MapReduce

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Hot Topics in Distributed Systems: Data-Intensive Computing
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Motivation: Large Scale Data Processing

- Want to:
  - Process lots of data (> 1 TB)
  - Automatically parallelize across hundreds/thousands of CPUs
  - Have status and monitoring tools
  - Provide clean abstraction for programmers
  - Make this easy

MapReduce

- "A simple and powerful interface that enables automatic parallelization and distribution of large-scale computations, combined with an implementation of this interface that achieves high performance on large clusters of commodity PCs."

Dean and Ghermawat, "MapReduce: Simplified Data Processing on Large Clusters", Google Inc.

Typical Problem

Map

- Iterate over a large number of records
- Extract something of interest from each
- Shuffle and sort intermediate results
- Aggregate intermediate results
- Generate final output

Reduce

- **Key idea:** provide an abstraction at the point of these two operations

MapReduce: Programming Model

- Process data using special map() and reduce() functions
- The map() function is called on every item in the input and emits a series of intermediate key/value pairs
- All values associated with a given key are grouped together
- The reduce() function is called on every unique key, and its value list, and emits a value that is added to the output

Programming Model

- Borrows from functional programming
- Users implement interface of two functions:

  - `map (in_key, in_value) -> (out_key, intermediate_value) list`

  - `reduce (out_key, intermediate_value list) -> out_value list`

map

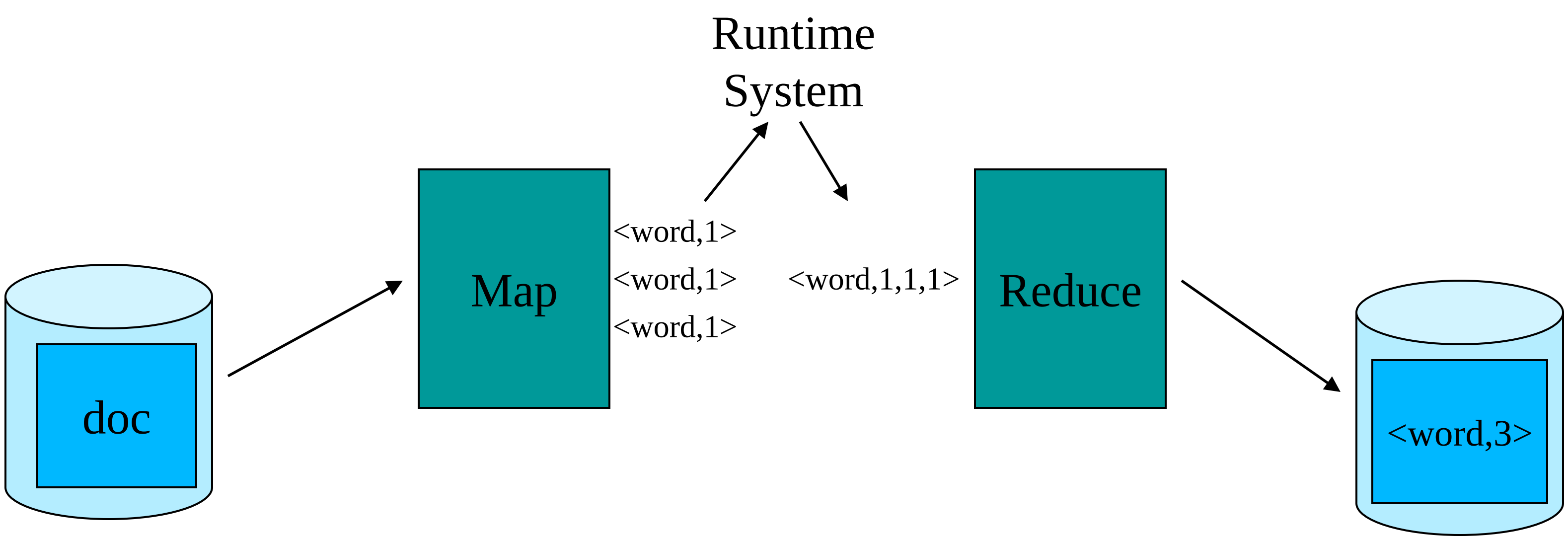
- Records from the data source (lines out of files, rows of a database, etc) are fed into the map function as key*value pairs: e.g., (filename, line).
- map() produces one or more *intermediate* values along with an output key from the input.

reduce

- After the map phase is over, all the intermediate values for a given output key are combined together into a list
- reduce() combines those intermediate values into one or more *final values* for that same output key
- (in practice, usually only one final value per key)

MapReduce Examples

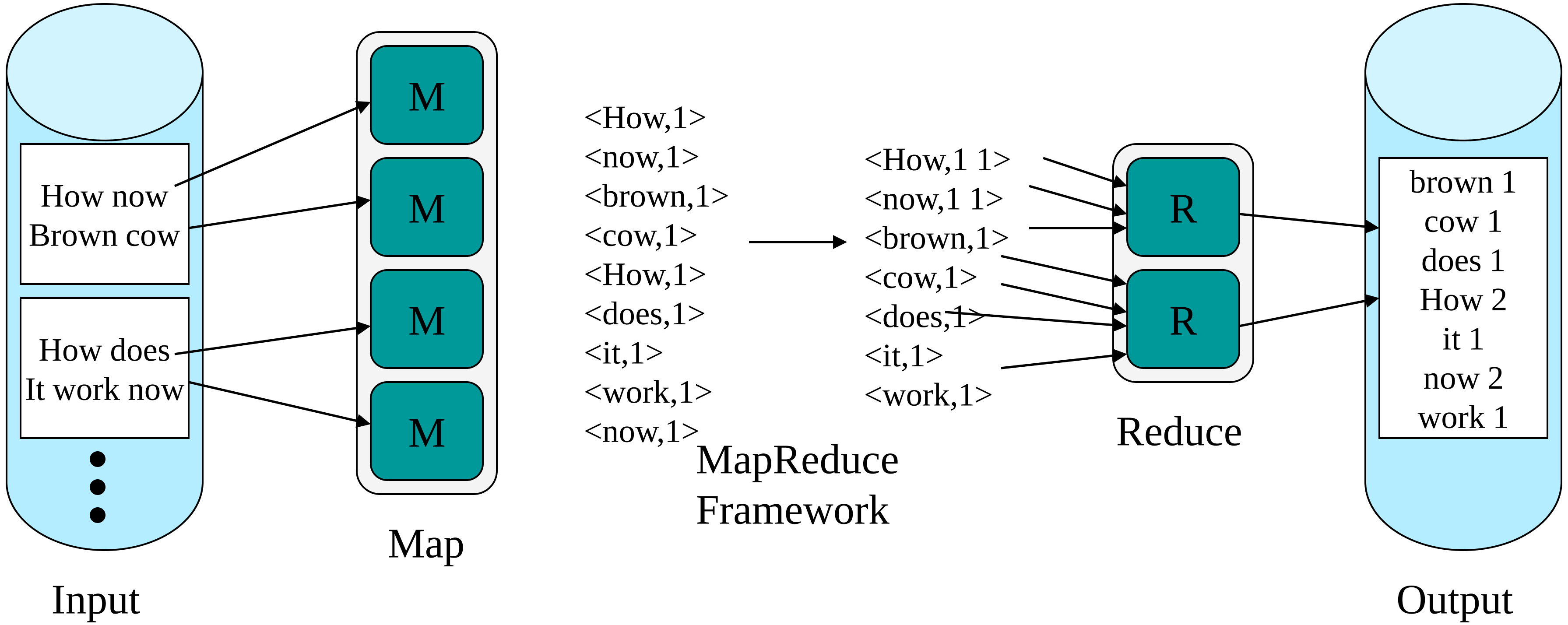
- Word frequency



MapReduce Examples

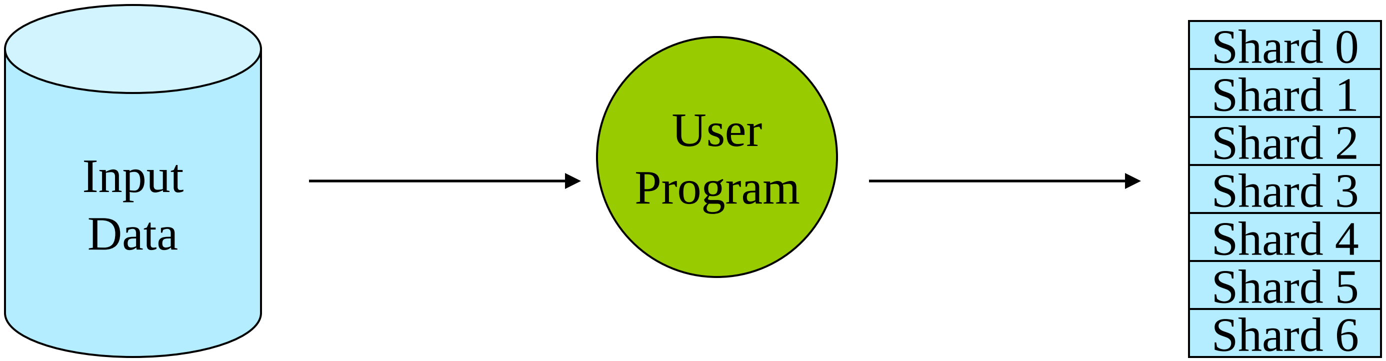
- Distributed grep
  - Map function emits <word, line_number> if word matches search criteria
  - Reduce function is the identity function
- URL access frequency
  - Map function processes web logs, emits <url, 1>
  - Reduce function sums values and emits <url, total>

MapReduce: Programming Model



MapReduce Execution Overview

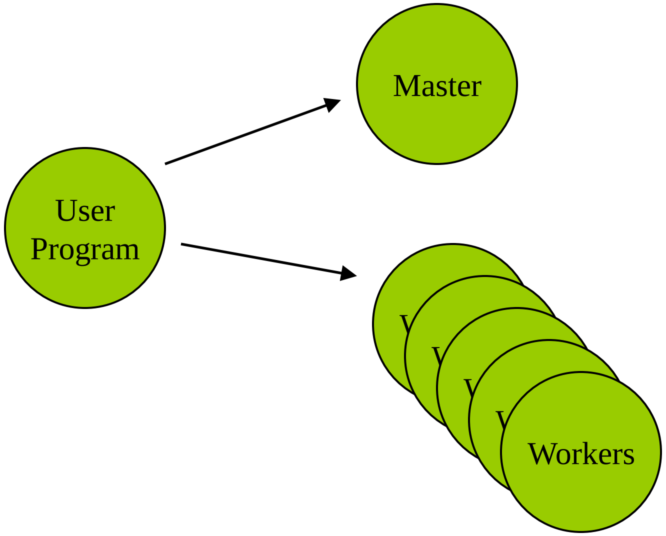
1. The user program, via the MapReduce library, shards the input data



* Shards are typically 16-64mb in size

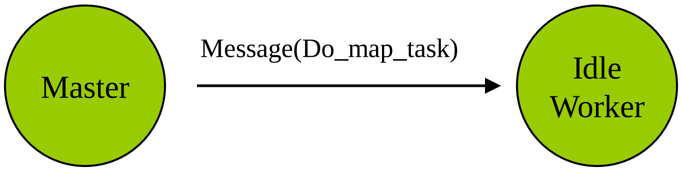
MapReduce Execution Overview

2. The user program creates process copies distributed on a machine cluster. One copy will be the “Master” and the others will be worker threads.



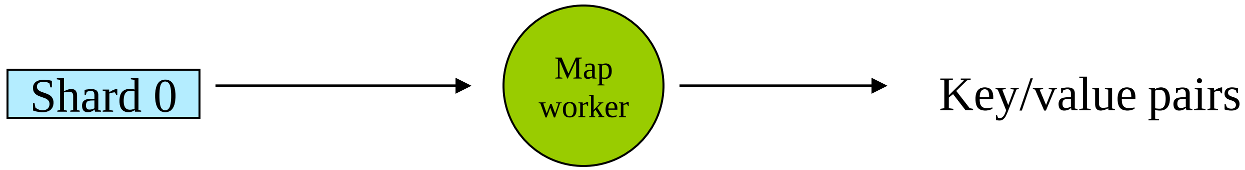
MapReduce Resources

3. The master distributes M map and R reduce tasks to idle workers.
   – M == number of shards
   – R == the intermediate key space is divided into R parts



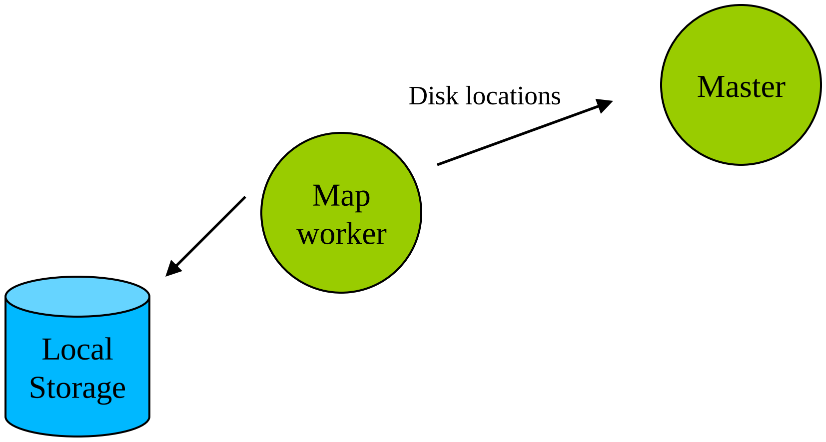
MapReduce Resources

4. Each map-task worker reads assigned input shard and outputs intermediate key/value pairs.
   – Output buffered in RAM.



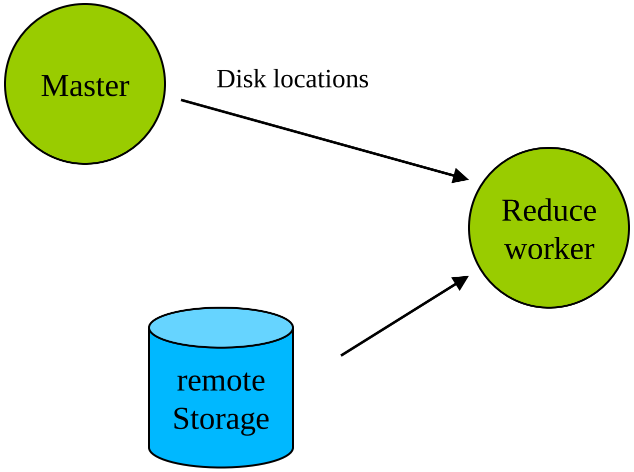
MapReduce Execution Overview

5. Each worker flushes intermediate values, partitioned into R regions, to disk and notifies the Master process.



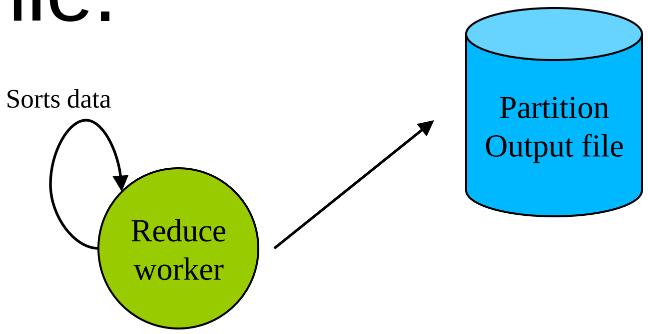
MapReduce Execution Overview

6. Master process gives disk locations to an available reduce-task worker who reads all associated intermediate data.



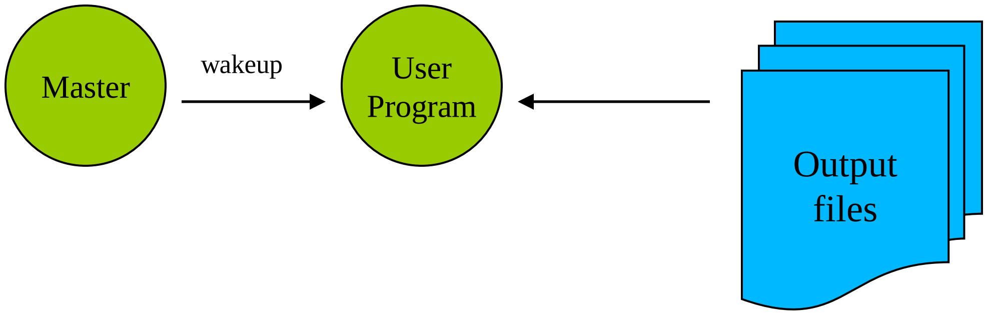
MapReduce Execution Overview

7. Each reduce-task worker sorts its intermediate data. Calls the reduce function, passing in unique keys and associated key values. Reduce function output appended to reduce-task's partition output file.



MapReduce Execution Overview

8. Master process wakes up user process when all tasks have completed. Output contained in R output files.



MapReduce Runtime System

1. Partitions input data
2. Schedules execution across a set of machines
3. Handles machine failure
4. Manages interprocess communication

Parallelism

- map() functions run in parallel, creating different intermediate values from different input data sets
- reduce() functions also run in parallel, each working on a different output key
- All values are processed *independently*
- Bottleneck: reduce phase can't start until map phase is completely finished.

Locality

- Master program divvies up tasks based on location of data: tries to have map() tasks on same machine as physical file data, or at least same rack
- map() task inputs are divided into 64 MB blocks: same size as Google File System chunks

Fault Tolerance

- Master detects worker failures
  - Re-executes completed & in-progress map() tasks
  - Re-executes in-progress reduce() tasks
- Master notices particular input key/values cause crashes in map(), and skips those values on re-execution.
  - Effect: Can work around bugs in third-party libraries!

Optimizations

- No reduce can start until map is complete:
  - A single slow disk controller can rate-limit the whole process
- Master redundantly executes “slow-moving” map tasks; uses results of first copy to finish

MapReduce Conclusions

- MapReduce has proven to be a useful abstraction
- Greatly simplifies large-scale computations at Google
- Functional programming paradigm can be applied to large-scale applications
- Fun to use: focus on problem, let library deal w/ messy details
- Greatly reduces parallel programming complexity
  – Reduces synchronization complexity
  – Automatically partitions data
  – Provides failure transparency
  – Handles load balancing

Hadoop

- Open source MapReduce implementation
  - http://hadoop.apache.org/core/index.html
- Uses
  - Hadoop Distributed Filesytem (HDFS)
    - http://hadoop.apache.org/core/docs/current/hdfs_design.html
  - Java
  - ssh

Questions

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