Introduction to

# Information Retrieval

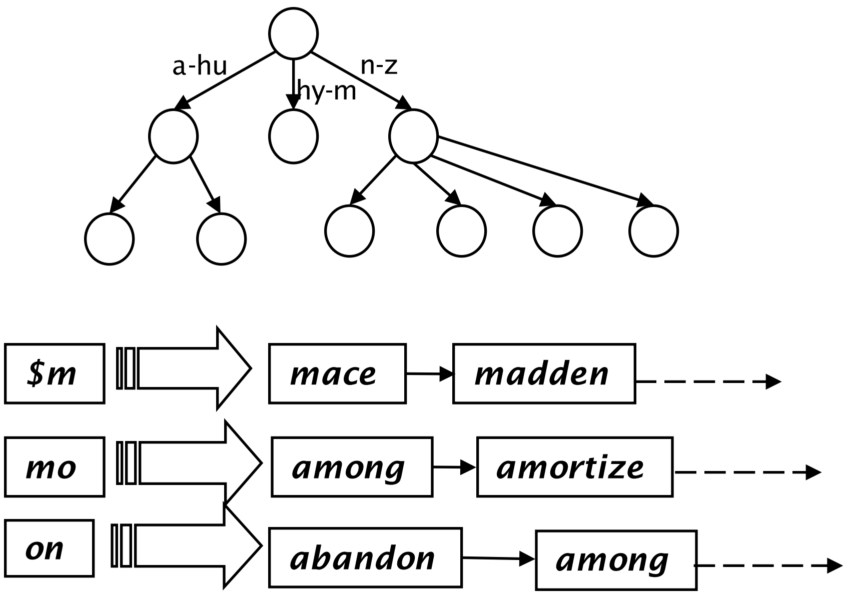
CS276: Information Retrieval and Web Search

Pandu Nayak and Prabhakar Raghavan

Lecture 4: 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 = $5 \times 10^{-3}$ s |
| b | transfer time per byte | 0.02 μs = $2 \times 10^{-8}$ 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

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## Extreme conditions create rare Antarctic clouds

Tue Aug 1, 2006 3:20am ET

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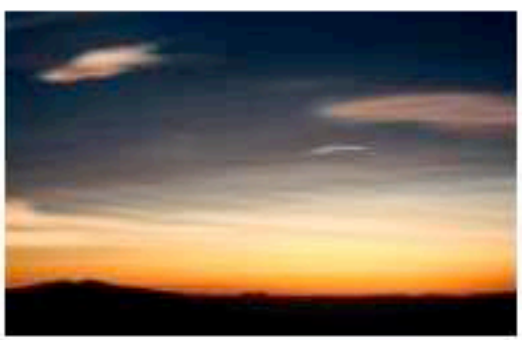


SYDNEY (Reuters) - Rare, mother-of-pearl colored clouds caused by extreme weather conditions above Antarctica are a possible indication of global warming, Australian scientists said on Tuesday.

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 |

4.5 bytes per word token vs. 7.5 bytes per word type: why?

# 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.

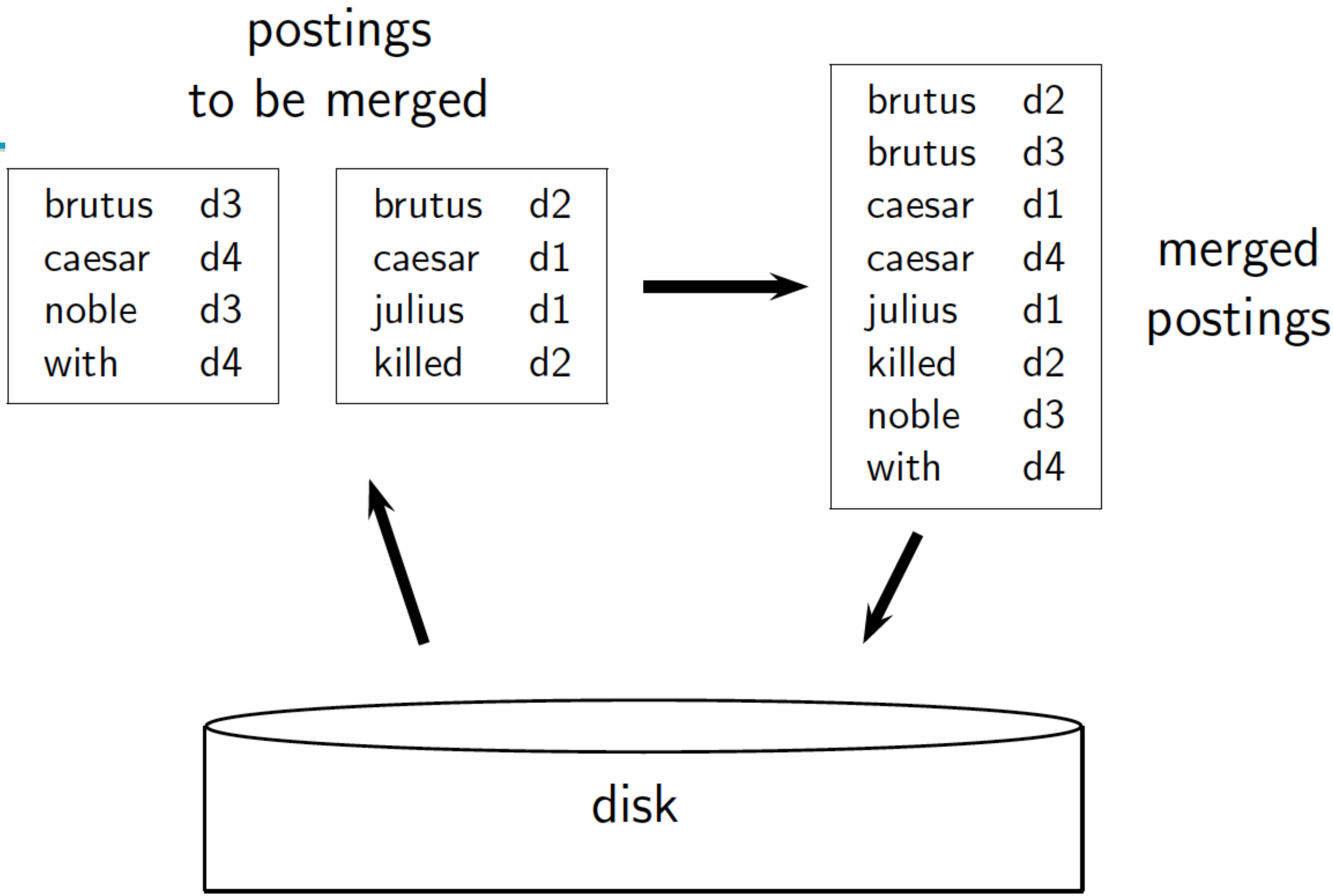
# Bottleneck

- 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, how long would this take?

# 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> ~ 10M such records
  - Can easily fit a couple into memory.
  - Will have 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.


postings
to be merged
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
merged
postings
disk

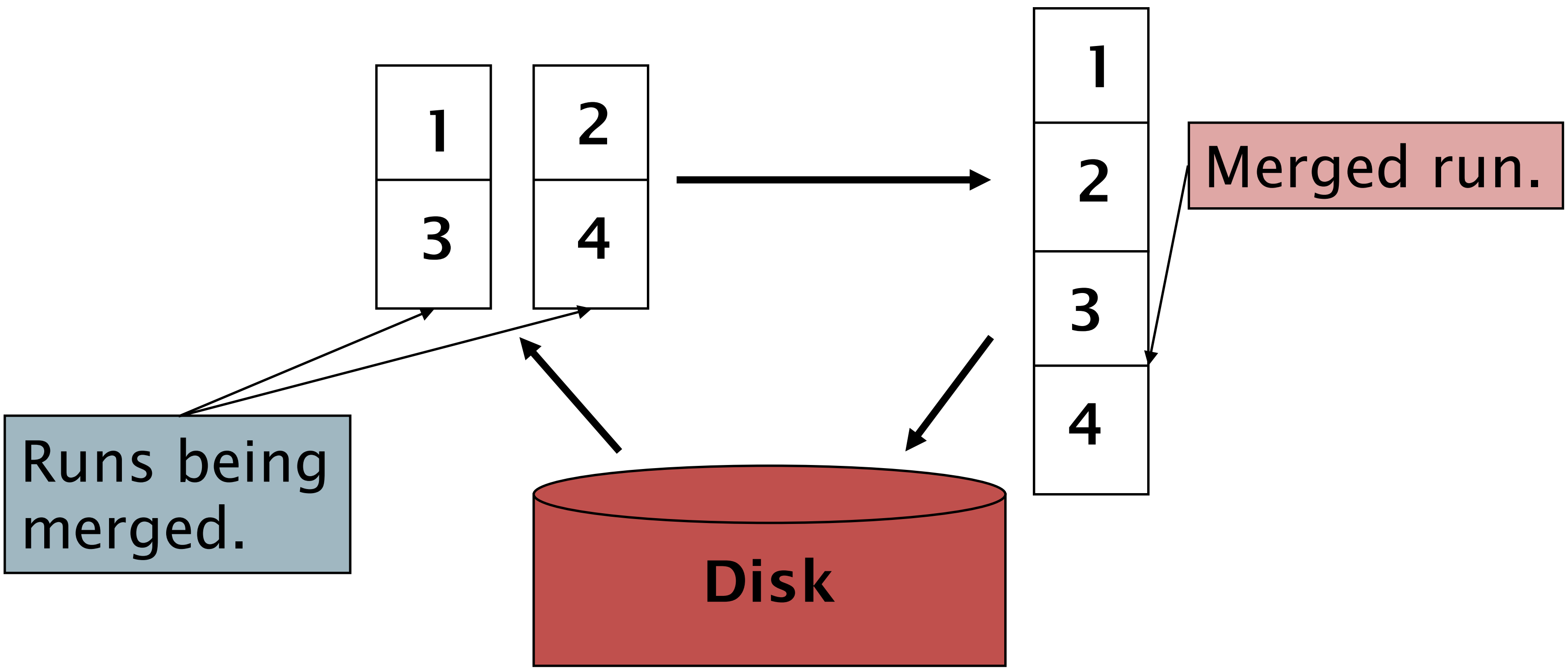
# Sorting 10 blocks of 10M records

- 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()
n ← 0
while (all documents have not been processed)
do n ← n + 1
    block ← ParseNextBlock()
    BSBI-Invert(block)
    WriteBlockToDisk(block, f_n)
MergeBlocks(f_1, . . . , f_n; f_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)
  output_file = NewFile()
  dictionary = NewHash()
  while (free memory available)
  do token ← next(token_stream)
     if term(token) ∉ dictionary
       then postings_list = AddToDictionary(dictionary, term(token))
       else postings_list = GetPostingsList(dictionary, term(token))
     if full(postings_list)
       then postings_list = DoublePostingsList(dictionary, term(token))
     AddToPostingsList(postings_list, docID(token))
  sorted_terms ← SortTerms(dictionary)
  WriteBlockToDisk(sorted_terms, dictionary, output_file)
  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)

# Massive data centers

- If in a non-fault-tolerant system with 1000 nodes, each node has 99.9% uptime, what is the uptime of the system?
- Answer: 63%
- Exercise: Calculate the number of servers failing per minute for an installation of 1 million servers.

# 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)

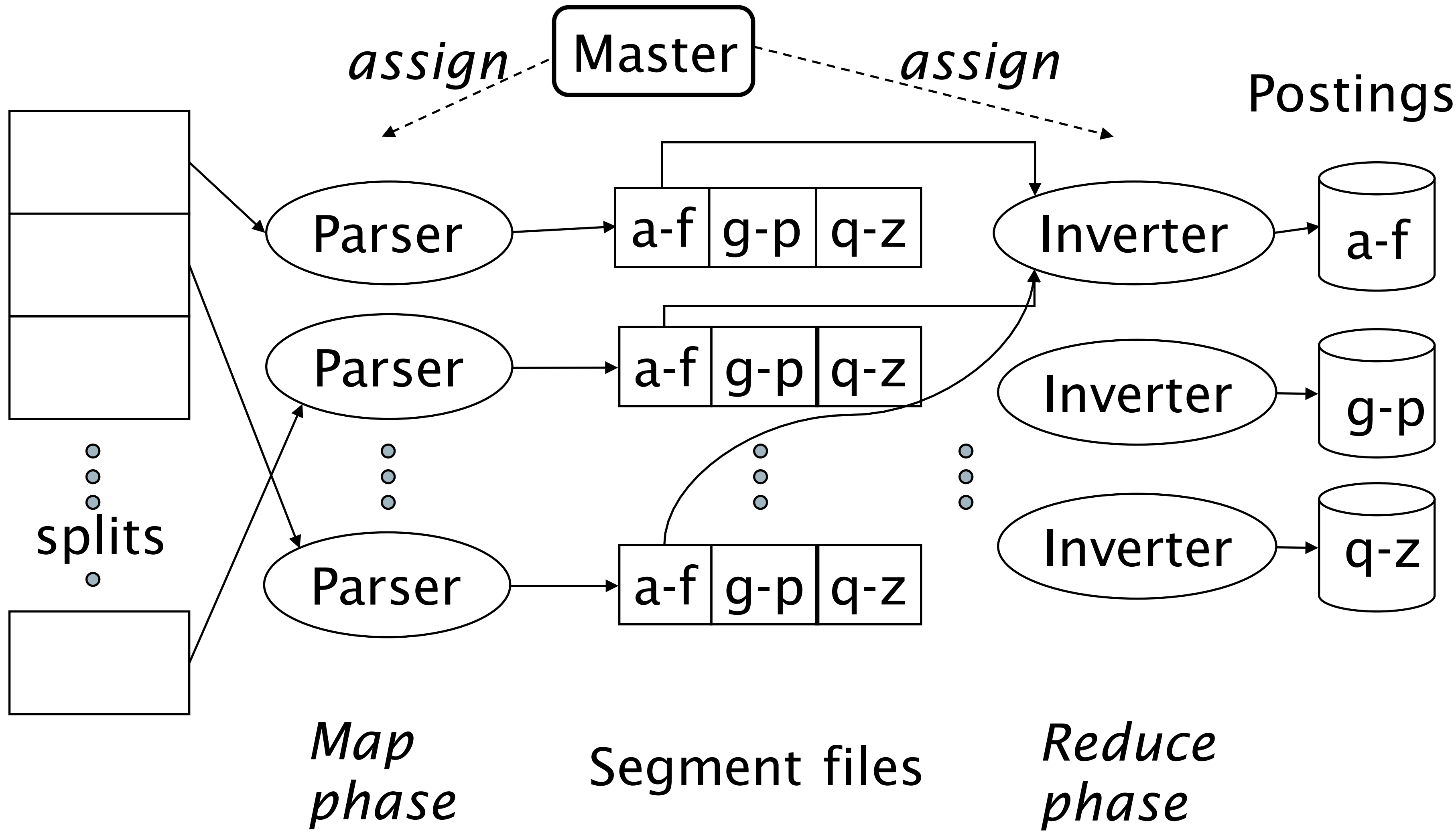
# Parsers

- 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 one term-partition.
- Sorts and writes to postings lists

# Data flow


Master
assign
assign
Postings
splits
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
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)>)

# 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)
  Z_0 ← Merge(Z_0, {token})
  if |Z_0| = n
    then for i ← 0 to ∞
           do if I_i ∈ indexes
                then Z_{i+1} ← Merge(I_i, Z_i)
                       (Z_{i+1} is a temporary index on disk.)
                     indexes ← indexes − {I_i}
                else I_i ← Z_i    (Z_i becomes the permanent index I_i.)
                     indexes ← indexes ∪ {I_i}
                     Break
         Z_0 ← ∅
```

```
LogarithmicMerge()
  Z_0 ← ∅    (Z_0 is the in-memory index.)
  indexes ← ∅
  while true
  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

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« 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

Why?

- 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)