Getting stuff done with Big Data

Lecture Two: Map Reduce and Hadoop

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Background

MR is a parallel programming model and associated infra-structure introduced by Google in 2004:

- Assumes large numbers of cheap, commodity machines.
- Failure is a part of life.
- Tailored for dealing with Big Data
- Simple
- Scales well

Background

Early Google Server (source: nialkennedy, flickr)

Background

Who uses it?

- Google (more than 1 million cores, rumours have it)
- Yahoo! (more than 100K cores)
- Facebook (8.8k cores, 12 PB storage)
- Twitter
- IBM
- Amazon Web services
- Edinburgh (!)
- Many many small start-ups

http://wiki.apache.org/hadoop/PoweredBy

MapReduce inside Google

Google

Googlers' hammer for 80% of our data crunching

- Large-scale web search indexing
- Clustering problems for Google News
- Produce reports for popular queries, e.g. Google Trend
- Processing of satellite imagery data
- Language model processing for statistical machine translation
- Large-scale machine learning problems
- Just a plain tool to reliably spawn large number of tasks
  - e.g. parallel data backup and restore

The other 20%? e.g. Pregel

Source: Zhao et al, Sigmetrics 09

Use of MapReduce inside Google

Google

Stats for Month	Aug.'04	Mar.'06	Sep.'07
Number of jobs	29,000	171,000	2,217,000
Avg. completion time (secs)	634	874	395
Machine years used	217	2,002	11,081
Map input data (TB)	3,288	52,254	403,152
Map output data (TB)	758	6,743	34,774
reduce output data (TB)	193	2,970	14,018
Avg. machines per job	157	268	394
Unique implementations			
Mapper	395	1958	4083
Reducer	269	1208	2418

From "MapReduce: simplified data processing on large clusters"

Components

Major components:

- 1: MR task scheduling and environment
  - Running jobs, dealing with moving data, coordination, failures etc
- 2: Distributed File System (DFS)
  - Storing data in a robust manner across a network; moving data to nodes
- 3: Distributed Hash Table (BigTable)
  - Random-access to data that is shared across the network

Hadoop is an open-source version of 1 and 2; *HBase (etc)* are similar to 3

MR

Tasks are run in parallel across the cluster(s):

- Computation moves to the data.
- Multiple instances of a task may be run at once
  - *Speculative execution* guards against task failure
- Tasks can be run *rack-aware*:
  - Tasks access data that is within the rack they are running on

MR

Data is stored across one or more clusters:

- Files are stored in *blocks*
- Blocks size is optimised for disk-cache size (often 64M)
- Blocks are replicated across the network
  - Replication adds fault tolerance
  - Replication increases the chance that the data is on the same machine as the task needing it
- Blocks are read sequentially and written sequentially
- Blocks are also spread evenly across the cluster

MR

Files are often big:

- 100s of GB or more
- Few, big files mean less overheads
- Hadoop currently does not support appending
  - Appending to a file is natural for streaming input
- Under Hadoop, blocks are write-only.

MR

Tasks and data are centrally managed:

- Dash-board to monitor and manage progress
- Under Hadoop, this is a single-point of failure

Possibility of moving jobs *across* data centres

- Take advantage of cheap electricity
- Deals with load-balancing, disasters etc

BigTable

BigTable is a form of Database:

- Based on *shared-nothing* architecture
- Petabyte scaling, across thousands of machines
- Has a simple data model
- Designed for managing structured data
  - Storing Web pages, URLs, etc
  - Key-value pairs
- BigTable provides random access to data
- Can be used as a source and sink for MR jobs

Programming Model

MR offers one restricted version of parallel programming:

- Coarse-grained.
- No inter-process communication.
- Communication is (generally) through files.

Programming Model

Mapping:

- The input data is divided into *shards*.
- The *Map* operation works over each shard and *emits key-value* pairs.
- Each mapper works in parallel.

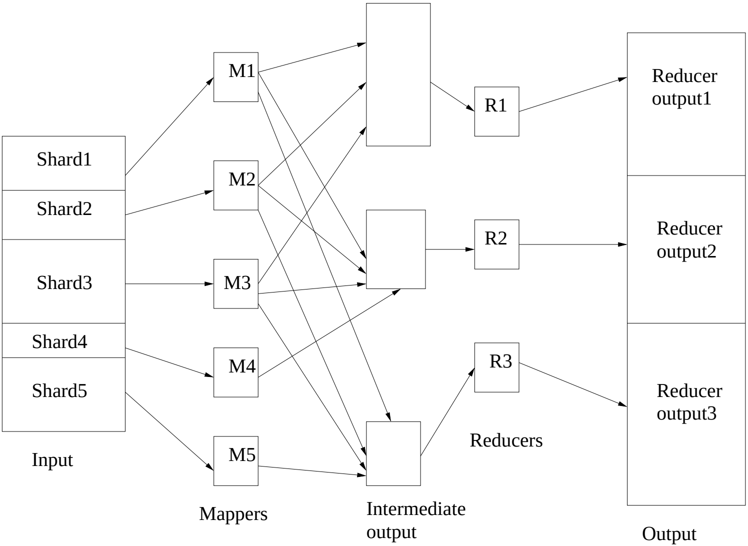
Keys and values can be anything which can be represented as a string.

Programming Model

Reducing:

- After mapping, each key-value pair is hashed on the key.
- Hashing sends that key-value pair to a given *reducer*.
  - All keys that hash to the same value are sent to the same reducer.
- The input to a reducer is sorted on the key.
  - Sorted input means that related key-value pairs are locally grouped together.

Programming Model



Programming Model

Note:

- Each Mapper and Reducer runs in parallel.
- There is no state sharing between tasks.
  - Task communication is achieved using either external resources or at start-time
- There need not be the same number of Mappers as Reducers.
  - It is possible to have *no* Reducers.

Programming Model

Note:

- Tasks read their input sequentially.
  - Sequential disk reading is far more efficient than random access
- Reducing starts once Mapping ends.
  - Sorting and merging etc can be interleaved.

Aside: Map-Reduce in one line

Under Unix, you can quickly test a MR job:

% cat input | mapper | sort -0 +1 | reducer > output

mapper is your Mapper and **reducer** is the Reducer

Example: Tokenisation

Example

Convert *John's* to *John +s*

- The input data will be a list of documents
- The output will be a list of tokenised documents
- There is no need to run a reducing stage

Example: Tokenisation

Mapper:

- Tokeniser reads input
- Emits tokenised output

Sentence ordering may not be honoured (how can we do this?)

Example: Word Counting

Example

Count the number of words in a collection of documents

- Our Mapper counts words in each shard.
- The Reducer gathers together partial counts for a given word and sums them

Example: Word Counting

Mapper:

- For each sentence, emit *word, 1* pair.
  - The key is the *word*
  - The value is the number 1

Example: Word Counting

Reducer:

- Each Reducer will see all instances of a given word.
- Sequential reads of the reducer input give partial counts of a word.
- Partial counts can be summed to give the total count.

Example: Word Counting

Input sentences:

- *the cat*
- *the dog*

Key	Value	
the	1	
cat	1	Mapper output
the	1	
dog	1	

Example: Word Counting

Reducer 1 input	Reducer 2 input
the, 1	*cat, 1*
the, 1	
dog, 1	

Reducer 1 output	Reducer 2 output
the, 2	*cat, 1*
dog, 1	

Map Reduce Efficiency

MR algorithms involve a lot of disk and network traffic:

- We typically start with Big Data
- Mappers can produce intermediate results that are *bigger* than the input data.
- Task input may not be on the same machine as that task.
    - This implies network traffic
- Per-reducer input needs to be sorted.

Map Reduce Efficiency

Sharding might not produce a balanced set of inputs for each Reducer:

- Often, the data is heavily skewed
  - Eg all function words might go to one Reducer
- Having an imbalanced set of inputs turns a parallel algorithm into a sequential one

Map Reduce Efficiency

Selecting the right number of Mappers and Reducers can improve speed

- More tasks mean each task might fit in memory / require less network access
- More tasks mean that failures are quicker to recover from.
- Fewer tasks have less of an over-head.

This is a matter of guess-work

Map Reduce Efficiency

Algorithmically, we can:

- Emit fewer key-value pairs
  - Each task can locally aggregate results and periodically emit them.
  - (This is called *combining*)
- Change the key
  - Key selection implies we partition the output. Some other selection might partition it more evenly

Midway Summary

- Introduced MR and the MR programming model
- Sample MR applications
- Looked at efficiency

History

Nutch started in 2002 by Doug Cutting and Mike Cazfarella

- Early open-source web-search engine
- Written in Java
- Realisation that it would not scale for the Web
  - 2004: Google MR and GFS papers appeared
  - 2005: Working MR implementation for Nutch
  - 2006: Hadoop became standalone project
- 2008: Hadoop broke world record for sorting 1TB of data

Hadoop Overview

Set of components (Java), implementing most of MR-related ecosystem:

- MapReduce
- HDFS (Hadoop distributed filesytem)
- Services on top:
  - HBase (BigTable)
  - Pig (sql-like job control)
- Job-control

Overview

Hadoop supports a variety of ways to implement MR jobs:

- Natively, as java
- Using the 'streaming' interface
  - Mappers and reducers can be in any language
  - Performance penalty, restricted functionality
- C++ hooks etc

Word Counting

Word counting using Hadoop:

- Use HDFS
- Specify the MR program
- Run the job

Note: all commands are for Hadoop 0.19

Word Counting

First need to upload data to HDFS

- Hadoop has a set of filesystem-like commands to do this:
  - **hadoop dfs -mkdir data**
  - **hadoop dfs -put file.text data/**
- This creates a new directory and uploads the file **file.txt** to HDFS
- We can verify that it is there:
  - **hadoop dfs -ls data/**

Word Counting

Mapper:

- Using Streaming, a Mapper reads from STDIN and writes to STDOUT
- Keys and Values are delimited (by default) using tabs.
- Records are split using newlines

Word Counting

Mapper:

```
while !eof(STDIN) do
    line = readLine(STDIN)
    wordList = split(line)
    foreach word in wordList do
        print word TAB 1 NEWLINE
    end
end
```

Word Counting

Reducer

```
prevWord = "" ; valueTotal = 0
while !eof(STDIN) do
    line = readLine(STDIN); (word,value) = split(line)
    if word eq prevWord or prevWord eq "" then
        valueTotal += value
        prevWord = word
    else
        print prevWord valueTotal NEWLINE
        prevWord = word; valueTotal = value
    end
end
print word valueTotal NEWLINE
```

Word Counting

Improving the Mapper

```
wordsCounts = {}
while !eof(STDIN) do
    line = readLine(STDIN)
    wordList = split(line)
    foreach word in wordList do
        wordCounts{word}++
    end
end
foreach word in keys(wordCounts) do
    count = wordCounts{word}
    print word TAB count NEWLINE
end
```

Word Counting

Our improved Mapper:

- Only emits one word-count pair, per word and shard
- This uses a *Combiner* technique
- Uses an unbounded amount of memory

Word counting 2 million tokens (Unix MR simulation)

Mapper	Time
Naive	1 minute 5 sec
Combiner	10 sec

How can you change it to use a *bounded* amount of memory?

Secondary Sorting

At times, we may want to resort the Reducer input:

- Hadoop only guarantees that the same keys are grouped together
- We may want to ensure that some key occurs before other ones
  - Eg when estimating the parameters of models we may want a normalising constant first

Secondary Sorting Example

Reducer input:

Ordinary	Resorted
loves mary 1	loves NULL 3
loves NULL 3	loves bob 2
loves bob 2	loves mary 1

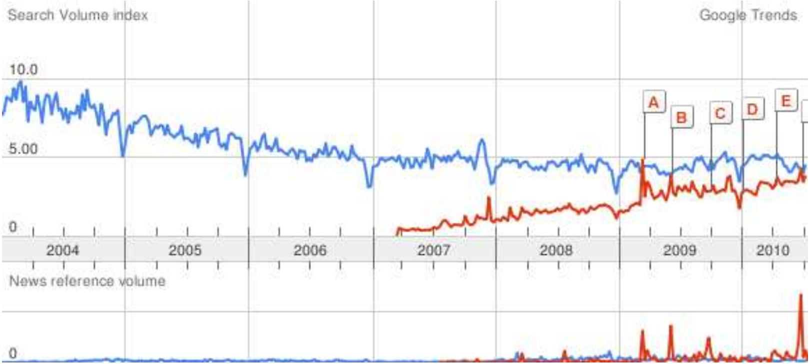
After reading each line we can immediately emit probabilities

Critique

MR has generated a lot of interest:

- It solves all scaling problems!
- Google use it, so it must be great
- Start-ups etc love it and they generate a lot of chatter in the Tech Press
  - Big companies use DBs and they don't talk about it
- Who needs complicated, expensive DBs anyway

Background



Google Trends: Blue (DBMS mentions), Red (Hadoop mentions)

Critique

Stonebraker *et al* considered whether MR can replace parallel databases

- P-DBs have been in development for 20+ years
- Robust, fast, scalable
- Based upon declarative data models

Critique

Which application classes might MR be a better choice than a P-DB?

- *Extract-transform-load* problems
  - Read data from multiple sources
  - Parse and clean it
  - Transform it
  - Store some of the data
- *Complex analytics*
  - Multiple passes over the data
  - Computing complex reports etc
- *Semi-structured data*
  - No single scheme for the data (eg logs from multiple sources)
- *Quick-and-dirty analyses*
  - Asking questions over the data, with minimum fuss and effort

Critique

Resulted indicated:

- For a range of core tasks, a P-DB was faster than Hadoop
  - P-DBs are flexible enough to deal eg with semi-structured data
- (Unclear whether this is implementation-specific)
- Hadoop was criticised as being too low-level
  - Higher-level abstractions such as *Pig* might help
- Hadoop was easier for quick-and-dirty tasks
  - Writing MR jobs can be easier than complex SQL queries
  - Non-specialists can quickly write MR jobs
- Hadoop is a lot cheaper

Critique

MR is not really suited for low-latency problems:

- Batch nature and lack of real-time guarantees means you shouldn't use it for front-end tasks

MR is not a good fit for problems which need global state information:

- Many Machine Learning algorithms require maintenance of centralised information and this implies a single task

Use the right tool for the job

Summary

- History
- Looked at major components
- Two examples
- Critique