

Information Retrieval

Lecture 3

Recap: lecture 2

- Stemming, tokenization etc.
- Faster postings merges
- Phrase queries

This lecture

- Index compression
 - Space for postings
 - Space for the dictionary
 - Will only look at space for the basic inverted index here
- Wild-card queries

Corpus size for estimates

- Consider $n = 1\text{M}$ documents, each with about 1K terms.
- Avg 6 bytes/term incl spaces/punctuation
 - 6GB of data.
- Say there are $m = 500\text{K}$ distinct terms among these.

Don't build the matrix

- 500K x 1M matrix has half-a-trillion 0's and 1's.
- But it has no more than one billion 1's.
 - matrix is extremely sparse.
- So we devised the inverted index
 - Devised query processing for it
- Where do we pay in storage?

Storage analysis

- First will consider space for pointers
 - Devise compression schemes
- Then will do the same for dictionary
- No analysis for wildcards etc.

Pointers: two conflicting forces

- A term like *Calpurnia* occurs in maybe one doc out of a million - would like to store this pointer using $\log_2 1M \sim 20$ bits.
- A term like *the* occurs in virtually every doc, so 20 bits/pointer is too expensive.
 - Prefer 0/1 vector in this case.

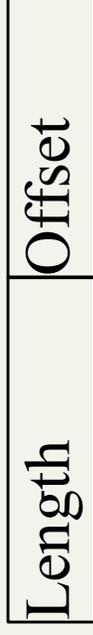
Postings file entry

- Store list of docs containing a term in increasing order of doc id.
 - *Brutus*: 33, 47, 154, 159, 202 ...
- Consequence: suffices to store *gaps*.
 - 33, 14, 107, 5, 43 ...
- Hope: most gaps encoded with far fewer than 20 bits.

Variable encoding

- For *Calpurnia*, will use ~20 bits/gap entry.
- For *the*, will use ~1 bit/gap entry.
- If the average gap for a term is G , want to use $\sim \log_2 G$ bits/gap entry.
- Key challenge: encode every integer (gap) with ~ as few bits as needed for that integer.

γ codes for gap encoding

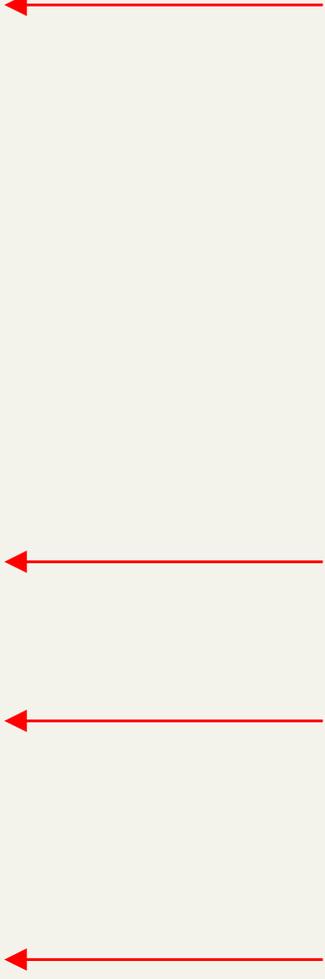


- Represent a gap G as the pair $\langle length, offset \rangle$
- $length$ is in unary and uses $\lfloor \log_2 G \rfloor + 1$ bits to specify the length of the binary encoding of
- $offset = G - 2^{\lfloor \log_2 G \rfloor}$
- e.g., 9 represented as $\langle 1110, 001 \rangle$.
- Encoding G takes $2 \lfloor \log_2 G \rfloor + 1$ bits.

Exercise

- Given the following sequence of γ -coded gaps, reconstruct the postings sequence:

111000111010101111101101111011



From these γ -decode and reconstruct gaps, then full postings.

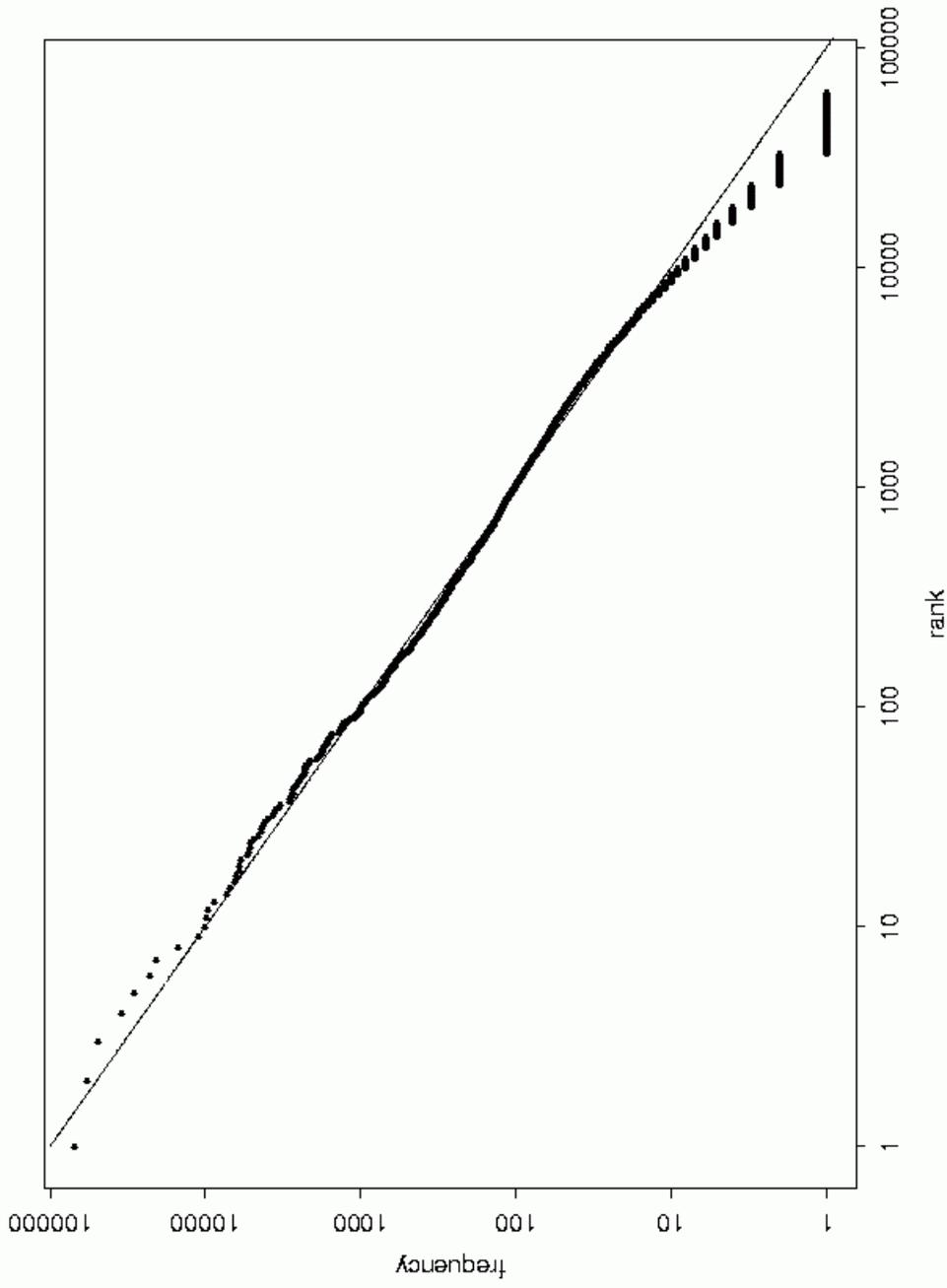
What we've just done

- Encoded each gap as tightly as possible, to within a factor of 2.
- For better tuning (and a simple analysis) - need a handle on the distribution of gap values.

Zipf's law

- The k th most frequent term has frequency proportional to $1/k$.
- Use this for a crude analysis of the space used by our postings file pointers.
 - Not yet ready for analysis of dictionary space.

Zipf's law log-log plot



Rough analysis based on Zipf

- Most frequent term occurs in n docs
 - n gaps of 1 each.
- Second most frequent term in $n/2$ docs
 - $n/2$ gaps of 2 each ...
- k th most frequent term in n/k docs
 - n/k gaps of k each - use $2\log_2 k + 1$ bits for each gap;
 - net of $\sim (2n/k) \cdot \log_2 k$ bits for k th most frequent term.

Sum over k from 1 to $m=500K$

- Do this by breaking values of k into groups:
 - group i consists of $2^{i-1} \leq k < 2^i$.
 - Group i has 2^{i-1} components in the sum, each contributing at most $(2ni)/2^{i-1}$.
 - Recall $n=1M$
- Summing over i from 1 to 19, we get a net estimate of 340Mbits $\sim 45MB$ for our index.



Work out calculation.

Caveats

- This is not the entire space for our index:
 - does not account for dictionary storage;
 - nor wildcards, etc.
 - as we get further, we'll store even more stuff in the index.
- Assumes Zipf's law applies to occurrence of terms in docs.
- All gaps for a term taken to be the same.
- Does not talk about query processing.

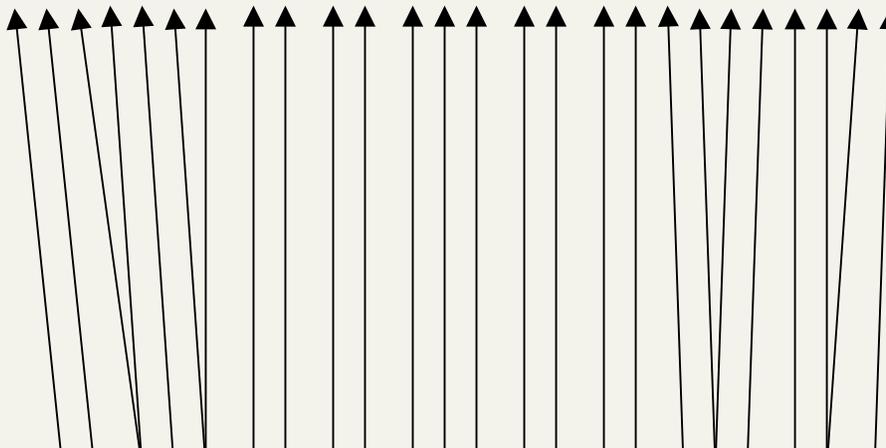
Dictionary and postings files

Term	Doc #	Freq
ambitious	2	1
be	2	1
brutus	1	1
brutus	2	1
capitol	1	1
caesar	1	1
caesar	2	2
did	1	1
enact	1	1
hath	2	1
I	1	2
i'	1	1
it	2	1
julius	1	1
killed	1	2
let	2	1
me	1	1
noble	2	1
so	2	1
the	1	1
the	2	1
told	2	1
you	2	1
was	1	1
was	2	1
with	2	1



Term	N docs	Tot Freq
ambitious	1	1
be	1	1
brutus	2	2
capitol	1	1
caesar	2	3
did	1	1
enact	1	1
hath	1	1
I	1	2
i'	1	1
it	1	1
julius	1	1
killed	1	2
let	1	1
me	1	1
noble	1	1
so	1	1
the	2	2
told	1	1
you	1	1
was	2	2
with	1	1

Doc #	Freq
2	1
2	1
1	1
2	1
1	1
1	1
1	1
2	2
1	1
1	1
2	1
1	1
1	1
2	2
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2	1
2	1
1	1
2	1
2	1
1	1
2	1
2	1



Usually in memory

Gap-encoded, on disk

Inverted index storage

- Have estimate pointer storage
- Next up: Dictionary storage
 - Dictionary in main memory, postings on disk
 - This is common, especially for something like a search engine where high throughput is essential, but can also store most of it on disk with small, in-memory index
- Tradeoffs between compression and query processing speed
 - Cascaded family of techniques

How big is the lexicon V ?

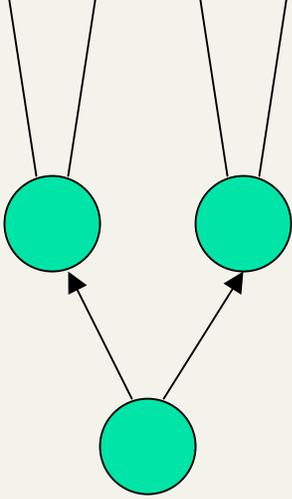
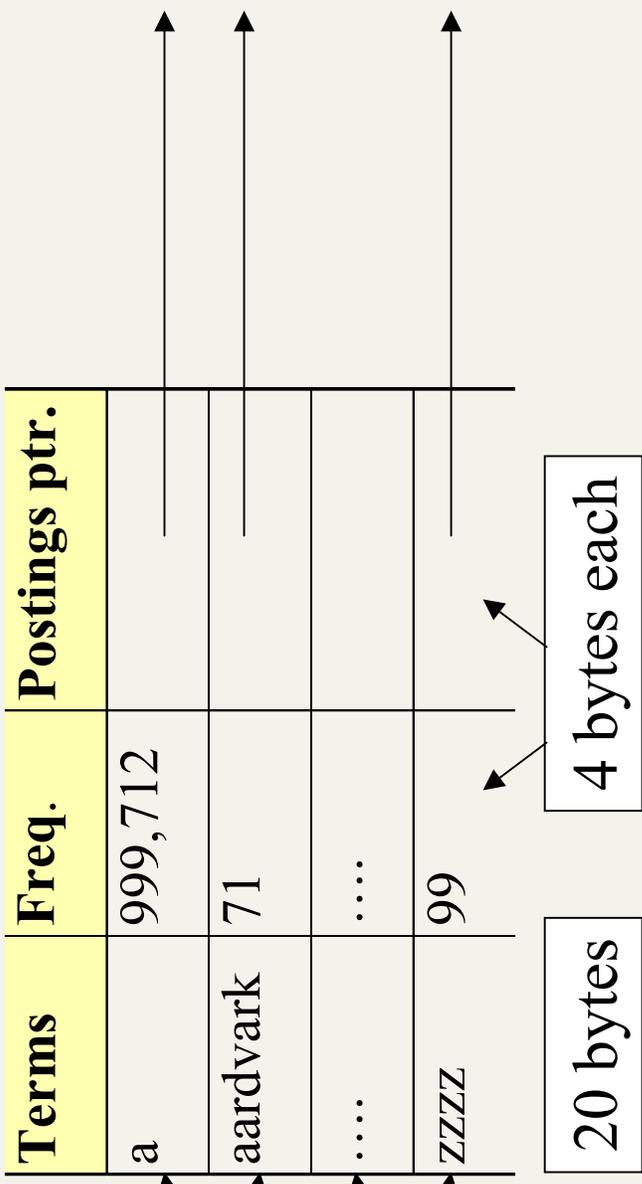
- Grows (but more slowly) with corpus size
- Empirically okay model:
$$V = kN^b$$
- where $b \approx 0.5$, $k \approx 30-100$; $N = \#$ tokens
- For instance TREC disks 1 and 2 (2 Gb; 750,000 newswire articles): $\sim 500,000$ terms
- V is decreased by case-folding, stemming
- Indexing all numbers could make it extremely large (so usually don't*)
- Spelling errors contribute a fair bit of size



Exercise: Can one derive this from Zipf's Law?

Dictionary storage - first cut

- Array of fixed-width entries
 - 500,000 terms; 28 bytes/term = 14MB.



Allows for fast binary search into dictionary

Exercises

- Is binary search really a good idea?
- What are the alternatives?

Fixed-width terms are wasteful

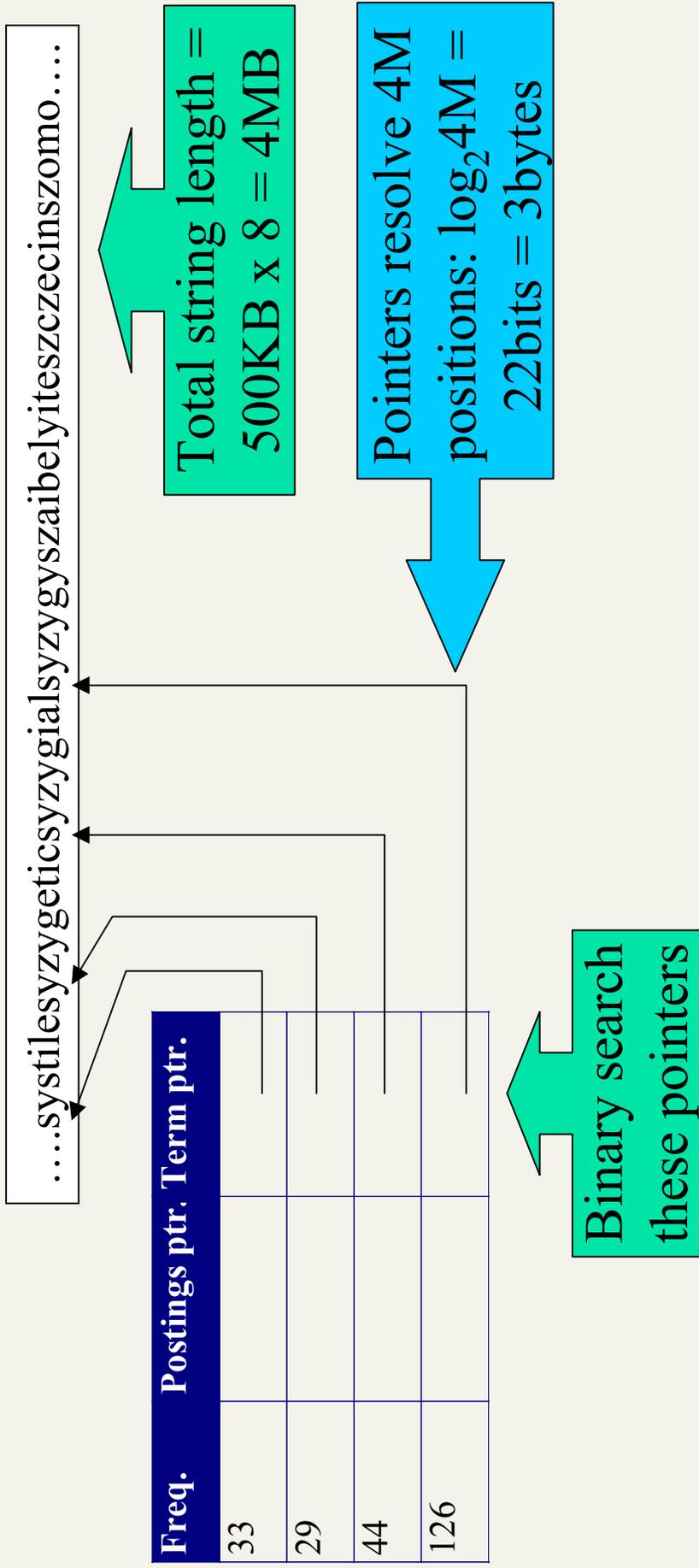
- Most of the bytes in the Term column are wasted – we allot 20 bytes for 1 letter terms.
 - And still can't handle *supercalifragilisticexpialidocious*.
- Written English averages ~4.5 characters.
 - Exercise: Why is/isn't this the number to use for estimating the dictionary size?
 - Short words dominate token counts.
- Average word in English: ~8 characters.

Explain this.

What are the corresponding numbers for Italian text?

Compressing the term list

- 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.

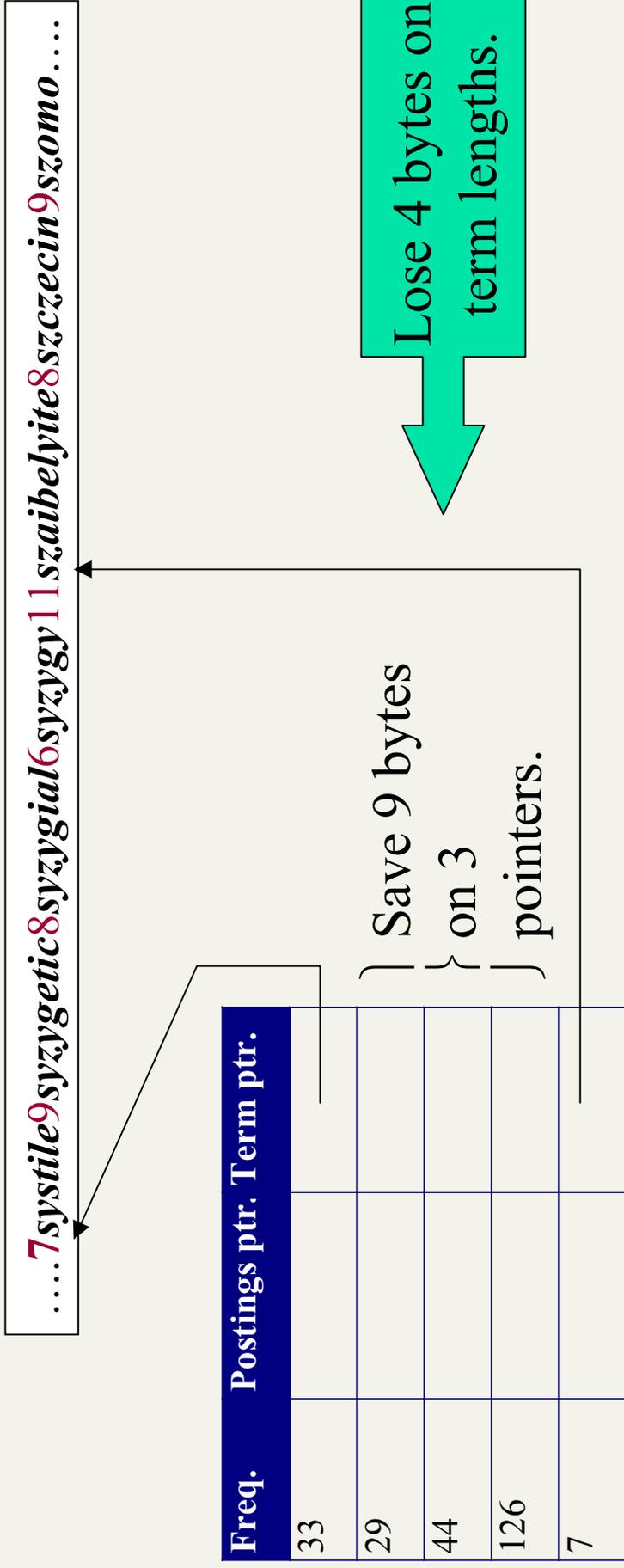


Total space for compressed list

- 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
 - 500K terms \Rightarrow 9.5MB
- } Now avg. 11 bytes/term, not 20.

Blocking

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



Net

- Where we used 3 bytes/pointer without blocking
 - $3 \times 4 = 12$ bytes for $k=4$ pointers, now we use $3 + 4 = 7$ bytes for 4 pointers.

Shaved another $\sim 0.5\text{MB}$; can save more with larger k .

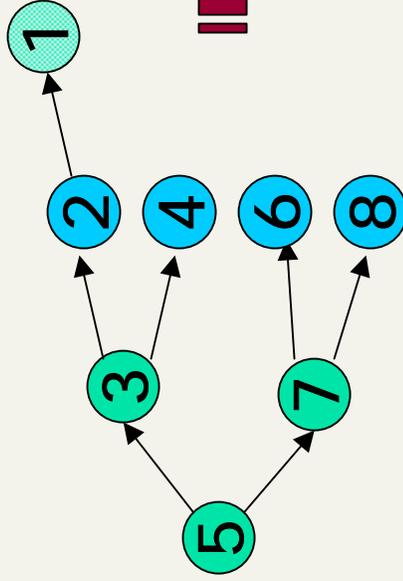
Why not go with larger k ?

Exercise

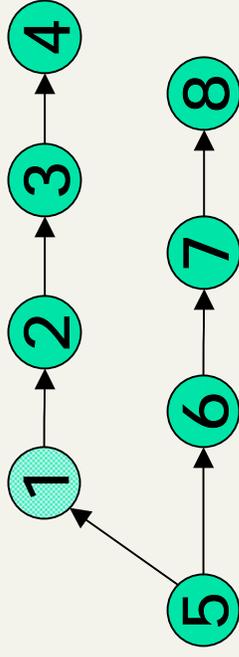
- Estimate the space usage (and savings compared to 9.5MB) with blocking, for block sizes of $k = 4, 8$ and 16 .

Impact on search

- Binary search down to 4-term block;
- Then linear search through terms in block.
- 8 documents: binary tree ave. = 2.6 compares
- Blocks of 4 (binary tree), ave. = 3 compares



$$= (1 + 2 \cdot 2 + 4 \cdot 3 + 4) / 8$$



$$= (1 + 2 \cdot 2 + 2 \cdot 3 + 2 \cdot 4 + 5) / 8$$

Exercise

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

Total space

- By increasing k , we could cut the pointer space in the dictionary, at the expense of search time; space 9.5MB \rightarrow ~8MB
- Adding in the 45MB for the postings, total 53MB for the simple Boolean inverted index

Some complicating factors

- Accented characters
 - Do we want to support accent-sensitive as well as accent-insensitive characters?
 - E.g., query *resume* expands to *resume* as well as *résumé*
 - But the query *résumé* should be executed as only *résumé*
 - Alternative, search application specifies
- If we store the accented as well as plain terms in the dictionary string, how can we support both query versions?

Index size

- Stemming/case folding cut
 - number of terms by ~40%
 - number of pointers by 10-20%
 - total space by ~30%
- Stop words
 - Rule of 30: ~30 words account for ~30% of all term occurrences in written text
 - Eliminating 150 commonest terms from indexing will cut almost 25% of space

Extreme compression (see MG)

- 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**{automata}**a**1♦e**2**♦ic**3**♦ion

Encodes *automat*

Extra length beyond *automat*.

Begins to resemble general string compression.

Extreme compression

- Using perfect hashing to store terms “within” their pointers
 - not good for vocabularies that change.
- Partition dictionary into pages
 - use B-tree on first terms of pages
 - pay a disk seek to grab each page
 - if we’re paying 1 disk seek anyway to get the postings, “only” another seek/query term.

Compression: Two alternatives

- Lossless compression: all information is preserved, but we try to encode it compactly
 - What IR people mostly do
- Lossy compression: discard some information
 - Using a stoplist can be thought of in this way
 - Techniques such as Latent Semantic Indexing (later) can be viewed as lossy compression
 - One could prune from postings entries unlikely to turn up in the top k list for query on word
 - Especially applicable to web search with huge numbers of documents but short queries (e.g.,

Carmel et al. *SIGIR 2002*)

Top k lists

- Don't store all postings entries for each term
 - Only the "best ones"
 - Which ones are the best ones?
- More on this subject later, when we get into ranking

Wild-card queries

Wild-card queries: *

- *mon**: find all docs containing any word beginning "mon".
- Easy with binary tree (or B-tree) lexicon: retrieve all words in range: $mon \leq w < moo$
- **mon*: find words ending in "mon": harder
 - Maintain an additional B-tree for terms *backwards*.

Now retrieve all words in range: $nom \leq w < non$.

Exercise: from this, how can we enumerate all terms meeting the wild-card query *pro*cent*?

Query processing

- At this point, we have an enumeration of all terms in the dictionary that match the wildcard query.
- We still have to look up the postings for each enumerated term.
- E.g., consider the query:
*se*ate AND fil*er*

This may result in the execution of many Boolean *AND* queries.

Permuterm index

- For term *hello* index under:
 - *hello\$, ello\$h, llo\$he, lo\$hel, o\$hell*
where \$ is a special symbol.
- Queries:
 - X lookup on X\$
 - *X lookup on X\$*
 - X*Y lookup on Y\$X*
- X* lookup on X*\$
- *X* lookup on X*
- X*Y*Z ???

Exercise!

Bigram indexes

- *Permuterm problem: \approx quadruples lexicon size*
- Another way: index all k -grams occurring in any word (any sequence of k chars)
- e.g., from text "*April is the cruelest month*" we get the 2-grams (*bigrams*)

\$a,ap,pr,ri,il,l\$, \$i,is,s\$, \$t,th,he,e\$, \$c,cr,ru,ue,el,le,es,st,t\$, \$m,mo,on,nt,h\$

- \$ is a special word boundary symbol

Processing n -gram wild-cards

- Query *mon** can now be run as
 - *\$m AND mo AND on*
- Fast, space efficient.
- But we'd enumerate *moon*.
- Must post-filter these terms against query.

Processing wild-card queries

- As before, we must execute a Boolean query for each enumerated, filtered term.
- Wild-cards can result in expensive query execution
 - Avoid encouraging “laziness” in the UI:

Type your search terms, use '*' if you need to.
E.g., Alex* will match Alexander.

Resources for this lecture

- MG 3.3, 3.4, 4.2