Introduction to
# Information Retrieval

CS276: Information Retrieval and Web Search
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Lecture 5: Index Compression



## Course work

- Problem set 1 due Thursday
- Programming exercise 1 will be handed out today





## Last lecture – index construction

- Sort-based indexing
  - Naïve in-memory inversion
  - Blocked Sort-Based Indexing
    - Merge sort is effective for disk-based sorting (avoid seeks!)
- Single-Pass In-Memory Indexing
  - 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
  - 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
- 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.
- Chap/Lecture 7: 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?
  - 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: $M = kT^b$
- $M$ is the size of the vocabulary, $T$ is the number of tokens in the collection
- Typical values: $30 \le k \le 100$ and $b \approx 0.5$
- 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

Fig 5.1 p81

For RCV1, the dashed line

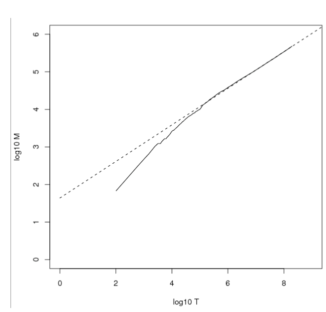
$\log_{10} M = 0.49 \log_{10} T + 1.64$

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 ($2 \times 10^{10}$) 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 $1/i$ .
- $cf_i \propto 1/i = K/i$ where *K* is a normalizing constant
- $cf_i$ is <u>collection frequency</u>: the number of occurrences of the term $t_i$ in the collection.





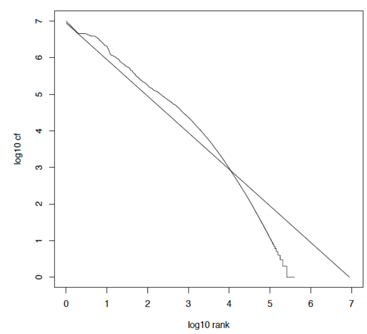
## Zipf consequences

- 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
  - Basic Boolean index only
  - No study of positional indexes, etc.
  - We will consider compression schemes





**DICTIONARY COMPRESSION**

## Why compress the dictionary?

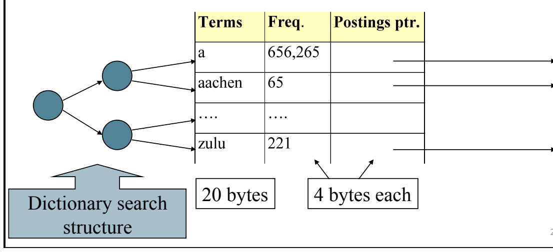
- Search begins with the dictionary
- We want to keep it in memory
- Memory footprint competition with other applications
- Embedded/mobile devices may have very little memory
- Even if the dictionary isn't in memory, we want it to be small for a fast search startup time
- So, compressing the dictionary is important





## Dictionary storage - first cut

- Array of fixed-width entries
  - ~400,000 terms; 28 bytes/term = 11.2 MB.








## Fixed-width terms are wasteful

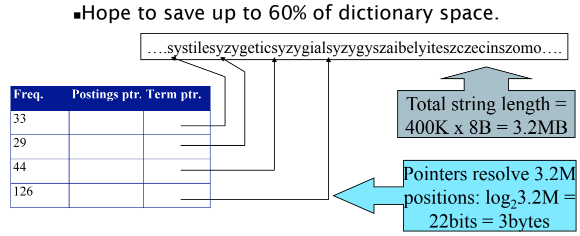
- Most of the bytes in the **Term** column are wasted – we allot 20 bytes for 1 letter terms.
  - And we still can't handle *supercalifragilisticexpialidocious* or *hydrochlorofluorocarbons.*
- Written English averages ~4.5 characters/word.
  - Exercise: Why is/isn't this the number to use for estimating 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.








## 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

} Now avg. 11 bytes/term, not 20.

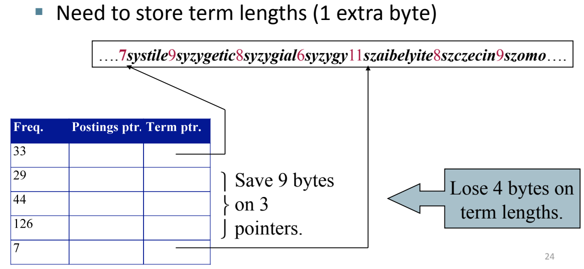
- Avg. 8 bytes per term in term string
- 400K terms x 19 ⇒ 7.6 MB (against 11.2MB for fixed width)





## Blocking

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



## Net

- Example for block size $k = 4$
- Where we used 3 bytes/pointer without blocking
  - 3 x 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*.

Why not go with larger *k*?





## Exercise

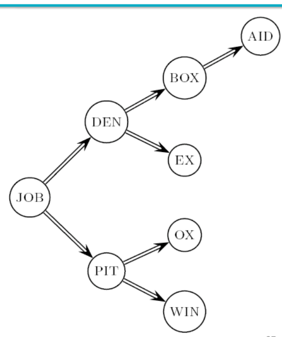
- Estimate the space usage (and savings compared to 7.6 MB) with blocking, for block sizes of *k = 4, 8* and *16.*





## 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

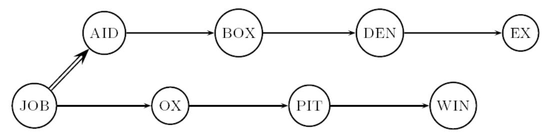



Exercise: what if the frequencies of query terms were non-uniform but known, how would you structure the dictionary search tree?





## 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+2·2+2·3+2·4+5)/8 = 3 compares





## Exercise

- 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 ***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 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 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 …
- Consequence: it suffices to store *gaps*.
  - 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 | 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





## 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* ≤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.





## 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).
- There is also recent work on word-aligned codes that pack a variable number of gaps into one word





## 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:
  111111111111111111111111111111111111111111
  111111111111111111111111111111111111110
- 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
  - 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 |





## 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
- 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 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.





## 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