

MapReduce

CompSci 516
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Announcement

- HW3 has been posted
(due on **March 23rd** after the spring break).
- Key components in HW3 are:
Apache Spark, Scala, and Unix variants.



Big Data

```
graph TD; A[Big Data] --> B[it cannot be stored in one machine]; A --> C[it cannot be processed in one machine]; B --> D[store the data sets on multiple machines]; D --> E[Google File System]; C --> F[parallelize computation on multiple machines]; F --> G[MapReduce];
```

it cannot be **stored**
in one machine



store the data sets
on multiple machines



Google File System

it cannot be **processed**
in one machine



parallelize computation
on multiple machines



Today!

MapReduce

But before we go into
MapReduce,
let me briefly talk about
Google File System

Google File System

- It is a distributed file system.
- When I say GFS in this slides, it means Google File System.
- For more information, please read GFS paper from SOSP 2003.

MapReduce

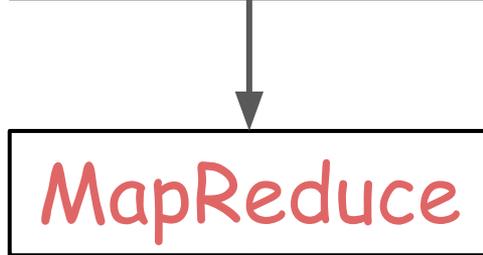
- MapReduce refers to Google MapReduce.
- Google published MapReduce paper in OSDI 2004, a year after the GFS paper.

Where does Google use MapReduce?

Input



- crawled documents
- web request logs



Output



- inverted indices
- graph structure of web documents
- summaries of the number of pages crawled per host
- the set of most frequent queries in a day

What is MapReduce?

It is a **programming model**

that **processes large data** by:

apply a function to each logical record in the input (**map**)

categorize and combine the intermediate results
into summary values (**reduce**)

Google's MapReduce is inspired
by
map and reduce functions
in functional programming
languages.

For example,
in Scala functional
programming language,

```
scala> val lst = List(1,2,3,4,5)
```

```
scala> lst.map( x => x + 1 )
```

```
res0: List[Int] = List(2,3,4,5,6)
```

For example,
in Scala functional
programming language,

```
scala> val lst = List(1,2,3,4,5)
```

```
scala> lst.reduce( (a, b) => a + b )
```

```
res0: Int = 15
```

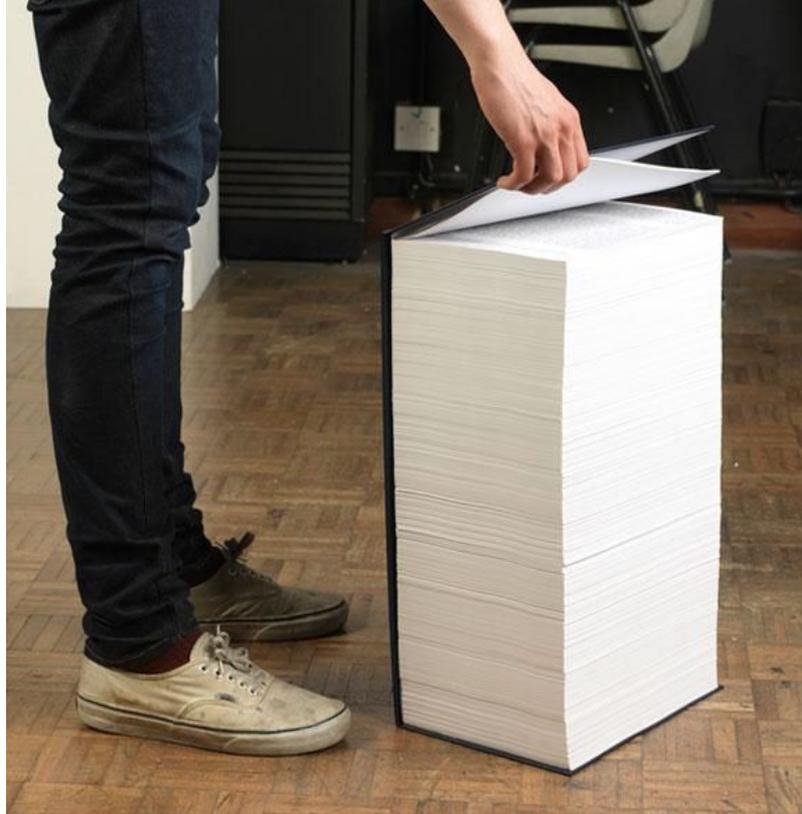
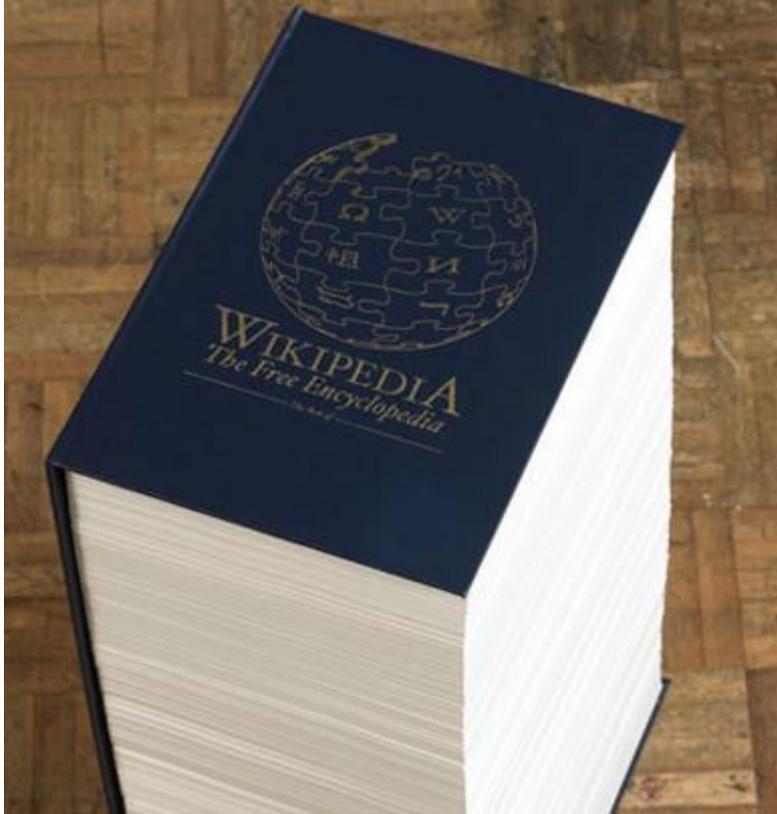
Ok, it makes sense
in one machine.

Then, how does Google
extend the functional idea
to multiple machines
in order to
process large data?



An English teacher asks you:

“Could you count the number of occurrences of each word in this book?”

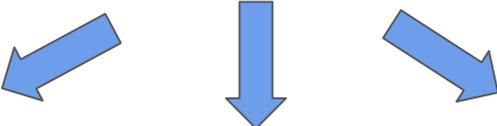


Um... Ok...

Let's divide the workload among classmates.



map



cloud 1
data 1



parallel 1
data 1
computer 1



map 1
cloud 1
parallel 1



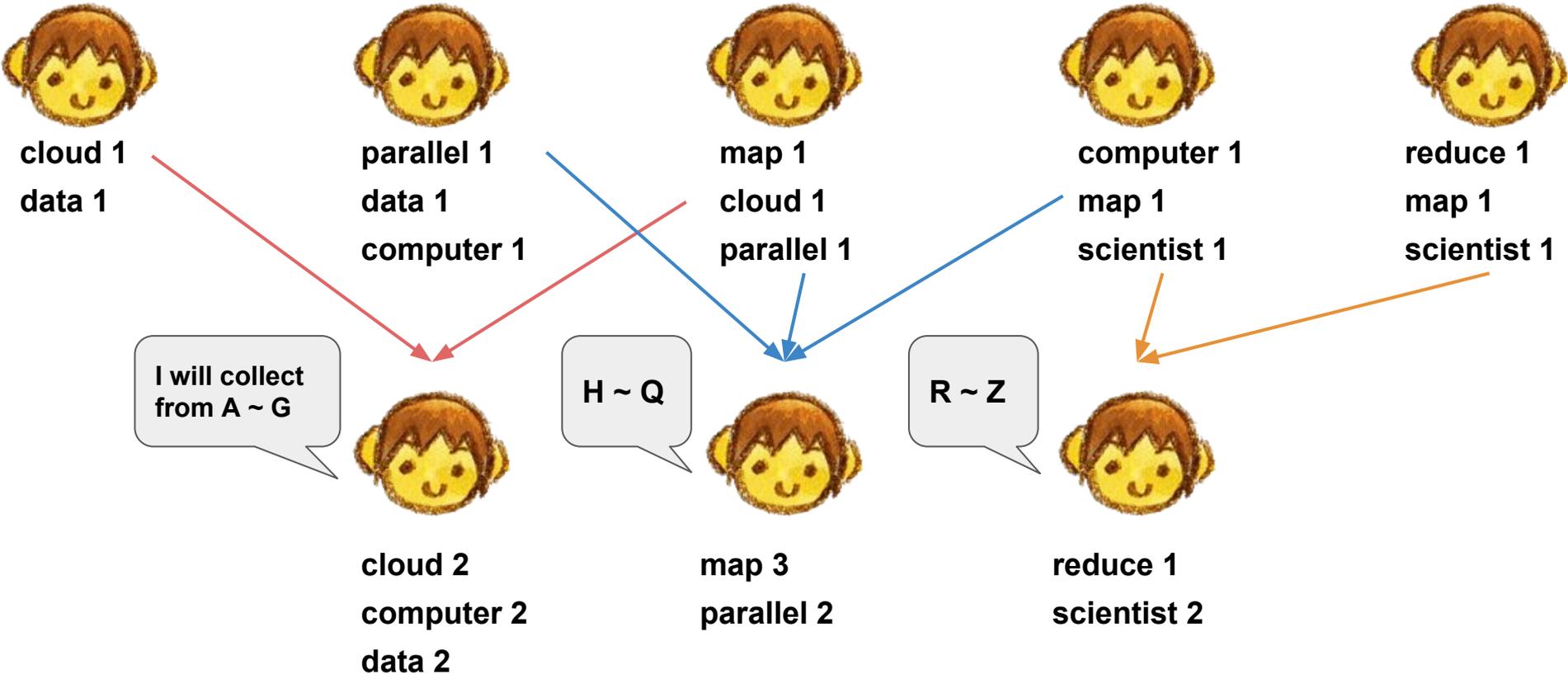
computer 1
map 1
scientist 1



reduce 1
map 1
scientist 1

And let few combine the intermediate results.

reduce



Why did MapReduce
become so popular?

Is it because **Google** uses it?



Distributed Computation Before MapReduce

Things to consider:

- how to divide the workload among multiple machines?
- how to distribute data and program to other machines?
- how to schedule tasks?
- what happens if a task fails while running?
- ... and ... and ...

Distributed Computation After MapReduce

Things to consider:

- how to write **Map** function?
- how to write **Reduce** function?

MapReduce lowered the knowledge barrier in distributed computation.



Developers needed
before MapReduce



Developers needed
after MapReduce

Given the brief intro to
MapReduce,

let's begin our journey to
real implementation details
in MapReduce !

Key Players in MapReduce

One Master

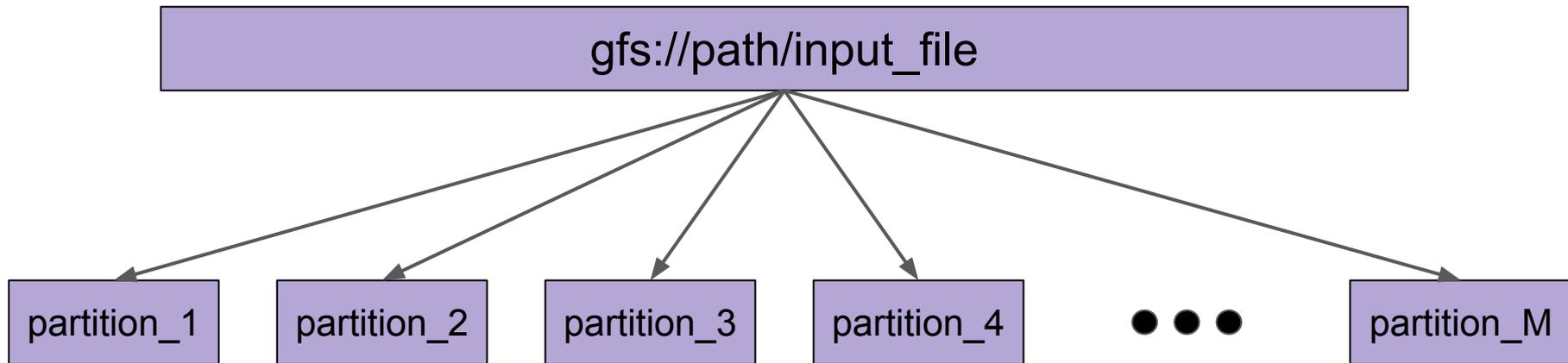
- coordinates many workers.
- assigns a task* to each worker.
(* task = partition of data + computation)

Multiple Workers

- Follow whatever the Master asks to do.

Execution Overview

1. The MapReduce library in the user program first splits the input file into M pieces.



2. The MapReduce library in the user program then starts up many copies of the program on a cluster of machines: one master and multiple workers .



master



worker 1



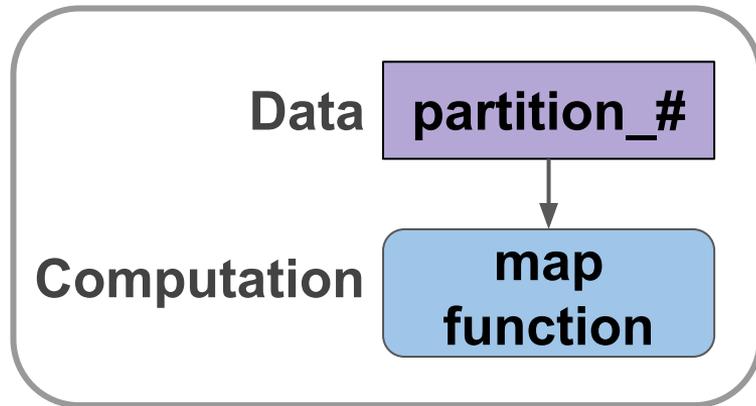
worker 2



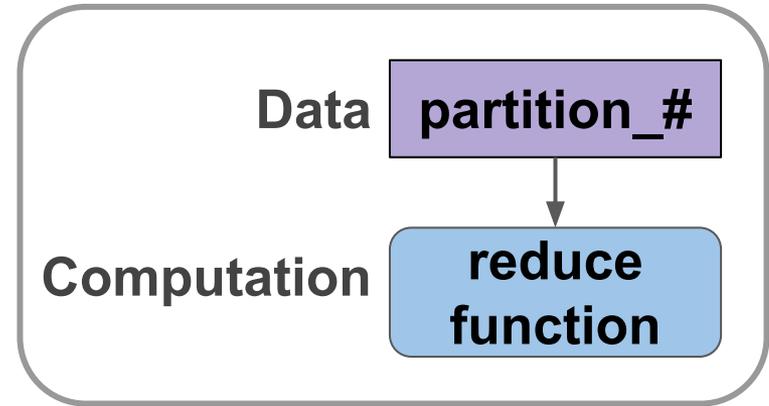
worker 3

There are M map tasks and R reduce tasks to assign.
(The figures below depicts task = data + computation)

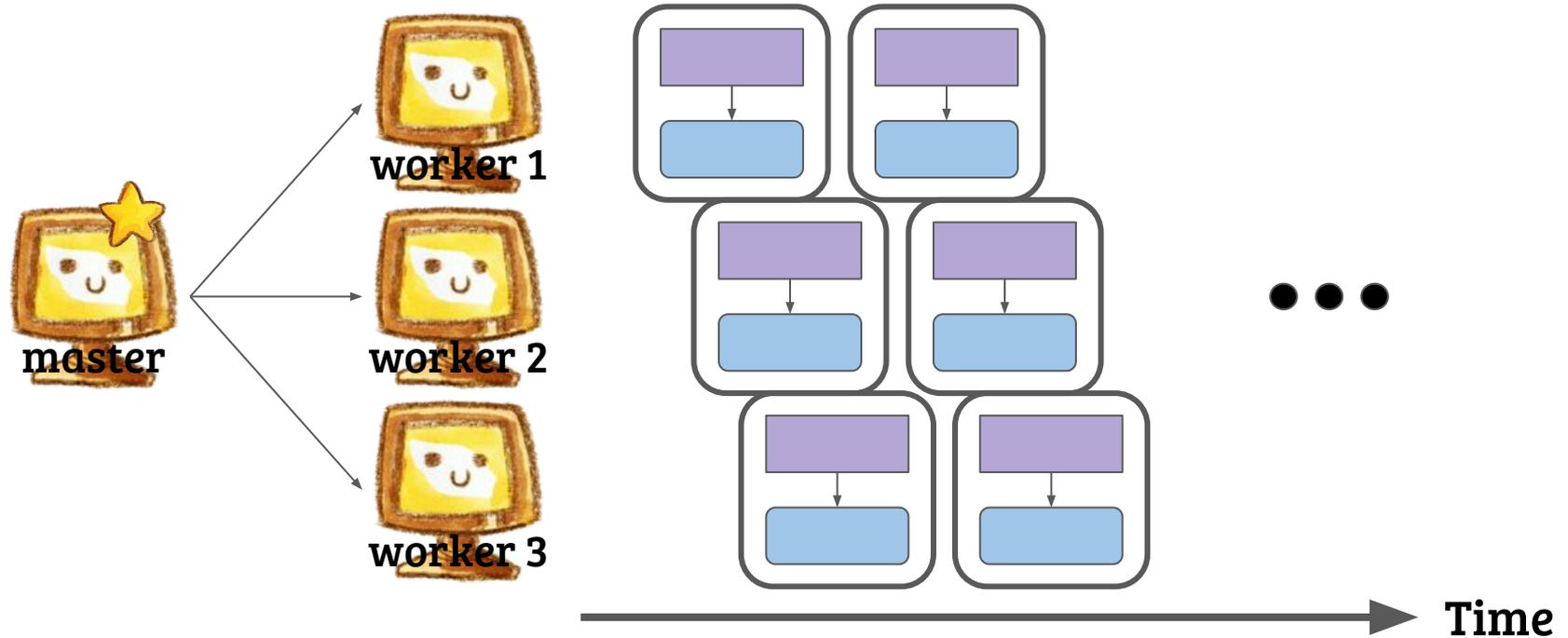
Map Task



Reduce Task



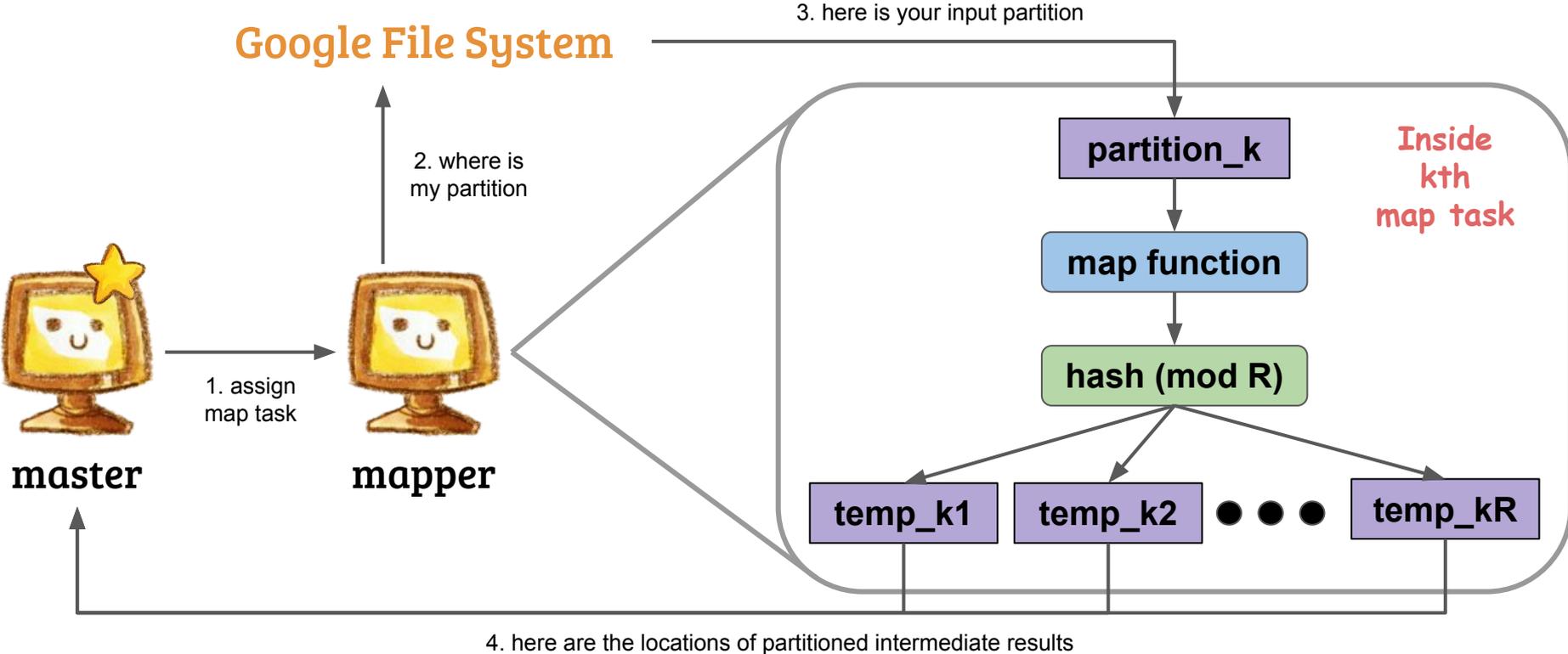
3. The master picks idle workers and assigns each one a map task.



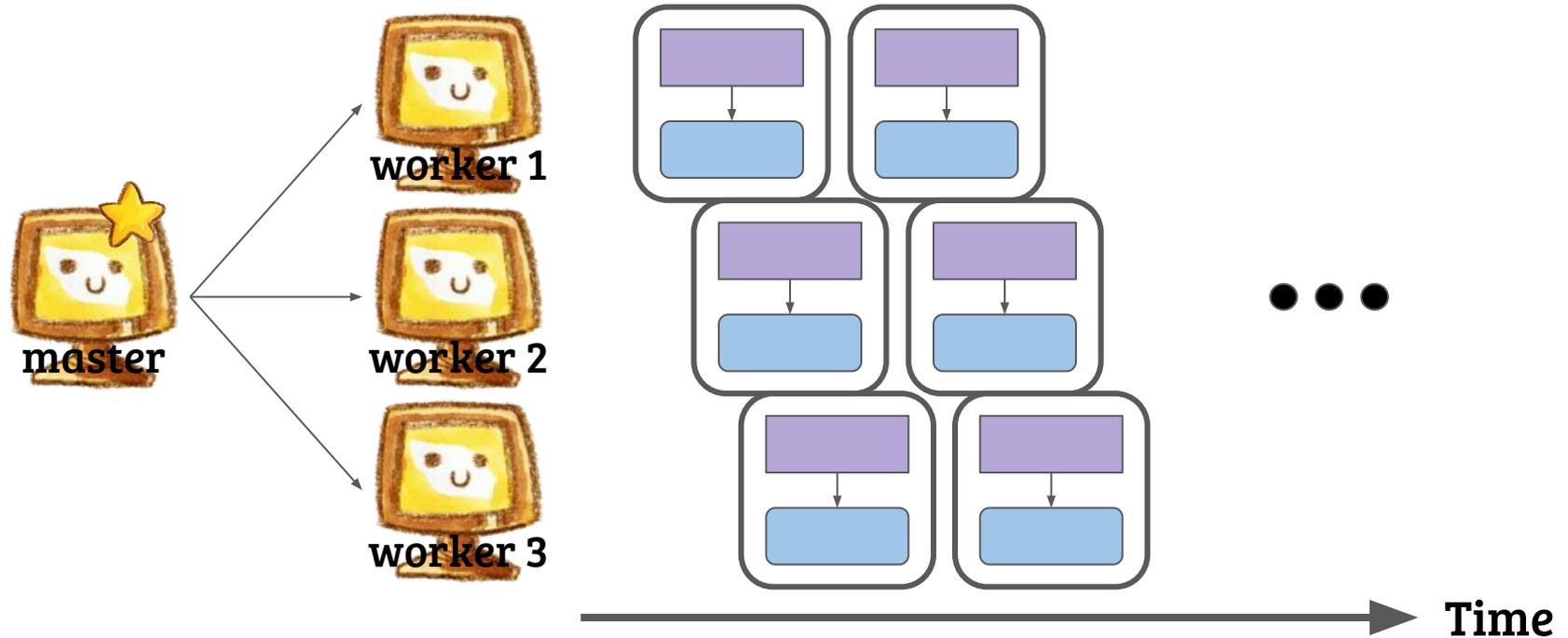
4. Map Phase (each mapper node)

- 1) Read in a corresponding input partition.
- 2) Apply the user-defined map function to each key/value pair in the partition.
- 3) Partition the result produced by the map function into R regions using the partitioning function.
- 4) Write the result into its local disk (not GFS).
- 5) Notify the master with the locations of each partitioned intermediate result.

Map Phase



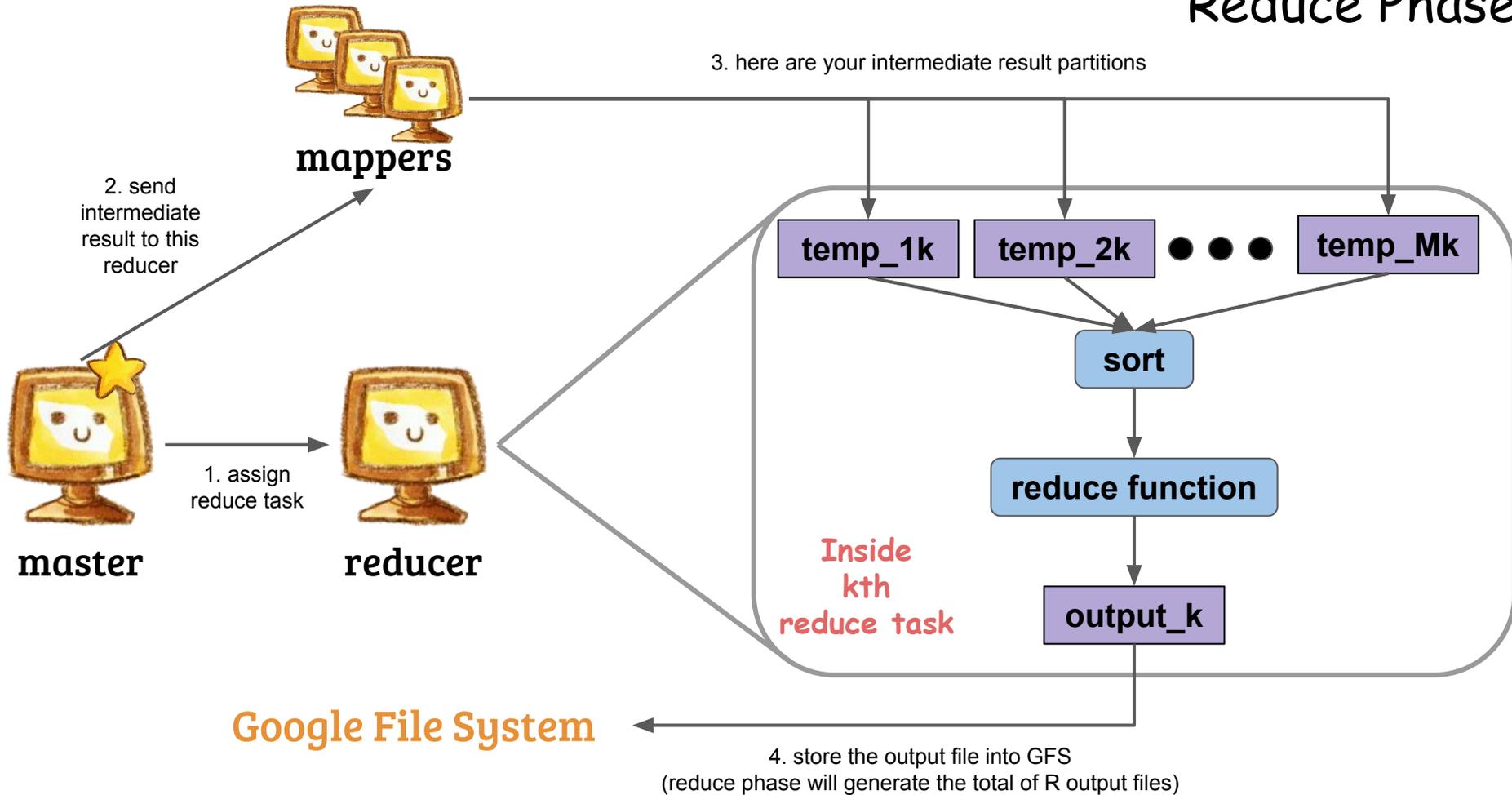
5. After all the map tasks are done, the master picks idle workers and assigns each one a reduce task.



6. Reduce Phase (each reducer node)

- 1) Read in all the corresponding intermediate result partitions from mapper nodes.
- 2) Sort the intermediate results by the intermediate keys.
- 3) Apply the user-defined reduce function on each intermediate key and the corresponding set of intermediate values.
- 4) Create one output file.

Reduce Phase



Fault Tolerance

Although the probability of a machine failure is low, the probability of a machine failing among thousands of machines is common.

How does MapReduce handle machine failures?

Worker Failure

- The master sends heartbeat to each worker node.
- If a worker node fails, the master reschedules the tasks handled by the worker.

Master Failure

- The whole MapReduce job gets restarted through a different master.

Locality

- The input data is managed by *GFS*.
- Choose the cluster of MapReduce machines such that those machines contain the input data on their local disk.
- We can conserve network bandwidth.

Task Granularity

- It is preferable to have the number of tasks to be multiples of worker nodes.
- Smaller the partition size, faster failover and better granularity in load balance.
But it incurs more overhead. Need a balance.

Backup Tasks

- In order to cope with a straggler, the master schedules backup executions of the remaining *in-progress* tasks.

MapReduce Pros and Cons

- MapReduce is good for off-line batch jobs on large data sets.
- MapReduce is not good for iterative jobs due to high I/O overhead as each iteration needs to read/write data from/to GFS.
- MapReduce is bad for jobs on small datasets and jobs that require low-latency response.

Apache Hadoop

- Apache Hadoop has an open-source version of GFS and MapReduce.
- GFS -> HDFS (Hadoop File System)
Google MapReduce -> Hadoop MapReduce
- You can download the software and implement your own MapReduce applications.

In HW3,

- We will be using Apache Spark, which is also a compute engine that can process large sets of data.
- Then, write Spark programs (like MapReduce program) -- PageRank algorithm!
- Lastly, run them on your local machine.
Each core in your machine will behave as a node.

In HW4,

- We will be using Apache Spark on Amazon Web Services (AWS).
- We will instantiate multiple virtual machines (AWS EC2), and run Spark applications on the cluster of machines.

References

- MapReduce: Simplified Data Processing on Large Cluster - Jeffrey Dean, et al. - 2004
- Resilient Distributed Datasets: A Fault-Tolerant Abstraction for In-Memory Cluster Computing - Matei Zaharia, et al. - 2012
- <http://www.slideshare.net/yongho/2011-h3>