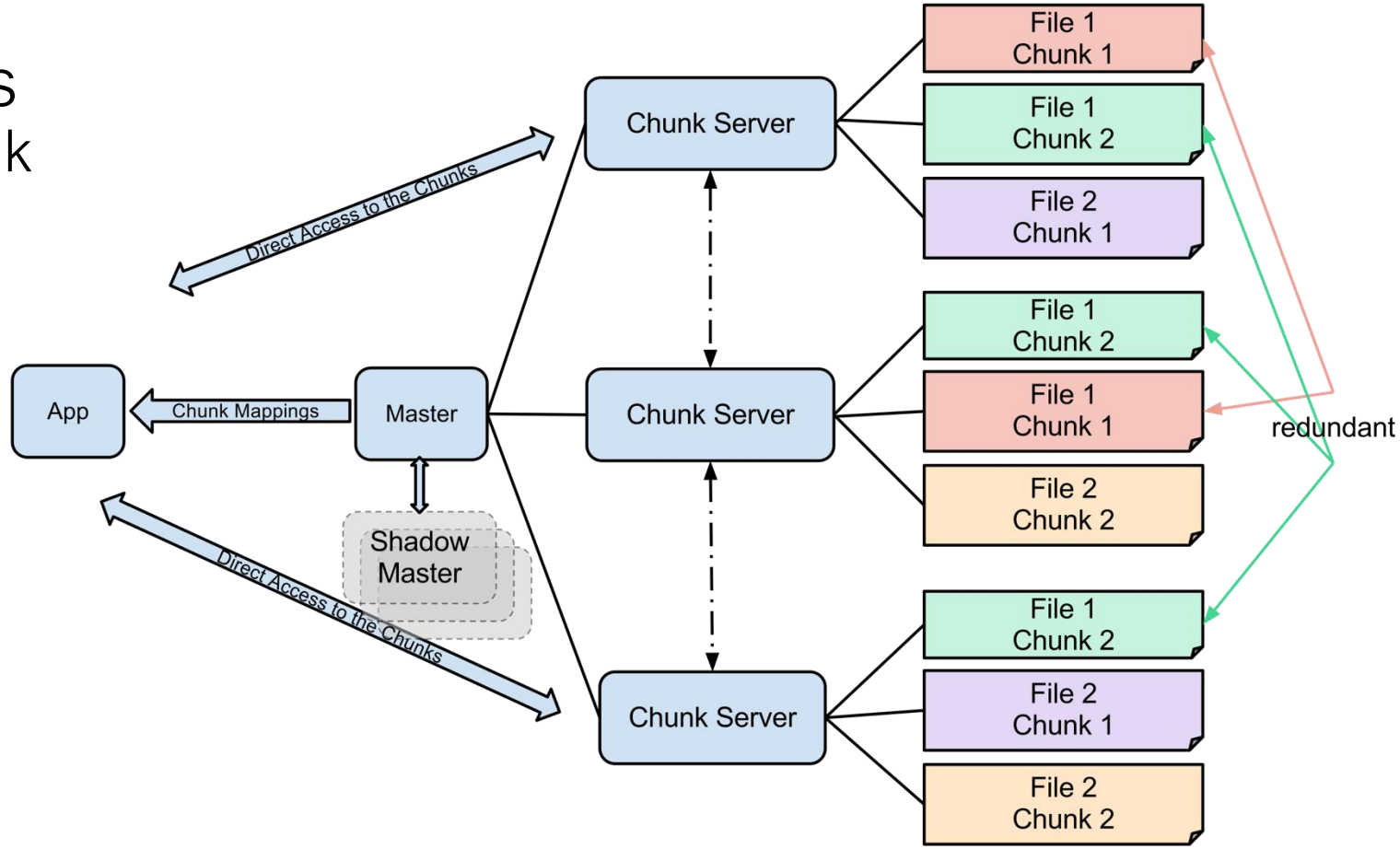
- A single master node for the cluster; master node itself is replicated
- Stores metadata (in memory): file names + chunk ids + chunk locations, access control
- Master keeps an operations log with checkpointing, similar to the recovery log
- Master keeps in sync with chunk servers using regular heartbeat messages



The Google File System (GFS)

Client library for file access

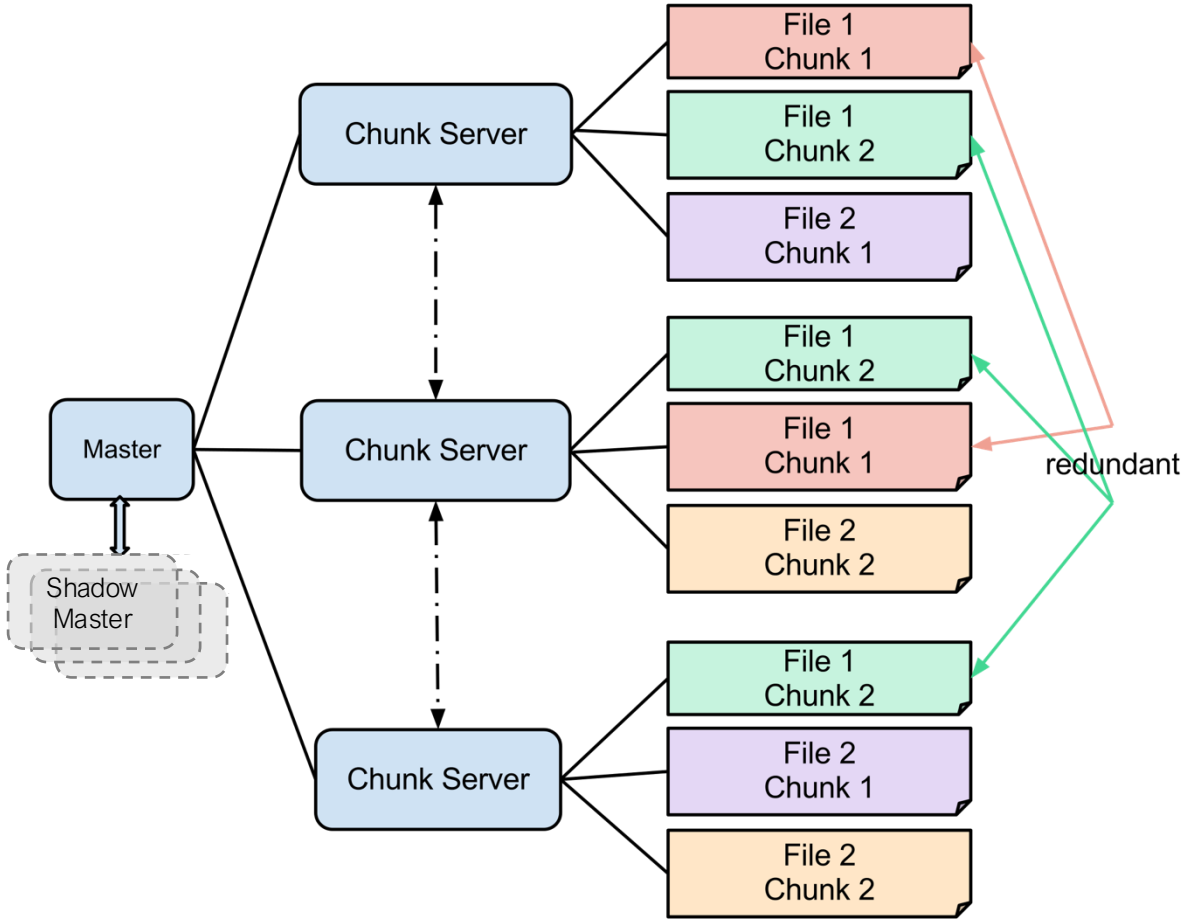
- Talks to master to find chunk servers
- Connects directly to chunk servers to access data



The Google File System (GFS)

Q: What's the benefit of having large chunk sizes (64MB vs file block sizes)

- Master node could become a bottleneck with large number of small files
- Target workload has many sequential reads
- Reduce network overhead



2. MapReduce

A brief history of MapReduce and Hadoop

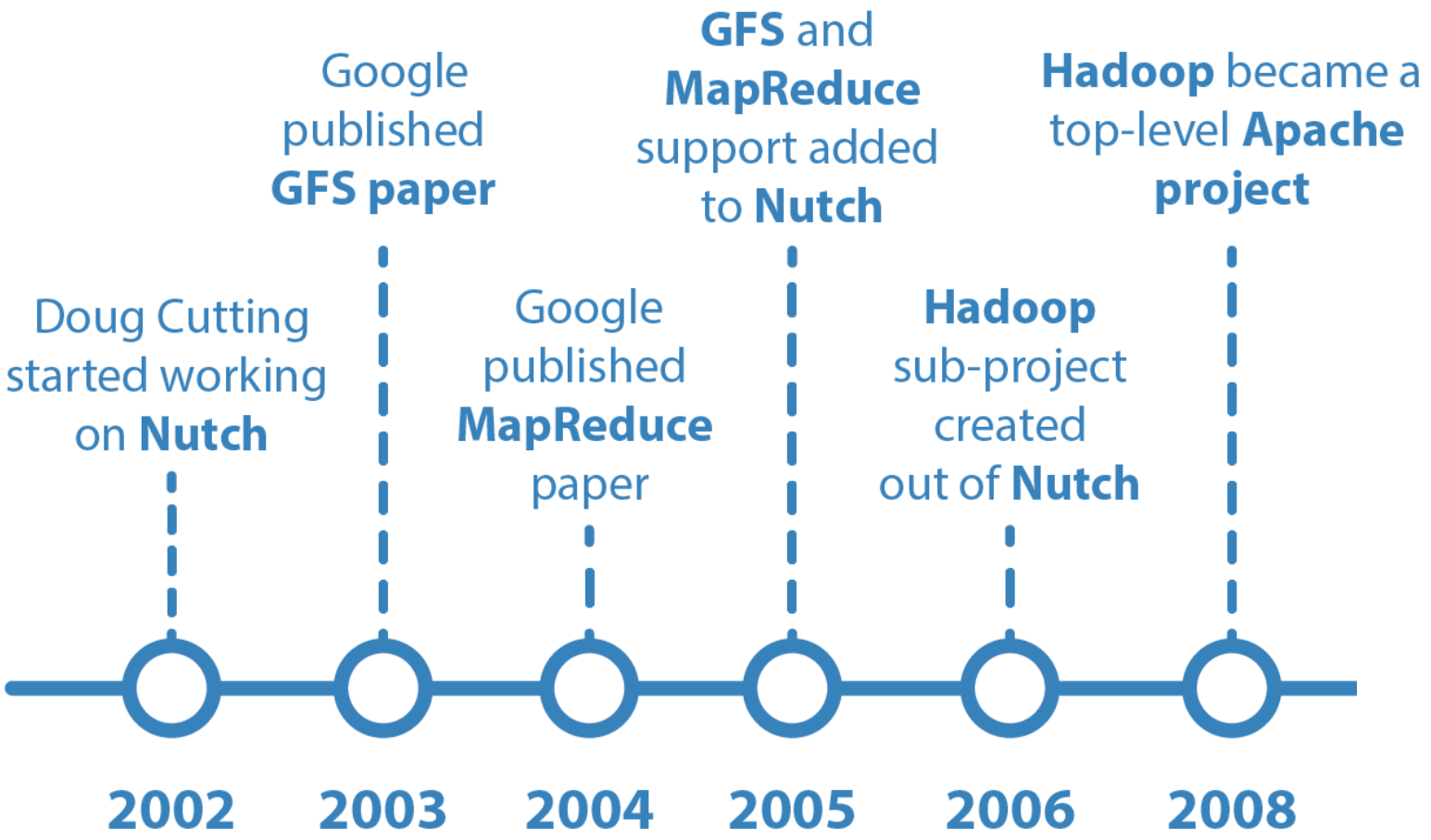


Image source: https://dzone.com/articles/lambda-architecture-with-apache-spark

MapReduce Overview

Read a lot of data

Map: extract something you care about from each record

Shuffle and Sort

Reduce: aggregate, summarize, filter, transform

Write the results

Paradigm stays the same,
Change map and reduce
functions for different problems

Slide source: Jeff Dean

Data Model

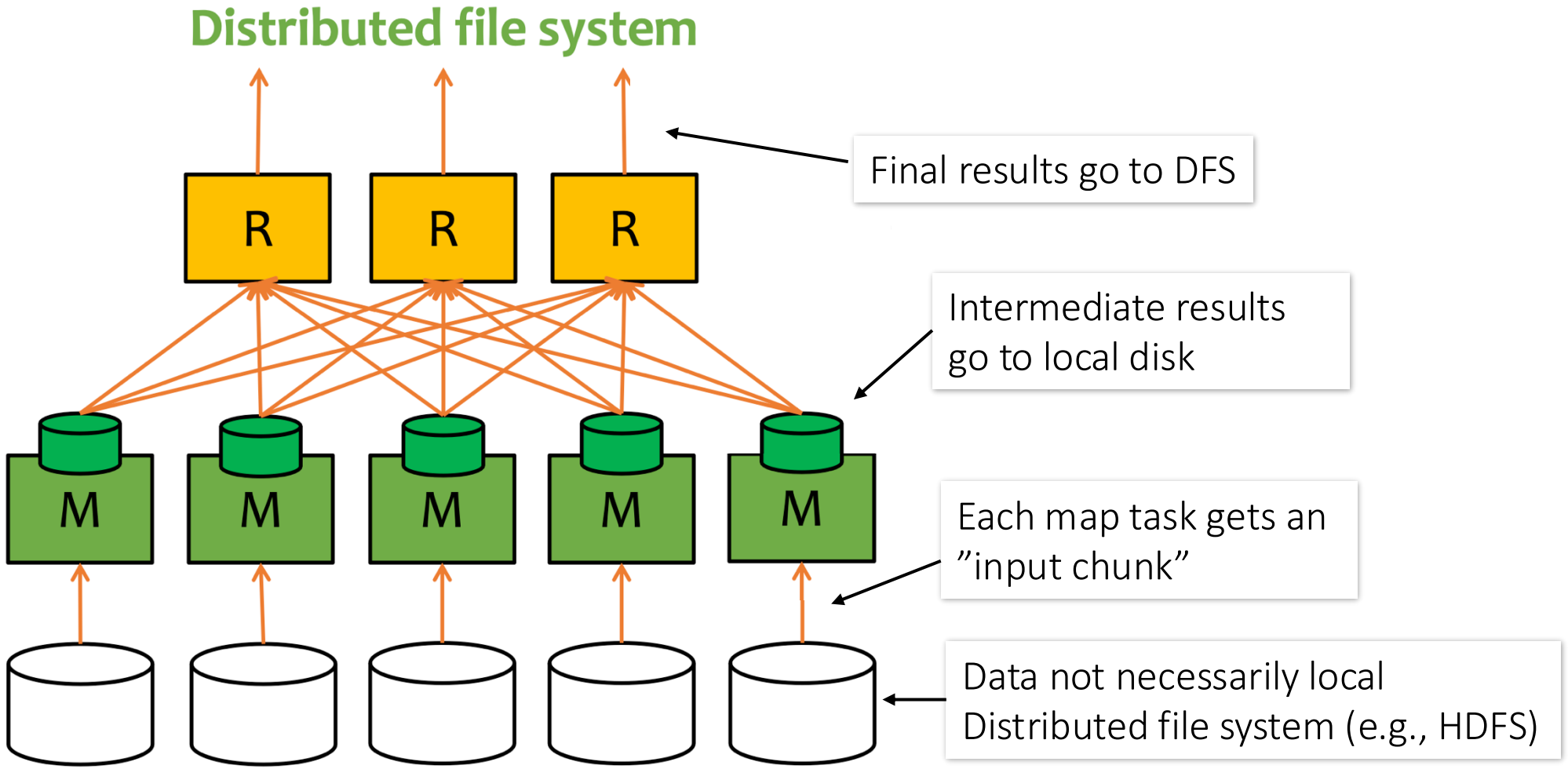
Data is stored as flat files, not relations!

A file = a bag of (key, value) pairs

A MapReduce program

- Input: a bag of (inputkey, value) pairs
- Output: a bag of (outputkey, value) pairs
  - outputkey is optional

MapReduce Overview



Example: Word counting

- Count the number of times each distinct word appears in large collection of documents

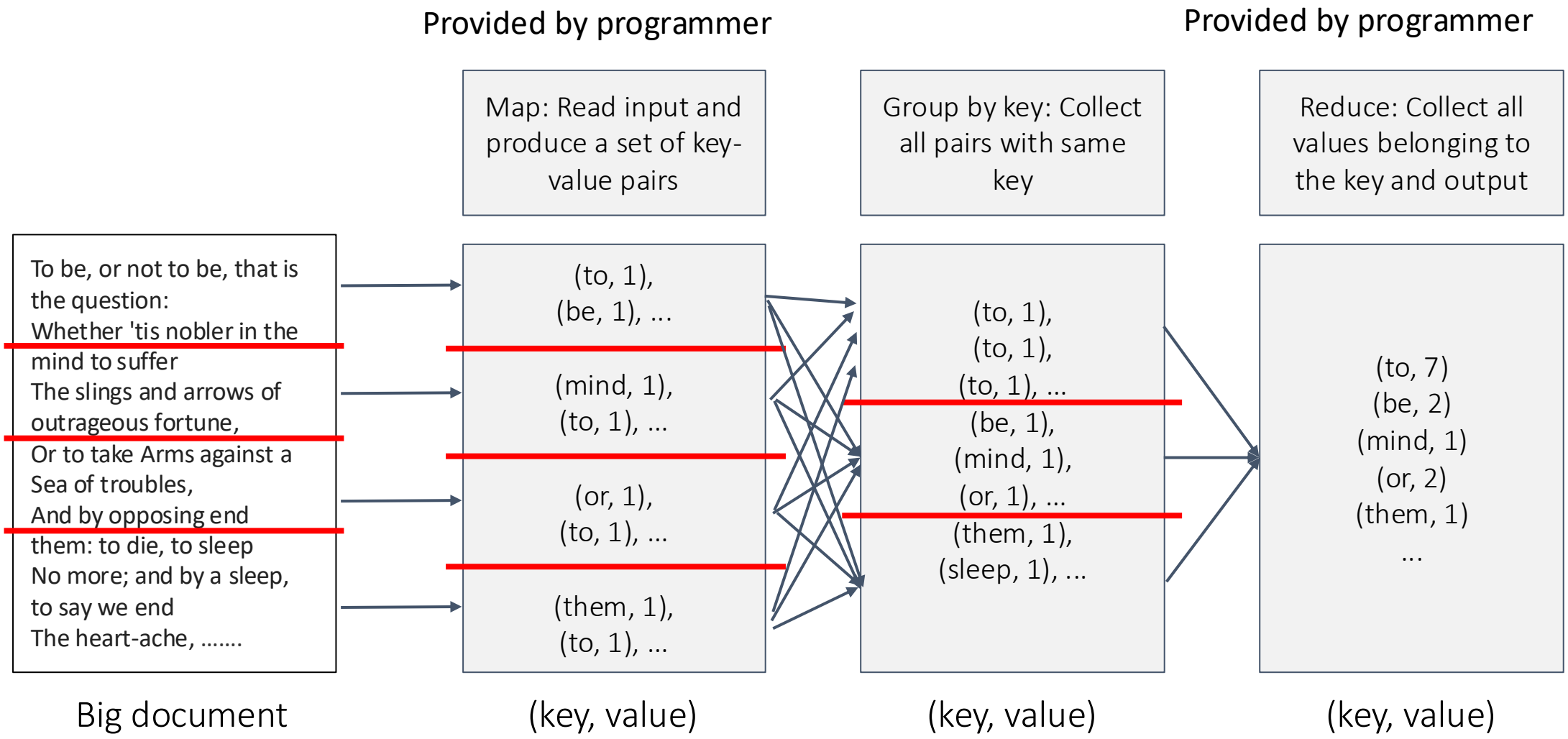
- Many applications:
  - Analyze web server logs to find popular URLs
  - Statistical machine translation (e.g., count frequency of all 5-word sequences in documents)

Map and Reduce functions for word counting

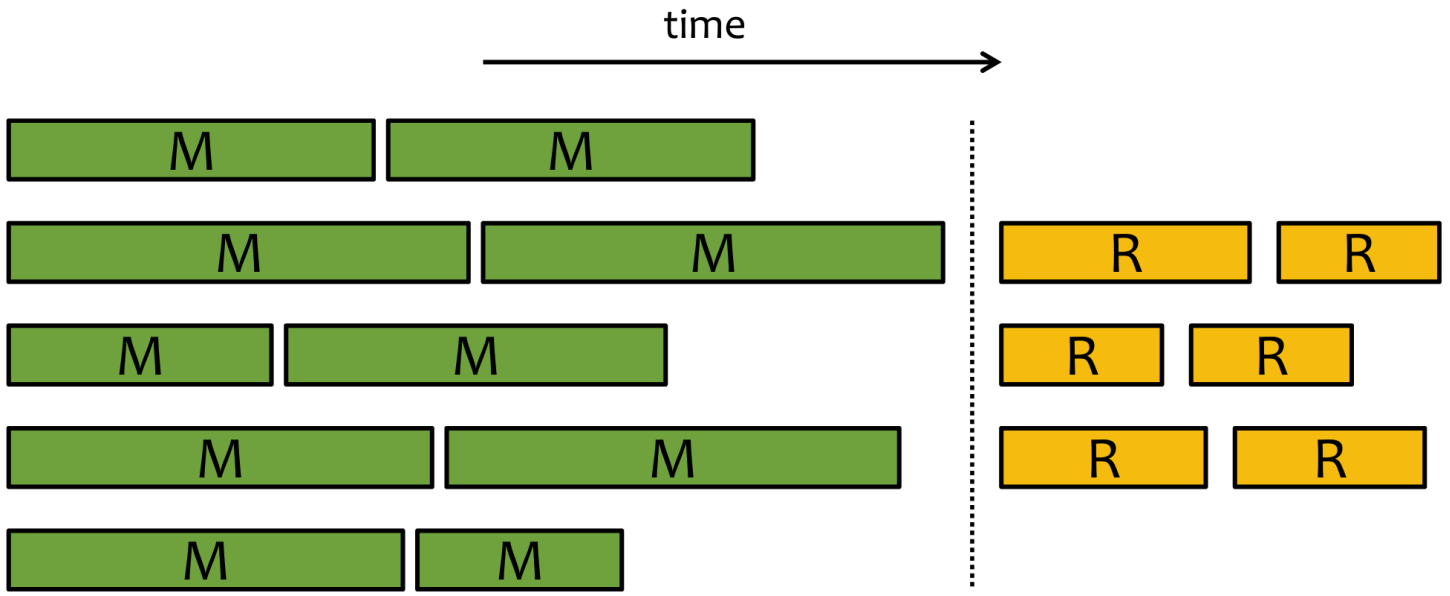
```
map(key, value):
// key: document name; value: text of the document
   for each word w in value:
     emit(w, 1)

reduce(key, values):
// key: a word; values: an iterator over counts
   result = 0
   for each count v in values:
     result += v
   emit(key, result)
```

Coding is simple. Do not need to worry about scaling and failure.

MapReduce: word counting



MapReduce execution timeline



- When there are more tasks than workers, tasks execute in “waves”
  - Boundaries between waves are usually blurred
- Reduce tasks can’t start until all map tasks are done

Fault Tolerance

MapReduce handles fault tolerance by writing intermediate files to disk:

- Mappers write file to local disk; if a mapper node crashes, all intermediate output on that node is list => re-run the mapper on another node
- If a reducer fails, mapper do not re-run
- Reducers read the files as input; if the server fails, the reduce task is restarted on another server

MapReduce Summary

- A style of programming for managing many large-scale computations in a way that is tolerant of hardware faults
  - Just need to write two functions called *Map* and *Reduce*
  - The system manages parallel execution, coordination of tasks that execute Map or reduce, and dealing with failures

- It has several implementations, including Hadoop, Spark, Flink, and the original Google implementation just called “MapReduce”