Google's MapReduce & Bigtable

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DUKE COMPUTER SCIENCE

With contents from D. Weld's lecture slides and E. Paulson's OS seminar slides at U. Washington

Announcements

- Two volunteers needed for next week
  - Christopher M. Jermaine, Subramanian Arumugam, Abhijit Pol, Alin Dobra: "Scalable approximate query processing with the DBO engine." *SIGMOD* 2007
  - Lyublena Antova, Christoph Koch, Dan Olteanu: "From complete to incomplete information and back." *SIGMOD* 2007
- Preliminary reading list will be posted by tomorrow
  - We will have one more iteration
- Beginning of this course may feel like "rapid-firing," as we quickly move across topics
  - Intended to broadly sample the literature and give you some ideas for projects
  - Will come back for more depth after project proposal presentations

Papers today

- Jeffrey Dean, Sanjay Ghemawat: "MapReduce: Simplified Data Processing on Large Clusters." *OSDI* 2004
- Fay Chang, Jeffrey Dean, Sanjay Ghemawat, Wilson C. Hsieh, Deborah A. Wallach, Michael Burrows, Tushar Chandra, Andrew Fikes, Robert Gruber: "Bigtable: A Distributed Storage System for Structured Data." *OSDI* 2006

☞ Let's look at what powers the all-powerful Google!

MapReduce

- What was a single phrase that you remembered after reading this paper?
- For me: ***restricted programming model***
  - Yes, there is stuff that you cannot do, but
  - The restrictions allow for better system-level support (optimization, fault tolerance, …)
  - A large class of problems still can be tackled

MapReduce motivation

- Large-scale data processing
  - Want to use 1000s of machines, but don't want hassle of managing things
- MapReduce provides
  - Automatic parallelization & distribution
  - Fault tolerance
  - I/O scheduling
  - Monitoring & status updates

map/reduce

- Programming model from Lisp (and other functional languages)
  - `(map square '(1 2 3 4))` ⇒ `(1 4 9 16)`
  - `(reduce + '(1 4 9 16))` ⇒ 30
- Many problems can be phrased this way
- Easy to distribute
- Nice failure/retry semantics

MapReduce of Google

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- map(*key*, *val*) ⇒ (*new-key*, *new-val*), …
  - Run on each item in an input set
  - Emit a list of key-value pairs
- reduce(*key*, *vals*) ⇒ *output*
  - Run for each unique key and all associated values emitted by map()
  - Emit output

Example: counting words in docs

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- Input: (*url*, *contents*) pairs
- map(*key*=*url*, *val*=*contents*):
  - For each word *w* in *contents*, emit (*w*, 1)
- reduce(*key*=*word*, *vals*=*counts*):
  - Sum up all values in *counts*
  - Emit result (*word*, *sum*)

Counting illustrated

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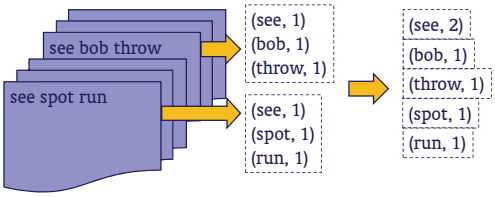

Example: inverted index

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- Input: (*docid*, *contents*) pairs
- map(*key*=*docid*, *val*=*contents*):
  - For each word *w* at *offset* in *contents*, emit (*w*, ⟨*docid*, *offset*⟩)
- reduce(*key*=*word*, *vals*=list of ⟨*docid*, *offset*⟩):
  - Sort *vals*
  - Emit (*word*, sorted list of ⟨*docid*, *offset*⟩)

Model is widely applicable

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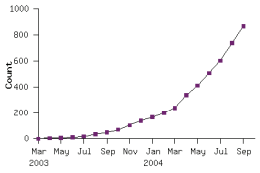
MapReduce programs at Google



☞ *For those of us who work in academia, how do we convince people that a model is "widely" applicable?*

Implementation overview

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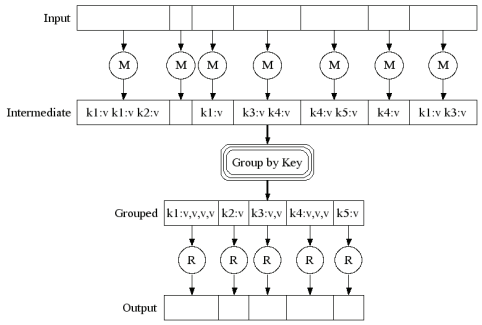
- Typical cluster
  - 100s/1000s of 2-CPU x86 machines, 2-4GB of memory
  - Limited bisection bandwidth
  - Storage is on local IDE disks
  - GFS: distributed file system manages data (*SOSP* 2003)
  - Job scheduling system: jobs made up of tasks; scheduler assigns tasks to machines
- MapReduce implemented as a C++ library linked into user programs

Execution: conceptual view

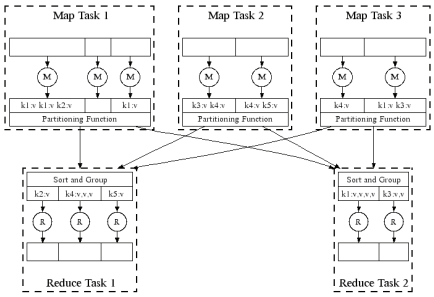


Execution details

- Split input key/value pairs into *M* chunks, run a map() task on each chunk in parallel
- Output from map() tasks is periodically written to local disk, partitioned into *R* regions according to intermediate (emitted) keys
- After all *M* map()s complete, each of the *R* reduce() task fetches its input regions from mappers, sorts (and thereby groups) data by intermediate keys, and processes each group
- Output from reduce() typically goes into *R* files in GFS
- ☞ A single "master" assigns and coordinate tasks

Execution: detailed view

Where is the "bottleneck"?



So why this big sync. barrier?

- Why not pipeline map and reduce phases?
  - Once map() produces an intermediate result, let reduce() consume it
  - ☞ *What would we gain from pipelining?*
- Googler's answer (cf. http://www.youtube.com/v/-vD6PUdf3Js)
  - No good reason to start reduce() when it isn't working full throttle
  - Not a good use of bandwidth—most of which is taken by input to map()
  - Mapper crashing is more difficult to handle—need to remember how much of its output has been consumed

Fault tolerance

- Handle faults using re-execution
  - Detect failure via periodic heartbeats
  - Re-execute in-progress reduce() tasks
  - Re-execute in-progress + completed (*why?*) map() tasks on the failed machine
- Master failure?
  - Could handle, but don't yet—unlikely

Refinements

- Redundant execution
  - Slow workers significantly delay completion
  - Near end of phase, spawn backup tasks—whoever finishes first "wins"
    - Alleviates the bottleneck between map/reduce somewhat
- Locality optimization
  - Try to schedule map() on the same machine with the input file block
- Skipping bad records
  - If master sees two failures for the same record, next restart will be told to skip the record
  - Can work around third-party bugs

More refinements

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- Ordering guarantees
  - Within a region, key/value pairs are processed in increasing key order
  - ☞*Can this guarantee be too strong?*
- Combiner
  - In same region: (key, val_1), $(key, val_2) \rightarrow (key, val_1 + val_2)$
  - Reduce intermediate result size
  - ☞*By the way, what does map/reduce remind you in databases?*
- Counters
  - E.g., number of key/value pairs processed
  - Periodically propagated to master; useful in monitoring
  - ☞*Can you just use map/reduce to implement a counter?*

Lessons learned

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- Restricted programming model
  - Restricted programming model
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  - Restricted programming model
  - Restricted programming model
  - …
- Locality is important to meet bandwidth constraint
- Simple solutions for nasty problems—especially when you have a massive farm of machines
  - E.g., re-execution

Bigtable motivation

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Google scale

- Lots of data
- Many incoming requests
- No commercial system is big enough
  - Couldn't afford it even if there was one
  - Might not have made appropriate design choices
- 450,000 machines
  - *NY Times* estimate, June 14, 2006

☞Bigtable: scalable, flexible, application-friendly data service

Building blocks

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- Google WorkQueue (scheduler)
- GFS: large-scale distributed file system (*SOSP* 2003)
  - Master: responsible for metadata
  - Chunk servers: responsible for r/w large chunks of data
  - Chunks replicated on 3 machines; master responsible for ensuring replicas exist
- Chubby: lock/file/name service (*OSDI* 2006)
  - Coarse-grained locks; can store small amount of data in a lock
  - 5 replicas; need a majority vote to be active

Data model: a big map

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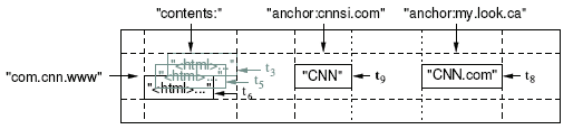

- Key: ⟨*row*, *column*, *timestamp*⟩
- Arbitrary "columns" on a row-by-row basis
  - Each column is identified by *family:qualifier*
  - Cell-oriented physical storage, because rows are sparse (do not have a fixed format)
- No integrity constraints
- No multirow transactions

Implementation: SSTable

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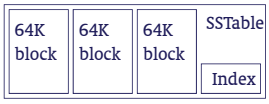
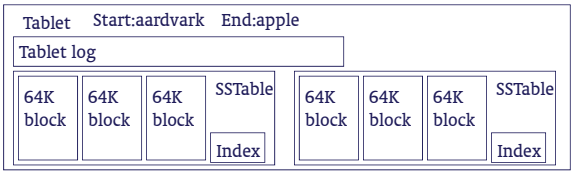


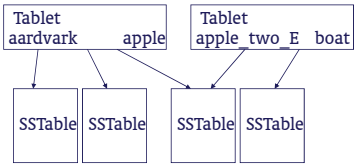
- Lives in GFS
- Immutable, sorted file of key-value pairs
- Chunks of data plus an index
  - Index is on block key ranges, not on values

Implementation: tablet



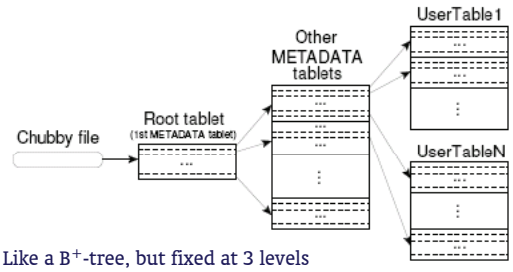
- 100-200 MB; split if it gets too long
- Contains data in some *row* range of a bigtable
- Implemented on top of multiple SSTables and a tablet log (in GFS)
  - Not a simple union of SSTables!

Implementation: bigtable



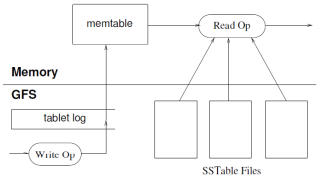
- A bigtable is horizontally partitioned into multiple non-overlapping tablets according to *row* ranges
- Tablets could share underlying SSTables!

Finding a tablet



- Like a B$^+$-tree, but fixed at 3 levels
- How can we avoid creating a bottleneck at the root?
  - Aggressively cache tablet locations
  - Lookup starts from leaf (bet on it being correct); reverse on miss

Serving a tablet



- Updates are logged
- Each SSTable corresponds to a batch of updates or a snapshot of the tablet taken at some earlier time
- Memtable (sorted by key) caches recent updates (those not yet reflected by SSTables)
- Reads consult both memtable and SSTables

Compactions

- Minor compaction
  - Memtable → a new SSTable
  - Reduce memory usage and redoing during recovery
- Merging compaction
  - A few SSTables + memtable → a new SSTable
  - Reduce number of SSTables
  - Can apply policies such as "keep only *N* older versions"
- Major compaction
  - All SSTables + memtable into one
  - Deleted data is now completely purged

Refinements

- Locality groups
  - Group similar column families
  - A separate SSTable for each local group
  - Avoid mingling data (e.g., page contents vs. metadata)
  - Small groups may even be kept in memory
- Compression
  - More effective due to locality grouping and versioning
- Bloom filters
  - Read may need to consult all SSTables
  - Use an in-memory Bloom filter to avoid GFS accesses

Some performance numbers

Experiment	# of Tablet Servers			
	1	50	250	500
random reads	1212	593	479	241
random reads (mem)	10811	8511	8000	6250
random writes	8850	3745	3425	2000
sequential reads	4425	2463	2625	2469
sequential writes	8547	3623	2451	1905
scans	15385	10526	9524	7843

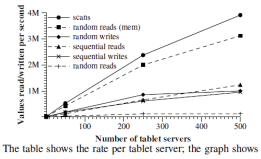


Figure 6: Number of 1000-byte values read/written per second. The table shows the rate per tablet server; the graph shows the aggregate rate.

- *In the table on the left, why is throughput going down when # of tablet servers increases?*
- *Why are random writes almost as efficient as sequential writes?*
- *What's the price we are paying for that?*

Lessons learned

- Don't go overboard with features
- Many types of failures are possible in a real system
- Big systems need proper system-level monitoring
- KISS = Keep It Simple, Stupid!

- For more info, see
  http://videosrv14.cs.washington.edu/info/videos/mp4/colloq/JDean_051018_OnDemand_100_256K_320x240.mp4

Discussion

So, in a course on databases, why are we starting with two systems papers?

- Analogous to MapReduce, relational algebra/SQL also followed a restricted programming model
- Analogous to Bigtable, relational database systems also aim to provide a scalable, flexible, application-friendly data service
- Many aspects of database research involve designing such abstractions
- Writing papers about designs is very difficult, but you have seen a couple of good examples!