Information Retrieval and Organisation

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Index Compression

Why Compression?

- Using less disk space
  (saves money)
- Caching: keep more stuff in memory
  (increases speed)
- Transferring data from disk to memory faster
  (again, increases speed)
  - It would be faster to "read compressed data and decompress" than "read uncompressed data"
  - Premise: decompression algorithms are fast
  - This is true of the decompression algorithms that we will use

Why Compression in IR?

- For dictionary,
  - Main motivation: make it small enough to keep in main memory
- For postings file,
  - Main motivation: reduce disk space needed; decrease time needed to read from disk
  - Large search engines keep significant part of postings in memory
- We will devise various compression schemes

Lossy vs Lossless Compression

- Lossless compression: preserve all information
- Lossy compression: discard some information
  - Several of the preprocessing steps can be viewed as lossy compression
    - eliminating numbers
    - casefolding
    - stop words
    - stemming
  - What can we gain with lossy compression?

Preprocessing for Reuters

	(distinct) terms			non-positional postings			tokens (= number of position entries in postings)		
	number	Δ%	T%	number	Δ%	T%	number	Δ%	T%
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

- Lossy compression can be problematic, e.g. phrase queries
- We will focus on lossless compression for the remainder of this chapter

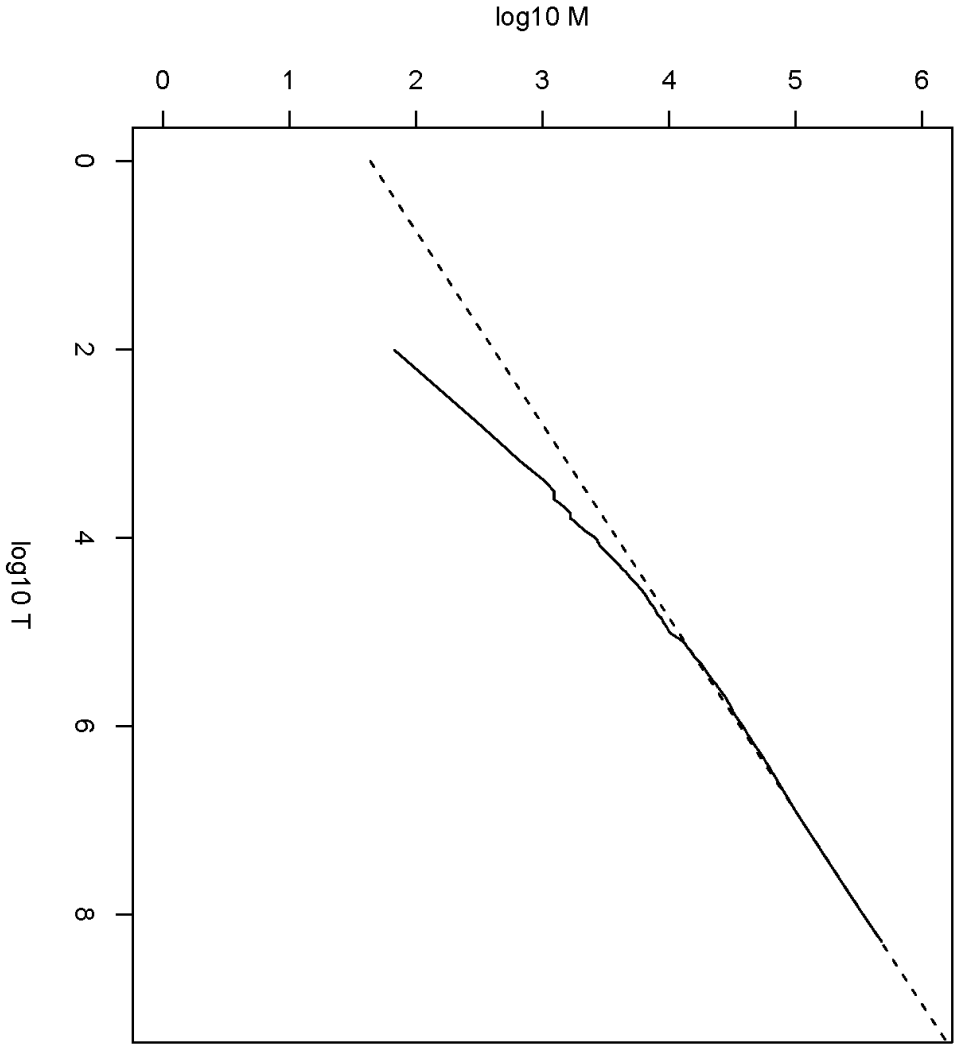
Analysing the Term Vocabulary

- Given a collection size (the number of tokens) T, can we estimate the vocabulary size M?
- Yes, we can using Heaps' law:

$$M = kT^b$$

  - k and b are two parameters, typically in the range of: $30 \leq k \leq 100$ and $b \approx 0.5$
  - For Reuters-RCV1, $k = 44$ and $b = 0.49$, which predicts 38,323 (actual number is 38,365)

Heaps' Law for Reuters-RCV1



Heaps' Law

- Implications of Heaps' Law:
  - dictionary size keeps growing with more documents (no maximum will be reached)
  - dictionary sizes will be quite large for large collections
- Has been shown empirically for large collections
- Dictionary compression is important for efficiency

Dictionary Compression

- The dictionary is small compared to the postings file, but
  - we want to keep (most of) it in memory
  - there is competition with other applications for memory
  - small memory sizes for cell phones or onboard computers
  - we want fast startup time
- So compressing the dictionary is useful

Dictionary as Fixed-Width Array

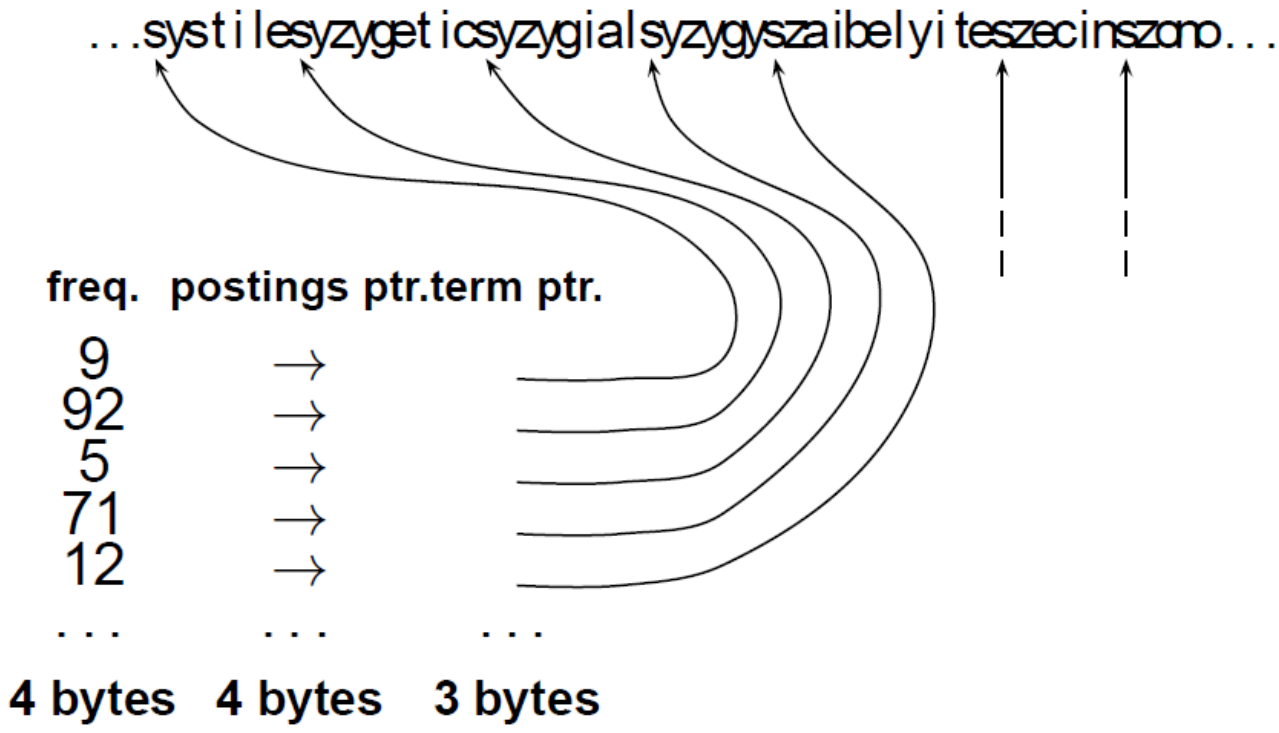
	term	document frequency	pointer to postings list
	a	656,265	$\longrightarrow$
	aachen	65	$\longrightarrow$
	...	...	...
	zulu	221	$\longrightarrow$
space needed:	20 bytes	4 bytes	4 bytes

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

Dictionary as Fixed-Width Array

- This is a bad idea
  - Most of the bytes in the term column are wasted
    - 20 bytes are allotted for a term of length 1
  - We can't handle very long words, e.g., "hydrochlorofluorocarbons"
- The average length of a term in English: 8 characters
  - How can we use on average 8 characters per term?

Dictionary as a String

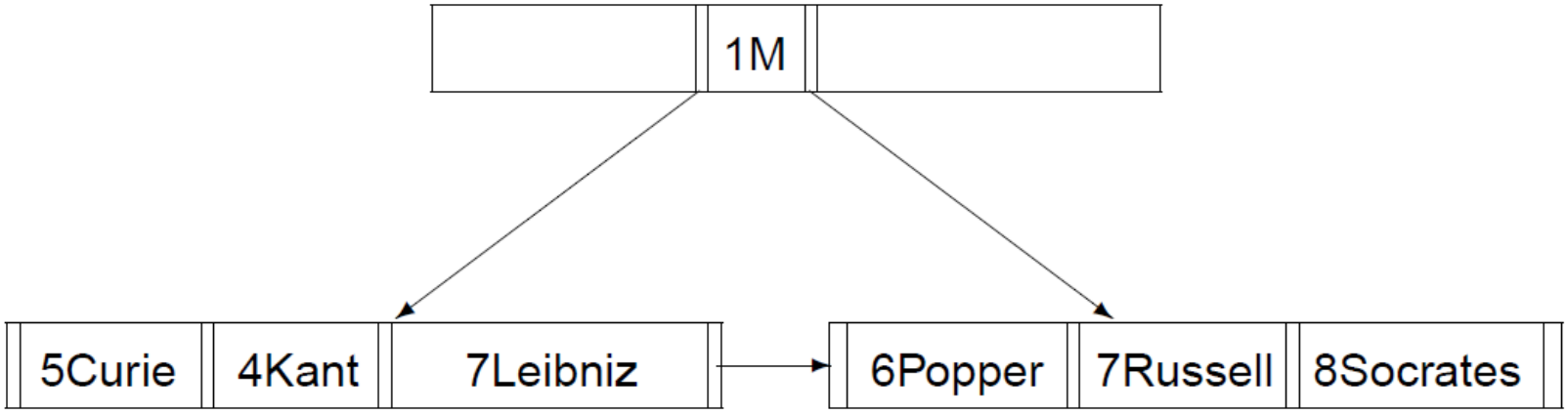


- Concatenate all terms into one big string (and use pointers in dictionary)
- Use binary search to find term

Dictionary as a String

- While this saves space, it is not very scalable
  - Once we run out of memory, we have to store (parts of) the dictionary on disk
  - Switching between main-memory and disk representation is awkward in this scheme
- We are going to look at prefix B-trees and some optimizations for them
  - NOTE: we deviate a bit from the textbook here

Prefix B-trees



- Only the leaves of the trees contain actual terms (+ frequency and postings pointer)
- Terms use variable space on page (every term preceded by length)
- Inner nodes use reference keys to separate pages, not actual terms

Prefix B-trees

- Compared to dictionary as a string, we replace the term pointers with inner nodes
- This will use slightly more memory, but allows for a much faster search
- B-trees are very good for disk-based indexing (if we run out of main memory)
- We can cache the most frequently used parts of the tree in main memory

Front Coding

- Many entries on a page share the same prefix
- We can exploit this by using front coding:
  - 1st number indicates how many letters to re-use from the beginning of previous word
  - 2nd number states how many letter to add to this
  - This is followed by the actual letters

word	front coding
automata	0,8,automata
automate	7,1,e
automatic	7,2,ic
automation	8,2,on
automotive	5,5,otive
bat	0,3,bat

Postings Compression

- The postings file is much larger than the dictionary
  - factor of at least 10
- Key desideratum: store each posting compactly.
  - A posting for our purposes is a docID.
  - For Reuters (800,000 documents), we would use 32 bits per docID when using 4-byte integers.
  - Alternatively, we can use $\log_2 800{,}000 \approx 20$ bits per docID.
  - Our goal: use a lot less than 20 bits per docID.

Key Idea: Store Gaps

- Each postings list is ordered in the increasing order of docID
  - `information`, 8: $\langle$ 3, 8, 12, 19, 22, 23, 26, 33 $\rangle$;
- It suffices to store *gaps*
  - `information`, 8: $\langle$ 3, 5, 4, 7, 3, 1, 3, 7 $\rangle$;
- The gaps for frequent terms are small.
  - That means, we can encode small gaps with fewer than 20 bits.

Gap Encoding

	encoding	postings list							
`the`	docIDs	...		283042		283043		283044	...
	gaps				1		1		...
`computer`	docIDs	...		283047		283154		283159	...
	gaps				107		5		...
`arachnocentric`	docIDs	252000		500100					
	gaps	252000	248100						

- For rare terms, such as `arachnocentric`, gaps can be quite large
  - We still need 20 bits to encode them
- Solution: use *variable length encoding*
  - Few bits for small gaps
  - Many bits for large gaps

Variable Byte (VB) Code

- Used by many commercial/research systems
- Good low-tech blend of variable-length coding and sensitivity to alignment matches (bit-level codes, see later).
  - Dedicate 1 bit (high bit) to be a *continuation bit* c.
  - If the gap G fits within 7 bits, binary-encode it in the 7 available bits and set $c = 1$.
  - Else: set $c = 0$, encode high-order 7 bits and then use one or more additional bytes to encode the lower order bits using the same algorithm.

VB Code Example

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

- Instead of bytes, we can also use a different "unit of alignment"
  - 32 bits (words), 16 bits, 4 bits (nibbles) etc.
- Variable byte alignment wastes space if you have many small gaps
  - nibbles do better on those

Bit-Level Encoding

- You can get even more compression with *bit-level* code
  - These use variable length bit codes
  - Have to be *prefix-free*, i.e. no valid codeword is allowed to be the prefix of another (like phone numbers)
- We are going to look at *Unary Code* and *Gamma Code* (or γ-Code)

Unary Code

- Represent n as n 1s with a final 0
  - Unary code for 3 is
    1110
  - Unary code for 40 is
    1111111111111111111111111111111111111110
- Only good for highly skewed data, i.e., very many very short gaps
- It is very inefficient for large numbers

Gamma Code (γ-Code)

- How many bits do we need to store a gap?
  - 1=1 (1 bit), 2=10 (2 bits), 3=11 (2 bits), 5=101 (3 bits), 13=1101 (4 bits), ...
  - The number of bits to store n: $1 + \log_2 \lfloor n \rfloor$
  - We don't have any gaps of 0, therefore 1 is the smallest number we have to encode
  - This means that we always have a leading 1
  - We can chop off the leading 1, and measure the *length* of the remaining bit-string: $\log_2 \lfloor n \rfloor$
  - We call the remaining bitstring the *offset*
  - Example: 13 is 1101,
    chop off leading 1 $\rightarrow$ 101:
    length $= 3$, offset $= 101$

Gamma Code

- Gamma Code encodes
  - the length in unary code
  - the offset in the usual binary code
- So, for our example:
  - 13 has a gamma code of 1110101:
    1110 for the length, 101 for the offset

More 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

Comparison

- So, which code is better?
  - Here is a comparison for some typical document collections:

method	bits per gap			
	Bible	GNUBib	Comact	TREC
Unary	262	909	487	1918
Gamma	6.51	5.68	4.48	6.63

- More details (+ another code, Delta Code) in:
  - I.H. Witten, A. Moffat und T.C. Bell, “Managing Gigabytes”, Morgan Kaufmann, 1999

Comparison

- Machines have word boundaries: 8, 16, 32 bits
- Compressing and manipulating at individual bit-granularity
  - yields better compression
  - can slow down query processing
- Variable byte alignment is potentially more efficient to process
  - Regardless of efficiency, variable byte is conceptually simpler at little additional space cost

Summary

- We can now create an index for highly efficient Boolean retrieval that is very space efficient
  - Only 10-15% of the total size of the text in the collection
- However, we have ignored positional and frequency information
  - For this reason, space savings are less in reality
  - But similar techniques can be used to compress positional information