MapReduce case study

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CS 240: *Computing Systems and Concurrency*
Lecture 1.1

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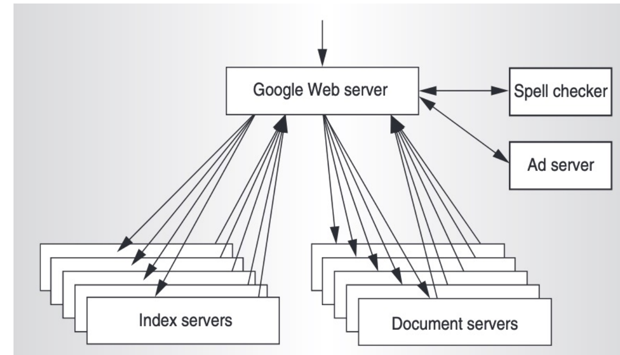
Why scalable analytics?

- Google’s index was perhaps one of the first “big data” problems
  - Crawler fetched 100s of millions of web pages
  - Needed to create giant indices from keywords
  - Too much work for any individual machine → needed to be spread across many machines



Barrosso et al., “Web Search for a Planet: The Google Cluster Architecture”, IEEE MICRO 23(2)

- Soon they also needed to compute various statistics on this data
  - For instance, how many documents contained a given keyword?
- This led to the development of the MapReduce framework

Key challenges

- Data is spread across (many) computers
  - What do we do if related data is on different computers, but we need all of it to perform some computation?
- Communication is expensive
  - Need to be smart about where data is stored, and when it is moved
- Coordination is key
  - The computation needs to be carefully orchestrated to get the correct result
  - … especially if there are failures, heterogeneous machines, etc.

Case Study: MapReduce

(Data-parallel programming at scale)

What is MapReduce?

- MapReduce is a famous distributed programming model
  - Invented at Google; paper published in 2004
  - At that time, it was used for the production indexing system

- Closed source, but open-source reimplementations exist
  - Example: Apache Hadoop

- Originally ran on GFS (The Google FileSystem)
  - GFS is designed for sequential reads and appends
  - This is the workload that MapReduce would produce!

Application: Word Count

```
SELECT count(word) FROM data
    GROUP BY word

cat data.txt
    | tr -s '[[:punct:][:space:]]' '\n'
    | sort | uniq -c
```

Using partial aggregation

1. Compute word counts from individual files
2. Then merge intermediate output
3. Compute word count on merged outputs

Using partial aggregation: data flow

1. In parallel, send to worker:
   - Compute word counts from individual files
   - Collect result, wait until all finished
2. Then merge intermediate output
3. Compute word count on merged intermediates

I don’t want to deal with all this!

- Wouldn't it be nice if there were some system that took care of all these details for you?
  - But every task is different!
  - Or is it? The detailed are different (what to compute, etc.), but the **data flow** is often same!
  - Maybe we can have a ‘generic’ solution?

- Ideally, just tell the system what needs to be done
- This is what frameworks like MapReduce (and Apache Spark and Apache Flink) do!

MapReduce: Programming Interface

```
map(key, value) -> list(<k’, v’>)
```

– Apply function to (key, value) pair and produces set of intermediate pairs

```
reduce(key, list<value>) -> <k’, v’>
```

– Applies aggregation function to values collected by key

– Outputs result

MapReduce example: Word Count

```
map(String key, String value):
   // key: document name; value: document line
   for each word w in value:
      EmitIntermediate(w, "1");


reduce(String key, Iterator values):
   // key: a word; value: a list of counts
   int result = 0;
   for each v in values:
      result += ParseInt(v);
   Emit(key, AsString(result));
```

MapReduce: Optimizations

```
combine(list<key, value>) -> list<k,v>
```

- Perform partial aggregation on mapper node:

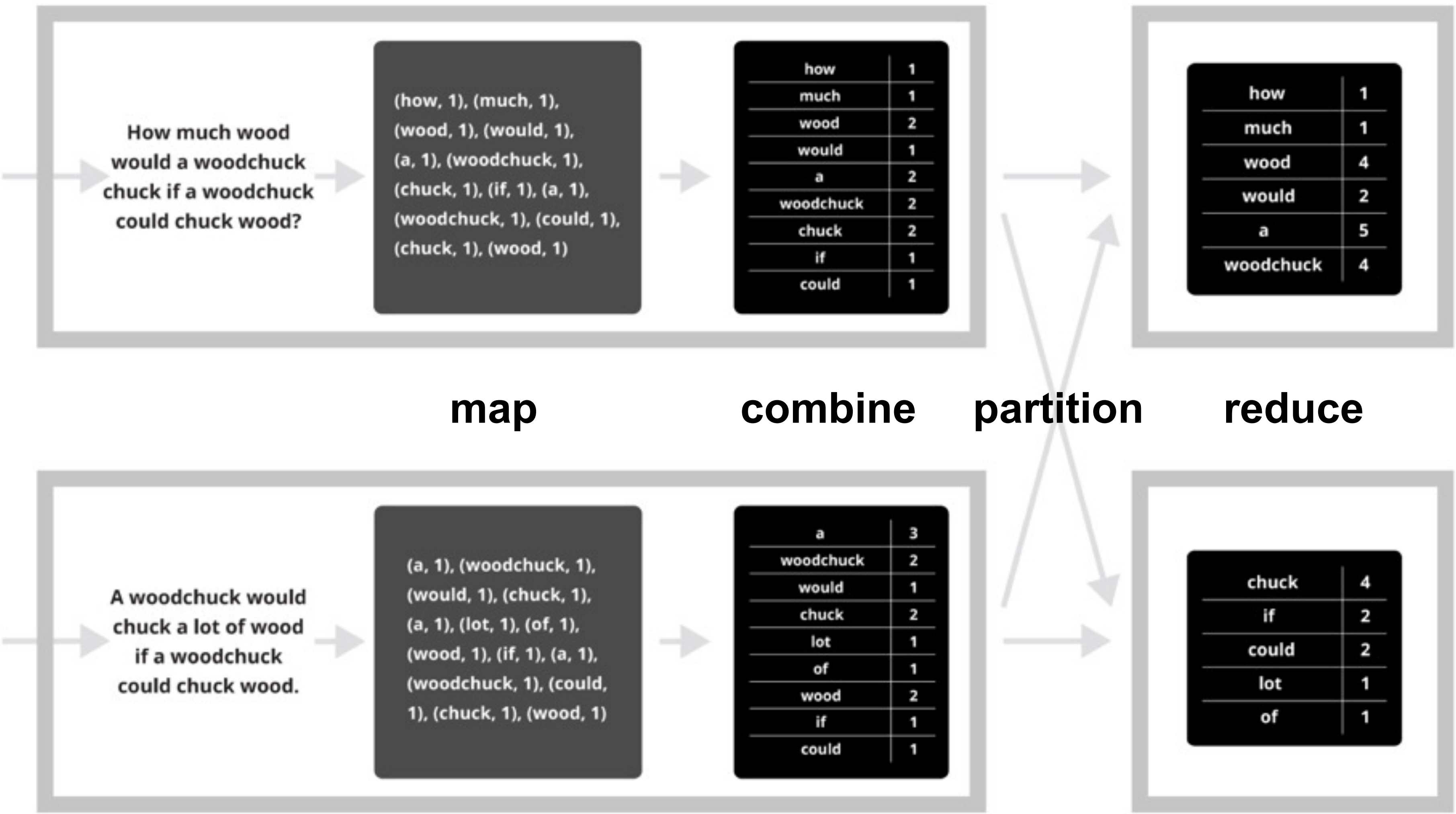
  <the, 1>, <the, 1>, <the, 1> → <the, 3>

- combine() should be commutative and associative

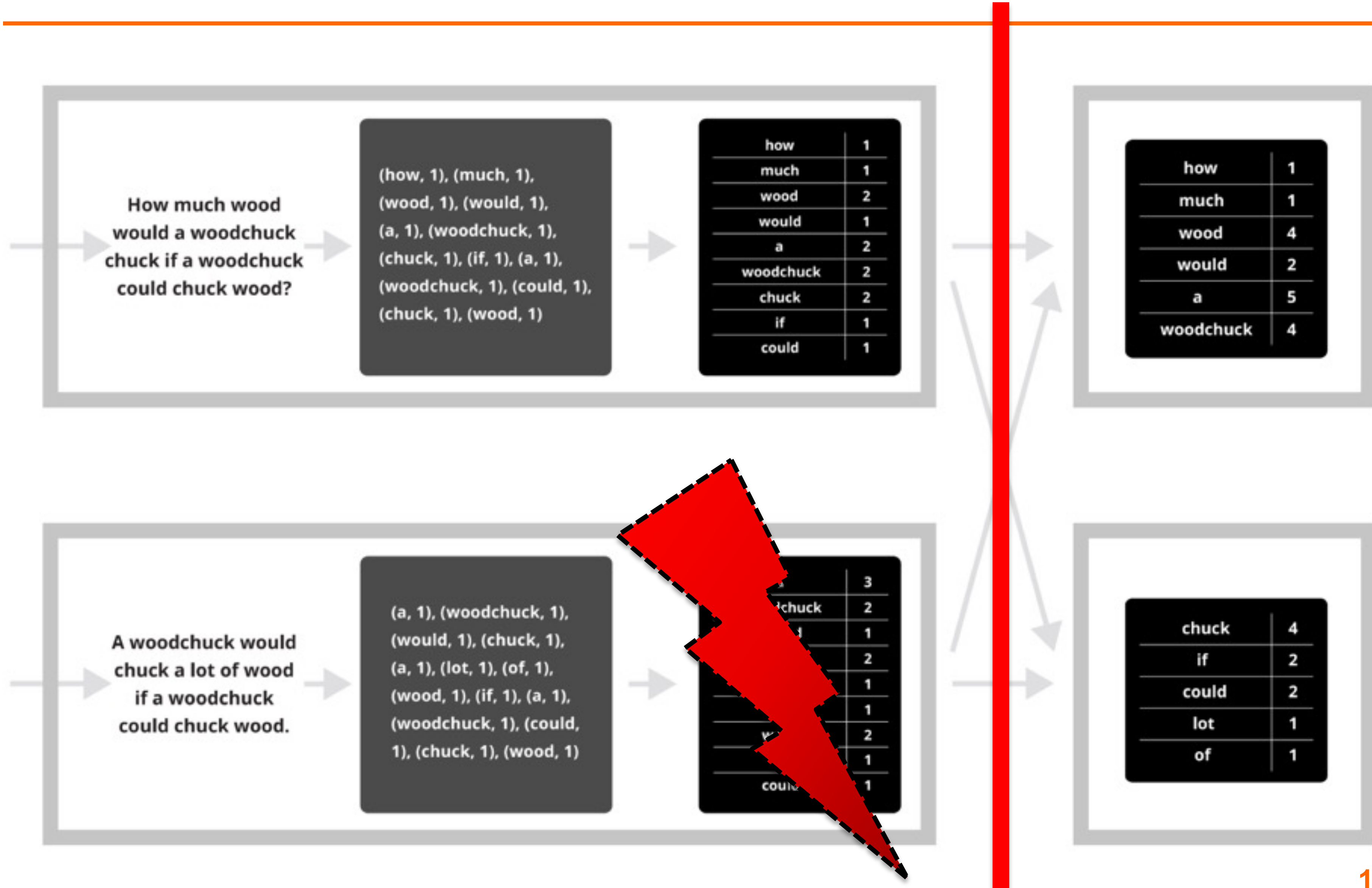
```
partition(key, int) -> int
```

- Need to aggregate intermediate vals with same key
- Given n partitions, map key to partition $0 \le i < n$
- Typically via hash(key) mod n

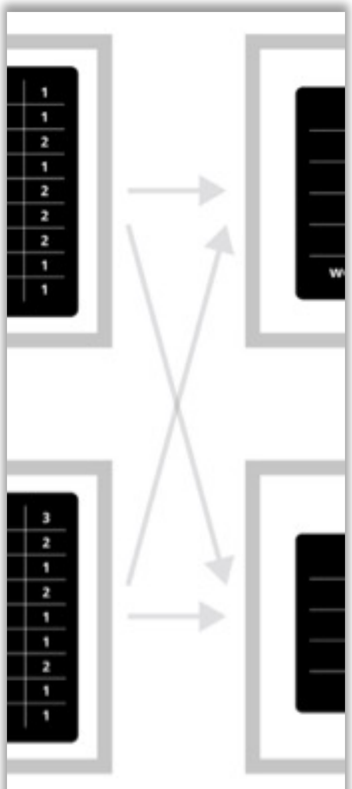
Putting it together…



Synchronization Barrier



Fault Tolerance in MapReduce



- Map worker writes intermediate output to local disk, separated by partitioning. Once completed, tells master node.
- Reduce worker told of location of map task outputs, pulls their partition's data from each mapper, execute function across data
- Note:
  - "All-to-all" shuffle b/w mappers and reducers
  - Written to disk ("materialized") b/w *each* stage

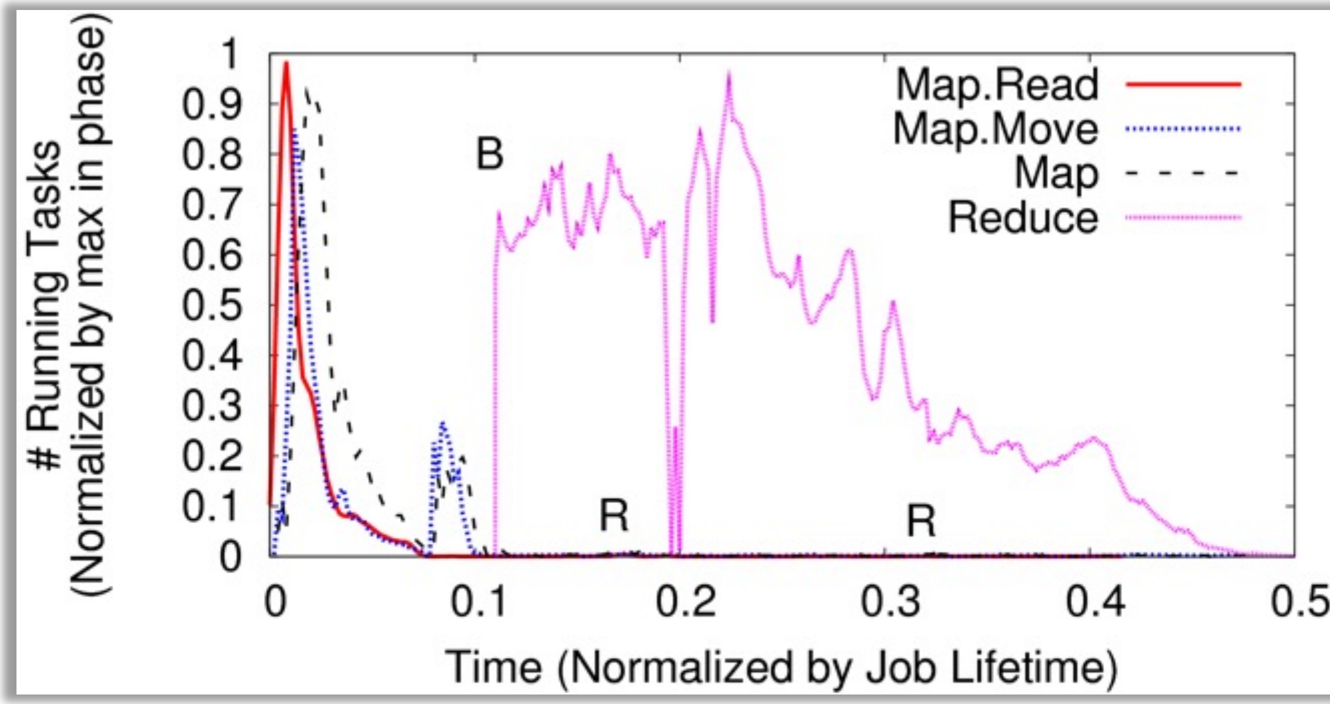
Fault Tolerance in MapReduce

- Master node monitors state of system
  - If master failures, job aborts and client notified

- Map worker failure
  - Both in-progress/completed tasks marked as idle
  - Reduce workers notified when map task is re-executed on another map worker

- Reducer worker failure
  - In-progress tasks are reset to idle (and re-executed)
  - Completed tasks had been written to global file system

Straggler Mitigation in MapReduce



- Tail latency means some workers finish late
- For slow map tasks, execute in parallel on second map worker as "backup", race to complete task

MapReduce: Limitations

- MapReduce worked very well for Google's initial use cases, and lots of others besides
  - No data dependencies within map/reduce phases → Good scalability

- But it does have some important limitations:
  - Complex operations have to be rewritten into 'map' and 'reduce' operations (possibly with several rounds of mapping and reducing)
  - Dataflows always read from and write to disk (why?) → limited speed

You'll build (simplified) MapReduce!

- Assignment 1: Sequential MapReduce
  - Learn to program in Go!
  - Due September 13

- Assignment 2: Distributed MapReduce
  - Learn Go's concurrency, network I/O, and RPCs
  - Due September 20