IR - INDEXING

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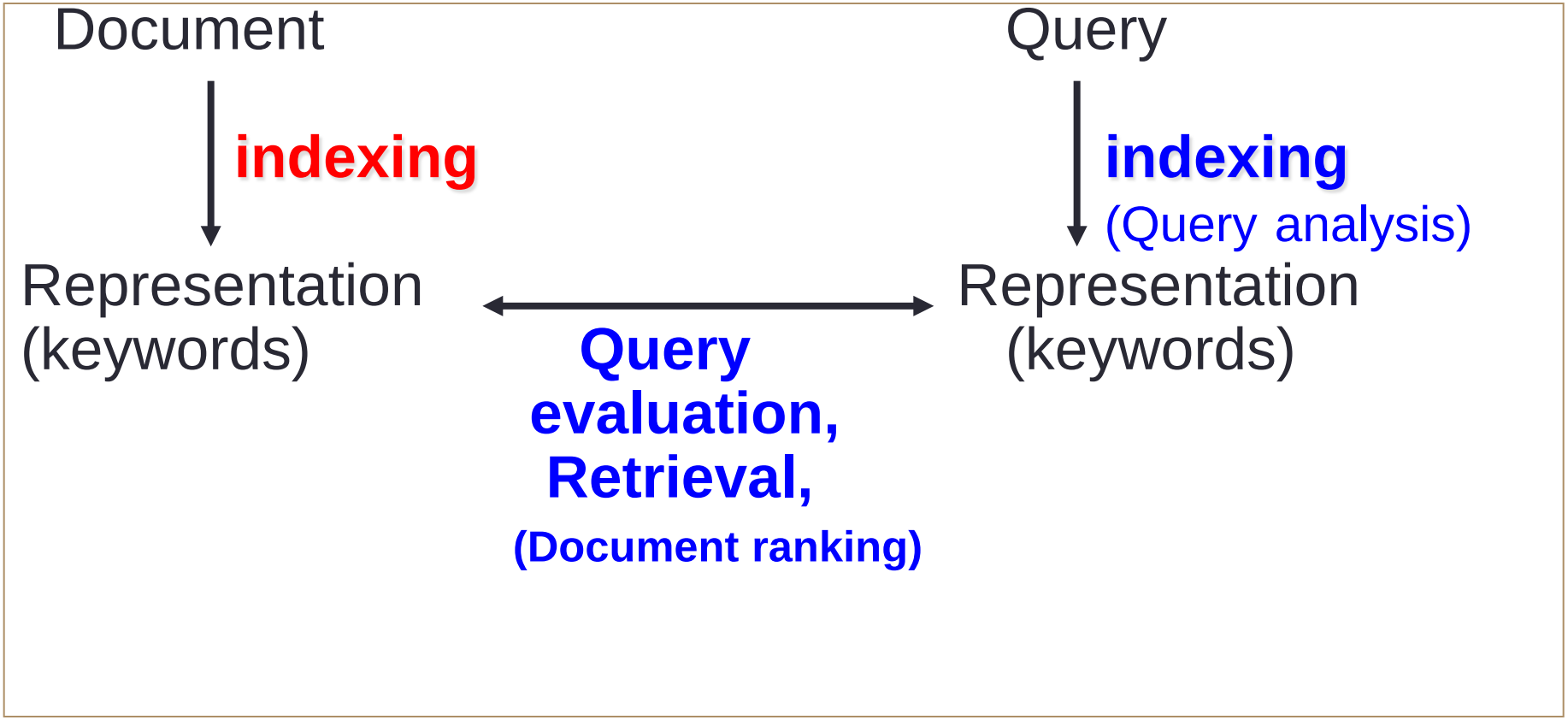
(based on the lectures of Manning and Raghavan)

Roadmap

- Last lecture: Overview of IR
- From this lecture on, more details
- Today: Indexing process
  - Basic operations
  - Means to speedup
  - Simple linguistic processing
  - Supporting proximity search
  - References
  - Questions

Indexing-based IR



Basics - Goals

- Recognize the contents of a document
  - What are the main topics of the document?
  - What are the basic units (indexing units) to represent them?
  - How to weight their importance?
- Support fast search given a query
  - Given a query, find the documents that contain the words.

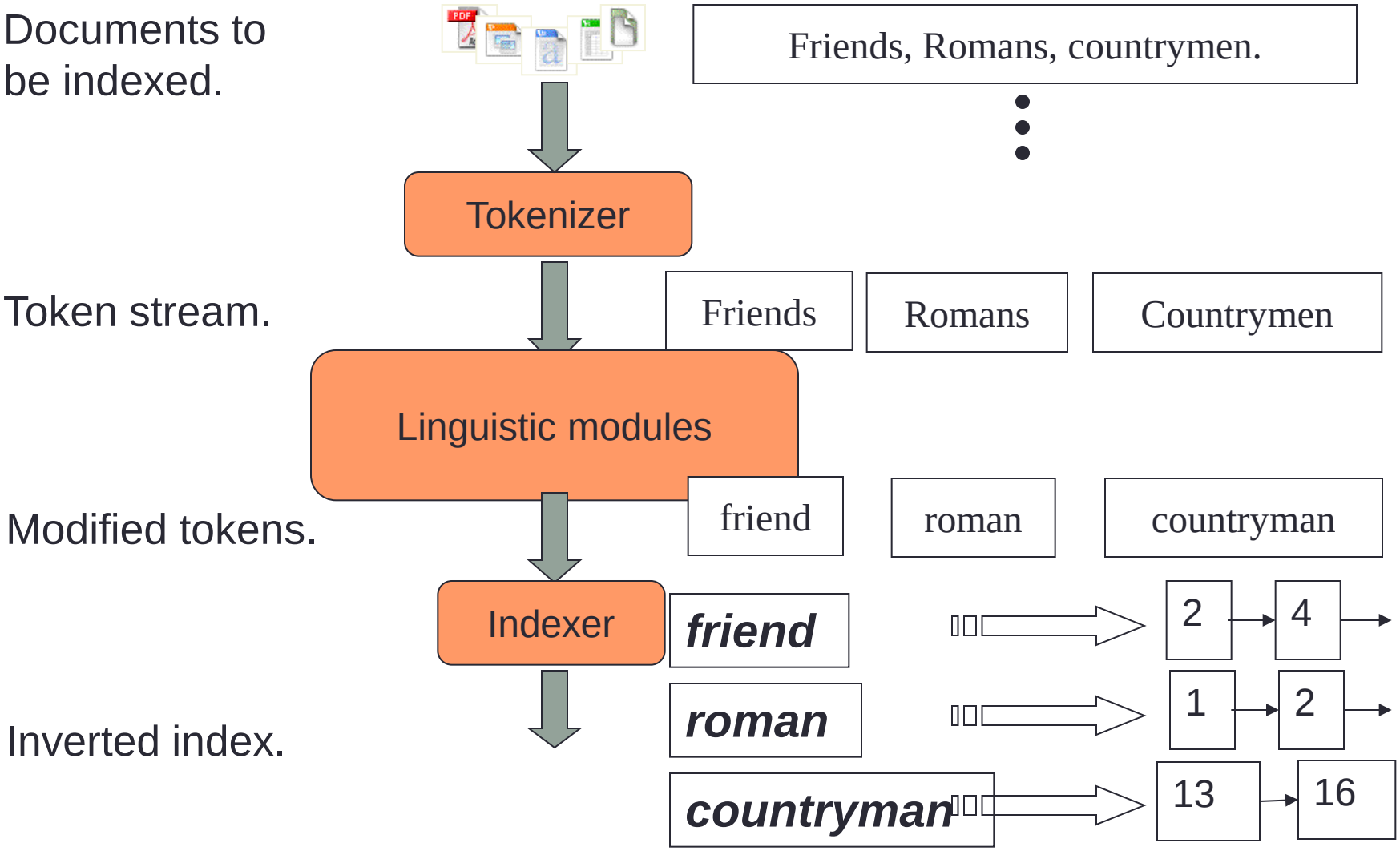
Basics - document

- Document: anything which one may search for, which contains information in different media (text, image, …)
  - This course: text
- Text document = description in a natural language
- Human vs. computer understanding
  - Read the text and understand the meaning
  - A computer cannot (yet) understand meaning as a human being, but can quickly process symbols (strings, words, …).
- Indexing process:
  - Let a computer “read” a text
  - Select the symbols to represent what it believes to be important
  - Create a representation (index) in order to support fast search

Basics – “Reading” a document

- Let us use words as the representation units
- Document parsing
  - Identify document format (text, Word, PDF, …)
  - Identify different text parts (title, text body, …) (note: often separate index for different parts)
  - Go through a text, and recognize the words
    - Tokenization
    - The elements recognized = tokens
  - Statistics for weighting
- Create index structures
- Search: Query words → corresponding documents

Basic indexing pipeline



Tokenization

- Input: "***Friends, Romans and Countrymen***"
- Output: Tokens
  - ***Friends***
  - ***Romans***
  - ***and***
  - ***Countrymen***
- Usually use space and punctuations
- Each such token is now a candidate for an index entry, after further processing

Tokenization: issues

- ***Finland's capital*** $\rightarrow$

  Finland? Finlands? Finland's?

- ***Hewlett-Packard*** $\rightarrow$

  Hewlett and ***Packard*** as two tokens?

  - ***State-of-the-art***: break up hyphenated sequence.
  - co-education ?
  - the hold-him-back-and-drag-him-away-maneuver ?

- ***San Francisco***: one token or two? How do you decide it is one token?

Tokenization: Numbers

- ***3/12/91***
- ***Mar. 12, 1991***
- ***55 B.C.***
- ***B-52***
- ***My PGP key is 324a3df234cb23e***
- ***100.2.86.144***
  - Generally, don't index as text.
  - Will often index "meta-data" separately
    - Creation date, format, etc.

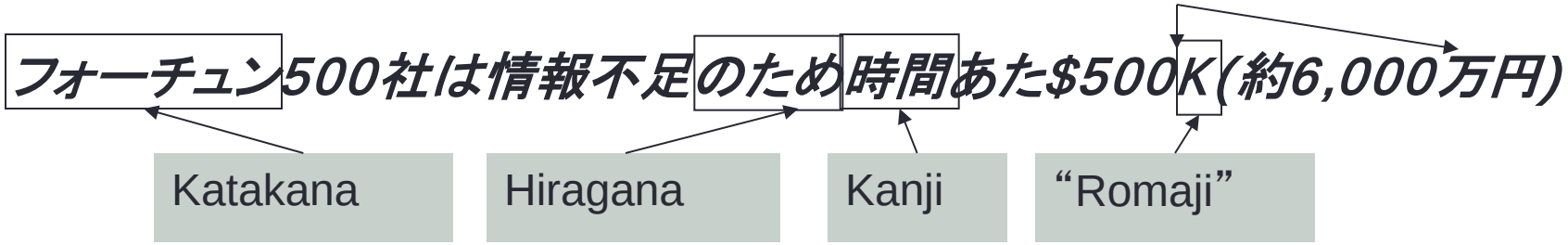
Tokenization: Language issues

- ***L'ensemble*** (the set) → one token or two?
  - ***L*** ? ***L'*** ? ***Le*** ?
  - Want ***ensemble*** to match with ***un ensemble***
  - but how about ***aujourd'hui*** (today)
  - → create a dictionary to store special words such as ***aujourd'hui***

- German noun compounds are not segmented
  - Lebensversicherungsgesellschaftsangestellter
  - 'life insurance company employee'
  - → resort to a post- processing of decompounding

Tokenization: language issues

- Chinese and Japanese have no spaces between words:
  - Not always guaranteed a unique tokenization
- Further complicated in Japanese, with multiple alphabets intermingled
  - Dates/amounts in multiple formats



End-user can express query entirely in hiragana!

Normalization

- Need to “normalize” terms in indexed text as well as query terms into the same form
  - We want to match ***U.S.A.*** and ***USA***
- We most commonly implicitly define equivalence classes of terms
  - e.g., by deleting periods in a term
  - U.S. → US

Case folding

- Reduce all letters to lower case
  - exception: upper case (in mid-sentence?)
    - e.g., ***General Motors***
    - ***Fed*** vs. ***fed***
    - ***SAIL*** vs. ***sail***
    - ***AIDS*** vs. ***aids***
  - Often best to lower case everything, since users will use lowercase regardless of ‘correct’ capitalization
  - Problems
    - Simple tokenization: U.S. → U, S
    - U.S. → us
- Question: Other problems in tokenization?

A naïve representation of indexing result: Term-document incidence

documents →

	Antony and Cleopatra	Julius Caesar	The Tempest	Hamlet	Othello	Macbeth
Antony	1	1	0	0	0	1
Brutus	1	1	0	1	0	0
Caesar	1	1	0	1	1	1
Calpurnia	0	1	0	0	0	0
Cleopatra	1	0	0	0	0	0
mercy	1	0	1	1	1	1
worser	1	0	1	1	1	0

terms

1 if document contains word, 0 otherwise

Simple Query

- Which plays of Shakespeare contain the words ***Brutus*** *AND* ***Caesar*** but *NOT* ***Calpurnia***?
- One could grep all of Shakespeare's plays for ***Brutus*** and ***Caesar,*** then strip out lines containing ***Calpurnia***?
  - Slow (for large corpora)
  - *NOT* ***Calpurnia*** is non-trivial
  - Other operations (e.g., find the word ***Romans*** near ***countrymen***) not feasible

Term-document incidence

	Antony and Cleopatra	Julius Caesar	The Tempest	Hamlet	Othello	Macbeth
Antony	1	1	0	0	0	1
Brutus	1	1	0	1	0	0
Caesar	1	1	0	1	1	1
Calpurnia	0	1	0	0	0	0
Cleopatra	1	0	0	0	0	0
mercy	1	0	1	1	1	1
worser	1	0	1	1	1	0

Brutus *AND* ***Caesar*** but *NOT* ***Calpurnia***

Answers to query

- Antony and Cleopatra, Act III, Scene ii
- *Agrippa* [Aside to DOMITIUS ENOBARBUS]: Why, Enobarbus,
- When Antony found Julius ***Caesar*** dead,
- He cried almost to roaring; and he wept
- When at Philippi he found ***Brutus*** slain.

- Hamlet, Act III, Scene ii
- *Lord Polonius:* I did enact Julius ***Caesar*** I was killed i' the
- Capitol; ***Brutus*** killed me.

Bigger corpora

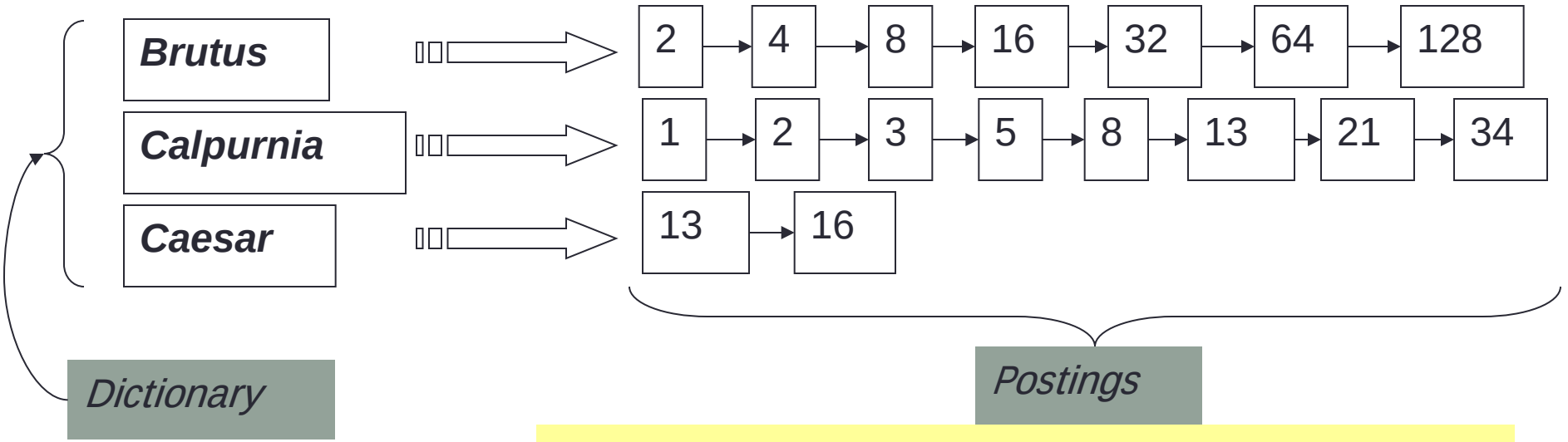
- Consider *n* = 1M documents, each with about 1K terms.
- Avg 6 bytes/term incl spaces/punctuation
  - 6GB of data in the documents.
- Say there are *m* = 500K *distinct* terms among these.
- 500K x 1M matrix has half-a-trillion 0's and 1's.
- But it has no more than one billion 1's.
  - matrix is extremely sparse.
- What's a better representation?
  - We only record the 1 positions.

Inverted index

- For each term *T*, we must store a list of all documents that contain *T*.
- Do we use an array or a list for this?

Inverted index

- Linked lists generally preferred to arrays
  - Dynamic space allocation
  - Insertion of terms into documents easy
  - Space overhead of pointers



Sorted by docID (more later on why).

Indexer steps

- Sequence of (Modified token, Document ID) pairs.

Doc 1

I did enact Julius Caesar I was killed i' the Capitol; Brutus killed me.

Doc 2

So let it be with Caesar. The noble Brutus hath told you Caesar was ambitious

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

- Sort by terms.

Core indexing step.

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

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

- Multiple term entries in a single document are merged.
- Frequency information is added.

Why frequency?
Will discuss later.

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

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

- The result is split into a *Dictionary* file and a *Postings* file.

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

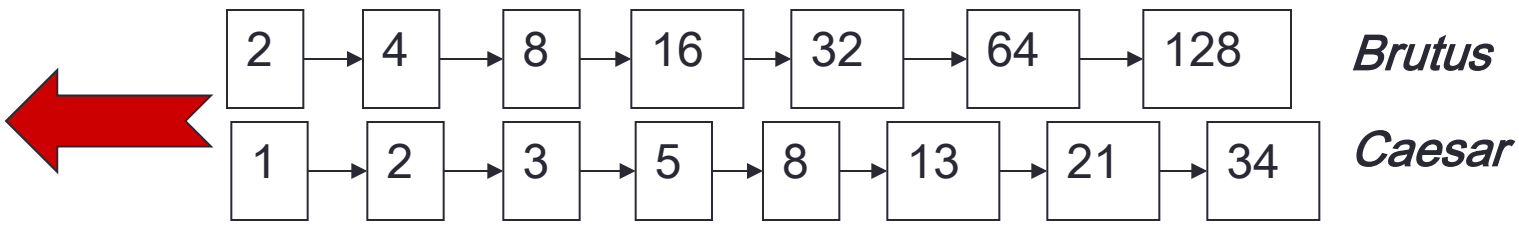
Doc #	Freq
2	1
2	1
1	1
2	1
1	1
1	1
2	2
1	1
1	1
2	1
1	2
1	1
2	1
1	1
1	2
2	1
1	1
2	1
2	1
1	1
2	1
2	1
2	1
1	1
2	1
2	1

Query processing

- Consider processing the query:

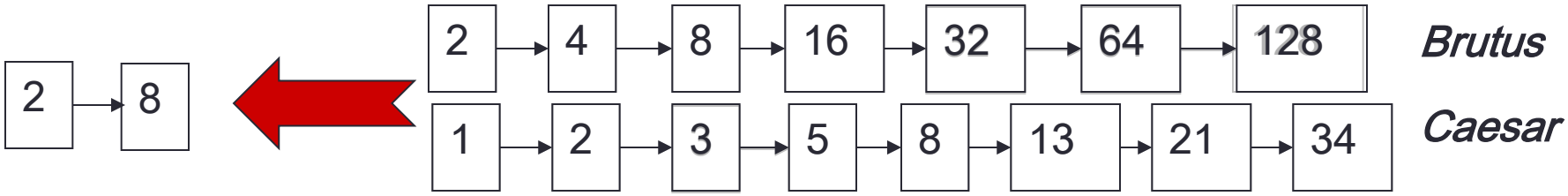
  Brutus *AND* ***Caesar***

  - Locate ***Brutus*** in the Dictionary;
    - Retrieve its postings.
  - Locate ***Caesar*** in the Dictionary;
    - Retrieve its postings.
  - "Merge" the two postings:



The merge

- Walk through the two postings simultaneously, in time linear in the total number of postings entries



If the list lengths are *x* and *y*, the merge takes O(*x*+*y*) operations.

Crucial: postings sorted by docID.

Boolean queries: Exact match

- Boolean Queries are queries using *AND, OR* and *NOT* together with query terms
  - Views each document as a set of words
  - Is precise: document matches condition or not.
- Primary commercial retrieval tool for 3 decades.
- Professional searchers (e.g., lawyers) still like Boolean queries:
  - You know exactly what you're getting.

Example: WestLaw http://www.westlaw.com/

- Largest commercial (paying subscribers) legal search service (started 1975; ranking added 1992)
- About 7 terabytes of data; 700,000 users
- Majority of users *still* use boolean queries
- Example query:
  - What is the statute of limitations in cases involving the federal tort claims act?
  - LIMIT! /3 STATUTE ACTION /S FEDERAL /2 TORT /3 CLAIM
- Long, precise queries; proximity operators; incrementally developed; not like web search

More general merges

- Exercise: Adapt the merge for the queries:

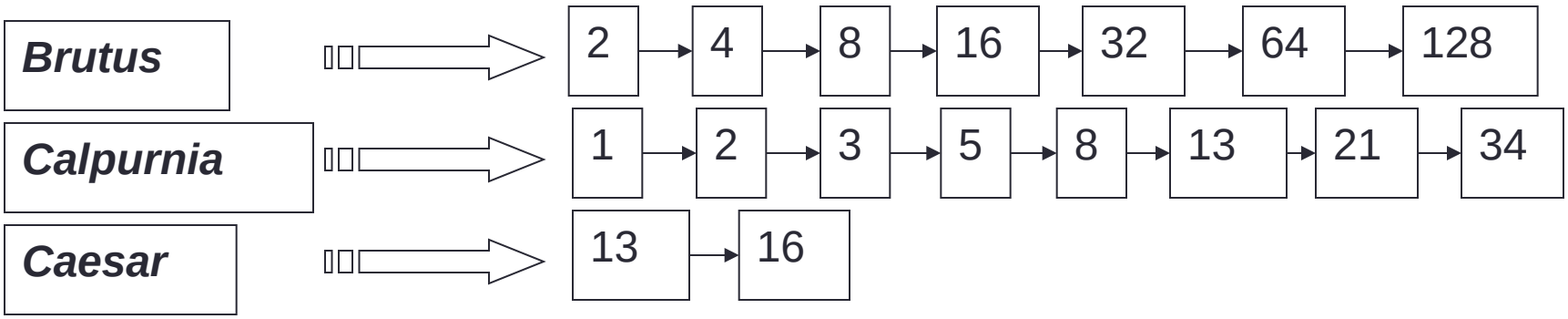
  Brutus *AND NOT* ***Caesar***

  Brutus *OR NOT* ***Caesar***

Q: Can we still run through the merge in time O(x+y)?

Query optimization

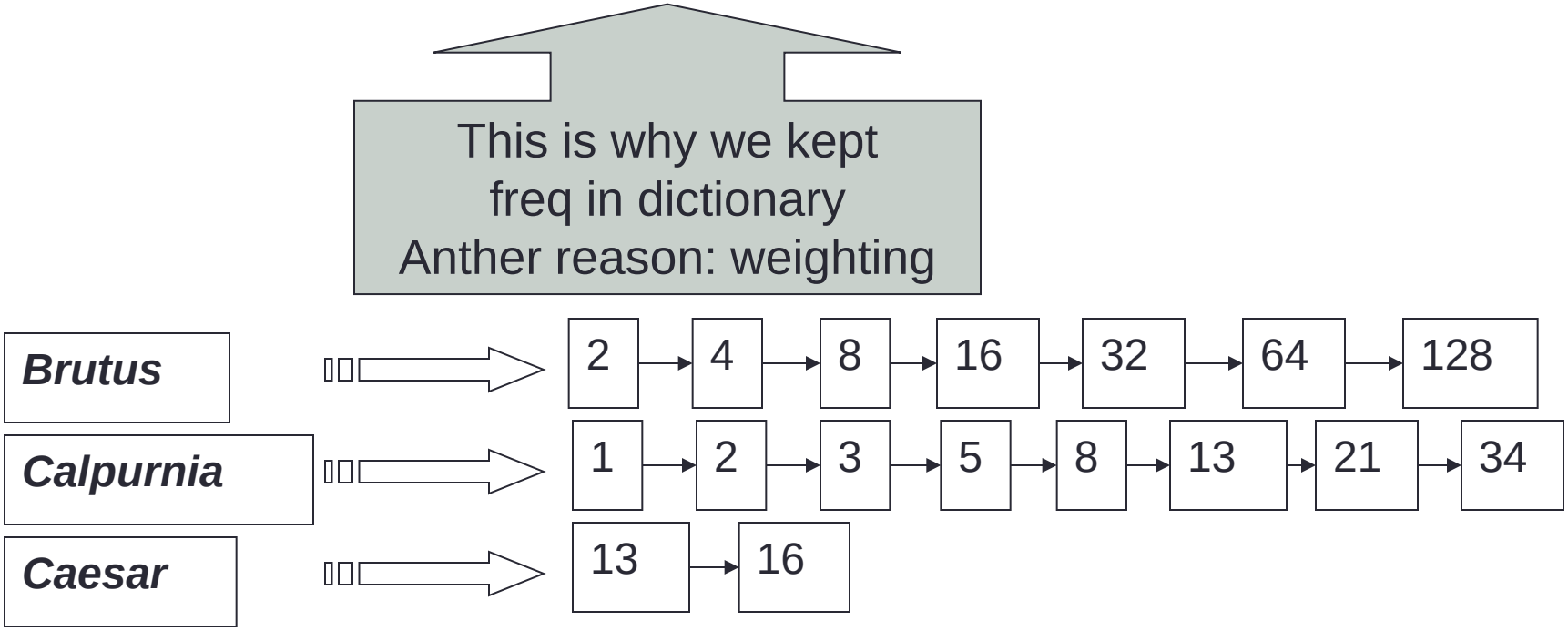
- What is the best order for query processing?
- Consider a query that is an *AND* of *t* terms.
- For each of the *t* terms, get its postings, then *AND* together.



Query: ***Brutus*** *AND* ***Calpurnia*** *AND* ***Caesar***

Query optimization example

- Process in order of increasing freq:
  - *start with smallest set, then keep cutting further*.



Execute the query as (***Caesar*** *AND* ***Brutus)*** *AND* ***Calpurnia***.

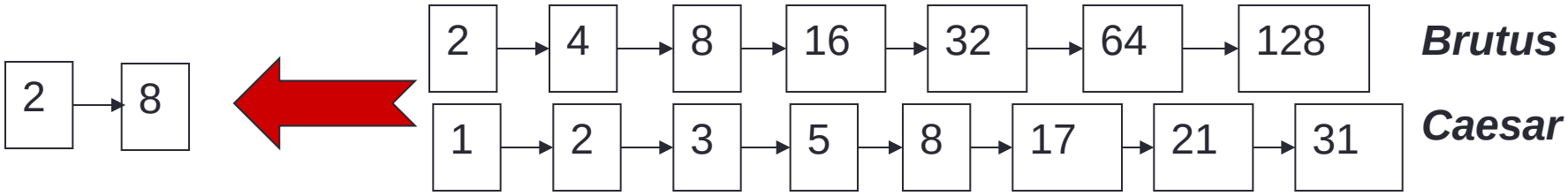
More general optimization

- e.g., *(**madding** OR **crowd**) AND (**ignoble** OR **strife**)*
- Get freq's for all terms.
- Estimate the size of each *OR* by the sum of its freq's (conservative).
- Process in increasing order of *OR* sizes.

FASTER POSTINGS MERGES: SKIP POINTERS

Recall basic merge

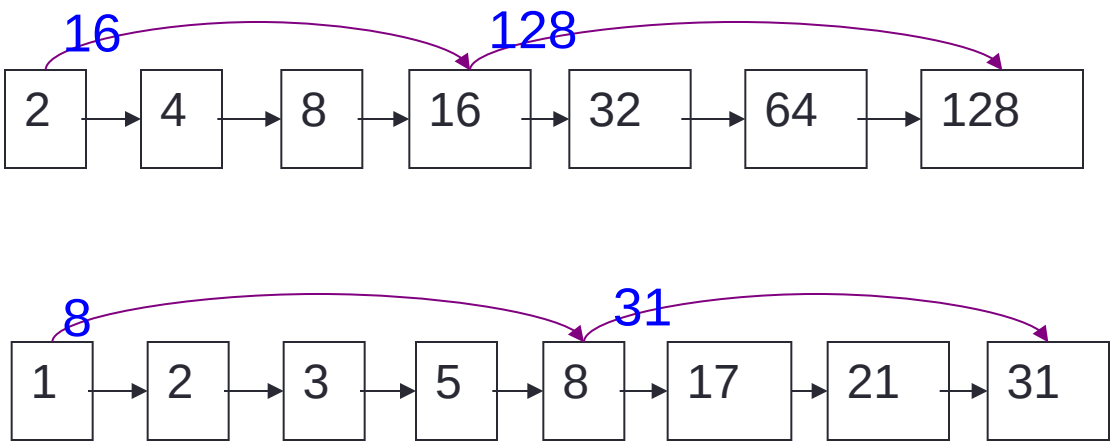
- Walk through the two postings simultaneously, in time linear in the total number of postings entries



If the list lengths are *m* and *n*, the merge takes O(*m*+*n*) operations.

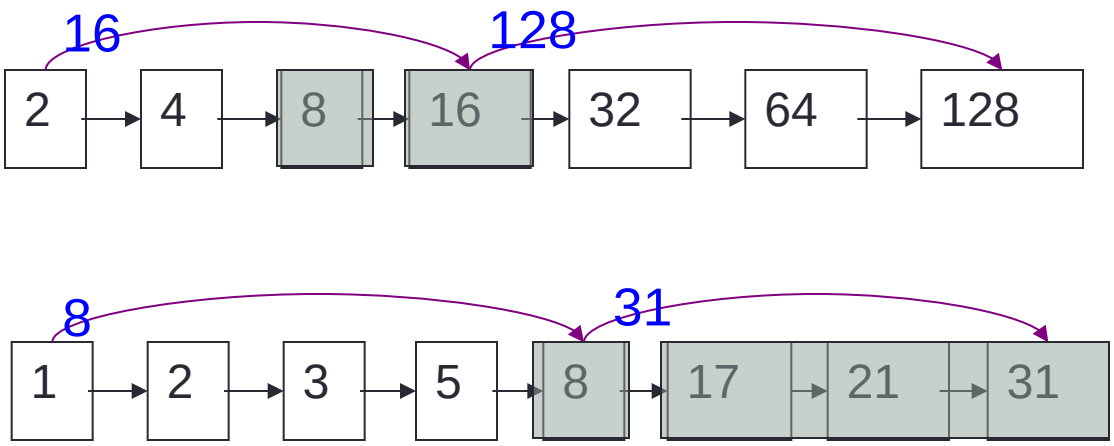
Can we do better?
Yes, if index isn't changing too fast.

Augment postings with skip pointers (at indexing time)



- Why?
- To skip postings that will not figure in the search results.
- How?
- Where do we place skip pointers?

Query processing with skip pointers



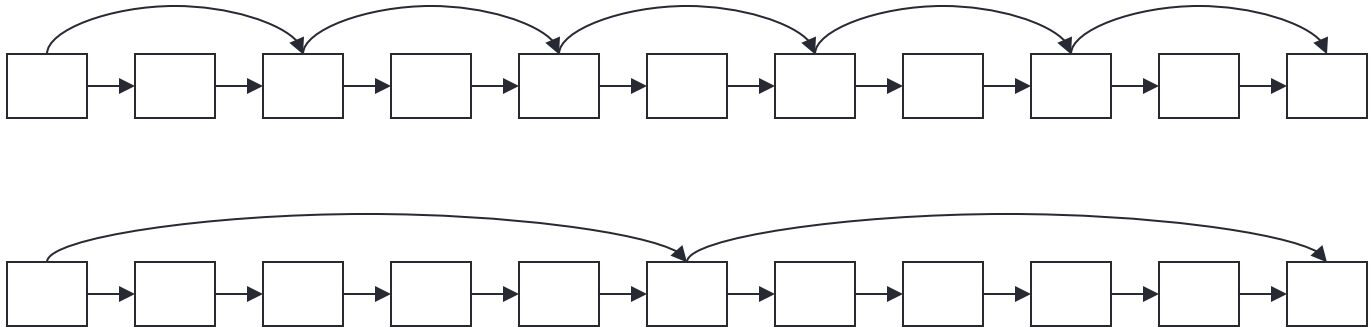
Suppose we've stepped through the lists until we process **8** on each list.

When we get to **16** on the top list, we see that its successor is **32**.

But the skip successor of **8** on the lower list is **31**, so we can skip ahead past the intervening postings.

Where do we place skips?

- Tradeoff:
  - More skips $\rightarrow$ shorter skip spans $\Rightarrow$ more likely to skip. But lots of comparisons to skip pointers.
  - Fewer skips $\rightarrow$ few pointer comparison, but then long skip spans $\Rightarrow$ few successful skips.



Placing skips

- Simple heuristic: for postings of length L, use $\sqrt{L}$ evenly-spaced skip pointers.
- This ignores the distribution of query terms.
- Easy if the index is relatively static; harder if L keeps changing because of updates.

- This definitely used to help; with modern hardware it may not (Bahle et al. 2002)
  - The cost of loading a bigger postings list outweighs the gain from quicker in memory merging

POSITIONAL INDEX - PROXIMITY

Positional indexes

- Store, for each ***term***, entries of the form:

  <number of docs containing ***term***;

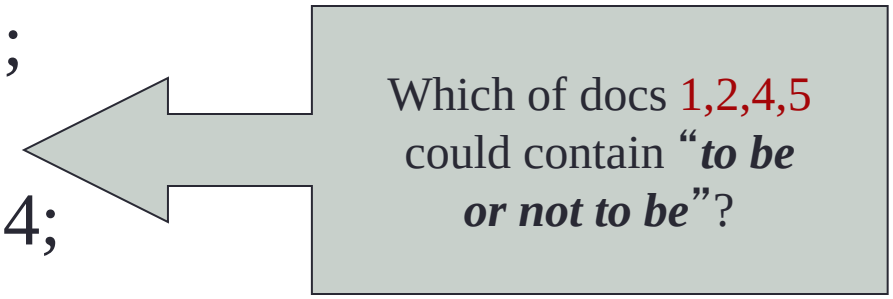
  doc1: position1, position2 … ;

  doc2: position1, position2 … ;

  etc.>

Positional index example

<***be***: 993427;
1: 7, 18, 33, 72, 86, 231;
2: 3, 149;
4: 17, 191, 291, 430, 434;
5: 363, 367, …>



- This expands postings storage *substantially*

Processing a phrase query

- Extract inverted index entries for each distinct term: ***to, be, or, not.***
- Merge their *doc:position* lists to enumerate all positions with "***to be or not to be***".
  - ***to****:*
    - *2*:1,17,74,222,551; *4*:8,16,190,429,433; *7*:13,23,191; ...
  - ***be****:*
    - *1*:17,19; *4*:17,191,291,430,434; *5*:14,19,101; ...
- Same general method for proximity searches (within *k* words)

Proximity queries

- LIMIT! /3 STATUTE /3 FEDERAL /2 TORT Here, /*k* means "within *k* words of".

- Exercise: How to adapt the linear merge of postings to handle proximity queries?

Positional index size

- Need an entry for each occurrence, not just once per document
- Index size depends on average document size
  - Average web page has <1000 terms
  - SEC filings, books, even some epic poems … easily 100,000 terms
- Consider a term with frequency 0.1%

Why?

Document size	Postings	Positional postings
1000	1	1
100,000	1	100

Rules of thumb

- A positional index is 2-4 as large as a non-positional index
- Positional index size 35-50% of volume of original text
- Caveat: all of this holds for “English-like” languages

TERM NORMALIZATION

Lemmatization

- Reduce inflectional/variant forms to base form (lemma)
- E.g.,
  - *am, are, is* → *be*
  - *computing* → compute
  - *car, cars, car's*, *cars'* → *car*
- *the boy's cars are different colors* → *the boy car be different color*
- Lemmatization implies doing “proper” reduction to dictionary headword form
  - Need Part-Of-Speech (POS) tagging

Stemming

- Reduce terms to their "roots"/stems before indexing
- "Stemming" suggest crude affix chopping
  - language dependent
  - e.g., ***automate(s), automatic, automation*** all reduced to ***automat***.

for example compressed and compression are both accepted as equivalent to compress.

for exampl compress and compress ar both accept as equival to compress

Porter's algorithm

- Commonest algorithm for stemming English
  - Results suggest at least as good as other stemming options
- Conventions + 5 phases of reductions
  - phases applied sequentially
  - each phase consists of a set of commands
  - sample convention: *Of the rules in a compound command, select the one that applies to the longest suffix.*

Porter algorithm

(Porter, M.F., 1980, An algorithm for suffix stripping, *Program*, **14**(3) :130-137)

- Step 1: plurals and past participles
  - SSES -> SS — caresses -> caress
  - (*v*) ING -> — motoring -> motor
- Step 2: adj->n, n->v, n->adj, …
  - (m>0) OUSNESS -> OUS — callousness -> callous
  - (m>0) ATIONAL -> ATE — relational -> relate
- Step 3:
  - (m>0) ICATE -> IC — triplicate -> triplic
- Step 4:
  - (m>1) AL -> — revival -> reviv vital -> vital
  - (m>1) ANCE -> — allowance -> allow
- Step 5:
  - (m>1) E -> — probate -> probat
  - (m > 1 and *d and *L) -> single letter — controll -> control

Other stemmers

- Other stemmers exist, e.g., Lovins stemmer
  http://www.comp.lancs.ac.uk/computing/research/stemming/general/lovins.htm
  - Single-pass, longest suffix removal (about 250 rules)
  - Motivated by Linguistics as well as IR
- Krovetz stemmer (R. Krovetz, 1993: "Viewing morphology as an inference process," in R. Korfhage et al., *Proc. 16th ACM SIGIR Conference*, Pittsburgh, June 27-July 1, 1993; pp. 191-202.)
  - Use a dictionary – if a word is in the dict, no change, otherwise, suffix removal
- Full morphological analysis – at most modest benefits for retrieval
- Do stemming and other normalizations help?
  - Often very mixed results: really help recall for some queries but harm precision on others
- Question:
  - Stemming usually remove suffixes. Can we also remove prefixes?

Example (from Croft et al.'s book)

- Original

Document will describe marketing strategies carried out by U.S. companies for their agricultural chemicals, …

- Porter

document describ market strategi carri compani agricultur chemic …

- Krovetz

document describe marketing strategy carry company agriculture chemical …

STOPLIST

Stopwords / Stoplist

- Stopword = word that is not meaning bearer

- Function words do not bear useful information for IR
  of, in, about, with, I, although, …
- Stoplist: contain stopwords, not to be used as index
  - Prepositions: of, in, from, …
  - Articles: the, a, …
  - Pronouns: I, you, …
  - Some adverbs and adjectives: already, appropriate, many, …
  - Some frequent nouns and verbs: document, ask, …

- The removal of stopwords usually improves IR effectiveness in TREC experiments
- But more conservative stoplist for web search
  - “To be or not to be”
- A few “standard” stoplists are commonly used.

Stoplist in Smart (571)

a
a's
able
about
above
according
accordingly
across
actually
after
afterwards
again
against
ain't
all
allow
allows
almost
alone
along
already
also
although
always
am
among
amongst
an
and
another
any
anybody
anyhow
anyone
anything
anyway
anyways
anywhere
apart
appear
appreciate
appropriate
are
aren't
around
as
aside
ask
asking
associated
at
available
away
awfully

Discussions

- What are the advantages of filtering out stop words?
  - Discard useless terms that may bring noise
  - Reduce the size of index (recall Zipf law)
- What problems this can create?
  - Difficult to decide on many frequent words: useful in some area but not in some others
  - A too large stoplist may discard useful terms
  - Stopwords in some cases (specific titles) may be useful
  - Silence in retrieval – document cannot be retrieved for this word

TERM WEIGHTING

Assigning Weights

- Weight = importance of the term in a document
  - Also how discriminative it is to distinguish the document from others
- Want to weight terms highly if they are
  - frequent in relevant documents … BUT
  - infrequent in the collection as a whole
- Typical good terms (high weights)
  - Technical terms that only appear in a few documents
  - Specific terms
- Typical weak terms (low weights)
  - General terms
  - Common terms in a language

Assigning Weights

- tf x idf measure:
  - term frequency (tf) – to measure local importance
  - inverse document frequency (idf) - discriminativity

$T_k = \text{term } k \text{ in document } D_i$

$tf_{ik} = \text{frequency of term } T_k \text{ in document } D_i$

$idf_k = \text{inverse document frequency of term } T_k \text{ in } C$

$N = \text{ total number of documents in the collection } C$

$n_k = \text{the number of documents in } C \text{ that contain } T_k$

$idf_k = \log(N / n_k)$

Some common *tf*idf* schemes

$$tf_{ik} = freq(t_k, D_i)$$

$$tf_{ik} = \log freq(t_k, D_i)$$

$$tf_{ik} = \log freq(t_k, D_i) + 1$$

$$tf_{ik} = \log(freq(t_k, D_i) + 1)$$

$$idf_k = \log(N / n_k)$$

$$w_{ik} = tf_{ik} * idf_k$$

tf x idf (cosine) normalization

- Normalize the term weights (so longer documents are not unfairly given more weight)
  - normalize usually means force all values to fall within a certain range, usually between 0 and 1, inclusive.

$$w_{ik} = \frac{tf_{ik} \log(N / n_k)}{\sqrt{\sum_{k=1}^{t} (tf_{ik})^2 [\log(N / n_k)]^2}}$$

Questions

- When should the weights of terms be calculated (hint: may require more than one step)?
- Is TF*IDF sufficient? What problems remain?

INDEX COMPRESSION

Corpus size for estimates

- Consider *n* = 1M documents, each with about *L*=1K terms.
- Avg 6 bytes/term incl spaces/punctuation
  - 6GB of data.
- Say there are *m* = 500K *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?

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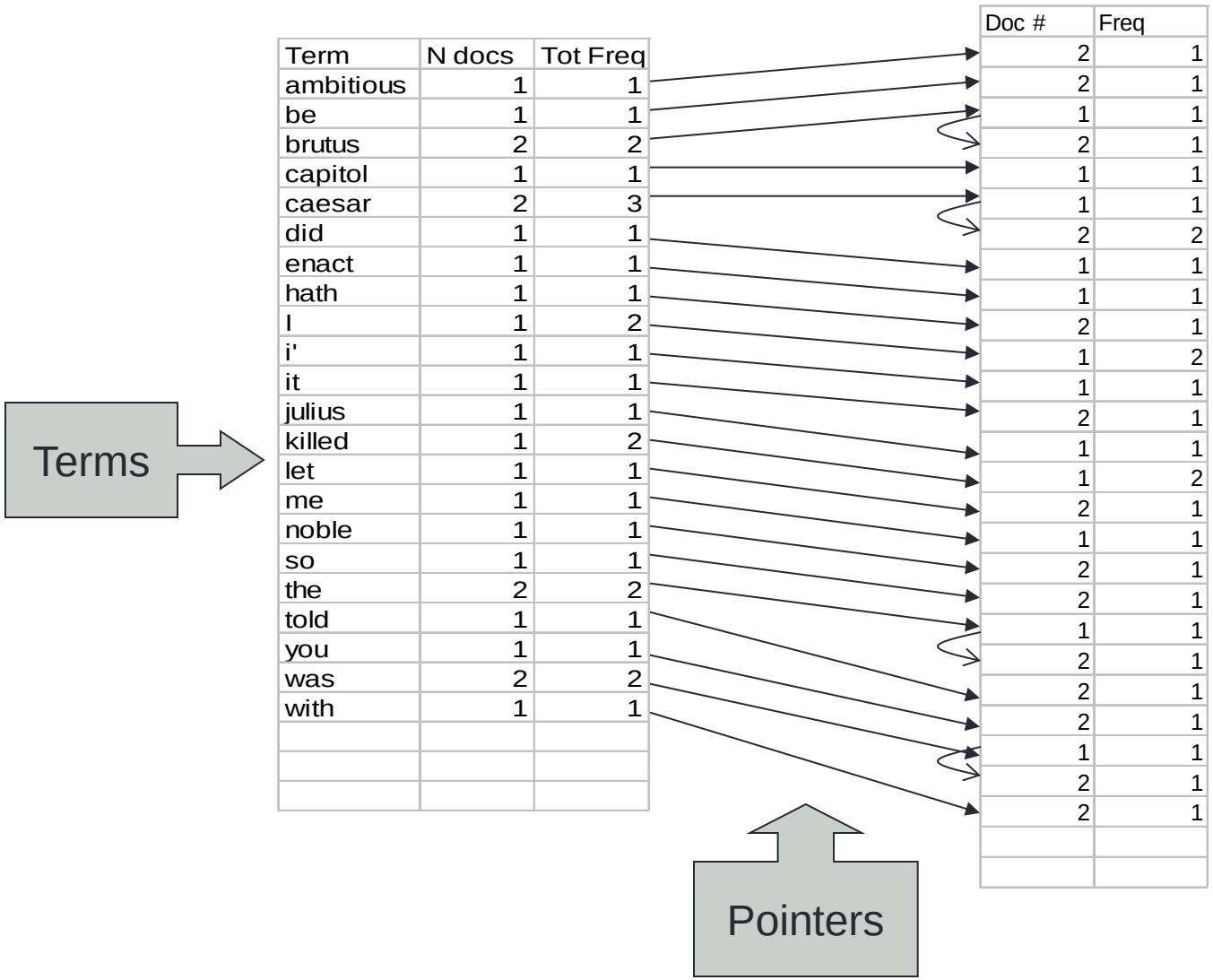


Term	N docs	Tot Freq
ambitious	1	1
be	1	1
brutus	2	2
capitol	1	1
caesar	2	3
did	1	1
enact	1	1
hath	1	1
I	1	2
i'	1	1
it	1	1
julius	1	1
killed	1	2
let	1	1
me	1	1
noble	1	1
so	1	1
the	2	2
told	1	1
you	1	1
was	2	2
with	1	1

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

Storage analysis (postings)

- First will consider space for postings pointers
- Basic Boolean index only
  - Devise compression schemes
- Then will do the same for dictionary
- No analysis for positional indexes, 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 ~ 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 – using gaps

- 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.
- How about a rare word?

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 ~$\log_2 G$ bits/gap entry.
- Key challenge: encode every integer (gap) with ~ as few bits as needed for that integer.

γ codes for gap encoding (Elias)

Length	Offset

- Represent a gap *G* as the pair <*length,offset*>
- *length* is in unary and uses $\lfloor \log_2 G \rfloor + 1$ bits to specify the length of the binary encoding of
- *offset* = $G - 2^{\lfloor \log_2 G \rfloor}$ in binary (remove the first 1)

Recall that the unary encoding of *x* is a sequence of *x* 1's followed by a 0.

γ codes for gap encoding

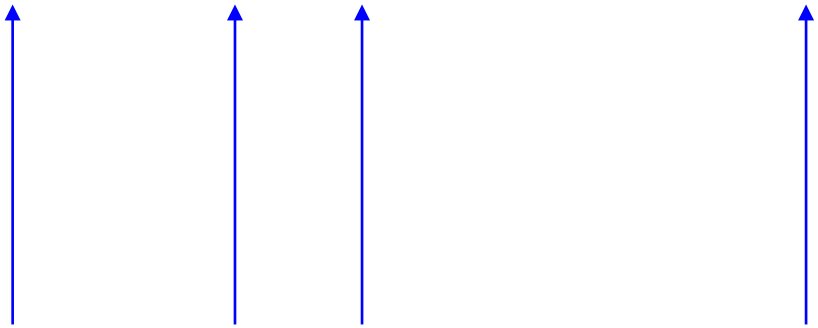
number	Unary code	length	offset	Γ code
0	0			
1	10	0		0,
2	110	10	0	10,0
9	1111111110	1110	001	1110,001

- e.g., 9 represented as <1110,001>
  - The offset uses 3 bits, the value of offset is 1001
- 2 is represented as <10,1>.
- Exercise: does zero have a γ code?
- Encoding G takes $2\lfloor \log_2 G \rfloor + 1$ bits.
  - γ codes are always of odd length.

Exercise

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

1110001110101011111101101111011



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

1001 110 11 111011 111

1001 1111 10010 1001101 1010100

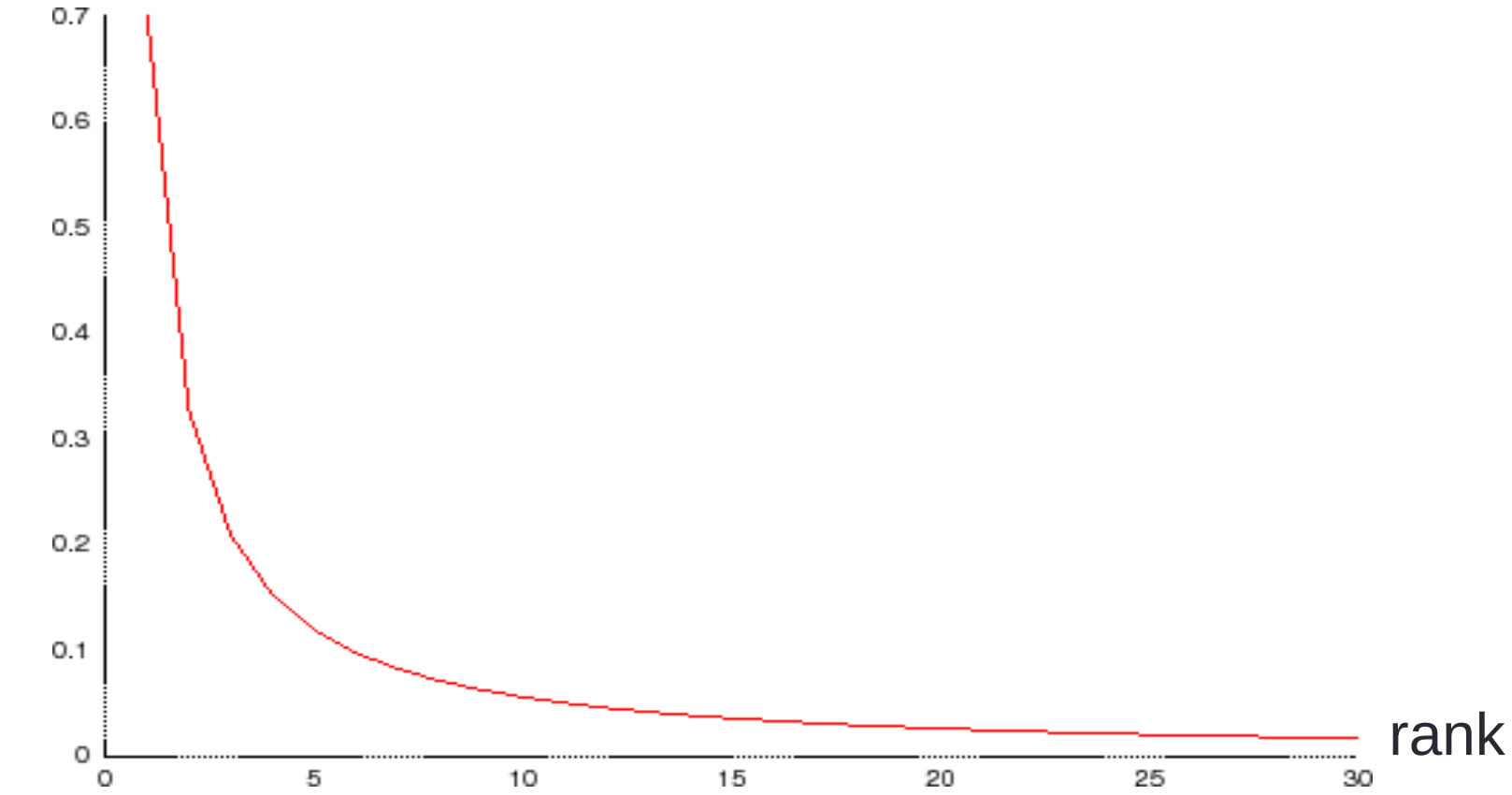
What we've just done

- 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.

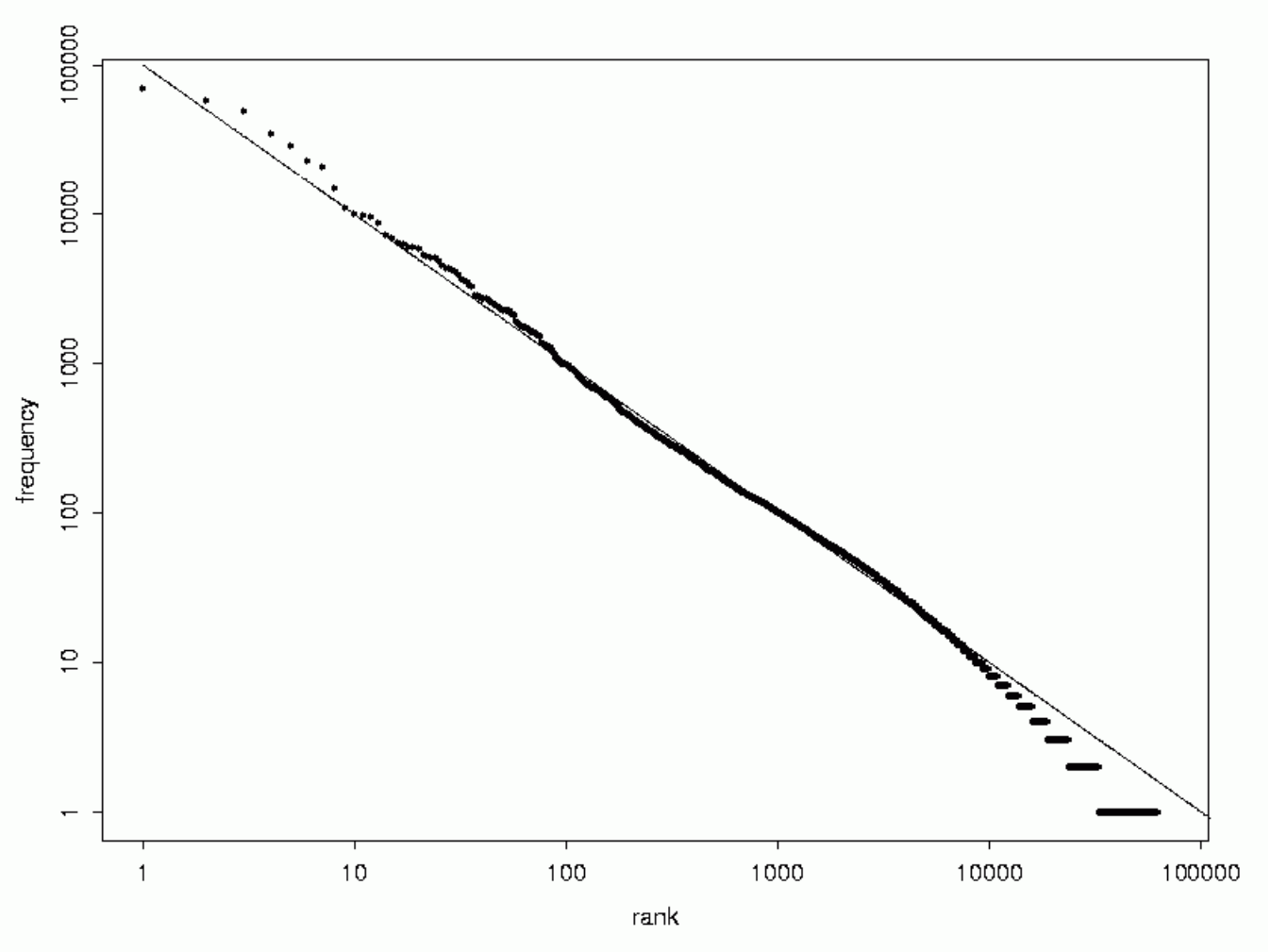
Zipf's law

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

Zipf law



Zipf's law log-log plot



Rough analysis based on Zipf

- The *i* th most frequent term has frequency (not count) proportional to 1/*i*
- Let this frequency be *c/i.*
- Then $\sum_{i=1}^{500,000} c/i = 1.$
- The *k* th Harmonic number is $H_k = \sum_{i=1}^{k} 1/i.$
- Thus *c* = 1/H_m , which is ~ 1/ln *m* = 1/ln(500k) ~ 1/13.
- So the *i* th most frequent term has frequency roughly 1/13*i.*

Postings analysis contd.

- Expected number of occurrences of the *i* th most frequent term in a doc of length *L* is:

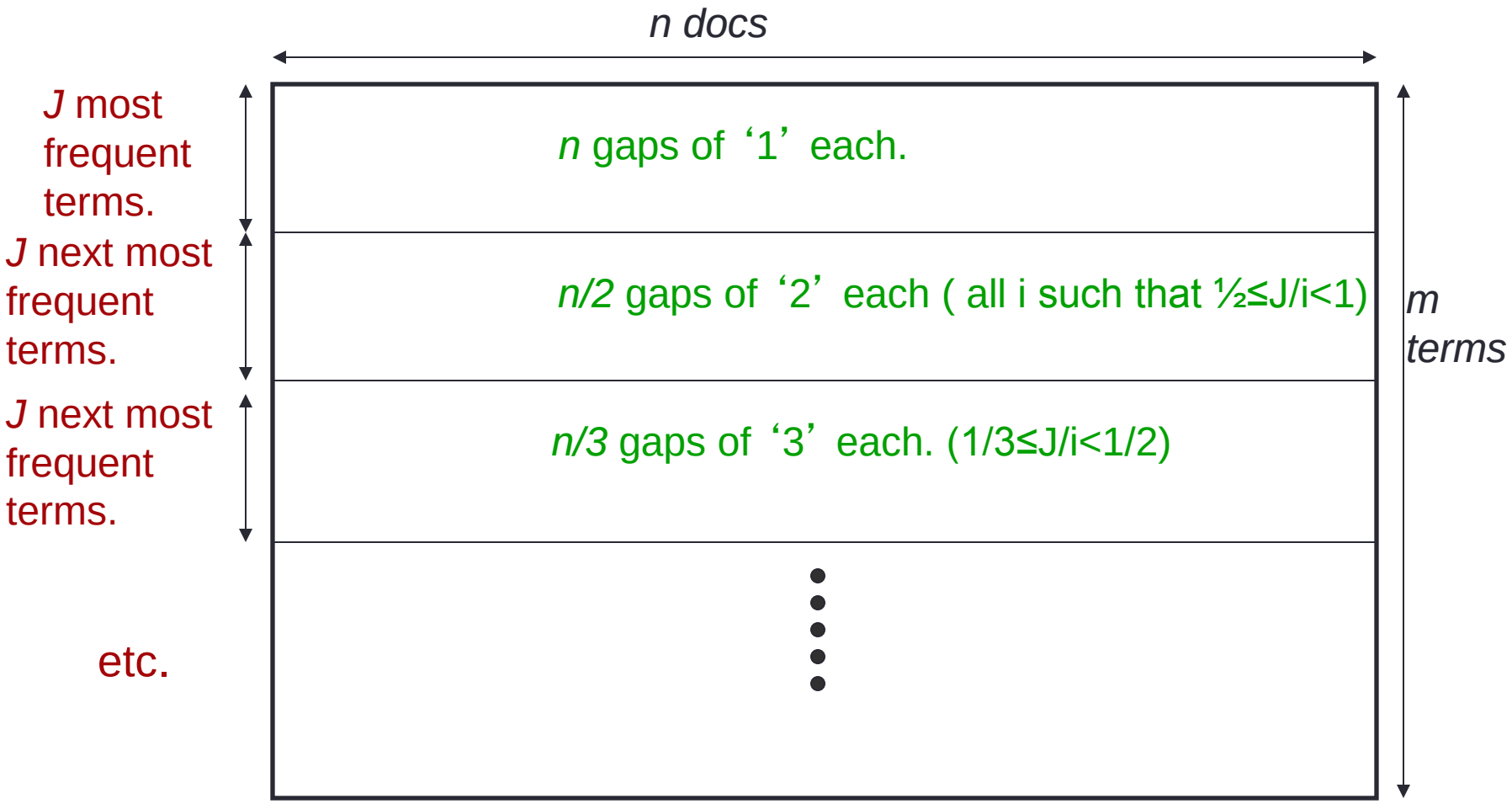
Lc/i ~ *L*/13*i* ~ 76/*i* for *L*=1000.

Let *J* = *Lc* ~ 76.

Then the *J* most frequent terms are likely to occur in every document. (J/i>=1 →i<=J)

Now imagine the term-document incidence matrix with rows sorted in decreasing order of term frequency:

Rows by decreasing frequency



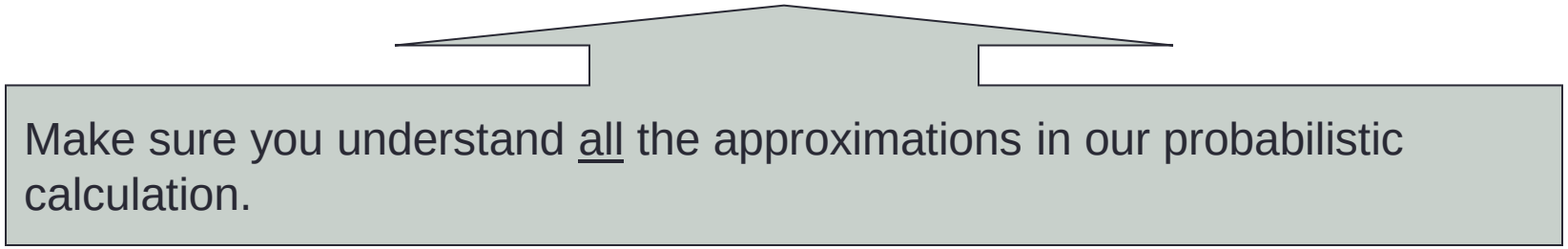
J-row blocks

- In the *i* th of these *J*-row blocks, we have *J* rows each with *n/i* gaps of *i* each.
- Encoding a gap of *i* takes us $2\log_2 i + 1$ bits (γ code)
- So such a row uses space ~ $(2n \log_2 i)/i$ bits (*n/i* gaps).
- For the entire block, $(2n J \log_2 i)/i$ bits, which in our case is ~ $1.5 \times 10^8 (\log_2 i)/i$ bits.

- Sum this over *i* from 1 upto *m/J* = 500K/76~ 6500. (Since there are *m/J* blocks.)

Exercise

- Work out the above sum and show it adds up to about 53 x 150 Mbits, which is about 1GByte.
- So we've taken 6GB of text and produced from it a 1GB index that can handle Boolean queries!



Caveats

- This is not the entire space for our index:
  - does not account for dictionary storage – next up;
  - 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.

More practical caveat

- γ codes are neat but in reality, machines have word boundaries – 16, 32 bits etc
  - Compressing and manipulating at individual bit-granularity is overkill in practice
  - Slows down architecture
- In practice, simpler word-aligned compression (see Scholer reference) better

Word-aligned compression

- Simple example: fix a word-width (say 16 bits)
- Dedicate one bit to be a *continuation bit c.*
- If the gap fits within 15 bits, binary-encode it in the 15 available bits and set c=0.
- Else set c=1 and use additional words until you have enough bits for encoding the gap.

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

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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
2	2
1	1
1	1
2	1
1	2
1	1
2	1
1	1
1	2
2	1
1	1
2	1
2	1
1	1
2	1
2	1
2	1
1	1
2	1
2	1

Usually in memory

Gap-encoded, on disk

Inverted index storage (dictionary)

- Have estimated 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
  - Time for lookup
  - Time for decompression

How big is the lexicon V?

- Grows (but more slowly) with corpus size
- Empirically okay model (Heaps' law):

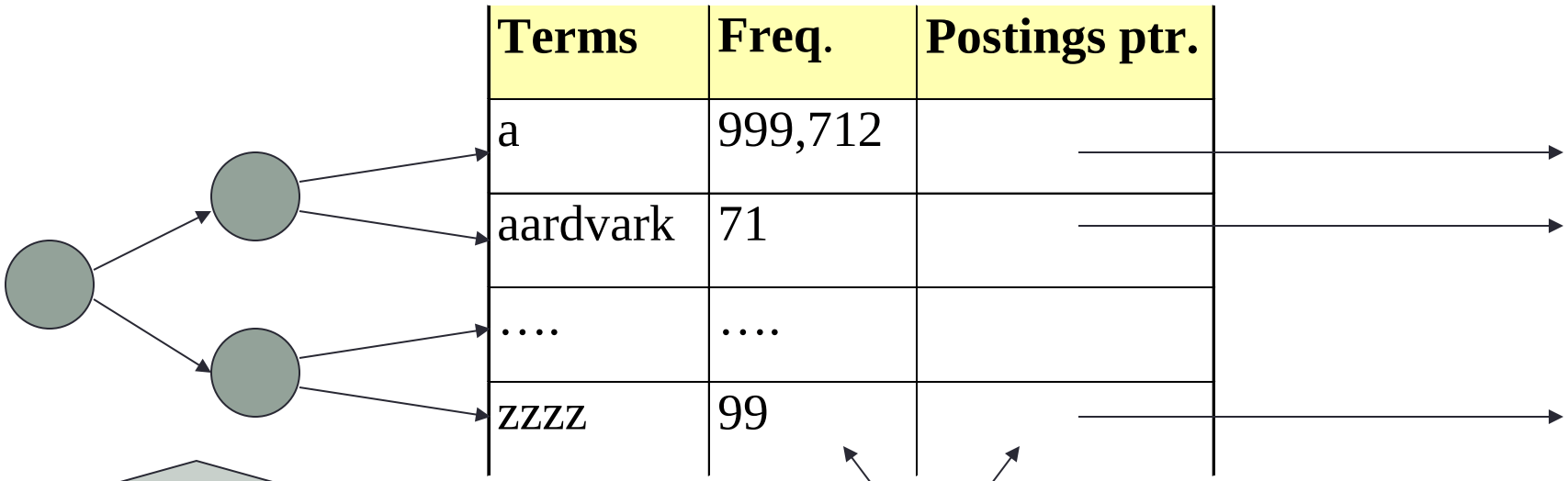
$$m = kN^b$$

- where m-vocabulary size, $b \approx 0.5$, $k \approx 30$–100; N = # tokens
- For instance TREC disks 1 and 2 (2 Gb; 750,000 newswire articles): ~ 500,000 terms
- *m* is decreased by case-folding, stemming

- Exercise: Can one derive this from Zipf's Law?
  - See http://arxiv.org/abs/1002.3861/

Dictionary storage - first cut

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

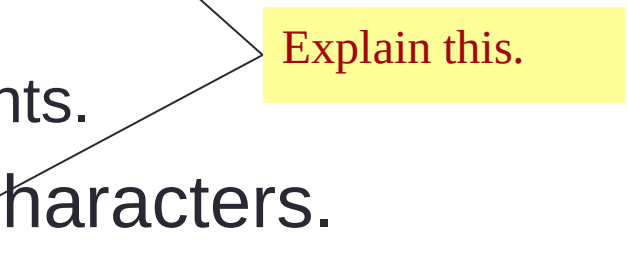


Exercises

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

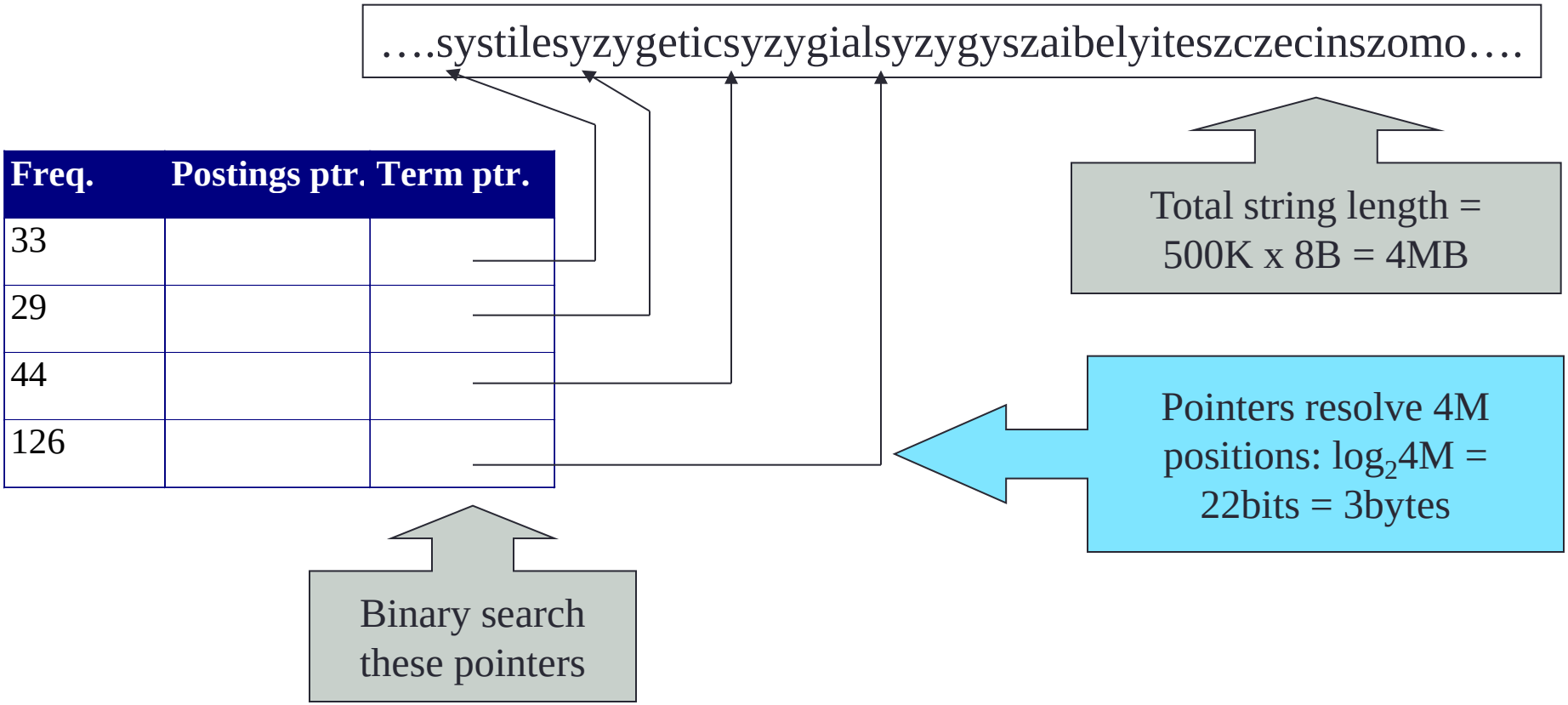
Fixed-width terms are wasteful

- 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.



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)

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

Save 9 bytes on 3 pointers.

Lose 4 bytes on term lengths.

Net

- Where we used 3 bytes/pointer without blocking
  - 3 x 4 = 12 bytes for *k*=4 pointers,

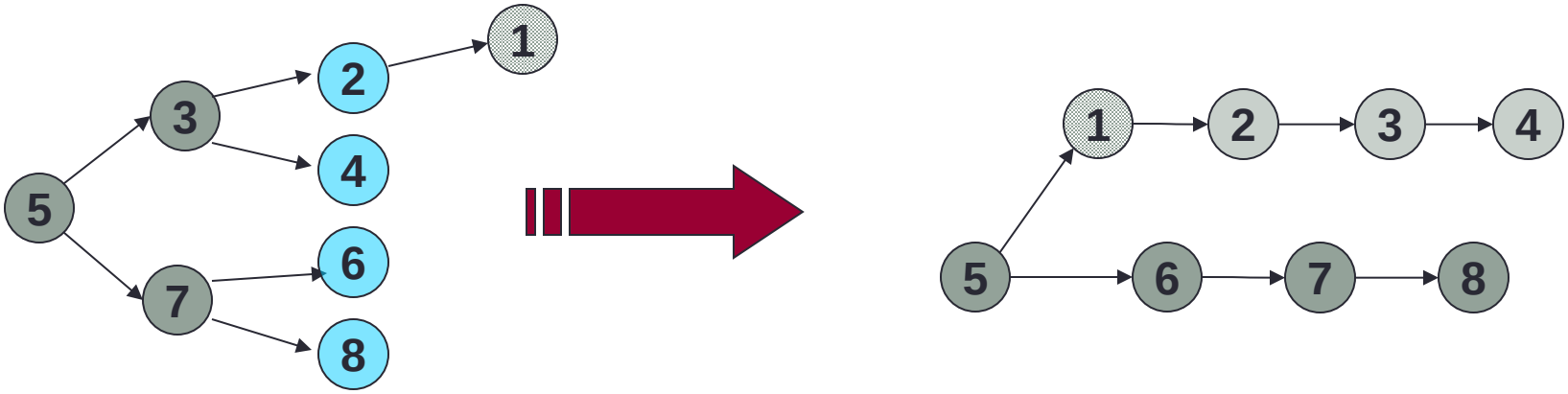
now we use 3+4=7 bytes for 4 pointers.

Shaved another ~0.5MB; can save more with larger *k*.

Why not go with larger *k*?

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+2·2+4·3+4)/8

=(1+2·2+2·3+2·4+5)/8

Total space

- By increasing *k*, we could cut the pointer space in the dictionary, at the expense of search time; space 9.5MB → ~8MB
- Net – postings take up most of the space
  - Generally kept on disk
  - Dictionary compressed in memory

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{***automat***}***a***1◊***e***2◊***ic***3◊***ion***

Encodes ***automat***

Extra length beyond ***automat.***

Begins to resemble general string compression.

Extreme compression

Large dictionary: partition into pages

- use B-tree on first terms of pages
- pay a disk seek to grab each page

Effect of compression on Reuters-RCV1

Data structure	Size (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

- Search speed is not taken into account
  - See Trotman for a comparison in speed.

Resources for further reading on compression

- F. Scholer, H.E. Williams and J. Zobel. Compression of Inverted Indexes For Fast Query Evaluation. Proc. ACM-SIGIR 2002.
- Andrew Trotman, Compressing Inverted Files, Information Retrieval, Volume 6, Number 1 / January, 2003, pp. 5-105.
- http://www.springerlink.com/content/n3238225n8322918/fulltext.pdf
- Special issue on index compression, Information retrieval, Volume 3, Number 1 / July, 2000 http://www.springerlink.com/content/2pbvu3xj98l6/?p=f4b0fc57d855415f9c02aa82ac0061a6&pi=24

Complete procedure of indexing

- For each document
  - For each token
    - If it is stopword, break
    - Stemming → term
    - If not in dictionary, add in dictionary: (term, term_id)
    - Increment term frequency, record position
  - Update document frequency
- Compute tf*idf weights
- Create inverted index
- Index compression

References

- Manning et al.: Chap. 1-5
- Croft et al.: Chap. 4-5