Introduction to Information Retrieval

http://informationretrieval.org

IIR 4: Index Construction

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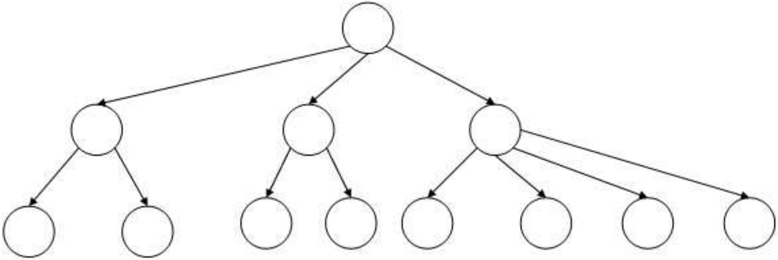
Overview

Outline

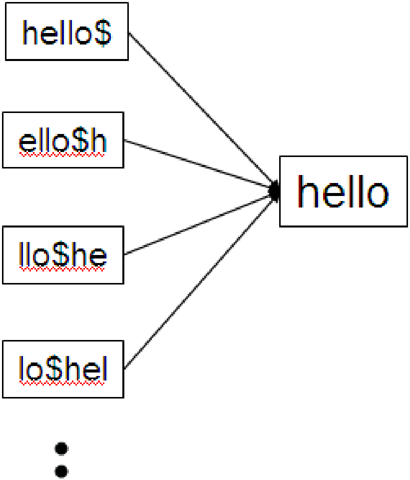
Dictionary as array of fixed-width entries

	term	document frequency	pointer to postings list
	a	656,265	$\longrightarrow$
	aachen	65	$\longrightarrow$
	...	...	...
	zulu	221	$\longrightarrow$
space needed:	20 bytes	4 bytes	4 bytes

B-tree for looking up entries in array



Wildcard queries using a permuterm index



Queries:

- For X, look up X$
- For X*, look up X*$
- For *X, look up X$*
- For *X*, look up X*
- For X*Y, look up Y$X*

k-gram indexes for spelling correction: *bordroom*

BO → aboard → about → boardroom → border

OR → border → lord → morbid → sordid

RD → aboard → ardent → boardroom → border

Levenshtein distance for spelling correction

LevenshteinDistance(s_1, s_2)

for $i \leftarrow 0$ **to** $|s_1|$
do $m[i, 0] = i$
for $j \leftarrow 0$ **to** $|s_2|$
do $m[0, j] = j$
for $i \leftarrow 1$ **to** $|s_1|$
do for $j \leftarrow 1$ **to** $|s_2|$
  do if $s_1[i] = s_2[j]$
    then $m[i, j] = \min\{m[i-1, j] + 1, m[i, j-1] + 1, m[i-1, j-1]\}$
    else $m[i, j] = \min\{m[i-1, j] + 1, m[i, j-1] + 1, m[i-1, j-1] + 1\}$
return $m[|s_1|, |s_2|]$

Operations: insert, delete, replace, copy

Exercise: Understand Peter Norvig's spelling corrector

```
import re, collections
def words(text): return re.findall('[a-z]+', text.lower())
def train(features):
model = collections.defaultdict(lambda: 1)
for f in features:
model[f] += 1
return model
NWORDS = train(words(file('big.txt').read()))
alphabet = 'abcdefghijklmnopqrstuvwxyz'
def edits1(word):
splits     = [(word[:i], word[i:]) for i in range(len(word) + 1)]
deletes    = [a + b[1:] for a, b in splits if b]
transposes = [a + b[1] + b[0] + b[2:] for a, b in splits if len(b) gt 1]
replaces   = [a + c + b[1:] for a, b in splits for c in alphabet if b]
inserts    = [a + c + b     for a, b in splits for c in alphabet]
return set(deletes + transposes + replaces + inserts)
def known_edits2(word):
return set(e2 for e1 in edits1(word) for e2 in
edits1(e1) if e2 in NWORDS)
def known(words): return set(w for w in words if w in NWORDS)
def correct(word):
candidates = known([word]) or known(edits1(word)) or
known_edits2(word) or [word]
return max(candidates, key=NWORDS.get)
```

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

Outline

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)
- 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
- 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 $= 5 \times 10^{-3}$ s
b	transfer time per byte	0.02 μs $= 2 \times 10^{-8}$ s
	processor's clock rate	10^9 s^{-1}
p	lowlevel 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 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

REUTERS

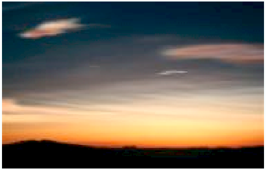
You are here: Home > News > Science > **Article**

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

Extreme conditions create rare Antarctic clouds

Tue Aug 1, 2006 3:20am ET

Email This Article | Print This Article | Reprint



[-] 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

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?

Exercise

Why does this algorithm not scale to very large collections?

Outline

Goal: construct the inverted index

BRUTUS	$\longrightarrow$	1	2	4	11	31	45	173	174	
CAESAR	$\longrightarrow$	1	2	4	5	6	16	57	132	...
CALPURNIA	$\longrightarrow$	2	31	54	101					
⋮										

dictionary **postings**

Index construction in IIR 1: Sort postings in memory

term	**docID**
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

$\Longrightarrow$

term	**docID**
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

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.

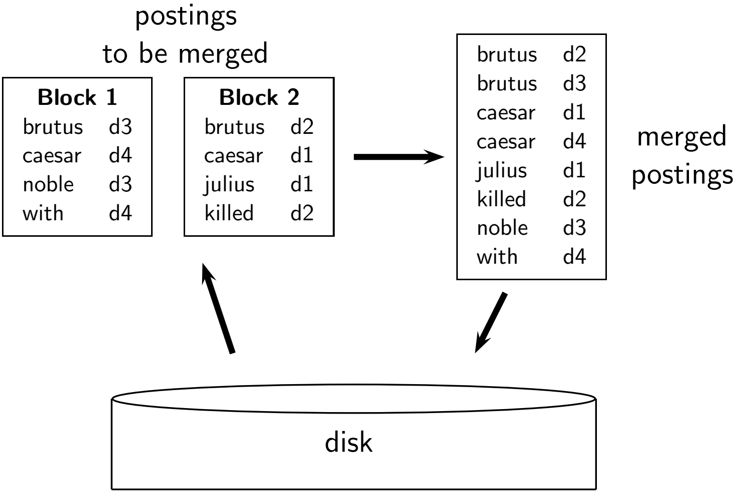
Same algorithm for disk?

- 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



Blocked Sort-Based Indexing

```
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)
```

Outline

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)
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

Outline

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.

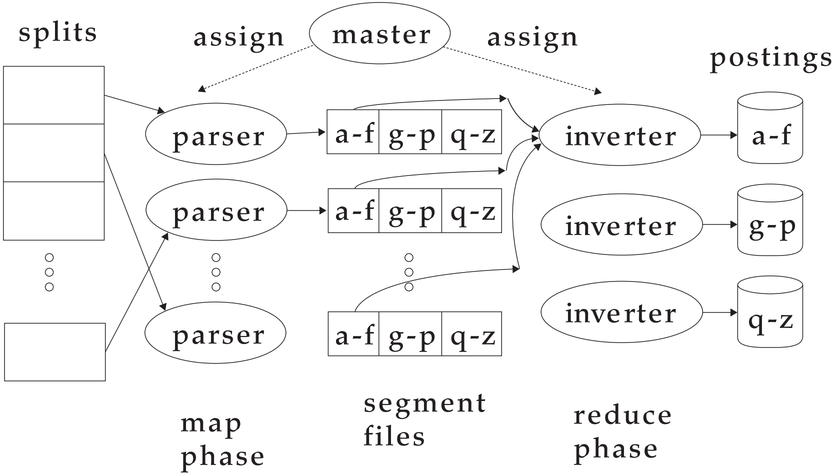
Parsers

- Master assigns a split to an idle parser machine.
- Parser reads a document at a time and emits (term,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 (term,docID) pairs (= postings) for one term-partition (e.g., for a-f).
- Sorts and writes to postings lists

Data flow


splits
assign
master
assign
postings
parser
a-f
g-p
q-z
inverter
a-f
parser
a-f
g-p
q-z
inverter
g-p
parser
a-f
g-p
q-z
inverter
q-z
map
phase
segment
files
reduce
phase

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.
- Why might a document-partitioned index be preferable?

Index construction in MapReduce

Schema of map and reduce functions

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

Instantiation of the schema for index construction

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

Example for index construction

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

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?

Outline

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.
  - $\rightarrow$ 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 (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) and write merger to I_1 etc.

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())
```

Binary numbers: $l_3 l_2 l_1 l_0 = 2^3 2^2 2^1 2^0$

- 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
  - $a + 2a + 3a + 4a + \ldots + na = a\frac{n(n+1)}{2} = O(n^2)$
- 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 `http://cislmu.org`
  - Original publication on MapReduce by Dean and Ghemawat (2004)
  - Original publication on SPIMI by Heinz and Zobel (2003)
  - YouTube video: Google data centers