MapReduce

Ioan Raicu
Computer Science Department
Illinois Institute of Technology

CS554: Data-Intensive Computing
March 8th, 2015
• Quiz #3 answers
• Project Proposals
• Feedback before Wednesday
  – Some groups might get a 2\textsuperscript{nd} chance to redo proposals
• Will post reading assignments today
• Plan for rest of the semester
  – MapReduce/Hadoop
  – Swift
  – Spark/Sparrow/Mesos
  – Ceph
  – Lustre/GPFS/PVFS
  – More to come
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
“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
• 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
• 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
• 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.
• 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)
• Word frequency
• 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

Input

Map

Reduce

Output

MapReduce Framework

brown 1
cow 1
does 1
How 2
it 1
now 2
work 1

<How, 1>
<now, 1>
<brown, 1>
<cow, 1>
<How, 1>
<does, 1>
<it, 1>
<work, 1>

brown 1
cow 1
does 1
How 2
it 1
now 2
work 1

<How, 1>
<now, 1>
<brown, 1>
<cow, 1>
<How, 1>
<does, 1>
<it, 1>
<work, 1>
1. The user program, via the MapReduce library, shards the input data

* Shards are typically 16-64mb in size
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.
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
4. Each map-task worker reads assigned input shard and outputs intermediate key/value pairs.
   - Output buffered in RAM.
5. Each worker flushes intermediate values, partitioned into R regions, to disk and notifies the Master process.
6. Master process gives disk locations to an available reduce-task worker who reads all associated intermediate data.
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.
8. Master process wakes up user process when all tasks have completed. Output contained in R output files.
1. Partitions input data
2. Schedules execution across a set of machines
3. Handles machine failure
4. Manages interprocess communication
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.
• 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
• 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!
• 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
Open source MapReduce implementation

Uses
  – Hadoop Distributed Filesystem (HDFS)
    • http://hadoop.apache.org/core/docs/current/hdfs_design.html
  – Java
  – ssh