Information Retrieval
Tutorial 3: Index Compression

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Outline

Review

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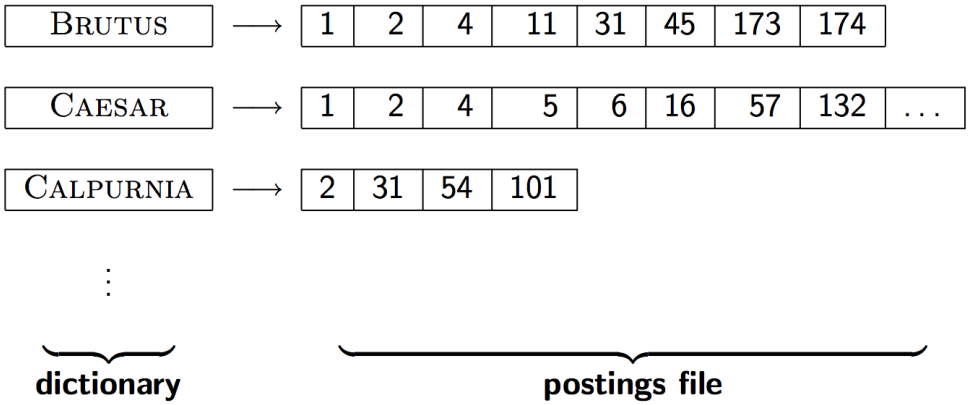

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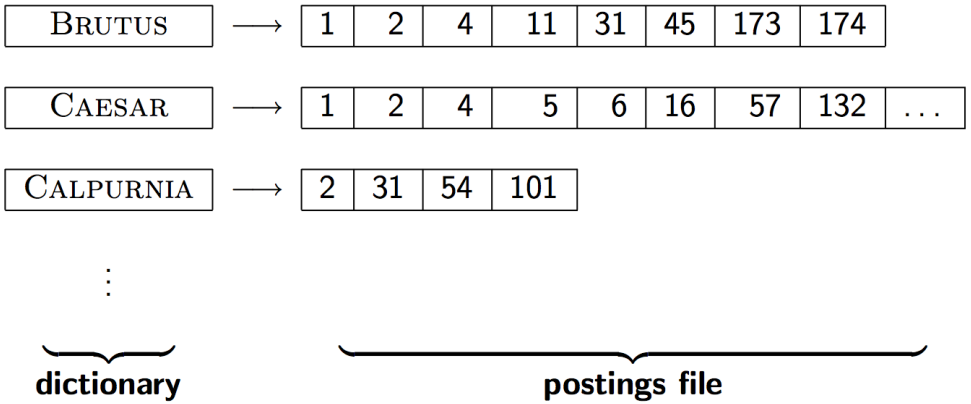

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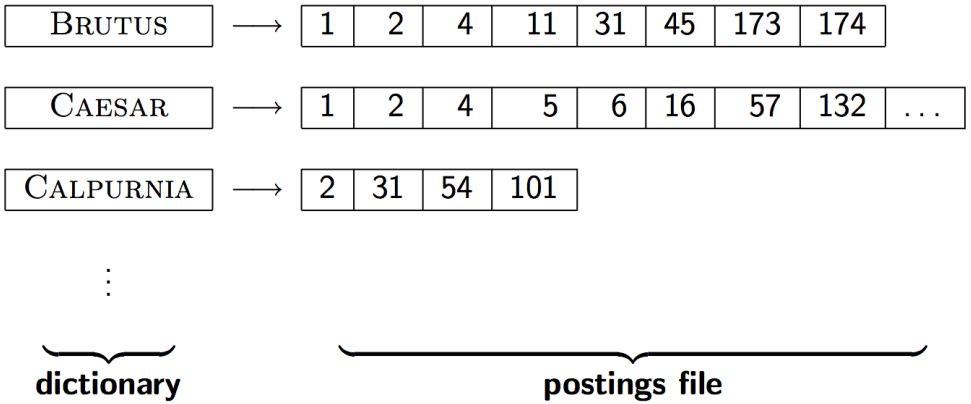

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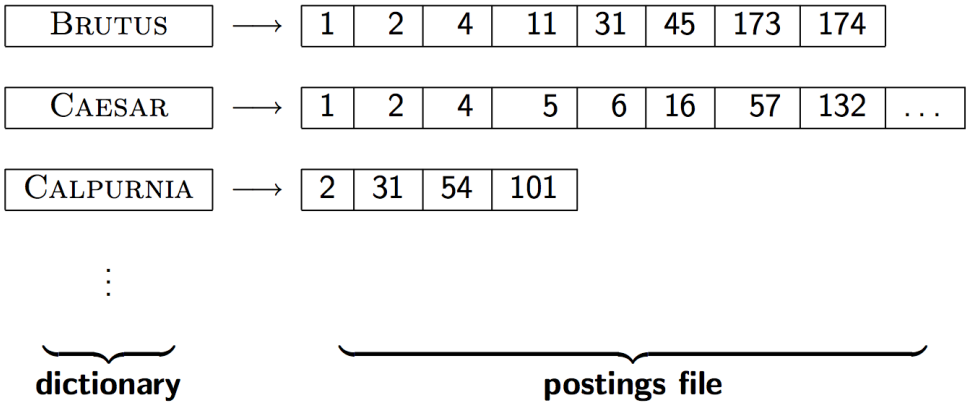

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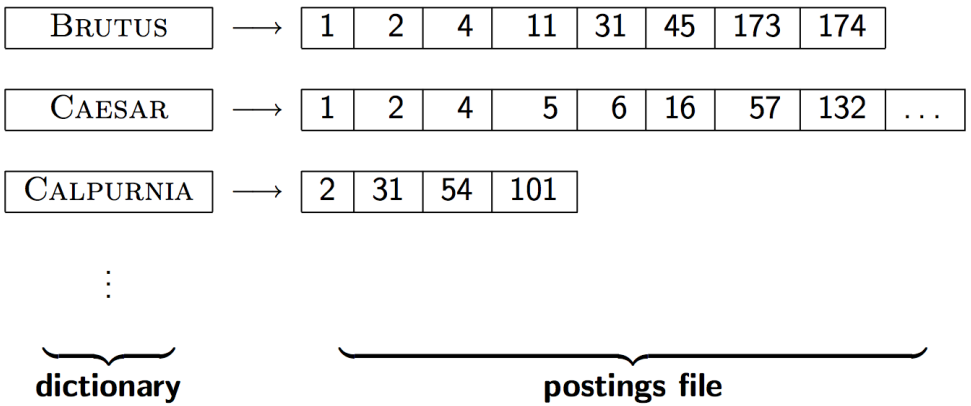

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- How can we compress the dictionary component of the inverted index?
- How can we compress the postings component of the inverted index?
- Term statistics: how are terms distributed in document collections?

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- We will devise various compression schemes for dictionary and postings.

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  - What we mostly do in index compression

Model collection: The Reuters collection

symbol	statistic	value
N	documents	800,000
L	avg. # word tokens per document	200
M	word types	400,000
	avg. # bytes per word token (incl. spaces/punct.)	6
	avg. # bytes per word token (without spaces/punct.)	4.5
	avg. # bytes per word type	7.5
T	non-positional postings	100,000,000

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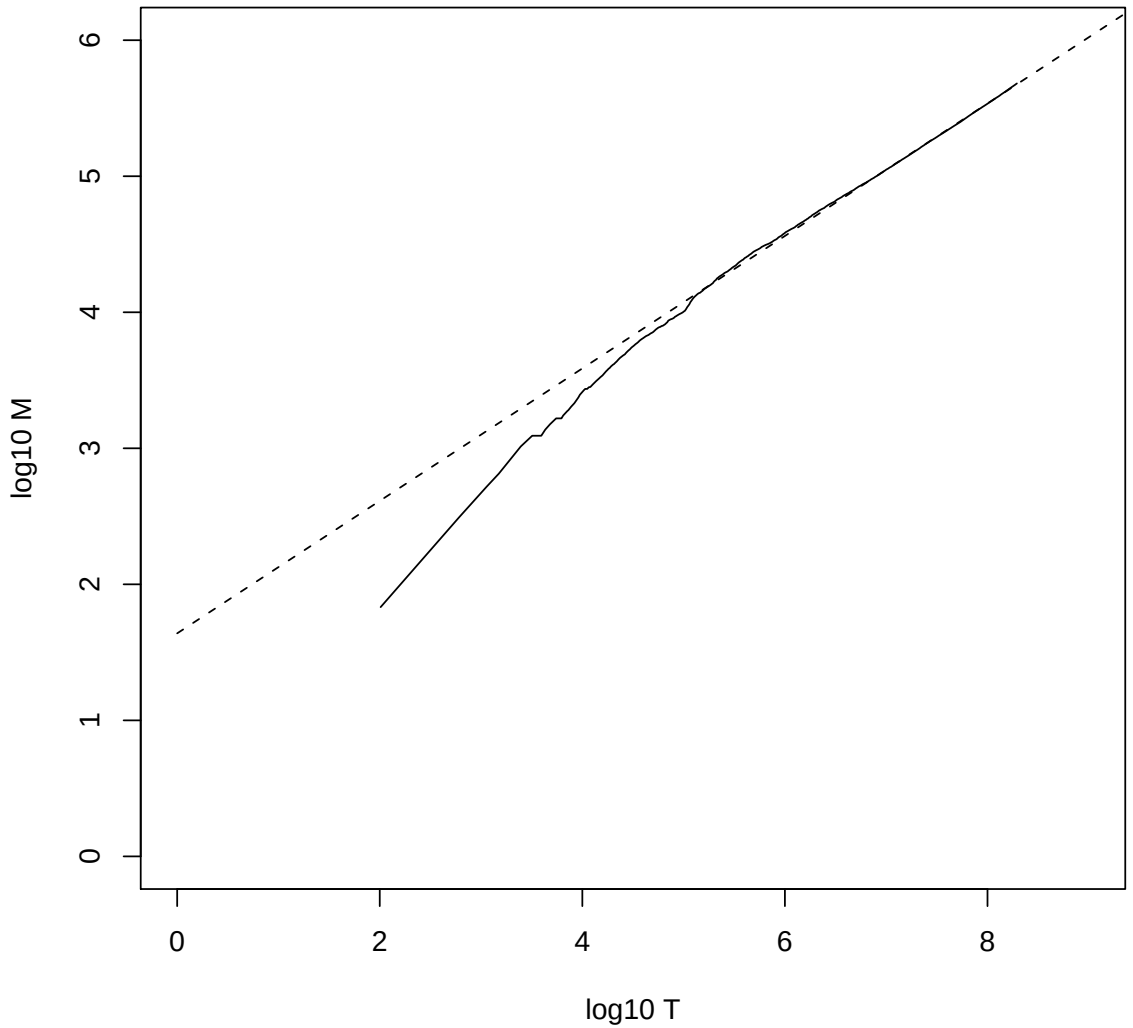
  - An empirical finding(Empirical law).

Heaps' law for Reuters



Vocabulary size M as a function of collection size T (number of tokens) for Reuters-RCV1. For these data, the dashed line $\log_{10} M = 0.49 * \log_{10} T + 1.64$ is the best least squares fit.
Thus, $M = 10^{1.64} T^{0.49}$ and $k = 10^{1.64} \approx 44$ and $b = 0.49$.

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- Empirical observation: fit is good in general.

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- $log(M) = logk + \frac{1}{2} log(20,000,000,000 * 200) = 7.778$ thus $M = 10^{7.778} \approx 6 * 10^7$

Basic knowledge to remember

To binary represent an integer n, number of bits need $= \lfloor log_2(n) \rfloor + 1$

$n = \{2\}_{10} = \{10\}_2$

$n = \{3\}_{10} = \{11\}_2$

$n = \{4\}_{10} = \{100\}_2$

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- But we want to keep it in memory.
- Also: competition with other applications, cell phones, onboard computers, fast startup time
- So compressing the dictionary is important.

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	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

Space for Reuters: (20+4+4)*400,000 = 11.2 MB

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- How can we use on average 8 characters per term?

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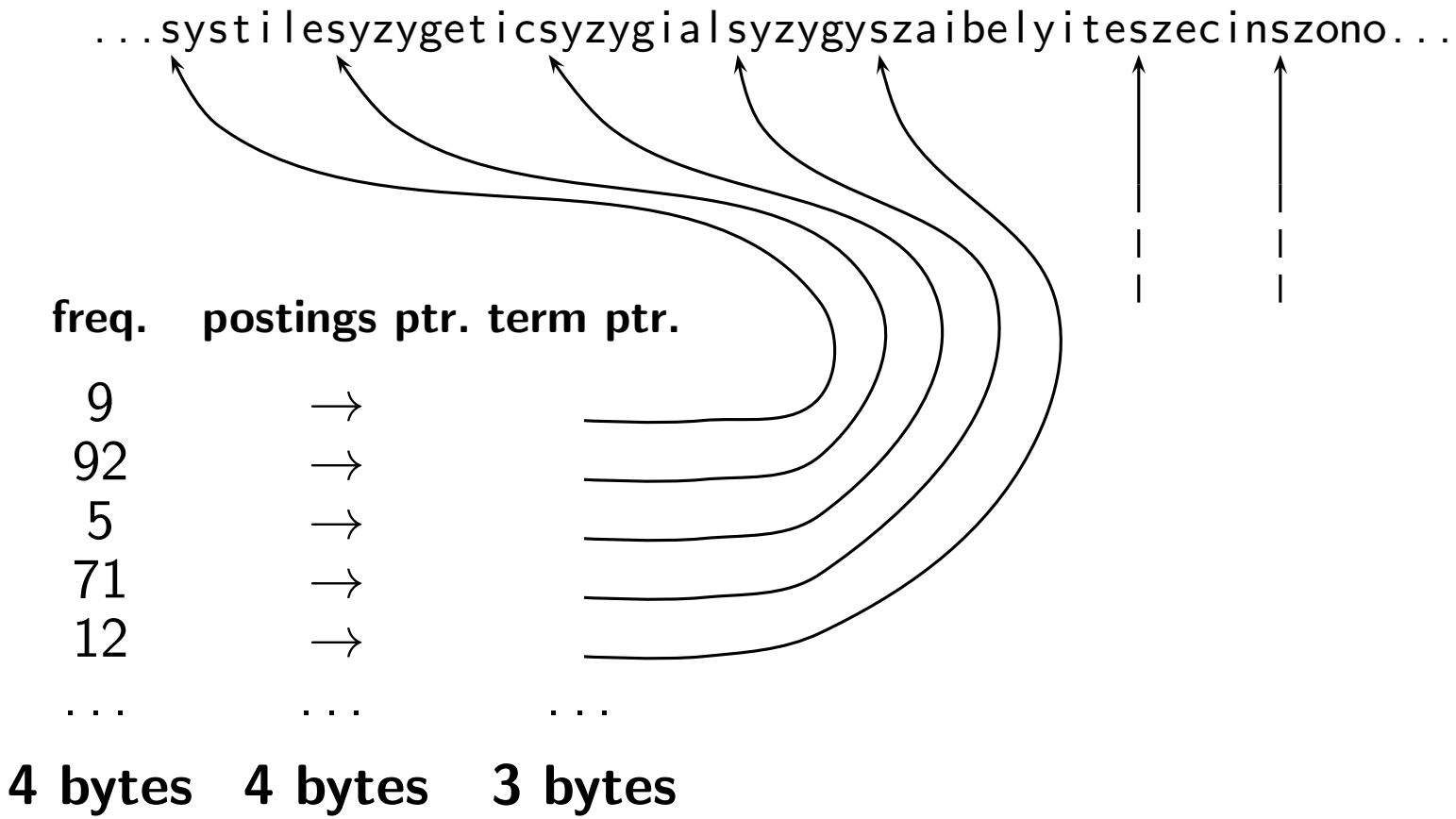

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- 3 bytes per pointer into string (need $\log_2 8 \cdot 400000 < 24$ bits to resolve $8 \cdot 400{,}000$ positions)
- Space: $400{,}000 \times (4 + 4 + 3 + 8) = 7.6$MB (compared to 11.2 MB for fixed-width array)

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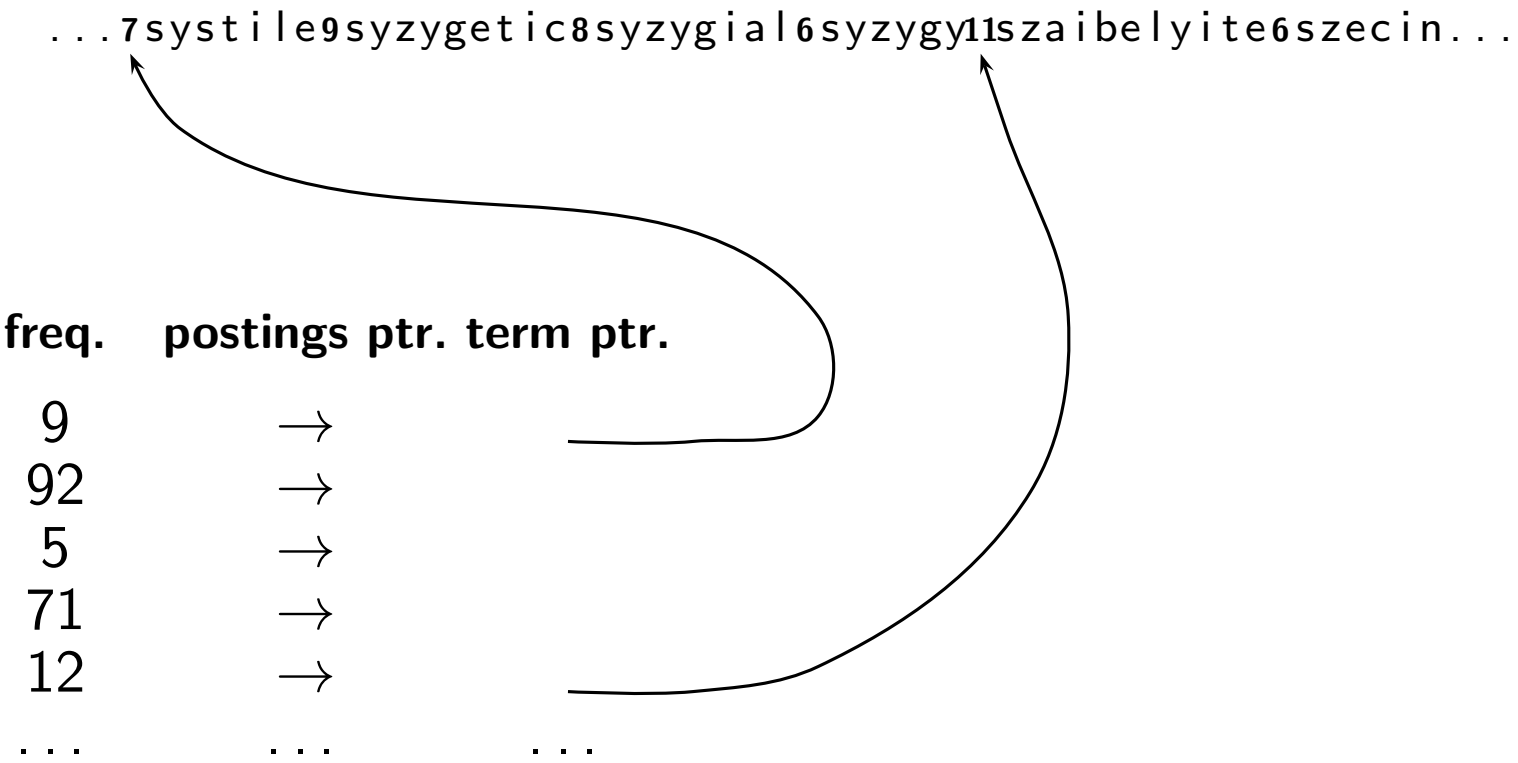

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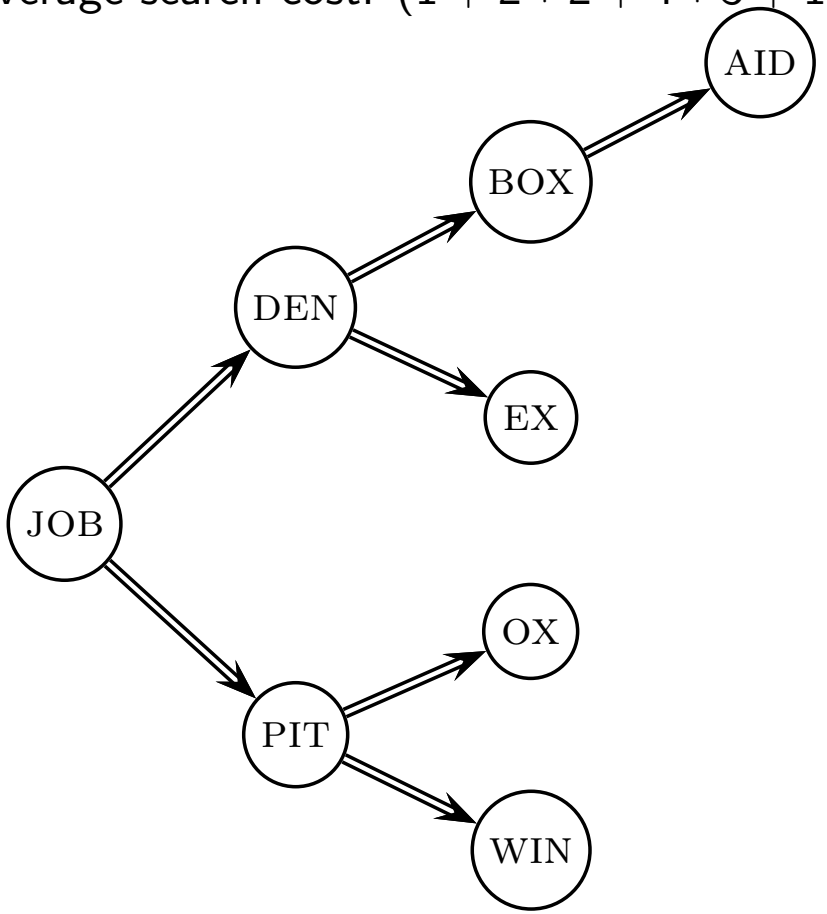
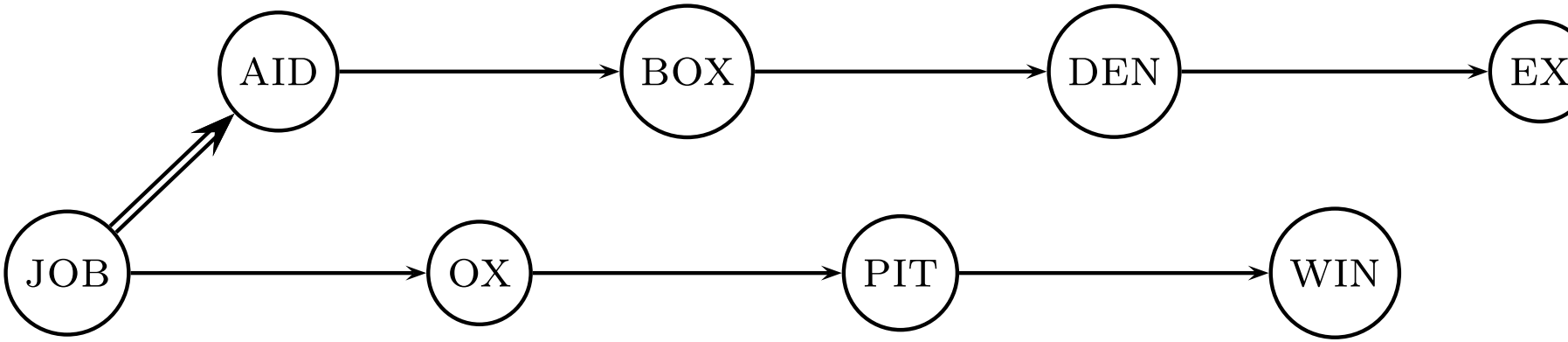
- Total savings: $400{,}000/4 * 5 = 0.5$ MB
- This reduces the size of the dictionary from 7.6 MB to 7.1 MB.

Lookup of a term without blocking

Average search cost: $(1 + 2 * 2 + 4 * 3 + 1 * 4)/8 \approx 2.6$ steps



Lookup of a term with blocking: (slightly) slower



Average search cost: $(2 + 3 + 4 + 5 + 1 + 2 + 3 + 4)/8 \approx 3$ steps.

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- Ans:We can't increase K arbitrarily, term look up time will go up. If we only have one pointer, we can't do binary search, have to go from beginning to the end to find the term.

Front coding

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

8 a u t o m a t a **8** a u t o m a t e **9** a u t o m a t i c **10** a u t o m a t i o n

. . . further compressed with front coding.

8 a u t o m a t ∗ a **1** ◇ e **2** ◇ i c **3** ◇ i o n

Dictionary compression for Reuters: Summary

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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

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- Our goal: use a lot less than 20 bits per docID.

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- Gaps for frequent terms are small.
- Thus: We can encode small gaps with fewer than 20 bits.

Gap encoding

	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								

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- Variable length encoding uses few bits for small gaps and many bits for large gaps.

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- At the end set the continuation bit of the last byte to 1 ($c = 1$) and of the other bytes to 0 ($c = 0$).

VB code examples

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

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- Encode length in unary code: 1110.
- Gamma code of 13 is the concatenation of length and offset: 1110101.

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- $135_2 = 10000111$ and $2_2 = 10$ thus doc_{135} and doc_2
- $6_2 = 110$ gamma code: 11010
- $4_2 = 100$ gamma code: 11000 and $9_2 = 1001$ gamma code: 1110001

Length of gamma code

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- The length of *offset* is $\lfloor \log_2 G \rfloor$ bits.
- The length of *length* is $\lfloor \log_2 G \rfloor + 1$ bits,
- So the length of the entire code is $2 \times \lfloor \log_2 G \rfloor + 1$ bits.
- γ codes are always of odd length.
- Gamma codes are within a factor of 2 of the optimal encoding length $\log_2 G$.