AI6122 Text Data Management & Analysis

Topic: Index Construction and Compression

Index construction

- How do we construct an index?
- What strategies can we use with limited main memory?

Lucene™ Features

Lucene offers powerful features through a simple API:

Scalable, High-Performance Indexing

- over 150GB/hour on modern hardware
- small RAM requirements -- only 1MB heap
- incremental indexing as fast as batch indexing
- index size roughly 20-30% the size of text indexed

Powerful, Accurate and Efficient Search Algorithms

- ranked searching -- best results returned first
- many powerful query types: phrase queries, wildcard queries, proximity queries, range queries and more
- fielded searching (e.g. title, author, contents)
- sorting by any field
- multiple-index searching with merged results
- allows simultaneous update and searching
- flexible faceting, highlighting, joins and result grouping
- fast, memory-efficient and typo-tolerant suggesters
- pluggable ranking models, including the Vector Space Model and Okapi BM25
- configurable storage engine (codecs)

https://lucene.apache.org/

An example document collection: RCV1

- RCV1:
  - One year of Reuters newswire (part of 1995 and 1996); not very large
  - As an example for applying scalable index construction algorithms, we will use the Reuters RCV1 collection.
  - Related datasets: http://archive.ics.uci.edu/ml/datasets/Reuters+RCV1+RCV2+Multilingual,+Multiview+Text+Categorization+Test+collection#

- There are many other datasets publicly available
  - Example: English Wikipedia dump https://dumps.wikimedia.org/enwiki/
  - Example: Amazon review dataset https://nijianmo.github.io/amazon/index.html
  - Example: Yelp data challenge https://www.yelp.com/dataset/challenge

Reuters RCV1

Symbol	Statistic	Value
N	Documents	800,000
L	Average number of tokens per document	200
M	Distinct terms (word types)	400,000
	Average number of bytes per token (include spaces/punctuations)	6
	Average number of bytes per token (without spaces/punctuations)	4.5
	Average number of bytes per term	7.5
	Number of tokens	100,000,000

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Extreme conditions create rare Antarctic clouds

Tue Aug 1, 2006 3:20am ET

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Index Construction

- When the data collection is larger than memory can hold
  - But not so huge

- Single-pass in-memory indexing (SPIMI)
  - Key idea 1: Generate separate <u>dictionaries</u> for each block of memory
  - Key idea 2: Accumulate postings in postings lists as they occur
  - With these two ideas we can generate a complete inverted index for each block.

- These separate indexes can then be merged into one big index for the document collection.

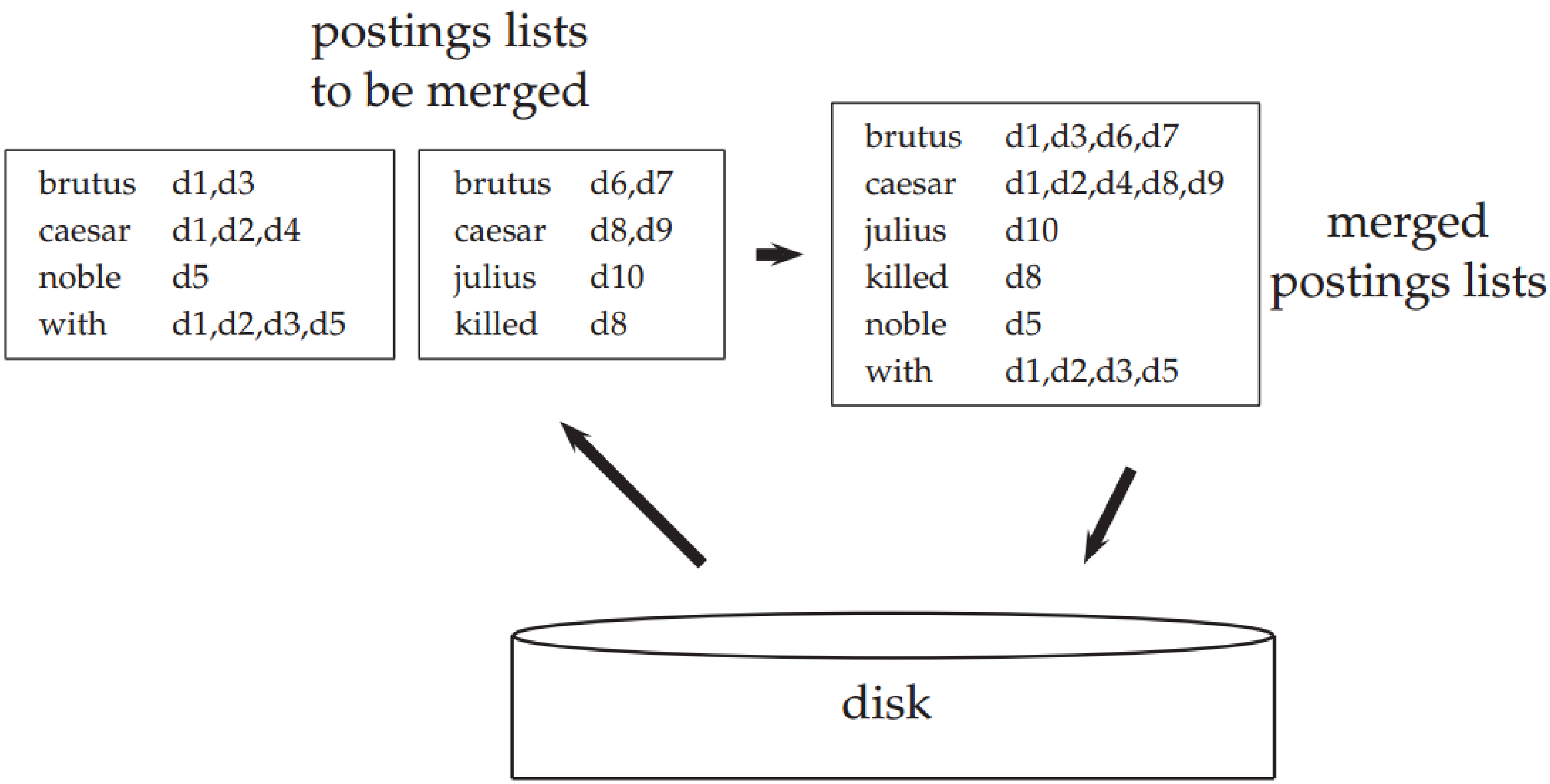
Inverted Index by SPIMI

```
SPIMI-INVERT(token_stream)
output_file = NEWFILE()
dictionary = NEWHASH()
while (free memory available)
do token ← next(token_stream)
    if term(token) ∉ dictionary
      then postings_list = ADDTODICTIONARY(dictionary, term(token))
      else postings_list = GETPOSTINGSLIST(dictionary, term(token))
    if full(postings_list)
      then postings_list = DOUBLEPOSTINGSLIST(dictionary, term(token))
    ADDTOPOSTINGSLIST(postings_list, docID(token))
sorted_terms ← SORTTERMS(dictionary)
WRITEBLOCKTODISK(sorted_terms, dictionary, output_file)
return output_file
```

Token = <term-docID> pair

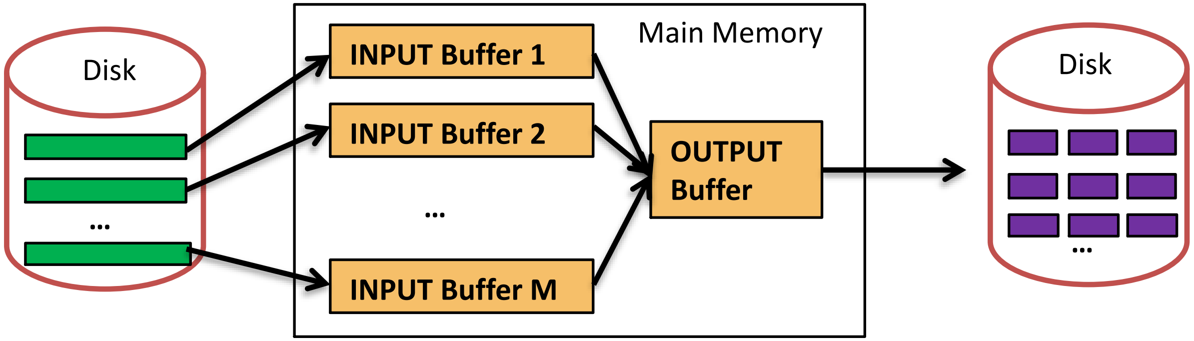
To facilitate the final merging

Merging two inverted indexes



Multi-way merge?

- Reading decent-sized chunks from all blocks simultaneously, one from each sorted block
- Merge the chunks and then write out a decent-sized output chunk



If the document collection is huge: Distributed Indexing

- Partition by documents (local index organization)
  - Documents are distributed to different subsets
  - One index is constructed for each subset of documents
  - A search query is broadcast to all indexes and results are merged
    - One machine handles a subrange of terms
  - More widely adopted in search engines

- Partition by terms (global index organization)
  - The dictionary of index terms are partitioned into subsets
  - One machine handles a subrange of terms
    - Each query term is processed by one computer node
  - Multiword queries require sending long postings between sets of nodes

- Next: how to perform term-partitioned index in parallel

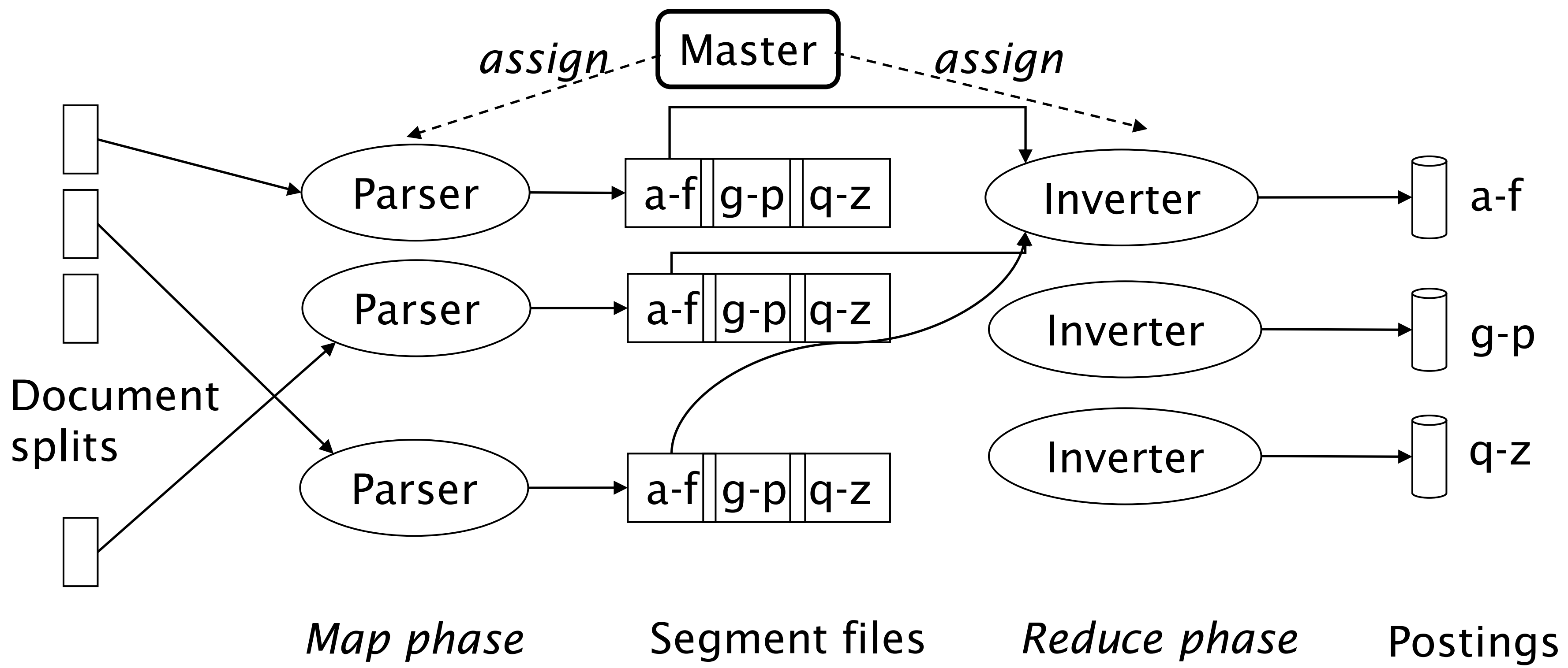
Term-partitioned distributed indexing in parallel

- Maintain a **master** machine **directing** the indexing job
  - Break up indexing into sets of (parallel) tasks.
  - Master machine assigns each task to an idle machine from a pool.

- For indexing, we use two sets of parallel tasks
  - **Parsers**
  - **Inverters**

- Break the input document collection into splits
  - Each split is a subset of documents

Term-partitioned distributed indexing: MapReduce



Parsers and Inverters

- Master assigns a split of documents to an idle parser machine

- Parser
  - reads a document at a time, and emits <term, docID> pairs
  - Parser writes pairs into ***j* partitions,** each partition is for a range of terms' first letters (e.g., ***a-f***, ***g-p***, ***q-z***) – here $j = 3$.

- An inverter
  - collects all <term, docID> pairs for one term-partition (e.g., ***a-f***)
  - Sorts and writes to postings lists

Schema for index construction in MapReduce

- MapReduce breaks a large problem into smaller parts using
  - key-value pairs (k, v)

- Schema of map and reduce functions
  - Map phase: input → list(k, v)
  - Reduce phase: (k,list(v)) → output

- Instantiation of the schema for **index construction**
  - map: collection → list(term, docID) Parser
  - reduce: (<term1, list(docID)>, <term2, list(docID)>, …) → (postings list1, postings list2, …) Inverter

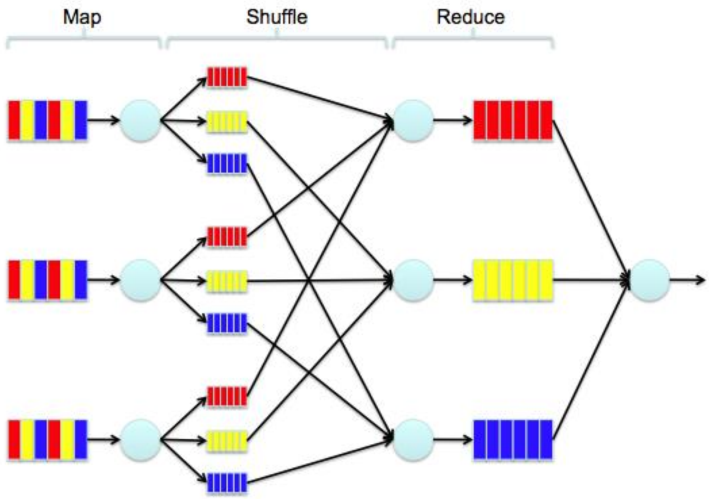
Example for index construction

- Map:
  - d1 : C came, C c’ed.
  - d2 : C died.

  → <C,d1>, <came,d1>, <C,d1>, <c’ed, d1>, <C, d2>, <died,d2>

- Reduce:
  - (<C,(d1,d2,d1)>, <died,(d2)>, <came,(d1)>, <c’ed,(d1)>)

  → (<C,(d1:2,d2:1)>, <died,(d2:1)>, <came,(d1:1)>, <c’ed,(d1:1)>)



Dynamic indexing

- Document collections may not be static
  - Documents come in over time and need to be inserted.
  - Documents are deleted and modified.

- This means that the dictionary and postings lists have to be modified:
  - Postings updates for terms already in dictionary
  - New terms added to dictionary

Simplest approach for dynamic indexing

- Two indexes (periodically, re-index into one main index)
  - Maintain “big” main index
  - New docs go into “small” auxiliary index
  - Search across both, merge results

- Deletions
  - Invalidation bit-vector for deleted docs
  - Filter docs output on a search result by this invalidation bit-vector

- Document updates: delete and reinsert

Index Compression

- Dictionary compression
- Postings compression

BRUTUS	→	1	2	4	11	31	45	173	174	
CAESAR	→	1	2	4	5	6	16	57	132	...
CALPURNIA	→	2	31	54	101					

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, which is true of the decompression algorithms we use here

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.

JPG vs PNG vs EPS/PDF

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

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Index parameters vs. index size

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

Vocabulary vs. collection size

- How big is the term vocabulary?
  - That is, how many distinct words are there?
- Can we assume an upper bound?
  - All possible sequences of letters of length 20?
- In practice, the vocabulary will keep growing with the collection size
  - Especially with Unicode ☺

Vocabulary vs. collection size

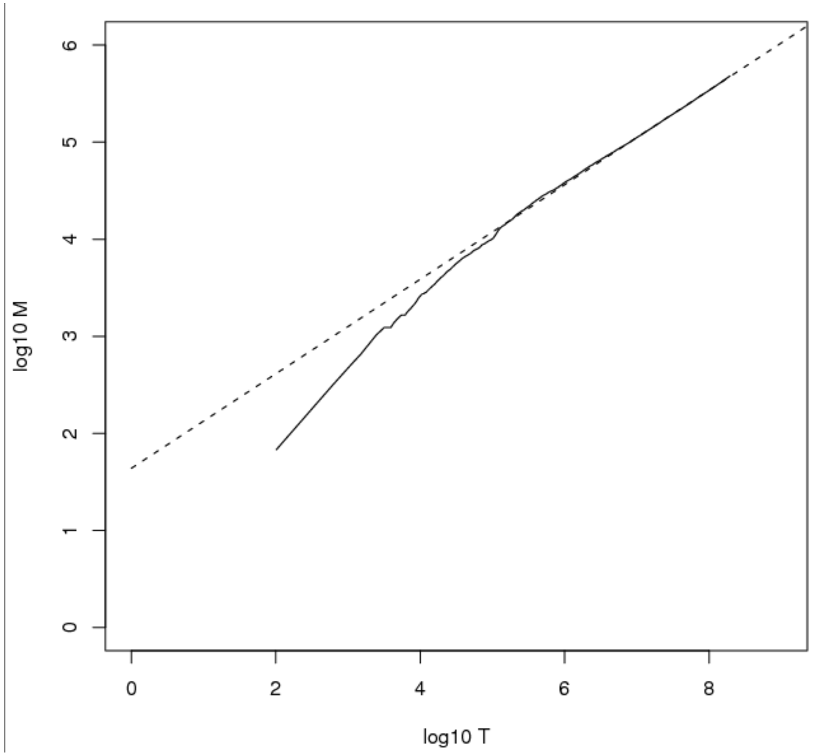
- How big is the term vocabulary (distinct words)?

- 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 relationship between the two in log-log space
  - An empirical finding ("empirical law")

Heaps' Law: $M = kT^b$

- For RCV1, the dashed line is the best least squares fit.
  - $\log_{10} M = 0.49 \log_{10} T + 1.64$
  - $M = 10^{1.64} T^{0.49}$
  - $k = 10^{1.64} \approx 44$ and b = 0.49.
  - Good empirical fit for Reuters RCV1 !



- Example:
  - for first 1,000,020 tokens, law predicts 38,323 terms;
  - Actual number: 38,365 terms

Zipf's law

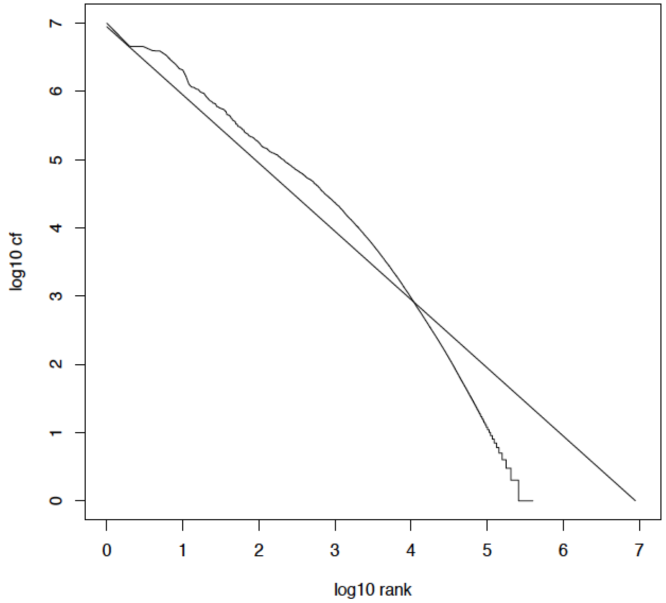
- Heaps' law gives the vocabulary size in collections.

- 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 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 **collection frequency**
    - The number of occurrences of the term t_i in the collection.

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: $cf_i = K/i$ 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



Index Compression

- Now, we will consider compressing the space for the dictionary and postings
  - Basic Boolean index only
  - Not considering positional indexes, etc.
  - We will consider different compression schemes

- 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

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….

DocFreq.	Postings ptr.	Term ptr.
33	→	→
29	→	→
44	→	→
126	→	→

Total string length =
400K x 8B = 3.2MB

Pointers resolve 3.2M positions:
$\log_2 3.2\text{M}$ = 22bits = 3 Bytes

Space for dictionary as a string

- Storage requirement:
  - 4 bytes per term for document frequency
  - 4 bytes per term for pointer to Postings.
  - 3 bytes per term pointer
  - Avg. 8 bytes per term in term string

Freq.	Postings ptr.	Term ptr.
33		
29		
44		
126		

- Total: 400K terms x 19 $\Rightarrow$ 7.6 MB

Can we do better? → Blocking

- Store pointers to every kth 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***….

Lose 4 bytes per 4 terms

Save 9 bytes per 4 terms

DocFreq.	Postings ptr.	Term ptr.
33		
29		
44		
126		
7		

Is Blocking effective

- Example for block size k = 4
  - Without blocking, we used 3 bytes/pointer: 3 x 4 = 12 bytes for every 4 terms
  - With blocking, we use 3 + 4 = 7 bytes for every 4 terms
  - This reduces the size of the dictionary from 7.6 MB to 7.1 MB.

- Shall we use larger k?
  - Better compression
  - Slower term lookup

Front coding – more compression

- Sorted words commonly have long common prefix
  - Store differences only, for last $k-1$ in a block of k
  - 8automata8automate9automatic10automation

→8***automat****a1◊***e***2◊***ic***3◊***ion***

Encodes ***automat***

Extra length beyond ***automat.***

- For RCV1 dictionary compression
  - Dictionary-as-String with pointers to every term, 7.6M
  - with blocking k = 4, 7.1M
  - With Blocking + front coding 5.9M

Postings compression

- The postings file is much larger than the dictionary
  - Factor of at least 10.
  - Compression: store each posting compactly.

- A posting for our purposes is a docID.
  - For Reuters (800,000 documents), we 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 $\log_2 1M \sim 20$ bits.

- A term like **<u>the</u>** occurs in virtually every doc, so 20 bits per 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.

	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 ~log2G 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 code example (we skip details)

1100111000 101 110100011000110001

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 Index Compression

Data	Size in MB
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
collection (text)	960
postings, uncompressed (32-bit words)	400
postings, uncompressed (20 bits)	250
postings, variable byte encoded	116
postings, γ–encoded (a coding scheme seldom used in practice)	101

Index compression summary

- We can now create an index for highly efficient Boolean retrieval that is very space efficient
  - However, we've ignored positional information

- Hence, space savings are less for indexes used in practice
  - But techniques substantially the same.