The MapReduce Paradigm

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with most slides shamelessly stolen from Jeff Dean and Yonatan Zunger

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Do We Need It?

If distributed computing is so hard, do we really need to do it?

Yes: Otherwise some problems are too big.

Example: 20+ billion web pages x 20KB = 400+ terabytes

- One computer can read 30-35 MB/sec from disk

  ~four months to read the web

- ~1,000 hard drives just to store the web
- Even more to *do* something with the data

Yes, We Do

Good news: same problem with 1000 machines, < 3 hours

Bad news: programming work

- communication and coordination
- recovering from machine failure (all the time!)
- status reporting
- debugging
- optimization
- locality

Bad news II: repeat for every problem you want to solve

How can we make this easier?

MapReduce

A simple programming model that applies to many large-scale computing problems

Hide messy details in MapReduce runtime library:

- automatic parallelization
- load balancing
- network and disk transfer optimization
- handling of machine failures
- robustness
- **improvements to core library benefit all users of library!**

Typical problem solved by MapReduce

Read a lot of data

Map: extract something you care about from each record

Shuffle and Sort

Reduce: aggregate, summarize, filter, or transform

Write the results

Outline stays the same,

Map and Reduce change to fit the problem

MapReduce Paradigm

Basic data type: the key-value pair (k,v).

For example, key = URL, value = HTML of the web page.

Programmer specifies two primary methods:

- Map: $(k, v) \mapsto <(k_1,v_1), (k_2,v_2), (k_3,v_3),\ldots,(k_n,v_n)>$
- Reduce: $(k', <v'_1, v'_2,\ldots,v'_{n'}>) \mapsto <(k', v''_1), (k', v''_2),\ldots,(k', v''_{n''})>$

All v' with same k' are reduced together.

(Remember the invisible “Shuffle and Sort” step.)

Example: Word Frequencies in Web Pages

A typical exercise for a new Google engineer in his or her first week

Input: files with one document per record

Specify a *map* function that takes a key/value pair
key = document URL
value = document contents

Output of map function is (potentially many) key/value pairs.
In our case, output (word, “1”) once per word in the document

“document1”, “to be or not to be”

↓

“to”, “1”
“be”, “1”
“or”, “1”
…

Example: Word Frequencies in Web Pages

MapReduce library gathers together all pairs with the same key (shuffle/sort)

Specify a *reduce* function that combines the values for a key
In our case, compute the sum

key	values	reduce output
key = "be"	values = "1", "1"	"2"
key = "not"	values = "1"	"1"
key = "or"	values = "1"	"1"
key = "to"	values = "1", "1"	"2"

Output of reduce (usually 0 or 1 value) paired with key and saved

"be", "2"
"not", "1"
"or", "1"
"to", "2"

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Under the hood: Scheduling

One master, many workers

- Input data split into *M* map tasks (typically 64 MB in size)
- Reduce phase partitioned into *R* reduce tasks (= # of output files)
- Tasks are assigned to workers dynamically
- Reasonable numbers inside Google: *M*=200,000; *R*=4,000; workers=2,000

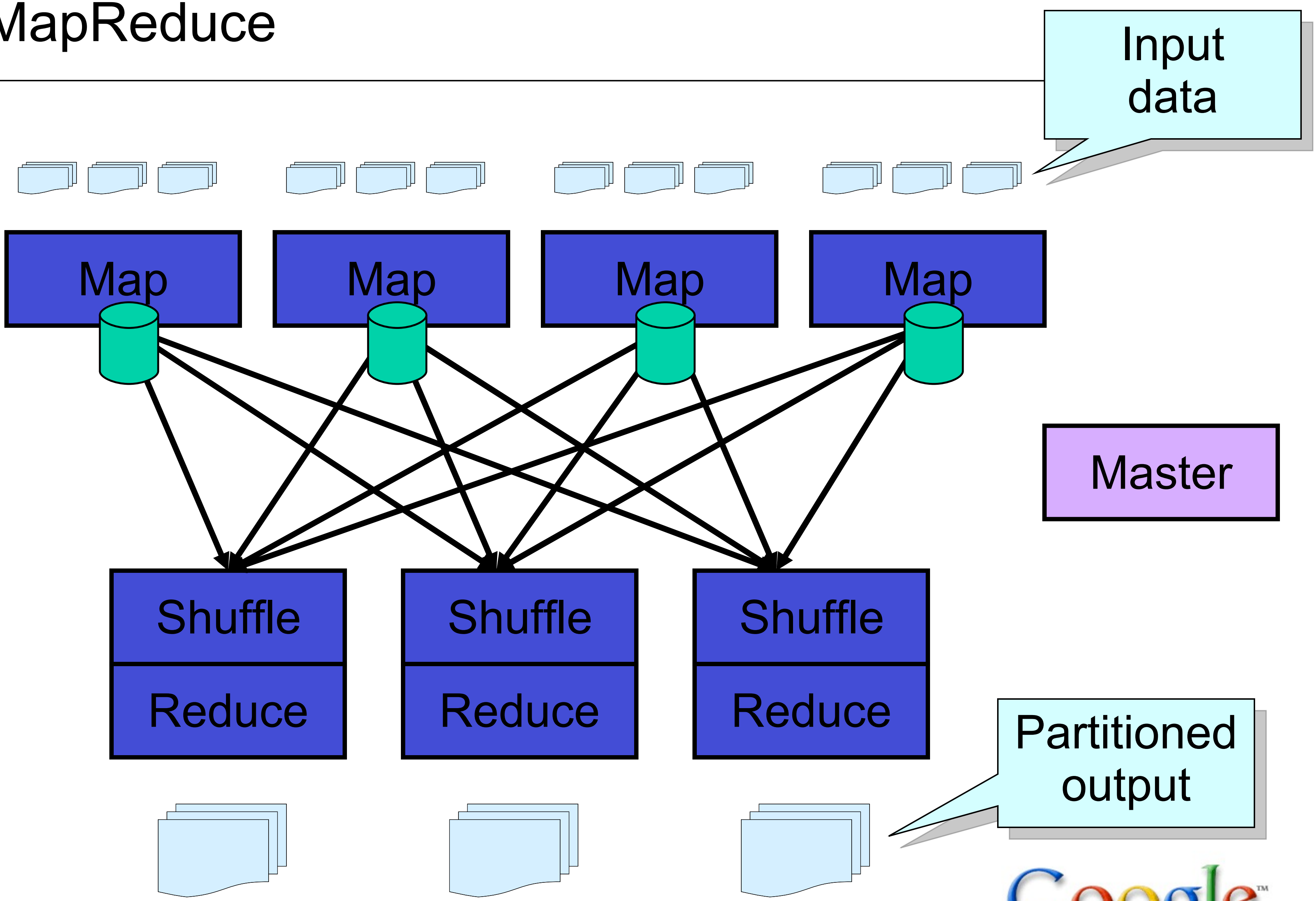
Master assigns each map task to a free worker

- Considers locality of data to worker when assigning task
- Worker reads task input (often from local disk!)
- Worker produces R **local files** containing intermediate (k,v) pairs

Master assigns each reduce task to a free worker

- Worker reads intermediate (k,v) pairs from map workers
- Worker sorts & applies user's Reduce op to produce the output
- User may specify Partition: which intermediate keys to which Reducers

MapReduce

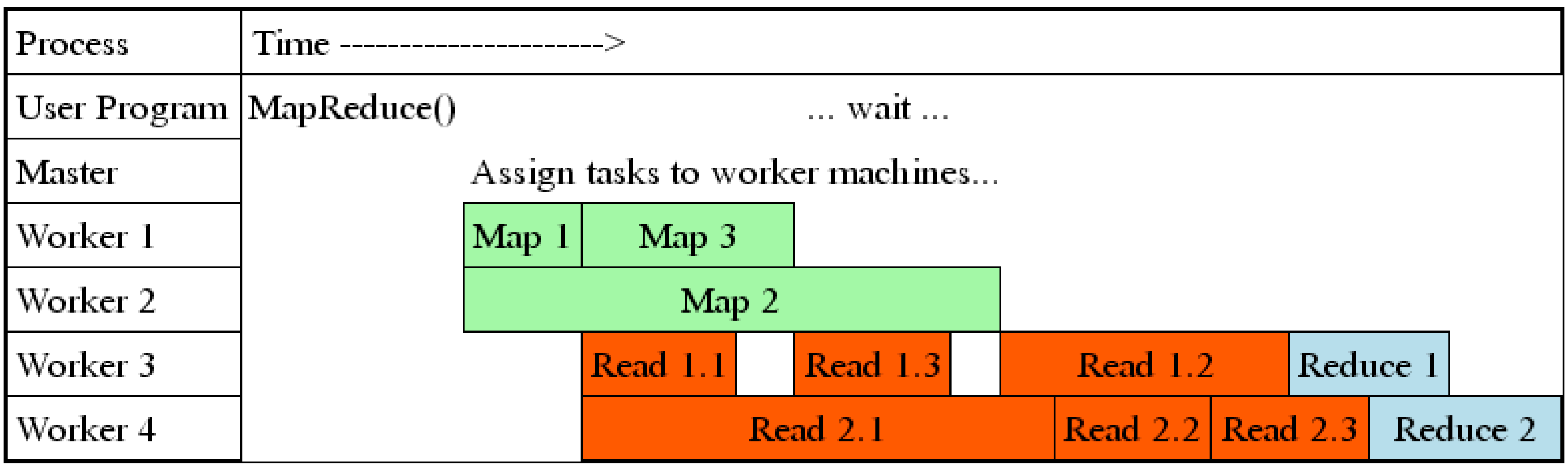


Input data
Map
Map
Map
Map
Master
Shuffle
Reduce
Shuffle
Reduce
Shuffle
Reduce
Partitioned output

MapReduce: Granularity

Fine granularity tasks: many more map tasks than machines

- Minimizes time for fault recovery
- Can pipeline shuffling with map execution
- Better dynamic load balancing



MapReduce: Fault Tolerance via Re-Execution

Worker failure:

- Detect failure via periodic heartbeats
- Re-execute completed and in-progress map tasks
- Re-execute in-progress reduce tasks
- Task completion committed through master

Master failure:

- State is checkpointed to replicated file system
- New master recovers & continues

Very Robust: lost 1600 of 1800 machines once, but finished fine

MapReduce: A Leaky Abstraction

MR insulates you from many concerns, but not all of them.

- Don't overload one reducer
- Don't leak memory, even a little!
- Static and global variables probably don't do what you expect

  (They can sometimes be useful, though!)
- Mappers might get rerun -- maybe on different data!

  Careful with side-effects: must be atomic, idempotent.

  Different reducers might see different versions!