Introduction to Information Retrieval

http://informationretrieval.org

IIR 5: Index Compression

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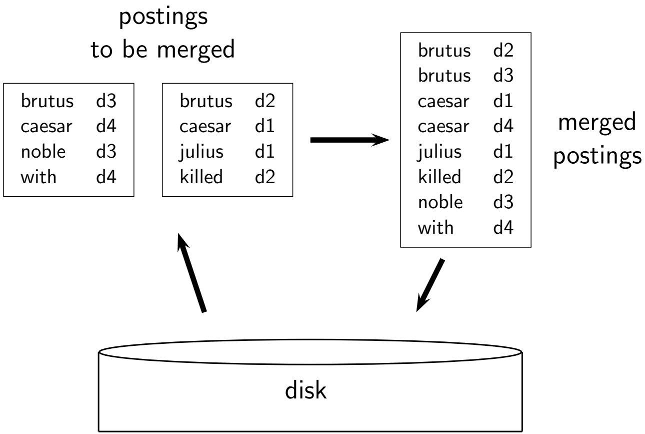
Overview

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

Outline

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

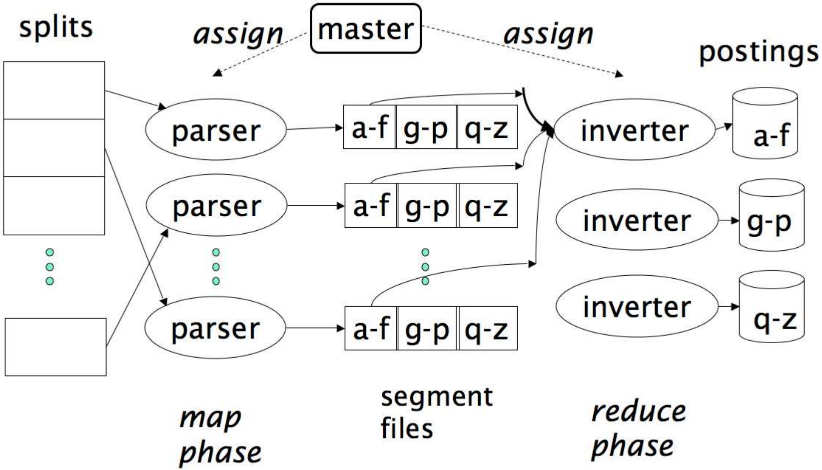
Blocked Sort-Based Indexing



SPIMI algorithm

```
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



Logarithmic merging

```
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())
```

Outline

Inverted index

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

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					
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dictionary **postings file**

Today:

- How much space do we need for the dictionary?
- How much space do we need for the postings file?
- How can we compress them?

Why compression? (in general)

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- This is true of the decompression algorithms we will use.

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  - Large search engines keep significant part of postings in memory
- We will devise various compression schemes.

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

size of	word types (term)			non-positional postings			positional postings (word tokens)		
	dictionary			non-positional index			positional index		
	size	Δ	cumul.	size	Δ	cumul.	size	Δ	cumul.
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 stop words	391,493	-0%	-19%	83,390,443	-14%	-24%	121,857,825	-31%	-38%
150 stop words	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%

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- Also: phrase queries.

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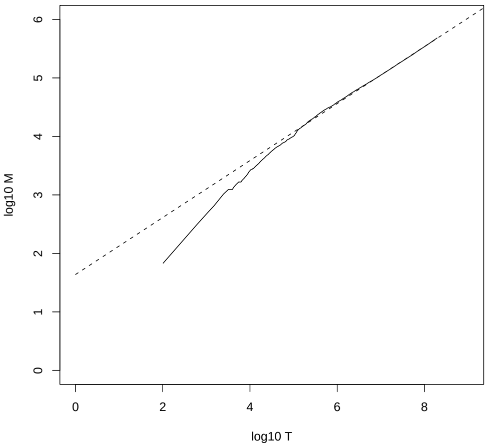
- Typical values for the parameters k and b are: $30 \leq k \leq 100$ and $b \approx 0.5$.
- Empirical law: Heaps' law is linear, i.e., the simplest possible relationship between collection size and vocabulary size in log-log space.

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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- What is the effect of including spelling errors vs. automatically correcting spelling errors on Heaps' law?

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- 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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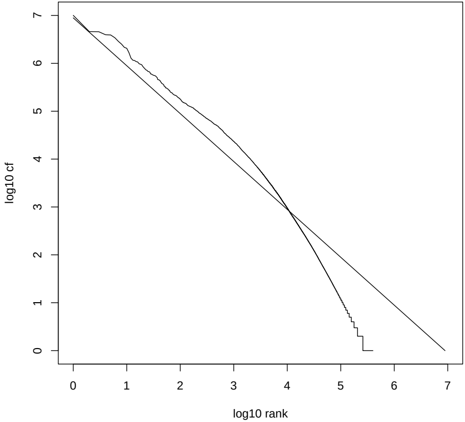
- Example of a power law

Zipf's law for Reuters



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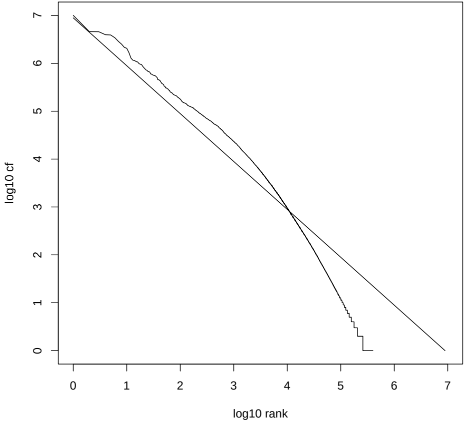

Fit is not great. What is important is the key insight: Few frequent terms, many rare terms.

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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

	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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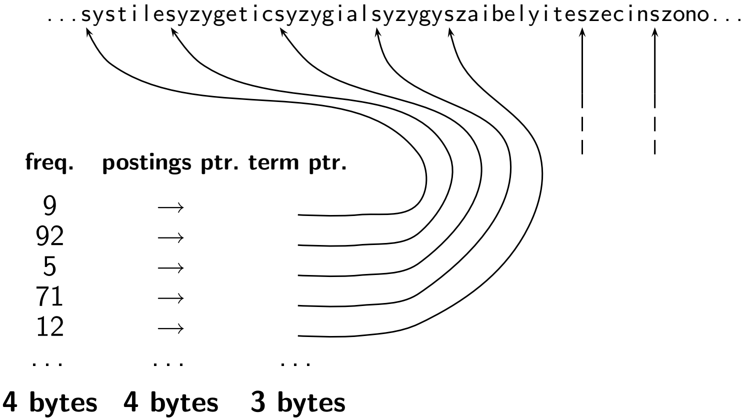
- We can't handle HYDROCHLOROFLUOROCARBONS and SUPERCALIFRAGILISTICEXPIALIDOCIOUS
- Average length of a term in English: 8 characters
- How can we use on average 8 characters per term?

Dictionary as a string



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- 8 bytes (on average) for term in string
- Space: $400{,}000 \times (4 + 4 + 3 + 8) = 7.6$MB (compared to 11.2 MB for fixed-width)

Dictionary as a string with blocking

. . . **7** s y s t i l e **9** s y z y g e t i c **8** s y z y g i a l **6** s y z y g y **11** s z a i b e l y i t e **6** s z e c i n . . .

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

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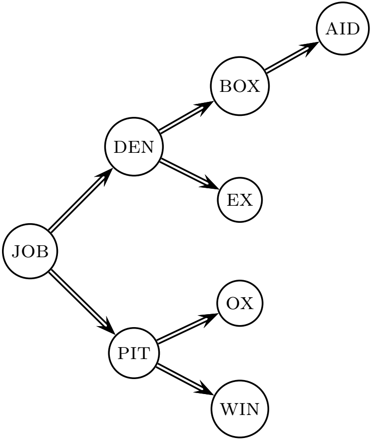
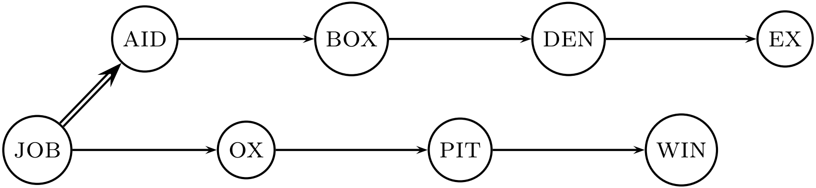
- We save $12 - (3 + 4) = 5$ bytes per block.
- Total savings: $400{,}000/4 * 5 = 0.5$ MB
- This reduces the size of the dictionary from 7.6 MB to 7.1 MB.

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

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

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Postings compression

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- Key desideratum: store each posting compactly.

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- Alternatively, we can use $\log_2 800{,}000 \approx 20$ 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 about 1 bit per gap (= posting).
- In order to implement this, we need to devise some form of variable length encoding.
- Use few bits for small gaps, 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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- See resources at the end

Variable byte code for 260?

Gamma codes for gap encoding

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- Gamma code of 13 is the concatenation of length and offset: 1110101.

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- Unary code for 40 is
  11111111111111111111111111111111111111110 .

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

Gamma code for 28?

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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 equal-probability gaps – but the distribution is actually highly skewed.

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- Even better: delta codes

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- Compressing and manipulating at individual bit-granularity can slow down query processing
- Variable byte alignment is potentially more efficient
- Regardless of efficiency, variable byte is conceptually simpler at little additional space cost

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	
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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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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

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- However, we've ignored positional and frequency information.
- For this reason, space savings are less in reality.

Resources

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- 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)