Index compression

CE-324: Modern Information Retrieval

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Most slides have been adapted from: Profs. Manning, Nayak & Raghavan (CS-276, Stanford)

Today

BRUTUS	→	1	2	4	11	31	45	173	174
CAESAR	→	1	2	4	5	6	16	57	132	...
CALPURNIA	→	2	31	54	101				

- Collection statistics in more detail (with RCV1)
  - How big will the dictionary and postings be?
- Dictionary compression
- Postings compression

Why compression (in general)?

- Use less disk space
  - Saves a little money
- Keep more stuff in memory
  - Increases speed
- Increase speed of data transfer from disk to memory
  - [read compressed data + decompress] is faster than [read uncompressed data]
  - Premise: Decompression algorithms are fast
    - True of the decompression algorithms we use

Why compression for inverted indexes?

- Dictionary
  - Make it small enough to keep in main memory
  - Make it so small that you can keep some postings lists in main memory too
- Postings file(s)
  - Reduce disk space needed
  - Decrease time needed to read postings lists from disk
  - Large search engines keep a significant part of the postings in memory.
    - Compression lets you keep more in memory

Compression

- Compressing the space for the dictionary and postings
  - Basic Boolean index only
  - No study of positional indexes, etc.
  - We will consider compression schemes

Reuters RCV1 statistics

symbol	statistic	value
N	# documents	800,000
L_{ave}	avg. # tokens per doc	200
M	terms (= word types)	400,000
	avg. # bytes per token (incl. spaces/punct.)	6
	avg. # bytes per token (without spaces/punct.)	4.5
	avg. # bytes per term	7.5
	non-positional postings	100,000,000

Index parameters vs. what we index
(details IIR Table 5.1, p.80)

	Dictionary (terms)			non-positional postings			positional postings		
	Size (K)	∆%	Total %	Size (K)	∆%	Total %	Size (K)	∆%	Total%
Unfiltered	484			109,971			197,879		
No numbers	474	-2	-2	100,680	-8	-8	179,158	-9	-9
Case folding	392	-17	-19	96,969	-3	-12	179,158	0	-9
30 stopwords	391	-0	-19	83,390	-14	-24	121,858	-31	-38
150 stopwords	391	-0	-19	67,002	-30	-39	94,517	-47	-52
stemming	322	-17	-33	63,812	-4	-42	94,517	0	-52

Exercise: give intuitions for all the ‘0’ entries. Why do some zero entries correspond to big deltas in other columns?

Lossless vs. lossy compression

- Lossless compression: All information is preserved.
  - What we mostly do in IR.
- Lossy compression: Discard some information

- Several of the preprocessing steps can be viewed as lossy compression:
  - case folding, stop words, stemming, number elimination.

- Prune postings entries that are unlikely to turn up in the top *k* list for any query.
  - Almost no loss quality for top *k* list.

Dictionary Compression

Why compress the dictionary?

- Search begins with the dictionary
- We want to keep it in memory
- Even if the dictionary isn't in memory, we want it to be small for a fast search startup time
- So, compressing the dictionary is important

Main goal of dictionary compression

- Fit it (or at least a large portion of it) in main memory
  - to support high query throughput

Vocabulary vs. collection size

- How big is the term vocabulary?
  - That is, how many distinct words are there?
- Can we assume an upper bound?
  - Not really: At least $70^{20} = 10^{37}$ different words of length 20
- In practice, the vocabulary will keep growing with the collection size
  - Especially with Unicode ☺

Vocabulary vs. collection size

- **Heaps' law**: $M = kT^b$
  - *M*: # terms
  - *T* : # tokens
  - Typical values: $30 \leq k \leq 100$ and $b \approx 0.5$

- In a log-log plot of vocabulary size *M* vs. *T*:
  - Heaps' law predicts a line with slope about ½
  - It is the simplest possible relationship between the two in log-log space
  - An empirical finding ("empirical law")

Heaps' Law

$$M = kT^b$$

- RCV1:
  - $M = 10^{1.64} T^{0.49}$
  - $k = 10^{1.64} \approx 44$
  - $b = 0.49$.

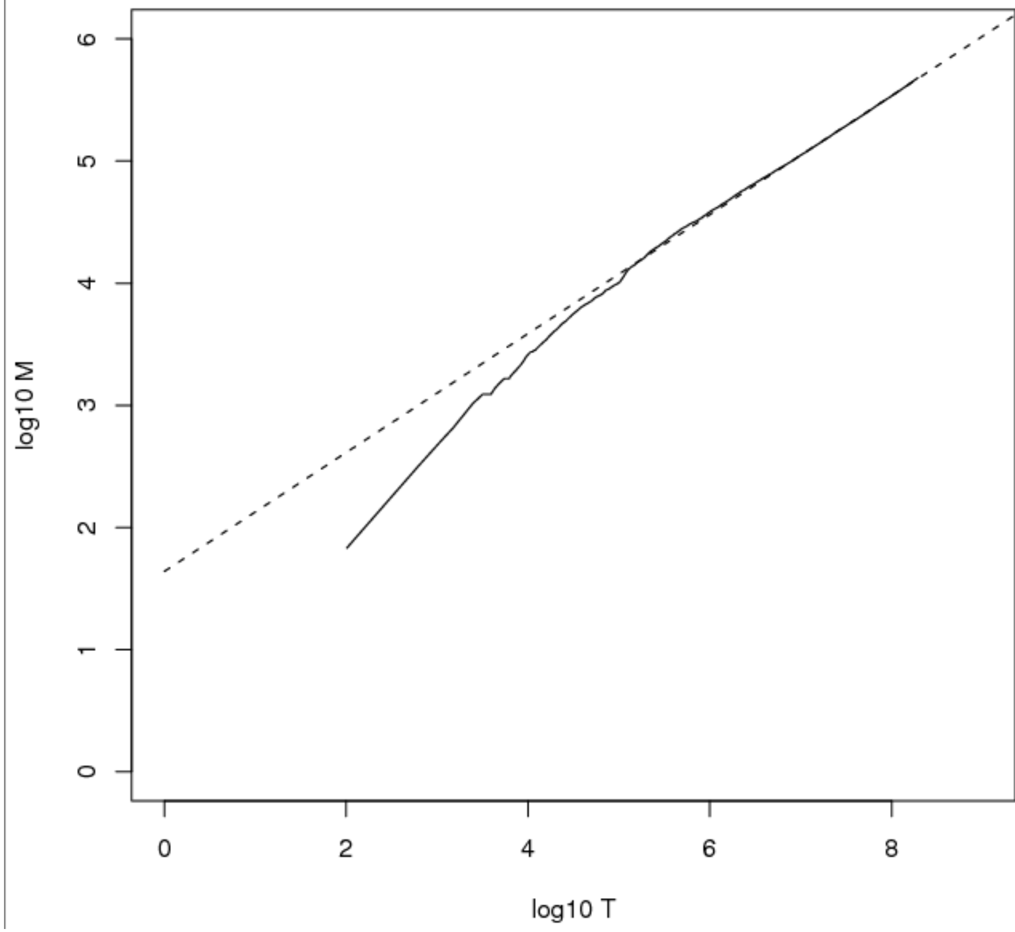
$$\log_{10} M = 0.49 \log_{10} T + 1.64$$

(best least squares fit)

For first 1,000,020 tokens,

predicts 38,323 terms;

actually, 38,365 terms



Good empirical fit for Reuters RCV1 !

A naïve dictionary

- An array of struct:

term	document frequency	pointer to postings list
a	656,265	$\longrightarrow$
aachen	65	$\longrightarrow$
...	...	...
zulu	221	$\longrightarrow$

20 bytes   4/8 bytes   4/8 bytes

- How do we store a dictionary in memory efficiently?
- How do we quickly look up elements at query time?

Fixed-width terms are wasteful

- Most of the bytes in the **Term** column are wasted.
  - We allow 20 bytes for 1 letter terms
  - Also we still can't handle *supercalifragilisticexpialidocious* or *hydrochlorofluorocarbons*.
- Written English averages ~4.5 characters/word.
- Ave. dictionary word in English: ~8 characters
  - How do we use ~8 characters per dictionary term?
- Short words dominate token counts but not type average.

Compressing the term list: Dictionary-as-a-string

- Store dictionary as a (long) string of characters:
  - Pointer to next word shows end of current word
  - Hope to save up to 60% of dictionary space.

….systilesyzygeticsyzygialsyzygyszaibelyiteszczecinszomo….

Freq.	Postings ptr.	Term ptr.
33		
29		
44		
126		

Total string length = $400K \times 8B = 3.2MB$

Pointers resolve 3.2M positions: $\log_2 3.2M$ = 22bits = 3bytes

Space for dictionary as a string

- 4 bytes per term for Freq.
- 4 bytes per term for pointer to Postings.
- 3 bytes per term pointer
- Avg. 8 bytes per term in term string

Now avg. 11 bytes/term, not 20.

- 400K terms x 19 ⇒ 7.6 MB

  (against 11.2MB for fixed width)

Blocking

- Store pointers to every *k*th term string.
  - Example below: *k*=4.
- Need to store term lengths (1 extra byte)

….7*systile*9*syzygetic*8*syzygial*6*syzygy*11*szaibelyite*8*szczecin*9*szomo*….

Freq.	Postings ptr.	Term ptr.
33		
29		
44		
126		
7		

Save 9 bytes on 3 pointers.

Lose 4 bytes on term lengths.

Blocking

- Example for block size *k* = 4
- Without blocking: 3 x 4 = 12 bytes
  - Where we used 3 bytes/pointer without blocking
- Blocking: 3 + 4 = 7 bytes.
- Size of the dictionary from 7.6 MB to 7.1 MB (Saved ~0.5MB).

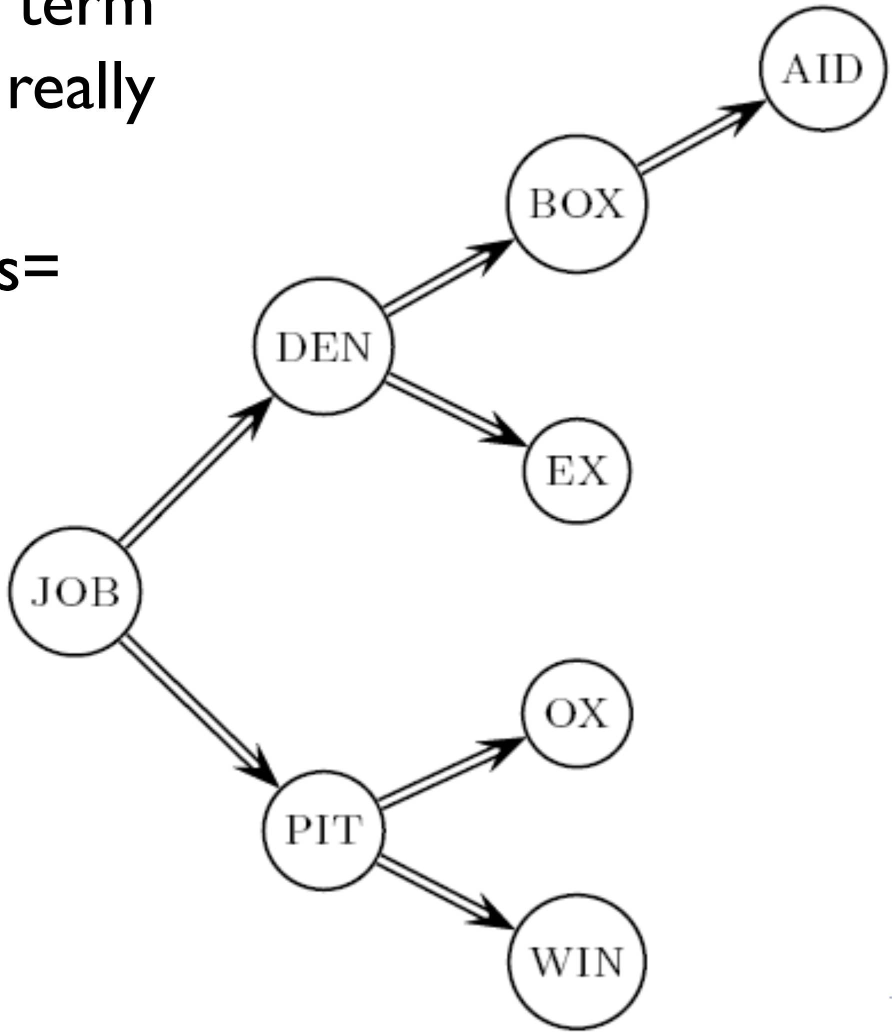
Why not go with larger *k*?

Dictionary search without blocking

- Assuming each dictionary term equally likely in query (not really so in practice!):

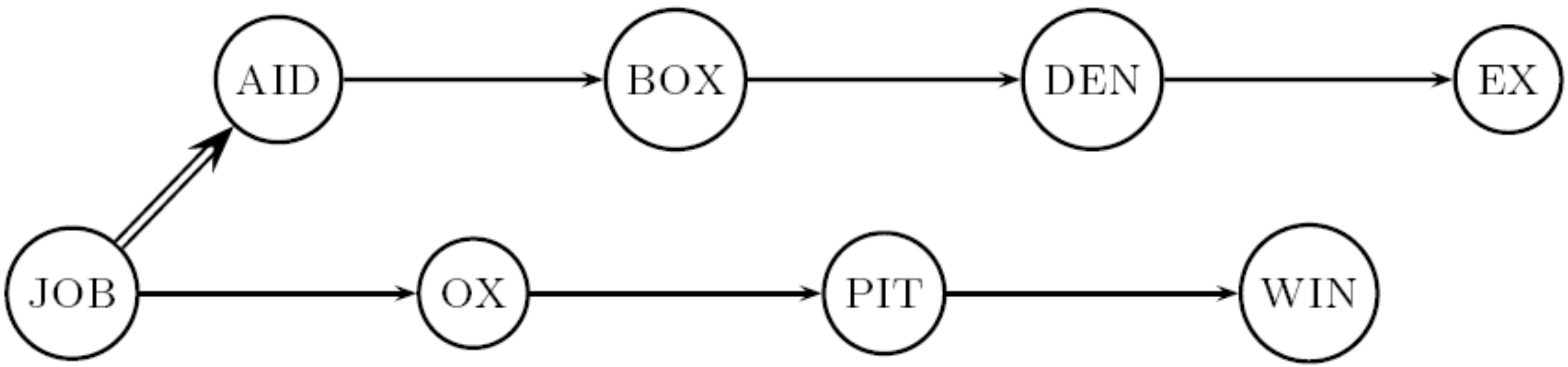
  average no. of comparisons=

  (1+2·2+4·3+4)/8 ~2.6



Exercise: what if the frequencies of query terms were non-uniform but known, how would you structure the dictionary search tree?

Dictionary search with blocking



- Binary search down to 4-term block;
  - Then linear search through terms in block.

- Blocks of 4 (binary tree):

  avg. = $(1+2\cdot2+2\cdot3+2\cdot4+5)/8 = 3$ compares

Front coding

- <u>Front-coding:</u>
  - Sorted words <u>commonly have long common prefix</u>
    - <u>store differences only (for last *k-1* in a block of *k*)</u>

8***automata***8***automate***9***automatic***10***automation***

→8***automat********a***1◊***e***2◊***ic***3◊***ion***

Encodes ***automat***

Extra length beyond ***automat.***

Begins to resemble general string compression.

RCV1 dictionary compression summary

Technique	Size in MB
Fixed width	11.2
Dictionary-as-String with pointers to every term	7.6
Also, blocking k = 4	7.1
Also, Blocking + front coding	5.9

Postings Compression

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 docs), we would use 32 bits (4 bytes) per docID when using 4-byte integers.
  - Alternatively, we can use $\log_2 800{,}000 \approx 20$ bits per docID.

- Our goal: use far fewer than 20 bits per docID.

Postings: two conflicting forces

- ***arachnocentric*** occurs in maybe one doc
  - we would like to store this posting using $\log_2$ 1M ~ 20 bits.

- ***the*** occurs in virtually every doc
  - 20 bits/posting is too expensive.
  - Prefer 0/1 bitmap vector in this case

Postings file entry

- We store the list of docs containing a term in increasing order of docID.
  - ***computer***: 33,47,154,159,202 …
- <u>Consequence</u>: it suffices to store *gaps*.
  - 33,14,107,5,43 …
- <u>Hope</u>: most gaps can be encoded/stored with far fewer than 20 bits.

Three postings entries

	encoding	postings list					
THE	docIDs	...	283042	283043	283044	283045	...
COMPUTER	docIDs	...	283047	283154	283159	283202	...
ARACHNOCENTRIC	docIDs	252000	500100				

Term frequencies

- Heaps' law gives the vocabulary size in collections.
- We also study the relative frequencies of terms.
- In natural language, there are a few very frequent terms and many very rare terms.

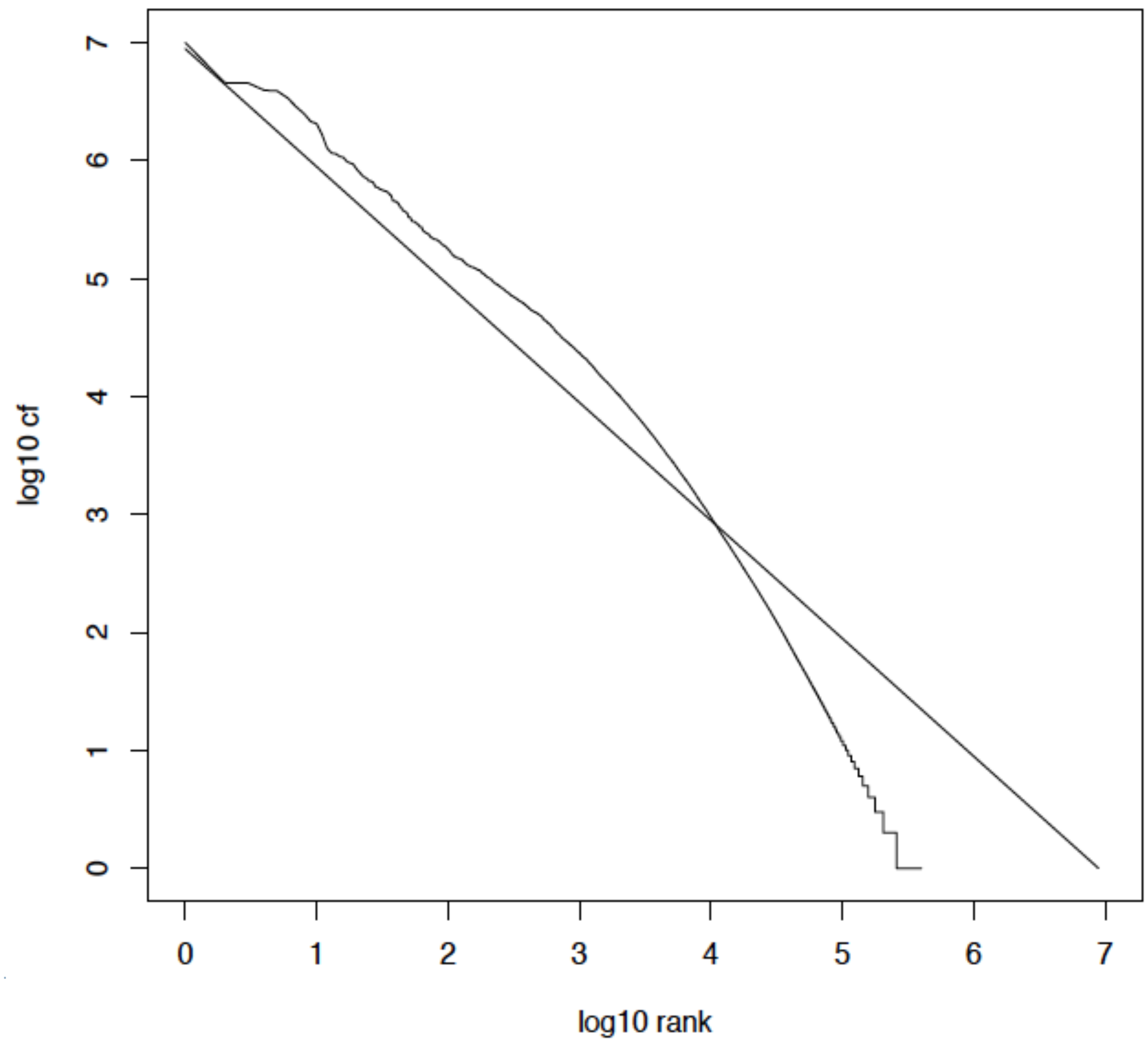
Zipf's law

- Zipf's law: The *i*th most frequent term has frequency proportional to 1/*i* .
- cf_i is collection frequency: the number of occurrences of the term t_i in the collection.

Zipf consequences

- Most frequent term occurs $\underline{cf_1}$ times
  - second most frequent term occurs $\underline{cf_1/2}$ times
  - third most frequent term occurs $\underline{cf_1/3}$ times …

Zipf’s law for Reuters RCV1



$$cf_i \propto \frac{1}{i}$$

Variable length encoding

- Average gap for a term: *G*
  - We want to use $\sim\log_2 G$ bits/gap entry.
- <u>Key challenge</u>: encode every integer (gap) with about as few bits as needed for that integer.
  - For a gap value *G*, we want to use close to $\log_2 G$ bits
- This requires a *variable length encoding*
  - using short codes for small numbers

Variable Byte (VB) codes

- Begin with one byte to store *G* and dedicate 1 bit in it to be a continuation bit *c*
  - If $G \leq 127$, binary-encode it in the 7 available bits
  - Else encode *G*'s lower-order 7 bits and then use additional bytes to encode the higher order bits recursively
  - At the end: set the continuation bits
    - the last byte $c = 1$
    - other bytes $c = 0$.

Example

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

Postings stored as the byte concatenation

000001101011100010000101000011010000110010110001

Key property: VB-encoded postings are uniquely prefix-decodable.

For a small gap (5), VB uses a whole byte.

Other variable unit codes

- Other "<u>unit of alignment</u>" instead of bytes:
  - 32 bits (words), 16 bits, 4 bits (nibbles).
  - Variable byte may waste space when many small gaps (nibbles do better)

- Variable byte codes:
  - Used by many commercial/research systems
  - Good low-tech blend of variable-length coding and sensitivity to computer memory alignment matches
    - vs. bit-level codes, which we look at next

Unary code

- Represent *n*: *n* 1s + a 0
  - 3:1110
  - 38:111111111111111111111111111111111111110
- This doesn't look promising, but….

Gamma codes

- We can compress better with bit-level codes
  - Gamma code: the best known bit-level.

- Represent a gap *G*: *length* + *offset*
  - *Offset*: *G* in binary, with the leading bit cut off
    - E.g., 13 → 1101 → 101
  - *Length:* length of offset encoded with *unary code*
    - E.g., 13 (offset 101), length is 3 → 1110.
  - Gamma code: *length* + *offset*
    - E.g., 13 → 1110101

Gamma code examples

number	length	offset	g-code
0			none
1	0		0
2	10	0	10,0
3	10	1	10,1
4	110	00	110,00
9	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 properties

- $G \rightarrow 2\lfloor \log G \rfloor + 1$ bits
  - Offset: $\lfloor \log G \rfloor$ bits
  - Length: $\lfloor \log G \rfloor + 1$ bits

- Properties:
  - always have an odd number of bits
  - almost within a factor of 2 of best possible ($\log_2 G$)
  - uniquely prefix-decodable, like VB
  - can be used for any distribution
  - parameter-free

Gamma seldom used in practice

- Machines have word boundaries (8, 16, 32, 64 bits)
  - Operations that cross word boundaries are slower
  - Compressing and manipulating at the 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

RCV1 compression

Data structure	Size in MB
dictionary, fixed-width	11.2
dictionary, term pointers into string	7.6
with blocking, k = 4	7.1
with blocking & front coding	5.9
collection (text, xml markup etc)	3,600
collection (text)	960
Term-doc incidence matrix	40,000
postings, uncompressed (32-bit words)	400
postings, uncompressed (20 bits)	250
postings, variable byte encoded	116
postings, g-encoded	101

Index compression: summary

- We can now create an index for highly efficient Boolean retrieval that is very space efficient
  - Only 4% of the total size of the collection
  - Only 10-15% of the total size of the text in the collection
- However, we've ignored positional information
- Hence, space savings are less for indexes used in practice
  - But techniques substantially the same.