

PV211: Introduction to Information Retrieval

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IIR 4: Index construction Handout version

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Overview

- 1 Introduction
- 2 BSBI algorithm
- 3 SPIMI algorithm
- 4 Distributed indexing
- 5 Dynamic indexing

Take-away

- Two index construction algorithms: **BSBI** (simple) and **SPIMI** (more realistic)
- **Distributed** index construction: MapReduce
- **Dynamic** index construction: how to keep the index up-to-date as the collection changes

Hardware basics

- Many design decisions in information retrieval are based on hardware constraints.
- We begin by reviewing hardware basics that we'll need in this course.

Hardware basics

- Access to data is **much faster in memory than on disk**. (roughly a factor of 10 SSD, 100+ for rotational disks)
- **Disk seeks are “idle” time**: No data is transferred from disk while the disk head is being positioned.
- To optimize transfer time from disk to memory: **one large chunk is faster than 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
- Assuming an efficient decompression algorithm, the total time of reading and then decompressing compressed data is usually less than reading uncompressed data.
- Servers used in IR systems typically have many **GBs of main memory** and **TBs of disk space**.
- **Fault tolerance is expensive**: It's cheaper to use many regular machines than one fault tolerant machine.

Some stats (ca. 2008)

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

RCV1 collection

- Shakespeare's collected works are not large enough for demonstrating many of the points in this course.
- As an example for applying scalable index construction algorithms, we will use the [Reuters RCV1](#) collection.
- English newswire articles sent over the wire in 1995 and 1996 (one year).

A Reuters RCV1 document



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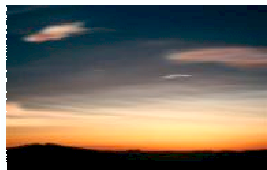
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Extreme conditions create rare Antarctic clouds

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

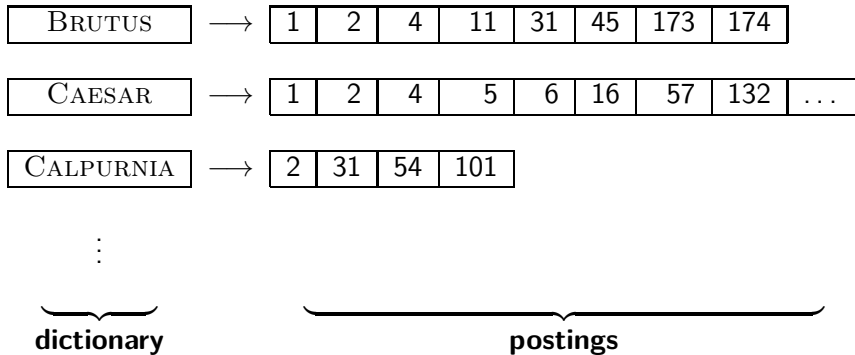
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Reuters RCV1 statistics

N	documents	800,000
L	tokens per document	200
M	terms (= word types)	400,000
	bytes per token (incl. spaces/punct.)	6
	bytes per token (without spaces/punct.)	4.5
	bytes per term (= word type)	7.5
T	non-positional postings	100,000,000

Exercise: Average frequency of a term (how many tokens)? 4.5
 bytes per word token vs. 7.5 bytes per word type: why the
 difference? How many positional postings?

Goal: construct the inverted index



Index construction in IIR 1: Sort postings in memory

term	docID		term	docID
l	1		ambitious	2
did	1		be	2
enact	1		brutus	1
julius	1		brutus	2
caesar	1		capitol	1
l	1		caesar	1
was	1		caesar	2
killed	1		caesar	2
i'	1		did	1
the	1		enact	1
capitol	1		hath	1
brutus	1		l	1
killed	1		l	1
me	1	⇒	i'	1
so	2		it	2
let	2		julius	1
it	2		killed	1
be	2		killed	1
with	2		let	2
caesar	2		me	1
the	2		noble	2
noble	2		so	2
brutus	2		the	1
hath	2		the	2
told	2		told	2
you	2		you	2
caesar	2		was	1
was	2		was	2
ambitious	2		with	2

Scaling index construction

- 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 index, we parse docs one at a time.
- The final postings for any term are incomplete until the end.
- Can we keep all postings in memory and then do the sort in-memory at the end?
- No, not for large collections
- Thus: We need to store intermediate results on disk.

Same algorithm for disk?

- Can we use the same index construction algorithm for larger collections, but by using disk instead of memory?
- No: Sorting very large sets of records on disk is too slow – too many disk seeks.
- We need an [external](#) sorting algorithm.

“External” sorting algorithm (using few disk seeks)

- We must sort $T = 100,000,000$ non-positional postings.
 - Each posting has size 12 bytes (4+4+4: termID, docID, term frequency).
- Define a **block** to consist of 10,000,000 such postings
 - We can easily fit that many postings into memory.
 - We will have 10 such blocks for RCV1.
- Basic idea of algorithm:
 - For each block: (i) accumulate postings, (ii) sort in memory, (iii) write to disk
 - Then merge the blocks into one long sorted order.

Merging two blocks

postings
to be merged

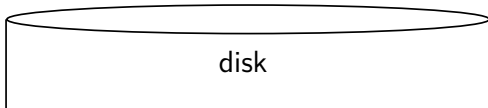
Block 1	
brutus	d3
caesar	d4
noble	d3
with	d4

Block 2	
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



Blocked Sort-Based Indexing

BSBIINDEXCONSTRUCTION()

```
1  $n \leftarrow 0$ 
2 while (all documents have not been processed)
3 do  $n \leftarrow n + 1$ 
4    $block \leftarrow \text{PARSENEXTBLOCK}()$ 
5    $\text{BSBI-INVERT}(block)$ 
6    $\text{WRITEBLOCKTODISK}(block, f_n)$ 
7  $\text{MERGEBLOCKS}(f_1, \dots, f_n; f_{\text{merged}})$ 
```

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.)

Single-pass in-memory indexing

- Abbreviation: SPIMI
- 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 computer cluster
- Individual machines are fault-prone.
 - Can unpredictably slow down or fail.
- How do we exploit such a pool of machines?

Google data centers (2007 estimates; Gartner)

- Google data centers mainly contain commodity machines.
- Data centers are distributed all over the world.
- 1 million servers, 3 million processors/cores
- Google installs 100,000 servers each quarter.
- Based on expenditures of 200–250 million dollars per year
- This would be 10% of the computing capacity of the world!
- If in a non-fault-tolerant system with 1000 nodes, each node has 99.9% uptime, what is the uptime of the system (assuming it does not tolerate failures)?
- Answer: 37%
- Suppose a server will fail after 3 years. For an installation of 1 million servers, what is the interval between machine failures?
- Answer: less than two minutes

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 define two sets of parallel tasks and deploy two types of machines to solve them:
 - Parsers
 - Inverters
- Break the input document collection into **splits** (corresponding to blocks in BSBI/SPIMI)
- Each split is a subset of documents.

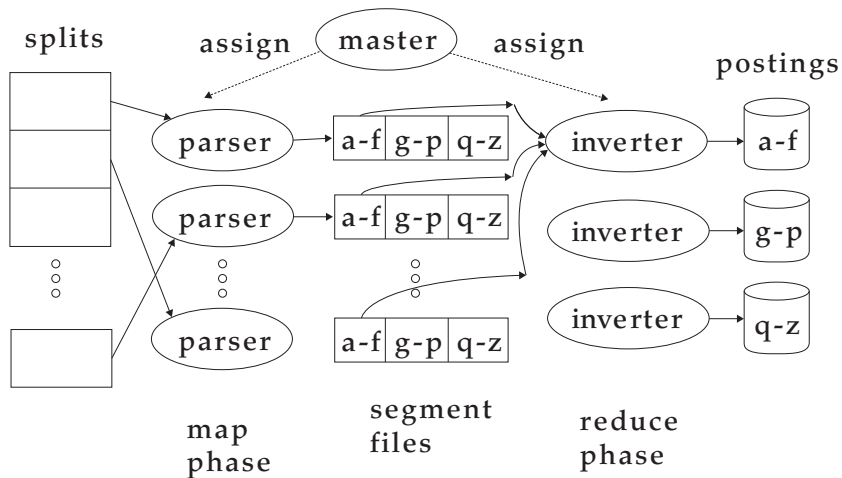
Parsers

- Master assigns a split to an idle parser machine.
- Parser reads a document at a time and **emits** (termID,docID)-pairs.
- Parser writes pairs into j term-partitions.
- Each for a range of terms' first letters
 - E.g., a-f, g-p, q-z (here: $j = 3$)

Inverters

- An inverter collects all (termID,docID) pairs (= postings) for one term-partition (e.g., for a–f).
- Sorts and writes to postings lists

Data flow



MapReduce

- The index construction algorithm we just described is an instance of MapReduce.
- MapReduce is a robust and conceptually simple framework for distributed computing . . .
- . . . without having to write code for the distribution part.
- The Google indexing system (ca. 2002) consisted of a number of phases, each implemented in MapReduce.
- Index construction was just one phase.
- Another phase: transform term-partitioned into document-partitioned index.

Index construction in MapReduce

Schema of map and reduce functions

map: input $\rightarrow \text{list}(k, v)$
 reduce: $(k, \text{list}(v)) \rightarrow \text{output}$

Instantiation of the schema for index construction

map: web collection $\rightarrow \text{list}(\text{termID}, \text{docID})$
 reduce: $((\text{termID}_1, \text{list}(\text{docID})), (\text{termID}_2, \text{list}(\text{docID})), \dots) \rightarrow (\text{postings_list}_1, \text{postings_list}_2, \dots)$

Example for index construction

map: $d_2 : C \text{ DIED}, d_1 : C \text{ CAME}, C \text{ C'ED}.$ $\rightarrow ((C, d_2), (DIED, d_2), (C, d_1), (CAME, d_1), (C, d_1), (C'ED, d_1))$
 reduce: $((C, (d_2, d_1, d_1)), (DIED, (d_2)), (CAME, (d_1)), (C'ED, (d_1))) \rightarrow ((C, (d_1:2, d_2:1)), (DIED, (d_2:1)), (CAME, (d_1:1)), (C'ED, (d_1:1)))$

Exercise

- What information does the task description contain that the master gives to a parser?
- What information does the parser report back to the master upon completion of the task?
- What information does the task description contain that the master gives to an inverter?
- What information does the inverter report back to the master upon completion of the task?

Dynamic indexing

- Up to now, we have assumed that collections are **static**.
- They rarely are: Documents are inserted, deleted and modified.
- This means that the dictionary and postings lists have to be **dynamically** modified.

Dynamic indexing: Simplest approach

- Maintain **big main index on disk**
- New docs go into **small auxiliary index in memory**.
- Search across both, merge results
- Periodically, merge auxiliary index into big index
- Deletions:
 - Invalidation bit-vector for deleted docs
 - Filter docs returned by index using this bit-vector

Issue with auxiliary and main index

- Frequent merges
- Poor search performance during index merge

Logarithmic merge

- Logarithmic merging amortizes the cost of merging indexes over time.
 - → Users see smaller effect on response times.
- Maintain a series of indexes, each twice as large as the previous one.
- Keep smallest (Z_0) in memory
- Larger ones (l_0, l_1, \dots) on disk
- If Z_0 gets too big ($> n$), write to disk as l_0
- ... or merge with l_0 (if l_0 already exists) and write merger to l_1 , etc.

LMERGEADDTOKEN(*indexes*, Z_0 , *token*)

```

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

```

LOGARITHMICMERGE()

```

1   $Z_0 \leftarrow \emptyset$  ( $Z_0$  is the in-memory index.)
2   $\text{indexes} \leftarrow \emptyset$ 
3  while true
4  do LMERGEADDTOKEN(indexes,  $Z_0$ , GETNEXTTOKEN())

```

Binary numbers: $l_3l_2l_1l_0 = 2^32^22^12^0$

- 0001
- 0010
- 0011
- 0100
- 0101
- 0110
- 0111
- 1000
- 1001
- 1010
- 1011
- 1100

Logarithmic merge

- Number of indexes bounded by $O(\log T)$ (T is total number of postings read so far)
- So query processing requires the merging of $O(\log T)$ indexes
- Time complexity of index construction is $O(T \log T)$.
 - ... because each of T postings is merged $O(\log T)$ times.
- Auxiliary index: index construction time is $O(T^2)$ as each posting is touched in each merge.
 - Suppose auxiliary index has size a
 - $a + 2a + 3a + 4a + \dots + na = a \frac{n(n+1)}{2} = O(n^2)$
- So logarithmic merging is an order of magnitude more efficient.

Dynamic indexing at large search engines

- Often a combination
 - Frequent incremental changes
 - Rotation of large parts of the index that can then be swapped in
 - Occasional complete rebuild (becomes harder with increasing size – not clear if Google can do a complete rebuild)

Building positional indexes

- Basically the same problem except that the intermediate data structures are large.

Take-away

- Two index construction algorithms: **BSBI** (simple) and **SPIMI** (more realistic)
- **Distributed** index construction: MapReduce
- **Dynamic** index construction: how to keep the index up-to-date as the collection changes

Resources

- Chapter 4 of IIR
- Resources at <https://www.fi.muni.cz/~sojka/PV211/> and <http://cislmu.org>, materials in MU IS and FI MU library
 - Original publication on MapReduce by Dean and Ghemawat (2004)
 - Original publication on SPIMI by Heinz and Zobel (2003)
 - YouTube video: Google data centers