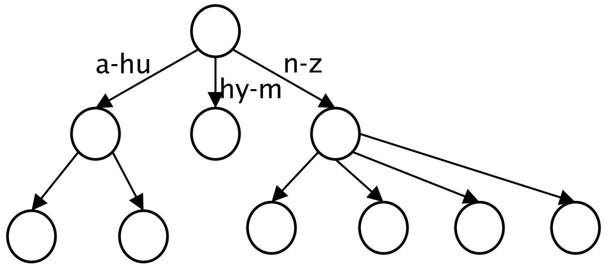
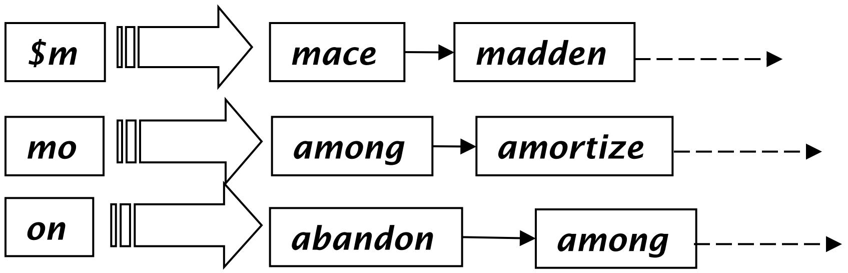
Index Construction

Plan

- Last lecture:
  - Dictionary data structures
  - Tolerant retrieval
    - Wildcards
    - Spell correction
    - Soundex
- This time:
  - Index construction





Index construction

- How do we construct an index?
- What strategies can we use with limited main memory?

Hardware basics

- Many design decisions in information retrieval are based on the characteristics of hardware
- We begin by reviewing hardware basics

Hardware basics

- Access to data in memory is ***much*** faster than access to data on disk.
- Disk seeks: No data is transferred from disk while the disk head is being positioned.
- Therefore: Transferring one large chunk of data from disk to memory is faster than transferring many small chunks.
- Disk I/O is block-based: Reading and writing of entire blocks (as opposed to smaller chunks).
- Block sizes: 8KB to 256 KB.

Hardware basics

- Servers used in IR systems now typically have several GB of main memory, sometimes tens of GB.
- Available disk space is several (2–3) orders of magnitude larger.
- Fault tolerance is very expensive: It's much cheaper to use many regular machines rather than one fault tolerant machine.

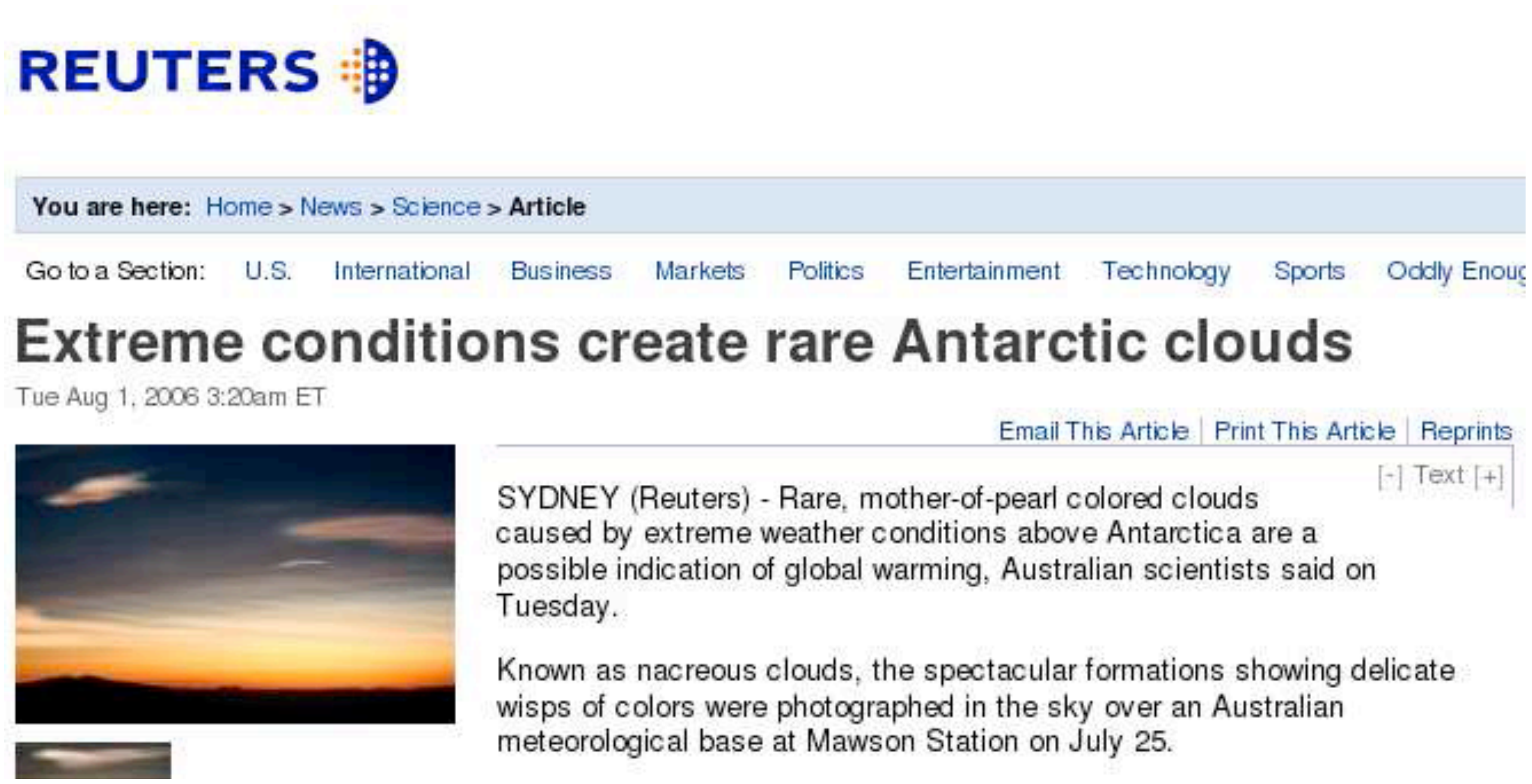
Hardware assumptions for this lecture

symbol	**statistic**	**value**
s	average seek time	5 ms = 5×10^{-3} s
b	transfer time per byte	0.02 μs = 2×10^{-8} s
	processor's clock rate	10^{9} s^{-1}
p	low-level operation (e.g., compare & swap a word)	0.01 μs = 10^{-8} s
	size of main memory	several GB
	size of disk space	1 TB or more

RCV1: Our collection for this lecture

- Shakespeare's collected works definitely aren't large enough for demonstrating many of the points in this course.
- The collection we'll use isn't really large enough either, but it's publicly available and is at least a more plausible example.
- As an example for applying scalable index construction algorithms, we will use the Reuters RCV1 collection.
- This is one year of Reuters newswire (part of 1995 and 1996)

A Reuters RCV1 document



REUTERS

You are here: Home > News > Science > **Article**

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Extreme conditions create rare Antarctic clouds

Tue Aug 1, 2006 3:20am ET

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[-] Text [+]

SYDNEY (Reuters) - Rare, mother-of-pearl colored clouds caused by extreme weather conditions above Antarctica are a possible indication of global warming, Australian scientists said on Tuesday.

Known as nacreous clouds, the spectacular formations showing delicate wisps of colors were photographed in the sky over an Australian meteorological base at Mawson Station on July 25.

Reuters RCV1 statistics

symbol	statistic	value
N	documents	800,000
L	avg. # tokens per doc	200
M	terms (= word types)	400,000
	avg. # bytes per token (incl. spaces/punct.)	6
	avg. # bytes per token (without spaces/punct.)	4.5
	avg. # bytes per term	7.5
	non-positional postings	100,000,000

Recall IIR 1 index construction

- Documents are parsed to extract words and these are saved with the Document ID.

Doc 1

I did enact Julius Caesar I was killed i' the Capitol; Brutus killed me.

Doc 2

So let it be with Caesar. The noble Brutus hath told you Caesar was ambitious

Term	Doc #
I	1
did	1
enact	1
julius	1
caesar	1
I	1
was	1
killed	1
i'	1
the	1
capitol	1
brutus	1
killed	1
me	1
so	2
let	2
it	2
be	2
with	2
caesar	2
the	2
noble	2
brutus	2
hath	2
told	2
you	2
caesar	2
was	2
ambitious	2

Key step

- After all documents have been parsed, the inverted file is sorted by terms.

We focus on this sort step.
We have 100M items to sort.

Term	Doc #
I	1
did	1
enact	1
julius	1
caesar	1
I	1
was	1
killed	1
i'	1
the	1
capitol	1
brutus	1
killed	1
me	1
so	2
let	2
it	2
be	2
with	2
caesar	2
the	2
noble	2
brutus	2
hath	2
told	2
you	2
caesar	2
was	2
ambitious	2

Term	Doc #
ambitious	2
be	2
brutus	1
brutus	2
capitol	1
caesar	1
caesar	2
caesar	2
did	1
enact	1
hath	1
I	1
I	1
i'	1
it	2
julius	1
killed	1
killed	1
let	2
me	1
noble	2
so	2
the	1
the	2
told	2
you	2
was	1
was	2
with	2

Scaling index construction

- In-memory index construction does not scale
  - Can't stuff entire collection into memory, sort, then write back
- How can we construct an index for very large collections?
- Taking into account the hardware constraints we just learned about . . .
- Memory, disk, speed, etc.

Sort-based index construction

- As we build the index, we parse docs one at a time.
  - While building the index, we cannot easily exploit compression tricks (you can, but much more complex)
- The final postings for any term are incomplete until the end.
- At 12 bytes per non-positional postings entry *(term, doc, freq)*, demands a lot of space for large collections.
- T = 100,000,000 in the case of RCV1
  - So … we can do this in memory in 2009, but typical collections are much larger. E.g., the *New York Times* provides an index of >150 years of newswire
- Thus: We need to store intermediate results on disk.

Sort using disk as "memory"?

- Can we use the same index construction algorithm for larger collections, but by using disk instead of memory?
- No: Sorting T = 100,000,000 records on disk is too slow – too many disk seeks.
- We need an *external* sorting algorithm.

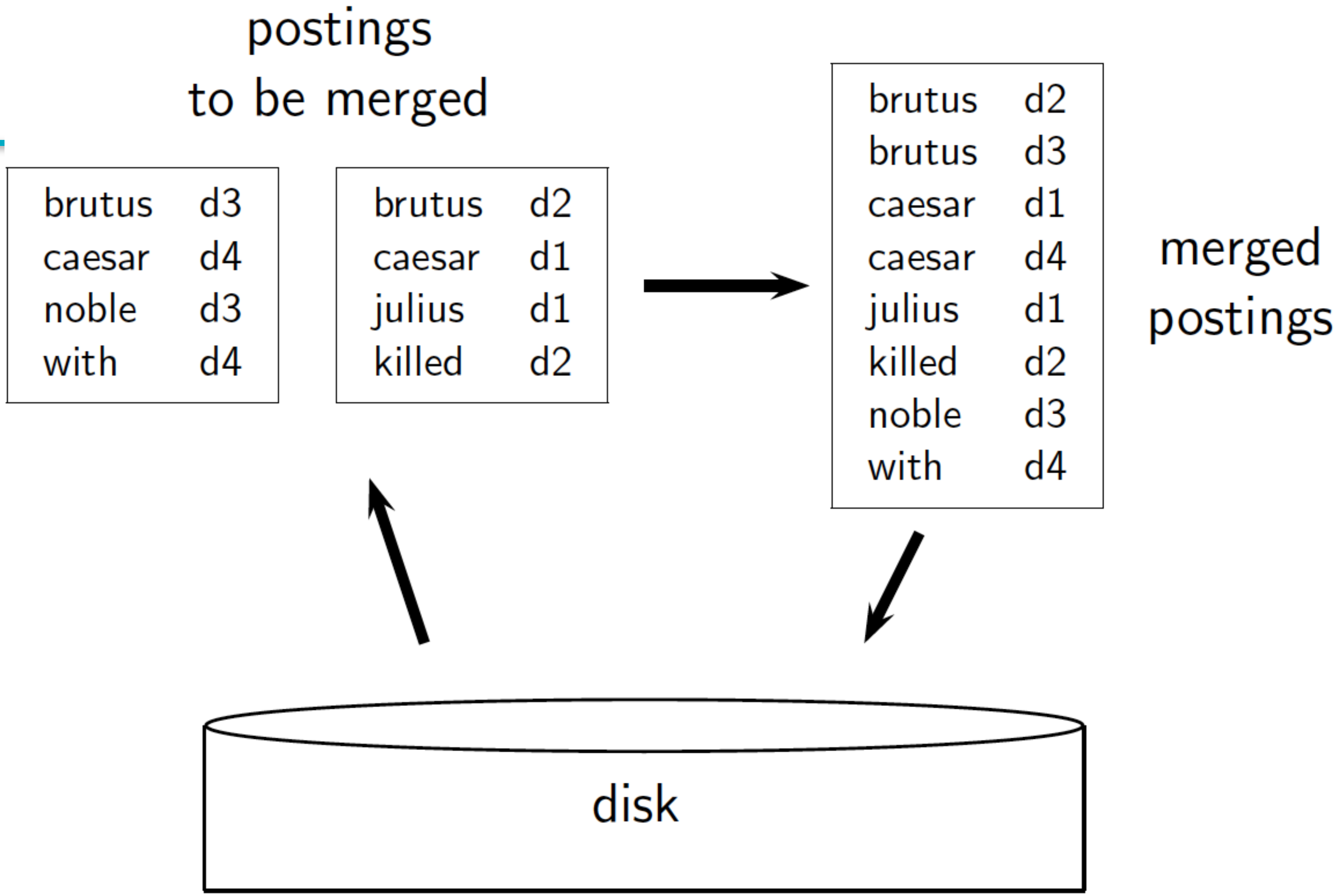
Bottleneck

- Parse and build postings entries one doc at a time
- Now sort postings entries by term (then by doc within each term)
- Doing this with random disk seeks would be too slow – must sort T=100M records

If every comparison took 2 disk seeks, and N items could be sorted with $N \log_2 N$ comparisons

BSBI: Blocked sort-based Indexing (Sorting with fewer disk seeks)

- 12-byte (4+4+4) records *(term, doc, freq).*
- These are generated as we parse docs.
- Must now sort 100M such 12-byte records by *term*.
- Define a <u>Block</u> $\boxed{\sim 10\text{M}}$ such records
  - Can easily fit a couple into memory.
  - Will have $\boxed{10}$ such blocks to start with.
- Basic idea of algorithm:
  - Accumulate postings for each block, sort, write to disk.
  - Then merge the blocks into one long sorted order.



brutus	d3
caesar	d4
noble	d3
with	d4

brutus	d2
caesar	d1
julius	d1
killed	d2

brutus	d2
brutus	d3
caesar	d1
caesar	d4
julius	d1
killed	d2
noble	d3
with	d4

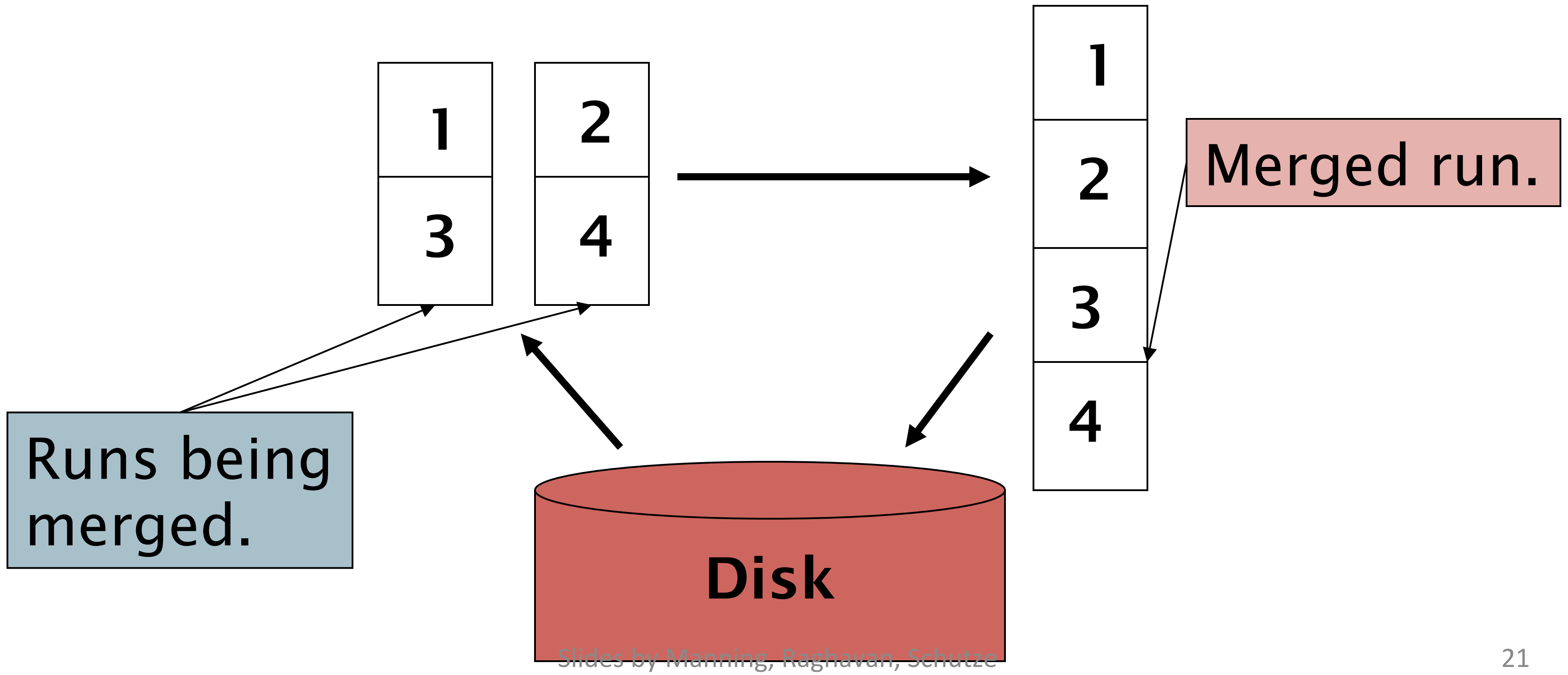
Sorting 10 blocks of 10M records

- First, read each block and sort within:
  - Quicksort takes 2*N* ln *N* expected steps
  - In our case 2 x (10M ln 10M) steps
- *Exercise: estimate total time to read each block from disk and and quicksort it.*
- 10 times this estimate – gives us 10 sorted *runs* of 10M records each.
- Done straightforwardly, need 2 copies of data on disk
  - But can optimize this

```
BSBIndexConstruction()
1  $n \leftarrow 0$
2  while (all documents have not been processed)
3  do $n \leftarrow n + 1$
4      $block \leftarrow$ ParseNextBlock()
5      BSBI-Invert($block$)
6      WriteBlockToDisk($block, f_n$)
7  MergeBlocks($f_1, \ldots, f_n; f_{\text{merged}}$)
```

How to merge the sorted runs?

- Can do binary merges, with a merge tree of $\log_2 10 = 4$ layers.
- During each layer, read into memory runs in blocks of 10M, merge, write back.



How to merge the sorted runs?

- But it is more efficient to do a multi-way merge, where you are reading from all blocks simultaneously
- Providing you read decent-sized chunks of each block into memory and then write out a decent-sized output chunk, then you' re not killed by disk seeks

Remaining problem with sort-based algorithm

- Our assumption was: we can keep the dictionary in memory.
- We need the dictionary (which grows dynamically) in order to implement a term to termID mapping.
- Actually, we could work with term,docID postings instead of termID,docID postings . . .
- . . . but then intermediate files become very large. (We would end up with a scalable, but very slow index construction method.)

SPIMI: Single-pass in-memory indexing

- Key idea 1: Generate separate dictionaries for each block – no need to maintain term-termID mapping across blocks.
- Key idea 2: Don't sort. Accumulate postings in postings lists as they occur.
- With these two ideas we can generate a complete inverted index for each block.
- These separate indexes can then be merged into one big index.

SPIMI-Invert

```
SPIMI-INVERT(token_stream)
1   output_file = NEWFILE()
2   dictionary = NEWHASH()
3   while (free memory available)
4   do token ← next(token_stream)
5       if term(token) ∉ dictionary
6         then postings_list = ADDTODICTIONARY(dictionary, term(token))
7         else postings_list = GETPOSTINGSLIST(dictionary, term(token))
8       if full(postings_list)
9         then postings_list = DOUBLEPOSTINGSLIST(dictionary, term(token))
10      ADDTOPOSTINGSLIST(postings_list, docID(token))
11  sorted_terms ← SORTTERMS(dictionary)
12  WRITEBLOCKTODISK(sorted_terms, dictionary, output_file)
13  return output_file
```

- Merging of blocks is analogous to BSBI.

SPIMI: Compression

- Compression makes SPIMI even more efficient.
  - Compression of terms
  - Compression of postings
- See next lecture

Distributed indexing

- For web-scale indexing (don't try this at home!):
  must use a distributed computing cluster
- Individual machines are fault-prone
  - Can unpredictably slow down or fail
- How do we exploit such a pool of machines?

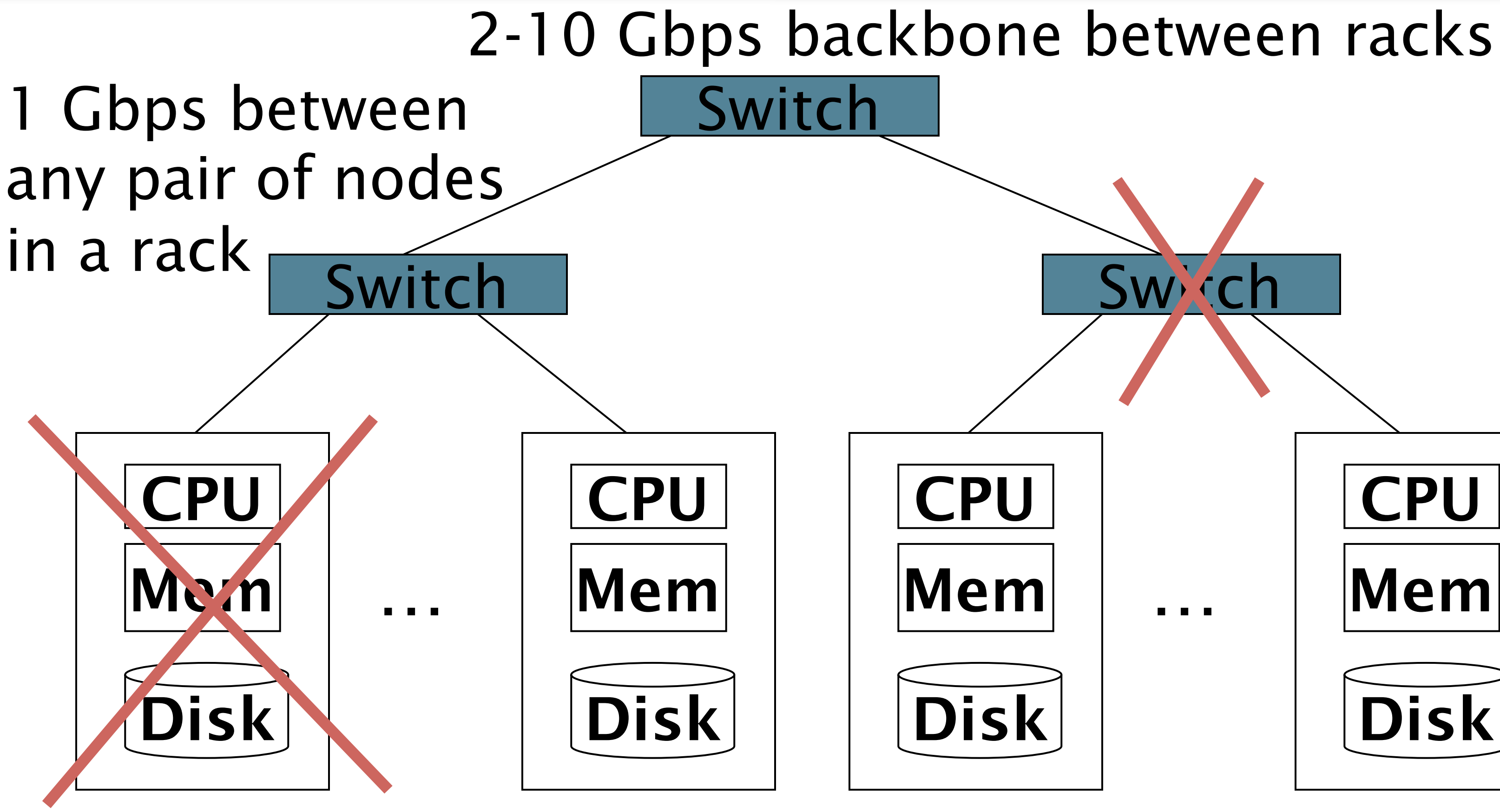
Web search engine data centers

- Web search data centers (Google, Bing, Baidu) mainly contain commodity machines.
- Data centers are distributed around the world.
- Estimate: Google ~1 million servers, 3 million processors/cores (Gartner 2007)

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


2-10 Gbps backbone between racks
1 Gbps between any pair of nodes in a rack
Switch
Switch
Switch
CPU
Mem
Disk
…
CPU
Mem
Disk
CPU
Mem
Disk
…
CPU
Mem
Disk

Each rack contains 16-64 nodes

M45: Open Academic Cluster

- Yahoo M45 cluster:
  - Datacenter in a Box (DiB)
  - 1000 nodes, 4000 cores, 3TB RAM, 1.5PB disk
  - High bandwidth connection to Internet
  - Located on Yahoo! campus
  - World's top 50 supercomputer

Large scale computing

- **Large scale computing** for **IR** problems on **commodity hardware:**
  - PCs connected in a network
  - Process huge datasets on many computers
- Challenges:
  - How do you distribute computation?
  - Distributed/parallel 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

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 1,000 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

- Problem:
  - If nodes fail, how to 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

- 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 Hadoop's HDFS
  - Stores metadata
  - Might be replicated
- Client library for file access:
  - Talks to master to find chunk servers
  - Connects directly to chunk servers 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

Warm up: Word Count (2)

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

Warm up: Word Count (3)

- Suppose we have a large corpus of documents
- Count occurrences of words:
  - **`words(docs/*) | sort | uniq -c`**
    - where **`words`** takes a file and outputs the words in it, one per a line
- Captures the essence of MapReduce
  - Great thing is it is naturally parallelizable

Map-Reduce: Overview

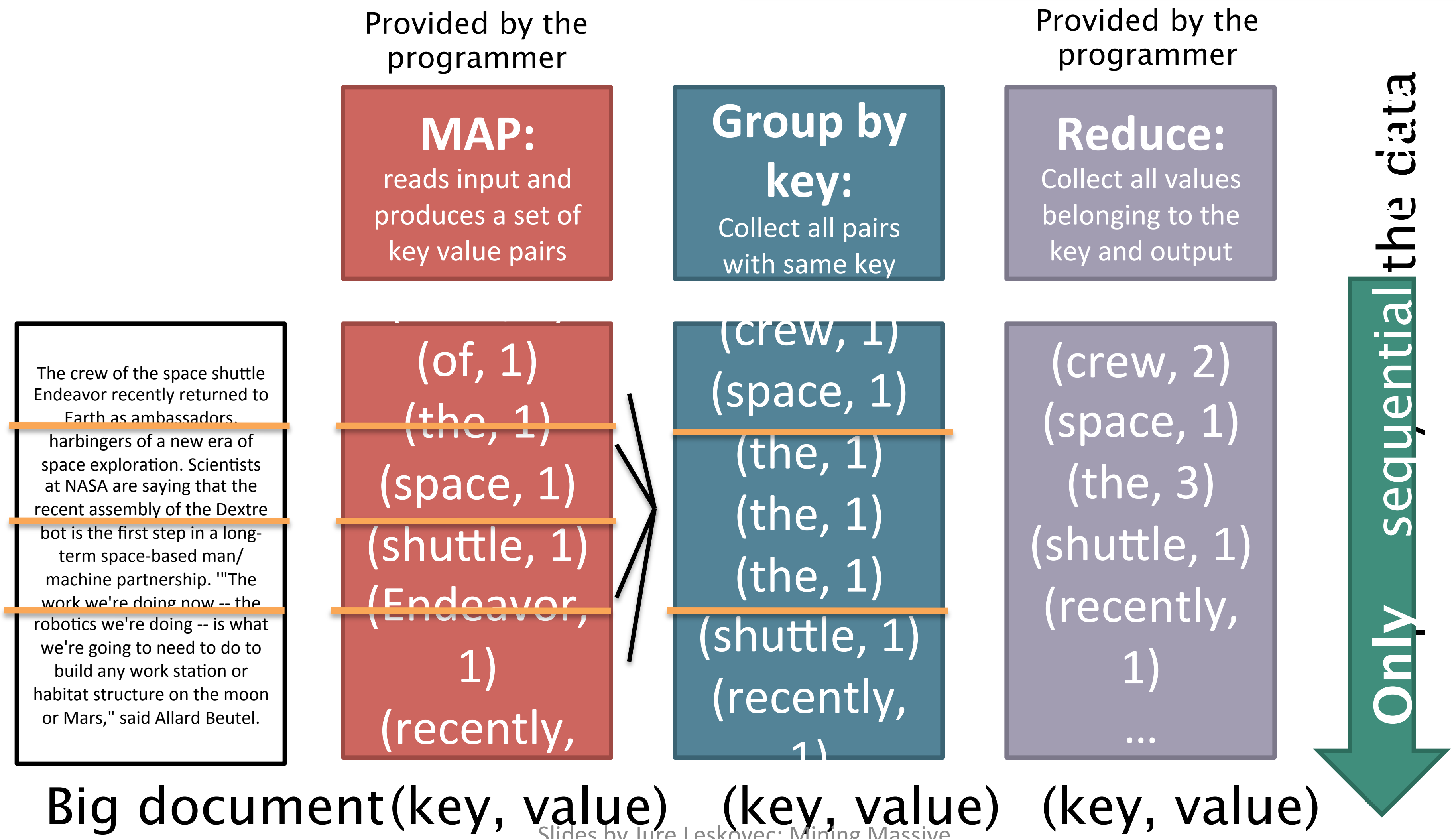
- Read a lot of data
- **Map:**
  - Extract something you care about
- Shuffle and Sort
- **Reduce:**
  - Aggregate, summarize, filter or transform
- Write the result

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 values v' with same key k' are reduced together and processed in v' order

Map-Reduce: Word counting



Provided by the programmer
MAP: reads input and produces a set of key value pairs
Group by key: Collect all pairs with same key
Provided by the programmer
Reduce: Collect all values belonging to the key and output
Only sequential reads of the data

The crew of the space shuttle Endeavor recently returned to Earth as ambassadors, harbingers of a new era of space exploration. Scientists at NASA are saying that the recent assembly of the Dextre bot is the first step in a long-term space-based man/machine partnership. '"The work we're doing now -- the robotics we're doing -- is what we're going to need to do to build any work station or habitat structure on the moon or Mars," said Allard Beutel.

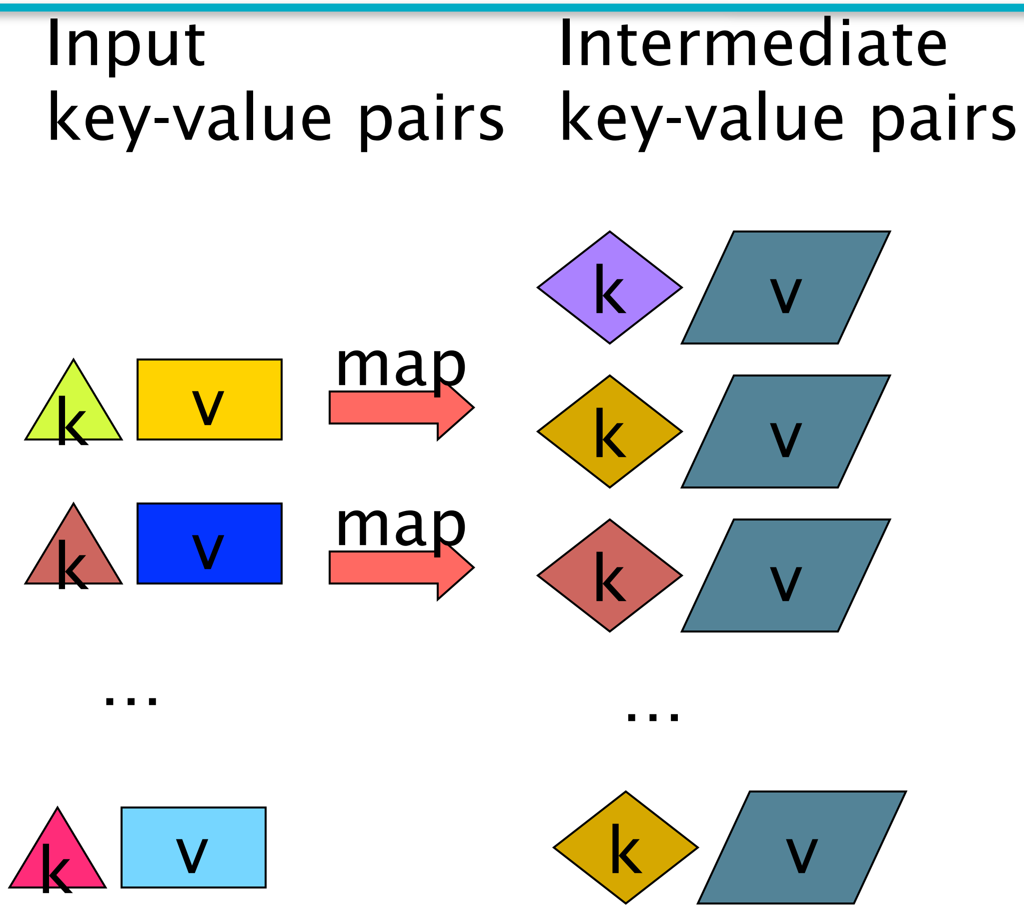
(of, 1)
(the, 1)
(space, 1)
(shuttle, 1)
(Endeavor, 1)
(recently,

(crew, 1)
(space, 1)
(the, 1)
(the, 1)
(the, 1)
(shuttle, 1)
(recently,

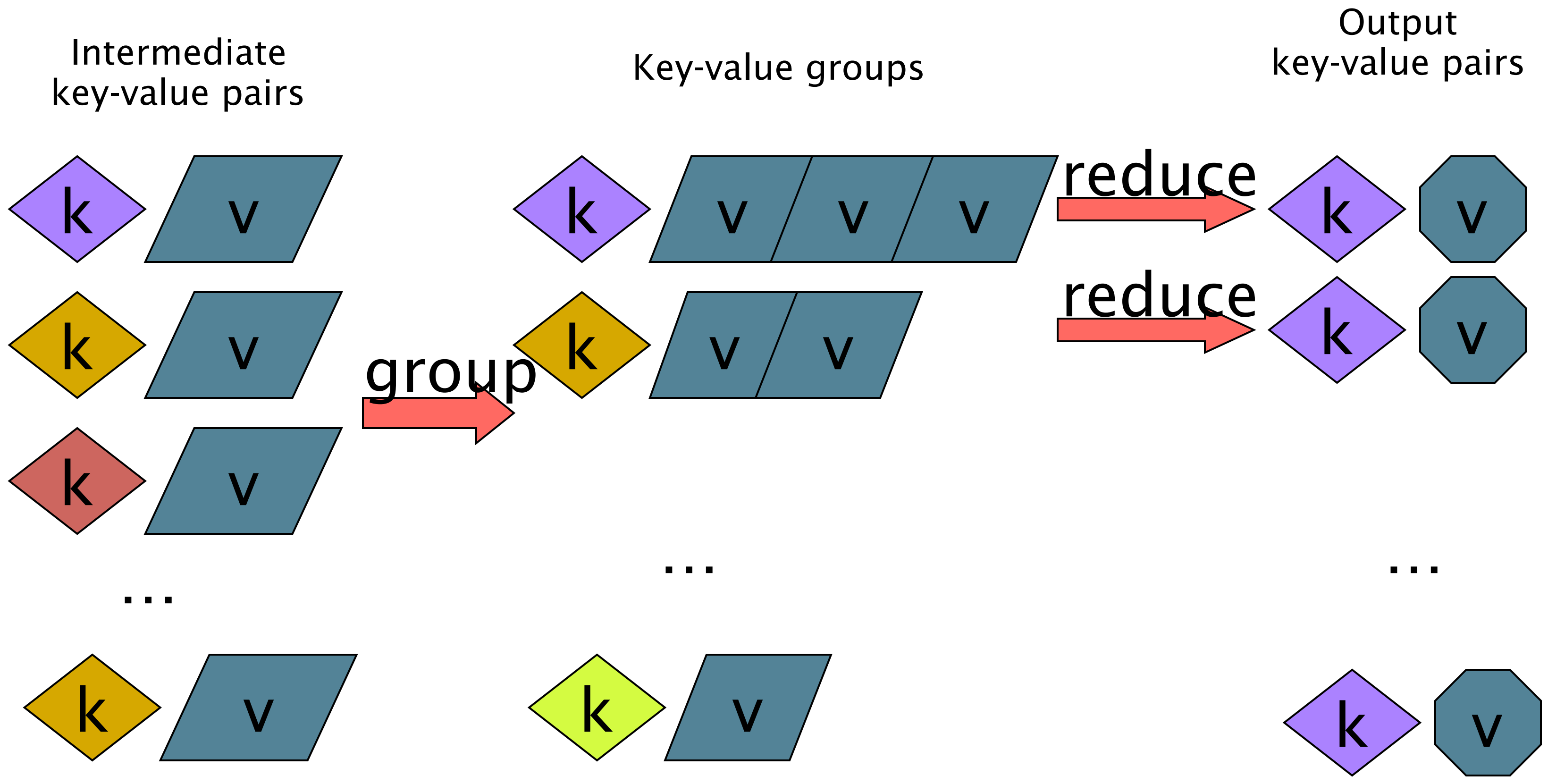
(crew, 2)
(space, 1)
(the, 3)
(shuttle, 1)
(recently, 1)
…

Big document (key, value) (key, value) (key, value)

MapReduce: The Map Step



MapReduce: The Reduce Step



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

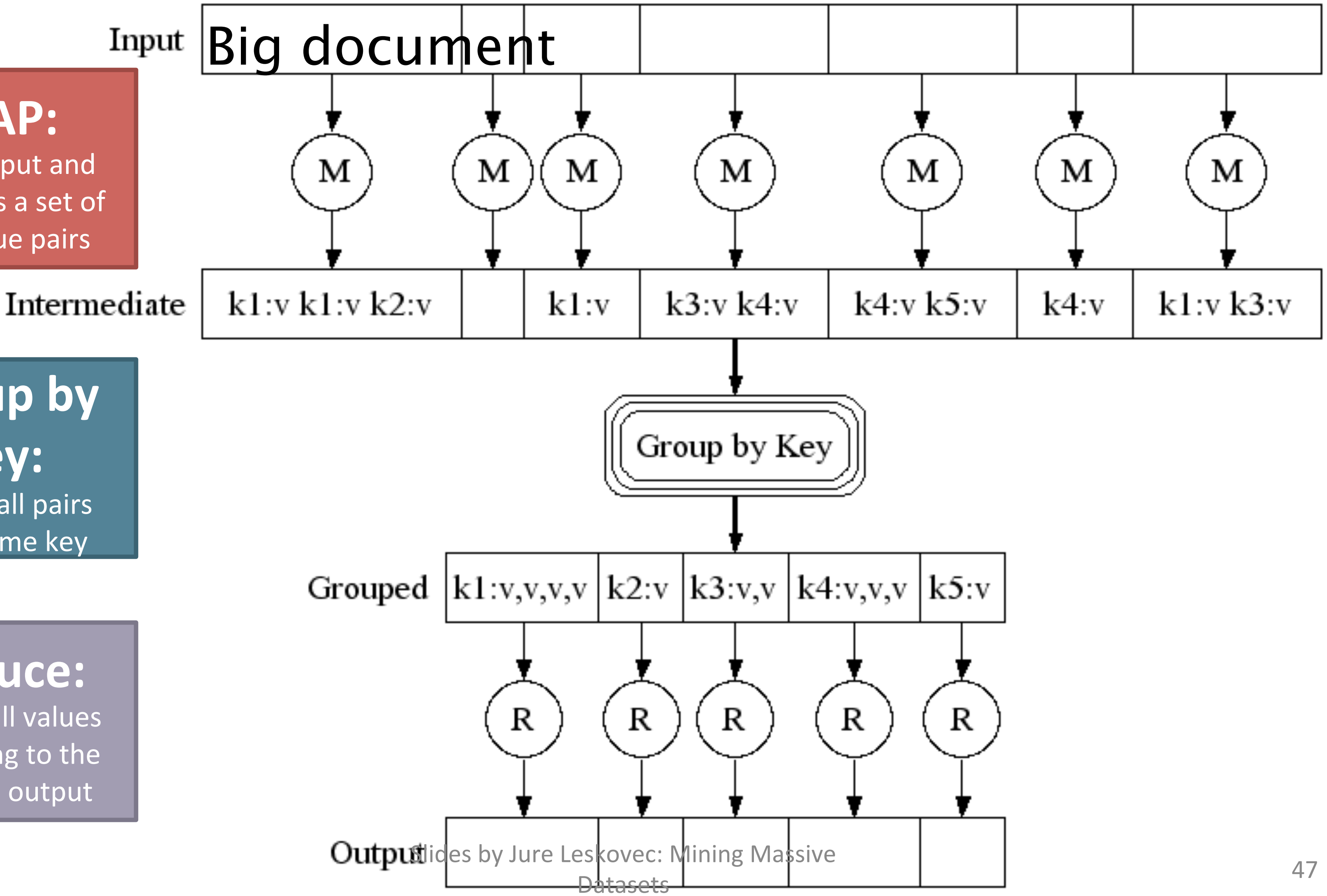
- Map-Reduce environment takes care of:
  - Partitioning the input data
  - Scheduling the program's execution across a set of machines
  - Handling machine failures
  - Managing required inter-machine communication
- Allows programmers without a PhD in parallel and distributed systems to use large distributed clusters

Map-Reduce: A diagram

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

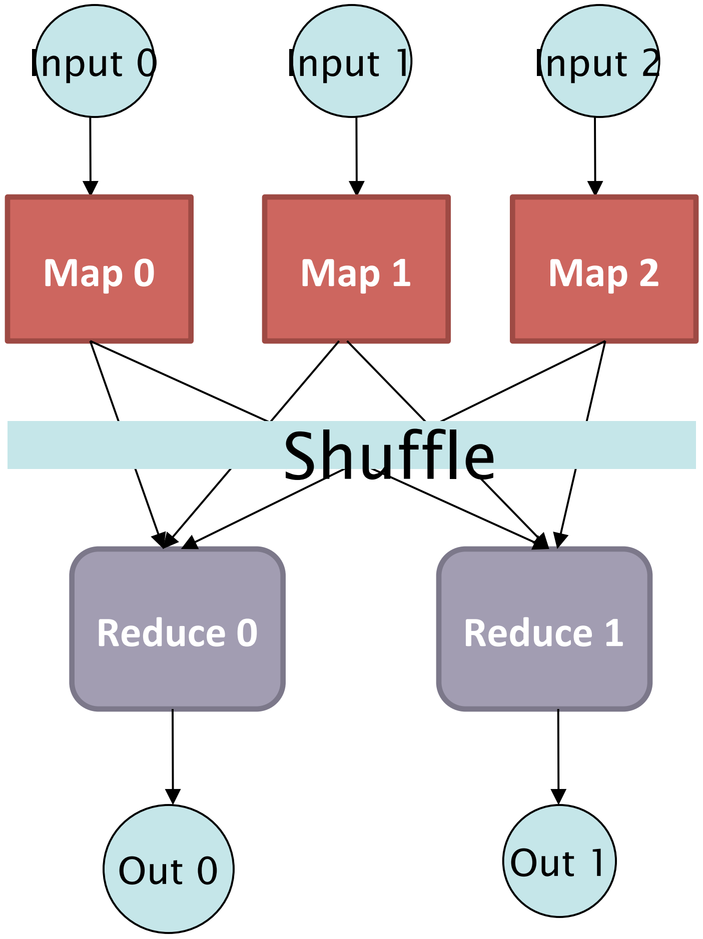
Group by key:
Collect all pairs with same key

Reduce:
Collect all values belonging to the key and output

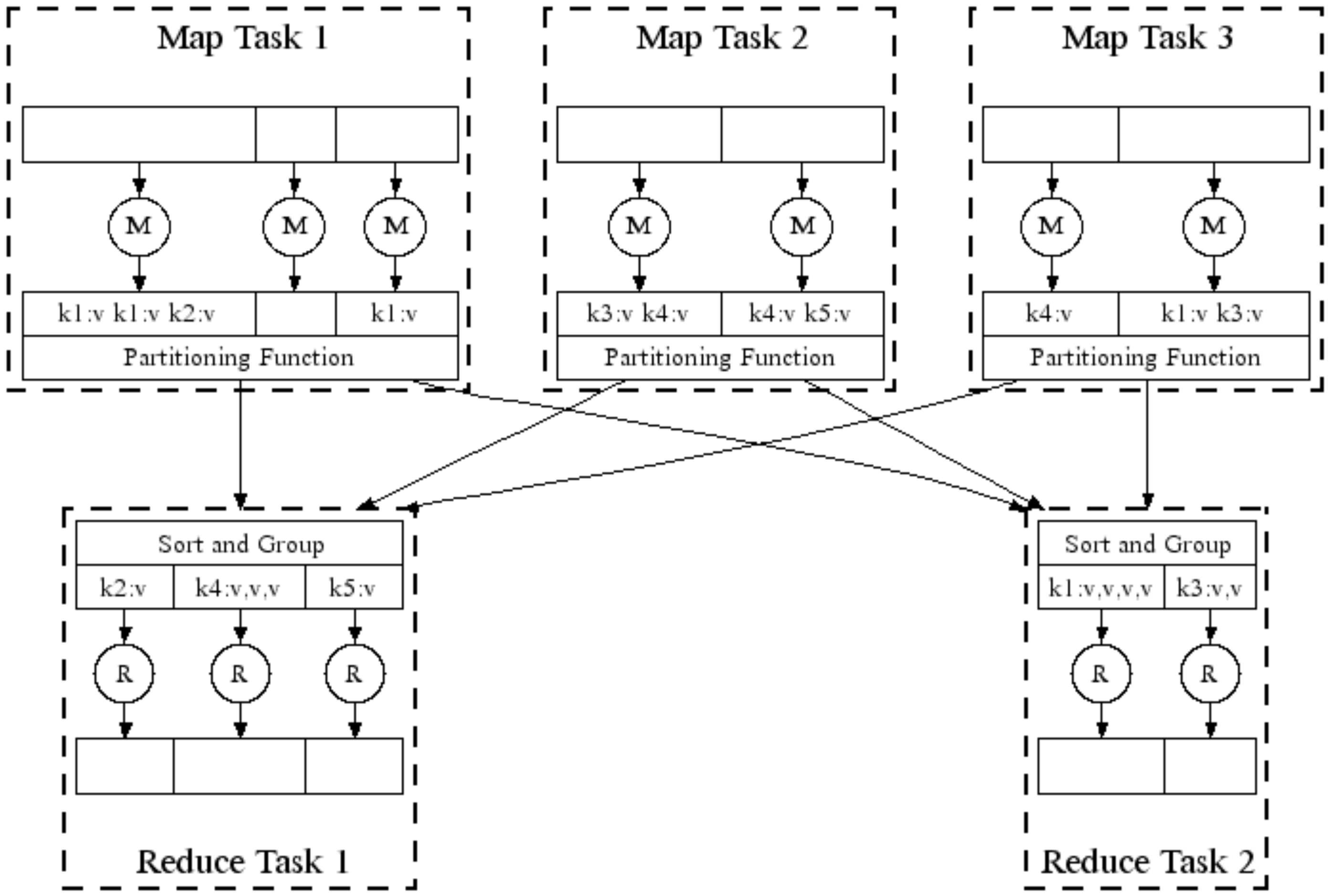


Map-Reduce

- 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



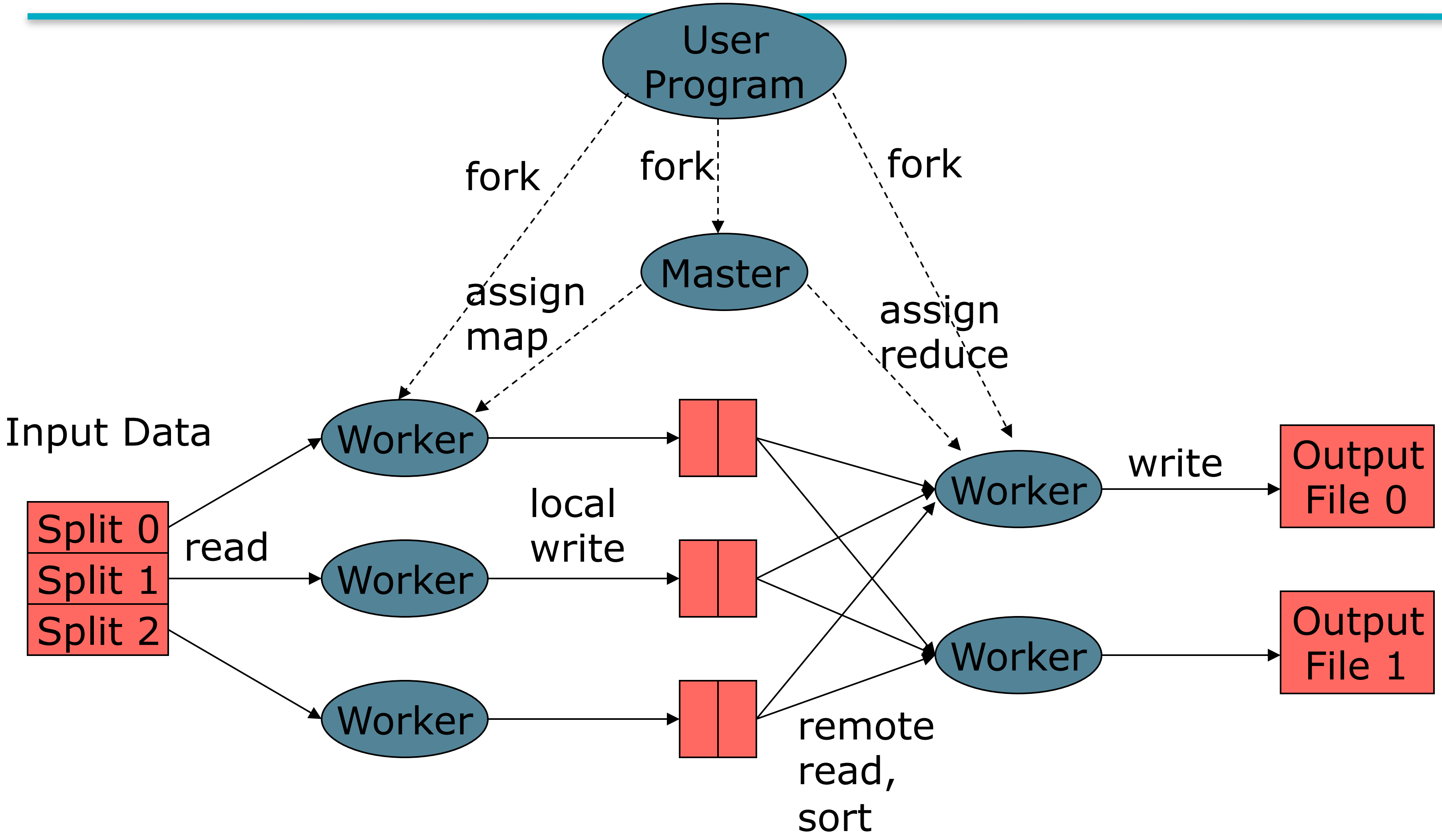
Implementation

- A program forks a *master* process and many *worker* processes.
- Input is partitioned into some number of *splits*.
- Worker processes are assigned either to perform Map on a split or Reduce for some set of intermediate keys.

Data flow

- Input and 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

Distributed Execution Overview



Responsibility of the Master

1. Assign Map and Reduce tasks to Workers.
2. Check that no Worker has died (because its processor failed).
3. Communicate results of Map to the Reduce tasks.

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

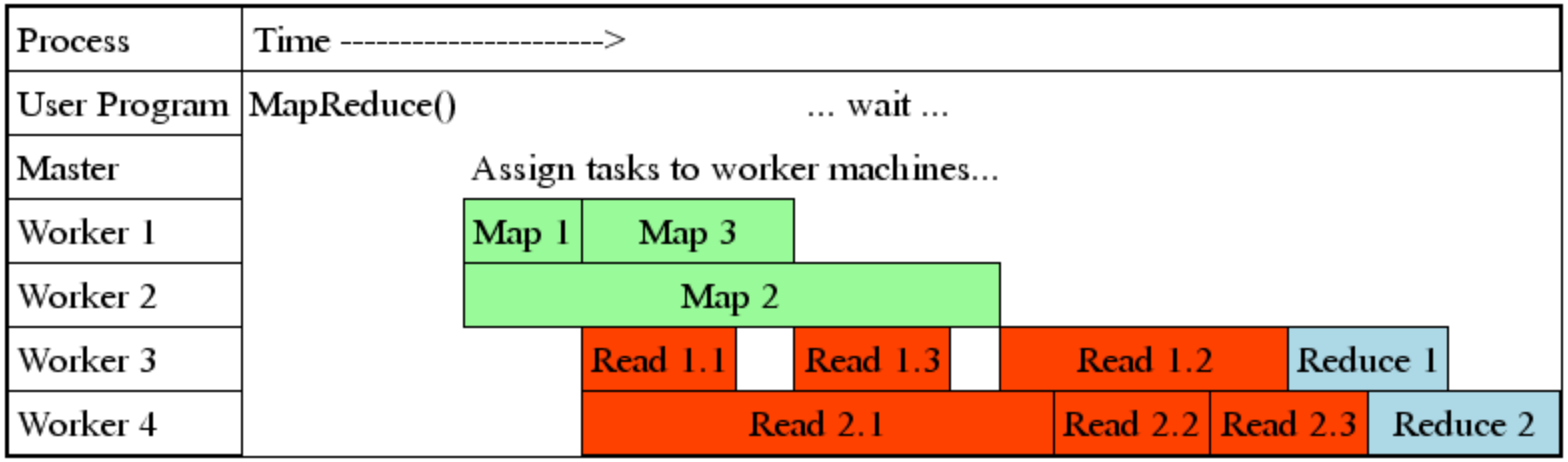
- Map worker failure
  - Map tasks completed or in-progress at worker are reset to idle
  - Reduce workers are notified when task is rescheduled on another worker
- Reduce worker failure
  - Only in-progress tasks are reset to idle
- Master failure
  - MapReduce task is aborted and client is notified

How many Map and Reduce jobs?

- M map tasks, R reduce tasks
- Rule of thumb:
  - Make M and R much larger than the number of nodes in cluster
  - One DFS chunk per map is common
  - Improves dynamic load balancing and speeds recovery from worker failure
- Usually R is smaller than M
  - because output is spread across R files

Task Granularity & Pipelining

- Fine granularity tasks: map tasks >> machines
  - Minimizes time for fault recovery
  - Can pipeline shuffling with map execution
  - Better dynamic load balancing



Distributed indexing

- Maintain a *master* machine directing the indexing job – considered "safe".
- Break up indexing into sets of (parallel) tasks.
- Master machine assigns each task to an idle machine from a pool.

Parallel tasks

- We will use two sets of parallel tasks
  - Parsers
  - Inverters
- Break the input document collection into *splits*
- Each split is a subset of documents (corresponding to blocks in BSBI/SPIMI)

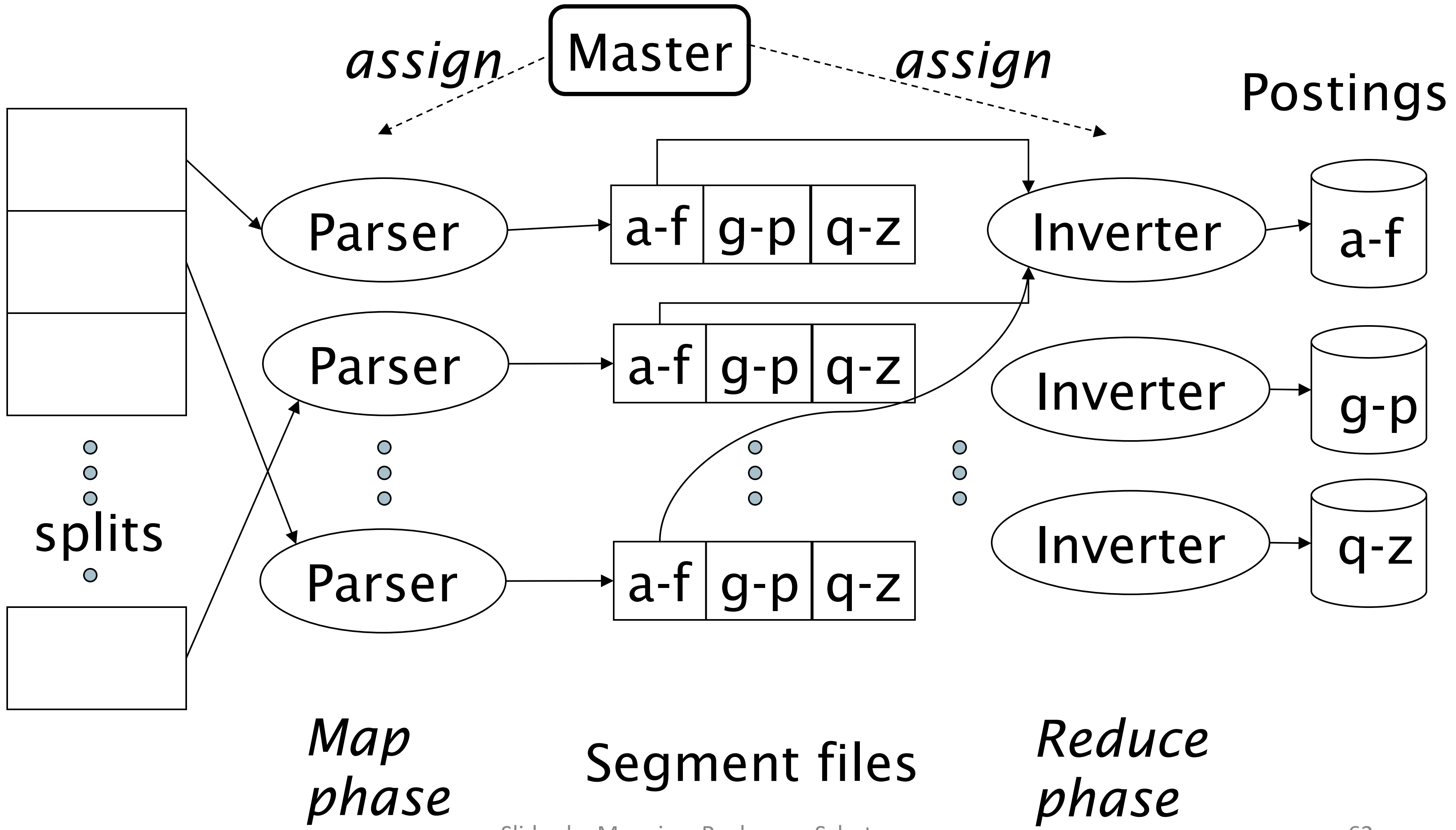
Parsers

- Master assigns a split to an idle parser machine
- Parser reads a document at a time and emits (term, doc) pairs
- Parser writes pairs into *j* partitions
- Each partition is for a range of terms' first letters
  - (e.g., ***a-f, g-p, q-z***) – here *j* = 3.
- Now to complete the index inversion

Inverters

- An inverter collects all (term,doc) pairs (= postings) for <u>one</u> term-partition.
- Sorts and writes to postings lists

Data flow


Master
assign
assign
Postings
Parser
Parser
Parser
a-f g-p q-z
a-f g-p q-z
a-f g-p q-z
Inverter
Inverter
Inverter
a-f
g-p
q-z
splits
Map phase
Segment files
Reduce phase

MapReduce

- The index construction algorithm we just described is an instance of *MapReduce*.
- MapReduce (Dean and Ghemawat 2004) is a robust and conceptually simple framework for distributed computing …
- … without having to write code for the distribution part.
- They describe the Google indexing system (ca. 2002) as consisting of a number of phases, each implemented in MapReduce.

MapReduce

- Index construction was just one phase.
- Another phase: transforming a term-partitioned index into a document-partitioned index.
  - *Term-partitioned:* one machine handles a subrange of terms
  - *Document-partitioned:* one machine handles a subrange of documents
- As we' ll discuss in the web part of the course, most search engines use a document-partitioned index … better load balancing, etc.

Schema for index construction in MapReduce

- **Schema of map and reduce functions**
- map: input → list(k, v) reduce: (k,list(v)) → output
- **Instantiation of the schema for index construction**
- map: collection → list(termID, docID)
- reduce: (<termID1, list(docID)>, <termID2, list(docID)>, …) → (postings list1, postings list2, …)

Example for index construction

- Map:
- d1 : C came, C c’ ed.
- d2 : C died. →
- <C,d1>, <came,d1>, <C,d1>, <c’ ed, d1>, <C, d2>, <died,d2>
- Reduce:
- (<C,(d1,d2,d1)>, <died,(d2)>, <came,(d1)>, <c’ ed, (d1)>) → (<C,(d1:2,d2:1)>, <died,(d2:1)>, <came, (d1:1)>, <c’ ed,(d1:1)>)

Example: Join By Map-Reduce

- **Compute the natural join *R(A,B)* ⋈ *S(B,C)***
- *R* and *S* are each stored in files
- Tuples are pairs *(a,b)* or *(b,c)*

A	B
a_1	b_1
a_2	b_1
a_3	b_2
a_4	b_3

R

⋈

B	C
b_2	c_1
b_2	c_2
b_3	c_3

S

=

A	C
a_3	c_1
a_3	c_2
a_4	c_3

Map-Reduce Join

- **Use a hash function *h* from B-values to *1...k***
- **A Map process turns:**
  - Each input tuple *R(a,b)* into key-value pair *(b,(a,R))*
  - Each input tuple *S(b,c)* into *(b,(c,S))*
- **Map processes** send each key-value pair with key *b* to Reduce process *h(b)*
  - Hadoop does this automatically; just tell it what *k* is.
- Each **Reduce process** matches all the pairs *(b,(a,R))* with all *(b,(c,S))* and outputs *(a,b,c)*.

Cost Measures for Algorithms

- **In MapReduce we quantify the cost of an algorithm using**

1. *Communication cost* = total I/O of all processes
2. *Elapsed communication cost* = max of I/O along any path
3. (*Elapsed*) *computation cost* analogous, but count only running time of processes

Note that here the big-O notation is not the most useful
(adding more machines is always an option)

Example: Cost Measures

- **For a map-reduce algorithm:**
  - **Communication cost =** input file size + 2 × (sum of the sizes of all files passed from Map processes to Reduce processes) + the sum of the output sizes of the Reduce processes.
  - **Elapsed communication cost** is the sum of the largest input + output for any map process, plus the same for any reduce process

What Cost Measures Mean

- Either the I/O (communication) or processing (computation) cost dominates
  - Ignore one or the other
- Total cost tells what you pay in rent from your friendly neighborhood cloud
- Elapsed cost is wall-clock time using parallelism

Cost of Map-Reduce Join

- **Total communication cost** $= O(|R|+|S|+|R \bowtie S|)$
- **Elapsed communication cost** = O(s)
  - We're going to pick ***k*** and the number of Map processes so that the I/O limit ***s*** is respected
  - We put a limit ***s*** on the amount of input or output that any one process can have. ***s* could be:**
    - What fits in main memory
    - What fits on local disk
- With proper indexes, computation cost is linear in the input + output size
  - So computation cost is like comm. cost

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

Cloud Computing

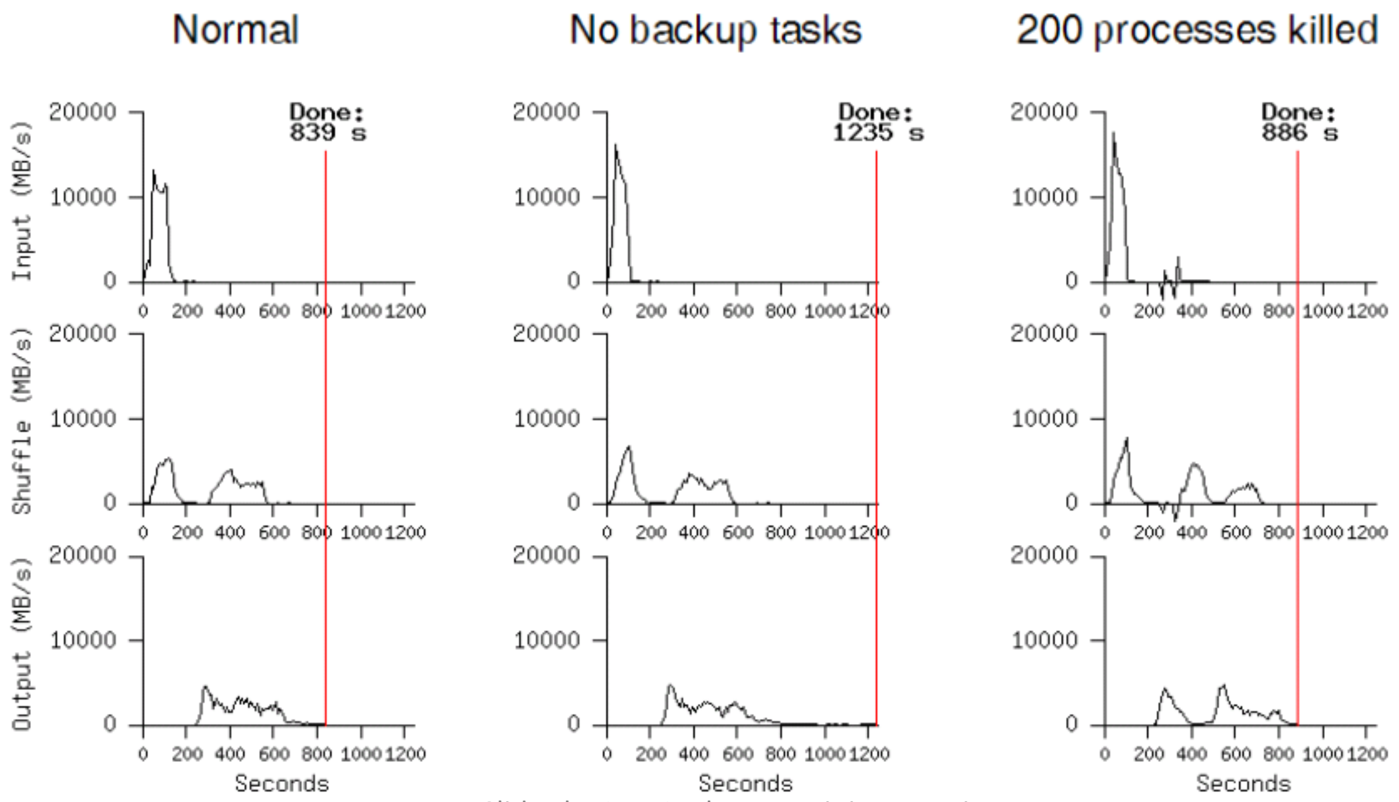
- Ability to rent computing by the hour
  - Additional services e.g., persistent storage
- Amazon's "Elastic Compute Cloud" (EC2)
- Aster Data and Hadoop can both be run on EC2

Refinement: Backup tasks

- Problem:
  - Slow workers significantly lengthen the job 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)) $\rightarrow$ v2
  - Usually same as the 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
- Reduce needs to ensure that records with the same intermediate key end up at the same worker
- System uses a default partition function:
  - 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

Dynamic indexing

- Up to now, we have assumed that collections are static.
- They rarely are:
  - Documents come in over time and need to be inserted.
  - Documents are deleted and modified.
- This means that the dictionary and postings lists have to be modified:
  - Postings updates for terms already in dictionary
  - New terms added to dictionary

Simplest approach

- Maintain "big" main index
- New docs go into "small" auxiliary index
- Search across both, merge results
- Deletions
  - Invalidation bit-vector for deleted docs
  - Filter docs output on a search result by this invalidation bit-vector
- Periodically, re-index into one main index

Issues with main and auxiliary indexes

- Problem of frequent merges – you touch stuff a lot
- Poor performance during merge
- Actually:
  - Merging of the auxiliary index into the main index is efficient if we keep a separate file for each postings list.
  - Merge is the same as a simple append.
  - But then we would need a lot of files – inefficient for OS.
- Assumption for the rest of the lecture: The index is one big file.
- In reality: Use a scheme somewhere in between (e.g., split very large postings lists, collect postings lists of length 1 in one file etc.)

Logarithmic merge

- Maintain a series of indexes, each twice as large as the previous one
  - At any time, some of these powers of 2 are instantiated
- Keep smallest (Z_0) in memory
- Larger ones (I_0, I_1, …) on disk
- If Z_0 gets too big (> *n*), write to disk as I_0
- or merge with I_0 (if I_0 already exists) as Z_1
- Either write merge Z_1 to disk as I_1 (if no I_1)
- Or merge with I_1 to form Z_2

```
LMergeAddToken($indexes, Z_0, token$)
1  $Z_0 \leftarrow$ Merge($Z_0, \{token\}$)
2  if $|Z_0| = n$
3    then for $i \leftarrow 0$ to $\infty$
4           do if $I_i \in indexes$
5                then $Z_{i+1} \leftarrow$ Merge($I_i, Z_i$)
6                       ($Z_{i+1}$ is a temporary index on disk.)
7                     $indexes \leftarrow indexes - \{I_i\}$
8                else $I_i \leftarrow Z_i$     ($Z_i$ becomes the permanent index $I_i$.)
9                     $indexes \leftarrow indexes \cup \{I_i\}$
10                    Break
11         $Z_0 \leftarrow \emptyset$
```

```
LogarithmicMerge()
1  $Z_0 \leftarrow \emptyset$     ($Z_0$ is the in-memory index.)
2  $indexes \leftarrow \emptyset$
3  while true
4  do LMergeAddToken($indexes, Z_0$, getNextToken())
```

Logarithmic merge

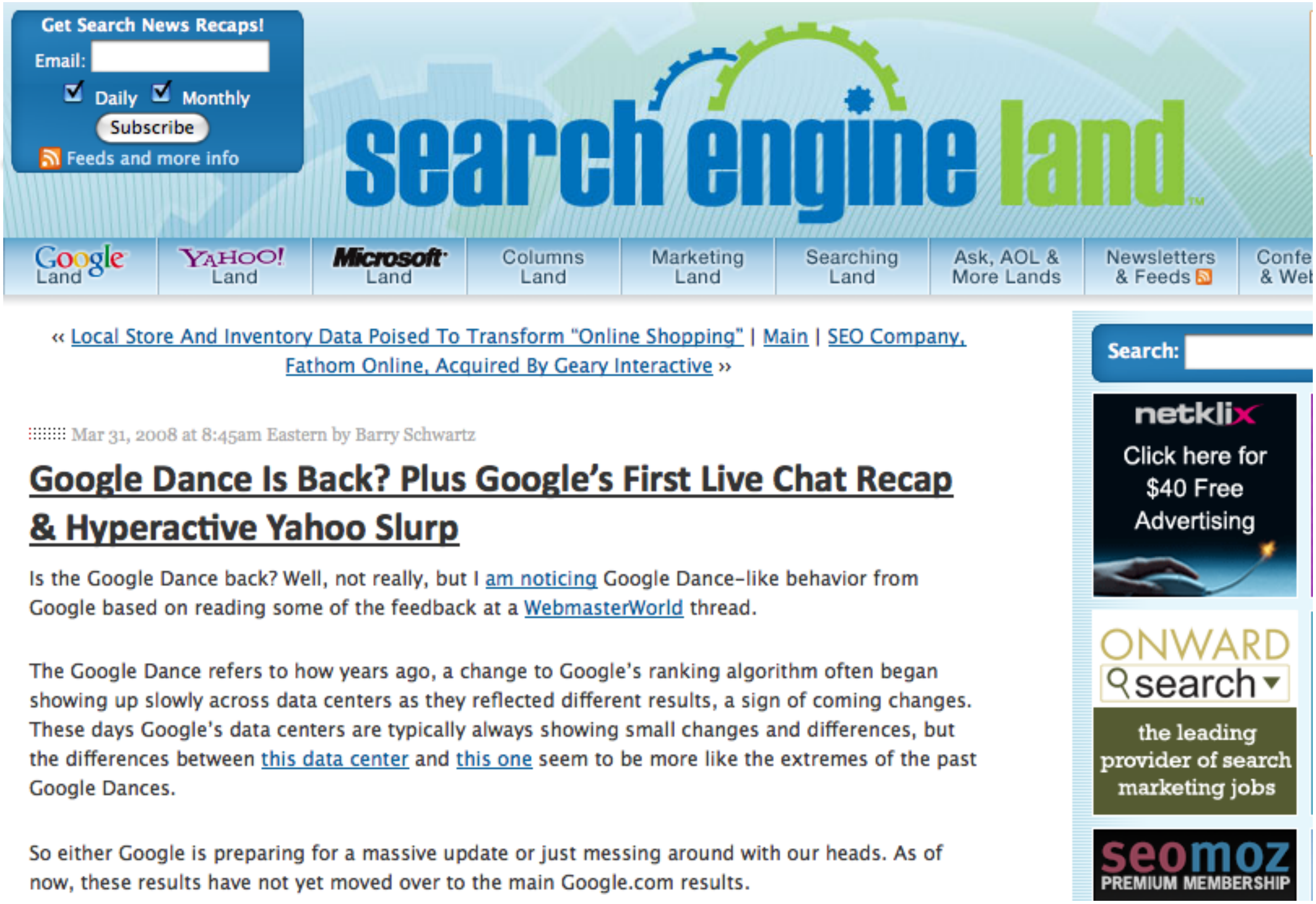
- Auxiliary and main index: index construction time is $O(T^2)$ as each posting is touched in each merge.
- Logarithmic merge: Each posting is merged O(log T) times, so complexity is O(T log T)
- So logarithmic merge is much more efficient for index construction
- But query processing now requires the merging of O(log T) indexes
  - Whereas it is O(1) if you just have a main and auxiliary index

Further issues with multiple indexes

- Collection-wide statistics are hard to maintain
- E.g., when we spoke of spell-correction: which of several corrected alternatives do we present to the user?
  - We said, pick the one with the most hits
- How do we maintain the top ones with multiple indexes and invalidation bit vectors?
  - One possibility: ignore everything but the main index for such ordering
- Will see more such statistics used in results ranking

Dynamic indexing at search engines

- All the large search engines now do dynamic indexing
- Their indices have frequent incremental changes
  - News items, blogs, new topical web pages
    - Sarah Palin, …
- But (sometimes/typically) they also periodically reconstruct the index from scratch
  - Query processing is then switched to the new index, and the old index is deleted



« Local Store And Inventory Data Poised To Transform "Online Shopping" | Main | SEO Company, Fathom Online, Acquired By Geary Interactive »

Mar 31, 2008 at 8:45am Eastern by Barry Schwartz

Google Dance Is Back? Plus Google's First Live Chat Recap & Hyperactive Yahoo Slurp

Is the Google Dance back? Well, not really, but I am noticing Google Dance-like behavior from Google based on reading some of the feedback at a WebmasterWorld thread.

The Google Dance refers to how years ago, a change to Google's ranking algorithm often began showing up slowly across data centers as they reflected different results, a sign of coming changes. These days Google's data centers are typically always showing small changes and differences, but the differences between this data center and this one seem to be more like the extremes of the past Google Dances.

So either Google is preparing for a massive update or just messing around with our heads. As of now, these results have not yet moved over to the main Google.com results.

Other sorts of indexes

- Positional indexes
  - Same sort of sorting problem … just larger
- Building character n-gram indexes:
  - As text is parsed, enumerate *n*-grams.
  - For each *n*-gram, need pointers to all dictionary terms containing it – the "postings".
  - Note that the same "postings entry" will arise repeatedly in parsing the docs – need efficient hashing to keep track of this.
    - E.g., that the trigram *uou* occurs in the term ***deciduous*** will be discovered on each text occurrence of ***deciduous***
    - Only need to process each term once

Resources for today's lecture

- Chapter 4 of IIR
- MG Chapter 5
- Original publication on MapReduce: Dean and Ghemawat (2004)
- Original publication on SPIMI: Heinz and Zobel (2003)

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/