Introduction to Information Retrieval

http://informationretrieval.org

IIR 5: Index Compression

Hinrich Schütze

Center for Information and Language Processing, University of Munich

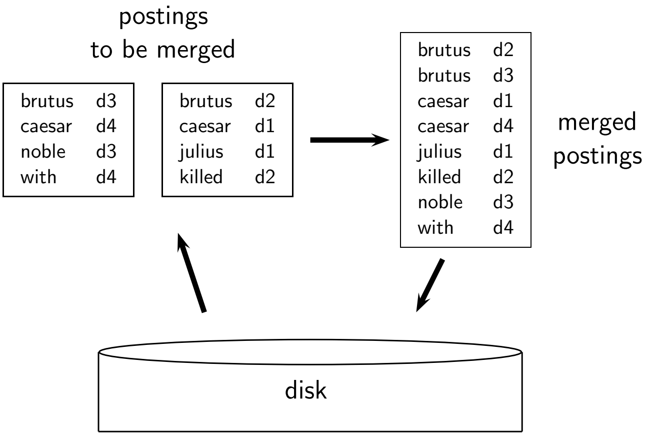
2014-04-17

Overview

Outline

1. Recap
2. Compression
3. Term statistics
4. Dictionary compression
5. Postings compression

Blocked Sort-Based Indexing



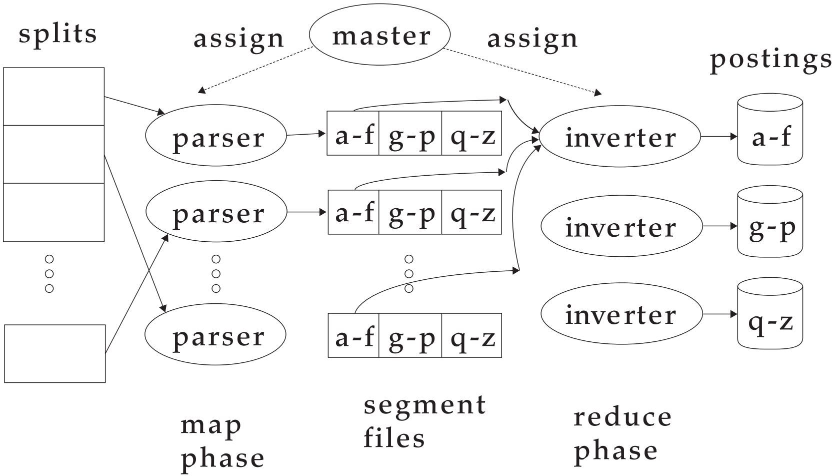
Single-pass in-memory indexing

- 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
```

MapReduce for index construction



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

Take-away today

For each term t, we store a list of all documents that contain t.

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 file**

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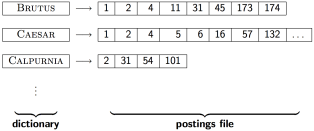

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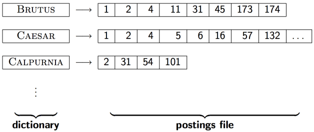

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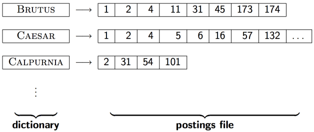

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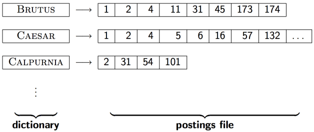

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- How can we compress the dictionary component of the inverted index?
- How can we compress the postings component of the inverted index?
- Term statistics: how are terms distributed in document collections?

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- We will devise various compression schemes for dictionary and postings.

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  - What we mostly do in index compression

Outline

Model collection: The Reuters collection

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

Effect of preprocessing for Reuters

	word types (terms)			non-positional postings			positional postings (word tokens)		
size of	dictionary			non-positional index			positional index		
	size	Δ	cml	size	Δ	cml	size	Δ	cml
unfiltered	484,494			109,971,179			197,879,290		
no numbers	473,723	-2	-2	100,680,242	-8	-8	179,158,204	-9	-9
case folding	391,523	-17	-19	96,969,056	-3	-12	179,158,204	-0	-9
30 stopw's	391,493	-0	-19	83,390,443	-14	-24	121,857,825	-31	-38
150 stopw's	391,373	-0	-19	67,001,847	-30	-39	94,516,599	-47	-52
stemming	322,383	-17	-33	63,812,300	-4	-42	94,516,599	-0	-52

Explain differences between numbers non-positional vs positional:
-3 vs -0, -14 vs -31, -30 vs -47, -4 vs -0

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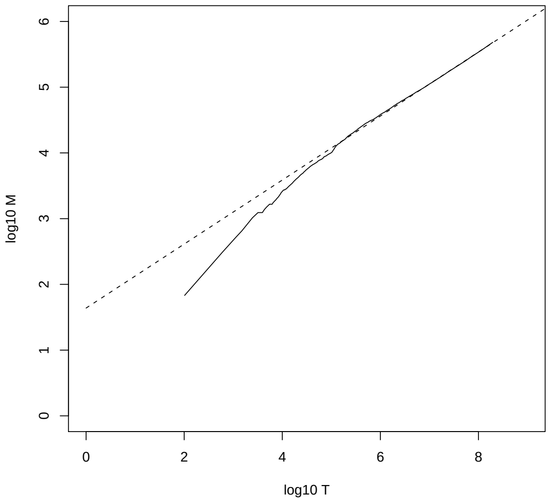
  - Empirical law

Heaps' law for Reuters



Vocabulary size M as a function of collection size T (number of tokens) for Reuters-RCV1. For these data, the dashed line $\log_{10} M = 0.49 * \log_{10} T + 1.64$ is the best least squares fit. Thus, $M = 10^{1.64} T^{0.49}$ and $k = 10^{1.64} \approx 44$ and $b = 0.49$.

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- Empirical observation: fit is good in general.

Exercise

1. What is the effect of including spelling errors vs. automatically correcting spelling errors on Heaps' law?
2. Compute vocabulary size M
   - Looking at a collection of web pages, you find that there are 3000 different terms in the first 10,000 tokens and 30,000 different terms in the first 1,000,000 tokens.
   - Assume a search engine indexes a total of 20,000,000,000 (2×10^{10}) pages, containing 200 tokens on average
   - What is the size of the vocabulary of the indexed collection as predicted by Heaps' law?

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- Example of a power law

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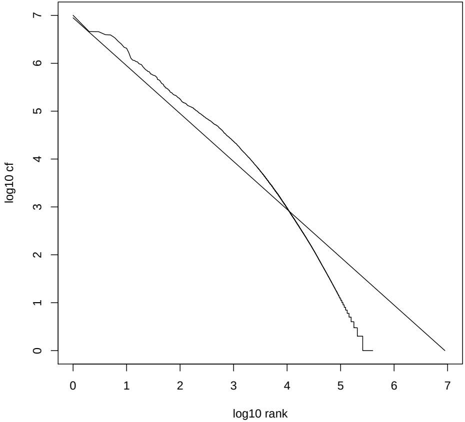

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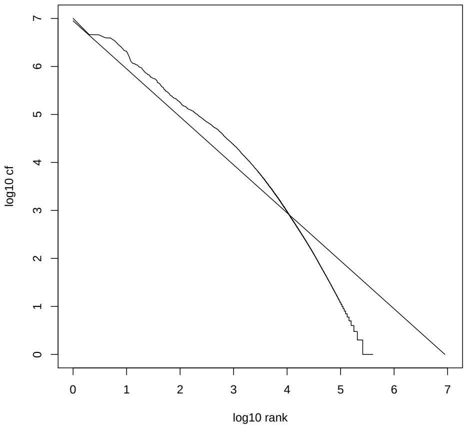

Fit is not great. What is important is the key insight: Few frequent terms, many rare terms.

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- The dictionary is small compared to the postings file.
- But we want to keep it in memory.
- Also: competition with other applications, cell phones, onboard computers, fast startup time
- So compressing the dictionary is important.

Recall: Dictionary as array of fixed-width entries

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	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

Space for Reuters: (20+4+4)*400,000 = 11.2 MB

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- How can we use on average 8 characters per term?

Dictionary as a string

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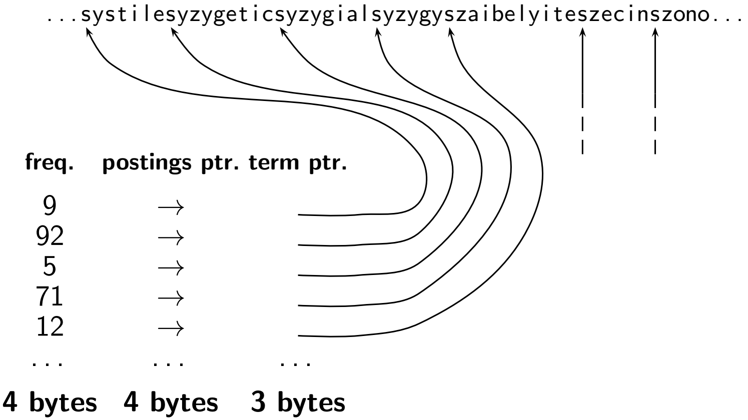

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- Space: $400{,}000 \times (4 + 4 + 3 + 8) = 7.6$MB (compared to 11.2 MB for fixed-width array)

Dictionary as a string with blocking

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. . . **7**systile**9**syzygetic**8**syzygial**6**syzygy**11**szaibelyite**6**szecin. . .

freq.	postings ptr.	term ptr.
9	→	
92	→	
5	→	
71	→	
12	→	
. . .	. . .	. . .

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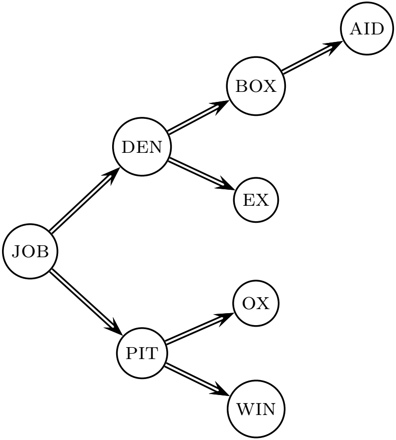
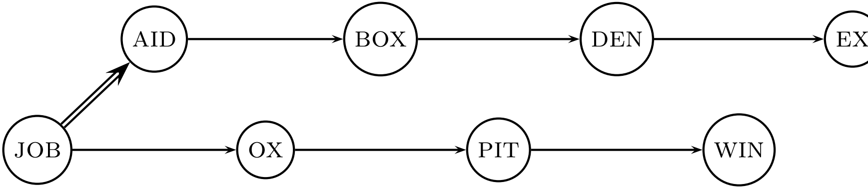
- Total savings: $400{,}000/4 * 5 = 0.5$ MB
- This reduces the size of the dictionary from 7.6 MB to 7.1 MB.

Lookup of a term without blocking



Lookup of a term with blocking: (slightly) slower



Front coding

One block in blocked compression ($k = 4$) ...

8 a u t o m a t a **8** a u t o m a t e **9** a u t o m a t i c **10** a u t o m a t i o n

$\Downarrow$

... further compressed with front coding.

8 a u t o m a t $*$ a **1** $\diamond$ e **2** $\diamond$ i c **3** $\diamond$ i o n

Dictionary compression for Reuters: Summary

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data structure	size in MB
dictionary, fixed-width	11.2
dictionary, term pointers into string	7.6
$\sim$, with blocking, $k = 4$	7.1
$\sim$, with blocking & front coding	5.9

Exercise

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- Which prefixes should be used for front coding? What are the tradeoffs?
- Input: list of terms (= the term vocabulary)
- Output: list of prefixes that will be used in front coding

Outline

1. Recap
2. Compression
3. Term statistics
4. Dictionary compression
5. Postings compression

Postings compression

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- For Reuters (800,000 documents), we would use 32 bits per docID when using 4-byte integers.
- Alternatively, we can use $\log_2 800{,}000 \approx 19.6 < 20$ bits per docID.
- Our goal: use a lot less than 20 bits per docID.

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- Gaps for frequent terms are small.
- Thus: We can encode small gaps with fewer than 20 bits.

Gap encoding

	encoding	postings list									
THE	docIDs	...		283042		283043		283044		283045	...
	gaps				1		1		1		...
COMPUTER	docIDs	...		283047		283154		283159		283202	...
	gaps				107		5		43		...
ARACHNOCENTRIC	docIDs	252000		500100							
	gaps	252000	248100								

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  - For THE and other very frequent terms, we will use only a few bits per gap (= posting).
- In order to implement this, we need to devise some form of variable length encoding.
- Variable length encoding uses few bits for small gaps and many bits for large gaps.

Variable byte (VB) code

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- At the end set the continuation bit of the last byte to 1 ($c = 1$) and of the other bytes to 0 ($c = 0$).

VB code examples

docIDs	824	829	215406
gaps		5	214577
VB code	00000110 10111000	10000101	00001101 00001100 10110001

VB code encoding algorithm

```
VBEncodeNumber(n)
bytes ← ⟨⟩
while true
do Prepend(bytes, n mod 128)
    if n < 128
       then Break
    n ← n div 128
bytes[Length(bytes)] += 128
return bytes
```

```
VBEncode(numbers)
bytestream ← ⟨⟩
for each n ∈ numbers
do bytes ← VBEncodeNumber(n)
    bytestream ← Extend(bytestream, bytes)
return bytestream
```

VB code decoding algorithm

```
VBDecode(bytestream)
numbers ← ⟨⟩
n ← 0
for i ← 1 to Length(bytestream)
do if bytestream[i] < 128
      then n ← 128 × n + bytestream[i]
      else n ← 128 × n + (bytestream[i] − 128)
           Append(numbers, n)
           n ← 0
return numbers
```

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- Variable byte alignment wastes space if you have many small gaps – nibbles do better on those.
- There is work on word-aligned codes that efficiently "pack" a variable number of gaps into one word – see resources at the end

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  - Unary code for 70 is:

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- Encode length in unary code: 1110.
- Gamma code of 13 is the concatenation of length and offset: 1110101.

Gamma code examples

number	unary code	length	offset	γ code
0	0			
1	10	0		0
2	110	10	0	10,0
3	1110	10	1	10,1
4	11110	110	00	110,00
9	1111111110	1110	001	1110,001
13		1110	101	1110,101
24		11110	1000	11110,1000
511		111111110	11111111	111111110,11111111
1025		11111111110	0000000001	11111111110,0000000001

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- Compute the variable byte code of 130
- Compute the gamma code of 130

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- γ codes are always of odd length.
- Gamma codes are within a factor of 2 of the optimal encoding length $\log_2 G$.
    - (assuming the frequency of a gap G is proportional to $\log_2 G$ – only approximately true)

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- This result is independent of the distribution of gaps!
- We can use gamma codes for any distribution. Gamma code is universal.
- Gamma code is parameter-free.

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- Compressing and manipulating at granularity of bits can be slow.
- Variable byte encoding is aligned and thus potentially more efficient.
- Regardless of efficiency, variable byte is conceptually simpler at little additional space cost.

Compression of Reuters

data structure	size in MB
dictionary, fixed-width	11.2
dictionary, term pointers into string	7.6
$\sim$, with blocking, $k = 4$	7.1
$\sim$, with blocking & front coding	5.9
collection (text, xml markup etc)	3600.0
collection (text)	960.0
T/D incidence matrix	40,000.0
postings, uncompressed (32-bit words)	400.0
postings, uncompressed (20 bits)	250.0
postings, variable byte encoded	116.0
postings, γ encoded	101.0

Term-document incidence matrix

	Anthony and Cleopatra	Julius Caesar	The Tempest	Hamlet	Othello	Macbeth	...
ANTHONY	1	1	0	0	0	1	
BRUTUS	1	1	0	1	0	0	
CAESAR	1	1	0	1	1	1	
CALPURNIA	0	1	0	0	0	0	
CLEOPATRA	1	0	0	0	0	0	
MERCY	1	0	1	1	1	1	
WORSER	1	0	1	1	1	0	
...							

Entry is 1 if term occurs. Example: CALPURNIA occurs in *Julius Caesar*.
Entry is 0 if term doesn't occur. Example: CALPURNIA doesn't occur in *The tempest*.

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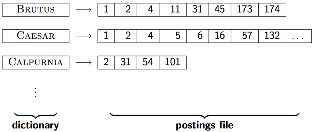
- Only 10-15% of the total size of the text in the collection.
- However, we've ignored positional and frequency information.
- For this reason, space savings are less in reality.

Take-away today

For each term t, we store a list of all documents that contain t.



- Motivation for compression in information retrieval systems
- How can we compress the dictionary component of the inverted index?
- How can we compress the postings component of the inverted index?
- Term statistics: how are terms distributed in document collections?

Resources

- Chapter 5 of IIR
- Resources at `http://cislmu.org`
  - Original publication on word-aligned binary codes by Anh and Moffat (2005); also: Anh and Moffat (2006a)
  - Original publication on variable byte codes by Scholer, Williams, Yiannis and Zobel (2002)
  - More details on compression (including compression of positions and frequencies) in Zobel and Moffat (2006)