CS 6400 A

Database Systems Concepts and Design

Lecture 23

11/17/25

Announcements

Project deliverables released (due Dec 1)

- Final report
- Code with README
- Team Dynamics Assessment Form

Final exam format

- Take home, no time limit
- To be released Dec 4 and due Dec 5
- Review lecture on Dec 1

So far: One query/update
One machine

Multiple query/updates
One machine

Transactions

One query/update
Multiple machines

Distributed query processing
MapReduce, Spark

Agenda

1. Distributed File System

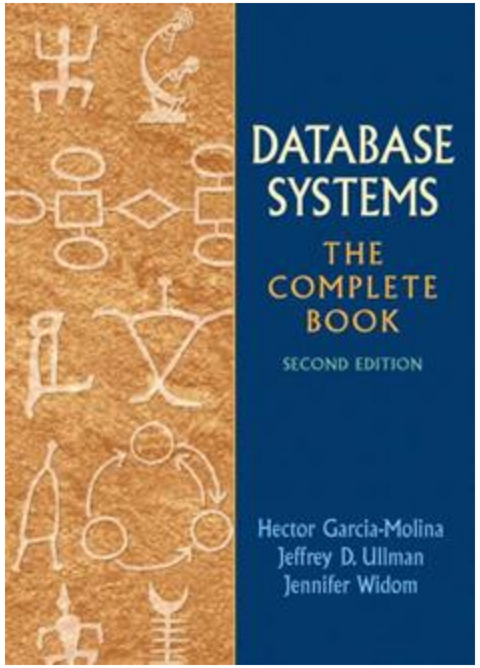
2. Map Reduce

3. Spark

Reading Materials

Database Systems: The Complete Book (2nd edition)

- Chapter 20 – Parallel and Distributed Databases



Research Papers:

- The Google File System
- MapReduce
- Spark

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

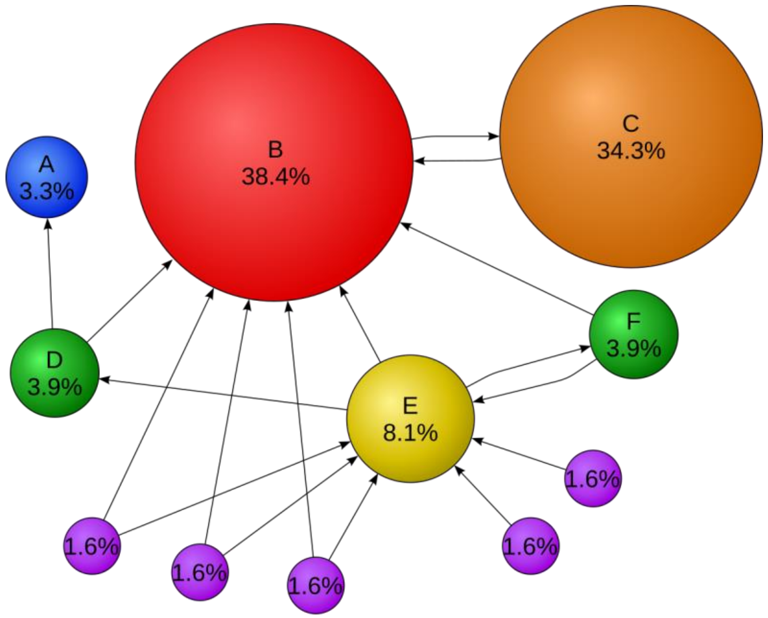


Image source: https://en.wikipedia.org/wiki/PageRank

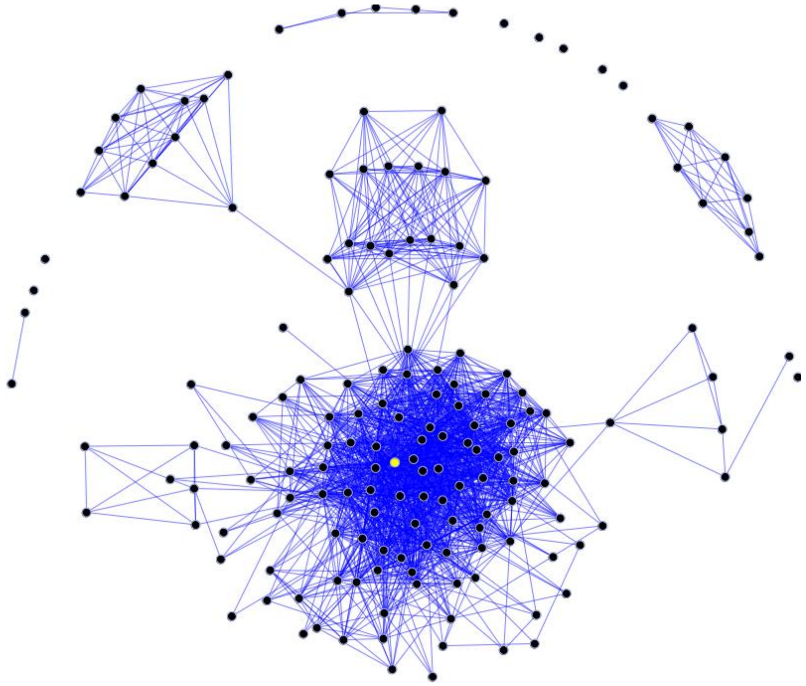


Image source: https://en.wikipedia.org/wiki/Social_graph

Horizontal vs Vertical Scaling

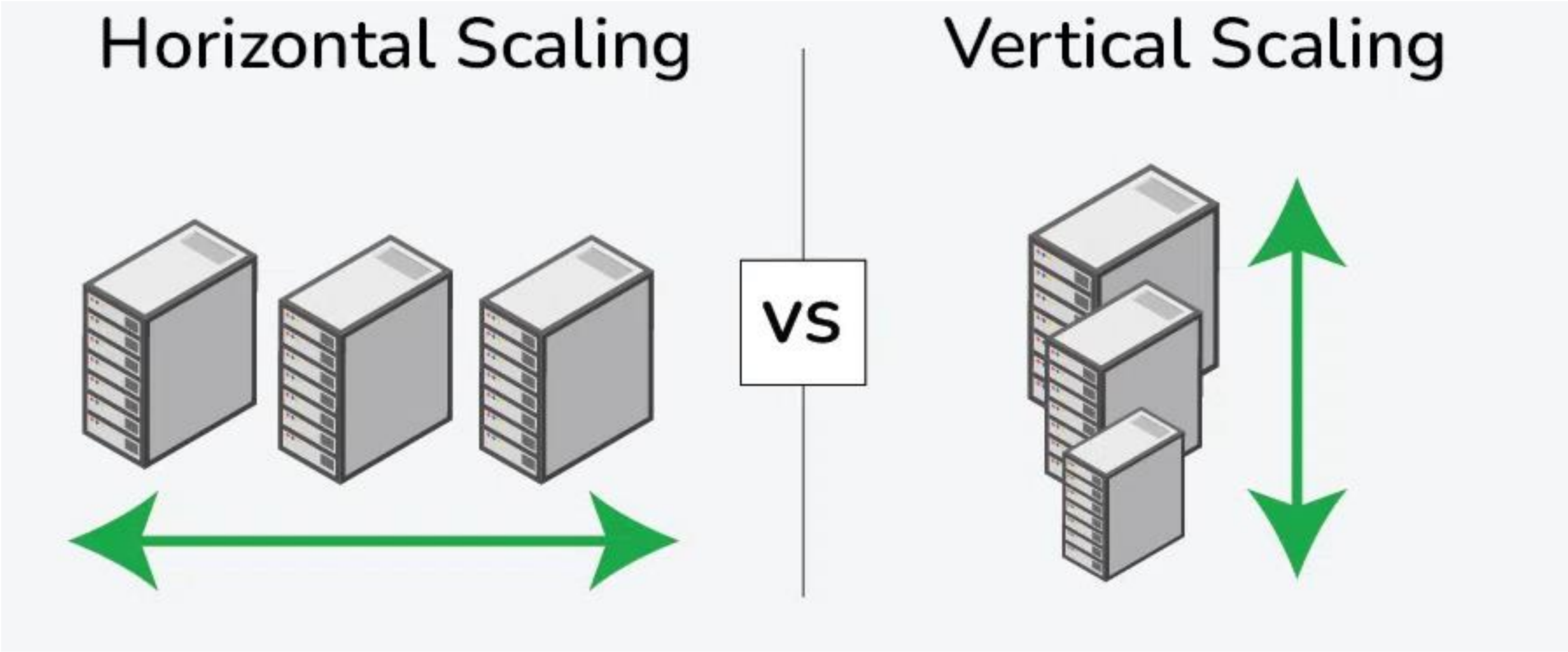


Image source: https://www.geeksforgeeks.org/system-design-horizontal-and-vertical-scaling/

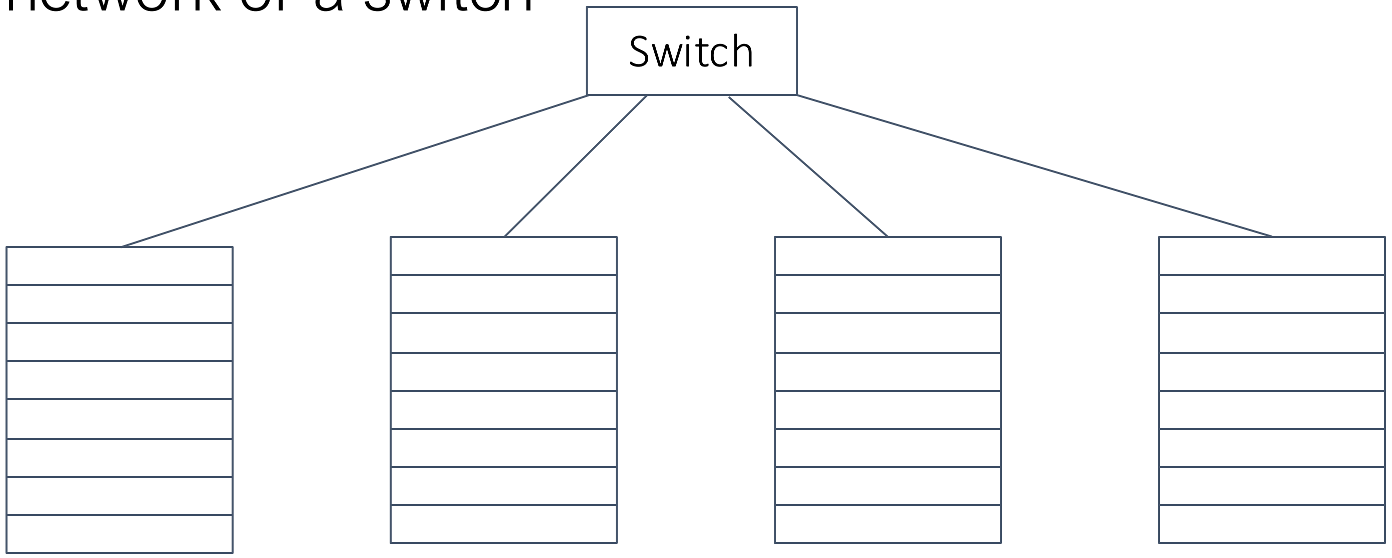
Horizontal scaling

- 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

Parallel-computing architecture

- 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

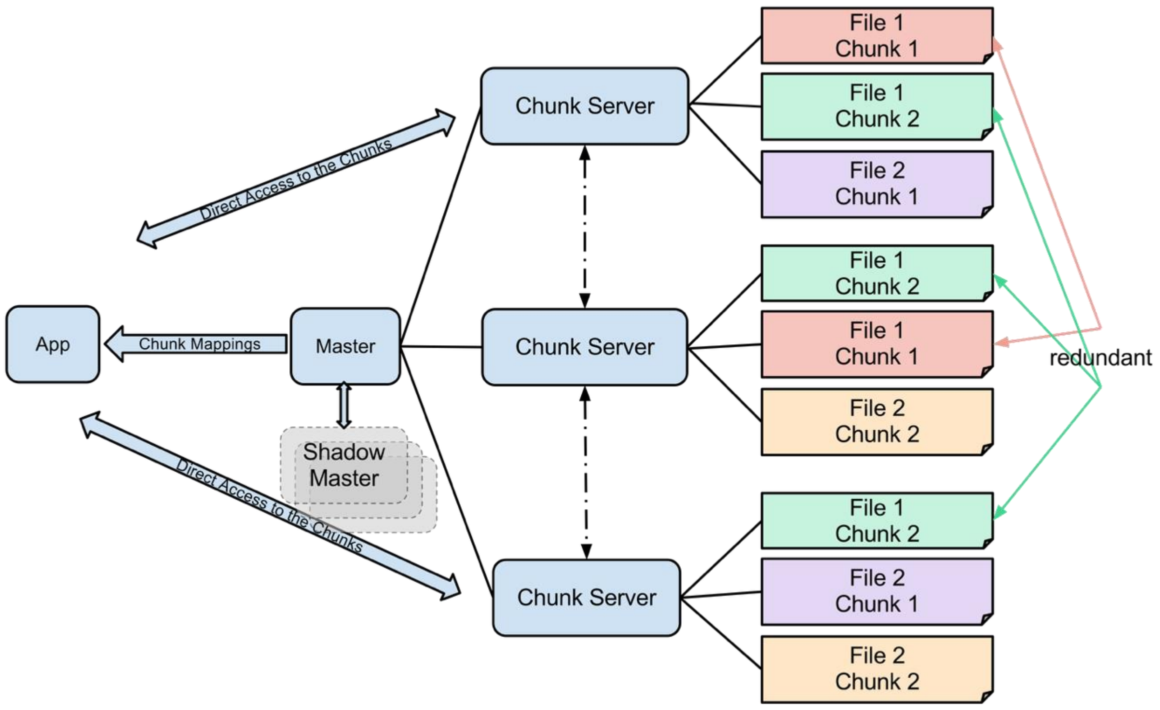
Distributed file system

- 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

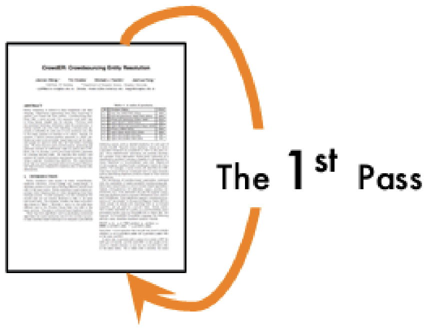
How to read a paper in depth

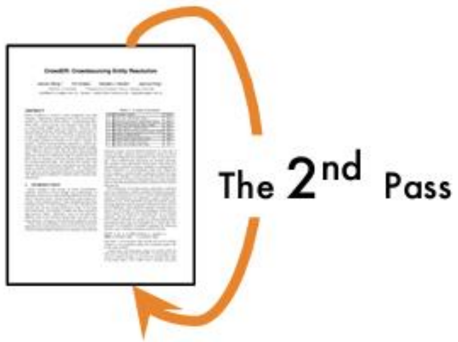
The "three-pass" approach [1]

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

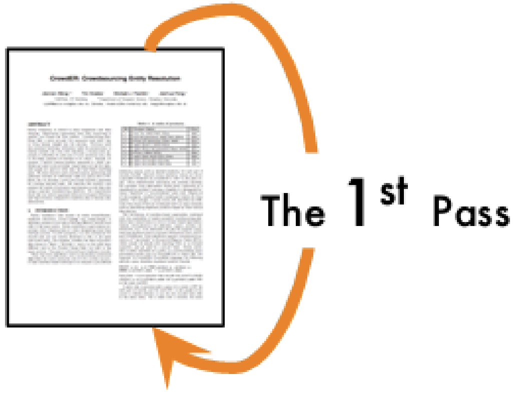
Goal: get bird's-eye view of the paper (5~10 min)

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

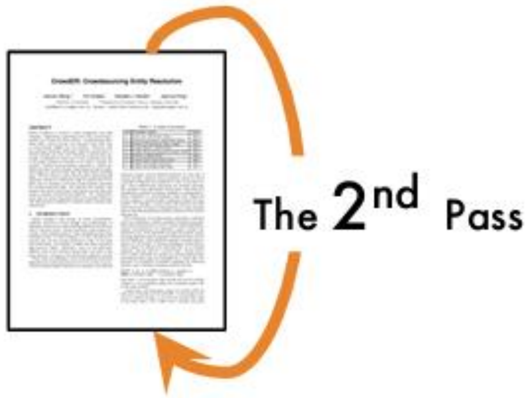
Goal: get a good understanding of the ”meat” of the paper

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

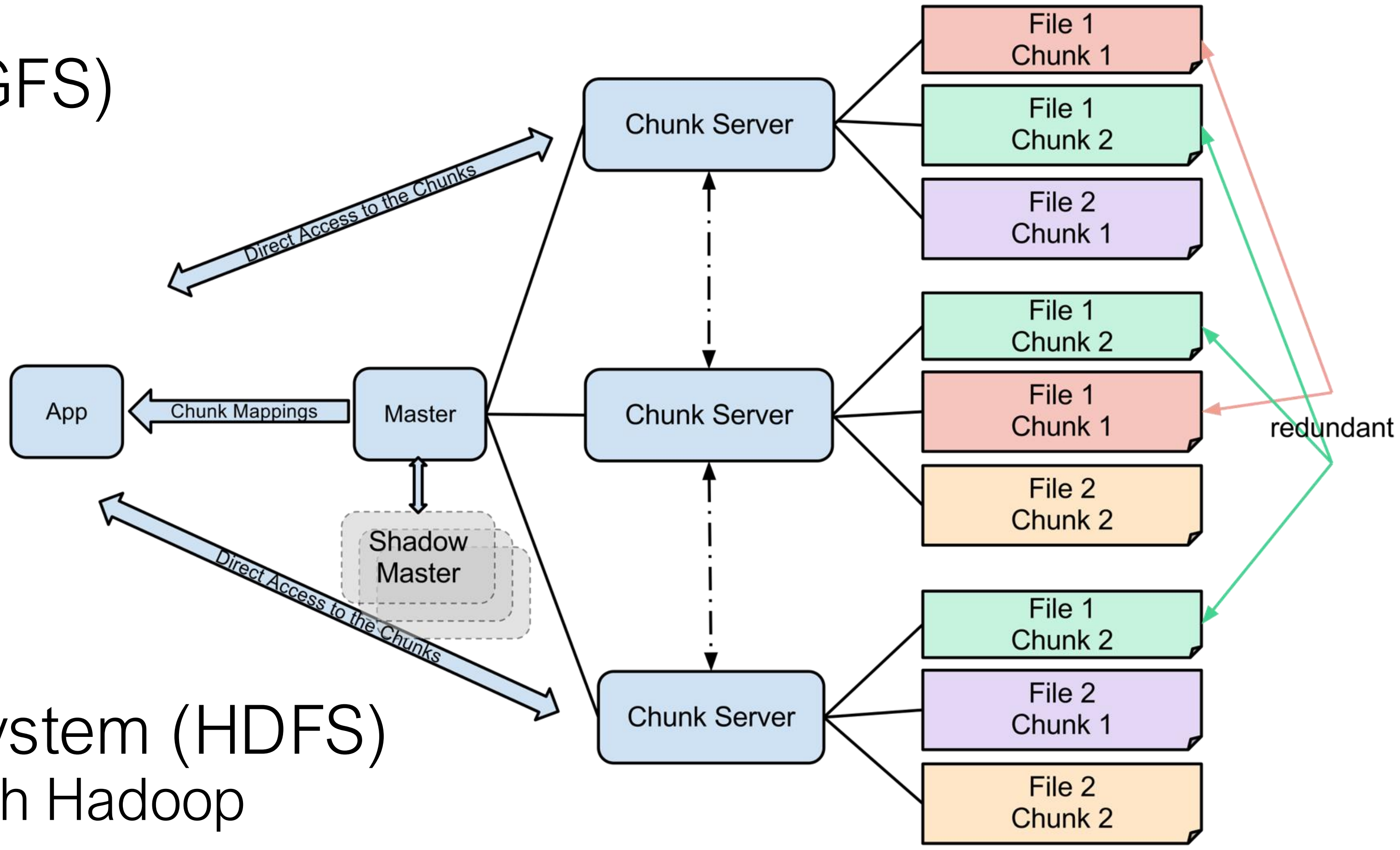
A Distributed File System (DFS) can be used when:

- 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)

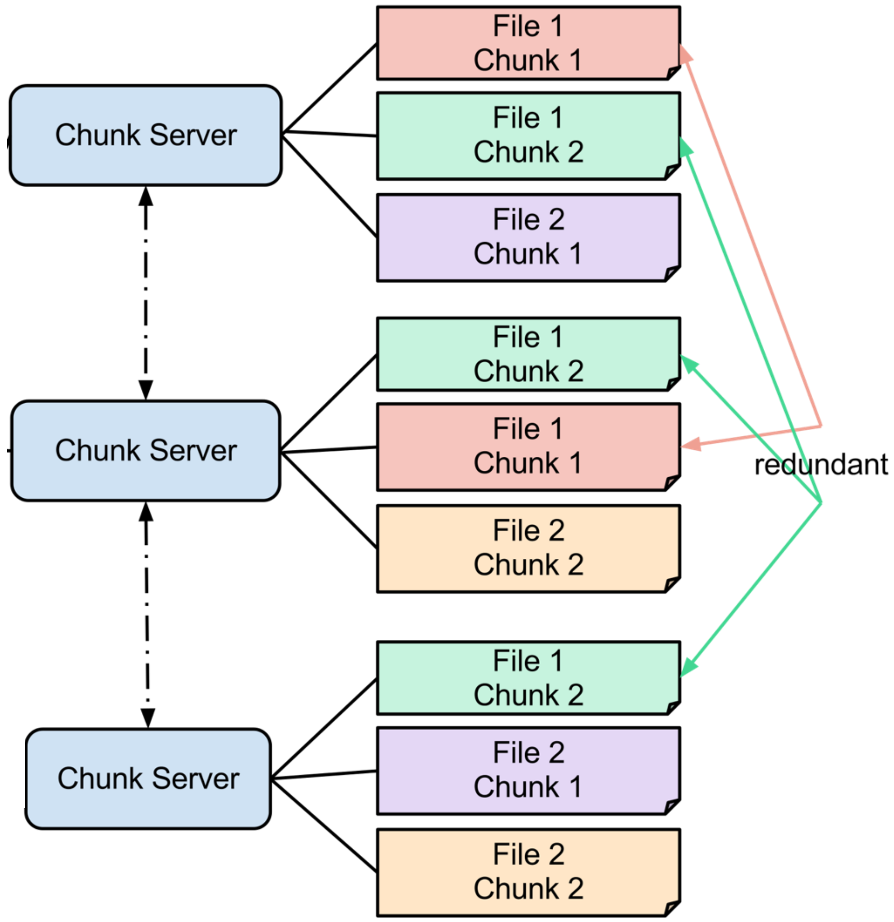
- Open-source DFS used with Hadoop

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

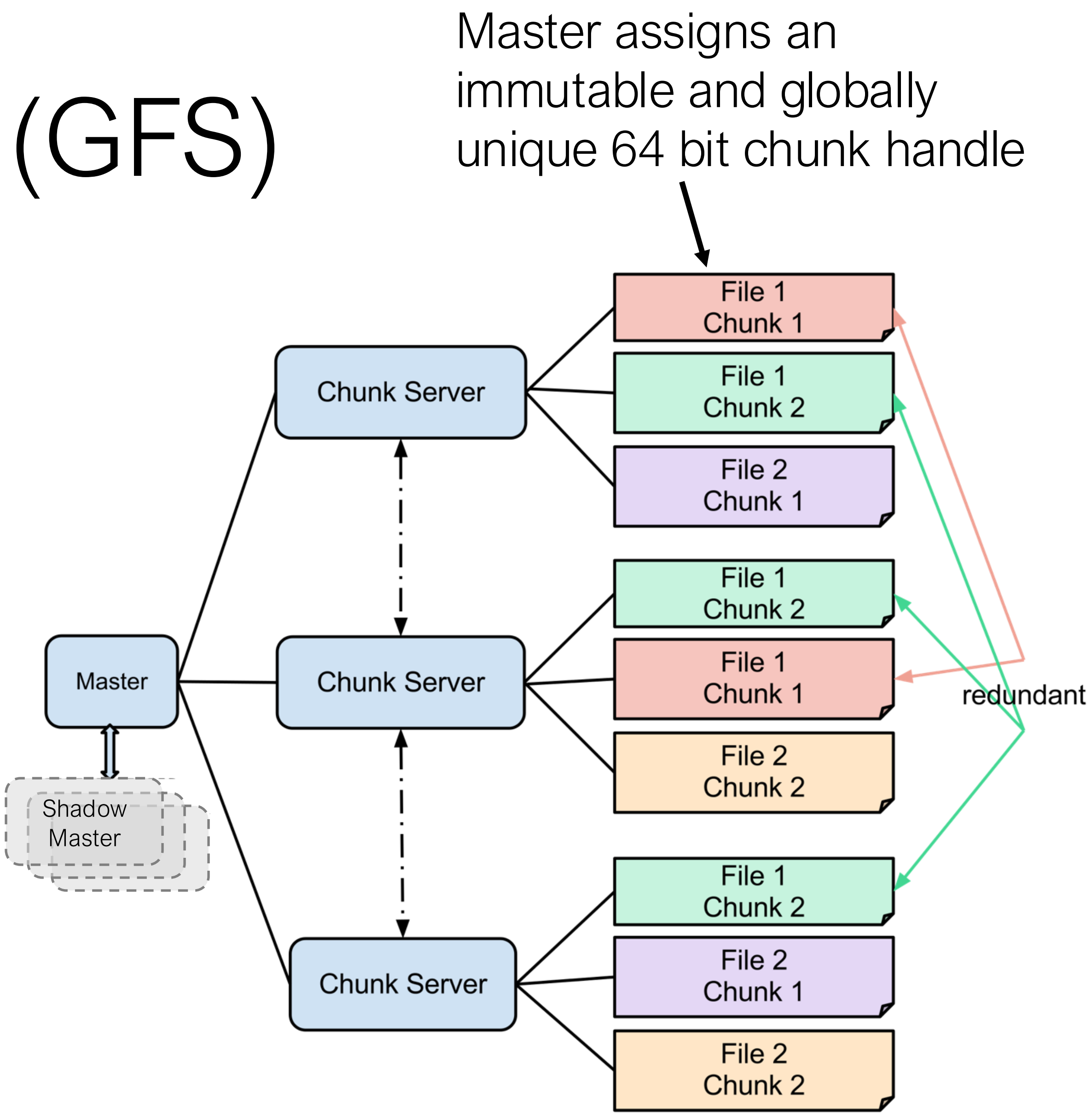
- Chunks are replicated (say 3 times) at different compute nodes (called chunks servers)
- The compute nodes should be located on different racks
- Chunk size and degree of replication decided by the user



The Google File System (GFS)

Master node

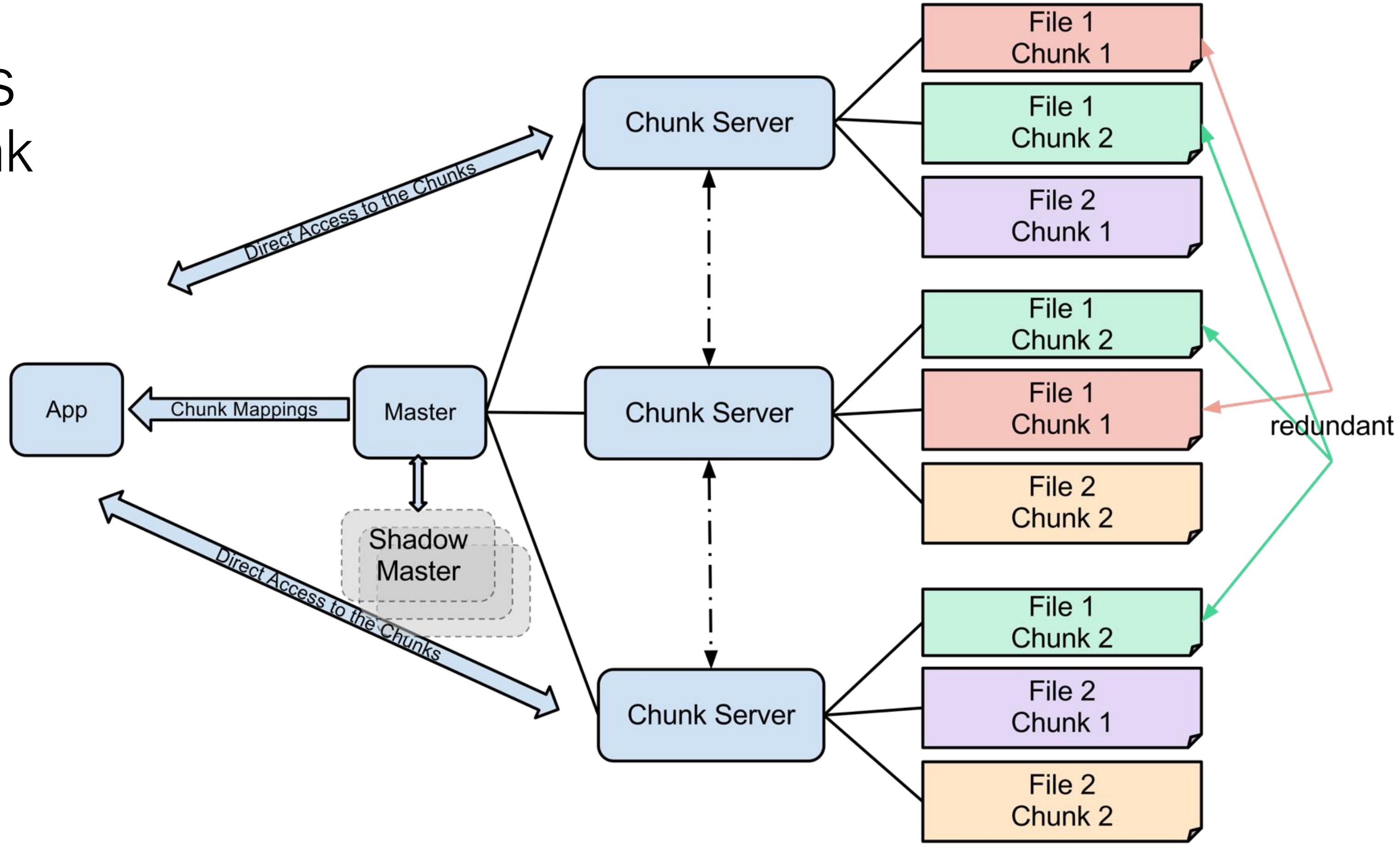
- A single master node for the cluster; master node itself is replicated
- Stores metadata (in memory): file names + chunk ids + chunk locations, access control
- Master keeps an operations log with checkpointing, similar to the recovery log
- Master keeps in sync with chunk servers using regular heartbeat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



The Google File System (GFS)

Client library for file access

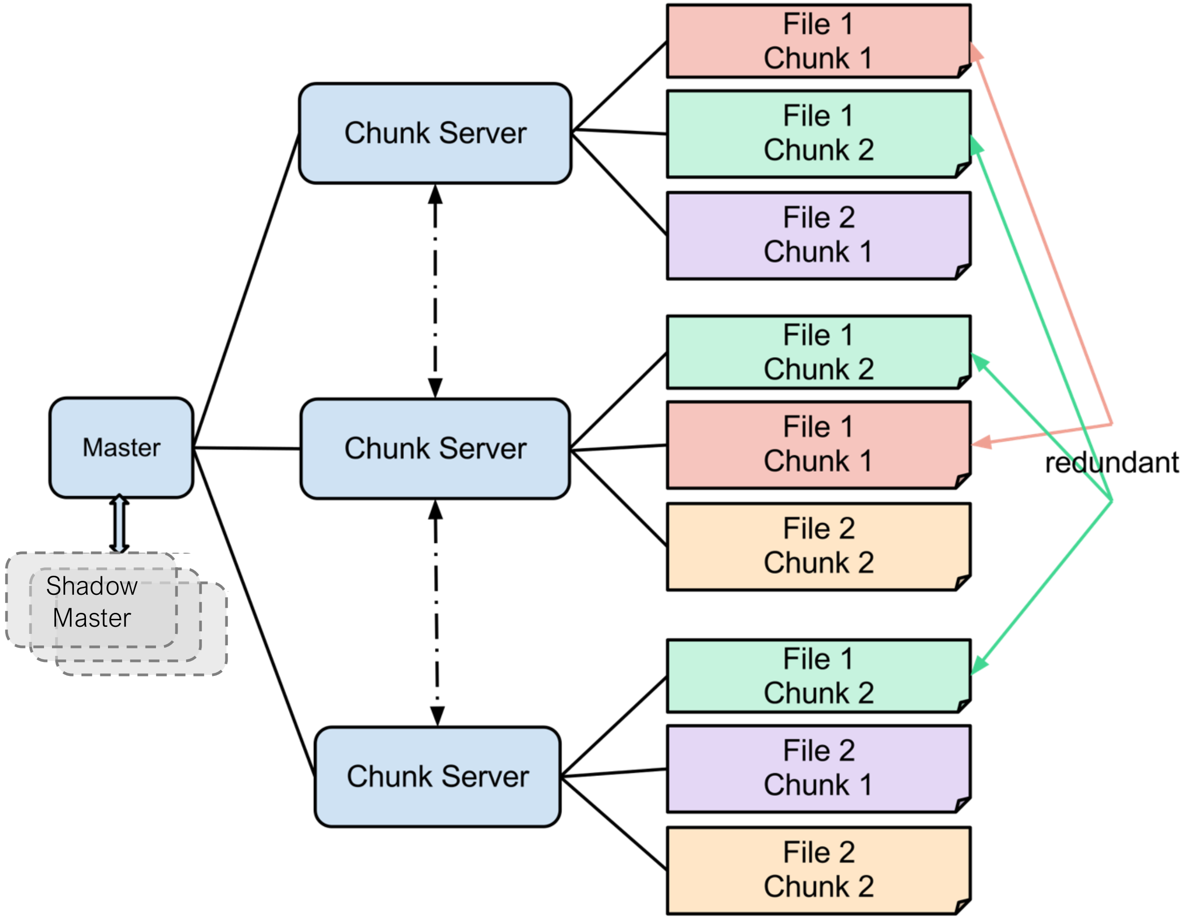
- Talks to master to find chunk servers
- Connects directly to chunk servers to access data



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

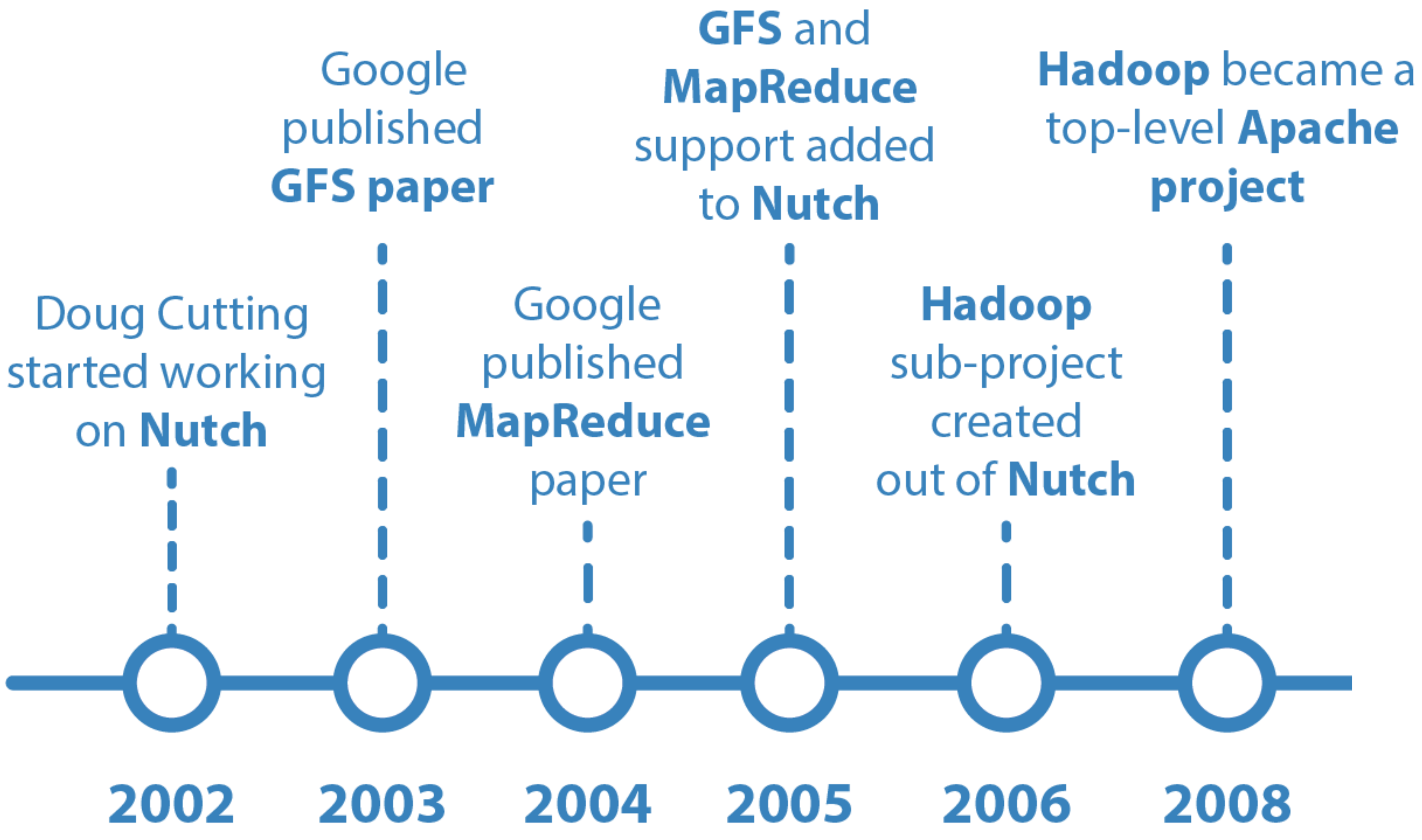


Image source: https://dzone.com/articles/lambda-architecture-with-apache-spark

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

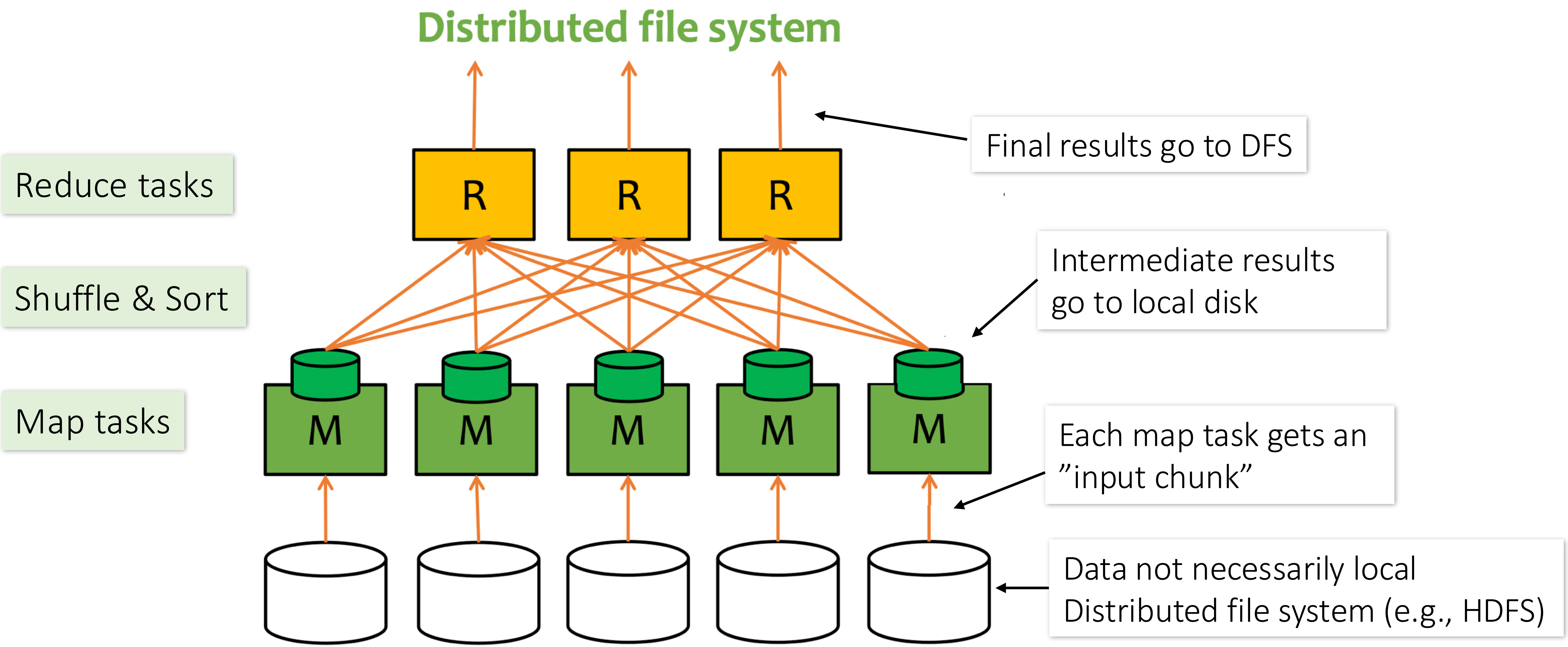
Data is stored as flat files, not relations!

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

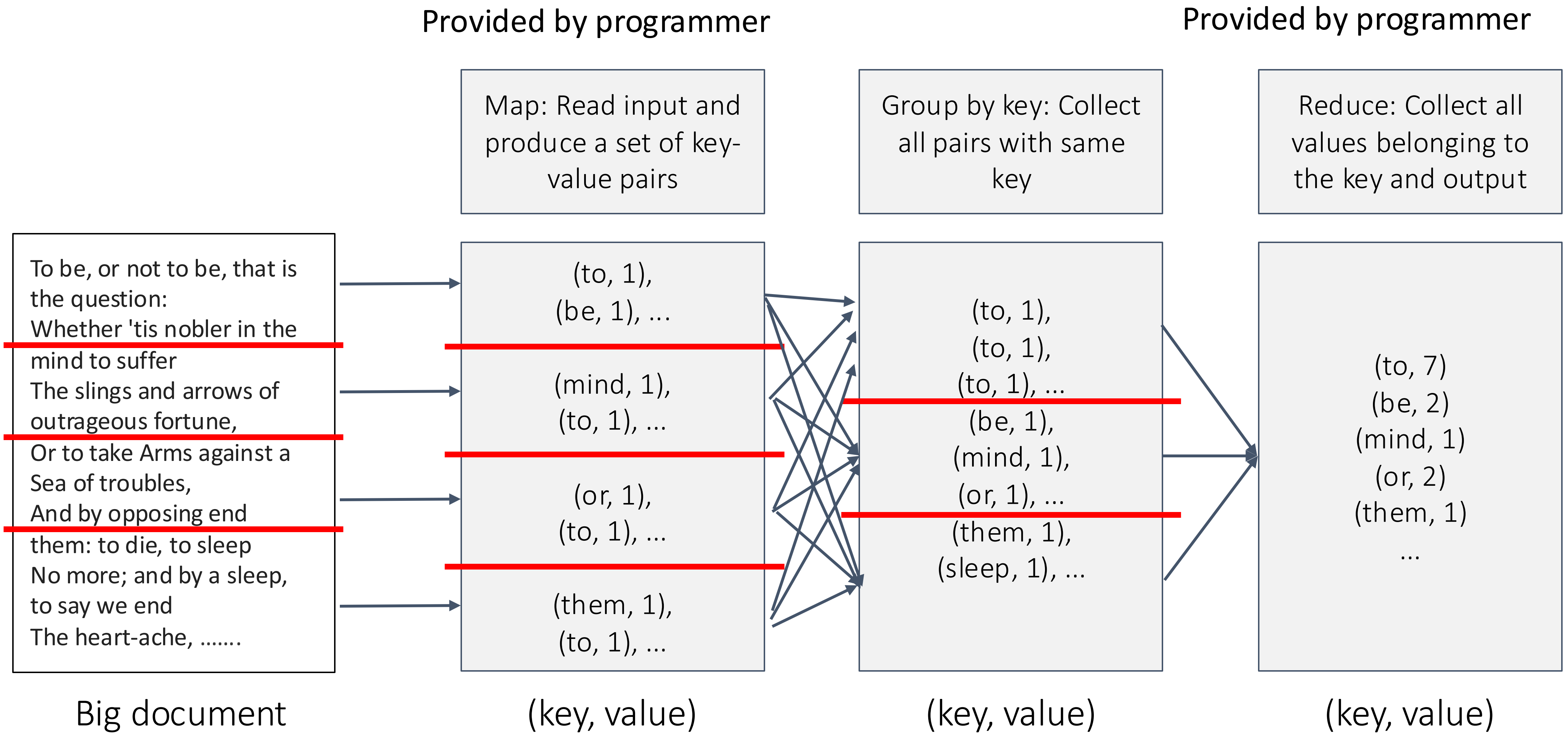
- Many applications:
  - Analyze web server logs to find popular URLs
  - Statistical machine translation (e.g., count frequency of all 5-word sequences in documents)

Map and Reduce functions for word counting

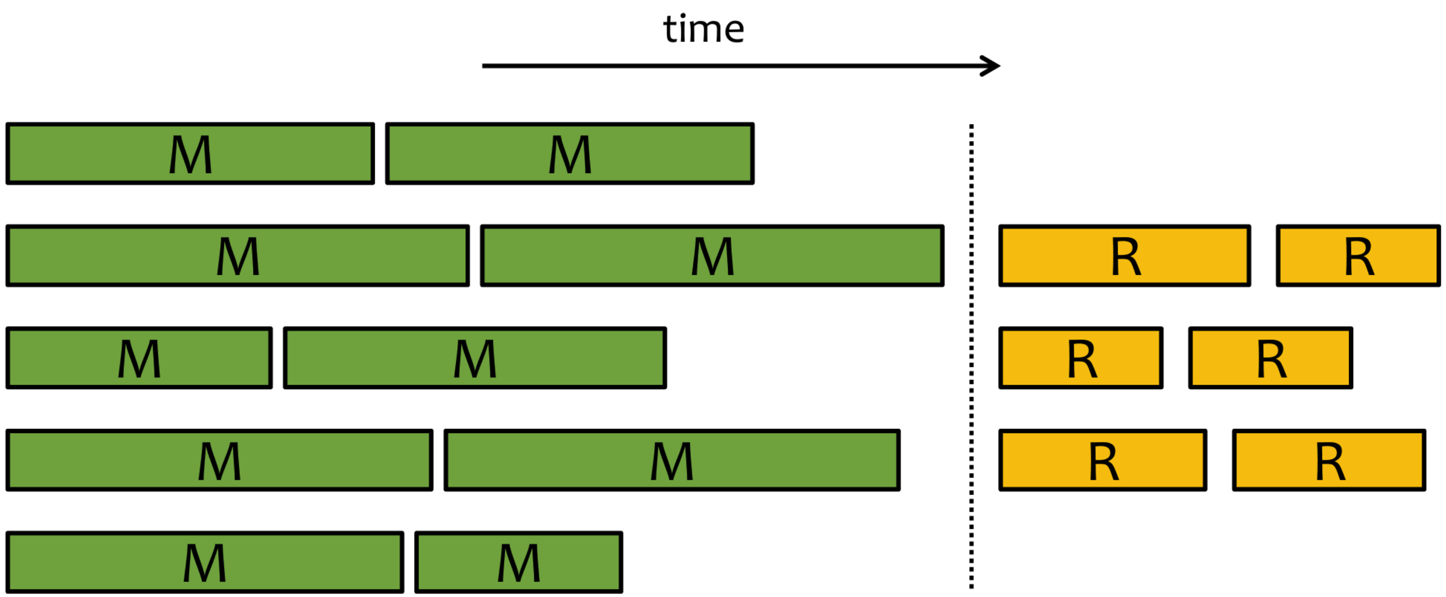
```
map(key, value):
// key: document name; value: text of the document
   for each word w in value:
     emit(w, 1)

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
- Reducers read the files as input; if the server fails, the reduce task is restarted on another server

MapReduce vs SQL

	MapReduce	Parallel DBMS
Programming	Imperative	Declarative
Indexing	No native support	B+ tree, hashing
Schema	Not required	Required
Flexibility	Highly flexible	Some flexibility via user defined functions
Fault Tolerance	Save intermediate results to disk – can restart fine-grained tasks during failure	Avoid saving intermediate results to disk – might need to restart a larger chunk of work (transaction) during failure

Reading: [A Comparison of Approaches to Large-Scale Data Analysis]

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

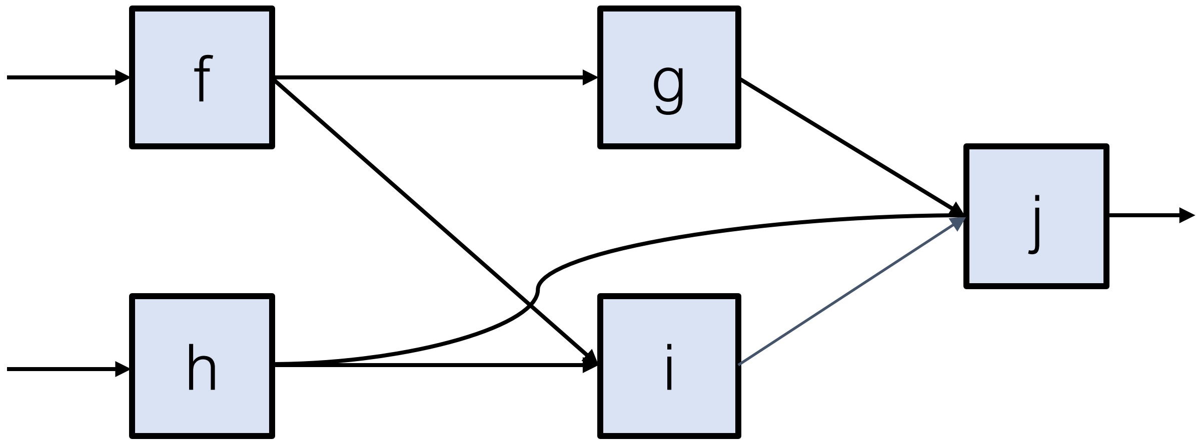
- It has several implementations, including Hadoop, Spark, Flink, and the original Google implementation just called “MapReduce”

3. Spark

Workflow systems

- Extends MapReduce by supporting acyclic networks of functions
  - Simple two-step workflow → any acyclic (DAG) workflow of functions
  - Each function implemented by a collection of tasks
  - A master controller is responsible for dividing work among tasks

- Examples: Apache Spark and Google TensorFlow

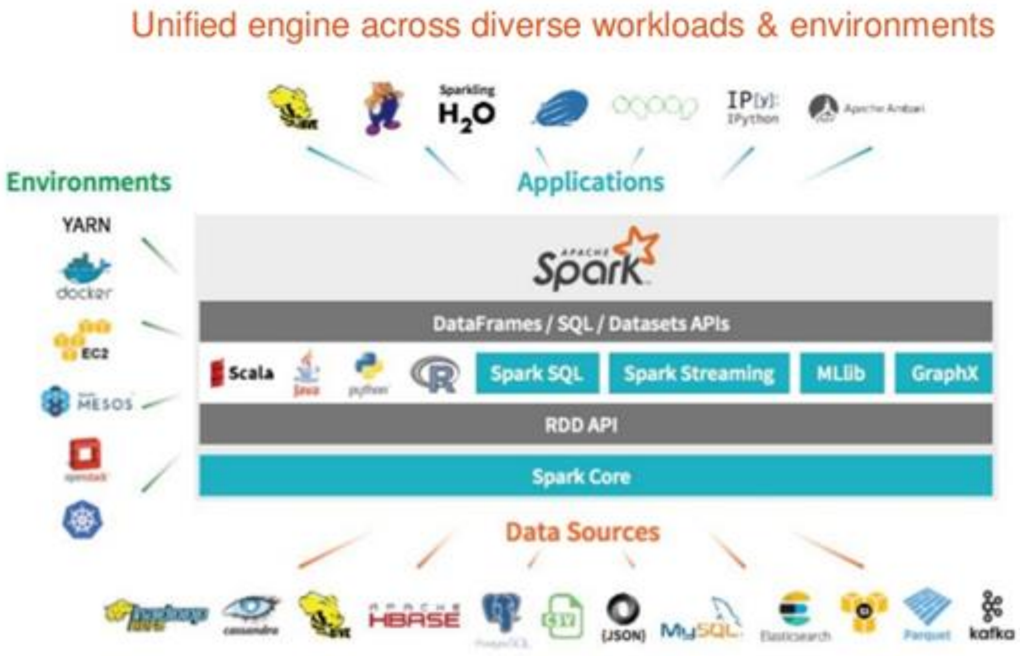


Blocking property

- Like MapReduce, workflow functions only deliver output after completion
- If task fails, no output is delivered to any successors in flow graph
- A master controller can therefore restart failed task at another compute node

Spark: most popular workflow system

- Developed by UC Berkeley and Databricks, now maintained by Apache
- Advantages over early workflow systems
  - More efficient failure handling
  - More efficient grouping of tasks among compute nodes and scheduling function execution
  - Integration of programing language features such as looping and function libraries



Data Model: Resilient distributed dataset (RDD)

Central data abstraction of Spark

A file of objects of one type

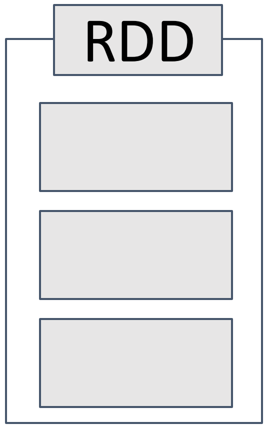
- Statically typed: RDD[T] has objects of type T

Immutable collections of objects, together with its lineage

- Lineage = how a dataset is computed

Spark is resilient against loss of any or all chunks of RDD

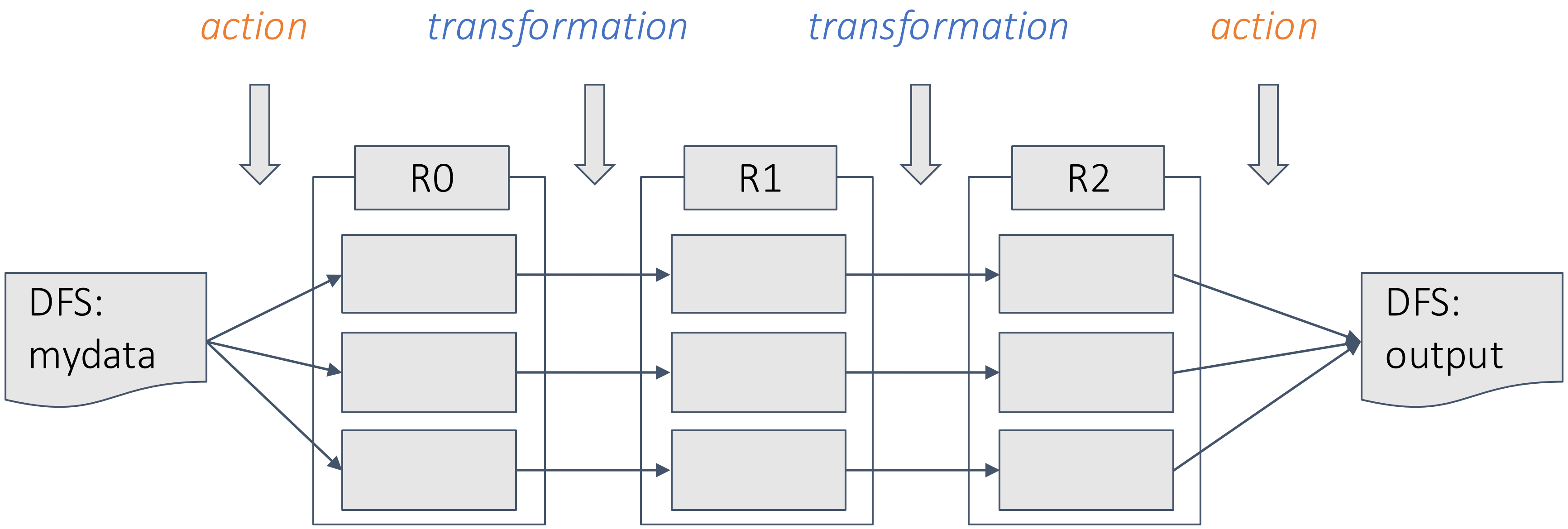
- If RDD in main memory is lost, can recompute lost partitions of RDD using lineage



Spark program

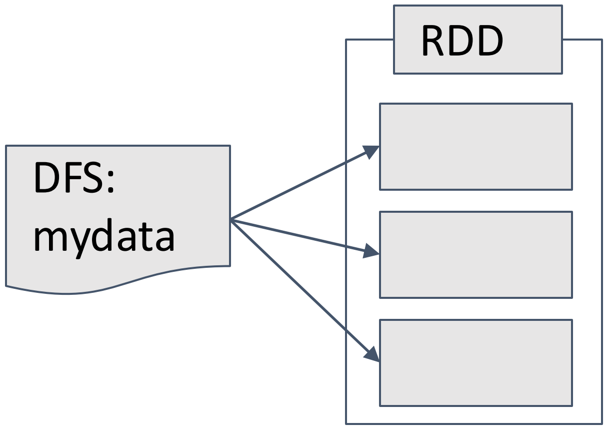
Sequence of steps of

- Transformations: apply some function to an RDD to produce another RDD
- Actions: Turn RDD into data in surrounding file system and vice versa



Example: average word length by letter

```
> avglens = sc.textFile(file)
```



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> avglens = sc.textFile(file) \
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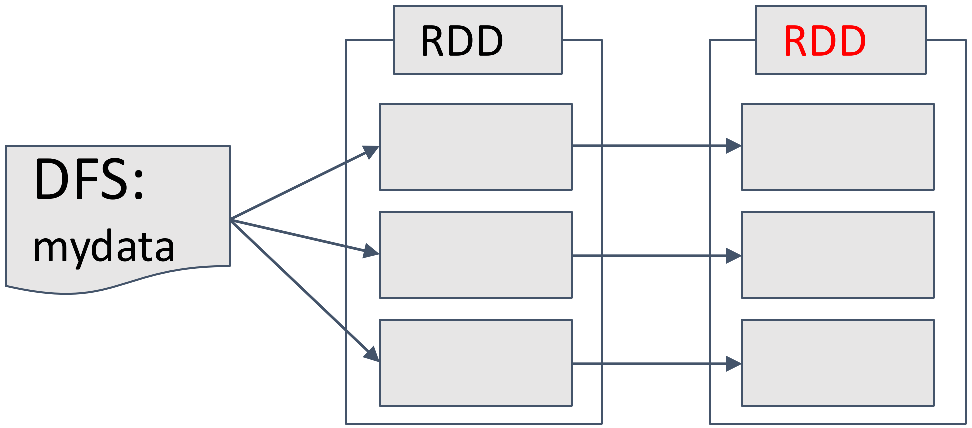

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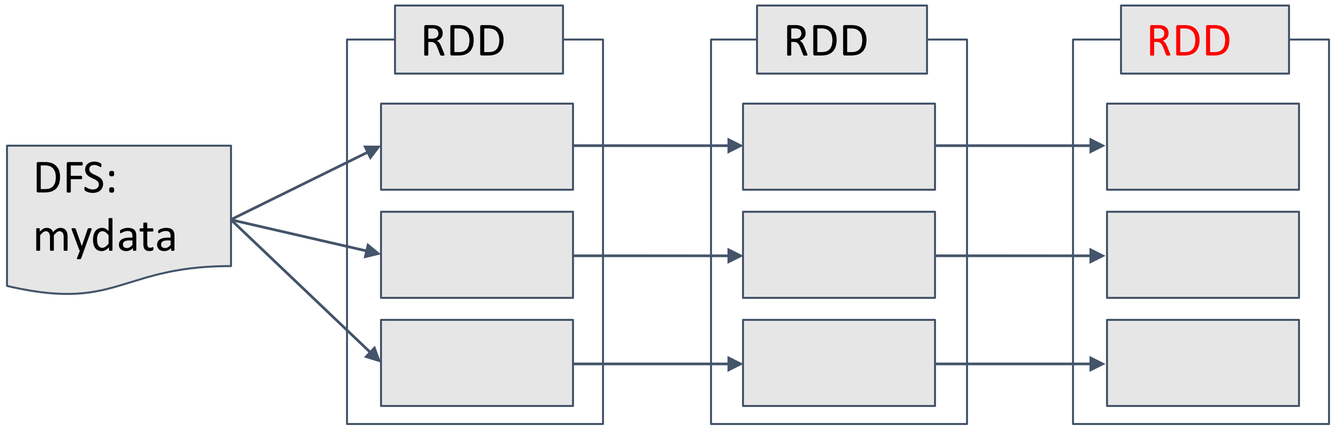

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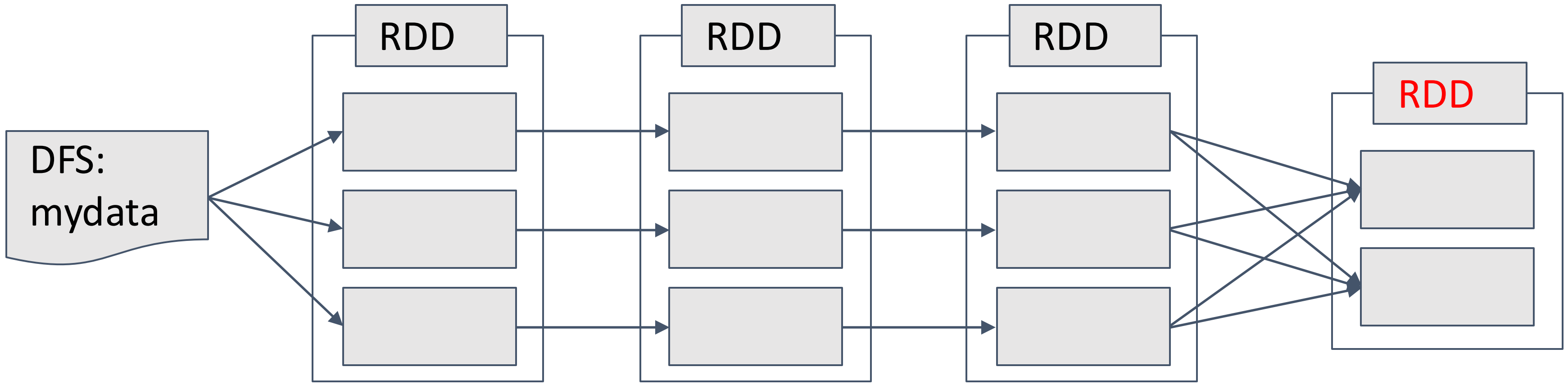
    .map(lambda word: (word[0], len(word))) \
    .groupByKey()
```



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      (k, sum(values)/len(values)))
```

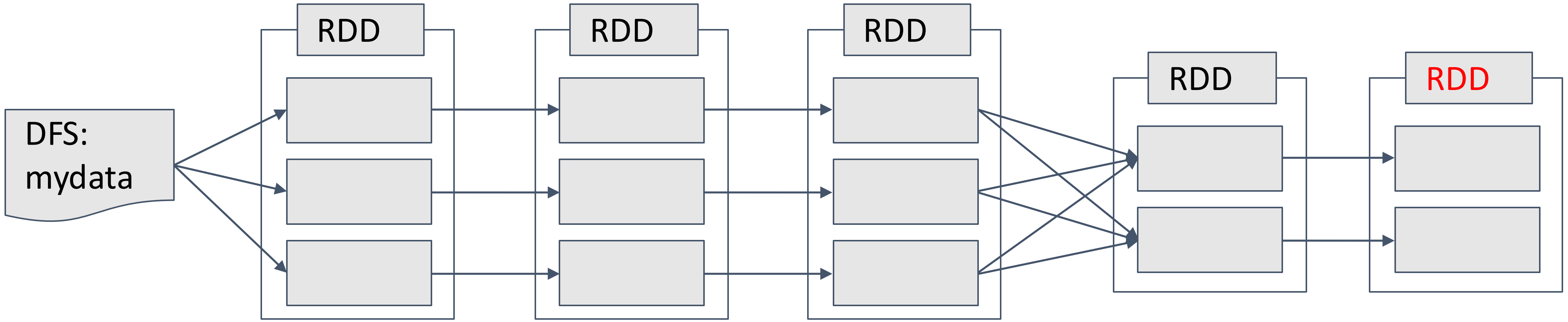

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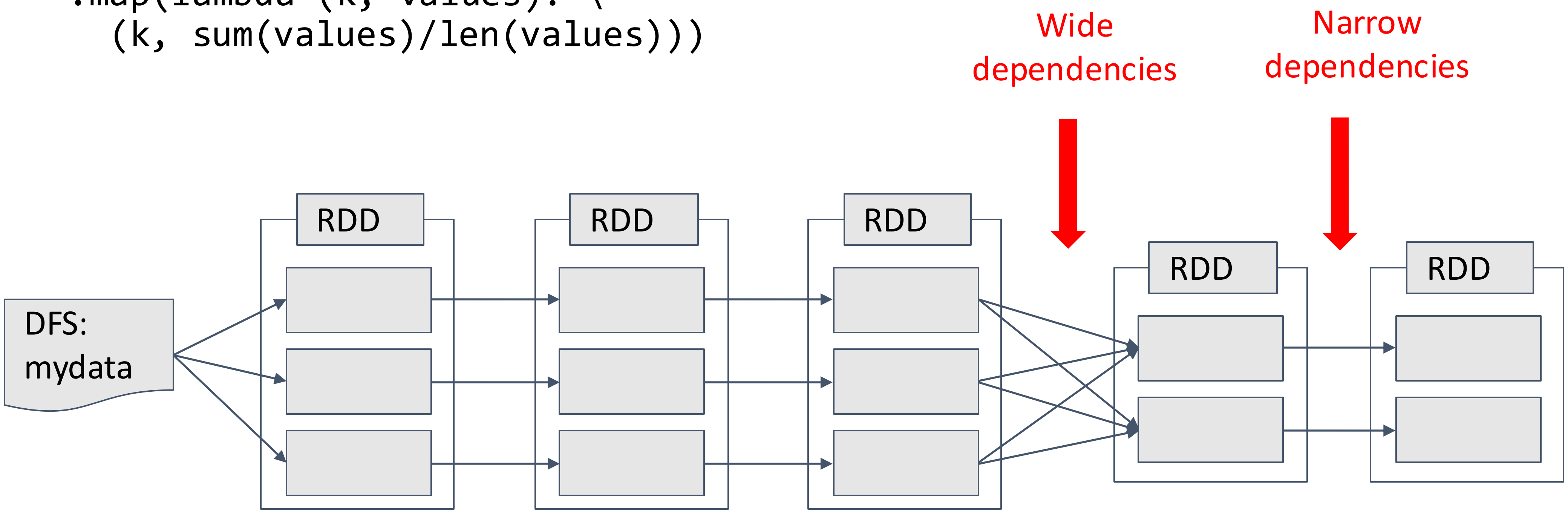


Map

- Transformation that takes function as parameter and applies it to every element of RDD
- Returns a new RDD where each input element is transformed into exactly one output element (one-to-one mapping).
- Not exactly the same as Map of MapReduce
  - In MapReduce, a Map function is applied to a key-value pair and produces a set of key-value pairs
  - In Spark, a Map function can apply to any object type, but produces exactly one object

```
> avglens = sc.textFile(file) \
    .flatMap(lambda line: line.split()) \
    .map(lambda word: (word[0], len(word))) \
    ...
```

Flatmap

- Transformation analogous to MapReduce Map, but no restriction on the type
- In comparison to a Spark Map, each object maps to a list of 0 or more objects
- All the lists are then “flattened” into a single RDD of objects

```
> avglens = sc.textFile(file) \
    .flatMap(lambda line: line.split()) \
    .map(lambda word: (word[0], len(word))) \
    ...
```

Filter

- Transformation that takes a predicate that applies to the RDD object type and returns elements that satisfy predicate

```
> avglens = sc.textFile(file) \
   .flatMap(lambda line: line.split()) \
   .filter(lambda word: word not in stoplist)) \
   ...
```

Reduce

- An action (not transformation) that returns a value instead of an RDD
- Takes parameter that is a function of type (V, V) => V
  - When applied to RDD, the function is repeatedly applied on pairs of elements to produce a single one
  - Function can be associative and commutative (e.g., addition), but this is not required

```
> totlen = sc.textFile(file) \
    .flatMap(lambda line: line.split()) \
    .map(lambda word: len(word)) \
    .reduce(lambda a, b: a + b)
```

Other examples of actions

- Actions are operations that trigger the execution of the Spark computation and return results to the driver program or write data to external storage systems

```
# Collect RDD elements to the drive program
collected_data = rdd.collect()

# Count the number of elements in the RDD
count = rdd.count()

# Get the first three elements of the RDD
element = rdd.take(3)

# Save RDD elements to a text file
rdd.saveAsTextFile(”output_folder”)
```

Relational database operations

- Some Spark operations behave like relational algebra operations on relations that are represented by RDD’s

Join

- Takes two RDD's of type key-value pair where the key types are the same
- For each pair (k, x) and (k, y), produce $(k, (x, y))$
- Output RDD consists of all such objects

```
> x = sc.parallelize([("a", 1), ("b", 4)])
> y = sc.parallelize([("a", 2), ("a", 3)])
> x.join(y).collect()
[('a', (1, 2)), ('a', (1, 3))]
```

GroupByKey

- Takes RDD of key-value pairs, produces a set of key-value pairs
  - The value type for the output is a list of values of the input type
- Sorts input RDD by key
- For each key k produces the pair (k, [v_1, v_2, …, v_n]) for v_i's associated with k

```
> avglens = sc.textFile(file) \
    .flatMap(lambda line: line.split()) \
    .map(lambda word: (word[0], len(word))) \
    .groupByKey() \
    ...
```

Spark implementation

Similar to MapReduce

- RDD is divided into chunks, which are given to different compute nodes
- Transformation on RDD can be performed in parallel on each of the chunks

Two key improvements

- Lazy evaluation of RDD’s
- Lineage for RDD’s

Lazy evaluation

Spark does not actually apply transformations to RDD's until it is required to do so (e.g., storing RDD to file system or returning a result to application)

```
val data = sc.textFile("input.txt")      // No execution yet
    .map(line => line.split(" "))        // Not executed
    .filter(words => words.length > 2)   // Still not executed
    .count()                             // Now it executes everything
```

Lazy evaluation

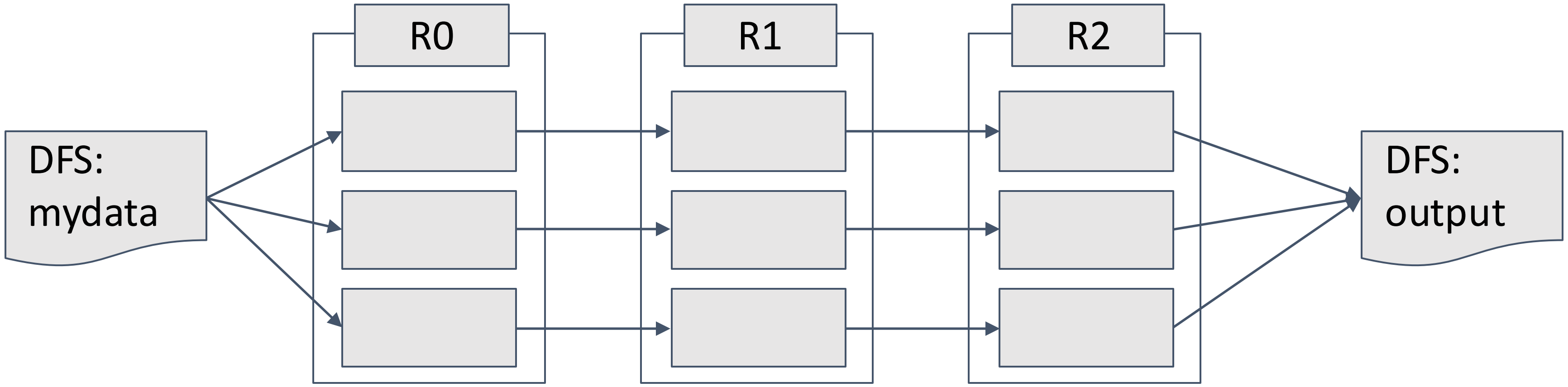
Spark does not actually apply transformations to RDD’s until it is required to do so (e.g., storing RDD to file system or returning a result to application)

Potential Benefits:

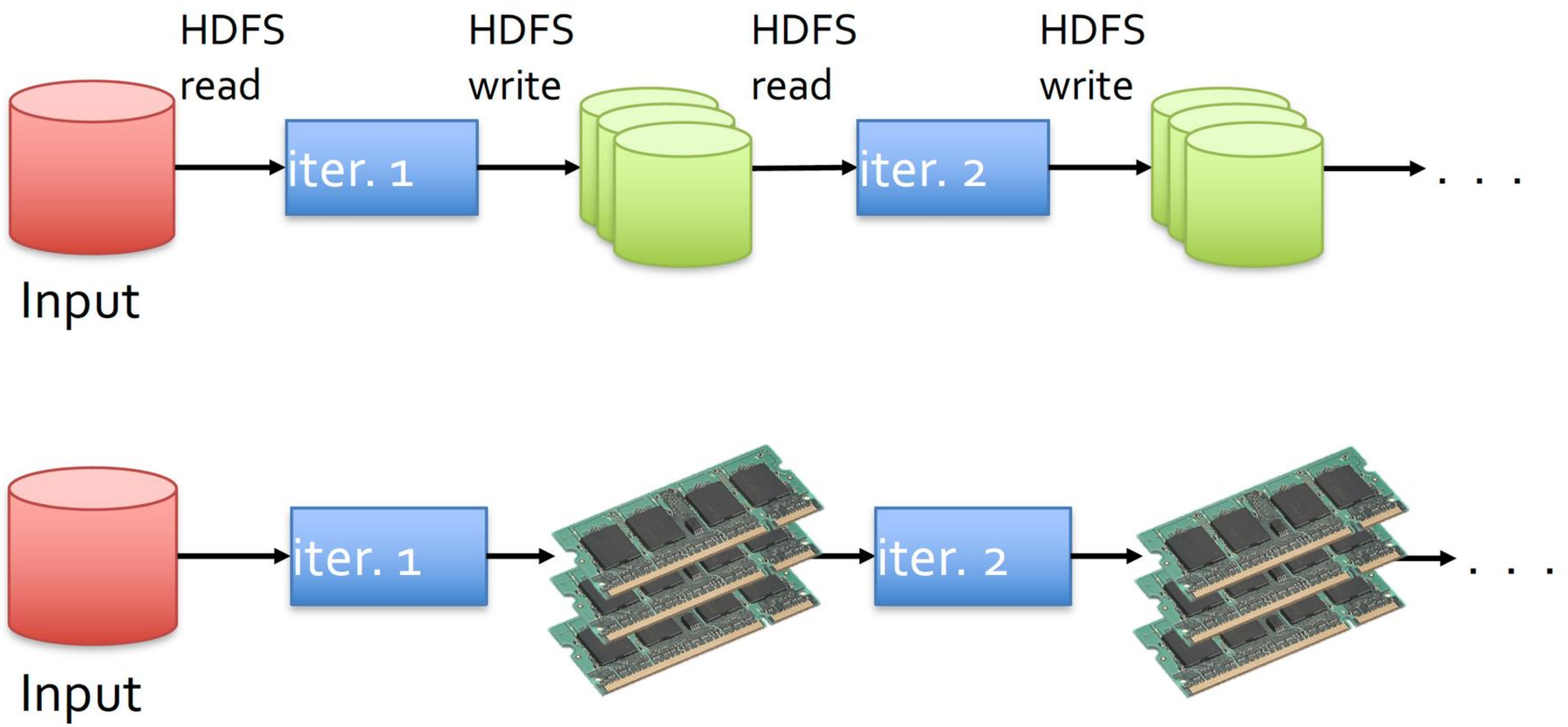
- Spark can analyze entire chain of operations and combining multiple operations to reduce unnecessary computations
- No immediate computation/memory usage; resources allocated only when needed
- Optimizes data shuffling and stages

Resilience of RDD's

- Spark records the *lineage* of every RDD, which can be used to re-create any RDD
  - If R_2 is lost, reconstruct from R_1
  - If R_1 is lost, reconstruct from R_0
  - If R_0 is lost, reconstruct from file system



Data Sharing in MapReduce vs Spark



MapReduce: disk

Spark: memory

This is why Spark is significantly faster for iterative algorithms

Spark programming guide and paper

- To learn more about writing Spark applications, please read the Spark programming guide: https://spark.apache.org/docs/latest/rdd-programming-guide.html

- Recommend reading: the Spark paper