MUNI FI



MapReduce: Simplified Data Processing on Large Clusters PA154 Language Modeling (7.3)

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Source: Jeff Dean, Sanjay Ghemawat Google, Inc. December, 2004 https://research.google/pubs/pub62/

Motivation: Large Scale Data Processing

Many tasks: Process lots of data to produce other data Want to use hundreds or thousands of CPUs

... but this needs to be easy

MapReduce provides:

- Automatic parallelization and distribution
- Fault-tolerance
- I/O scheduling
- Status and monitoring

Programming model

Input & Output: each a set of key/value pairs Programmer specifies two functions:

map (in_key, in_value) -> list(out_key, intermediate_value)

- Processes input key/value pair
- Produces set of intermediate pairs

reduce (out_key, list(intermediate_value)) -> list(out_value)

- Combines all intermediate values for a particular key
- Produces a set of merged output values (usually just one)

Inspired by similar primitives in LISP and other languages

Example: Count word occurrences

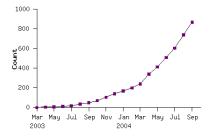
```
map(String input_key, String input_value):
  // input_key: document name
  // input_value: document contents
  for each word w in input_value:
    EmitIntermediate(w, "1");
reduce(String output_key, Iterator intermediate_values):
  // output_key: a word
  // output_values: a list of counts
  int result = 0:
  for each v in intermediate_values:
    result += ParseInt(v);
  Emit(AsString(result));
```

Pseudocode: See appendix in paper for real code

Model is Widely Applicable

MapReduce Programs In Google Source Tree

...



Example uses:

...

distributed grep term-vector per host document clustering distributed sort web access log stats machine learning

...

web link-graph reversal inverted index construction statistical machine translation

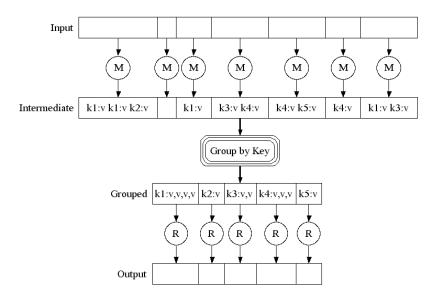
Implementation Overview

Typical cluster:

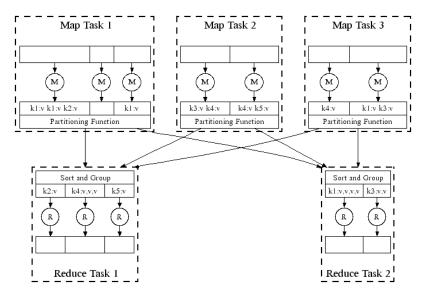
- 100s/1000s of 2-CPU x86 machines, 2-4 GB of memory
- Limited bisection bandwidth
- Storage is on local IDE disks
- GFS: distributed file system manages data (SOSP'03)
- Job scheduling system: jobs made up of tasks, scheduler assigns tasks to machines

Implementation is a C++ library linked into user programs

Execution



Parallel Execution



Task Granularity And Pipelining

Fine granularity tasks: many more map tasks than machines

- Minimizes time for fault recovery
- Can pipeline shuffling with map execution
- Better dynamic load balancing

Often use 200,000 map/5000 reduce tasks/ 2000 machines

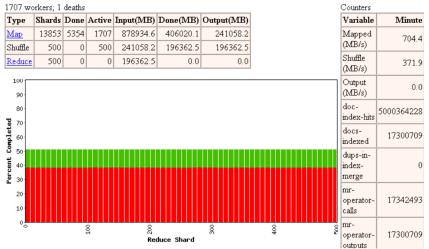
Process	Time>										
User Program	MapReduce()				wait						
Master		Assign	tasks to we	ərk	er machines.						
Worker 1		Map 1	Map 3								
Worker 2			Map	2							
Worker 3			Read 1.1		Read 1.3		Read 1.2		Redu	ice 1	
Worker 4				Re	ad 2.1		Read 2.2	Read	d 2.3	Redu	ce 2

23 woi	rkers; 0 d	leaths						Counters	
Гуре	Shards	Done	Active	Input(MB)	Done(MB)	Output(MB)		Variable	
<u>Map</u>	13853	<u> </u>			1314.4			Mapped (MB/s)	Γ
huffle .educe	500 500	<u> </u>		717.0 0.0				(MB/s)	Γ
100 90								Output (MB/s)	Γ
80 · 70 ·								doc- index-hits	1
70 60 50								docs- indexed	Γ
50 40 30								dups-in- index- merge	
20-								mr- operator-	
10 0			100-	0 2 Re t	duce Shard		400 00 00	operator- calls mr- operator-	

Started: Fri Nov 7 09:51:07 2003 -- up 0 hr 00 min 18 sec

1707 wa	orkers; 1	deaths						Counters	
Туре	Shards	Done	Active	Input(MB)	Done(MB)	Output(MB)		Variable	Minute
Map	13853		1707	878934.6				Mapped (MB/s)	699.1
Shuffle <u>Reduce</u>	500 500				57113.7	57113.7 0.0		Shuffle (MB/s)	349.5
100 90								Output (MB/s)	0.0
80- 8 70-								doc- index-hits	5004411944
onplet								docs- indexed	17290135
Jercent Co 30-								dups-in- index- merge	0
20-								mr- operator- calls	17331371
0			100	007 Re	duce Shard	00	400 00 00	mr- operator- outputs	17290135

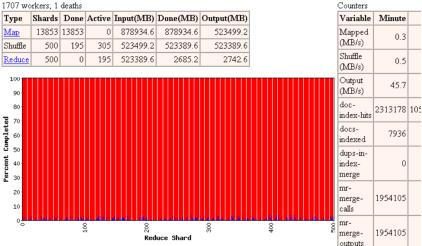
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Started: Fri Nov 7 09:51:07 2003 -- up 0 hr 10 min 18 sec

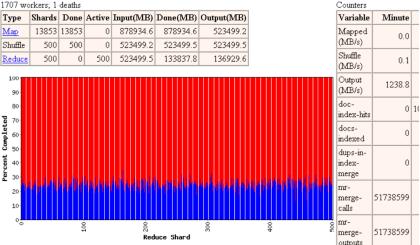
1707 workers; 1 deaths Counters Shards Done Active Input(MB) Done(MB) Output(MB) Variable Туре Minute 13853 8841 1707 878934.6 621608.5 369459.8 Map Mapped 706.5 (MB/s) Shuffle 369459.8 326986.8 326986.8 500 0 500 Shuffle Reduce 500 0 Û 326986.8 0.0 0.0 419.2 (MB/s) 100 Output 0.0 (MB/s) 90 doc-80 4982870667 index-hits Percent Completed 70 docs-17229926 60 indexed 50 dups-in-40 indexmerge 30 mr-20 17272056 operator-10 calls 송 mr-001 200 300 8 17229926 operator-Reduce Shard outputs

Started: Fri Nov 7 09:51:07 2003 -- up 0 hr 15 min 31 sec



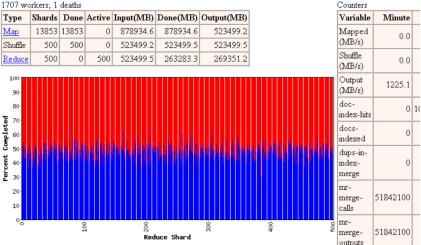
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1707 workers; 1 deaths



Started: Fri Nov 7 09:51:07 2003 -- up 0 hr 31 min 34 sec

1707 workers; 1 deaths



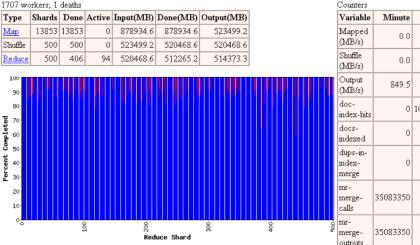
Started: Fri Nov 7 09:51:07 2003 -- up 0 hr 33 min 22 sec

¹⁷⁰⁷ workers; 1 deaths

Counters Shards Done Active Input(MB) Done(MB) Output(MB) Variable Minute Туре 13853 13853 878934.6 878934.6 Map 0 523499.2 Mapped 0.0 (MB/s) Shuffle 500 523499.2 523499.5 523499.5 500 Û Shuffle Reduce 500 0 500 523499.5 390447.6 399457.2 0.0 (MB/s) Output 100 1222.0 (MB/s) 90 doc-80 0 10 index-hits Percent Completed 70 docs-60 0 indexed 50 dups-in-40 index-0 merge 30 mr-20 51640600 merge-10 calls 형 mr-001 200 Ś 8 51640600 merge-Reduce Shard outputs

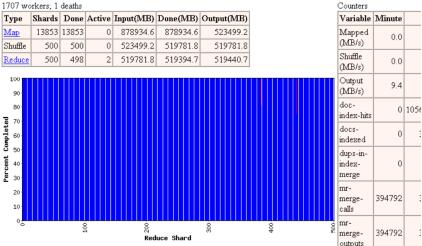
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1707 workers; 1 deaths

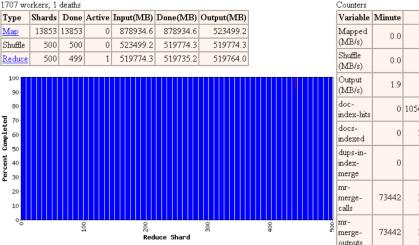


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1707 workers; 1 deaths



Started: Fri Nov 7 09:51:07 2003 -- up 0 hr 38 min 56 sec



Started: Fri Nov 7 09:51:07 2003 -- up 0 hr 40 min 43 sec

1707 workers; 1 deaths

Fault tolerance: Handled via re-execution

On worker failure:

- Detect failure via periodic heartbeats
- Re-execute completed and in-progress map tasks
- Re-execute in progress reduce tasks
- Task completion committed through master
- Master failure:
 - Could handle, but don't yet (master failure unlikely)

Robust: lost 1600 of 1800 machines once, but finished fine

Semantics in presence of failures: see paper

Refinement: Redundant Execution

Slow workers significantly lengthen completion time

- Other jobs consuming resources on machine
- Bad disks with soft errors transfer data very slowly
- Weird things: processor caches disabled (!!)

Solution: Near end of phase, spawn backup copies of tasks

Whichever one finishes first "wins"

Effect: Dramatically shortens job completion time

Refinement: Locality Optimization

Master scheduling policy:

- Asks GFS for locations of replicas of input file blocks
- Map tasks typically split into 64MB (== GFS block size)
- Map tasks scheduled so GFS input block replica are on same machine or same rack

Effect: Thousands of machines read input at local disk speedWithout this, rack switches limit read rate

Refinement: Skipping Bad Records

Map/Reduce functions sometimes fail for particular inputs

- Best solution is to debug & fix, but not always possible
- On seg fault:
 - Send UDP packet to master from signal handler
 - Include sequence number of record being processed
- If master sees two failures for same record:
 - Next worker is told to skip the record

Effect: Can work around bugs in third-party libraries

Other Refinements (see paper)

- Sorting guarantees within each reduce partition
- Compression of intermediate data
- Combiner: useful for saving network bandwidth
- Local execution for debugging/testing
- User-defined counters

Performance

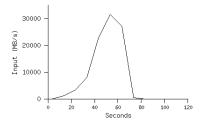
Tests run on cluster of 1800 machines:

- 4 GB of memory
- Dual-processor 2 GHz Xeons with Hyperthreading
- Dual 160 GB IDE disks
- Gigabit Ethernet per machine
- Bisection bandwidth approximately 100 Gbps

Two benchmarks:

- MR_Grep Scan 10¹⁰ 100-byte records to extract records matching a rare pattern (92K matching records)
- MR_Sort Sort 10¹⁰ 100-byte records (modeled after TeraSort benchmark)

MR_Grep



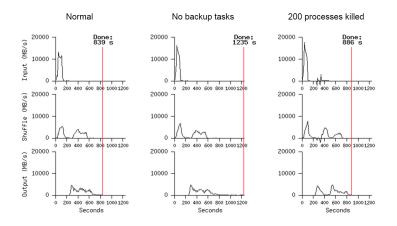
Locality optimization helps:

- 1800 machines read 1 TB of data at peak of \approx 31 GB/s
- Without this, rack switches would limit to 10 GB/s

Startup overhead is significant for short jobs

MR_Sort

Backup tasks reduce job completion time significantlySystem deals well with failures



Experience: Rewrite of Production Indexing System

Rewrote Google's production indexing system using MapReduce

- Set of 10, 14, 17, 21, 24 MapReduce operations
- New code is simpler, easier to understand
- MapReduce takes care of failures, slow machines
- Easy to make indexing faster by adding more machines

Usage: MapReduce jobs run in August 2004

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

Related Work

- Programming model inspired by functional language primitives
- Partitioning/shuffling similar to many large-scale sorting systems
 - NOW-Sort ['97]
- Re-execution for fault tolerance
 - BAD-FS ['04] and TACC ['97]
- Locality optimization has parallels with Active Disks/Diamond work
 - Active Disks ['01], Diamond ['04]
- Backup tasks similar to Eager Scheduling in Charlotte system
 - Charlotte ['96]
- Dynamic load balancing solves similar problem as River's distributed queues
 - River ['99]

Conclusions

MapReduce has proven to be a useful abstraction

- Greatly simplifies large-scale computations at Google
- Fun to use: focus on problem, let library deal w/ messy details

Thanks to Josh Levenberg, who has made many significant improvements and to everyone else at Google who has used and helped to improve MapReduce.