CS3245

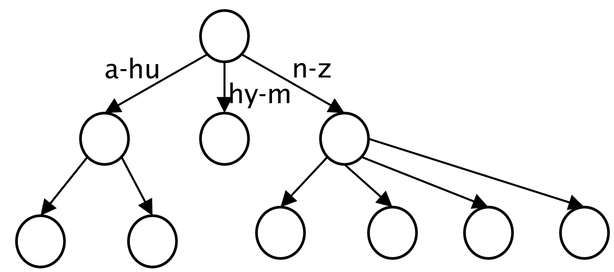
Information Retrieval

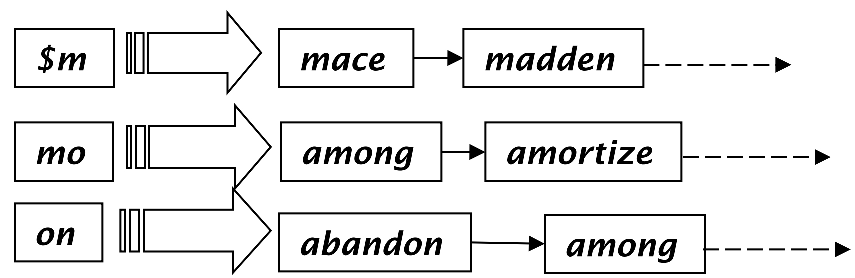
Lecture 5: Index Construction

5

Last Time

- Dictionary data structures
- Tolerant retrieval
  - Wildcards
  - Spelling correction
  - Soundex





Today: Index construction

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

1. BSBI / SPIMI
2. Distributed Indexing
3. Dynamic Indexing
4. Other Indexing

Hardware basics

Many design decisions in information retrieval are based on the characteristics of hardware

Especially with respect to the bottleneck:

Hard Drive Storage

- Seek Time – time to move to a random location
- Transfer Time – time to transfer a data block

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 tens of GB of main memory.
- 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

symbol	statistic	value
s	average seek time	5 ms = 5 x 10^{-3} s
b	transfer time per byte	0.02 μs = 2 x 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

This was in 2007, but it's still largely applicable.

Hardware assumptions (Flash SSDs)

symbol	**statistic**	**value**
s	average seek time	.1 ms = 1×10^{-4} s
b	transfer time per byte	0.01 μs = 1×10^{-8} s

Ten times faster seek, 2x transfer time.
(Price also 10x more per GB of storage)

RCV1: Our collection for this lecture

- The successor to the Reuters-21578, which you used for your homework assignment. Larger by 35 times.
  - The collection we'll use isn't really large enough either, but it is publicly available and is a more plausible example.
- As an example for applying scalable index construction algorithms, we will use the Reuters RCV1 collection in lecture.
- This is one year of Reuters newswire (part of 1995 and 1996)

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

Where do all those extra terms come from if English vocabulary is only ~30K?

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

Recap: Wk 2 index construction

- Documents are parsed to extract words, saved along with its 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 lexicographically, by its 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.
- How can we construct an index for very large collections?
- Taking into account the hardware constraints we just learned about . . .
- Memory, disk, speed, etc.

1. 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 9+ bytes per non-positional postings entry (4 bytes each for *docID, freq*, more for *term* if needed), it demands 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.

Blanks on slides, you may want to fill in

Use the same algorithm for disk?

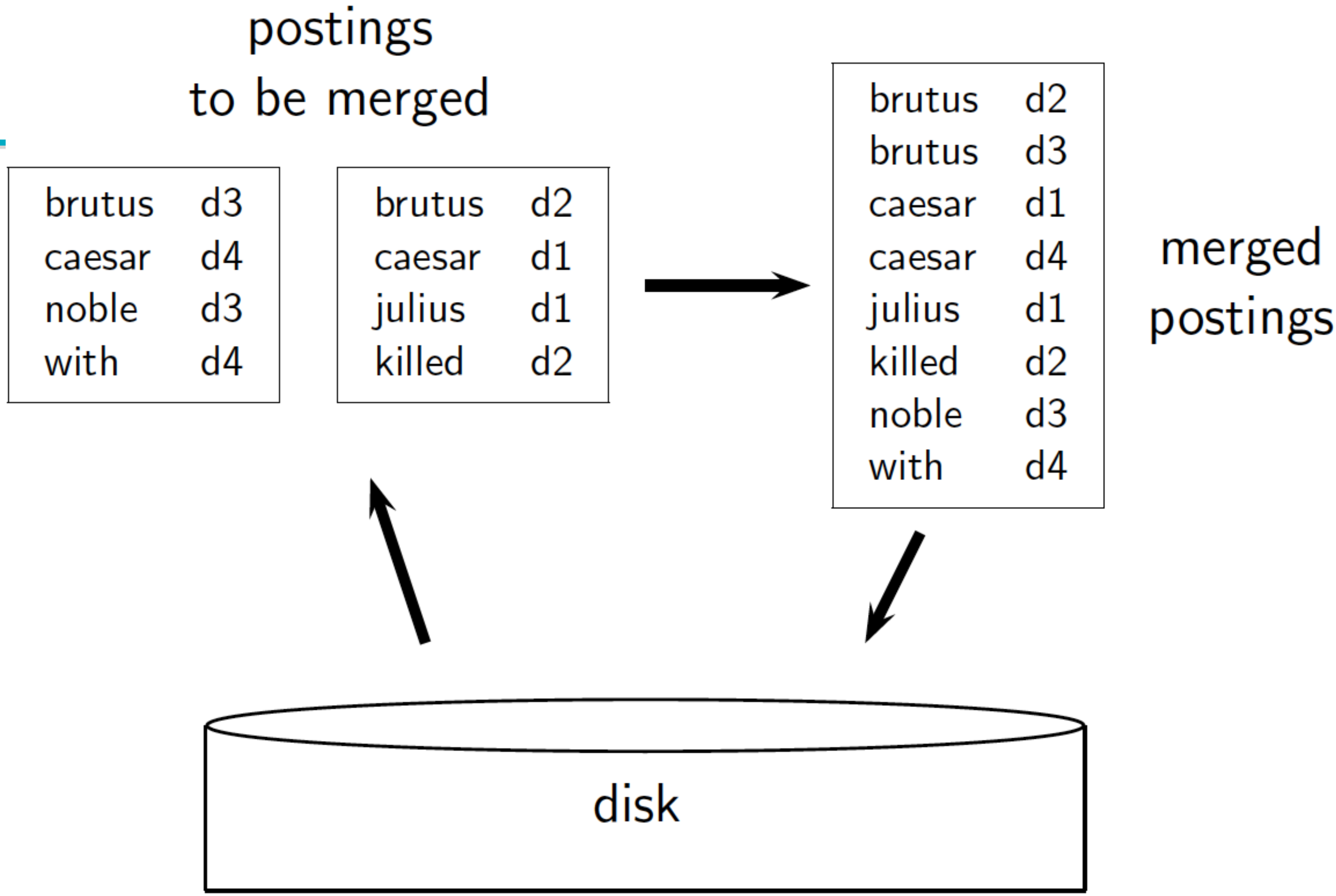
- Can we use the same index construction algorithm for larger collections, but by using disk instead of memory?

Bottleneck

- Parse and build postings entries one doc at a time
- Now sort postings entries by term (then by doc within each term)
  - As terms are of variable length, create the dictionary to map terms to termIDs with small fixed number of bytes (e.g., 4 bytes)
- Doing this with random disk seeks would be too slow – must sort *T*=100M records

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

- 12-byte (4+4+4) records *(termID, docID, freq).*
- These are generated as we parse docs.
- Must now sort 100M 12-byte records by *termID*.
- Define a <u>Block</u> as ~ 10M such records
  - Can easily fit a couple into memory.
  - Will have 10 such blocks for our collection.
- 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 (Also a tutorial question): estimate total time to read each block from disk and and quicksort it.

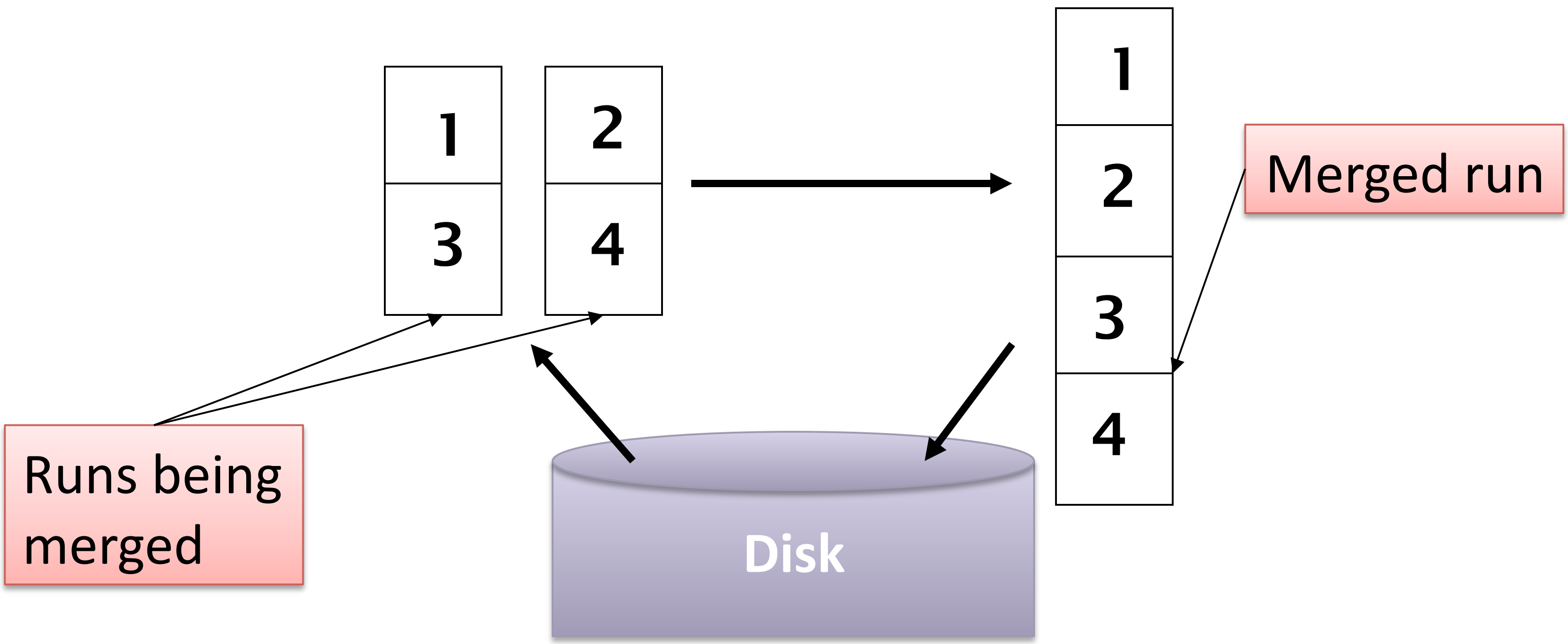
- 10 times this estimate – gives us 10 sorted *runs* of 10M records each.
- Done straightforwardly, need 2 copies of data on disk
  - But can optimize this

Blanks on slides, you may want to fill in

```
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?

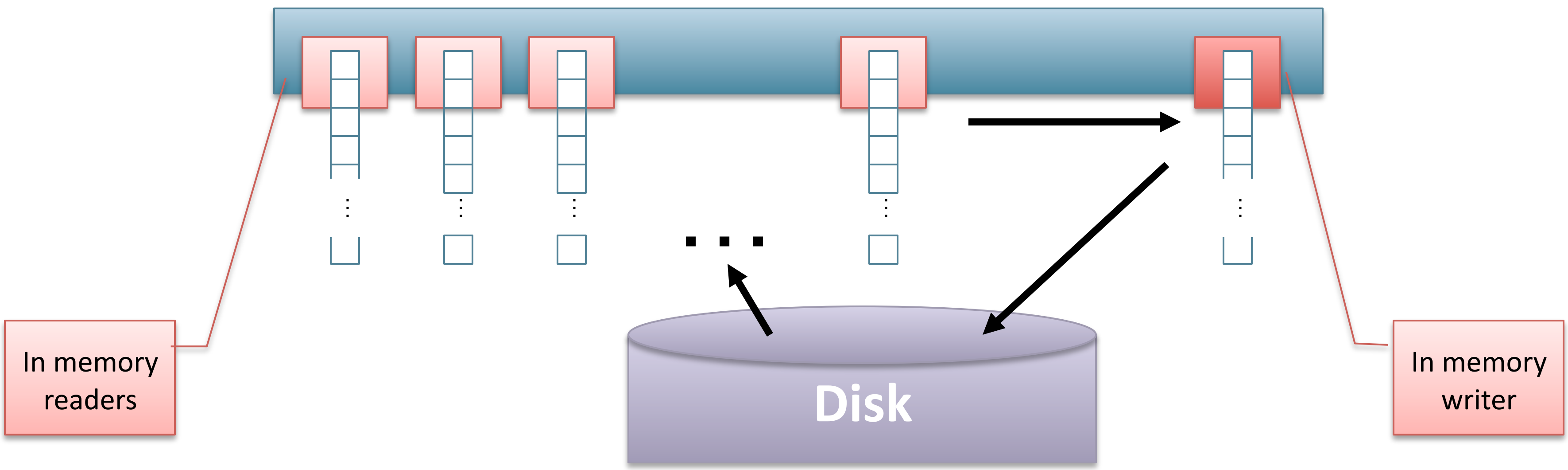
- Can do binary merges, with a merge tree of $\log_2 10 = 4$ layers.
- During each layer, read into memory runs in blocks of 10M, merge, write back.



How to merge the sorted runs?

Second method (better):

- It is more efficient to do a *n*-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 your efficiency isn't lost 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 keep the 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 indices can then be merged into one big index.

Blanks on slides, you may want to fill in

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

DISTRIBUTED INDEXING

2. 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?

(Google) Data Centers

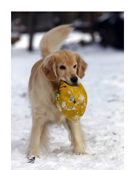
- Google data centers mainly contain commodity machines, and are distributed worldwide.
- Estimate: a total of 1 million servers, 3 million processors/cores (Gartner 2007 [yes, 2007!])
- Estimate: Google installs 100,000 servers each quarter.
  - Based on expenditures of 200–250 million dollars per year
- Must be fault tolerant. Even with 99.9+% uptime, there often will be one or more machines down in a data center.

Distributed indexing

- Maintain a *master* machine directing the indexing job – considered "safe".
  - Master nodes can fail too!

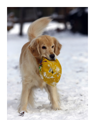

- Break up indexing into sets of (parallel) tasks.
- Master machine assigns each task to an idle machine from a pool.

Index!



Woof (ok)!

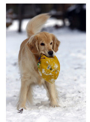
Parallel tasks

- 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 

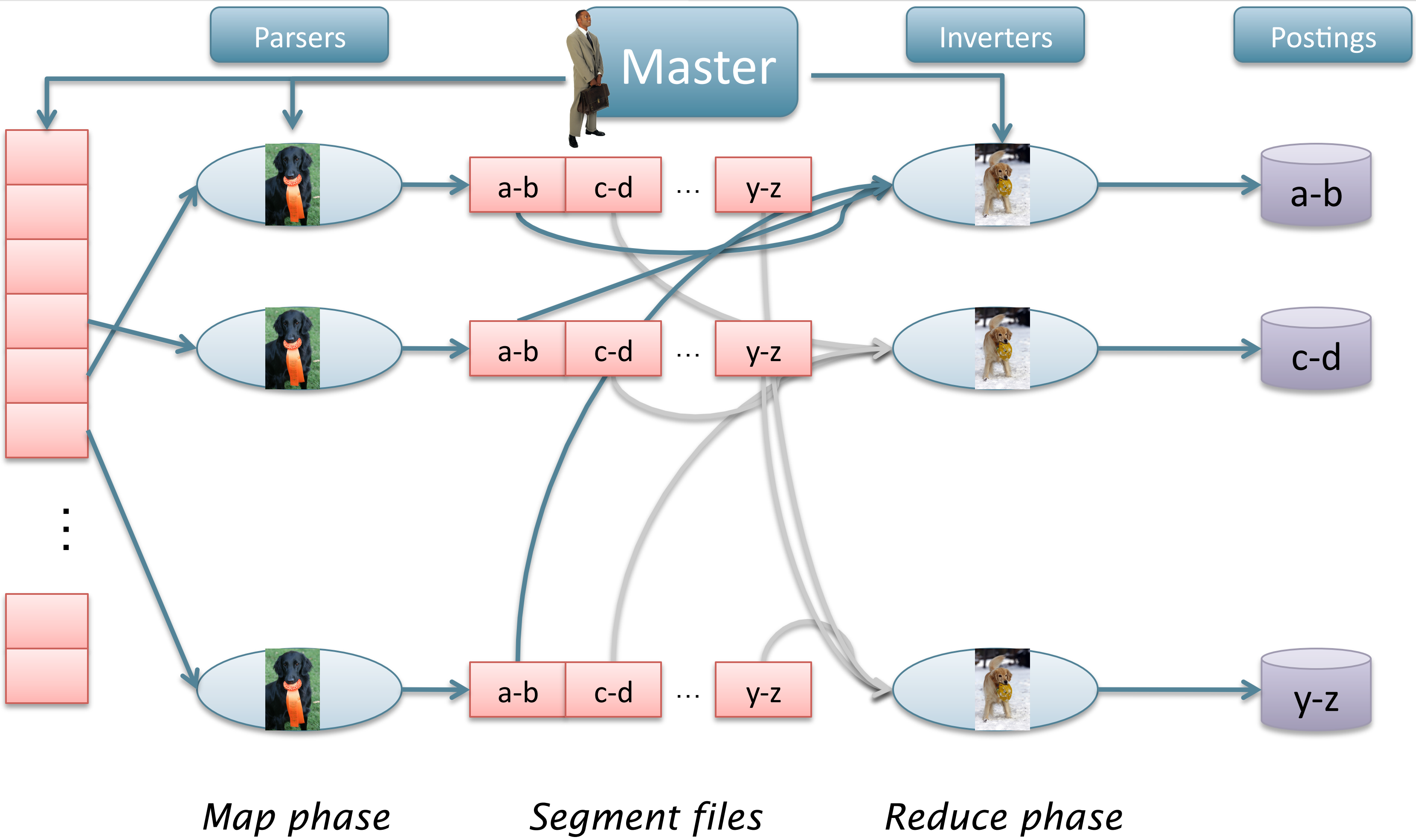
- Master assigns a split to an idle parser machine
- Parser reads a document at a time and emits (term, doc) pairs
- Parser writes pairs into *j* partitions
- Each partition is for a range of terms' first letters
  - (e.g., ***a-f, g-p, q-z***) – here *j* = 3.
- Now to complete the index inversion

Inverters



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

Data flow


Parsers
Master
Inverters
Postings
a-b
c-d
…
y-z
a-b
c-d
y-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
- Most search engines use a document-partitioned index … better load balancing and other properties

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: web collection → list(termID, docID)
- reduce: (<termID1, list(docID)>, <termID2, list(docID)>, …) → (postings list1, postings list2, …)

Example for index construction

- map: d2 : C died. d1 : C came, C c'ed. → (<C, d2>, <died,d2>, <C,d1>, <came,d1>, <C,d1>, <c'ed, d1>
- reduce: (<C,(d2,d1,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

3. Dynamic indexing

- Up to now, we have assumed that collections are static.
- In practice, 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

2nd simplest approach

- Maintain “big” main index
- New docs go into “small” (in memory) 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
  - Assuming T total # of postings and n as size of auxiliary index, we touch each posting up to *floor(T/n)* times.

Issues with main and auxiliary indexes

- Problem of frequent merges – modify lots of files, inefficient
- 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 (for the main index).
  - Then merge is the same as an append.
  - But then we would need a lot of files – inefficient for O/S.
- We'll deal with the index (postings-file) as 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

- Idea: maintain a series of indexes, each twice as large as the previous one.
- Keep smallest (Z_0) in memory
- Larger ones (I_0, I_1, …) on disk

Loop for log levels

- 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

  … etc.

$\textsc{LMergeAddToken}(\textit{indexes}, Z_0, \textit{token})$

$Z_0 \leftarrow \textsc{Merge}(Z_0, \{\textit{token}\})$
if $|Z_0| = n$
  then for $i \leftarrow 0$ **to** ∞
    do if $I_i \in \textit{indexes}$
      then $Z_{i+1} \leftarrow \textsc{Merge}(I_i, Z_i)$
        (Z_{i+1} is a temporary index on disk.)
        $\textit{indexes} \leftarrow \textit{indexes} - \{I_i\}$
      else $I_i \leftarrow Z_i$ *(Z_i becomes the permanent index I_i.)*
        $\textit{indexes} \leftarrow \textit{indexes} \cup \{I_i\}$
        $\textsc{Break}$
    $Z_0 \leftarrow \emptyset$

$\textsc{LogarithmicMerge}()$

$Z_0 \leftarrow \emptyset$ *(Z_0 is the in-memory index.)*
$\textit{indexes} \leftarrow \emptyset$
while true
do $\textsc{LMergeAddToken}(\textit{indexes}, Z_0, \textsc{getNextToken}())$

Logarithmic merge

- Auxiliary and main index: index construction time is $O(T^2/n) \approx O(T^2)$, as each posting redone 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 $O(\log T)$ indices
  - 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 spelling 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
    - Murbarak, COE, TFR, …
- 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 then deleted

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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.

Search:

4. Other Indexing Problems

- Positional indexes
  - Same sort of sorting problem … just larger

Why?

- Building character n-gram indices:
  - As text is parsed, enumerate *n*-grams.
  - For each *n*-gram, need pointers to all dictionary terms containing it – the "postings".
- User access rights
  - In intranet search, certain users have privilege to see and search only certain documents
  - Implement using access control list, intersect with search results, just like bit-vector invalidation for deletions
  - Impacts collection level statistics

Summary

- Indexing
  - Both basic as well as important variants
    - BSBI – sort key values to merge, needs dictionary
    - SPIMI – build mini indices and merge them, no dictionary
  - Distributed
    - Described MapReduce architecture – a good illustration of distributed computing
  - Dynamic
    - Tradeoff between querying and indexing complexity

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)