Introduction to Information Retrieval

http://informationretrieval.org

IIR 4: Index Construction

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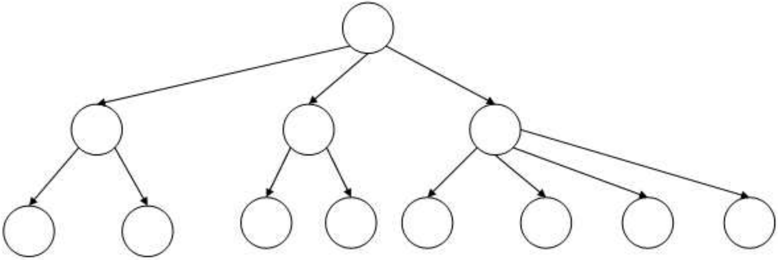
Overview

Outline

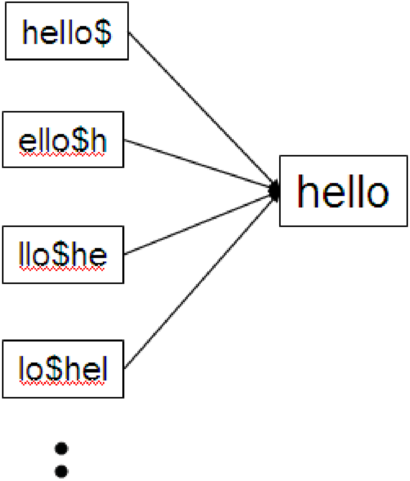
Dictionary as array of fixed-width entries

	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



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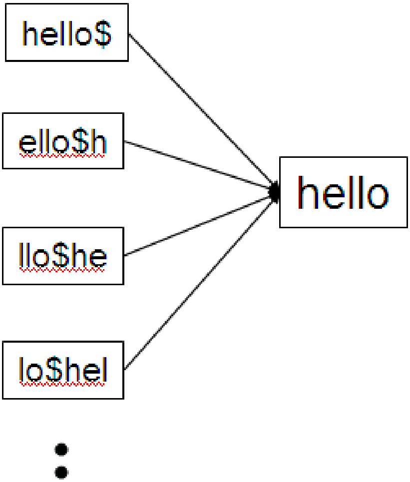

Queries:

- 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 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

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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

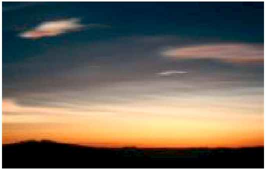
REUTERS

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



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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

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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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

Dictionary		Postings								
BRUTUS	→	1	2	4	11	31	45	173	174	
CAESAR	→	1	2	4	5	6	16	57	132	...
CALPURNIA	→	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
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i'	1
it	2
julius	1
killed	1
killed	1
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me	1
noble	2
so	2
the	1
the	2
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you	2
was	1
was	2
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- Thus: We need to store intermediate results on disk.

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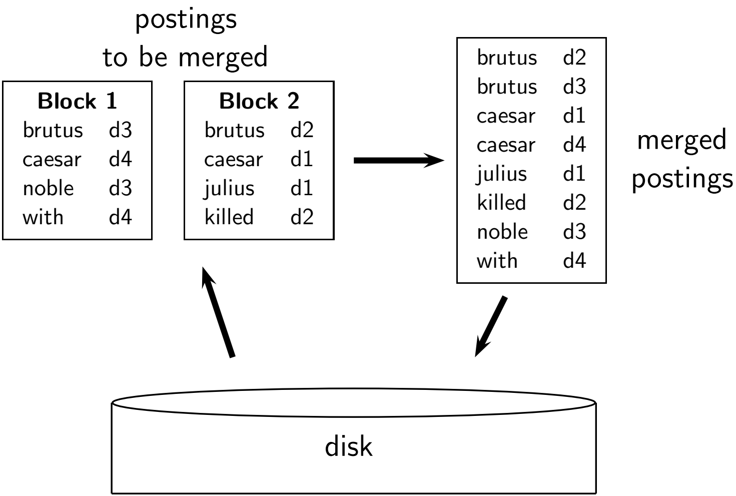
  - Then merge the blocks into one long sorted order.

Merging two blocks



Blocked Sort-Based Indexing

BSBIndexConstruction()
$n \leftarrow 0$
while (all documents have not been processed)
do $n \leftarrow n + 1$
    $block \leftarrow$ ParseNextBlock()
    BSBI-Invert($block$)
    WriteBlockToDisk($block, f_n$)
MergeBlocks($f_1, \ldots, f_n; f_{\text{merged}}$)

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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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    - See next lecture

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

Distributed indexing

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- Individual machines are fault-prone.
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- How do we exploit such a pool of machines?

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- Answer: less than two minutes

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

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

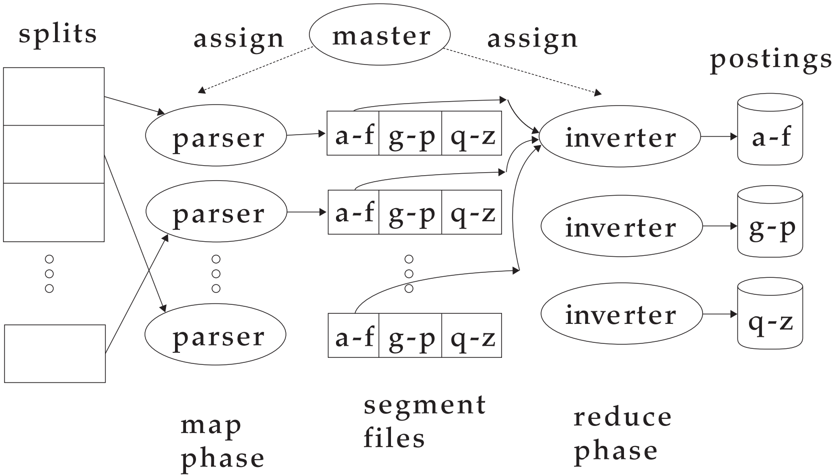
Parsers

- 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
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map phase
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- 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.

MapReduce

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

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

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

Issue with auxiliary and main index

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- Poor search performance during index merge

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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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- So logarithmic merging is an order of magnitude more efficient.

Dynamic indexing at large search engines

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  - 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://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