Distributed Systems

18. MapReduce

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Credit

Much of this information is from Google:

- Google Code University [no longer supported]
  http://code.google.com/edu/parallel/mapreduce-tutorial.html
- MapReduce: The programming model and practice
  research.google.com/pubs/pub36249.html

See also: http://hadoop.apache.org/common/docs/current/

for the Apache Hadoop version

Read this (the definitive paper):

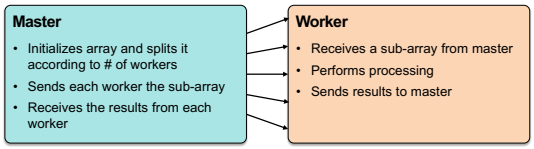
http://labs.google.com/papers/mapreduce.html

Background

- Traditional programming is serial
- Parallel programming
  - Break processing into parts that can be executed concurrently on multiple processors
- Challenge
  - Identify tasks that can run concurrently and/or groups of data that can be processed concurrently
  - Not all problems can be parallelized

Simplest environment for parallel processing

- No dependency among data
- Data can be split into lots of smaller chunks - **shards**
- Each process can work on a chunk
- Master/worker approach



MapReduce

- Created by Google in 2004
  - Jeffrey Dean and Sanjay Ghemawat
- Inspired by LISP
  - Map(function, set of values)
    - Applies function to each value in the set
      (map 'length '(() (a) (a b) (a b c))) ⇒ (0 1 2 3)
  - Reduce(function, set of values)
    - Combines all the values using a binary function (e.g., +)
      (reduce #'+ '(1 2 3 4 5)) ⇒ 15

MapReduce

- MapReduce
  - Framework for parallel computing
  - Programmers get simple API
  - Don't have to worry about handling
    - parallelization
    - data distribution
    - load balancing
    - fault tolerance
- Allows one to process huge amounts of data (terabytes and petabytes) on thousands of processors

Who has it?

- Google
  - Original proprietary implementation
- Apache Hadoop MapReduce
  - Most common (open-source) implementation
  - Built to specs defined by Google
- Amazon Elastic MapReduce
  - Uses Hadoop MapReduce running on Amazon EC2
    … or Microsoft Azure HDInsight
    … or Google Cloud MapReduce for App Engine

MapReduce

- Map
  Grab the relevant data from the source
  User function gets called for each chunk of input
  Spits out (key, value) pairs
- Reduce
  Aggregate the results
  User function gets called for each unique key with all values corresponding to that key

MapReduce

- Map: (input shard) → intermediate(key/value pairs)
  - Automatically partition input data into *M* shards
  - Discard unnecessary data and generate (key, value) sets
  - Framework groups together all intermediate values with the same intermediate key & pass them to the *Reduce* function
- Reduce: intermediate(key/value pairs) → result files
  - Input: key & set of values
  - Merge these values together to form a smaller set of values

  Reduce workers are distributed by partitioning the intermediate key space into R pieces using a partitioning function (e.g., *hash(key) mod R*)

  The user specifies the # of partitions (R) and the partitioning function

MapReduce: what happens in between?

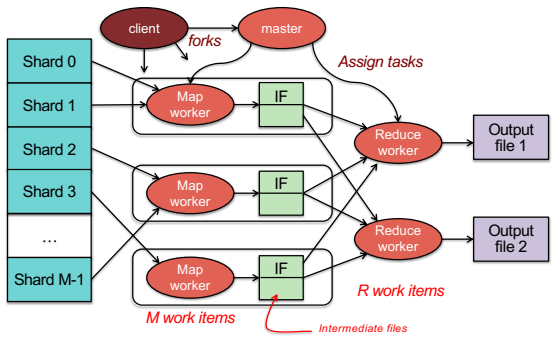
- Map
  - Grab the relevant data from the source (parse into key, value)
  - Write it to an intermediate file
- Partition
  - Partitioning: identify which of *R* reducers will handle which keys
  - Map partitions data to target it to one of *R* Reduce workers based on a partitioning function (both *R* and partitioning function user defined)

Map Worker

- Shuffle & Sort
  - Shuffle: Fetch the relevant partition of the output from all mappers
  - Sort by keys (different mappers may have sent data with the same key)
- Reduce
  - Input is the sorted output of mappers
  - Call the user *Reduce* function per key with the list of values for that key to aggregate the results

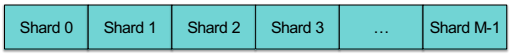
Reduce Worker

MapReduce: the complete picture



Step 1: Split input files into chunks (shards)

- Break up the input data into *M* pieces (typically 64 MB)

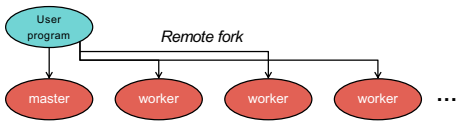


Input files

Divided into *M* shards

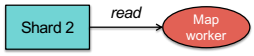
Step 2: Fork processes

- Start up many copies of the program on a cluster of machines
  - **One master**: scheduler & coordinator
  - Lots of workers
- Idle workers are assigned either:
  - map tasks (each works on a shard) – there are *M* map tasks
  - reduce tasks (each works on intermediate files) – there are *R*
    - *R* = # partitions, defined by the user



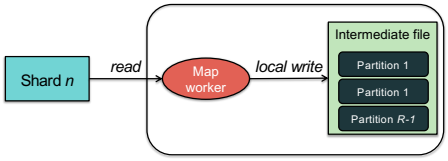
Step 3: Run Map Tasks

- Reads contents of the input shard assigned to it
- Parses key/value pairs out of the input data
- Passes each pair to a user-defined *map* function
  - Produces intermediate key/value pairs
  - These are buffered in memory



Step 4: Create intermediate files

- Intermediate key/value pairs produced by the user's *map* function buffered in memory and are periodically written to the local disk
  - Partitioned into *R* regions by a partitioning function

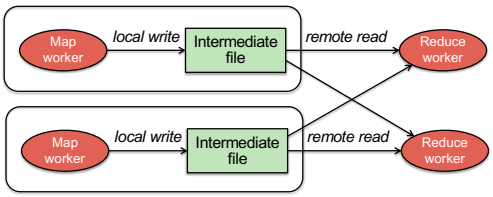


Step 4a. Partitioning

- Map data will be processed by Reduce workers
  - User's *Reduce* function will be called once per unique key generated by *Map*.
- We first need to sort all the (*key, value*) data by keys and decide which Reduce worker processes which keys
  - The Reduce worker will do the sorting
- **Partition function**
  Decides which of *R* reduce workers will work on which key
  - Default function: *hash(key) mod R*
  - Map worker partitions the data by keys
- Each Reduce worker will later read their partition from every Map worker

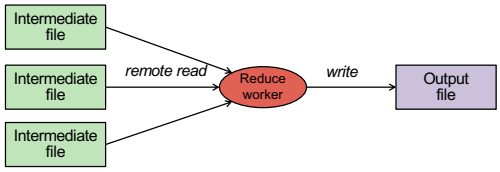
Step 5: Reduce Task: sorting

- Reduce worker gets notified by the master about the location of intermediate files for its partition
- Shuffle: Uses RPCs to read the data from the local disks of the map workers
- Sort: When the *reduce* worker reads intermediate data for its partition
  - It sorts the data by the intermediate keys
  - All occurrences of the same key are grouped together



Step 6: Reduce Task: *Reduce*

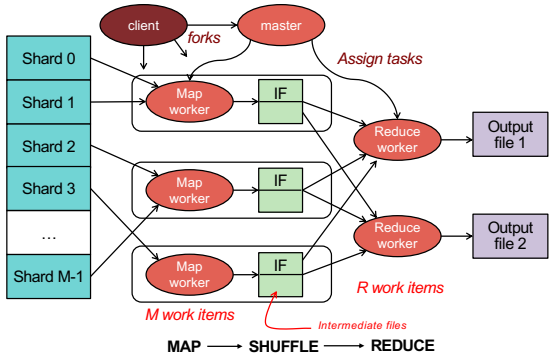
- The sort phase grouped data with a unique intermediate key
- User's ***Reduce*** function is given the key and the set of intermediate values for that key
  < key, (value1, value2, value3, value4, ...) >
- The output of the *Reduce* function is appended to an output file



Step 7: Return to user

- When all *map* and *reduce* tasks have completed, the master wakes up the user program
- The *MapReduce* call in the user program returns and the program can resume execution.
  - Output of *MapReduce* is available in *R* output files

MapReduce: the complete picture



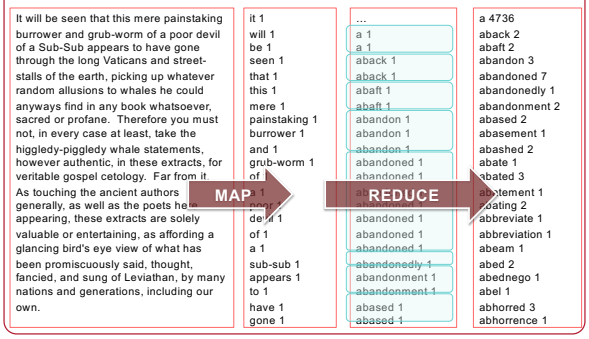
Example

- Count # occurrences of each word in a collection of documents
- Map:
  - Parse data; output each word and a count (1)
- Reduce:
  - Sort: sort by keys (words)
  - Reduce: Sum together counts each key (word)

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

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

Example



Fault tolerance

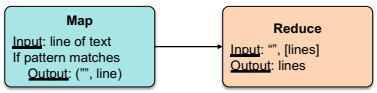
- Master pings each worker periodically
  - If no response is received within a certain time, the worker is marked as *failed*
  - *Map* or *reduce* tasks given to this worker are reset back to the initial state and rescheduled for other workers.

Locality

- **Input and Output files**
  - GFS (Google File System)
  - Bigtable
- MapReduce (often) **runs on** GFS chunkservers
  - Keep computation close to the files if possible
- Master tries to schedule *map* worker on one of the machines that has a copy of the input chunk it needs.

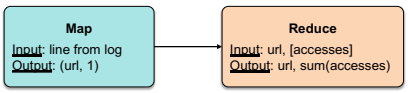
Other Examples

- Distributed grep (search for words)
  - *Search for words in lots of documents*
  - Map: emit a line if it matches a given pattern
  - Reduce: just copy the intermediate data to the output



Other Examples

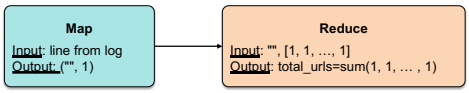
- List URL access counts
  - *Find the count of each URL in web logs*
  - Map: process logs of web page access; output <URL, 1>
  - Reduce: add all values for the same URL



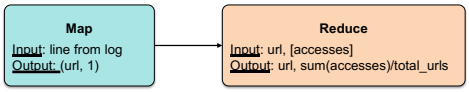
Other Examples

- Count URL access **frequency**
  - *Find the frequency of each URL in web logs*
  - Run 1: just count total URLs
  - Run 2: just like URL count but now we stored **total_urls**

Run 1

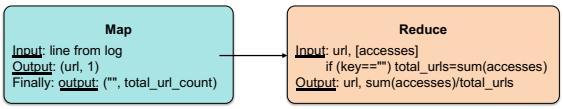


Run 2



Other Examples

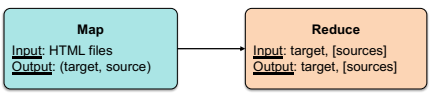
- Count URL access **frequency**
  - *Can we avoid processing the input data twice?*
  - Technically, no, but there's a hack
    - Map task sends its total URL count to *all* reducers with **key=""**
    - The key **""** happens to be the one that gets processed first
  - **Map**: process logs of web page access
    - Output <URL, 1>
    - Output total URL count to all reducers
  - **Reduce**: add all values for the same URL



Other Examples

- Reverse web-link graph
  - *Find where page links come from*
  - Map: output <target, source> for each link to *target* in a page *source*
  - Reduce: concatenate the list of all source URLs associated with a target.

    Output <target, list(source)>

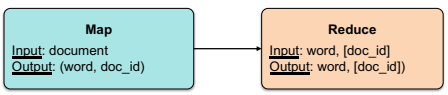


The *reduce* function does nothing!

Other Examples

- Inverted index
  - *Find what documents contain a specific word*
  - Map: parse document, emit <word, document-ID> pairs
  - Reduce: for each word, sort the corresponding document IDs

    Emit a <word, list(document-ID)> pair
    The set of all output pairs is an inverted index



Other Examples

- Stock summary
  - *Find average daily gain of each company from 1/1/2000 – 12/31/2015*
  - Data is a set of lines: { date, company, start_price, end_price }

Map
If (date >= "1/1/2000" && date <= "12/31/2015")
Output: (company, end_price-start_price)

Reduce
Input: company, [daily_gains]
Output: word, average([daily_gains])

Other Examples: Two rounds

- Average salaries in regions
  - *Show zip codes where average salaries are in the ranges:*
    (1) < $100K (2) $100K … $500K (3) > $500K
  - Data is a set of lines: { name, age, address, zip, salary }

Map
Output: (zip, salary)

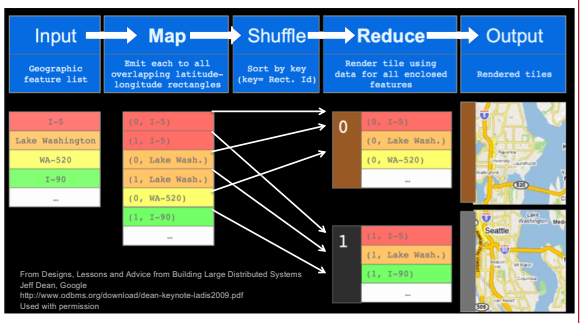
Reduce
Input: zip, [salary]
Output: zip, average([salary])

Show average salary for each zip code

Map(zip, salary)
```
if (salary < 100K)
    output("<$100K", zip)
else if (salary > 500K)
    output(">$500K", zip)
else
    output("$100-500K", zip)
```

Reduce
Input: range, [zips]
Output: range
For z in zips
    output(z)

MapReduce for Rendering Map Tiles



MapReduce Summary

- Get a lot of data
- Map
  - Parse & extract items of interest
- Sort (shuffle) & partition
- Reduce
  - Aggregate results
- Write to output files

All is not perfect

- MapReduce was used to process webpage data collected by Google's crawlers.
  - It would extract the links and metadata needed to search the pages
  - Determine the site's PageRank
- The process took around eight hours.
  - Results were moved to search servers.
  - This was done continuously.

Web crawlers → MapReduce → Migrate to search servers

~ 8 hours!

All is not perfect

- Web has become more dynamic
  - an 8+ hour delay is a lot for some sites
- Goal: refresh certain pages within seconds
- MapReduce
  - Batch-oriented
  - Not suited for near-real-time processes
  - Cannot start a new phase until the previous has completed
    - Reduce cannot start until all Map workers have completed
  - Suffers from "stragglers" – workers that take too long (or fail)
  - This was done continuously
- MapReduce is still used for many Google services
- Search framework updated in 2009-2010: Caffeine
  - Index updated by making direct changes to data stored in Bigtable
  - Data resides in Colossus (GFS2) instead of GFS

In Practice

- Most data not simple files
  - B-trees, tables, SQL databases, memory-mapped key-values
- Hardly ever use textual data: slow & hard to parse
  - Most I/O encoded with Protocol Buffers

More info

- Good tutorial presentation & examples at:
  http://research.google.com/pubs/pub36249.html
- The definitive paper:
  http://labs.google.com/papers/mapreduce.html

The End

