
FREQUENCY
PATTERSON
MULTI
INVERTED
ONE
QUERIES
CONFUSING
PROGRESSED
WEIGHTING
WORD
BUSINESS
MONEY
QUEUING
DATA
MATHEMATICAL
ENGINES
MICROSOFT
PURPLE
REUTERS
KNOWING
SORT
EVALUATE
COLORFUL
STEMMING
DOCUMENTS
DIFFICULT
SCORE
SPEEDY
AGGREGATE
STUDIED
DIGGING
INTERESTING
STATISTICS
INTRACTABLE
GROWING
DISCOVERING
COSINE
ENTHRALLING
MAGICAL
CORPUS
QUERY
TECHNOLOGICAL
SPECIAL
COOL
RELATIONAL
AMAZING
BRIGHT
NEEDED
BIG
UNSTRUCTURED
HOW
RANK
INDEX
CHALLENGE
NEED
MATH
STOP
IMPORTANT
MODIFY
TECHNICAL
CONSUMING
LARGE
COMPLEX
INFO
ORGANIZATION
FOR
WEB
PARSING
DOCS
OF
TEXT
AND
GET
HADOOP
FAST
FUN
SEARCH
INFORMATION
TO
EFFICIENT
IN
LIST
MAP
WAY
SCORES
SLOW
EXPENSIVE
SCIENCE
CRAWL
RETRIEVE
METADATA
GOOGLE
A
ALL
VAST
SEARCHING
WWW
HARD
PAGE
TIME
TRUST
ABOUT
NOT
DOCUMENT
CRAWLER
TRICKY
ALGORITHMIC
THE
INDEXING
SAD
FUTURE
COMPLICATED
OVERLOAD
CRAWLERS
SCHOLARLY
EVOLVING
RETRIEVAL
DATABASE
STUFF
THINGS
QUIRKY
SEXY
SEARCHES
FRUSTRATING
SORTING
EXCITING
EFFICIENTLY
WIKIPEDIA
RETRIEVING
MOVE
CRAWLING
USEFUL
DISTRIBUTED
KEY
DIFFERENT
VARIED
DISTRIBUTEDLY
THROUGH
LINEAR
POSTING
HAPPY
RELEVANT
GATHER
POLITE

05 Index Compression

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

"Δ%" indicates the reduction in size from the previous line.
"T%" is the cumulative (``total'') reduction from unfiltered.

size of	word types (terms)			non-positional postings			positional postings		
	dictionary			non-positional index			positional index		
	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 stopwords	391,493	-0	-19	83,390,443	-14	-24	121,857,825	-31	-38
150 stopwords	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

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

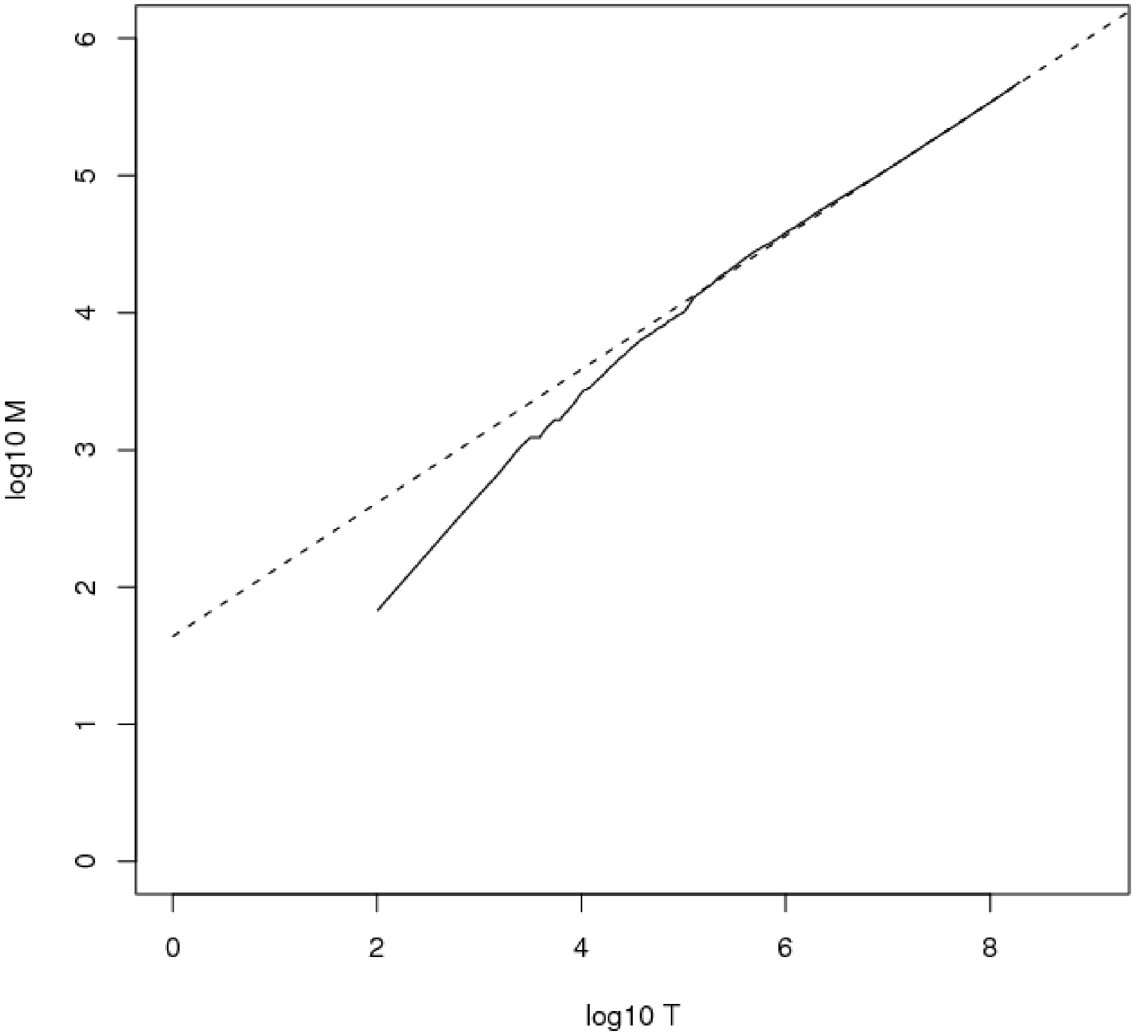
- How big is the term vocabulary?
  - That is, how many distinct words are there?
- Can we assume an upper bound?
  - Not really: At least $70^{20} = 10^{37}$ different words of length 20
- In practice, the vocabulary will keep growing with the collection size
  - Especially with Unicode ☺

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

- 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?

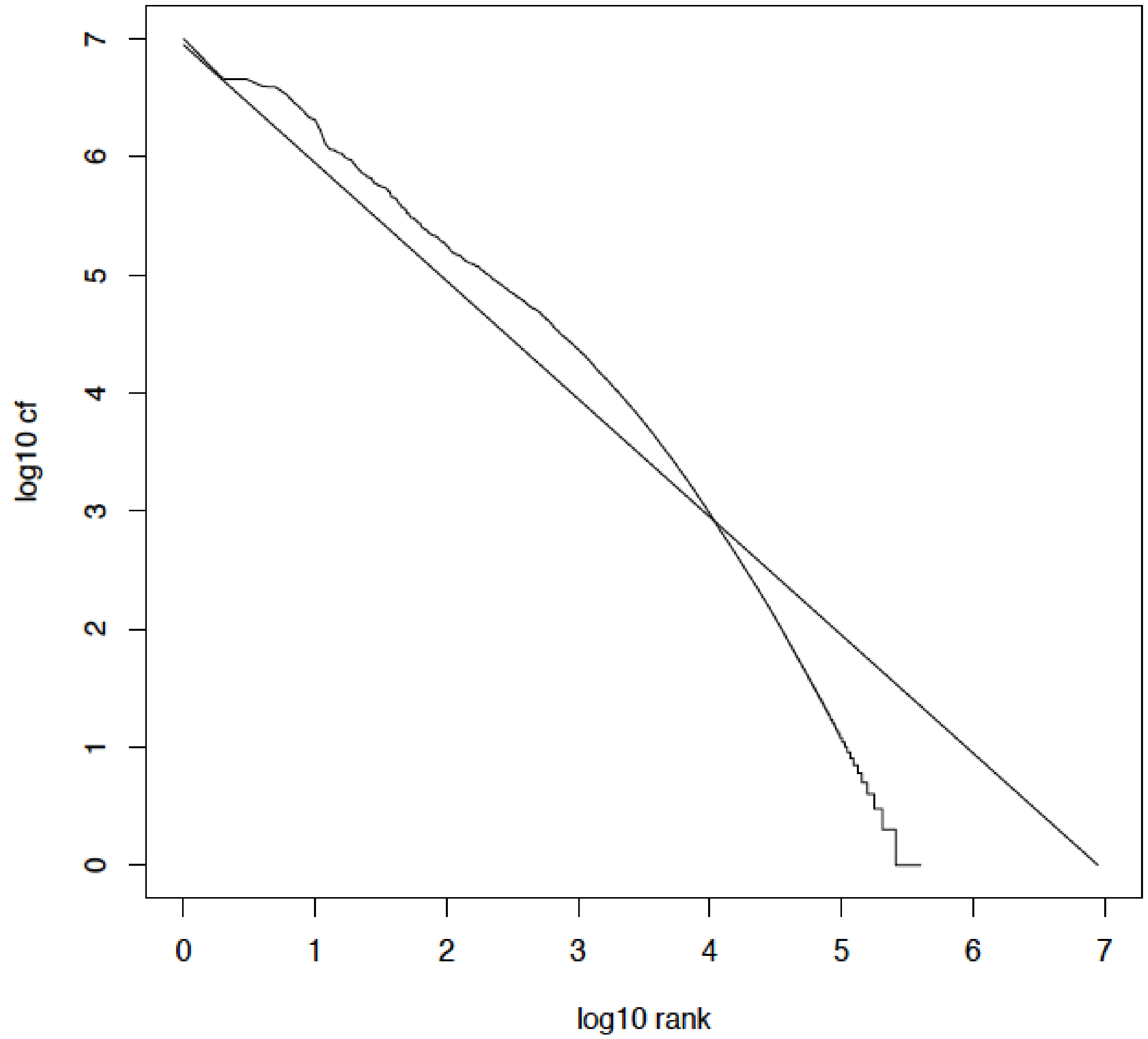
Zipf’s law

- 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 <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

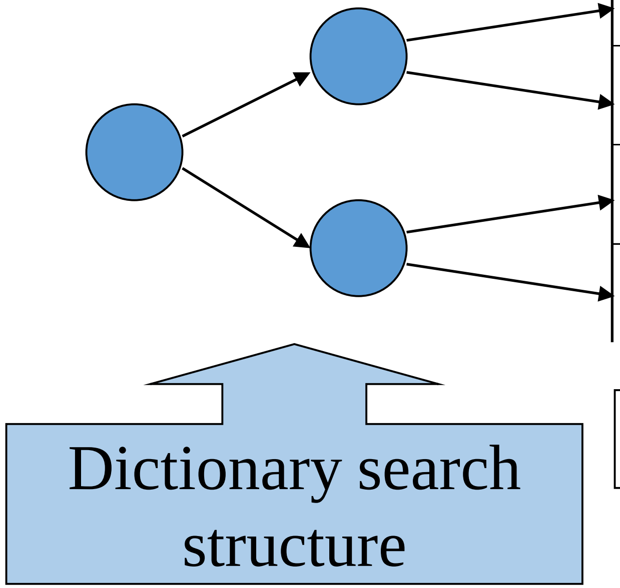
Dictionary Compression

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.



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.

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*?

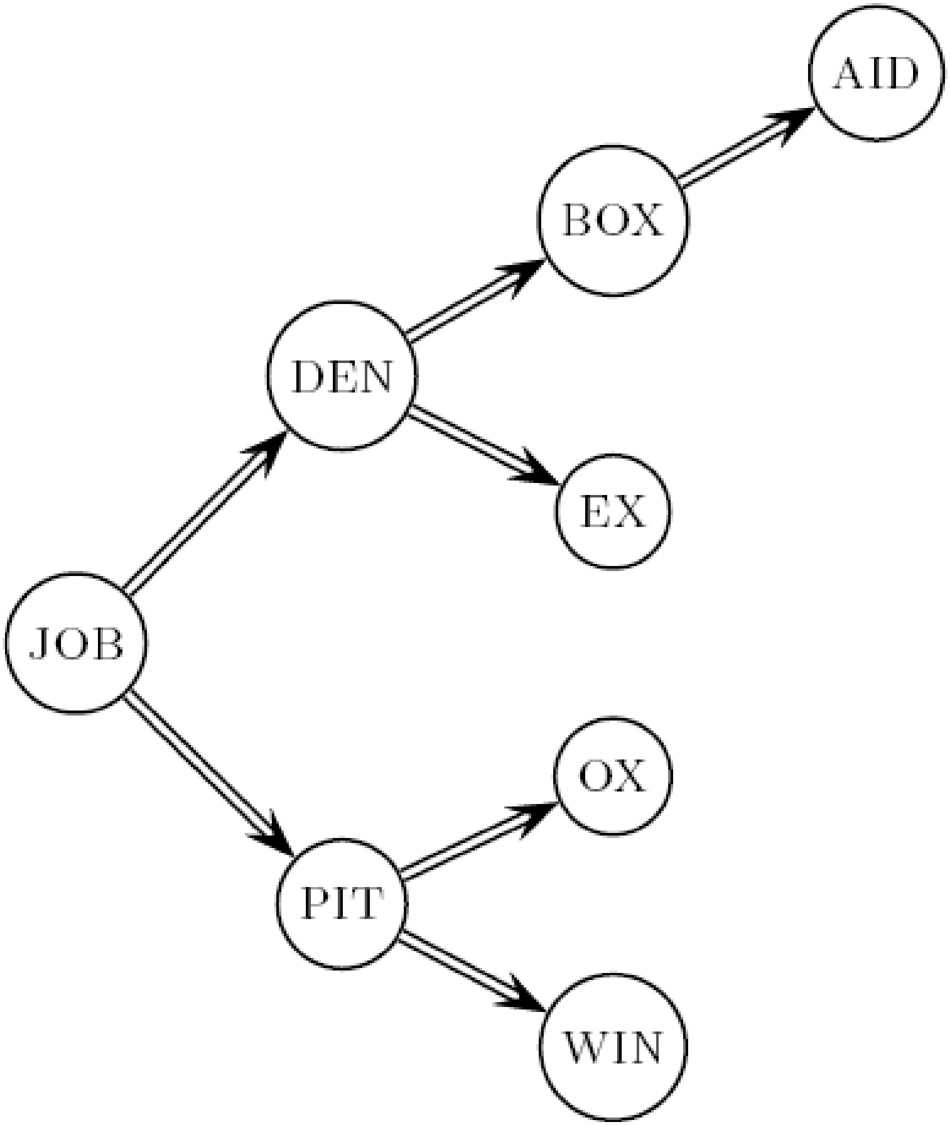
Exercise

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

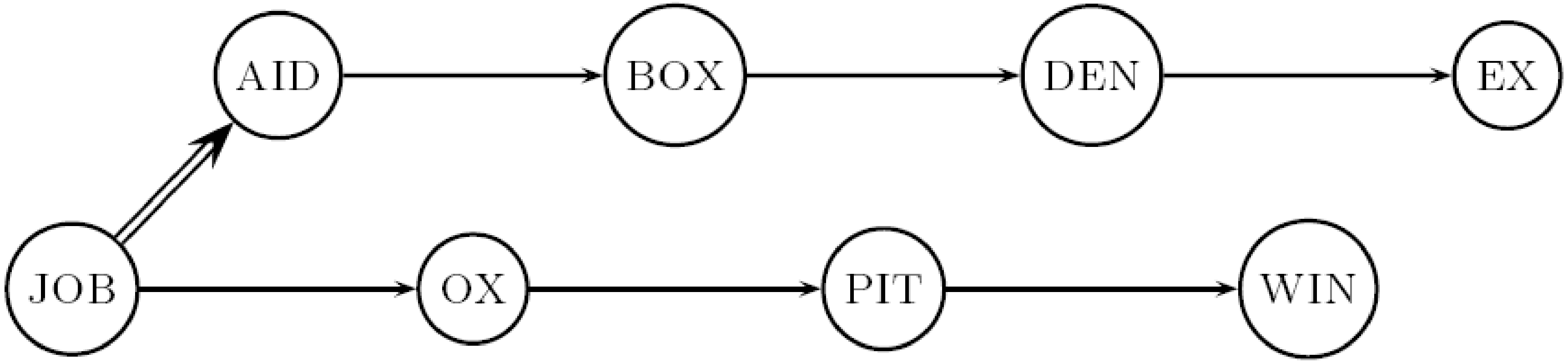
Dictionary search without blocking

- Assuming each dictionary term equally likely in query (not really so in practice!), average number of comparisons = $(1+2\cdot 2+4\cdot 3+4)/8 \approx 2.6$

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 $\log_2 1\text{M} \sim 20$ 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,$\boxed{154,159}$,202 …
- <u>Consequence</u>: it suffices to store *gaps*.
  - 33,14,107,$\boxed{5}$,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	...
	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 $\sim\log_2 G$ bits/gap entry.
- <u>Key challenge</u>: encode every integer (gap) with about as few bits as needed for that integer.
- 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 $G \leq 127$, 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.

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:

11111111111111111111111111111111111111111111111111
111111111111111111111111111111 0

- 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 $2\lfloor \log_2 G \rfloor + 1$ bits
  - Length of offset is $\lfloor \log_2 G \rfloor$ bits
  - Length of length is $\lfloor \log_2 G \rfloor + 1$ 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