CS60092: Information Retrieval

Index Compression

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Last lecture – index construction

- Sort-based indexing
  - Naïve in-memory inversion
  - Blocked Sort-Based Indexing (BSBI)
    - Merge sort is effective for hard disk–based sorting (avoid seeks!)
- Single-Pass In-Memory Indexing (SPIMI)
  - No global dictionary
    - Generate separate dictionary for each block
  - Don’t sort postings
    - Accumulate postings in postings lists as they occur
- Distributed indexing using MapReduce
- Dynamic indexing: Multiple indices, logarithmic merge

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

- Save a little money; give users more space

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
- We will devise various IR-specific compression schemes

Recall Reuters RCV1

symbol	statistic	value
N	documents	800,000
L	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)

size of	word types (terms)			non-positional postings			positional postings		
	dictionary			non-positional index			positional index		
	Size (K)	∆%	cumul %	Size (K)	∆ %	cumul %	Size (K)	∆ %	cumul %
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.

Chapter 7: Prune postings entries that are unlikely to turn up in the top *k* list for any query.

- Almost no loss of quality in top *k* list.

Vocabulary size 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 size vs. collection size

Heaps' law: $M = kT^b$

M is the size of the vocabulary, T is the number of tokens in the collection

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 (linear) relationship between the two in log-log space
  - $\log M = \log k + b \log T$
- An empirical finding ("empirical law")

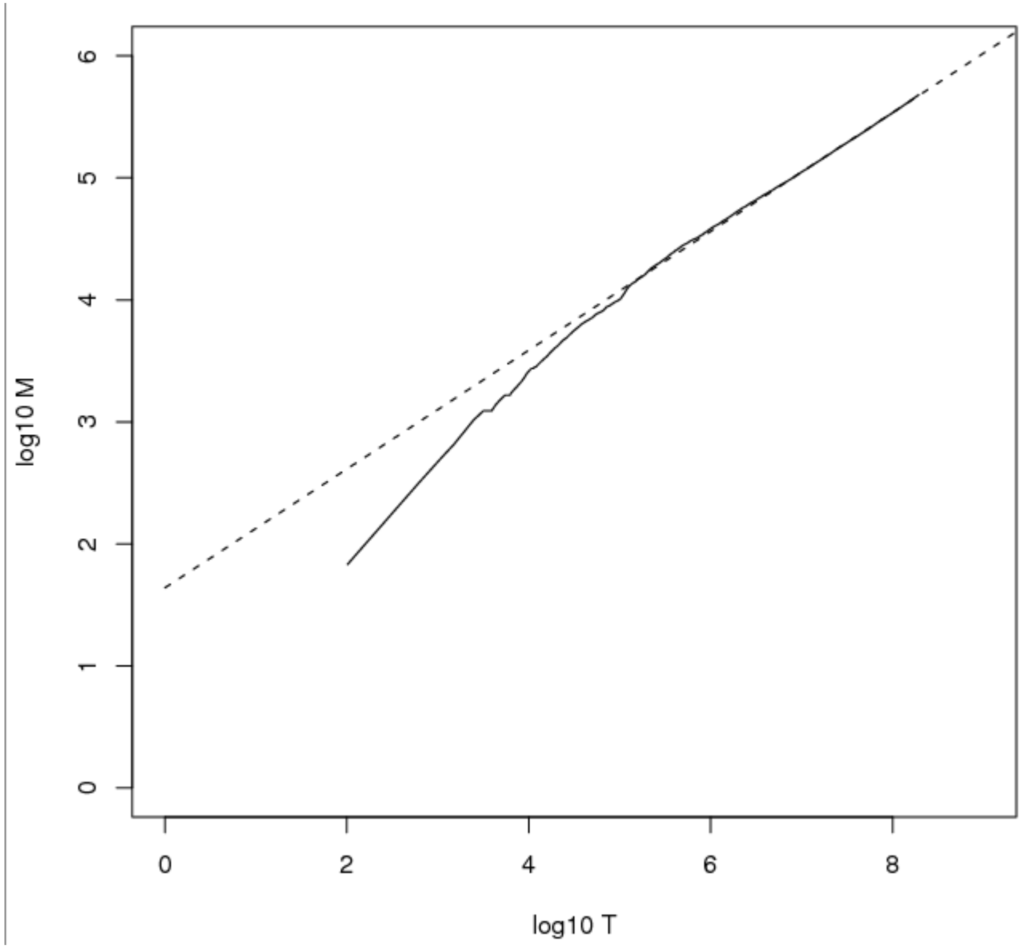
Heaps' Law

Fig 5.1 p81

For RCV1, the dashed line $\log_{10}M = 0.49 \log_{10}T + 1.64$ is the best least squares fit. Thus, $M = 10^{1.64}T^{0.49}$ so $k = 10^{1.64} \approx 44$ and $b = 0.49$.

Good empirical fit for Reuters RCV1 !

For first 1,000,020 tokens, law predicts 38,323 terms; actually, 38,365 terms



Exercises

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

Compute the vocabulary size *M* for this scenario:

- 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?

Zipf's law

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 very many very rare terms.
Zipf's law: The i^{th} most frequent term has frequency proportional to $1/i$.
$\mathrm{cf}_i \propto 1/i = K/i$ where K is a normalizing constant
cf_i is collection frequency: the number of occurrences of the term t_i in the collection.

Zipf consequences

If the most frequent term (*the*) occurs cf_1 times

then the second most frequent term (*of*) occurs $cf_1/2$ times

the third most frequent term (*and*) occurs $cf_1/3$ times …

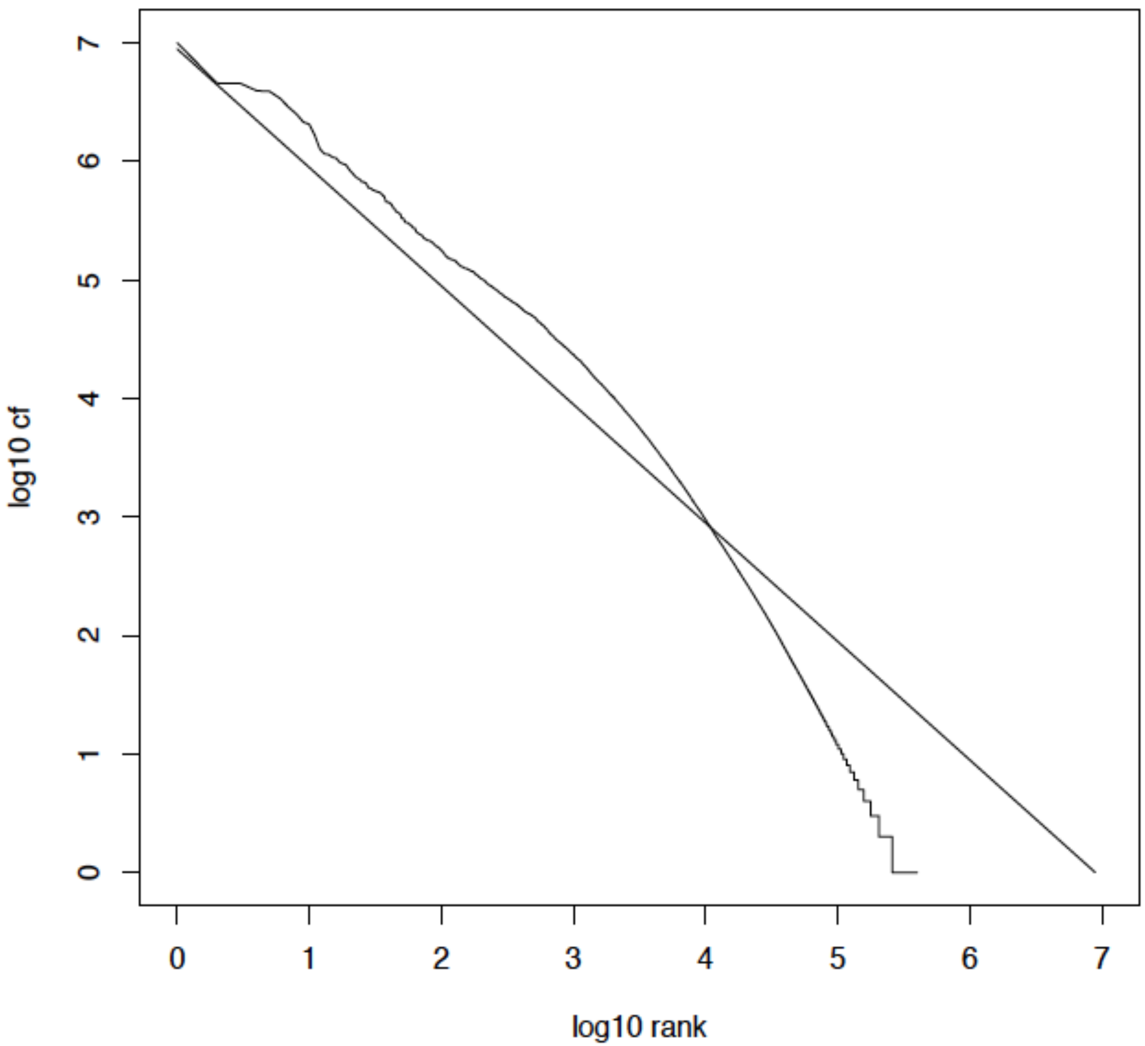
Equivalent: $cf_i = K/i$ where K is a normalizing factor, so

$\log cf_i = \log K - \log i$

Linear relationship between $\log cf_i$ and $\log i$

Another power law relationship

Zipf's law for Reuters RCV1



Compression

Now, we will consider compressing the space for the dictionary and postings. We'll do:

- Basic Boolean index only
- No study of positional indexes, etc.

But these ideas can be extended

We will consider compression schemes

DICTIONARY COMPRESSION

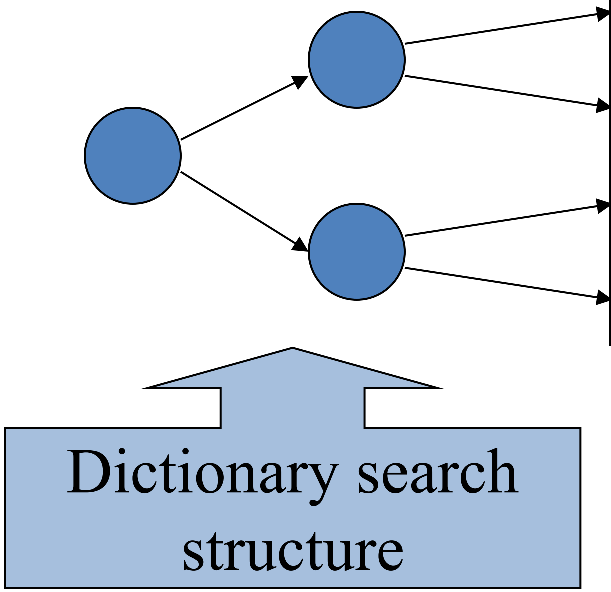
Why compress the dictionary?

Search begins with the dictionary
We want to keep it in memory
Memory footprint competition with other applications
Embedded/mobile devices may have very little 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

Dictionary storage – naïve version

Array of fixed-width entries

- ~400,000 terms; 28 bytes/term = 11.2 MB.



Terms	Freq.	Postings ptr.
a	656,265	
aachen	65	
….	….	
zulu	221	

20 bytes

4 bytes each

Fixed-width terms are wasteful

Most of the bytes in the **Term** column are wasted – we allot 20 bytes for 1 letter terms.

- And we still can't handle *supercalifragilisticexpialidocious* or *hydrochlorofluorocarbons.*

Written English averages ~4.5 characters/word.

- Exercise: Why is/isn't this the number to use for estimating the dictionary size?

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 x 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
400K terms x 19 $\Rightarrow$ 7.6 MB (against 11.2MB for fixed width)

Now avg. 11 bytes/term, not 20.

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 Net Gains

Example for block size $k = 4$

Where we used 3 bytes/pointer without blocking

$3 \times 4 = 12$ bytes,

now we use $3 + 4 = 7$ bytes.

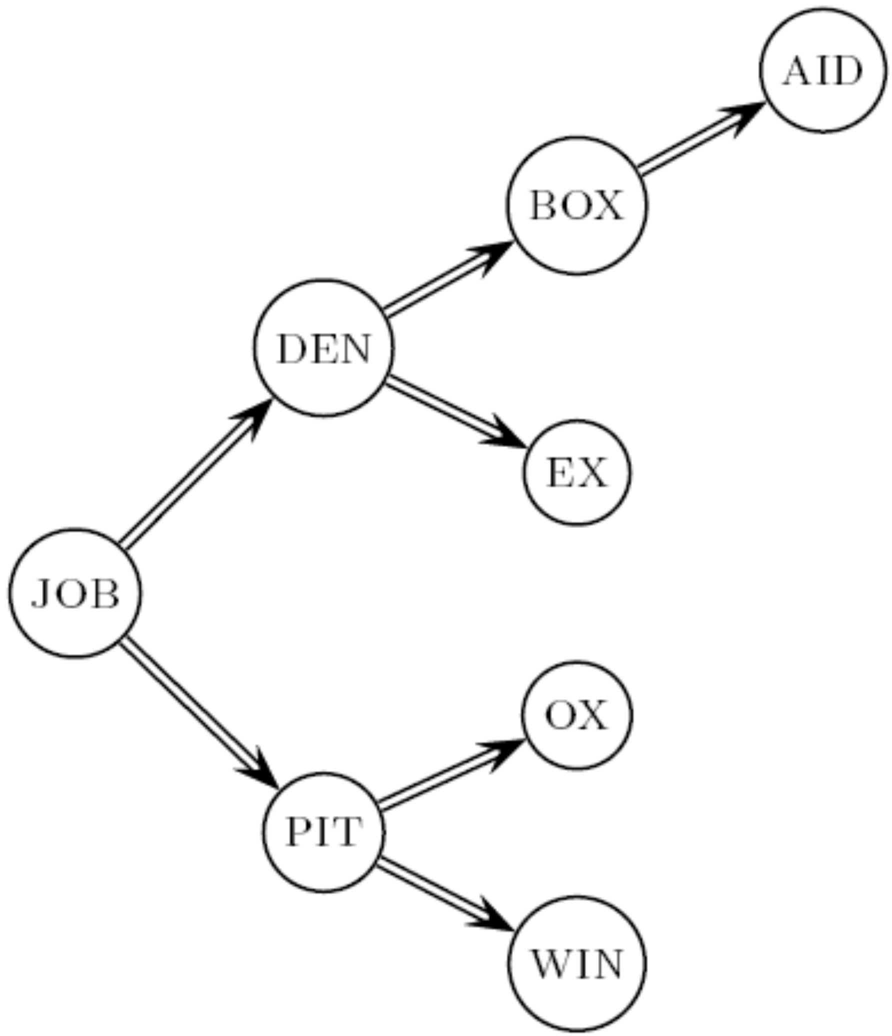
Shaved another ~0.5MB. This reduces the size of the dictionary from 7.6 MB to 7.1 MB.

We can save more with larger k.

Question: Why not go with larger k?

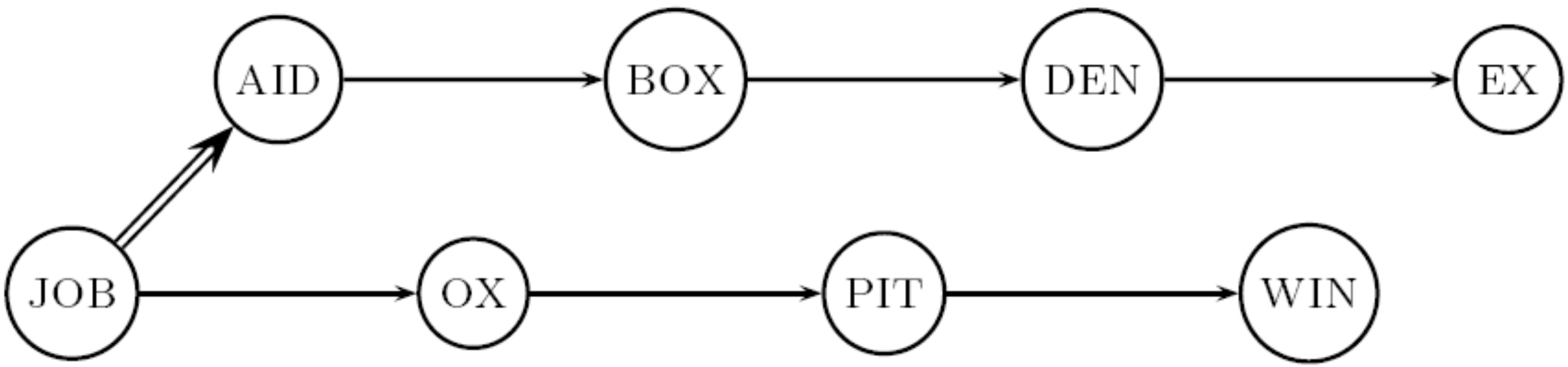
Dictionary search without blocking

Assuming each dictionary term equally likely in query (not really so in practice!), average number 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. = $(1+2\cdot 2+2\cdot 3+2\cdot 4+5)/8 = 3$ compares

Exercises

Estimate the space usage (and savings compared to 7.6 MB) with blocking, for block sizes of $k = 4, 8$ and 16.

Estimate the impact on search performance (and slowdown compared to k=1) with blocking, for block sizes of $k = 4, 8$ and 16.

Front coding

Front-coding:

Sorted words commonly have long common prefix – store differences only (for last *k-1* in a block of *k*)

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

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

Encodes prefix ***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
+ blocking, *k* = 4	7.1
+ blocking + front coding	5.9

POSTINGS COMPRESSION

Postings compression

The postings file is much larger than the dictionary, factor of at least 10, often over 100 times larger

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 far fewer than 20 bits per docID.

Postings: two conflicting forces

A term like ***arachnocentric*** occurs in maybe one doc out of a million – we would like to store this posting using $\log_2$ 1M ≈ 20 bits.

A term like ***the*** occurs in virtually every doc, so 20 bits/posting ≈ 2MB is too expensive.

- Prefer 0/1 bitmap vector in this case (≈100K)

Gap encoding of postings file entries

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.

- Especially for common words

Three postings entries

	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								

Variable length encoding

Aim:

For ***arachnocentric***, we will use ~20 bits/gap entry.

For ***the***, we will use ~1 bit/gap entry.

If the average gap for a term is G, we want to use ~$\log_2 G$ bits/gap entry.

Key challenge: encode every integer (gap) with about as few bits as needed for that integer.

This requires a *variable length encoding*

Variable length codes achieve this by using short codes for small numbers

Unary code

Represent *n* as *n* 1s with a final 0.
Unary code for 3 is 1110.
Unary code for 40 is
11111111111111111111111111111111111111110 .
Unary code for 80 is:
11111111111111111111111111111111111111111111111111111
1111111111111111111111111110

This doesn't look promising, but....

- Optimal if $P(n) = 2^{-n}$
- We can use it as part of our solution

Gamma codes

We can compress better with bit-level codes

The Gamma code is the best known of these.

Represent a gap *G* as a pair *length* and *offset*

offset is *G* in binary, with the leading bit cut off

For example 13 → 1101 → 101

length is the length of offset

For 13 (offset 101), this is 3.

We encode *length* with *unary code*: 1110.

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

Gamma code examples

number	length	offset	γ-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

Reminder: bitwise operations

For compression, you need to use bitwise operators

Python

- & bit
- << left shift bits, >> right shift; LACKS >>> zero fill right shift
- Recipes:
  - Extract 7 bits: a & 0x7f00 >> 8 ; if take high-order bit add: & 0x7f
  - Combine 3 5-bit numbers: a | (b << 5) | (c << 10)
  - Lookup tables rather than decoding can be faster, yet still small

Gamma code properties

G is encoded using $2\lfloor \log G \rfloor + 1$ bits
- Length of offset is $\lfloor \log G \rfloor$ bits
- Length of length is $\lfloor \log G \rfloor + 1$ bits

All gamma codes have an odd number of bits

Almost within a factor of 2 of best possible, $\log_2 G$

Gamma code is uniquely prefix-decodable, like VB

Gamma code can be used for any distribution
- Optimal for $P(n) \approx 1/(2n^2)$

Gamma code is 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 too slow

- All modern practice is to use byte or word aligned codes
  - Variable byte encoding is a faster, conceptually simpler compression scheme, with decent compression

Variable Byte (VB) codes

For a gap value *G,* we want to use close to the fewest bytes needed to hold $\log_2 G$ bits

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 and set $c = 1$

Else encode *G*'s lower-order 7 bits and then use additional bytes to encode the higher order bits using the same algorithm

At the end set the continuation bit of the last byte to 1 ($c = 1$) – and for the 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.

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)	3,600.0
collection (text)	960.0
Term-doc 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

Other variable unit codes

- Variable byte codes are used by many real systems
  - Good low-tech blend of variable-length coding and sensitivity to computer memory alignment matches
- Byte alignment wastes space if you have many small gaps – as gap encoding often makes
- More modern work mainly uses the ideas:
  - Be word aligned (32 or 64 bits; even faster)
  - Encode several gaps at the same time
  - Often assume a maximum gap size, perhaps with an escape

Group Variable Integer code

Used by Google around turn of millennium….

Jeff Dean, keynote at WSDM 2009 and presentations at CS276

Encodes 4 integers in blocks of size 5–17 bytes

First byte: four 2-bit binary length fields

$\boxed{L_1 \mid L_2 \mid L_3 \mid L_4}$, $L_j \in \{1,2,3,4\}$

Then, $L_1+L_2+L_3+L_4$ bytes (between 4–16) hold 4 numbers

Each number can use 8/16/24/32 bits. Max gap length ~4 billion

It was suggested that this was about twice as fast as VB encoding

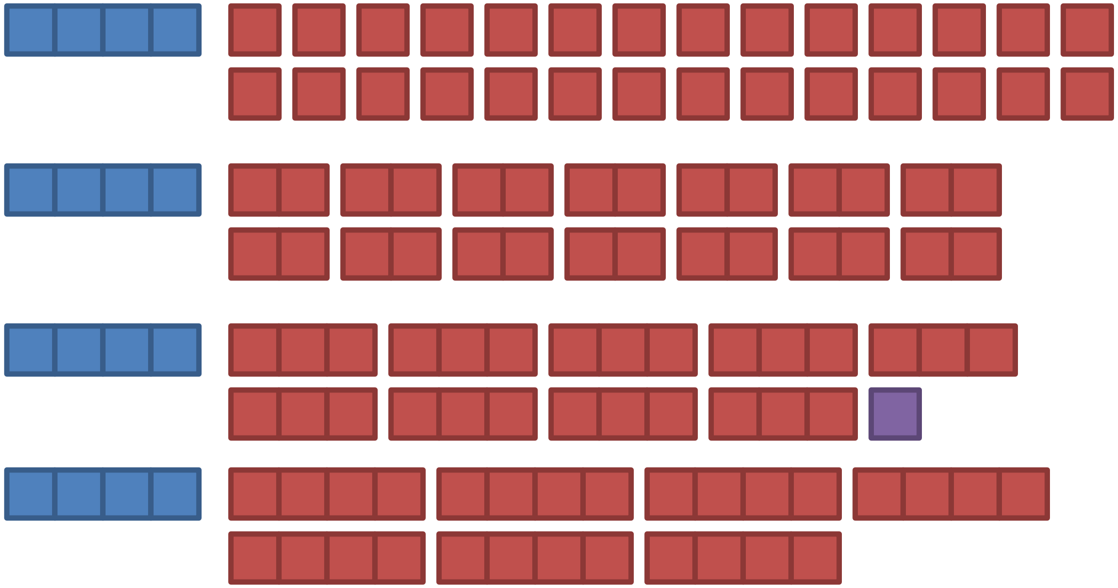
Decoding gaps is much simpler – no bit masking

First byte can be decoded with lookup table or switch

Simple-9 [Anh & Moffat, 2004]

A word-aligned, multiple number encoding scheme

How can we store several numbers in 32 bits with a format selector?



Simple9 Encoding Scheme [Anh & Moffat, 2004]

Encoding block: 4 bytes (32 bits)
Most significant nibble (4 bits) describe the layout of the 28 other bits as follows:

Layout (4 bits)	n numbers of b bits each $n * b \leq 28$

- 0: a single 28-bit number
- 1: two 14-bit numbers
- 2: three 9-bit numbers (and one spare bit)
- 3: four 7-bit numbers
- 4: five 5-bit numbers (and three spare bits)
- 5: seven 4-bit numbers
- 6: nine 3-bit numbers (and one spare bit)
- 7: fourteen two-bit numbers
- 8: twenty-eight one-bit numbers

Simple16 is a variant with 5 additional (uneven) configurations
Efficiently decoded with hand-coded decoder, using bit masks
Extended Simple Family – idea applies to 64-bit words, etc.

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

We’ve ignored positional information

Hence, space savings are less for indexes used in practice

- But techniques substantially the same

Resources for today's lecture

IIR 5

MG 3.3, 3.4.

F. Scholer, H.E. Williams and J. Zobel. 2002. Compression of Inverted Indexes For Fast Query Evaluation. *Proc. ACM-SIGIR 2002*.

- Variable byte codes

V. N. Anh and A. Moffat. 2005. Inverted Index Compression Using Word-Aligned Binary Codes. *Information Retrieval* 8: 151–166.

- Word aligned codes

End of Slides