Introduction to Information Retrieval

http://informationretrieval.org

IIR 4: Index Construction

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Overview

1. Recap
2. Introduction
3. BSBI algorithm
4. SPIMI algorithm
5. Distributed indexing
6. Dynamic indexing

Outline

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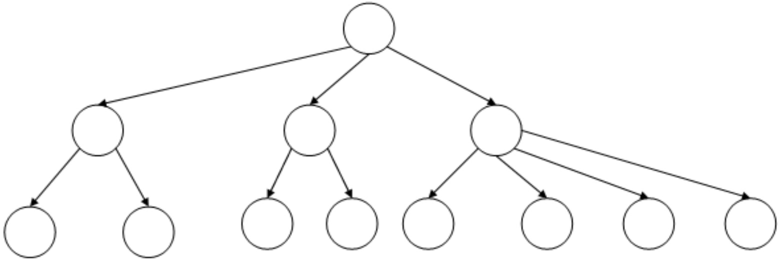
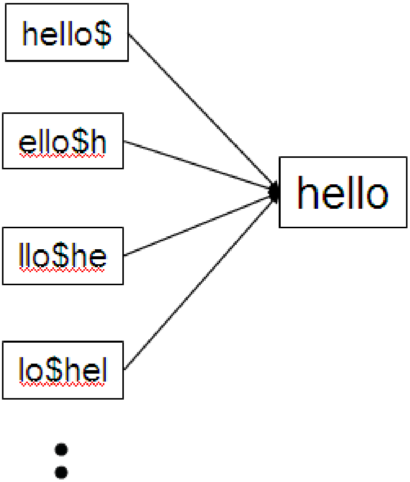
Dictionary as array of fixed-width entries

	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



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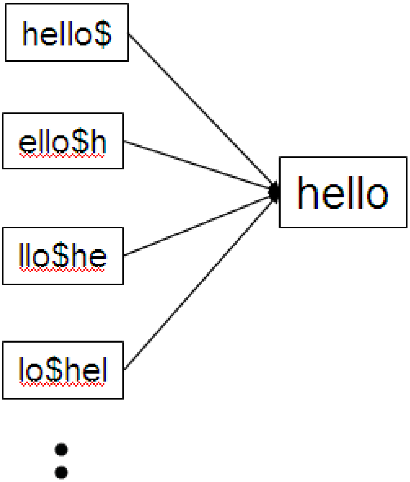

Queries:

- 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

$\textsc{LevenshteinDistance}(s_1, s_2)$

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)
```

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- 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

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Hardware basics

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- We begin by reviewing hardware basics that we'll need in this course.

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- Servers used in IR systems typically have several GB of main memory, sometimes tens of GB, and TBs or 100s of GB 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

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- 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

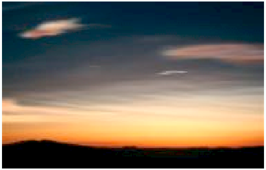
You are here: Home > News > Science > **Article**

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
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T	non-positional postings	100,000,000

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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?

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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
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capitol	1
caesar	1
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me	1
noble	2
so	2
the	1
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told	2
you	2
was	1
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- But in-memory index construction does not scale for large collections.
- Thus: We need to store intermediate results on disk.

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- We need an external sorting algorithm.

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  - 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

brutus	d2
brutus	d3

Block 1

Block 2

caesar	d1
brutus	d3

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)
```

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    BSBI-Invert(*block*)
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MergeBlocks($f_1, \ldots, f_n; f_{\text{merged}}$)

- Key decision: What is the size of one block?

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- 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.)

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- 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
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Merging of blocks is analogous to BSBI.

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- Compression makes SPIMI even more efficient.
  - Compression of terms
  - Compression of postings
  - See next lecture

Exercise: Time 1 machine needs for Google size collection

```
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)
```

symbol	statistic	value
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b	transfer time per byte	0.02 μs $= 2 \times 10^{-8}$ s
	processor's clock rate	10^9 s^{-1}
p	lowlevel operation	0.01 μs $= 10^{-8}$ s
	number of machines	1
	size of main memory	8 GB
	size of disk space	unlimited
N	documents	10^{11} (on disk)
L	avg. # word tokens per document	10^3
M	terms (= word types)	10^8
	avg. # bytes per word token (incl. spaces/punct.)	6
	avg. # bytes per word token (without spaces/punct.)	4.5
	avg. # bytes per term (= word type)	7.5

Hint: You have to make several simplifying assumptions – that's ok, just state them clearly.

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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?

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- Suppose a server will fail after 3 years. For an installation of 1 million servers, what is the interval between machine failures?

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- 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

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- Master machine assigns each task to an idle machine from a pool.

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- Break the input document collection into splits (corresponding to blocks in BSBI/SPIMI)
- Each split is a subset of documents.

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  - E.g., a-f, g-p, q-z (here: $j = 3$)

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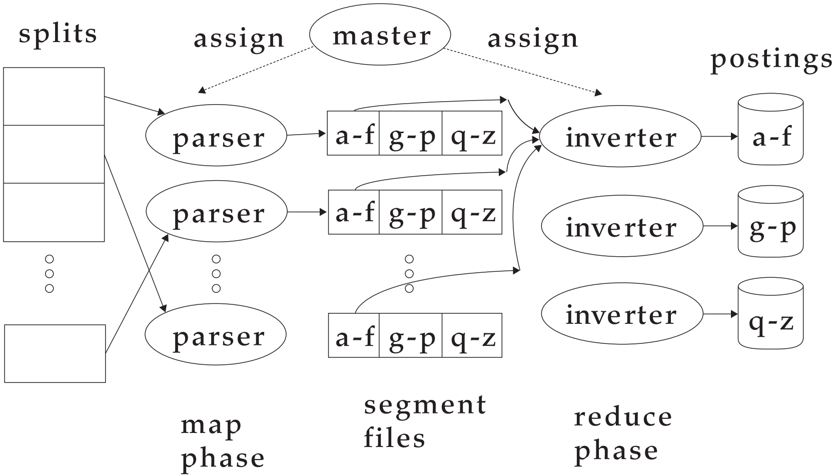
- Sorts and writes to postings lists

Data flow


splits
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
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map phase
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- 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	$\rightarrow$ list(k, v)
reduce:	(k,list(v))	$\rightarrow$ output

Instantiation of the schema for index construction

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

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

1. Recap
2. Introduction
3. BSBI algorithm
4. SPIMI algorithm
5. Distributed indexing
6. Dynamic indexing

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- This means that the dictionary and postings lists have to be dynamically modified.

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  - Filter docs returned by index using this bit-vector

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  - But then we would need a lot of files – inefficient.
- 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 into several files, collect small postings lists in one file etc.)

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- ...or merge with I_0 (if I_0 already exists) and write merger to I_1 etc.

LMergeAddToken(*indexes*, Z_0, *token*)

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

LogarithmicMerge()

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

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  - $a + 2a + 3a + 4a + \ldots + na = a\frac{n(n+1)}{2} = O(n^2)$
- So logarithming merging is an order of magnitude more efficient.

Dynamic indexing at large search engines

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  - 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

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://ifnlp.org/ir`
  - Original publication on MapReduce by Dean and Ghemawat (2004)
  - Original publication on SPIMI by Heinz and Zobel (2003)
  - YouTube video: Google data centers