Introduction to Information Retrieval

— Index Compression (Posting) ——

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 documents), we would use 32 bits per docID when using 4-byte integers.
- Alternatively, we can use log2 800,000 ≈ 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 log2 1M ~ 20 bits.
- A term like **the** occurs in virtually every doc, so 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.
 - o **computer**: 33,47,**154,159**,202
- Consequence: it suffices to store gaps.
 - o 33,14,107,**5**,43 ...
- Hope: most gaps can be encoded/stored with far fewer than 20 bits.

Three postings entries

	encoding	postings	list								
THE	doclDs	0.00 K		283042		283043		283044		283045	
	gaps				1		1		1		
COMPUTER	doclDs	***		283047		283154		283159		283202	
	gaps				107		5		43		
ARACHNOCENTRIC	doclDs	252000		500100							72:
	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 ~log2G bits/gap entry.
- <u>Key challenge</u>: 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

Variable Byte (VB) codes

- For a gap value G, we want to use close to the fewest bytes needed to hold log₂ G bits
- Begin with one byte to store G and dedicate 1 bit in it to be a continuation bit c

Variable Byte (VB) codes

- If G ≤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.

1 x	x 0	у	/
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Example 824 = 1100111000 = 00000110 10111000

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

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

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

- Convert to Binary.
- Group the bits in 7s
- For LSB put a 1 in the 8th bit
- For all other put a 0
- i or an other para c

• 00001001 01001000 11101101

156781 = 100110010001101101

 Waste – 4 bits. - this 4 bits is not a big deal when the number is big but big wastage when the number is small.

Other variable unit codes

- Instead of bytes, we can also use a different "unit of alignment": 32 bits (words), 16 bits, 4 bits (nibbles).
- Variable byte alignment wastes space if you have many small gaps nibbles do better in such cases.
- 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 as n 1s with a final 0.
- Unary code for 3 is 1110.
- Unary code for 40 is

Unary code for 80 is:

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

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
 - \circ For example 13 \rightarrow 1101 \rightarrow 101

Gamma codes

- 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 – G – 2log₂(G)

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	000000001	11111111110,0000000001

- 11110101101111110110 Can I tell how many numbers are there, if I know that this is encode by gamma code
- Gamma code is taking almost similar space to a normal code but still you are getting the decipherable property.

Gamma code properties

- G is encoded using 2 | log G | + 1 bits
 - Length of offset is | log G | bits
 - Length of length is | log G | + 1 bits
- All gamma codes have an odd number of bits
- Almost within a factor of 2 of best possible, log₂ G

Gamma code properties

- Gamma code is uniquely prefix-decodable, like VB
- Gamma code can be used for any distribution
- Gamma code is parameter-free

Gamma seldom used in practice

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)	3,600.0
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

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.

Index parameters vs. what we index

(docid, number of times the term, pos1, pos2)

size of	word types (terms)			non-positional postings			positional postings		
	dictionary		non-positional index			positional index			
	Size (K)	$\Delta\%$	cumul %	Size (K)	$^{\Delta}_{\%}$	cumul %	Size (K)	$^{\Delta}_{\%}$	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? 32

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.

Vocabulary vs. collection size

- How big is the term vocabulary?
 - o That is, how many distinct words are there?
- Can we assume an upper bound?
 - Not really: At least 7020 = 1037 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 is the size of the vocabulary, T is the number of tokens in the collection
- Typical values: $30 \le k \le 100$ and $b \approx 0.5$ T = 100 M = o(10), T = 10000, M= o(100)
- 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

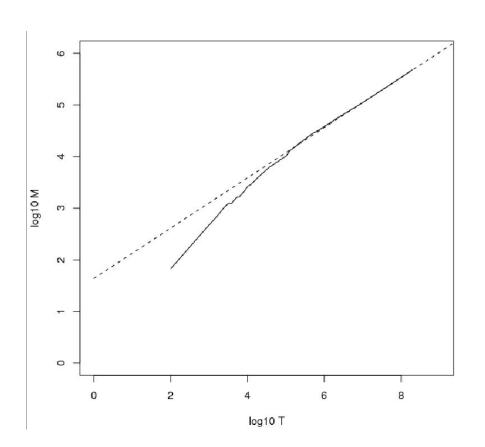
For RCV1, the dashed line $log_{10}M = 0.49 log_{10}T + 1.64$ is the best least squares fit.

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

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



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 ith most frequent term has frequency proportional to 1/i.

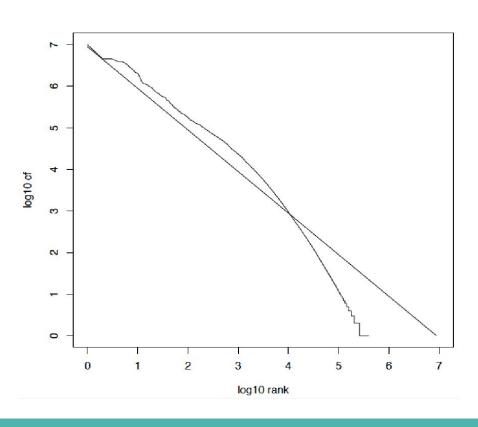
where K is a normalizing constant

• cfi is collection frequency: the number of occurrences of the term ti in the collection. 100, 50, 33, 25, 20, 17

Zipf consequences

- If the most frequent term (the) occurs cf1 times
 - then the second most frequent term (of) occurs cf1/2 times
 - the third most frequent term (and) occurs cf1/3 times ...
- Equivalent: **cfi = K/i** where K is a normalizing factor, so
 - log cfi = log K log i
 - Linear relationship between log cfi and log i
- Another power law relationship

Zipf's law for Reuters RCV1



- Exponentially decaying
- Sum of the rare words is small
- Limited number of words.
- Accuracy of a search system which tackles only popular words accuracy of the search system which tackles popular as well as rare words = DELTA which is SMALL
- Cost of a search system which tackles only popular words Cost of the search system which tackles popular as well as rare words = GAMMA which is LARGE

- Zipf's Law
- Sum of the rare words is not small
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- Accuracy of a search system which tackles only popular words accuracy of the search system which tackles popular as well as rare words = DELTA which is LARGE
- Cost of a search system which tackles only popular words Cost of the search system which tackles popular as well as rare words = GAMMA which is LARGE
