MapReduce

CS345a: Data Mining
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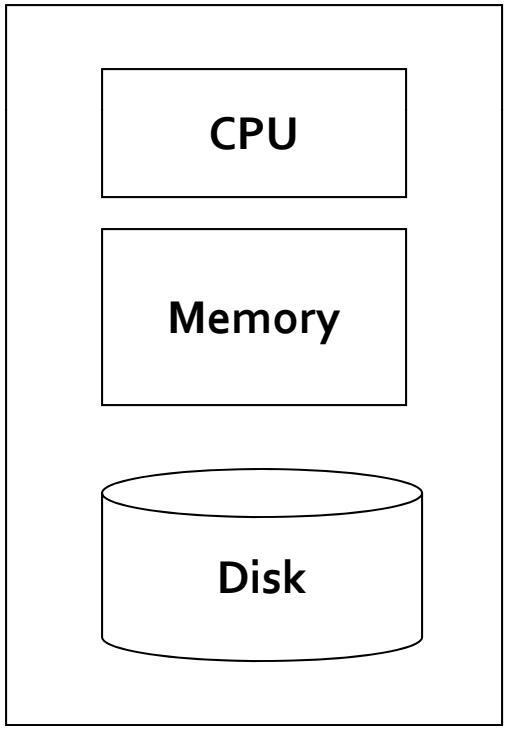
Single-node architecture



Machine Learning, Statistics

"Classical" Data Mining

Motivation (Google example)

- 20+ billion web pages x 20KB = 400+ TB
- 1 computer reads 30-35 MB/sec from disk
  - ~4 months to read the web
- ~1,000 hard drives to store the web

- Even more to do something with the data

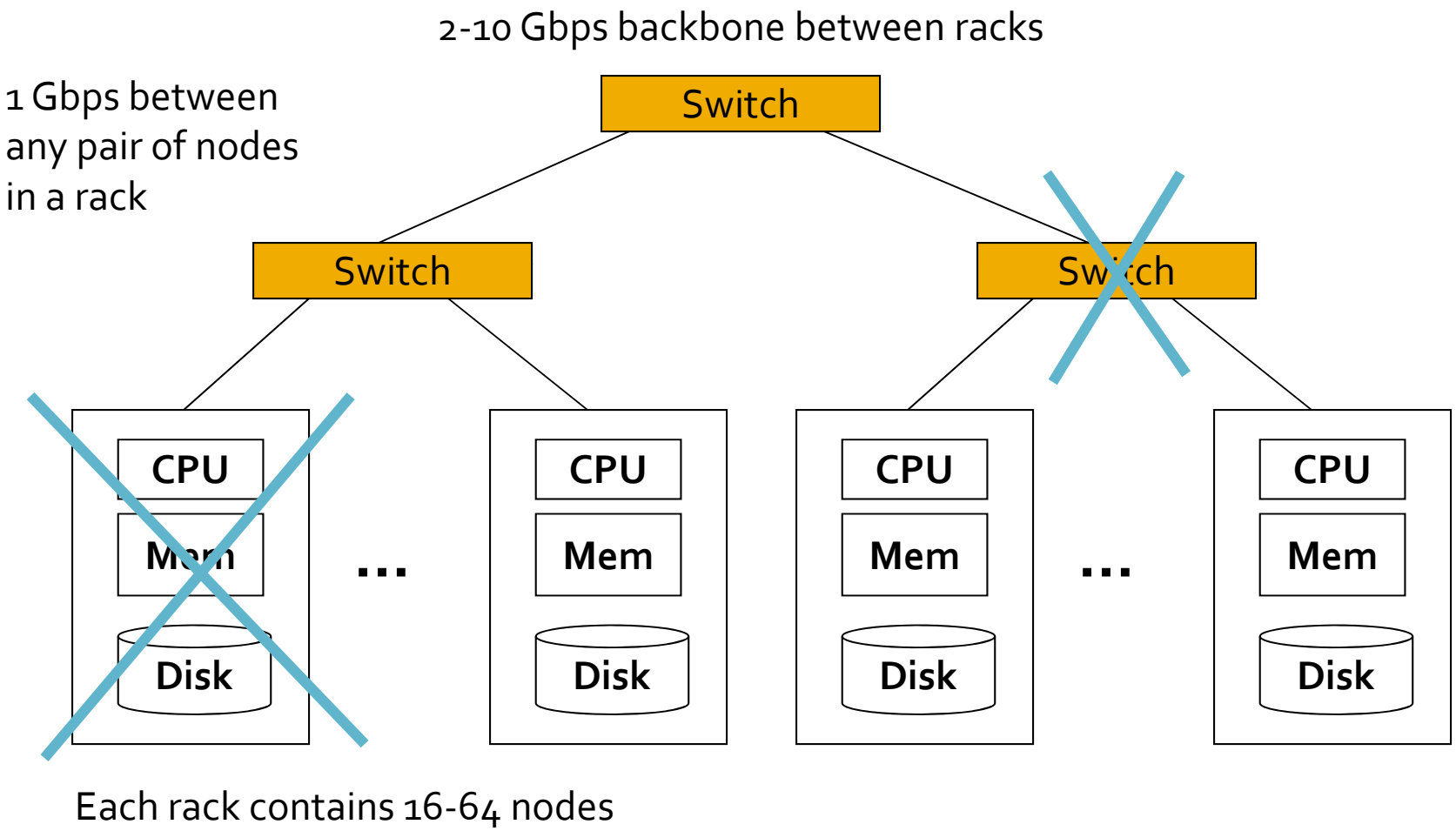
Commodity Clusters

- Web data sets can be very large
  - Tens to hundreds of terabytes
- Cannot mine on a single server
- Standard architecture emerging:
  - Cluster of commodity Linux nodes
  - Gigabit ethernet interconnect
- How to organize computations on this architecture?
  - Mask issues such as hardware failure

Big computation – Big machines

- Traditional big-iron box (circa 2003)
  - 8 2GHz Xeons
  - 64GB RAM
  - 8TB disk
  - 758,000 USD
- Prototypical Google rack (circa 2003)
  - 176 2GHz Xeons
  - 176GB RAM
  - ~7TB disk
  - 278,000 USD
- In Aug 2006 Google had ~450,000 machines

Cluster Architecture



Large scale computing

- **Large scale computing** for **data mining** problems on **commodity hardware**
  - PCs connected in a network
  - Need to process huge datasets on large clusters of computers
- Challenges:
  - How do you distribute computation?
  - Distributed programming is hard
  - Machines fail
- **Map-reduce** addresses all of the above
  - Google's computational/data manipulation model
  - Elegant way to work with big data

M45: Open Academic Cluster

- Yahoo's collaboration with academia
  - Foster open research
  - Focus on large-scale, highly parallel computing
- Seed Facility: **M45**
  - Datacenter in a Box (DiB)
  - 1000 nodes, 4000 cores, 3TB RAM, 1.5PB disk
  - High bandwidth connection to Internet
  - Located on Yahoo! corporate campus
  - World's top 50 supercomputer

Implications

- Implications of such computing environment
  - Single machine performance does not matter
    - Add more machines
  - Machines break
    - One server may stay up 3 years (1,000 days)
    - If you have 1,0000 servers, expect to loose 1/day
  - How can we make it easy to write distributed programs?

Idea and solution

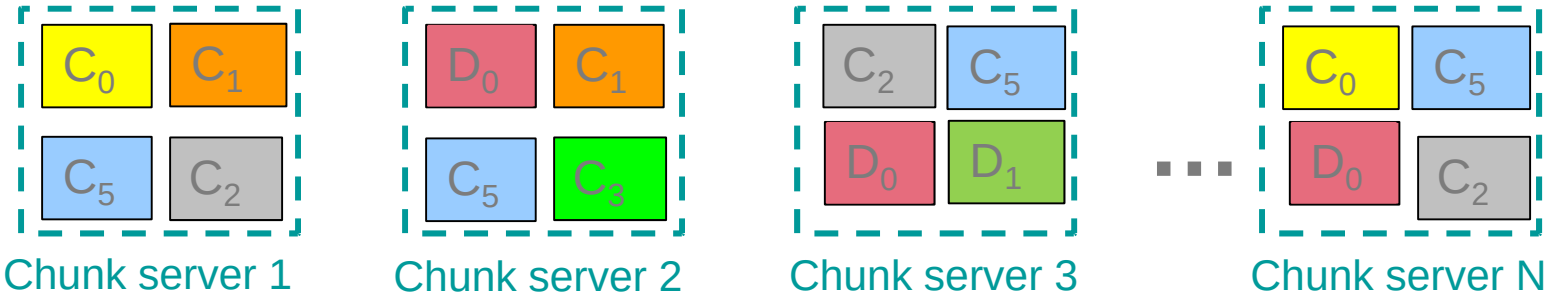
- **Idea**
  - Bring computation close to the data
  - Store files multiple times for reliability
- **Need**
  - Programming model
    - Map-Reduce
  - Infrastructure – File system
    - Google: GFS
    - Hadoop: HDFS

Stable storage

- First order problem: if nodes can fail, how can we store data persistently?
- Answer: Distributed File System
  - Provides global file namespace
  - Google GFS; Hadoop HDFS; Kosmix KFS
- Typical usage pattern
  - Huge files (100s of GB to TB)
  - Data is rarely updated in place
  - Reads and appends are common

Distributed File System

- Reliable distributed file system for petabyte scale
- Data kept in 64-megabyte "chunks" spread across thousands of machines
- Each chunk replicated, usually 3 times, on different machines
  - Seamless recovery from disk or machine failure



Bring computation directly to the data!

Distributed File System

- Chunk Servers
  - File is split into contiguous chunks
  - Typically each chunk is 16-64MB
  - Each chunk replicated (usually 2x or 3x)
  - Try to keep replicas in different racks
- Master node
  - a.k.a. Name Nodes in HDFS
  - Stores metadata
  - Might be replicated
- Client library for file access
  - Talks to master to find chunk servers
  - Connects directly to chunkservers to access data

Warm up: Word Count

- We have a large file of words:
  - one word per line
- Count the number of times each distinct word appears in the file
- Sample application:
  - analyze web server logs to find popular URLs

Word Count (2)

- Case 1: Entire file fits in memory
- Case 2: File too large for mem, but all <word, count> pairs fit in mem
- Case 3: File on disk, too many distinct words to fit in memory
  - **`sort datafile | uniq –c`**

Word Count (3)

- To make it slightly harder, suppose we have a large corpus of documents
- Count the number of times each distinct word occurs in the corpus
  - **`words(docs/*) | sort | uniq -c`**
  - where **`words`** takes a file and outputs the words in it, one to a line
- The above captures the essence of MapReduce
  - Great thing is it is naturally parallelizable

Map-Reduce: Overview

- Read a lot of data
- **Map**
  - Extract something you care about
- Shuffle and Sort
- **Reduce**
  - Aggregate, summarize, filter or transform
- Write the data

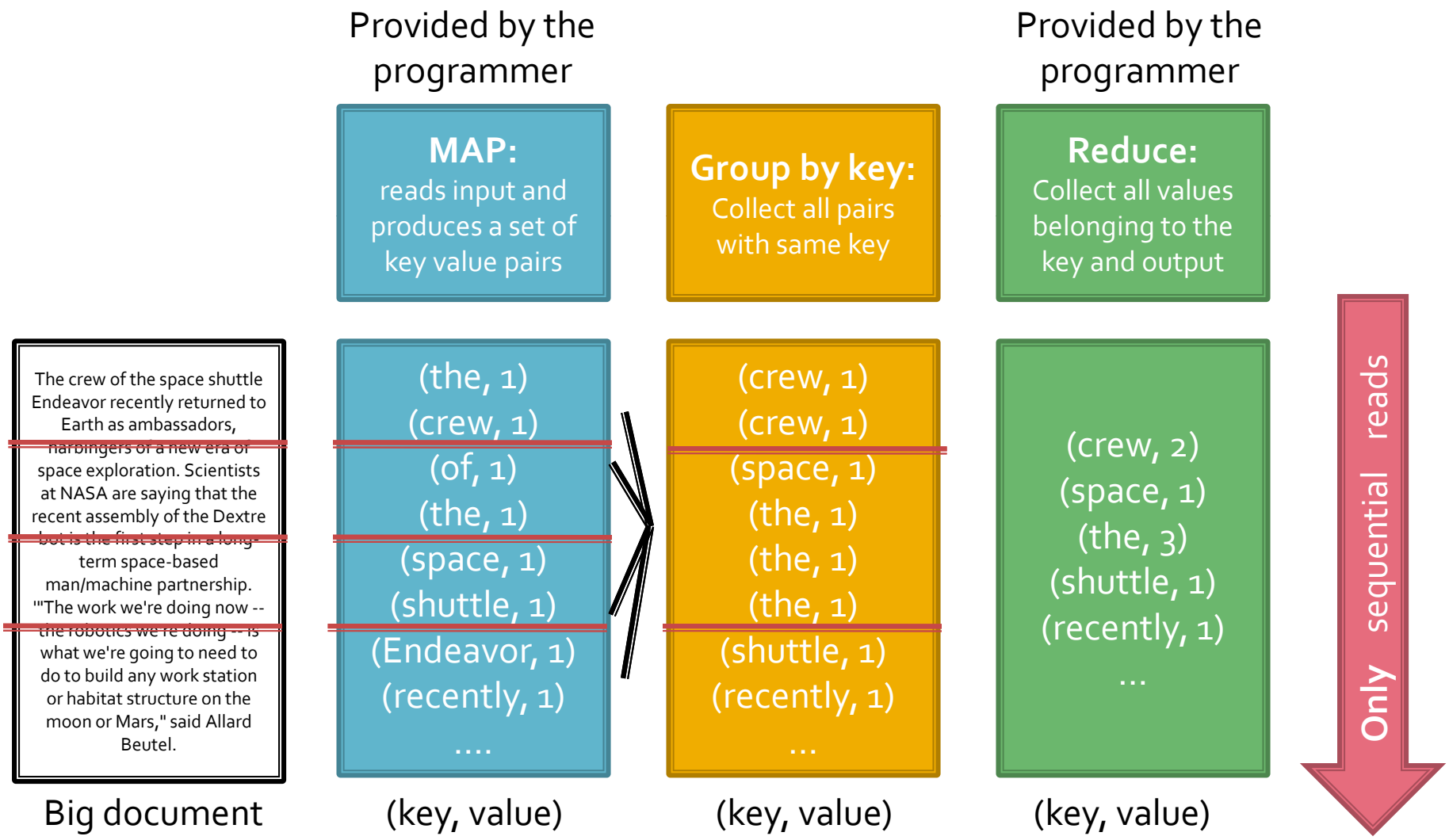
Outline stays the same, **map** and **reduce** change to fit the problem

More specifically

- Program specifies two primary methods:
  - Map(k,v) → <k', v'>*
  - Reduce(k', <v'>*) → <k', v''>*

- All v' with same k' are reduced together and processed in v' order

Map-Reduce: Word counting



Word Count using MapReduce

```
map(key, value):
// key: document name; value: text of document
    for each word w in value:
        emit(w, 1)
```

```
reduce(key, values):
// key: a word; value: an iterator over counts
        result = 0
        for each count v in values:
            result += v
        emit(result)
```

Map-Reduce: Environment

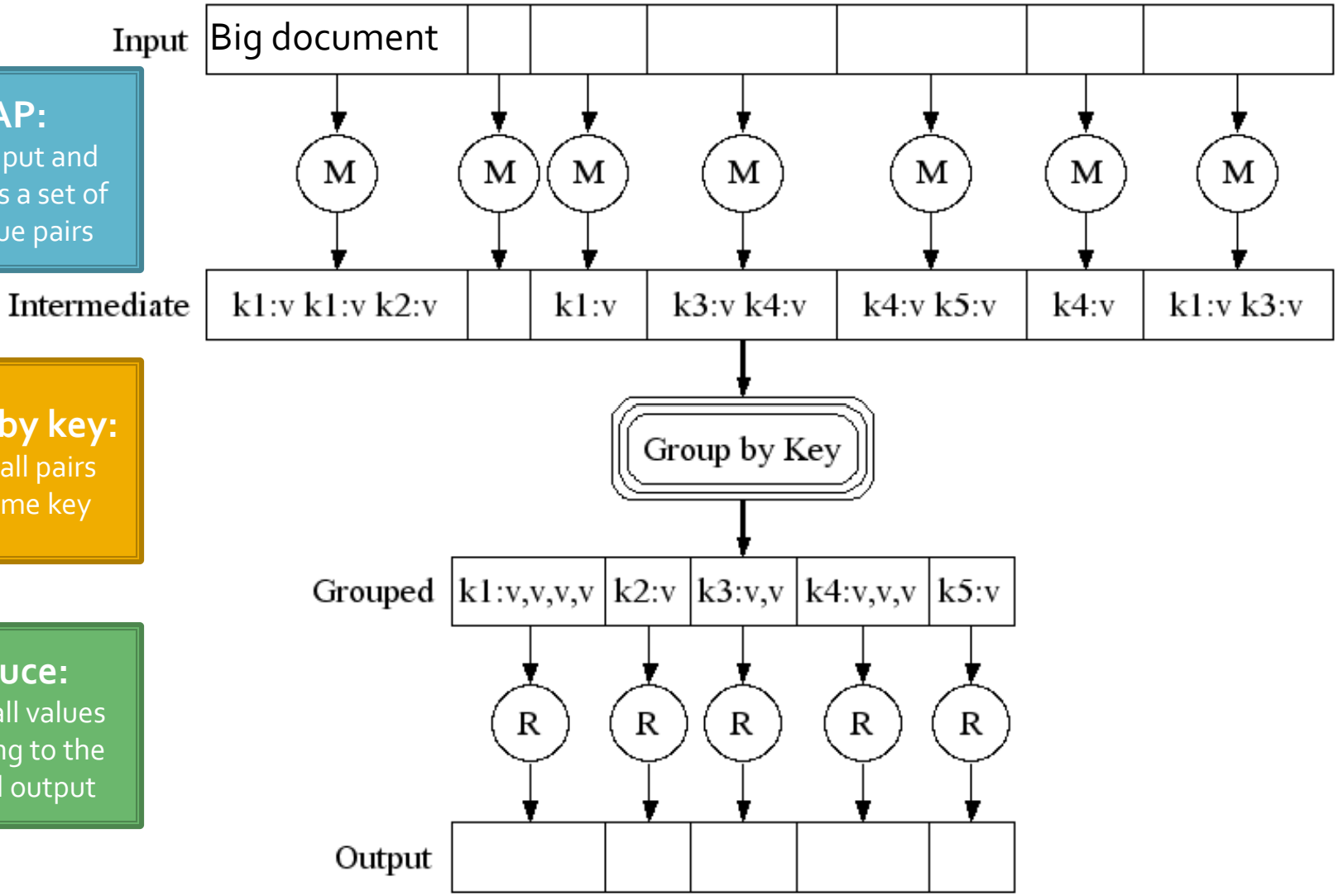
- Map-Reduce environment takes care of:
  - Partitioning the input data
  - Scheduling the program's execution across a set of machines
  - Handling machine failures
  - Managing required inter-machine communication
- Allows programmers without any experience with parallel and distributed systems to easily utilize the resources of a large distributed cluster

Map-Reduce: A diagram

MAP:
reads input and produces a set of key value pairs

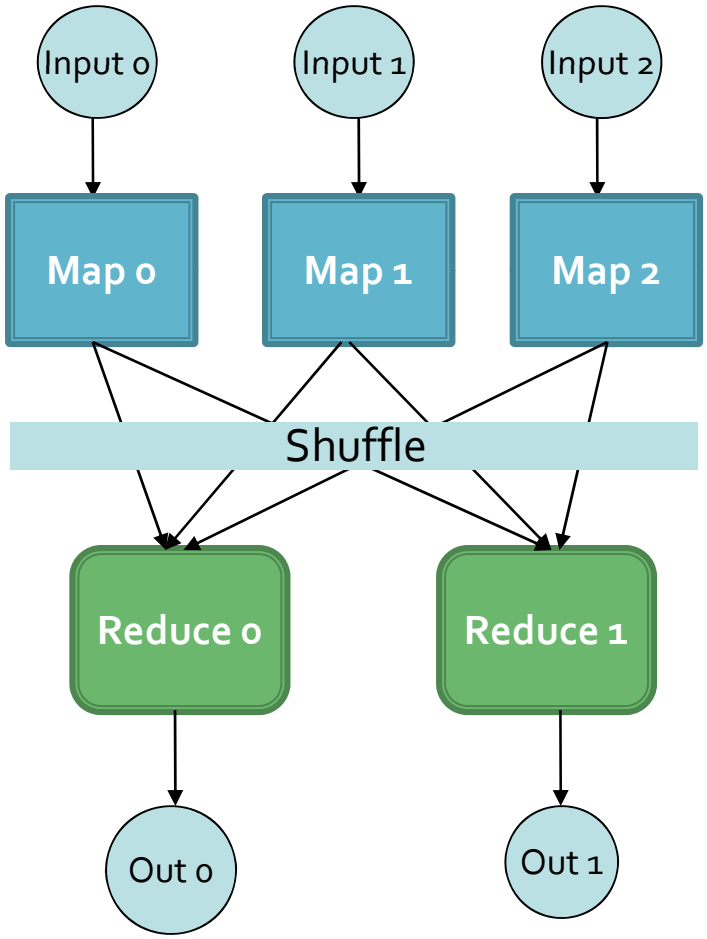
Group by key:
Collect all pairs with same key

Reduce:
Collect all values belonging to the key and output

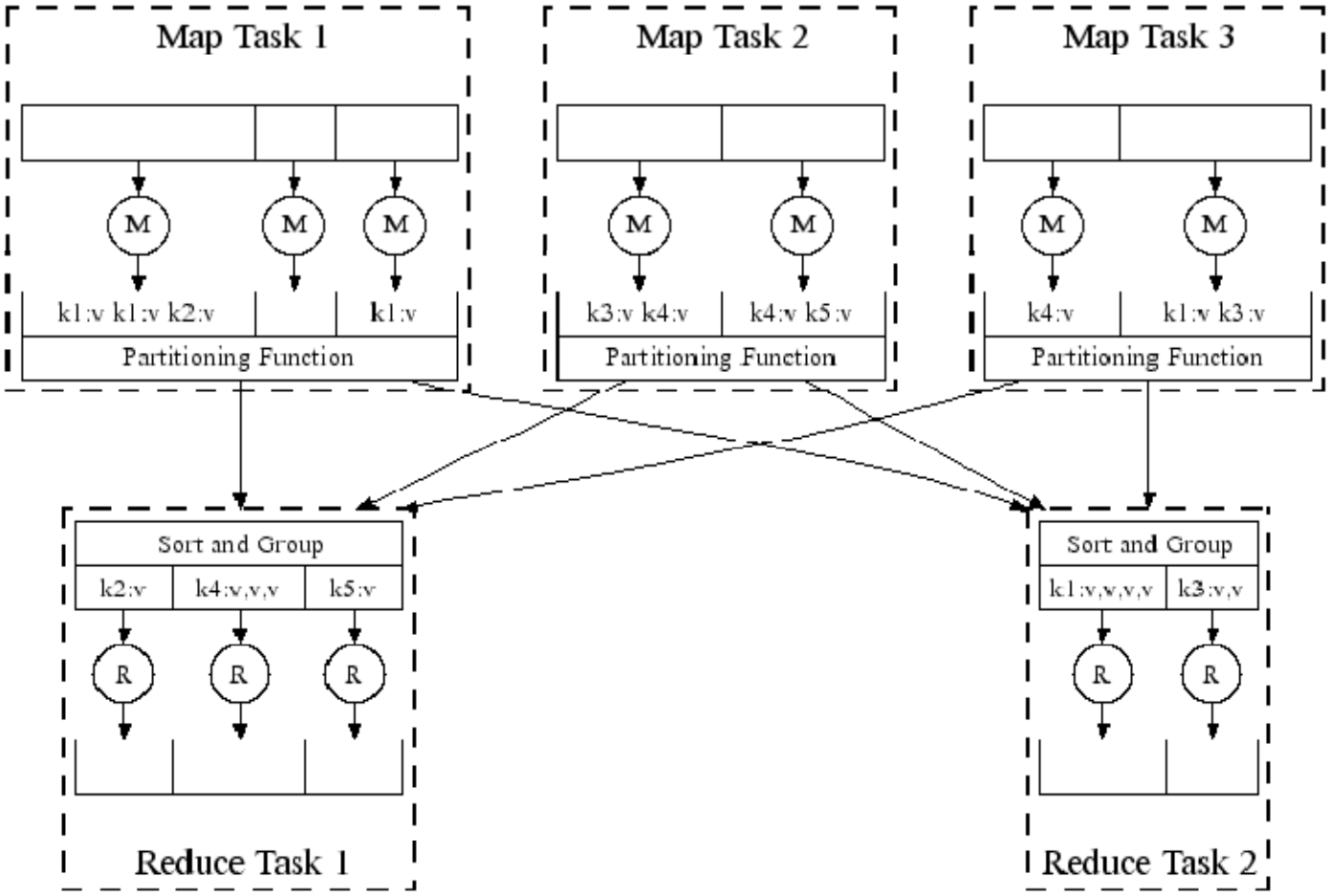


Map-Reduce

- Programmer specifies
  - Map and Reduce and input files
- **Workflow**
  - Read inputs as a set of key-value-pairs
  - **Map** transforms input kv-pairs into a new set of k'v'-pairs
  - Sorts & Shuffles the k'v'-pairs to output nodes
  - All k'v'-pairs with a given k' are sent to the same **reduce**
  - **Reduce** processes all k'v'-pairs grouped by key into new k''v''-pairs
  - Write the resulting pairs to files
- All phases are distributed with many tasks doing the work



Map-Reduce: in Parallel



Data flow

- Input, final output are stored on a distributed file system
  - Scheduler tries to schedule map tasks “close” to physical storage location of input data
- Intermediate results are stored on local FS of map and reduce workers
- Output is often input to another map reduce task

Coordination

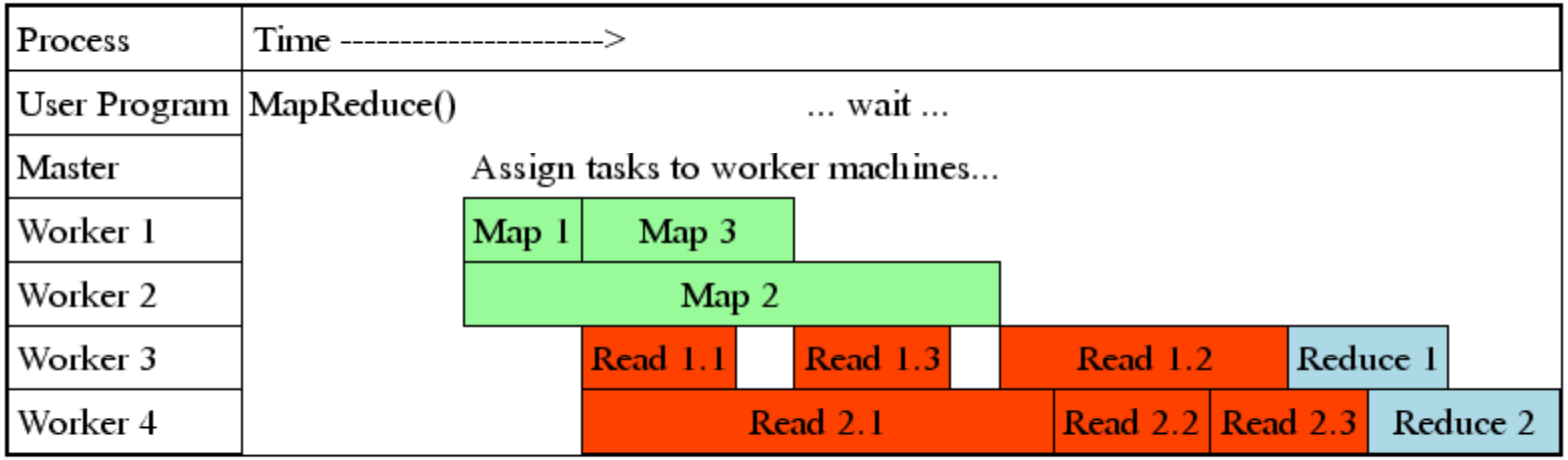
- Master data structures
  - Task status: (idle, in-progress, completed)
  - Idle tasks get scheduled as workers become available
  - When a map task completes, it sends the master the location and sizes of its R intermediate files, one for each reducer
  - Master pushes this info to reducers
- Master pings workers periodically to detect failures

Failures

- Map worker failure
  - Map tasks completed or in-progress at worker are reset to idle
  - Reduce workers are notified when task is rescheduled on another worker
- Reduce worker failure
  - Only in-progress tasks are reset to idle
- Master failure
  - MapReduce task is aborted and client is notified

Task Granularity & Pipelining

- Fine granularity tasks: map tasks >> machines
  - Minimizes time for fault recovery
  - Can pipeline shuffling with map execution
  - Better dynamic load balancing
- Often use 200,000 map & 5,000 reduce tasks
- Running on 2,000 machines

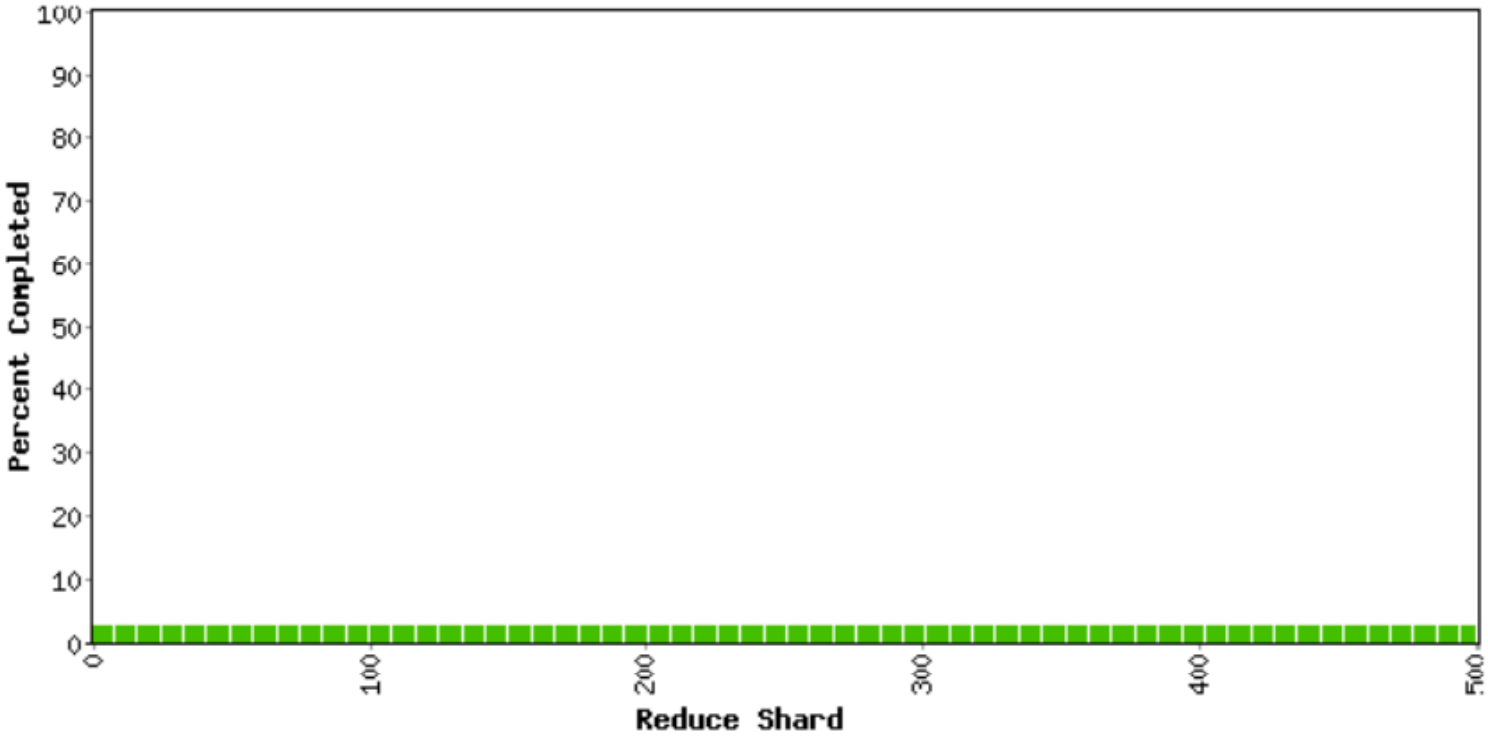


MapReduce status: MR_Indexer-beta6-large-2003_10_28_00_03

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

323 workers; 0 deaths

Type	Shards	Done	Active	Input(MB)	Done(MB)	Output(MB)
Map	13853	0	323	878934.6	1314.4	717.0
Shuffle	500	0	323	717.0	0.0	0.0
Reduce	500	0	0	0.0	0.0	0.0



Counters

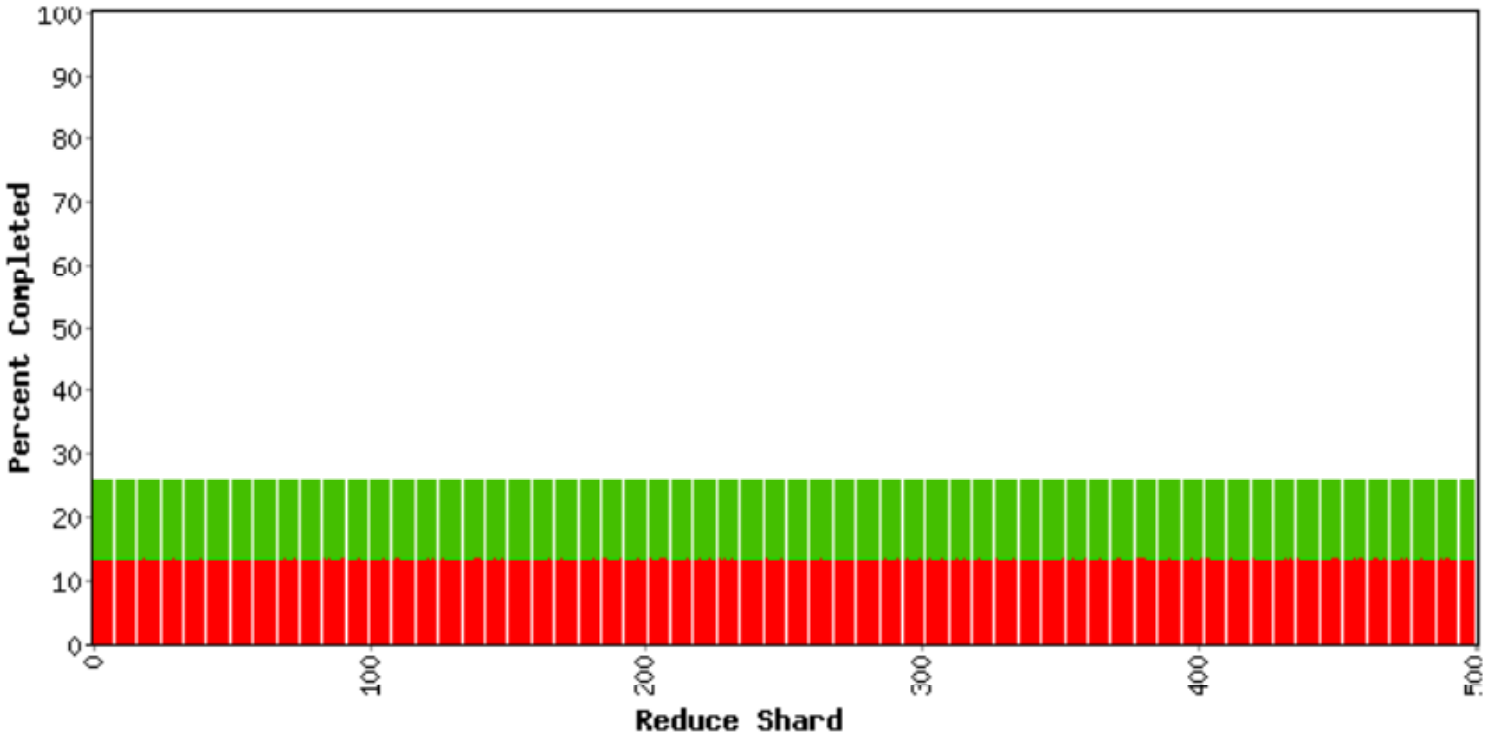
Variable	Minute
Mapped (MB/s)	72.5
Shuffle (MB/s)	0.0
Output (MB/s)	0.0
doc-index-hits	145825686
docs-indexed	506631
dups-in-index-merge	0
mr-operator-calls	508192
mr-operator-	506631

MapReduce status: MR_Indexer-beta6-large-2003_10_28_00_03

Started: Fri Nov 7 09:51:07 2003 -- up 0 hr 05 min 07 sec

1707 workers; 1 deaths

Type	Shards	Done	Active	Input(MB)	Done(MB)	Output(MB)
Map	13853	1857	1707	878934.6	191995.8	113936.6
Shuffle	500	0	500	113936.6	57113.7	57113.7
Reduce	500	0	0	57113.7	0.0	0.0



Counters

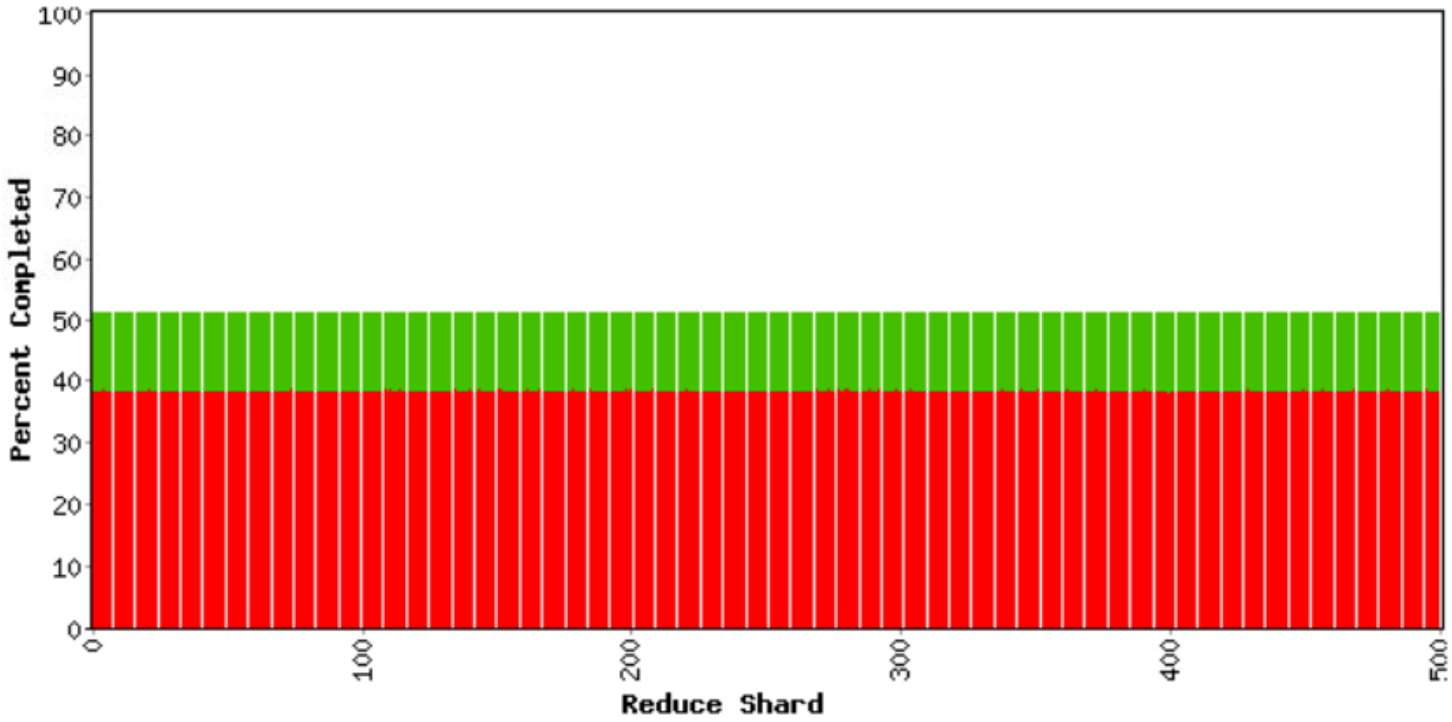
Variable	Minute
Mapped (MB/s)	699.1
Shuffle (MB/s)	349.5
Output (MB/s)	0.0
doc-index-hits	5004411944
docs-indexed	17290135
dups-in-index-merge	0
mr-operator-calls	17331371
mr-operator-outputs	17290135

MapReduce status: MR_Indexer-beta6-large-2003_10_28_00_03

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

1707 workers; 1 deaths

Type	Shards	Done	Active	Input(MB)	Done(MB)	Output(MB)
Map	13853	5354	1707	878934.6	406020.1	241058.2
Shuffle	500	0	500	241058.2	196362.5	196362.5
Reduce	500	0	0	196362.5	0.0	0.0



Counters

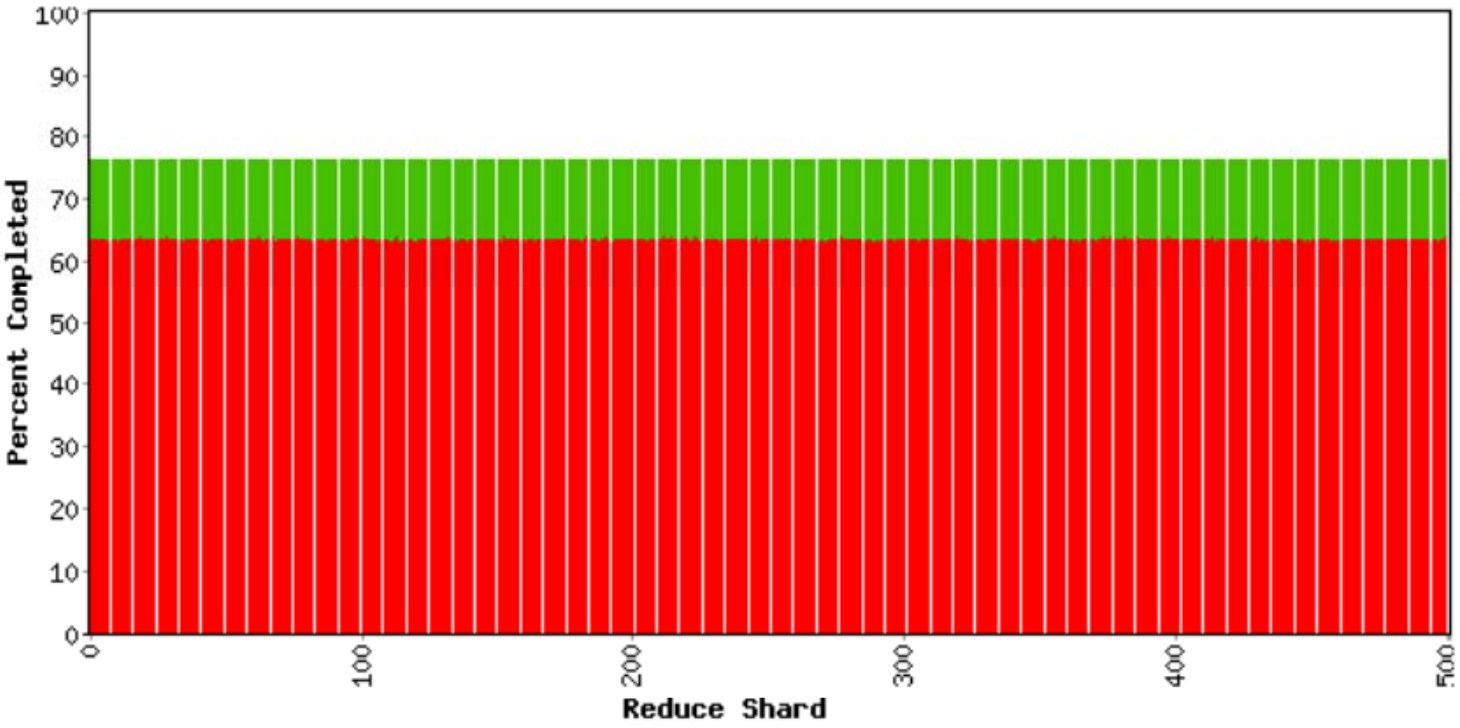
Variable	Minute
Mapped (MB/s)	704.4
Shuffle (MB/s)	371.9
Output (MB/s)	0.0
doc-index-hits	5000364228
docs-indexed	17300709
dups-in-index-merge	0
mr-operator-calls	17342493
mr-operator-outputs	17300709

MapReduce status: MR_Indexer-beta6-large-2003_10_28_00_03

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

1707 workers; 1 deaths

Type	Shards	Done	Active	Input(MB)	Done(MB)	Output(MB)
Map	13853	8841	1707	878934.6	621608.5	369459.8
Shuffle	500	0	500	369459.8	326986.8	326986.8
Reduce	500	0	0	326986.8	0.0	0.0



Counters

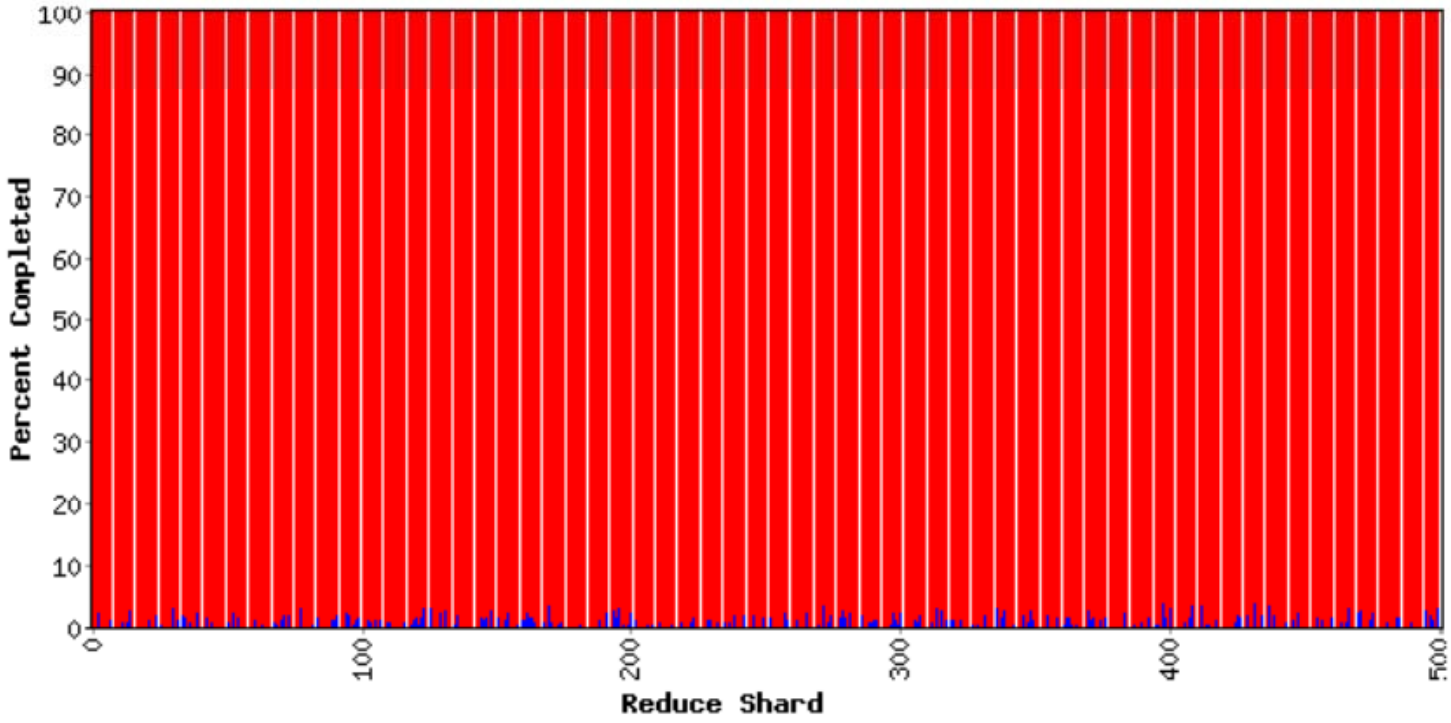
Variable	Minute
Mapped (MB/s)	706.5
Shuffle (MB/s)	419.2
Output (MB/s)	0.0
doc-index-hits	4982870667
docs-indexed	17229926
dups-in-index-merge	0
mr-operator-calls	17272056
mr-operator-outputs	17229926

MapReduce status: MR_Indexer-beta6-large-2003_10_28_00_03

Started: Fri Nov 7 09:51:07 2003 -- up 0 hr 29 min 45 sec

1707 workers; 1 deaths

Type	Shards	Done	Active	Input(MB)	Done(MB)	Output(MB)
Map	13853	13853	0	878934.6	878934.6	523499.2
Shuffle	500	195	305	523499.2	523389.6	523389.6
Reduce	500	0	195	523389.6	2685.2	2742.6



Counters

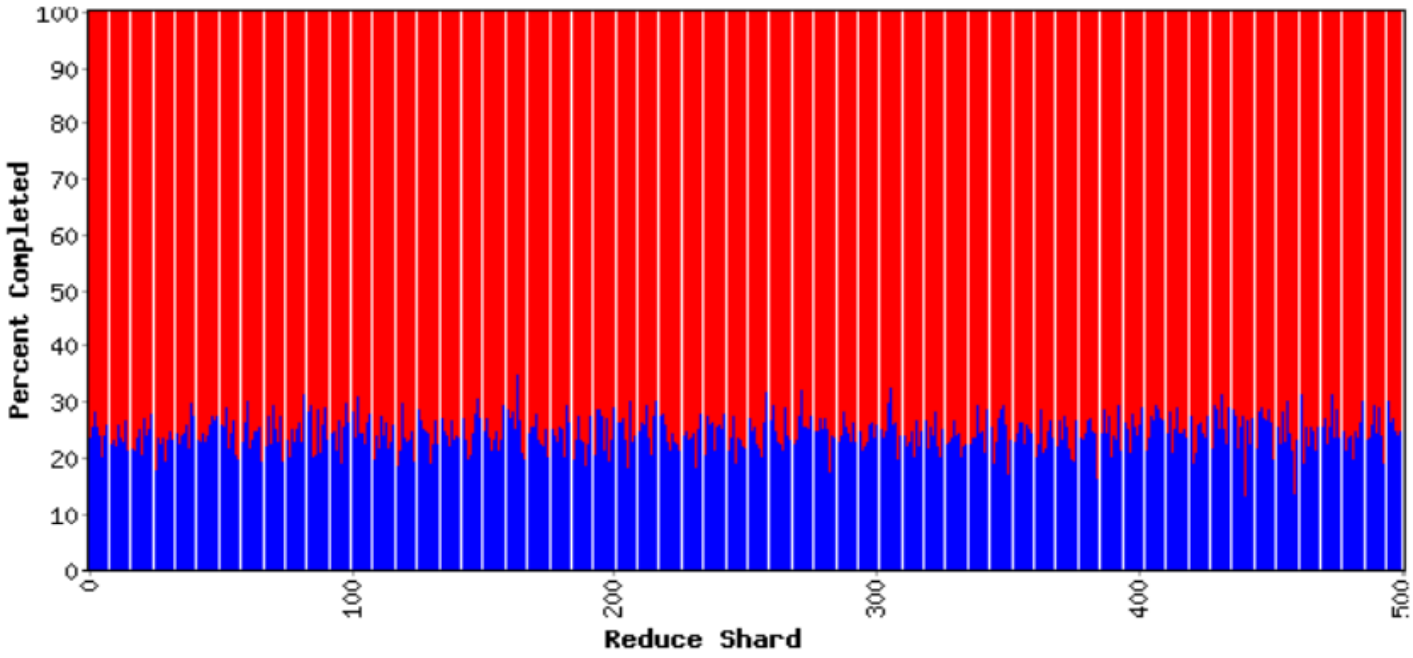
Variable	Minute	
Mapped (MB/s)	0.3	
Shuffle (MB/s)	0.5	
Output (MB/s)	45.7	
doc-index-hits	2313178	10
docs-indexed	7936	
dups-in-index-merge	0	
mr-merge-calls	1954105	
mr-merge-outputs	1954105	

MapReduce status: MR_Indexer-beta6-large-2003_10_28_00_03

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

1707 workers; 1 deaths

Type	Shards	Done	Active	Input(MB)	Done(MB)	Output(MB)
Map	13853	13853	0	878934.6	878934.6	523499.2
Shuffle	500	500	0	523499.2	523499.5	523499.5
Reduce	500	0	500	523499.5	133837.8	136929.6



Counters

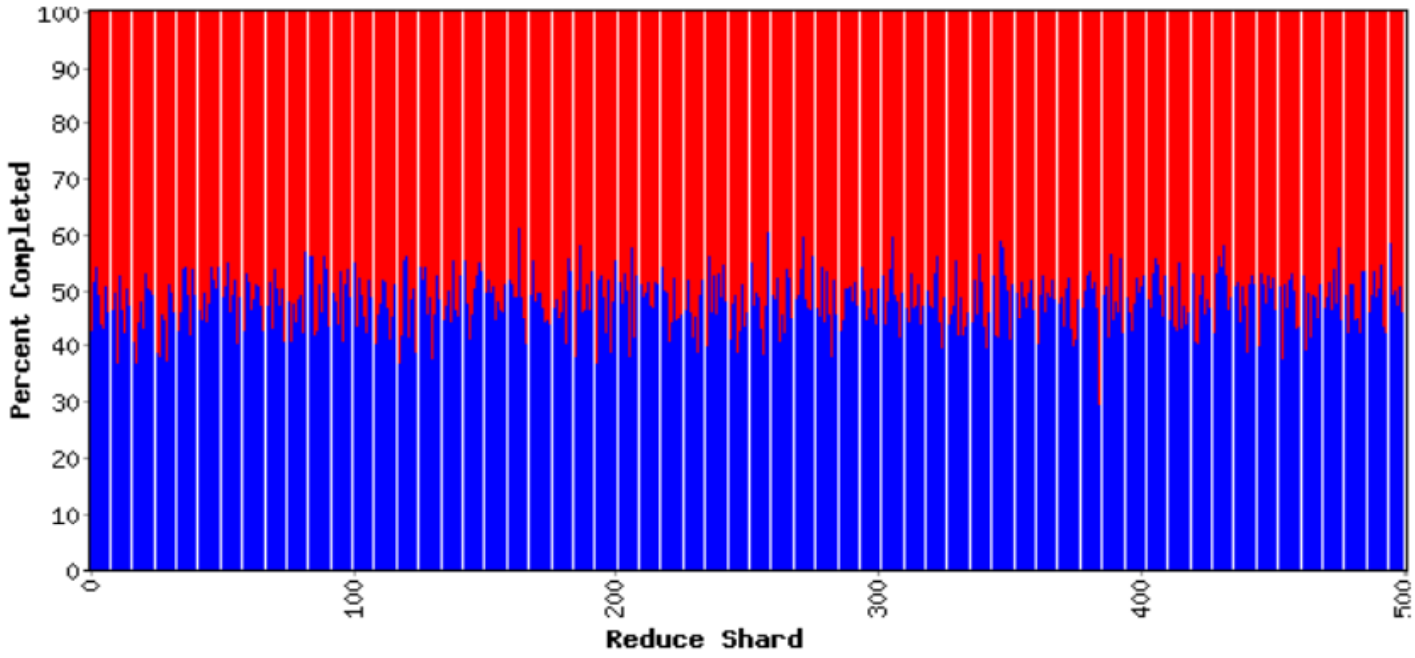
Variable	Minute	
Mapped (MB/s)	0.0	
Shuffle (MB/s)	0.1	
Output (MB/s)	1238.8	
doc-index-hits	0	1(
docs-indexed	0	
dups-in-index-merge	0	
mr-merge-calls	51738599	
mr-merge-outputs	51738599	

MapReduce status: MR_Indexer-beta6-large-2003_10_28_00_03

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

1707 workers; 1 deaths

Type	Shards	Done	Active	Input(MB)	Done(MB)	Output(MB)
Map	13853	13853	0	878934.6	878934.6	523499.2
Shuffle	500	500	0	523499.2	523499.5	523499.5
Reduce	500	0	500	523499.5	263283.3	269351.2



Counters

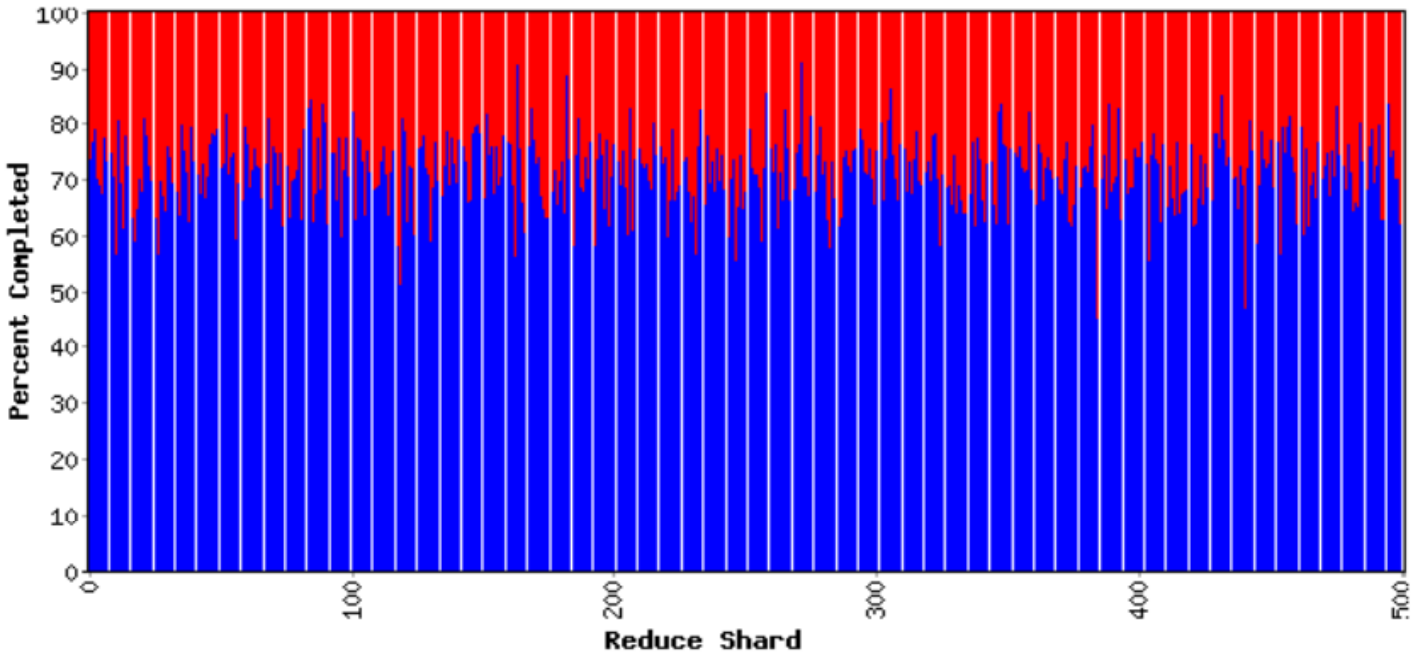
Variable	Minute	
Mapped (MB/s)	0.0	
Shuffle (MB/s)	0.0	
Output (MB/s)	1225.1	
doc-index-hits	0	1(
docs-indexed	0	
dups-in-index-merge	0	
mr-merge-calls	51842100	
mr-merge-outputs	51842100	

MapReduce status: MR_Indexer-beta6-large-2003_10_28_00_03

Started: Fri Nov 7 09:51:07 2003 -- up 0 hr 35 min 08 sec

1707 workers; 1 deaths

Type	Shards	Done	Active	Input(MB)	Done(MB)	Output(MB)
Map	13853	13853	0	878934.6	878934.6	523499.2
Shuffle	500	500	0	523499.2	523499.5	523499.5
Reduce	500	0	500	523499.5	390447.6	399457.2



Counters

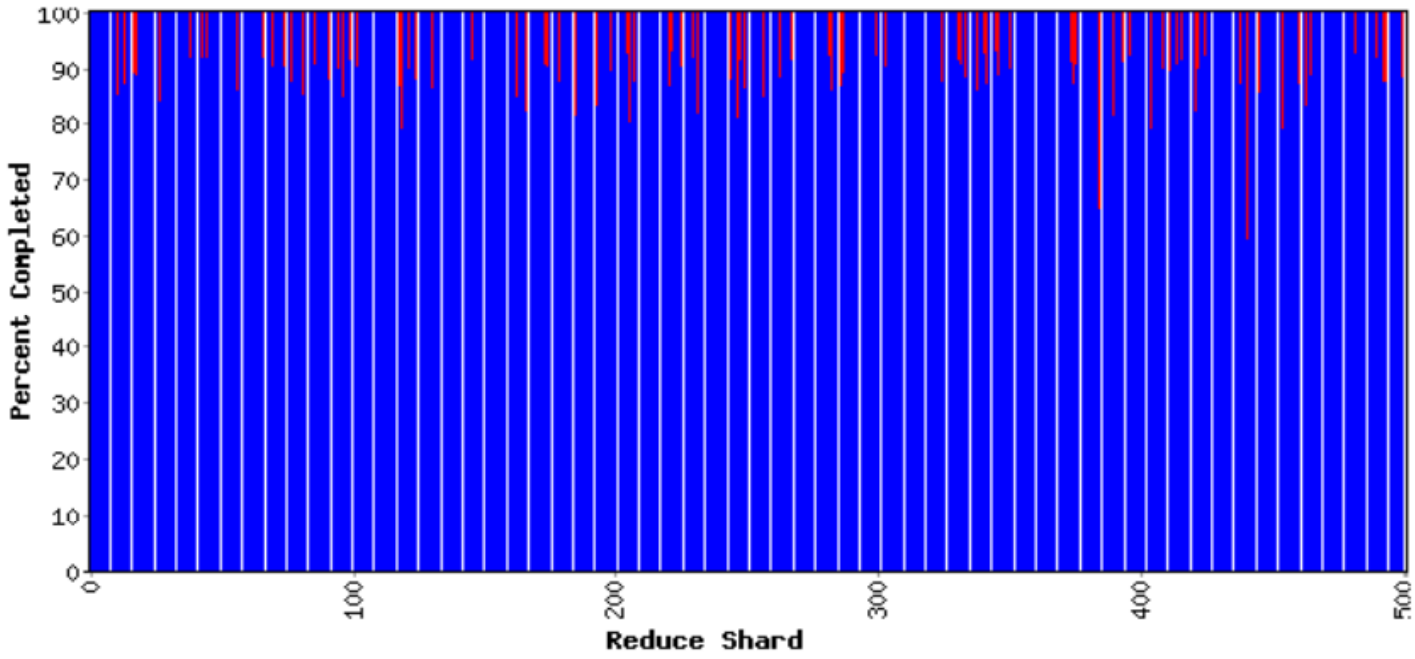
Variable	Minute
Mapped (MB/s)	0.0
Shuffle (MB/s)	0.0
Output (MB/s)	1222.0
doc-index-hits	0
docs-indexed	0
dups-in-index-merge	0
mr-merge-calls	51640600
mr-merge-outputs	51640600

MapReduce status: MR_Indexer-beta6-large-2003_10_28_00_03

Started: Fri Nov 7 09:51:07 2003 -- up 0 hr 37 min 01 sec

1707 workers; 1 deaths

Type	Shards	Done	Active	Input(MB)	Done(MB)	Output(MB)
Map	13853	13853	0	878934.6	878934.6	523499.2
Shuffle	500	500	0	523499.2	520468.6	520468.6
Reduce	500	406	94	520468.6	512265.2	514373.3



Counters

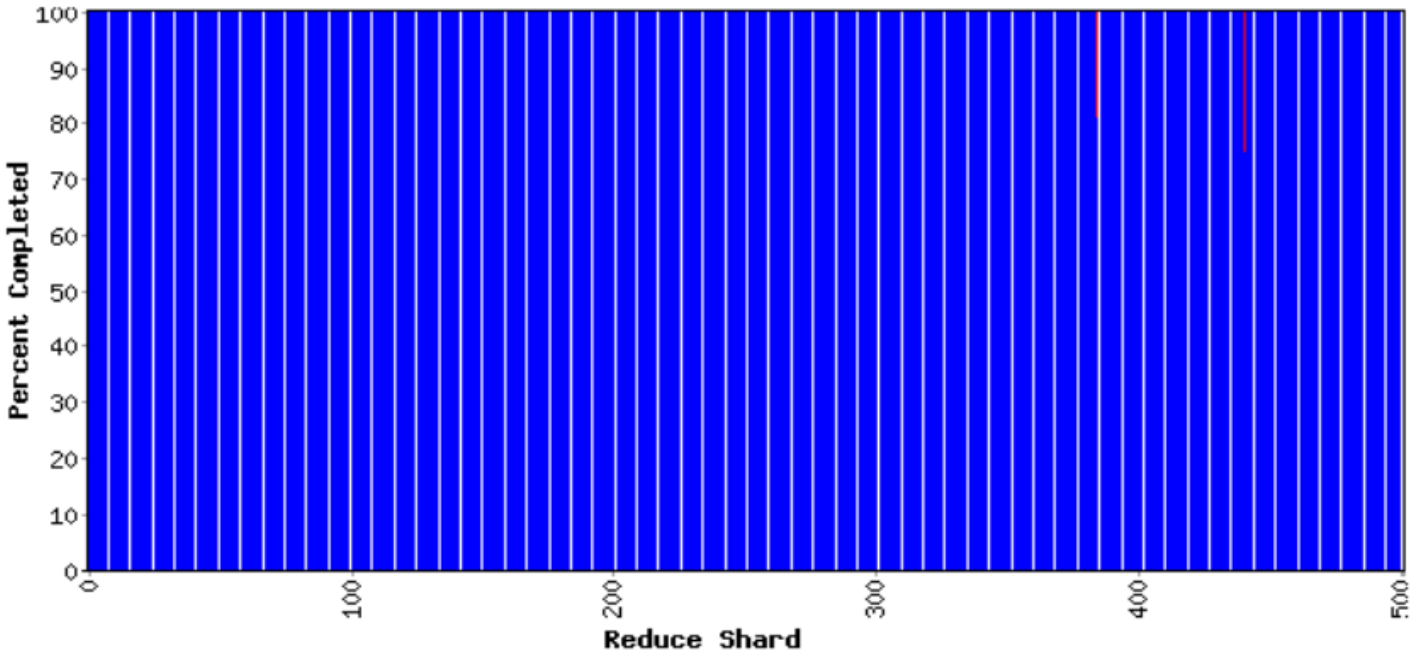
Variable	Minute
Mapped (MB/s)	0.0
Shuffle (MB/s)	0.0
Output (MB/s)	849.5
doc-index-hits	0
docs-indexed	0
dups-in-index-merge	0
mr-merge-calls	35083350
mr-merge-outputs	35083350

MapReduce status: MR_Indexer-beta6-large-2003_10_28_00_03

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

1707 workers; 1 deaths

Type	Shards	Done	Active	Input(MB)	Done(MB)	Output(MB)
Map	13853	13853	0	878934.6	878934.6	523499.2
Shuffle	500	500	0	523499.2	519781.8	519781.8
Reduce	500	498	2	519781.8	519394.7	519440.7



Counters

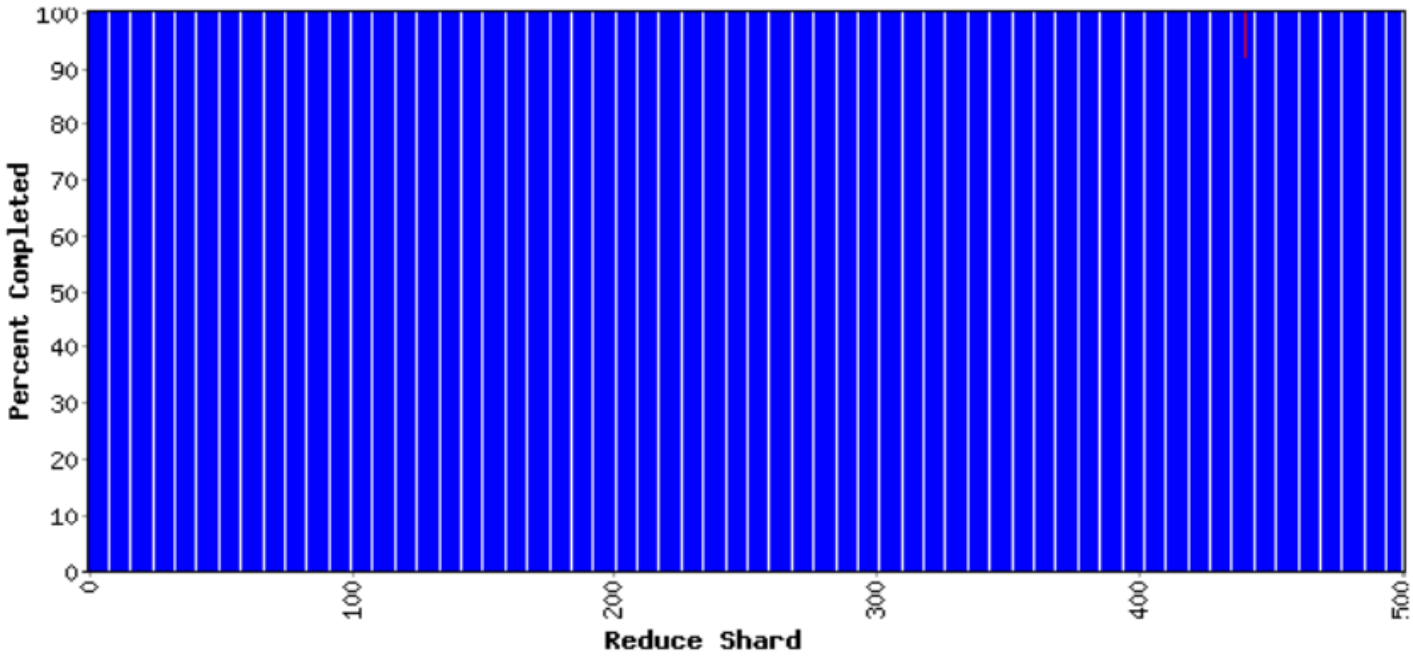
Variable	Minute	
Mapped (MB/s)	0.0	
Shuffle (MB/s)	0.0	
Output (MB/s)	9.4	
doc-index-hits	0	1056
docs-indexed	0	3
dups-in-index-merge	0	
mr-merge-calls	394792	3
mr-merge-outputs	394792	3

MapReduce status: MR_Indexer-beta6-large-2003_10_28_00_03

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

1707 workers; 1 deaths

Type	Shards	Done	Active	Input(MB)	Done(MB)	Output(MB)
Map	13853	13853	0	878934.6	878934.6	523499.2
Shuffle	500	500	0	523499.2	519774.3	519774.3
Reduce	500	499	1	519774.3	519735.2	519764.0



Counters

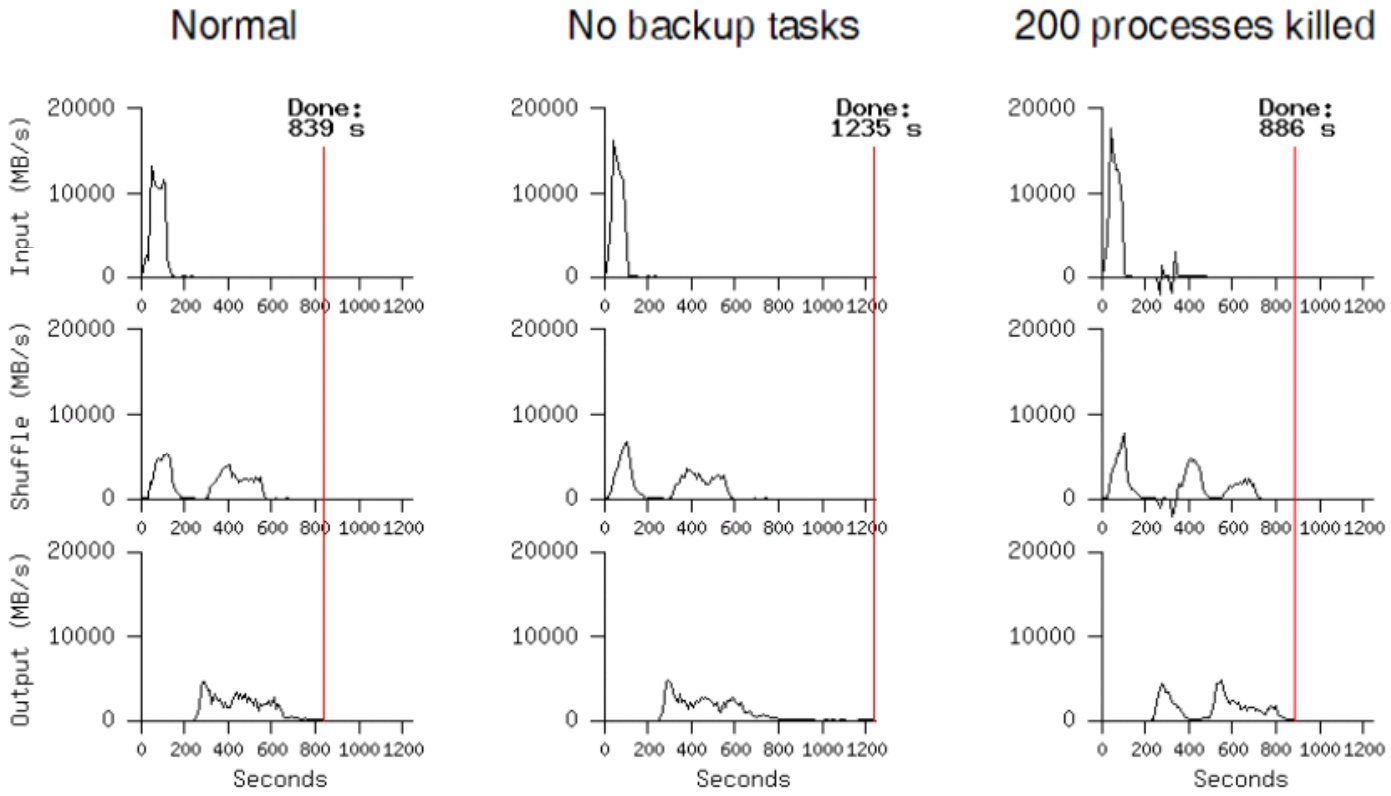
Variable	Minute	
Mapped (MB/s)	0.0	
Shuffle (MB/s)	0.0	
Output (MB/s)	1.9	
doc-index-hits	0	105
docs-indexed	0	
dups-in-index-merge	0	
mr-merge-calls	73442	
mr-merge-outputs	73442	

Refinement: Backup tasks

- Slow workers significantly slow the completion time:
  - Other jobs on the machine
  - Bad disks
  - Weird things
- Solution:
  - Near end of phase, spawn backup copies of tasks
    - Whichever one finishes first "wins"
- Effect:
  - Dramatically shortens job completion time

Refinements: Backup tasks

- Backup tasks reduce job time
- System deals with failures



Refinements: Combiners

- Often a map task will produce many pairs of the form (k,v1), (k,v2), … for the same key k
  - E.g., popular words in Word Count
- Can save network time by pre-aggregating at mapper
  - combine(k1, list(v1)) → v2
  - Usually same as reduce function
- Works only if reduce function is commutative and associative

Refinements: Partition Function

- Inputs to map tasks are created by contiguous splits of input file
- For reduce, we need to ensure that records with the same intermediate key end up at the same worker
- System uses a default partition function e.g., hash(key) mod R
- Sometimes useful to override
  - E.g., hash(hostname(URL)) mod R ensures URLs from a host end up in the same output file

Problems for Map-Reduce

- Input does not have to be big
- E.g., want to simulate disease spreading in a (small) social network
- **Input**:
  - Each line: node id, virus parameters (death, birth rate)
- **Map**:
  - Reads a line of input and simulate the virus
  - Output: triplets (node id, virus id, hit time)
- **Reduce**:
  - Collect the node IDs and see which nodes are most vulnerable

Example 1: Host size

- Suppose we have a large web corpus
- Let's look at the metadata file
  - Lines of the form (URL, size, date, …)
- For each host, find the total number of bytes
  - i.e., the sum of the page sizes for all URLs from that host

Example 2: Language model

- Statistical machine translation:
  - Need to count number of times every 5-word sequence occurs in a large corpuse of duments
- Easy with MapReduce:
  - Map: extract (5-word sequence, count) from document
  - Reduce: combine counts

Example 3: Distributed Grep

- Find all occurrences of the given pattern in a very large set of files

Example 4: Graph reversal

- Given a directed graph as an adjacency list:

src1: dest11, dest12, …
src2: dest21, dest22, …

- Construct the graph in which all the links are reversed

Implementations

- Google
  - Not available outside Google
- Hadoop
  - An open-source implementation in Java
  - Uses HDFS for stable storage
  - Download: http://lucene.apache.org/hadoop/
- Aster Data
  - Cluster-optimized SQL Database that also implements MapReduce
  - Made available free of charge for this class

Cloud Computing

- Ability to rent computing by the hour
  - Additional services e.g., persistent storage
- We will be using Amazon's "Elastic Compute Cloud" (EC2)
- Aster Data and Hadoop can both be run on EC2
- In discussions with Amazon to provide access free of charge for class

Reading

- Jeffrey Dean and Sanjay Ghemawat,

  MapReduce: Simplified Data Processing on Large Clusters
  http://labs.google.com/papers/mapreduce.html

- Sanjay Ghemawat, Howard Gobioff, and Shun-Tak Leung, **The Google File System**
  http://labs.google.com/papers/gfs.html

Resources

- **Hadoop Wiki**
  - Introduction
    - http://wiki.apache.org/lucene-hadoop/
  - Getting Started
    - http://wiki.apache.org/lucene-hadoop/GettingStartedWithHadoop
  - Map/Reduce Overview
    - http://wiki.apache.org/lucene-hadoop/HadoopMapReduce
    - http://wiki.apache.org/lucene-hadoop/HadoopMapRedClasses
  - Eclipse Environment
    - http://wiki.apache.org/lucene-hadoop/EclipseEnvironment
- **Javadoc**
  - http://lucene.apache.org/hadoop/docs/api/

Resources

- **Releases from Apache download mirrors**
  - http://www.apache.org/dyn/closer.cgi/lucene/hadoop/
- **Nightly builds of source**
  - http://people.apache.org/dist/lucene/hadoop/nightly/
- **Source code from subversion**
  - http://lucene.apache.org/hadoop/version_control.html

Further reading

- 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]