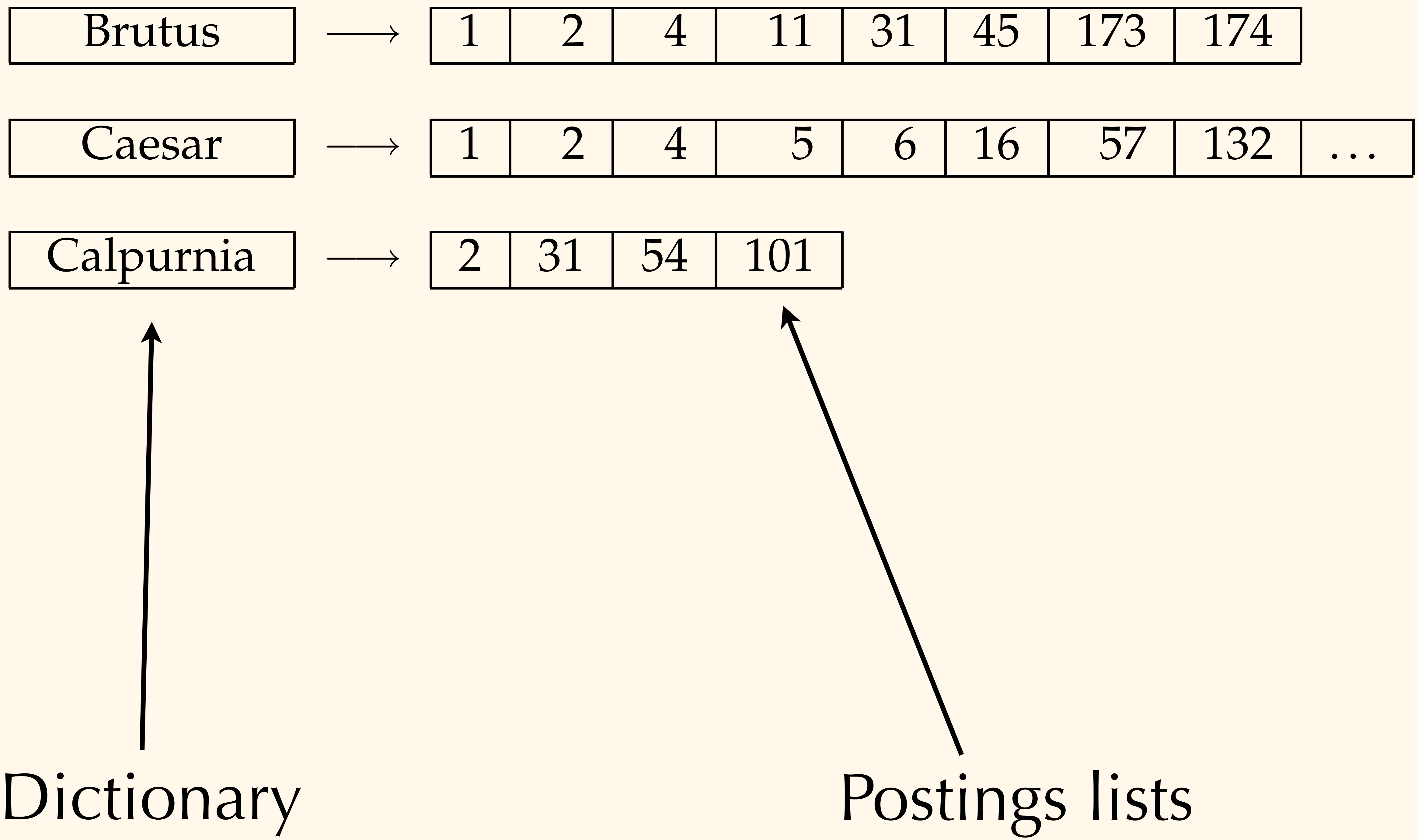
Index Construction & Compression: Agenda

- Practical considerations
- Building indices
  - Static indexing approaches
  - Dynamic indexing
- Storing indices
  - Dictionary compression
  - Posting list compression

Our friend, the inverted index:



Basic steps to for building an index:

1. Pass through collection, pair terms and docIDs
2. Group docIDs by term
3. Convert <term, docID> tuples to <term, [docID...]> tuples; calculate other misc. statistics

When the collection can fit in memory, this is very simple...

One measurement motivates most index construction & compression techniques:

Statistic	Value
average seek time	$5 \text{ ms} = 5 \times 10^{-3}$ s
transfer time per byte	$0.02\,\mu\text{s} = 2 \times 10^{-8}$ s
processor's clock rate	10^9 s^{-1}
lowlevel operation	
(e.g., compare & swap a word)	$0.01\,\mu\text{s} = 10^{-8}$ s

$$10^{-3} \ggg 10^{-8}$$

The central idea:

If we can't fit everything in memory...

... we'll need to use a disk-based *external sorting algorithm*...

... and do it in such a way as to minimize disk seeks.

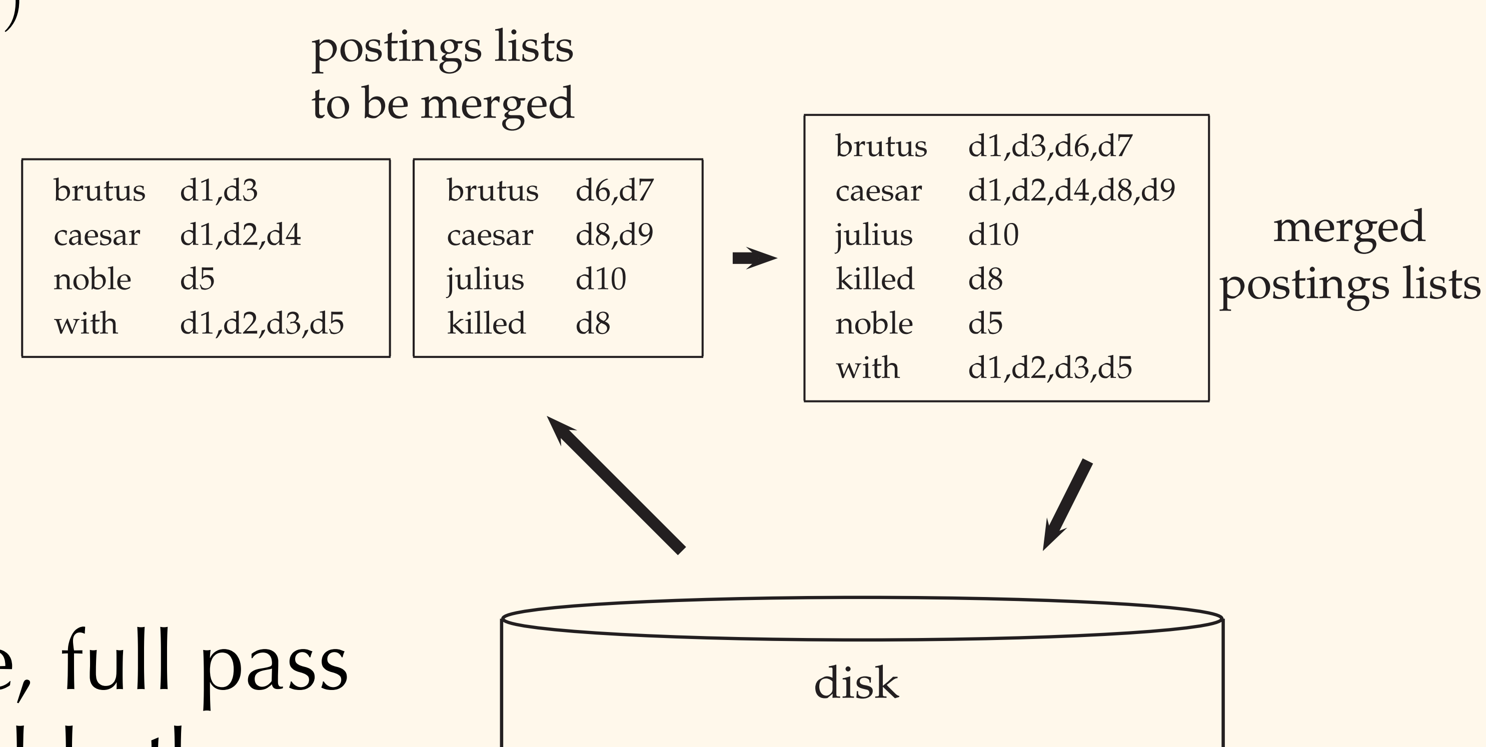
Disks store data in contiguous chunks, or "blocks"...

... and that's how operating systems get data from disks.

Blocked sort-based indexing (BBSI)

The basic idea: make many block-sized indices, and then merge them.

```
BSBIndexConstruction() *
n ← 0
while (all documents have not been processed)
do n ← n + 1
    block ← ParseNextBlock()
    BSBI-Invert(block)
    WriteBlockToDisk(block, f_n)
MergeBlocks(f_1, ..., f_n; f_merged)
```



* We also have to do a separate, full pass through the collection to assemble the dictionary and compute termIDs.

Blocked sort-based indexing (BBSI)

BBSI has an important limitation:

Even though the postings are split up by block size...

... the dictionary is not.

We still must maintain a term->termID data structure that is shared by all blocks, and this might not fit in memory.

Single-pass in-memory indexing (SPIMI)

The basic idea: make many *independent* block-sized indices, and then merge them.

```
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
```

Key difference: uses raw terms instead of shared termIDs, so each block has its own dictionary.

Also: lower overhead, so larger blocks can be processed.

Distributed Indexing:

For very large collections, it may make sense to distribute indexing across multiple computers.

Map-Reduce is a common distributed-computing paradigm.

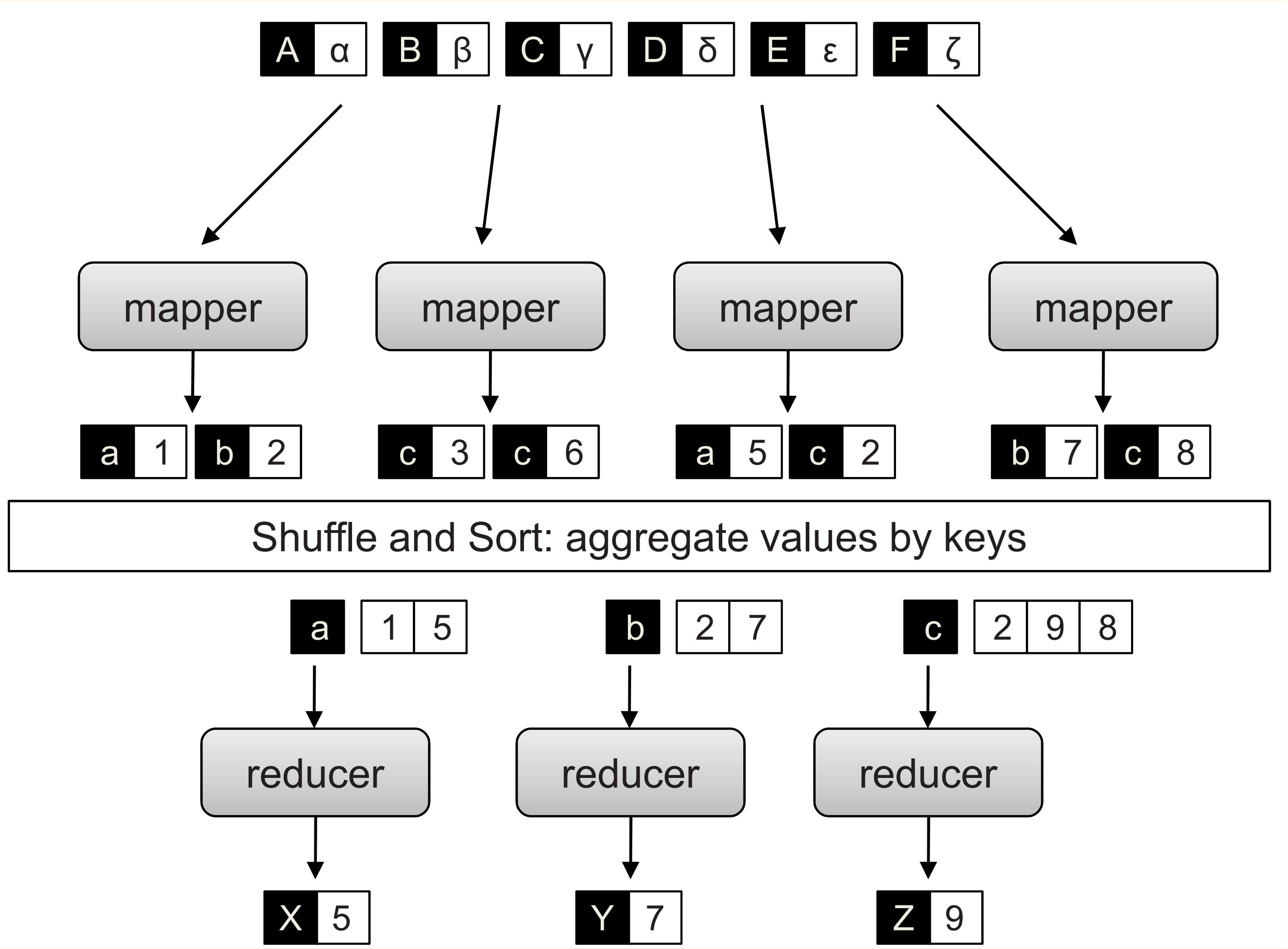


Figure from Lin & Dyer 2010.

Distributed Indexing:

```
class Mapper
    procedure Map(docid n, doc d)
        H ← new AssociativeArray
        for all term t ∈ doc d do
            H{t} ← H{t} + 1
        for all term t ∈ H do
            Emit(term t, posting ⟨n, H{t}⟩)
```

```
class Reducer
    procedure Reduce(term t, postings [⟨n1, f1⟩, ⟨n2, f2⟩ . . .])
        P ← new List
        for all posting ⟨a, f⟩ ∈ postings [⟨n1, f1⟩, ⟨n2, f2⟩ . . .] do
            P.Add(⟨a, f⟩)
        P.Sort()
        Emit(term t, postings P)
```

Figure from Lin & Dyer 2010.

Distributed Indexing:

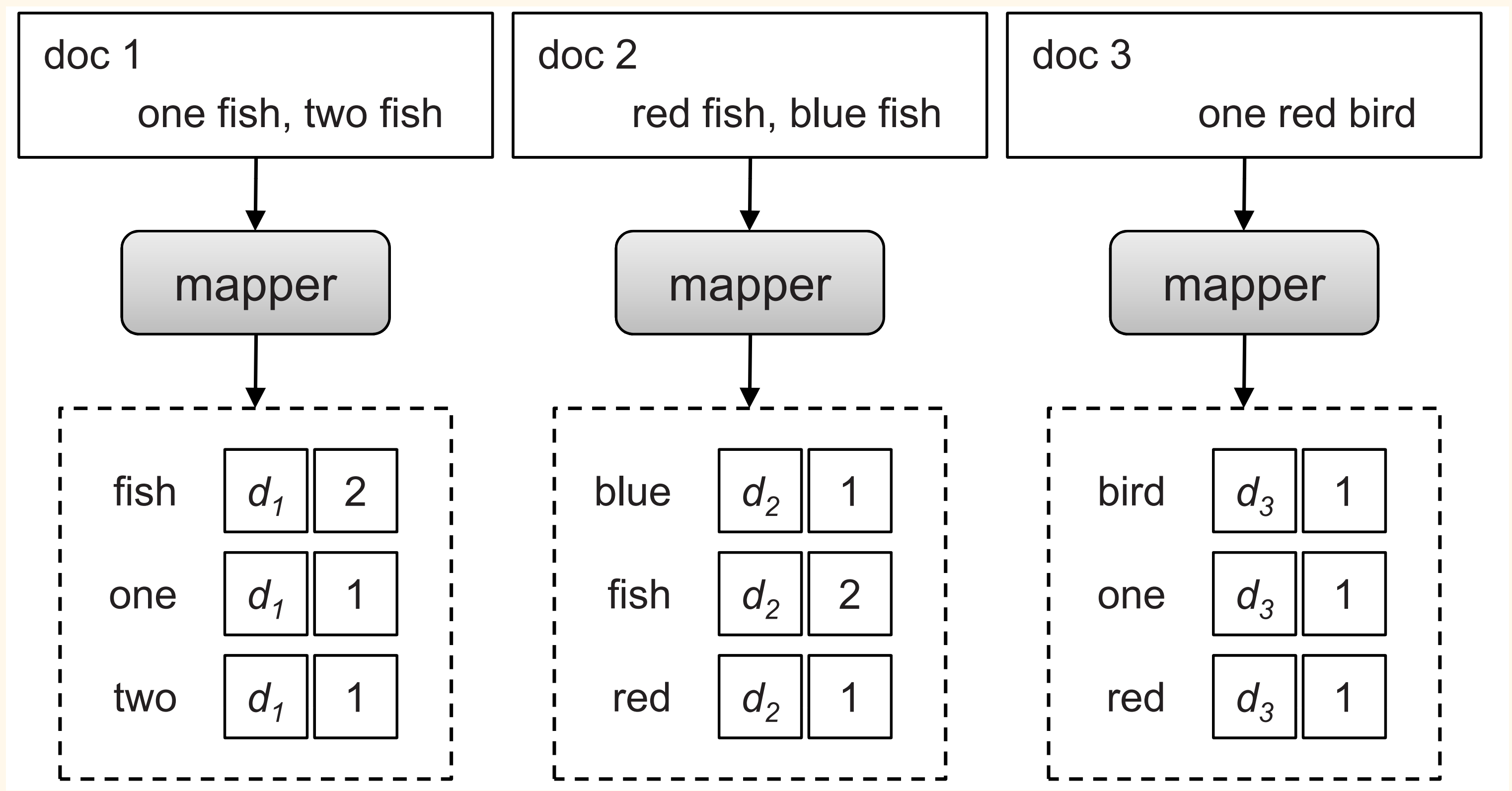


Figure from Lin & Dyer 2010.

Distributed Indexing:

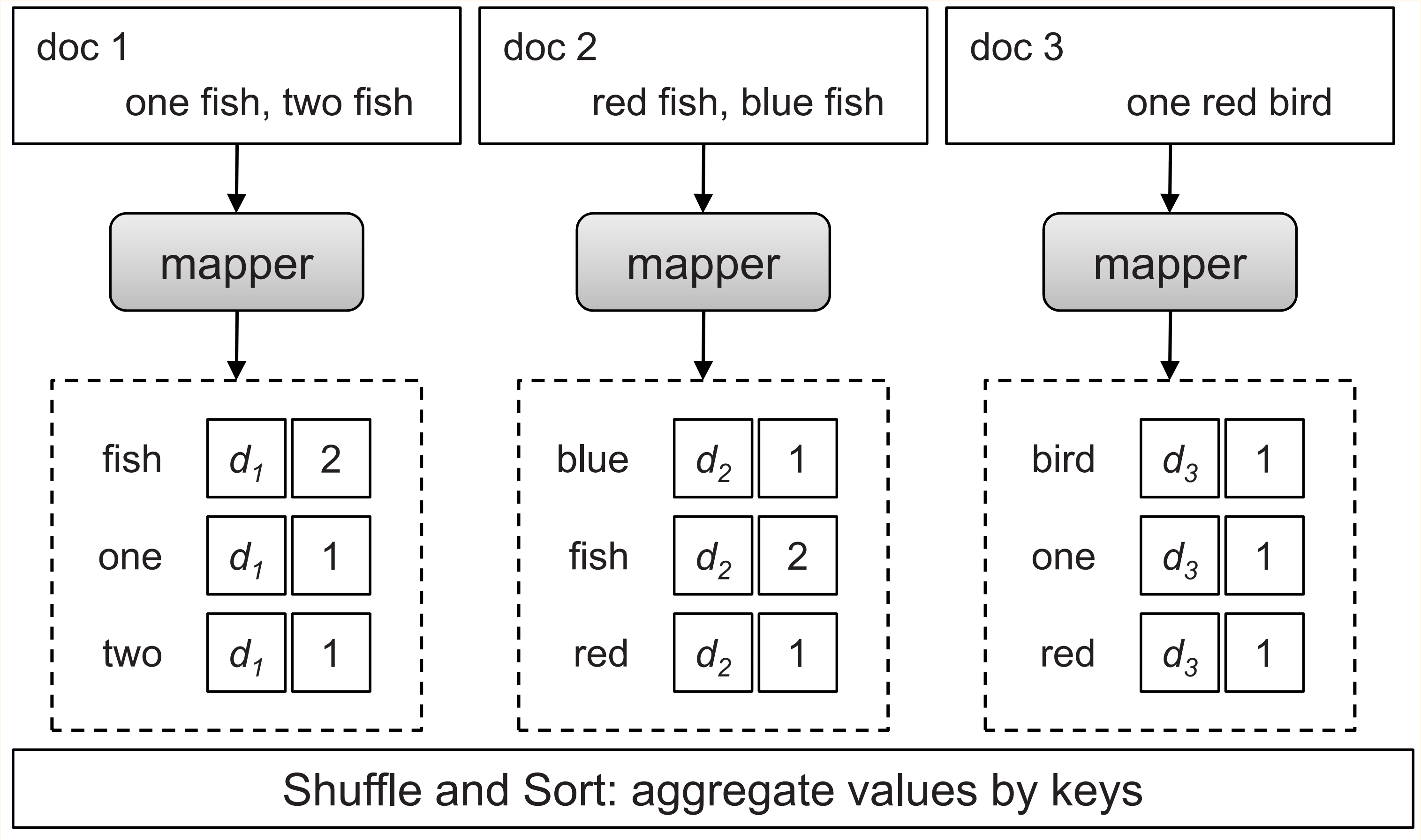


Figure from Lin & Dyer 2010.

Distributed Indexing:

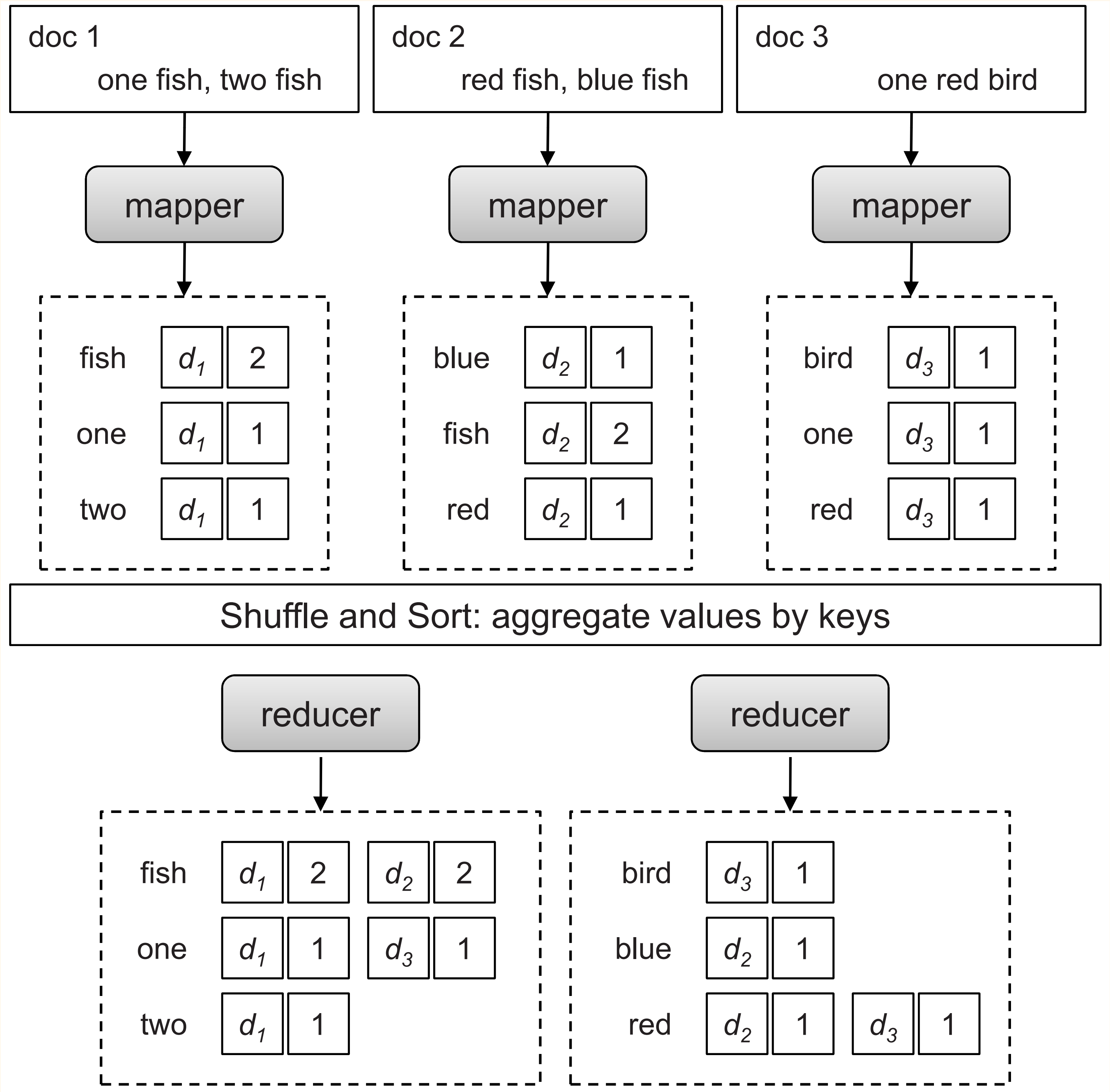


Figure from Lin & Dyer 2010.

Distributed Indexing:

```
class Mapper
    method Map(docid n, doc d)
        H ← new AssociativeArray
        for all term t ∈ doc d do
            H{t} ← H{t} + 1
        for all term t ∈ H do
            Emit(tuple ⟨t, n⟩, tf H{t})

class Reducer
    method Initialize
        t_prev ← ∅
        P ← new PostingsList
    method Reduce(tuple ⟨t, n⟩, tf [f])
        if t ≠ t_prev ∧ t_prev ≠ ∅ then
            Emit(term t, postings P)
            P.Reset()
        P.Add(⟨n, f⟩)
        t_prev ← t
    method Close
        Emit(term t, postings P)
```

Figure from Lin & Dyer 2010.

What happens when new data needs to be added to an index?

1. Maintain an “auxiliary index” containing the new data, query both, and merge periodically;
2. Build a second full index periodically and “switch over” when it’s done.

Option 1 is attractive but complex; option 2 is less flexible and expensive but is simpler.

How to represent auxiliary index?

The easiest way is as a large collection of posting files- then, merging is just a simple append operation.

However, most file systems don't appreciate having millions of files (also disk seek time, etc.).

So, the tradeoff is: for merge speed, we want as small an auxiliary index as possible...

... but large enough to not run into storage-related complications; also, we want to minimize merges.

Also, the naïve approach results in overall $O(T^2)$ index construction time (because each posting list has to be merged in each merge).

Can we do better?

Solution: Logarithmic merging.

- Maintain a series of indexes, each twice as large as the previous one
  - At any time, some of these powers of 2 are instantiated
- Keep smallest (Z_0) in memory
- Larger ones (I_0, I_1, …) on disk
- If Z_0 gets too big (> *n*), write to disk as I_0
- or merge with I_0 (if I_0 already exists) as Z_1
- Either write merge Z_1 to disk as I_1 (if no I_1)
- Or merge with I_1 to form Z_2

Taken from Manning, et al.'s slides on the subject.

Solution: Logarithmic merging.

Index construction is now O(TlogT) on average, since each posting is only merged logT times…

But query performance just went down: we have to merge log T indices to deliver results.

Also, it is now much harder to maintain collection-wide statistics (needed for spelling suggestion, result ranking, etc.).

Index Construction & Compression: Agenda

- Practical considerations
- Building indices
  - Static indexing approaches
  - Dynamic indexing
- Storing indices
  - Dictionary compression
  - Posting list compression

Why compress?

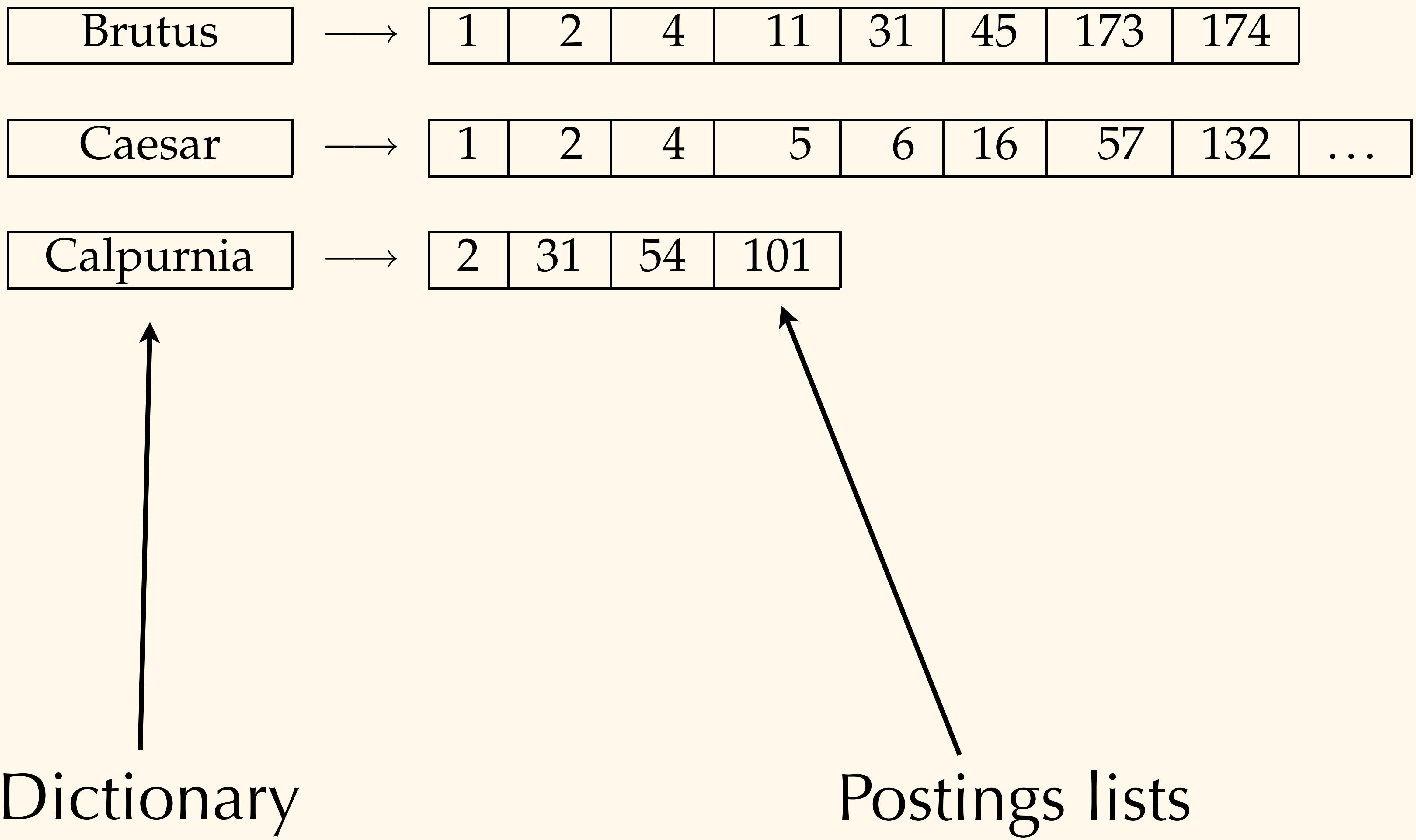
The obvious answer: to save disk space.

A less obvious answer: to keep more data in the computer's cache.

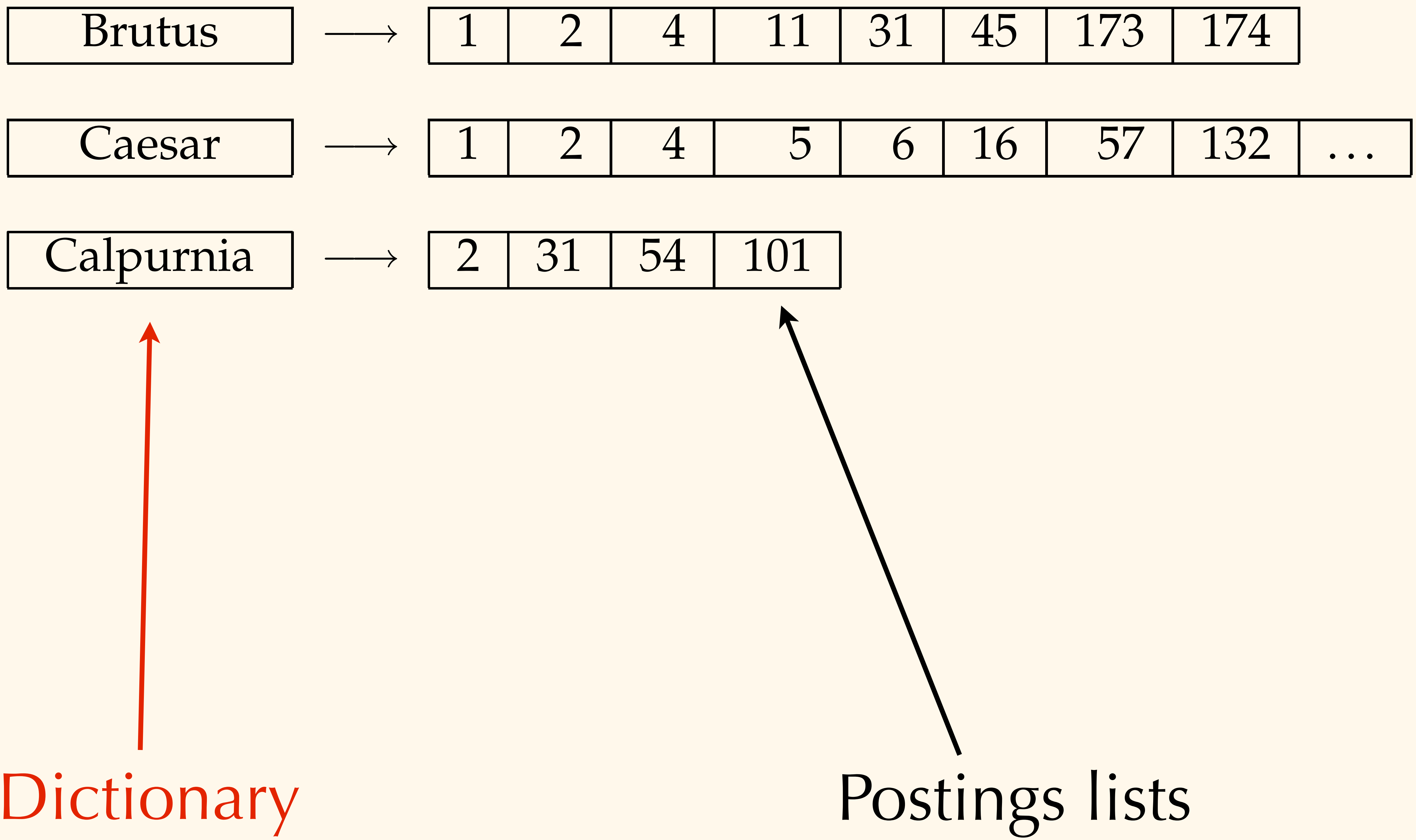
Statistic	Value
average seek time	$5 \text{ ms} = 5 \times 10^{-3} \text{ s}$
transfer time per byte	$0.02\ \mu\text{s} = 2 \times 10^{-8} \text{ s}$
processor's clock rate	10^9 s^{-1}
lowlevel operation	
(e.g., compare & swap a word)	$0.01\ \mu\text{s} = 10^{-8} \text{ s}$

We can decompress data much faster than the disk can get it to us!

There are two ways to compress an index:



There are two ways to compress an index:



Pre-processing is one approach to dictionary compression:

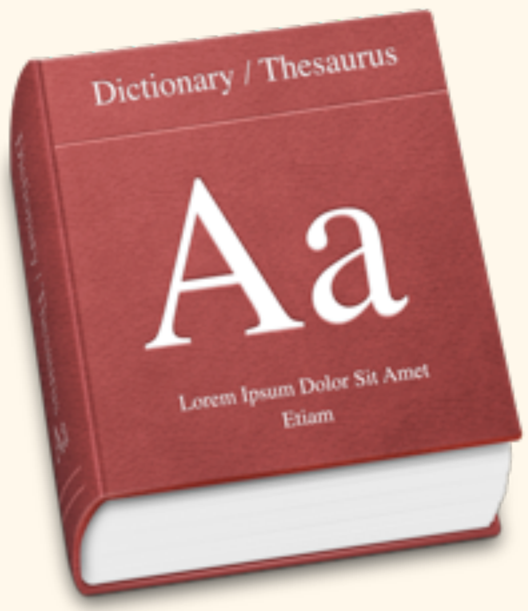
	(distinct) terms		
	number	Δ%	T%
unfiltered	484,494		
no numbers	473,723	−2	−2
case folding	391,523	−17	−19
30 stop words	391,493	−0	−19
150 stop words	391,373	−0	−19
stemming	322,383	−17	−33

Fewer dictionary terms == smaller dictionary, fewer posting lists, etc.

Note that this is language-dependent!

	(distinct) terms			nonpositional postings		
	number	Δ%	T%	number	Δ%	T%
unfiltered	484,494			109,971,179		
no numbers	473,723	−2	−2	100,680,242	−8	−8
case folding	391,523	−17	−19	96,969,056	−3	−12
30 stop words	391,493	−0	−19	83,390,443	−14	−24
150 stop words	391,373	−0	−19	67,001,847	−30	−39
stemming	322,383	−17	−33	63,812,300	−4	−42

How to estimate the number of terms in a collection?



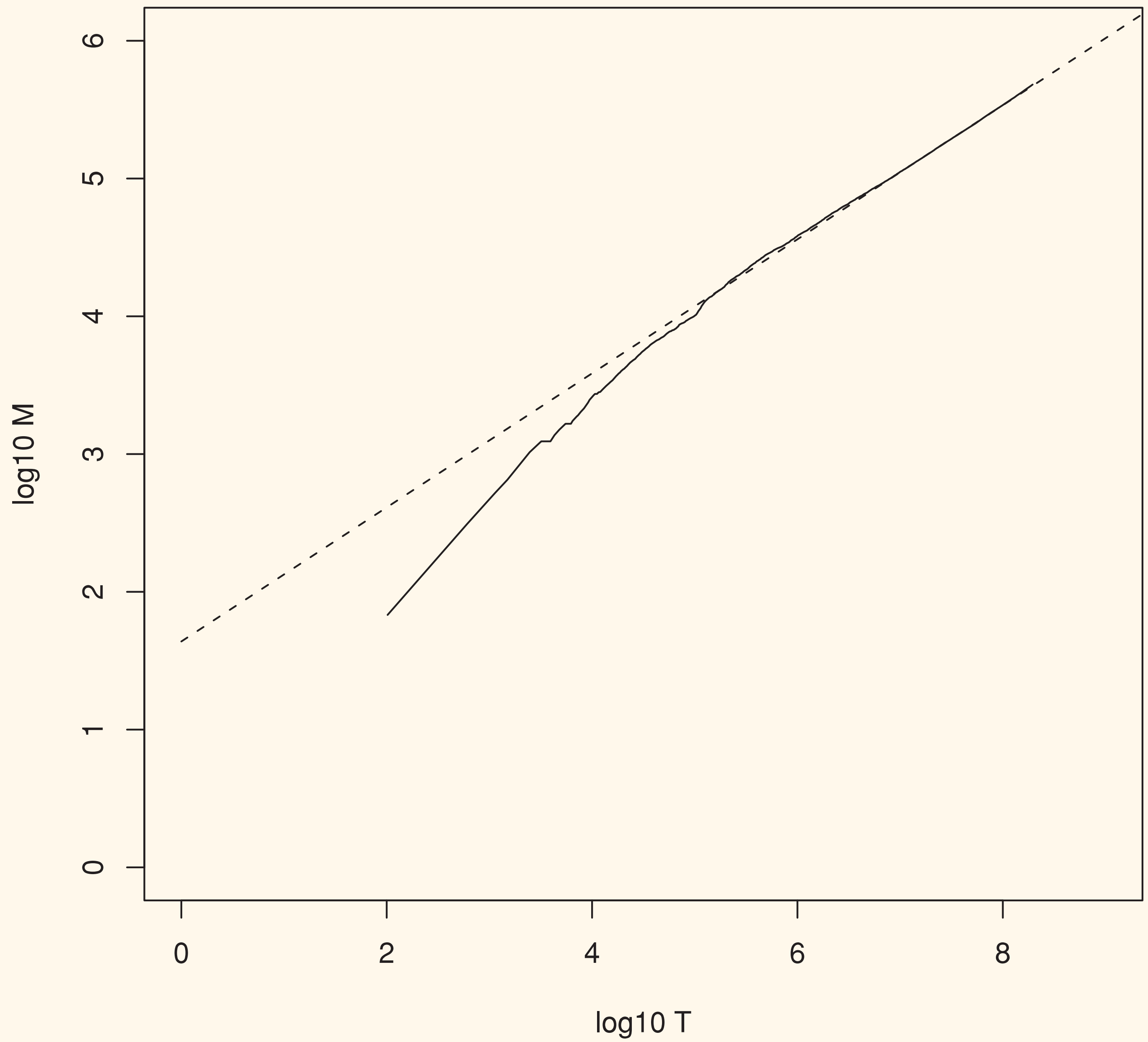
Counting the number of distinct words in, say, the OED is a tempting way to start...

... but often results in dramatically under-estimated counts.

(Think names of places, products, genes/proteins, etc.)

How to estimate the number of terms in a collection?

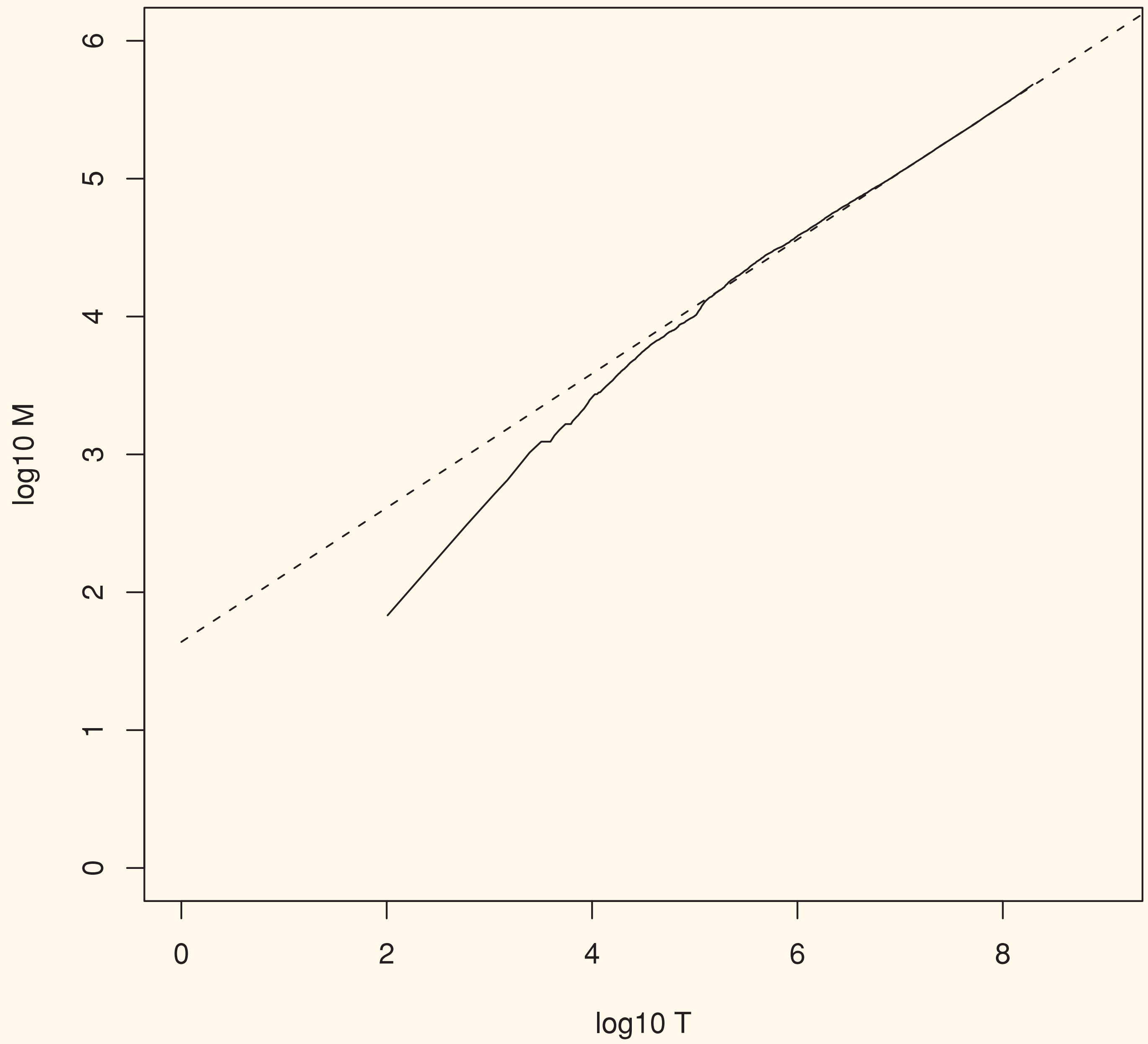
$$M = kT^b$$



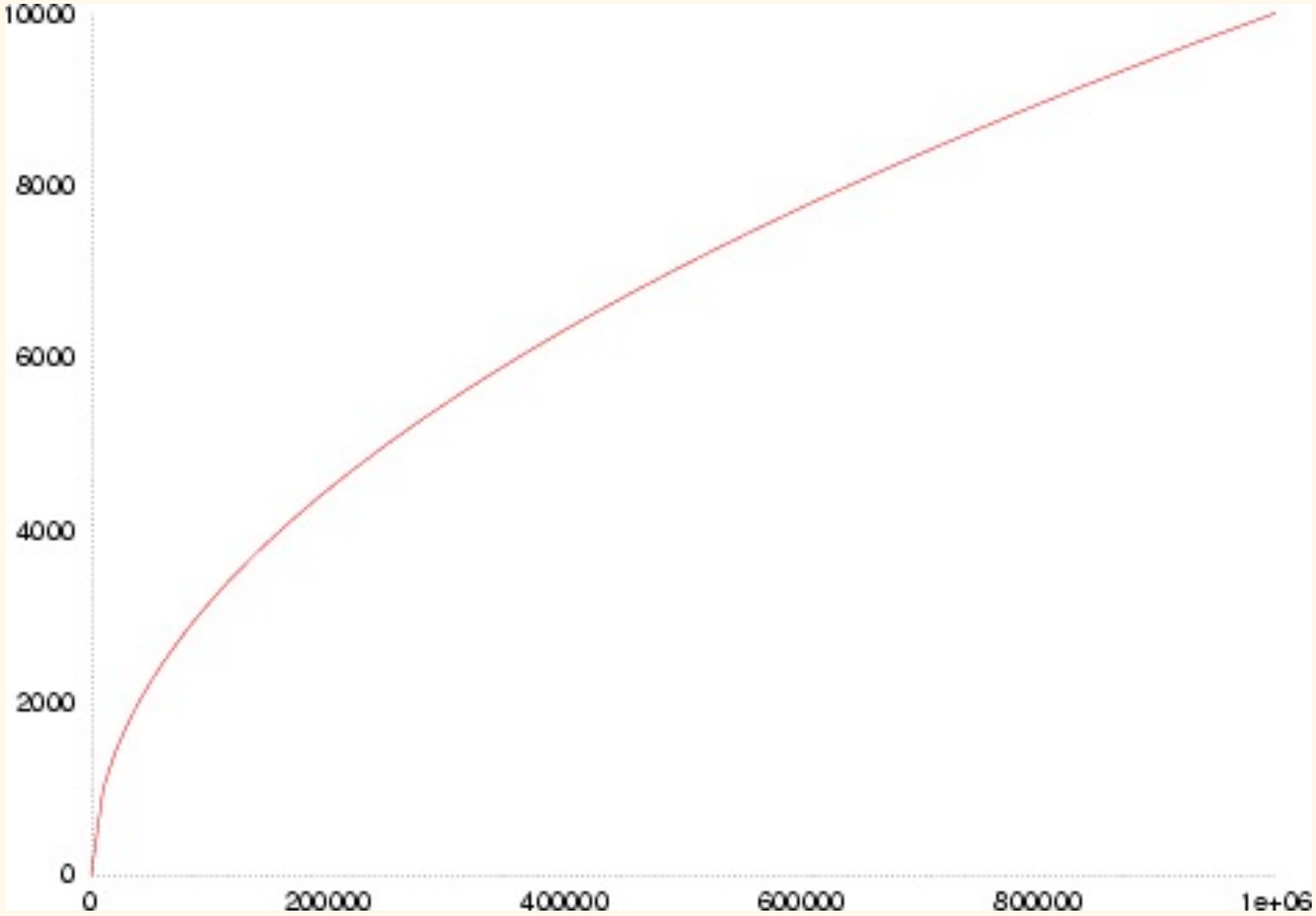
Heaps' law curve for vocab size *M* in collection of size *T* tokens.

How to estimate the number of terms in a collection?

$$M = kT^b$$

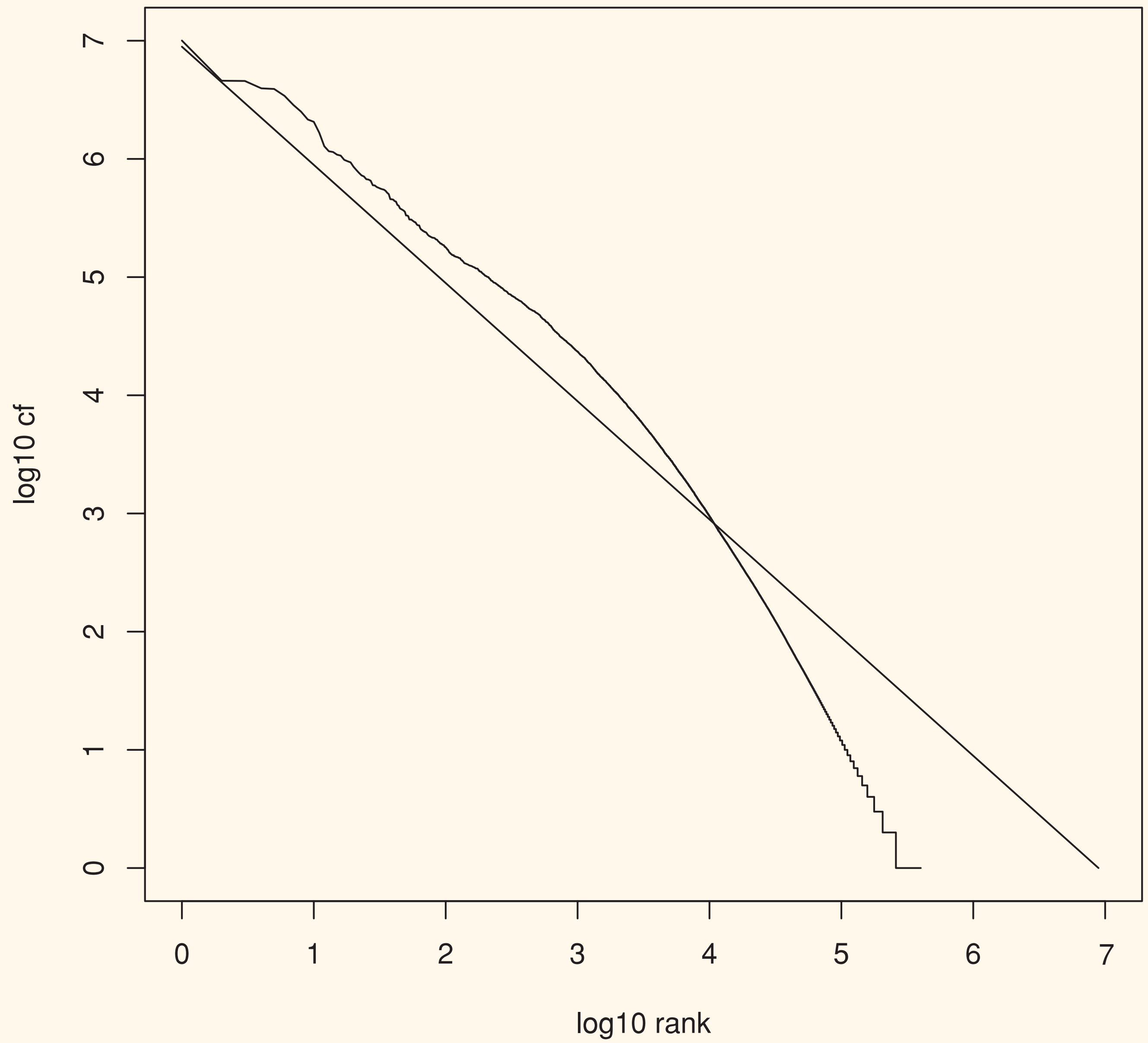


Implication: M increases continually (i.e., doesn't plateau once the collection gets to a certain size).



https://en.wikipedia.org/wiki/Heaps'_law

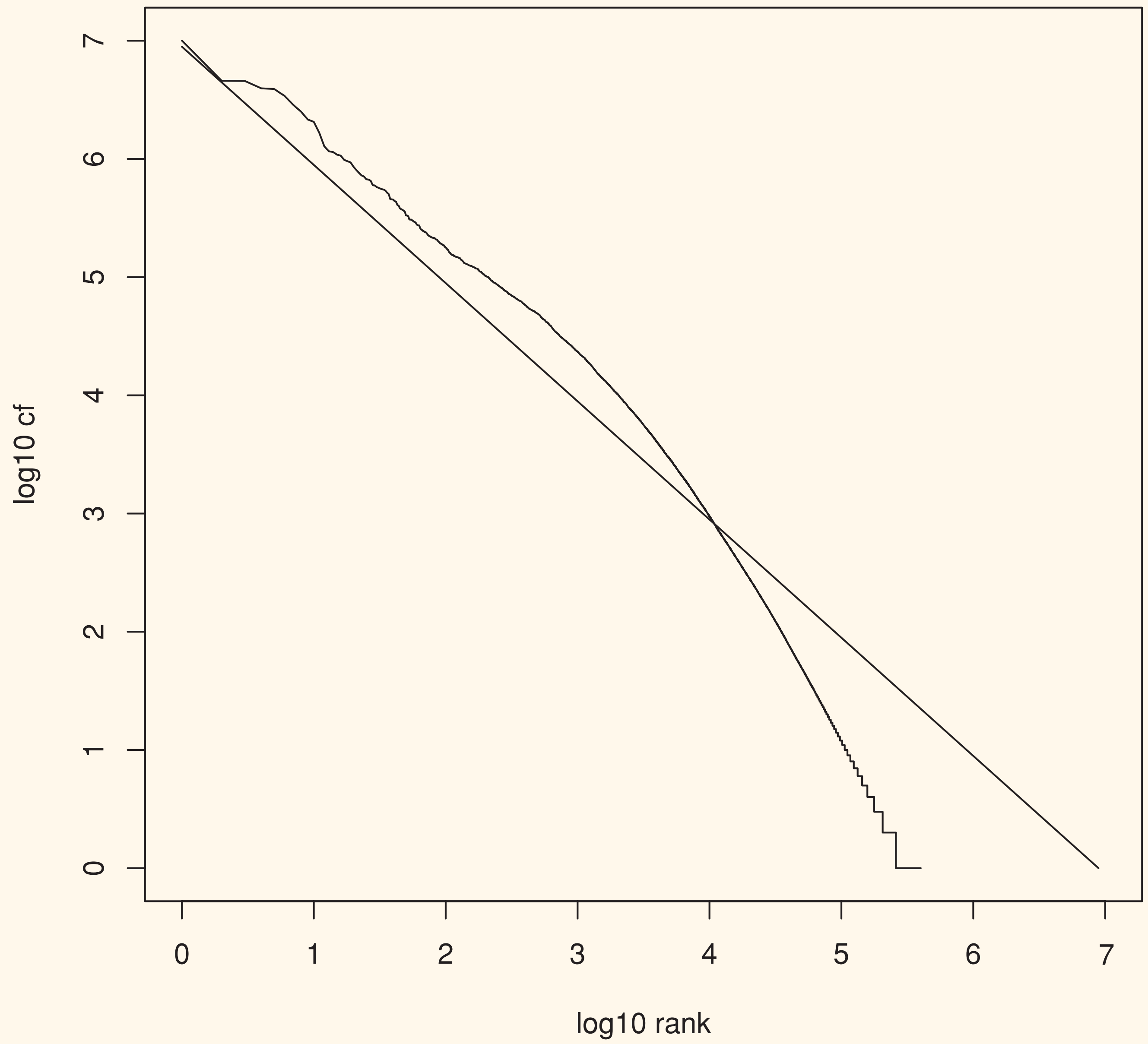
What about term distribution within collection?



$$\mathrm{cf}_i \propto \frac{1}{i}$$

Zipf's law: collection frequency of a term decreases rapidly with rank.

What about term distribution within collection?



Implication: A small number of terms are very common; most are rare.

The point of dictionary compression:

Fit as much of the dictionary as possible in main memory.

Because of Heap’s law, large collections will have large dictionaries...

... and many search engines are multilingual!

Warning: here there be pointers...

Warning: here there be caveats...

#1: For the rest of today, we shall pretend that all text is ASCII.

Warning: here there be caveats...

Also: the book uses a 32-bit address space. Large collections need more.

The simplest possible dictionary structure:

	term	document frequency	pointer to postings list
	a	656,265	$\longrightarrow$
	aachen	65	$\longrightarrow$
	…	…	…
	zulu	221	$\longrightarrow$
space needed:	20 bytes	4 bytes	4 bytes

In RCV1*, 11.2 MB needed to store 400,000 dictionary entries.

RCV1: "Reuters Corpus Volume 1," a newswire corpus.

The simplest possible dictionary structure:

	term	document frequency	pointer to postings list
	a	656,265	$\longrightarrow$
	aachen	65	$\longrightarrow$
	…	…	…
	zulu	221	$\longrightarrow$
space needed:	20 bytes	4 bytes	4 bytes

Fixed-width entries are both wasteful and limiting, but are simple to implement.

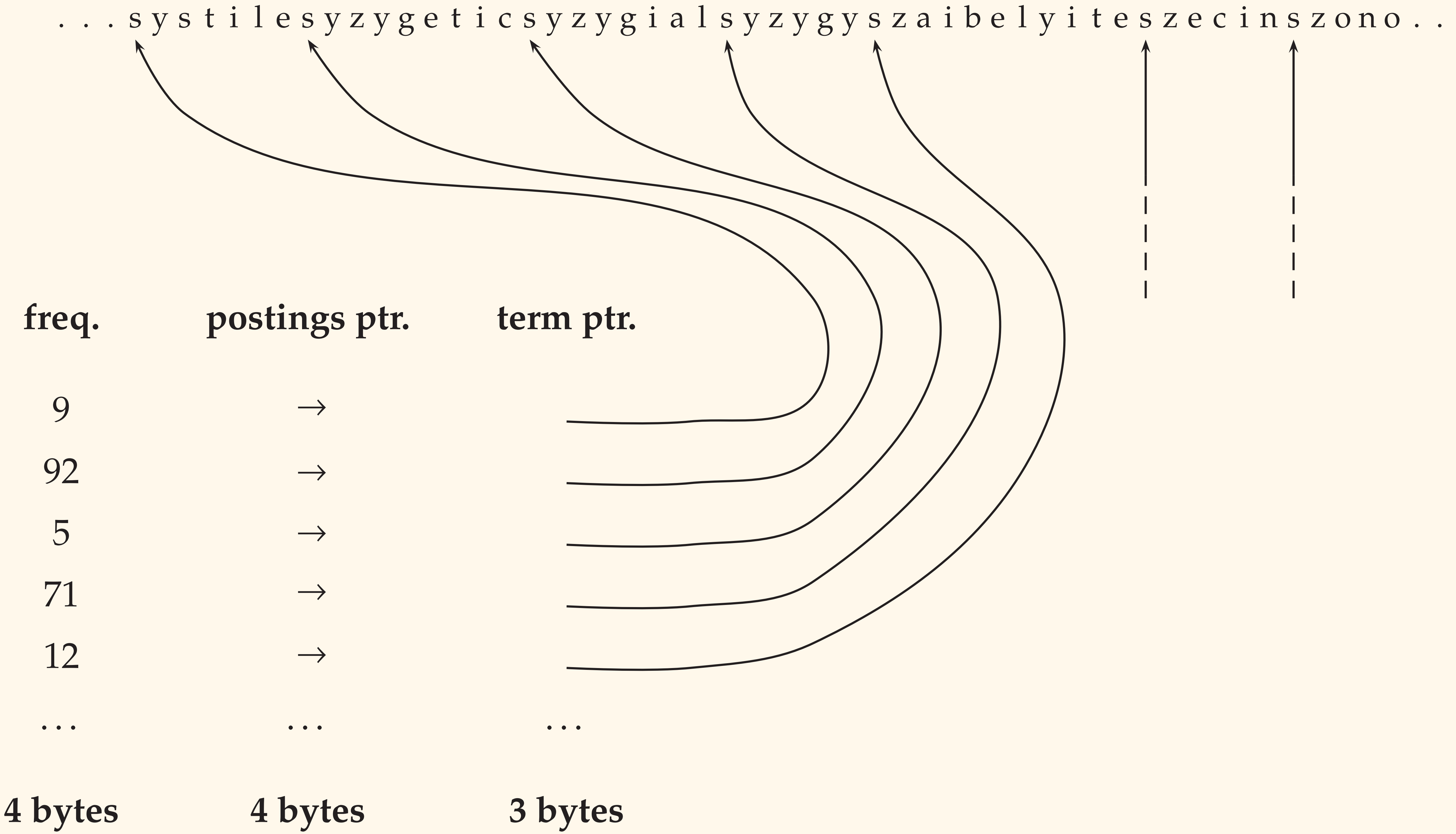
Next: dictionary-as-a-string

...systilesyzygeticsyzygialsyzygyszaibelyiteszecinszono...

freq.	**postings ptr.**	**term ptr.**
9	→	
92	→	
5	→	
71	→	
12	→	
...	...	...
4 bytes	**4 bytes**	**3 bytes**

In RCV1, 7.6 MB needed to store 400,000 dictionary entries.

Next: dictionary-as-a-string



Some of the space saved by the variable width is offset by the need for term pointers.

Blocked storage:

. . . **7** s y s t i l e **9** s y z y g e t i c **8** s y z y g i a l **6** s y z y g y **11** s z a i b e l y i t e **6** s z e c i n . . .

freq.	**postings ptr.**	**term ptr.**
9	→	
92	→	
5	→	
71	→	
12	→	
…	…	…

Pick blocks of size *k*, and only store pointer to first term of each block. Add in-band term lengths to dictionary string.

Blocked storage:

. . . **7**systile**9**syzygetic**8**syzygial**6**syzygy**11**szaibelyite**6**szecin . . .

freq.	**postings ptr.**	**term ptr.**
9	→	
92	→	
5	→	
71	→	
12	→	
…	…	…

This saves *k* - *1* term pointers, but adds *k* bytes for term lengths.

Blocked storage:

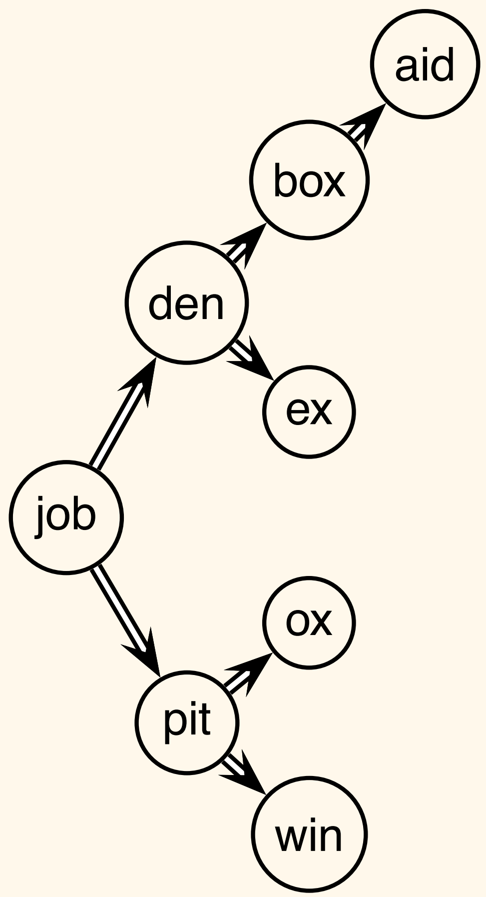
. . . **7** s y s t i l e **9** s y z y g e t i c **8** s y z y g i a l **6** s y z y g y **11** s z a i b e l y i t e **6** s z e c i n . . .

freq.	**postings ptr.**	**term ptr.**
9	→	
92	→	
5	→	
71	→	
12	→	
…	…	…

For RCV1, we are now down to 7.1 megabytes.

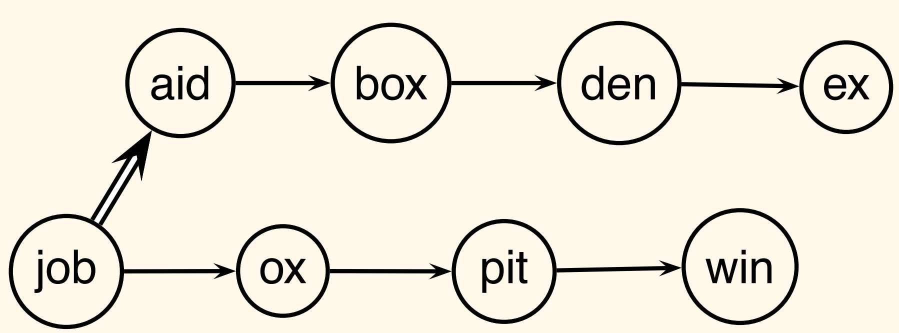
But there is always a tradeoff: Term lookup now takes more time.

(a)



Seeking through the uncompressed dictionary involves on average 25% fewer steps.

(b)



Front coding takes advantage of common prefixes to save space.

One block in blocked compression ($k = 4$) ...

8automata**8**automate**9**automatic**10**automation

$\Downarrow$

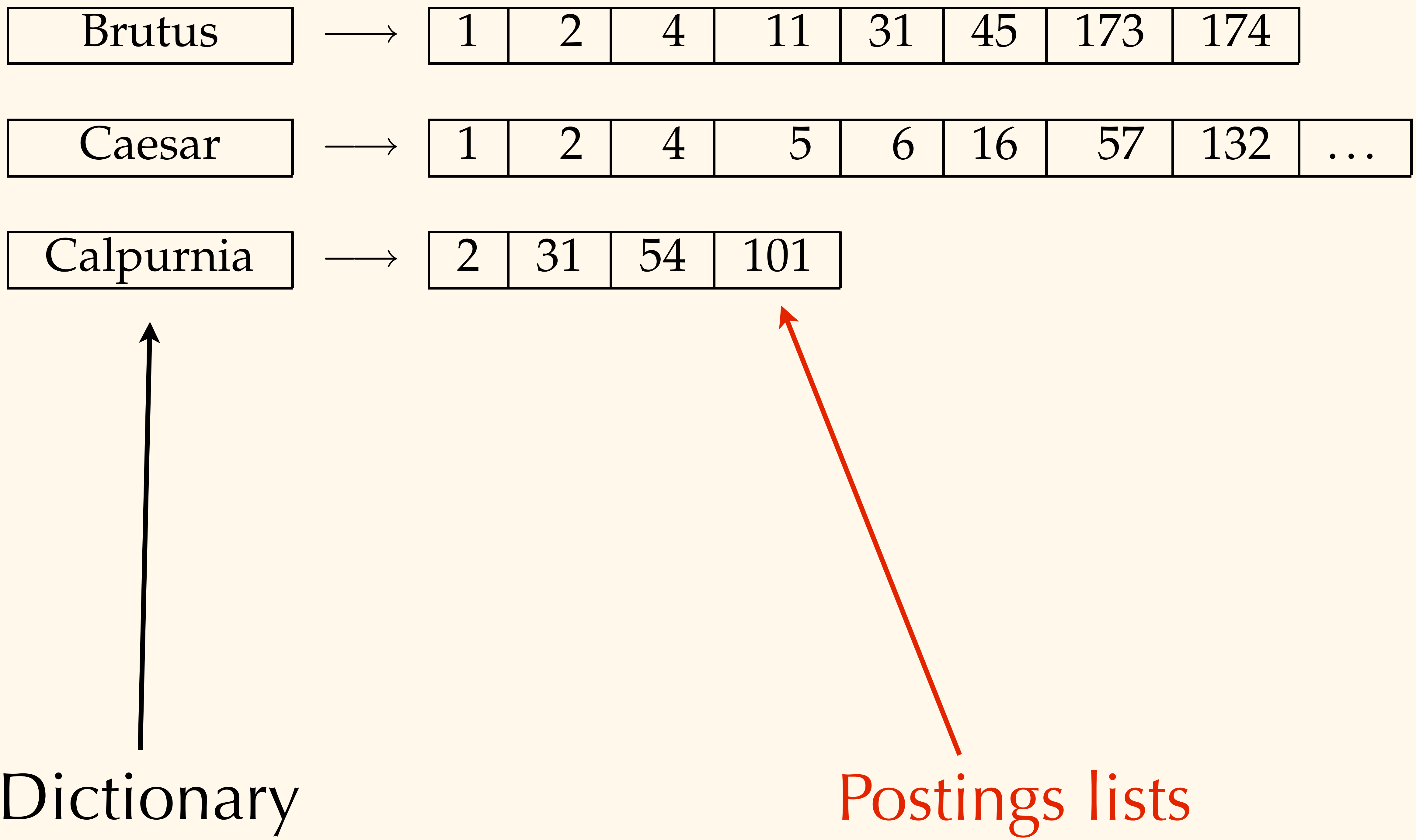
... further compressed with front coding.

8automat$*$a**1**$\diamond$e**2**$\diamond$ic**3**$\diamond$ion

Dictionary compression for Reuters-RCV1.

data structure	size in MB
dictionary, fixed-width	11.2
dictionary, term pointers into string	7.6
$\sim$, with blocking, $k = 4$	7.1
$\sim$, with blocking & front coding	5.9

There are two ways to compress an index:



Simplest approach to posting list:

Store lists of complete docIDs.

RCV1 has 800,000 documents, so we need $\log_2 800,000 = 20$ bits per docID.

Approximately 250 MB uncompressed.

800,000 is tiny; bigger collections need more bits per docID (many more).

Key observation: postings for frequent terms are often close together in the collection.

What if we store *gaps* or *offsets* between docIDs rather than docIDs themselves?

	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							

Many words wouldn’t need a full 20 bits to be represented...

We can use a variable byte code to more efficiently use space:

docIDs	824	829	215406
gaps		5	214577
VB code	00000110 10111000	10000101	00001101 00001100 10110001

Figure 5.8 in the book gives an example algorithm...

Using this scheme achieves >50% reduction in posting list space (down to 116 MB).

In practice, these schemes can be applied to different units than bytes (16-bit words, etc.).

Variable-byte encodings are simple and work well… but can we do better?

Yes, by using bit-level encodings (like the γ encoding).

But is it *enough* better to be worth the significant hassle? Probably not.

data structure	size in MB
dictionary, fixed-width	11.2
dictionary, term pointers into string	7.6
$\sim$, with blocking, $k = 4$	7.1
$\sim$, with blocking & front coding	5.9
collection (text, xml markup etc)	3600.0
collection (text)	960.0
term 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

Next up: Experimental evaluation.