CS60092: Information Retrieval

Index Construction Algorithms, Dynamic Indexes

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Index construction

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

Recall 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.

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

RCV1: Our collection for this lecture

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)

The collection isn't really large enough, but it's publicly available and is a plausible example.

A Reuters RCV1 document

REUTERS

You are here: Home > News > Science > Article

Go to a Section: U.S. International Business Markets Politics Entertainment Technology Sports Oddly Enoug

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

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

Sort-based index construction

As we build the index, we parse docs one at a time.

- The final postings for any term are incomplete until the end.

At 8 bytes per *(termID, docID)*, demands a lot of space for large collections.

T = 100,000,000 in the case of RCV1

- So … we can do this in memory today, 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.

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 hardware constraints. . .

- Memory, disk, speed, etc.

Let's review some hardware basics

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 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 assumptions (circa 2007)

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

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.

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External memory indexing

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

8-byte records *(termID, docID)*

These are generated as we parse docs

Must now sort 100M such 8-byte records by *termID*

Define a Block ~ 10M such records

- Can easily fit a couple into memory
- Will have 10 such blocks to start with

Basic idea of algorithm:

1. Accumulate postings for each block, sort, write to disk
2. Then merge the blocks into one long sorted order

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

```
BSBIndexConstruction()
 1  n ← 0
 2  while (all documents have not been processed)
 3  do n ← n + 1
 4       block ← ParseNextBlock()
 5       BSBI-Invert(block)
 6       WriteBlockToDisk(block, f_n)
 7  MergeBlocks(f_1, ..., f_n; f_merged)
```

Sorting 10 blocks of 10M records

First, read each block and sort within:

- Quicksort takes O(*N* ln *N)* expected steps
- In our case *N=10M*

10 times this estimate – gives us 10 sorted *runs* of 10M records each.

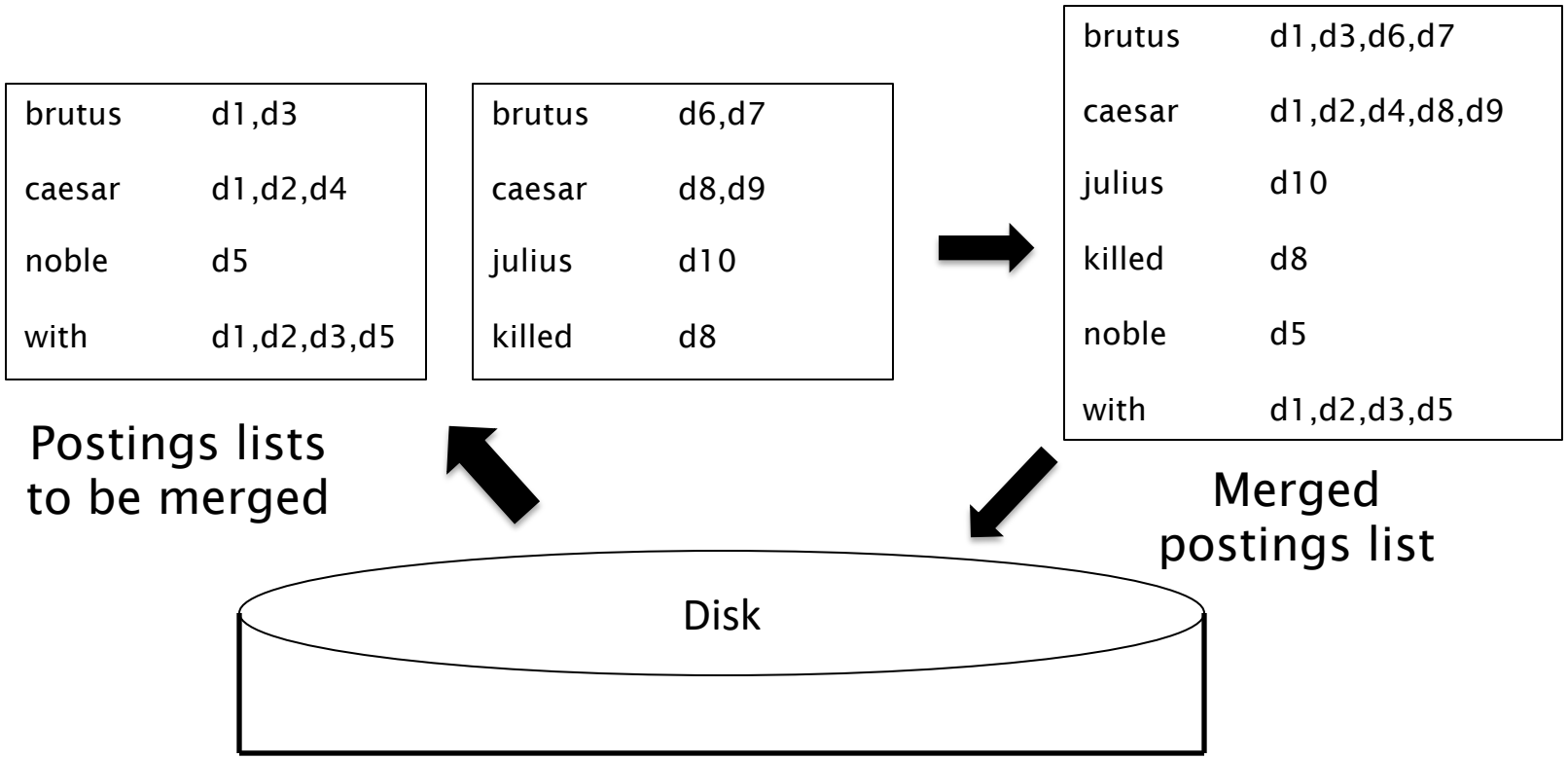
Done straightforwardly, need 2 copies of data on disk

- But can optimize this

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

1. Open all block files simultaneously and maintain a read buffer for each one and a write buffer for the output file
2. In each iteration, pick the lowest termID that hasn't been processed using a priority queue
3. Merge all postings lists for that termID and write it out

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.

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 in action

Input token

Caesar d1
with d1
Brutus d1
Caesar d2
with d2
Brutus d3
with d3
Caesar d4
noble d5
with d5

Dictionary

brutus d1 d3

with d1 d2 d3 d5
noble d5

caesar d1 d2 d4

Sorted dictionary

brutus d1 d3

caesar d1 d2 d4

noble d5

with d1 d2 d3 d5

SPIMI: Compression

Compression makes SPIMI even more efficient.

- Compression of terms
- Compression of postings

More on this later …

Original publication on SPIMI: Heinz and Zobel (2003)

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Distributed indexing

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 entire system?

Answer: 37% - meaning, 63% of the time one or more servers is down.

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

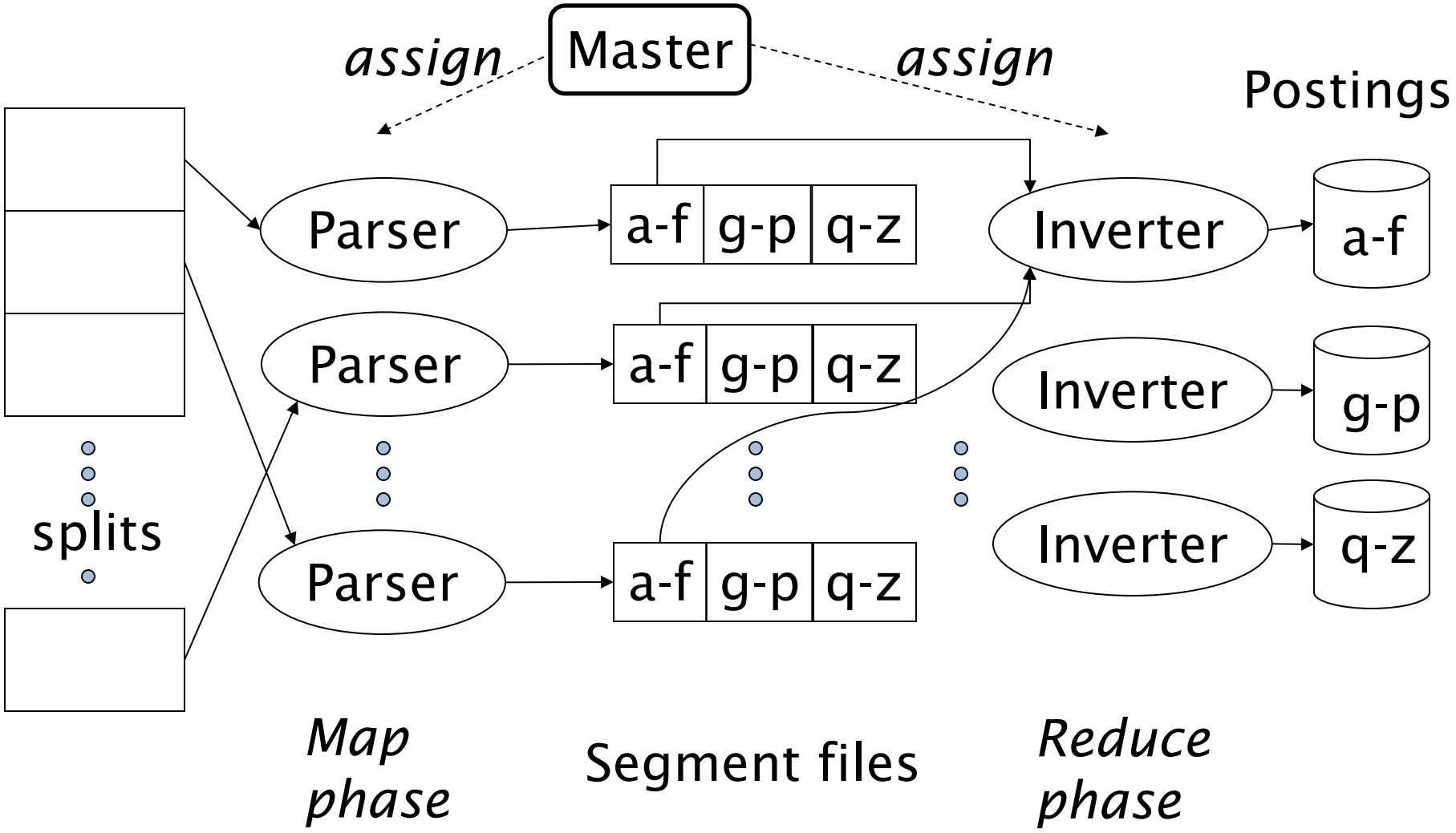
We will use two sets of parallel tasks

- Parsers
- Inverters

Break the input document collection into *splits*

Each split is a subset of documents (corresponding to blocks in BSBI/SPIMI)

Data flow


assign
Master
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

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

Example: Each partition is for a range of terms' first letters

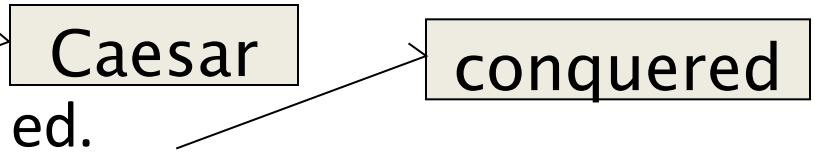
(e.g., ***a-f, g-p, q-z***) – here *j* = 3.

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

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

Index construction

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.

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.

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, …)

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Dynamic indexing

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

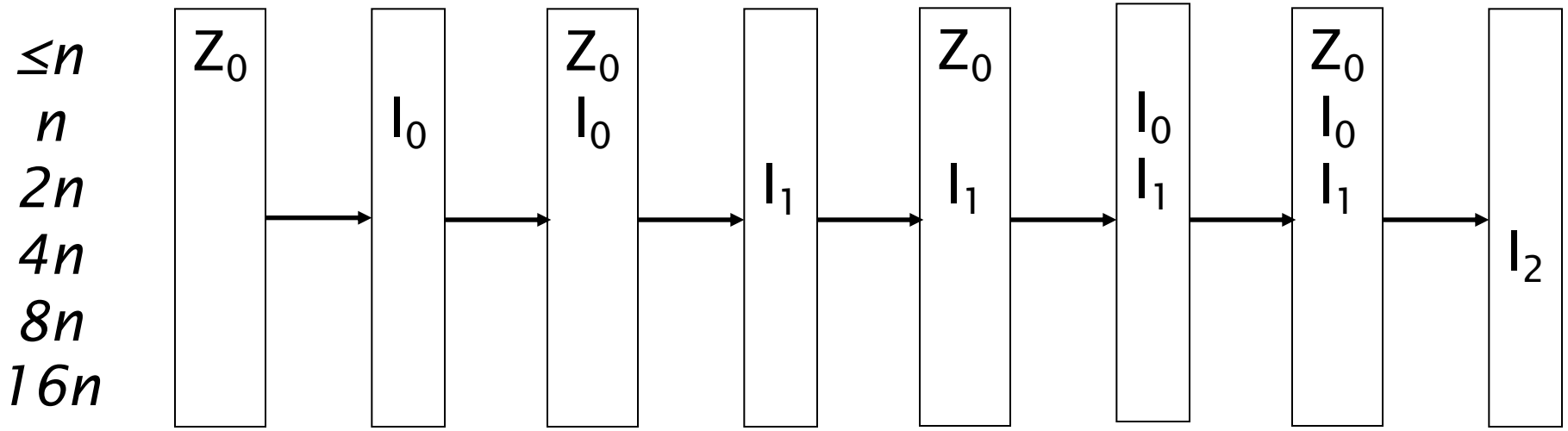
Keep smallest (Z_0) in memory, Larger ones (I_0, I_1, …) on disk

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

…

Logarithmic merge in action



```
LMergeAddToken(indexes, Z_0, token)
 1  Z_0 ← Merge(Z_0, {token})
 2  if |Z_0| = n
 3     then for i ← 0 to ∞
 4          do if I_i ∈ indexes
 5               then Z_{i+1} ← Merge(I_i, Z_i)
 6                    (Z_{i+1} is a temporary index on disk.)
 7                    indexes ← indexes − {I_i}
 8               else I_i ← Z_i     (Z_i becomes the permanent index I_i.)
 9                    indexes ← indexes ∪ {I_i}
10                    Break
11          Z_0 ← ∅
```

```
LogarithmicMerge()
1  Z_0 ← ∅     (Z_0 is the in-memory index.)
2  indexes ← ∅
3  while true
4  do LMergeAddToken(indexes, Z_0, getNextToken())
```

Logarithmic merge

Auxiliary and main index:

- T/n merges where T is # of postings and n is size of auxiliary
- Index construction time is $O(T^2/n)$ as in the worst case a posting is touched T/n times

Logarithmic merge: Each posting is merged at most O(log (T/n)) times, so complexity is O(T log (T/n))

So logarithmic merge is much more efficient for index construction

But query processing now requires the merging of O(log (T/n)) 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 speak of spell-correction: which of several corrected alternatives do we present to the user?

- We may want to 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

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

Earlybird: Real-time search at Twitter

Requirements for real-time search

- Low latency, high throughput query evaluation
- High ingestion rate and immediate data availability
- Concurrent reads and writes of the index
- Dominance of temporal signal

Earlybird: Index organization

Earlybird consists of multiple index segments

- Each segment is relatively small, holding up to 2^{23} tweets
- Each posting in a segment is a 32 bit word: 24 bits for the tweet id and 8 bits for the position in the tweet

Only one segment can be written to at any given time

- Small enough to be in memory
- New postings are simply appended to the postings list
- But the postings list is traversed backwards to prioritize newer tweets

The remaining segments are optimized for read-only

- Postings sorted in reverse chronological order (newest first)

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"

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)
Earlybird: Busch et al, ICDE 2012

End of Slides