MapReduce: Simplified Data Processing on Large Clusters

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Problem

- When applied on to big data, simple algorithms become more complicated
  - Parallelized computations
  - Distributed data
  - Failure handling
- How can we abstract away these common difficulties, allowing the programmer to be able to write simple code for their simple algorithms?

Core Ideas

- Require the programmer to state their problem in terms of two functions, map and reduce
- Handle the scalability concerns inside the system, instead of requiring the programmer to handle them
- Require the programmer to only write code about the easy to understand functionality

Map, Reduce, and MapReduce

- map: (k1,v1) -> list (k2, v2)
- reduce: (k2, list v2) -> list (v2)
- mapreduce: list (k1,v1) -> list (k2, list v2)

Example

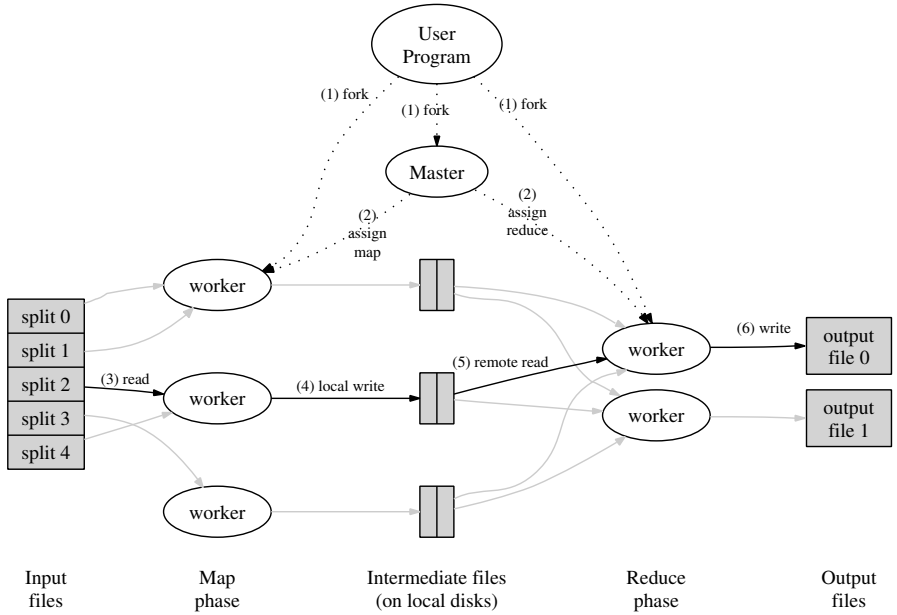
- Word Count in a lot of documents

```
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));
```

Architecture

- Large clusters of commodity PCs
- Input files partitioned into M splits
- Intermediate keys partitioned into R distributions
- Written to disk, remotely read by workers



Master vs Worker

- Only 1 master, many (thousands) workers
- Workers do the computations of maps and reduces
- Masters handle failures, assign tasks to workers

Failure Detection and Recovery

- Master pings workers to determine if they are failed
- Map worker failure:
  - Reexecute map tasks
- Reduce worker failure:
  - Redo if not completed, don’t otherwise
- Master failure:
  - Do nothing

Locality

- Use GFS for file storage of input data
- Map tasks assigned to minimize network time

Task Granularity

- Map phase has M pieces
- Reduce phase has R pieces
- M + R > # machines
  - Dynamic load balancing
  - Worker failure recovery

Backup Tasks

- Stragglers happen
  - Hard disk issues
  - Bad scheduling
- Have back up executions
  - Executions complete when primary or backup complete
- Occurs intelligently

Refinements

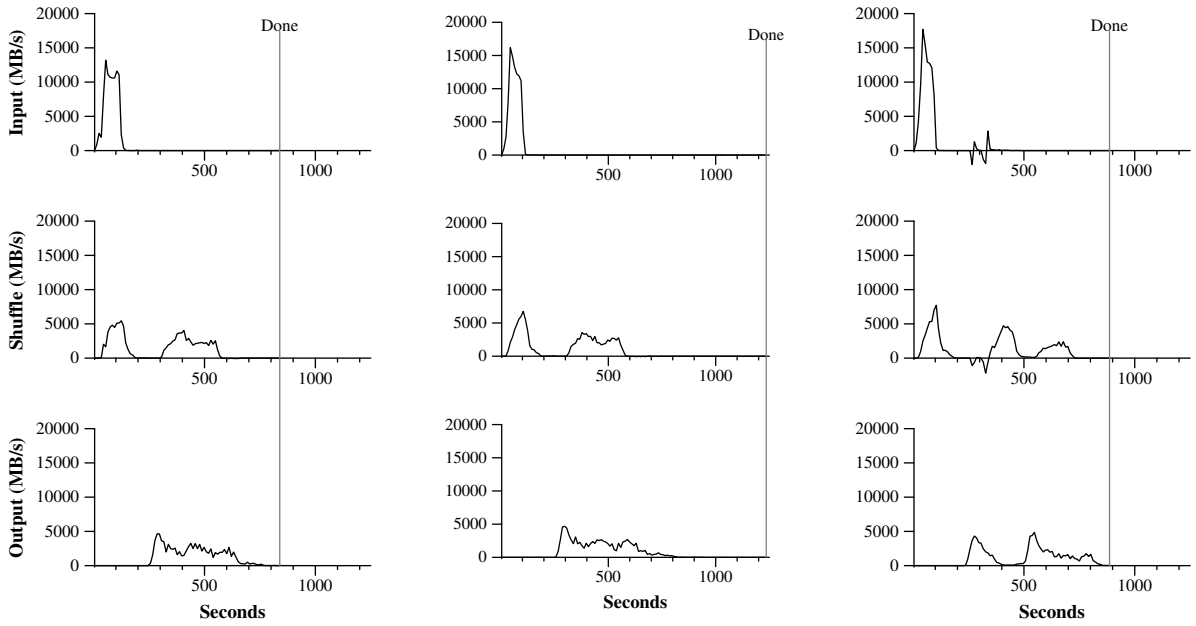
- Partitioning Function
- Ordering Guarantees
- Combiner Function
- Input and Output Types
- Side-effects
- Skipping Bad Records
- Local Execution
- Status Information
- Counters

Performance Setup

- Measured on 1800 machine cluster
  - 2GHz processors
  - 4GB memory
  - 2 160GB disks
  - Gigabit Ethernet

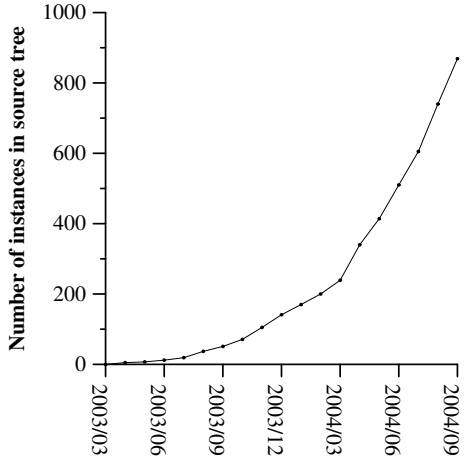
Performance

- Grep
  - 10^10 100 byte records in 150s
- Sort
  - 10^10 100 byte records in 891s



(a) Normal execution (b) No backup tasks (c) 200 tasks killed

Figure 3: Data transfer rates over time for different executions of the sort program



Number of jobs	29,423
Average job completion time	634 secs
Machine days used	79,186 days
Input data read	3,288 TB
Intermediate data produced	758 TB
Output data written	193 TB
Average worker machines per job	157
Average worker deaths per job	1.2
Average map tasks per job	3,351
Average reduce tasks per job	55
Unique *map* implementations	395
Unique *reduce* implementations	269
Unique *map/reduce* combinations	426

Table 1: MapReduce jobs run in August 2004

Pros/Cons

- Pros
  - Nice abstraction
  - Resilient to failures
  - Lots of different extensions for different functionality
  - Speedy for a certain amount of data
- Cons
  - Doesn’t scale to giant amounts of data (master requires O(M*R) info)
  - Lot of disk IO
  - Requires batches to be completed before going to next stage
  - Not all problems can be expressed in terms of map and reduce

Further Work

- MapReduce Online
  - Pipeline the stages
- Google's Cloud DataFlow
  - "Simple, powerful model for building batch and streaming parallel data processing pipelines"
- Hadoop
  - Utilizes mapreduce alongside storage
  - JobTracker and TaskTracker
- Piccolo
  - In memory
- Dryad
  - Directed graph of vertices and channels