Google's MapReduce

Simplified Data Processing on Large Clusters
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Summary

What?

- General-purpose library for large-scale distributed data processing;
- Fault-tolerant;
- Hides implementation details from programmers.

Why?

- Google processes vast quantities of data...
  - And has large clusters of machines.
- Writing elegant code for distributed processing is tricky.

Writing MapReduce code

The programmer defines two functions:

- map(k1, v1) -> list(k2,v2)
  - Takes input as a key/value pair, applies the function code
  - Returns a list of 'intermediate' k/v pairs.
- reduce(k2,(list v2)) -> list(v2)
  - Iterates over the list of values, applying the reduce function as necessary.

MapReduce groups all equal *intermediate* keys to be passed into reduce

Code example: word frequency

```
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));
```

Implementations

- Many different implementations to suit different architectures;

- They describe the process for Google's cluster:
  - 100s-1000s of networked machines;
  - Locally networked - Gigabit ethernet;
  - Distributed filesystem (GFS)

- Not entirely applicable to other designs – refined by trial & error

Execution model

- MapReduce library picks a `master node'.
- And splits input into *M* map tasks, and *R* reduce tasks.
  - *M,R* user defined.
    - Optimally, *M* splits input into ~16-64MB tasks;
    - *R* a small multiple of number of machines;
    - O(M*R) memory usage on the master.

- Input files are then distributed across the cluster...
- And MapReduce tasks are spawned on each node.

Execution model (cont'd)

- All nodes initially idle;
- The master assigns idle workers a map or a reduce task.
- If a worker receives a map, it:
  - Parses out k/v pairs, runs these through the map function;
  - Buffers and periodically writes intermediate k/v pairs;
  - Location of intermediate output sent to the master.
- If a worker receives a reduce, it:
  - Gets the intermediate data location from the master;
  - Pulls this over the network;
  - Sorts and iterates over values, applying reduce function;
  - Writes the end result to one of *R* final output files.

So far, so theoretical…

Above process is good, but we don’t live in a perfect world.

Machine failures:

- Are pretty likely in large clusters!
- Workers are periodically pinged;
  - If they timeout, the task is reallocated.
  - (Even if the worker is a completed map task – local data!)

Great, but what if the master dies?

- They assume it doesn’t!
- Only one machine, so failure is unlikely.
- But possible to write configuration stores as ‘checkpoints’.
- MapReduce operation fails

Stragglers - she just won’t run any faster!

`Stragglers’ are a significant problem in large clusters.

- Could be due to poor hardware or slow IO
- A few slow machines significantly increase completion time.

So start `backup’ tasks for remaining processes when nearly done.

- Little (~4%) overhead, large performance increase

Refinements

- Network bandwidth is scarce
  - Split the input data multiple times across many nodes
  - Master tries to assign maps on nodes with a local copy of the relevant data;
  - Failing that, a node where it's close.

- Reduce tasks are split with a `partitioning function'
  - Default: (hash(key) mod *R*)
  - But users can specify their own
    - E.g. (hash(hostname(url/key)) mod *R*)
    - To group all data from the same hostname into an output file

Another refinement…

`Combiner' functions useful where we have many of the same intermediate k/v. E.g. (the, 1).

- Combiner performs a local reduce prior to writing the intermediate keys.
- Allegedly significantly increases performance.
  - By writing less intermediate k/v pairs, so less I/O?

Bugs & Debugging

- Deterministic bugs repeatedly crashing an operation;
  - MapReduce will never complete.
  - If an op crashes twice, the master skips that record.

- Can also run MapReduce locally (no distributed debugging).

- Master runs an internal webserver.
  - Provides auxiliary information:
    - *x*/*y* tasks completed
    - Bytes in/out
    - # failed nodes/operations
    - Among others...

Performance

- Benchmarked with a cluster:
  - ~1800 machines;
  - 2x2Ghz CPUs;
  - ~3GB available memory;
  - Gigabit ethernet.

- Two benchmarking procedures:
  - Grep for a 3-char string in 1TB data;
  - Sort 1TB data (`Terrasort').

- Tasks representative of normal MapReduce usage:
  - Extract infrequent data from large dataset;
  - Parse/reorganise large collection of data.

Distributed Grep

- Total time of ~140s
- Of which 60s is startup overhead...
- Slow 'warm-up' while adding more machines.
- 30GB/s peak on 1734 workers.

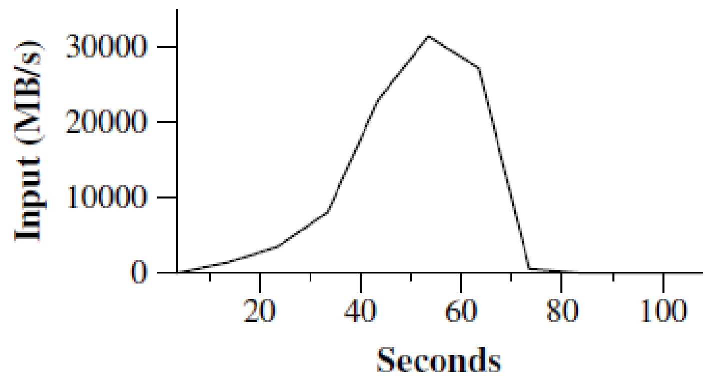
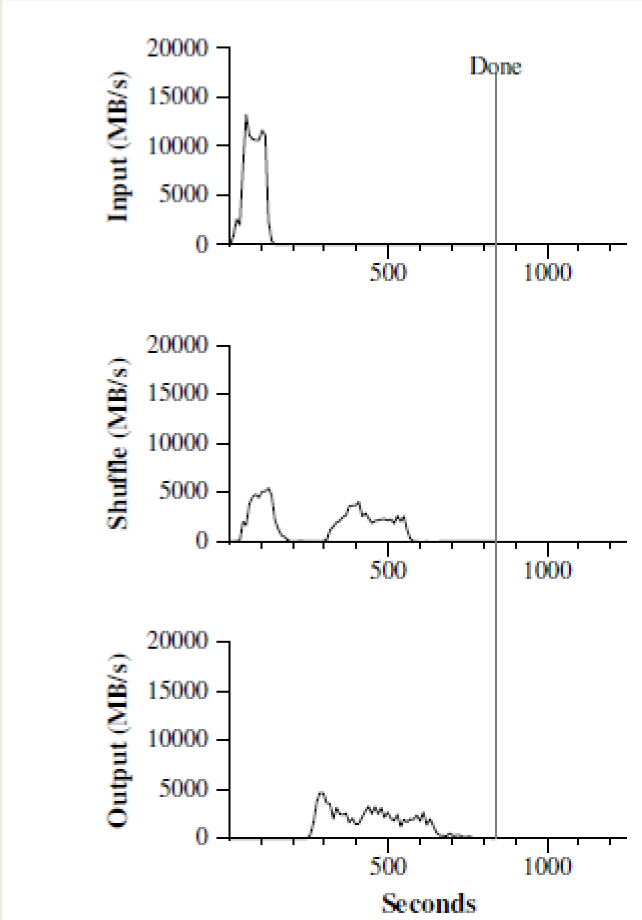


Figure 2: Data transfer rate over time

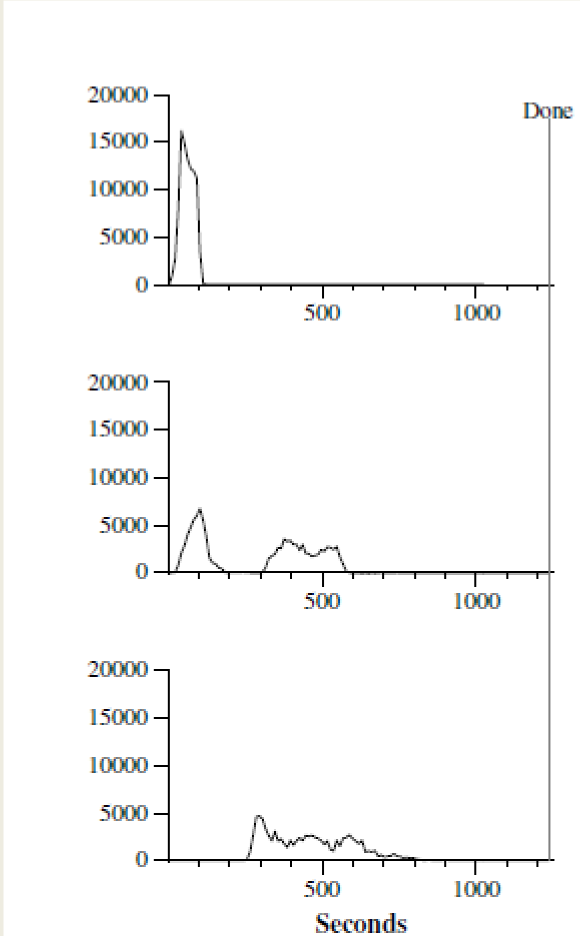
1TB Sort (50LoC(!))

- Takes ~890s. (40s startup)
- Best prior time – 1057s.
- Throughput is < half that of Grep
  - Because sorting requires heavy I/O of intermediates.



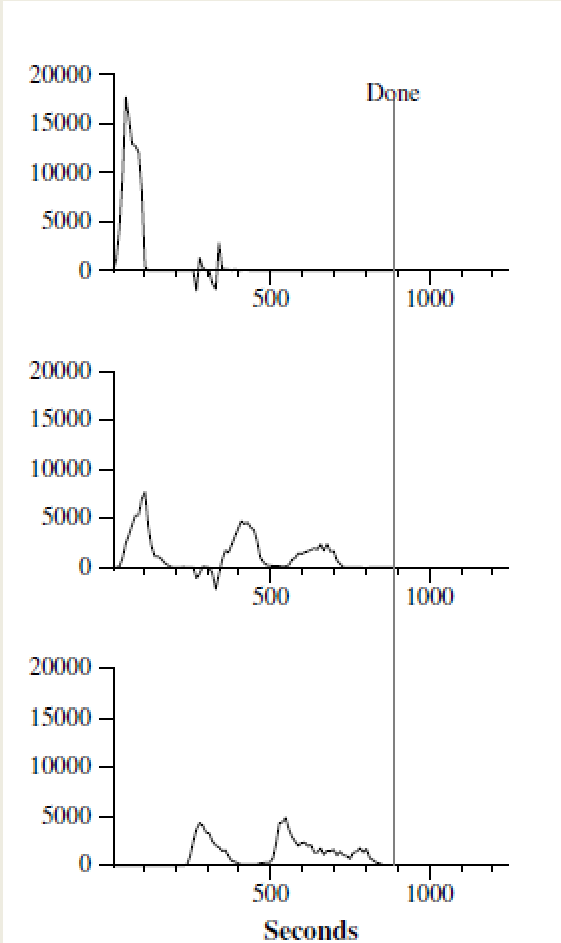
The trouble with stragglers...

- Same, but with backup tasks disabled.
- Vast majority of work done by ~800s (as we'd expect...)
- But the last 5 tasks take an extra 300s to finish.
- Total of 1283s – 44% increase.



Murder.

- Same task again, but killing off 200 workers.
- New tasks allocated, takes a total of 933s.
- Only 5% time increase.



Conclusions/findings

- Particularly useful in some domains:
  - Distributed grep;
  - Counting URL hits from server logs;
  - Term-vectors per host;
  - Distributed sort;
- Makes life easier for Google engineers.
- Code consolidation – one function 3800->700 LoC.
- Increases worker efficiency.
- Conserving bandwidth is important.
- Library is well liked/used.

Comments/criticisms

- Lots of unnecessary explanation of their own environment/clusters.
- Little in-depth discussion of *using* the library.
  - But perhaps more suited to a technical manual...

- No real comparison of benchmarks against existing solutions!
  - Not impressive if previous benchmark was done on 6 P2s!

Thank you!

Questions...