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8 - Index Construction

Information Retrieval

by

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Lecture – 08

✧ Topics Covered So Far

- ✧ Bi-Word Index
- ✧ Wild Card Queries
- ✧ Permuterm Index
- ✧ K-gram Index (k = 2 □ Bigram Index)
- ✧ Spell Correction

✧ Now: Index Construction

- ✧ Approaches to Index Construction in IR

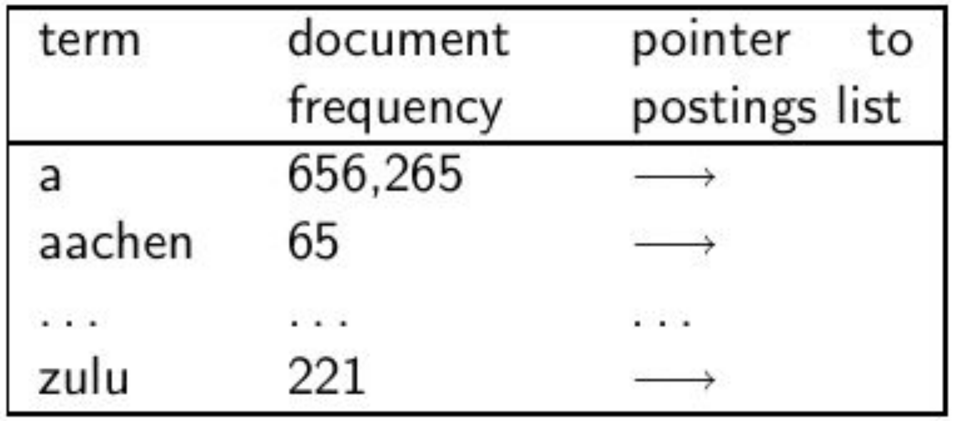
Recap: Spelling Tasks

- Spelling Error Detection
- Spelling Error Correction:
  - Autocorrect
    - hte□the
  - Suggest a correction
  - Suggestion lists

Topics to be covered

- BSBI algorithm
- SPIMI algorithm
- Distributed indexing
- Dynamic indexing

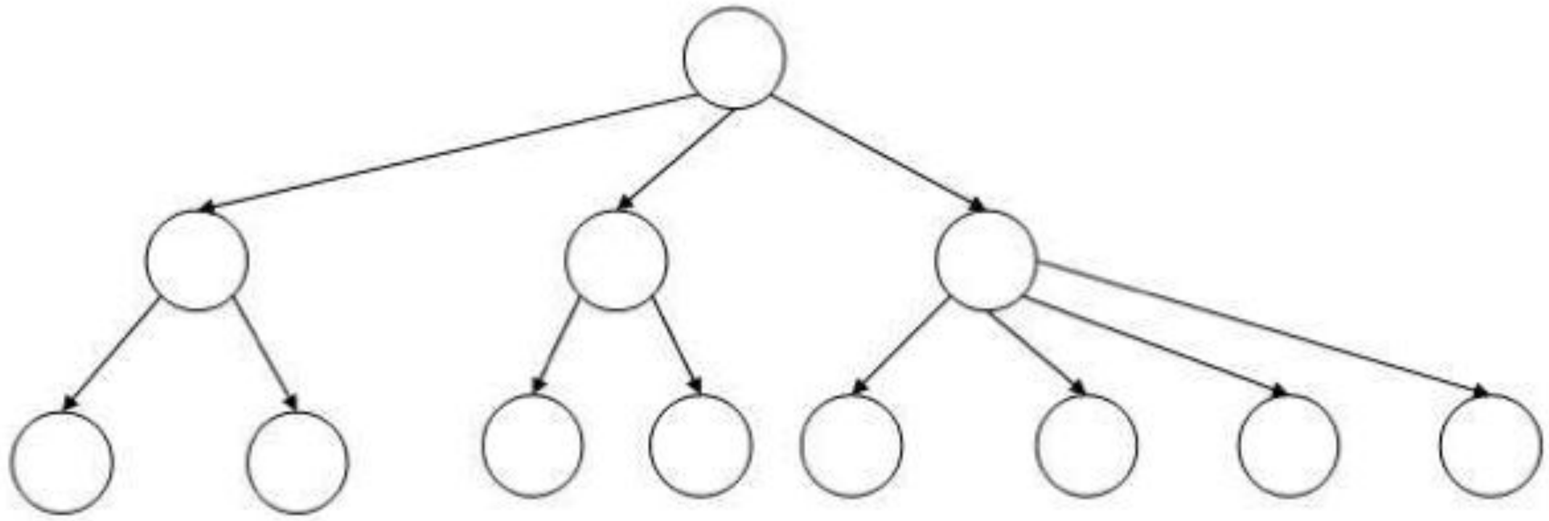
Dictionary as array of fixed-width entries



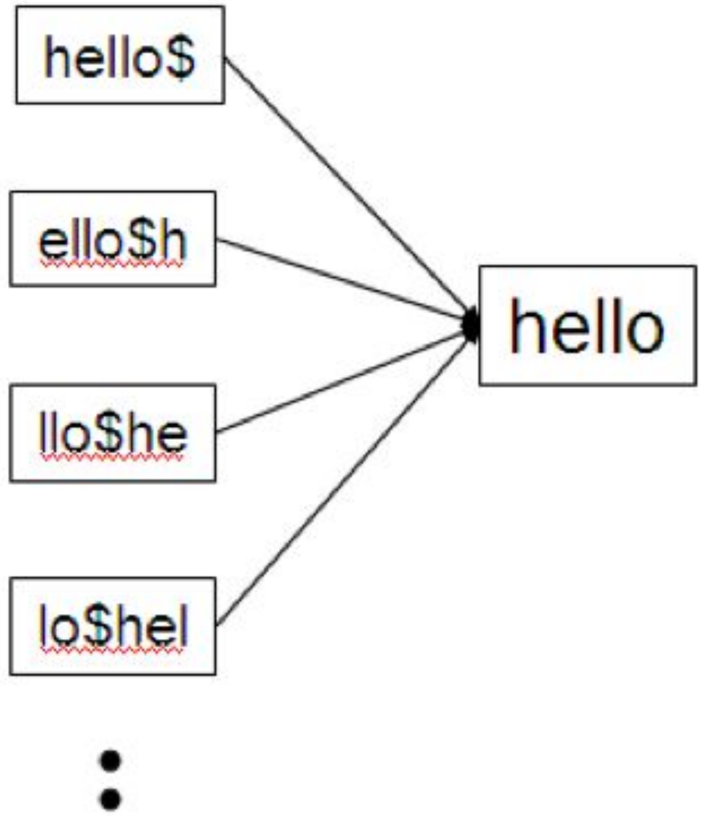
term	document frequency	pointer to postings list
a	656,265	$\longrightarrow$
aachen	65	$\longrightarrow$
...	...	...
zulu	221	$\longrightarrow$

space needed: 20 bytes 4 bytes 4 bytes

B-tree for looking up entries in array



Wildcard queries using a permuterm index



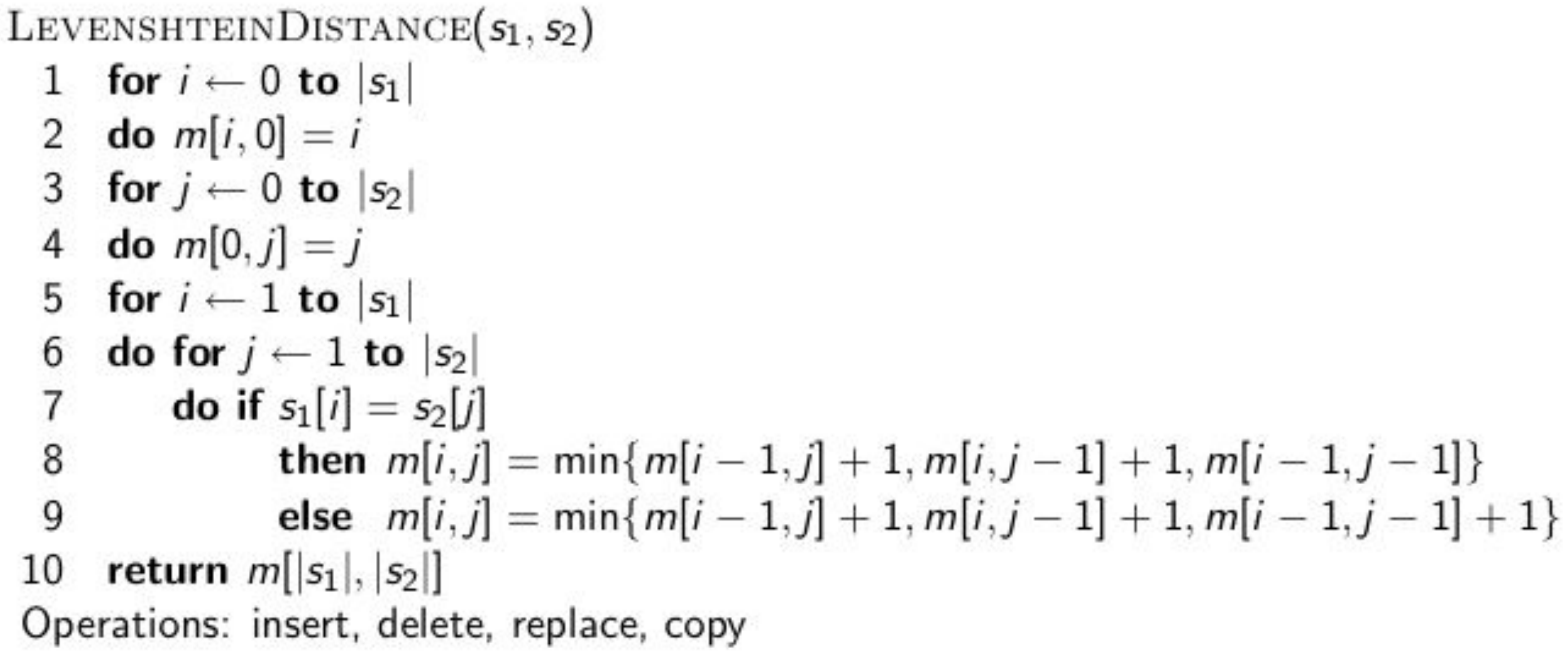
Queries:

- For X, look up X$
- For X*, look up X*$
- For *X, look up X$*
- For *X*, look up X*
- For X*Y, look up Y$X*

k-gram indexes for spelling correction: bordroom

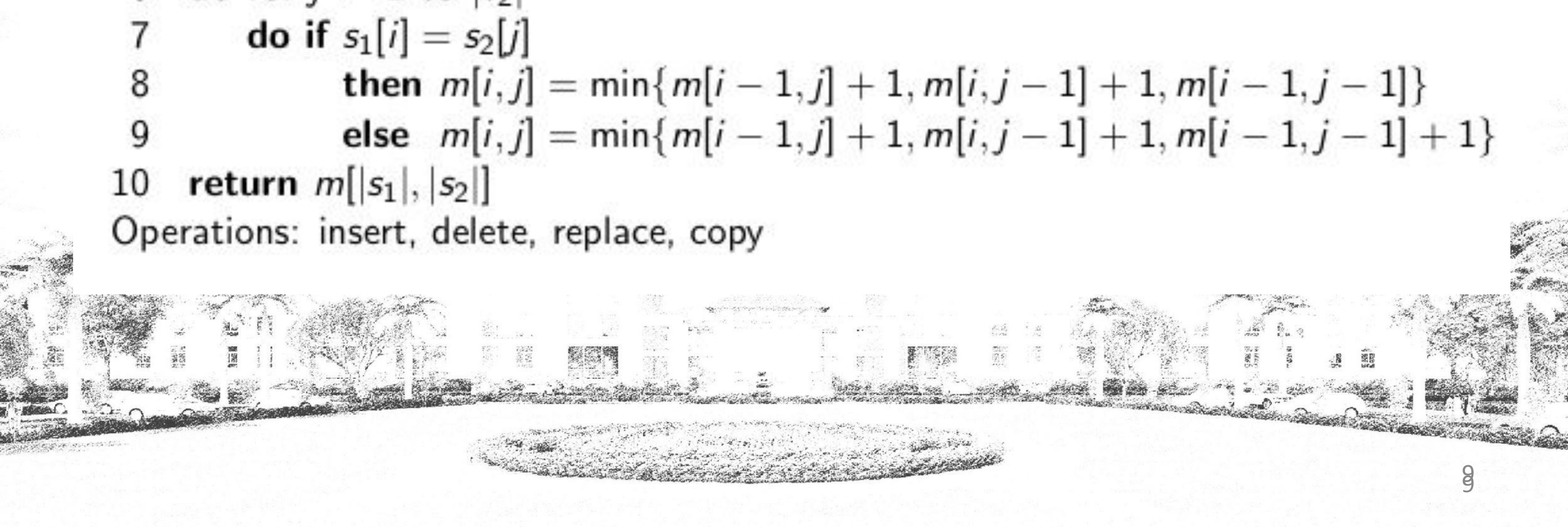
$$\begin{tikzcd}
\boxed{\text{BO}} \arrow[r] & \boxed{\text{aboard}} \arrow[r] & \boxed{\text{about}} \arrow[r] & \boxed{\text{boardroom}} \arrow[r] & \boxed{\text{border}} \\
\boxed{\text{OR}} \arrow[r] & \boxed{\text{border}} \arrow[r] & \boxed{\text{lord}} \arrow[r] & \boxed{\text{morbid}} \arrow[r] & \boxed{\text{sordid}} \\
\boxed{\text{RD}} \arrow[r] & \boxed{\text{aboard}} \arrow[r] & \boxed{\text{ardent}} \arrow[r] & \boxed{\text{boardroom}} \arrow[r] & \boxed{\text{border}}
\end{tikzcd}$$

Levenshtein distance for spelling correction

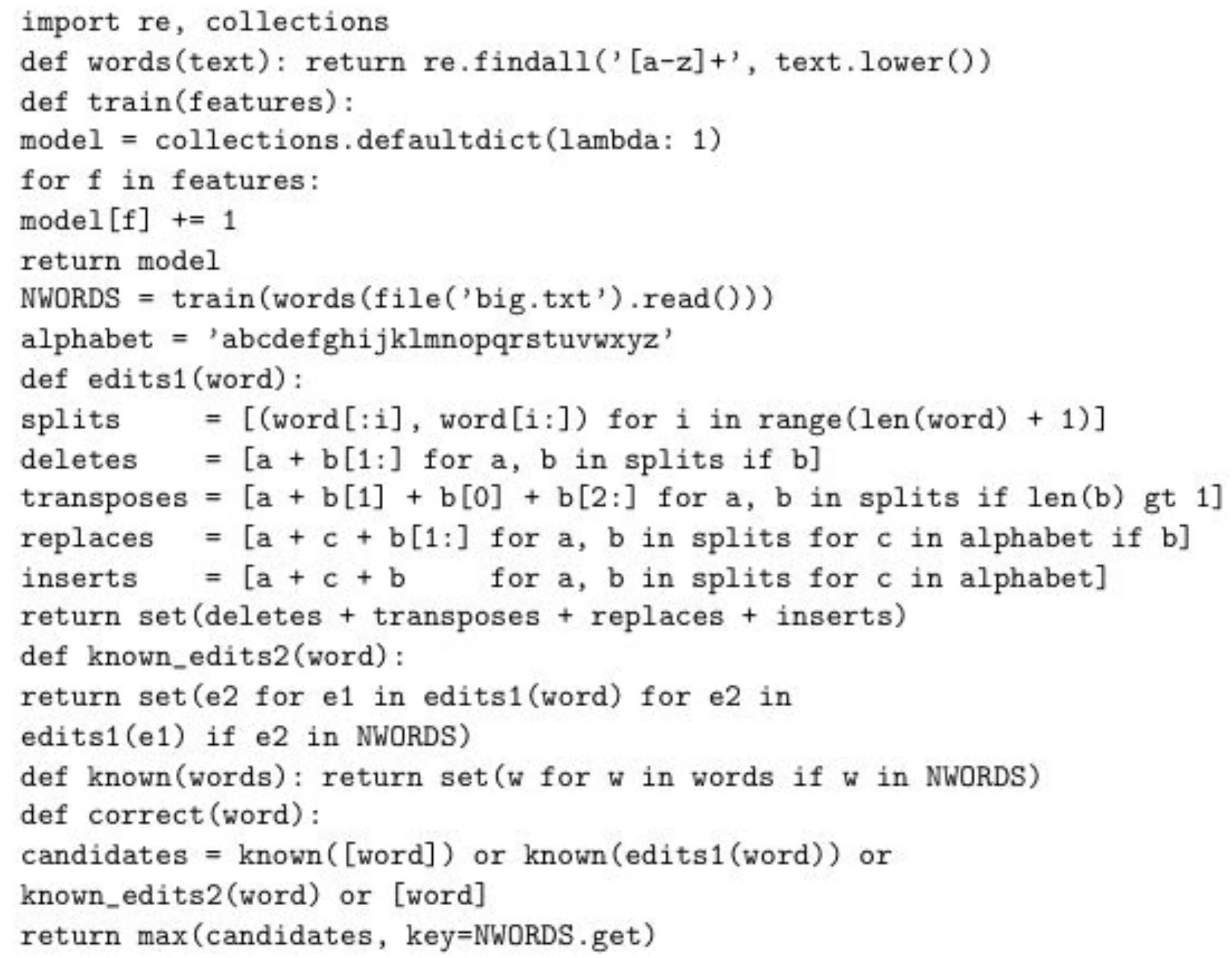


```
LevenshteinDistance($s_1, s_2$)
for $i \leftarrow 0$ to $|s_1|$
do $m[i, 0] = i$
for $j \leftarrow 0$ to $|s_2|$
do $m[0, j] = j$
for $i \leftarrow 1$ to $|s_1|$
do for $j \leftarrow 1$ to $|s_2|$
    do if $s_1[i] = s_2[j]$
        then $m[i, j] = \min\{m[i-1, j] + 1, m[i, j-1] + 1, m[i-1, j-1]\}$
        else $m[i, j] = \min\{m[i-1, j] + 1, m[i, j-1] + 1, m[i-1, j-1] + 1\}$
return $m[|s_1|, |s_2|]$
```

Operations: insert, delete, replace, copy



Exercise: Understand Peter Norvig's spelling corrector



```
import re, collections
def words(text): return re.findall('[a-z]+', text.lower())
def train(features):
model = collections.defaultdict(lambda: 1)
for f in features:
model[f] += 1
return model
NWORDS = train(words(file('big.txt').read()))
alphabet = 'abcdefghijklmnopqrstuvwxyz'
def edits1(word):
splits     = [(word[:i], word[i:]) for i in range(len(word) + 1)]
deletes    = [a + b[1:] for a, b in splits if b]
transposes = [a + b[1] + b[0] + b[2:] for a, b in splits if len(b) gt 1]
replaces   = [a + c + b[1:] for a, b in splits for c in alphabet if b]
inserts    = [a + c + b     for a, b in splits for c in alphabet]
return set(deletes + transposes + replaces + inserts)
def known_edits2(word):
return set(e2 for e1 in edits1(word) for e2 in
edits1(e1) if e2 in NWORDS)
def known(words): return set(w for w in words if w in NWORDS)
def correct(word):
candidates = known([word]) or known(edits1(word)) or
known_edits2(word) or [word]
return max(candidates, key=NWORDS.get)
```

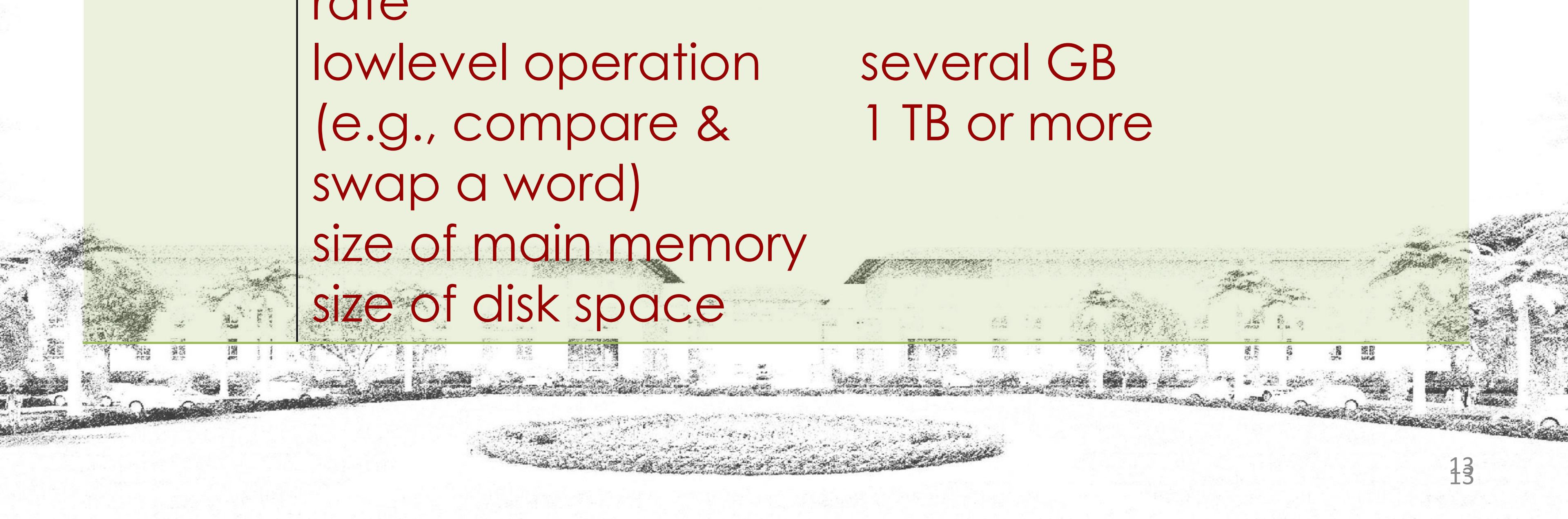
Hardware basics

- Many design decisions in information retrieval are based on hardware constraints.
- Access to data is much faster in memory than on disk. (roughly a factor of 10)
- Disk seeks are “idle” time: No data is transferred from disk while the disk head is being positioned.
- To optimize transfer time from disk to memory: one large chunk is faster than many small chunks.

Hardware basics

- Disk I/O is block-based: Reading and writing of entire blocks (as opposed to smaller chunks). Block sizes: 8KB to 256 KB
- Servers used in IR systems typically have several GB of main memory, sometimes tens of GB, and TBs or 100s of GB of disk space.
- Fault tolerance is expensive: It's cheaper to use many regular machines than one fault tolerant machine.

Some stats (ca. 2008)



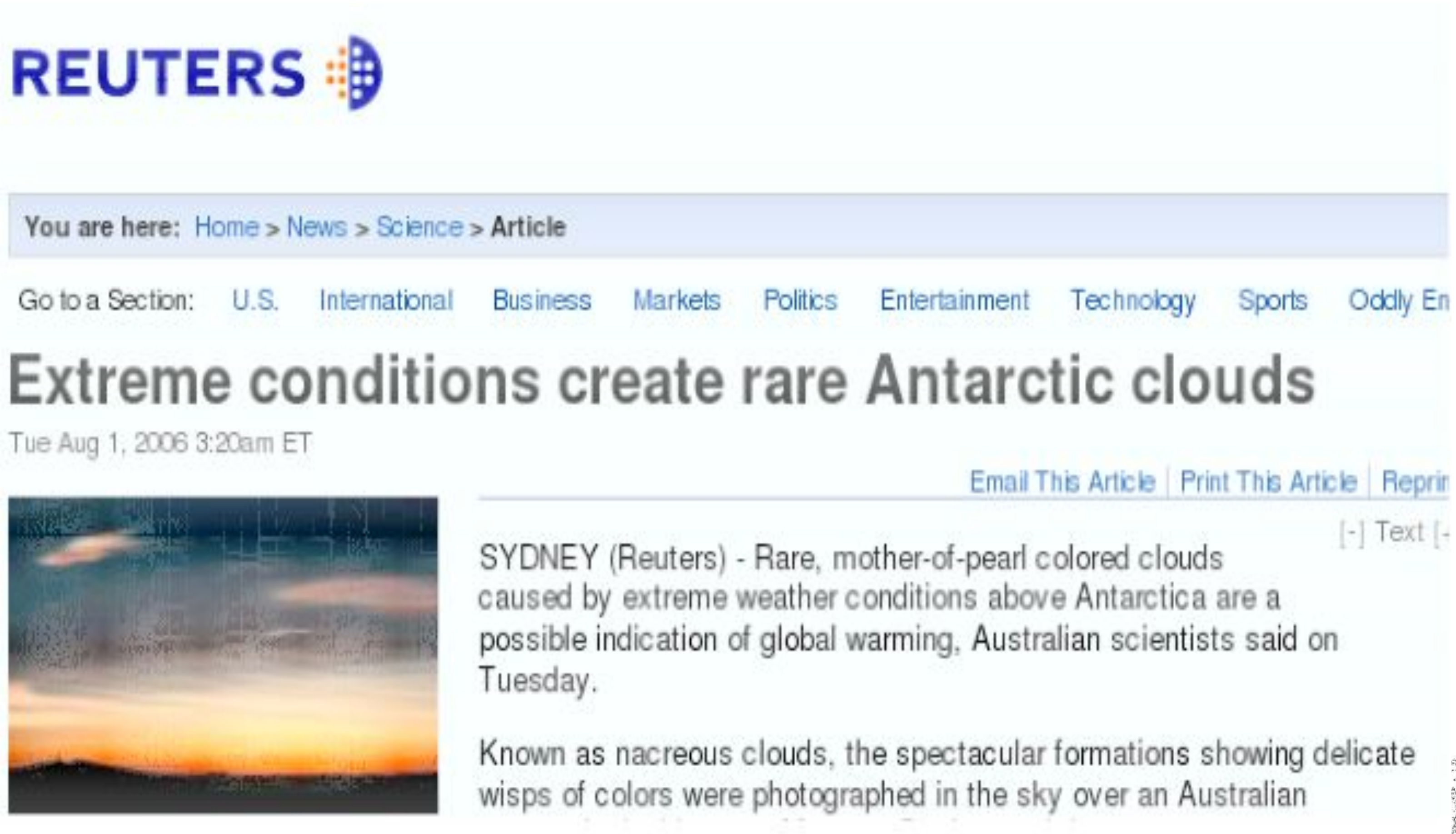
symbol	statistic	value
s	average seek time	5 ms = 5×10^{-3} s
b	transfer time per byte	0.02 μs = 2×10^{-8} s
P	processor's clock rate	10^{9} s^{-1}
	lowlevel operation (e.g., compare & swap a word)	0.01 μs = 10^{-8} s
	size of main memory	several GB
	size of disk space	1 TB or more

13

RCV1 Collection

- Shakespeare's collected works are not large enough for demonstrating many of the points in this course.
- As an example for applying scalable index construction algorithms, we will use the Reuters RCV1 collection.
- English newswire articles sent over the wire in 1995 and 1996 (one year).

A Reuters RCV1 document



REUTERS

You are here: Home > News > Science > Article

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Extreme conditions create rare Antarctic clouds

Tue Aug 1, 2006 3:20am ET

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[-] Text [-

SYDNEY (Reuters) - Rare, mother-of-pearl colored clouds caused by extreme weather conditions above Antarctica are a possible indication of global warming, Australian scientists said on Tuesday.

Known as nacreous clouds, the spectacular formations showing delicate wisps of colors were photographed in the sky over an Australian

Reuters RCV1 statistics

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

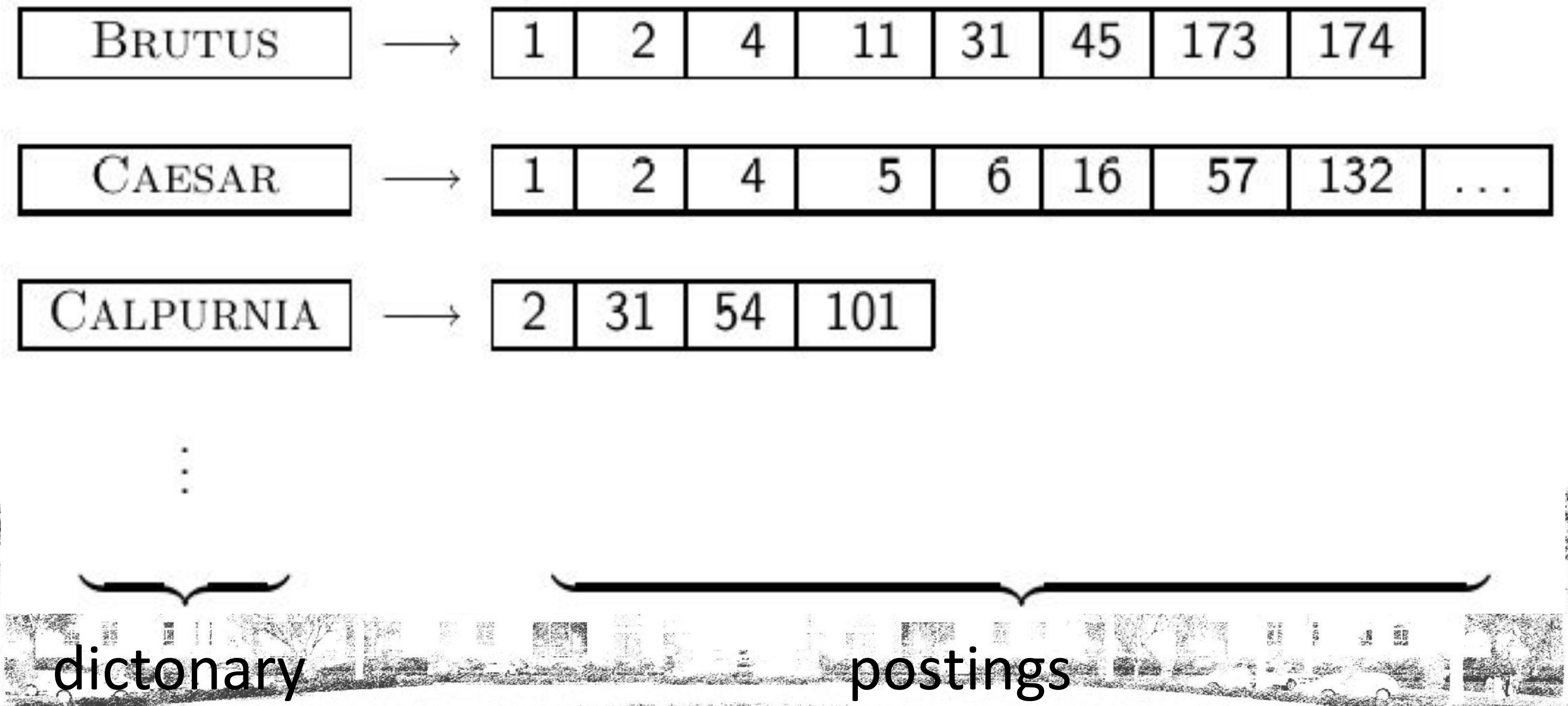
Exercise: Average frequency of a term (how many tokens)?

4.5 bytes per word token vs. 7.5 bytes per word type:

- Why the difference?
- How many positional postings?

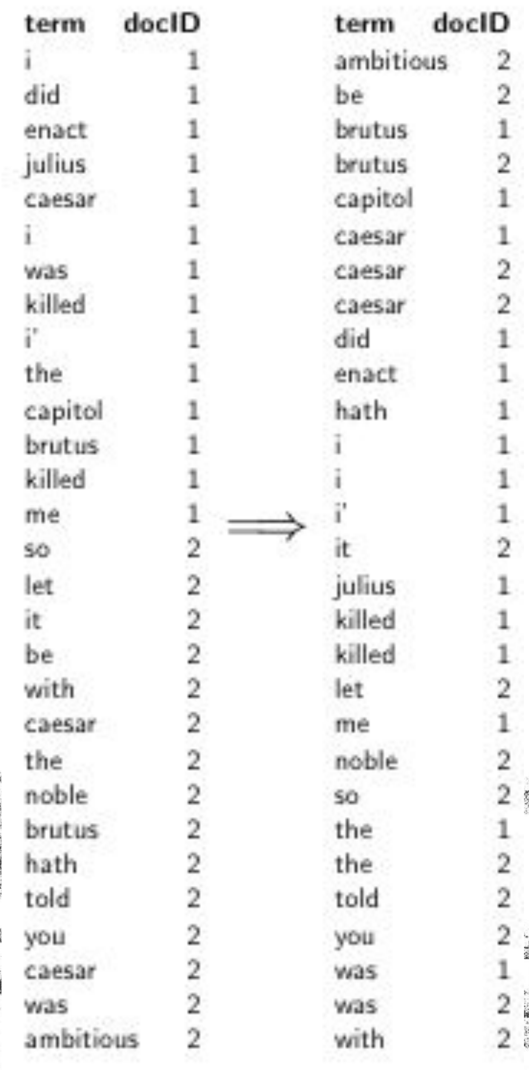
Blocked Sort Based Indexing

Goal: construct the inverted Index


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

18

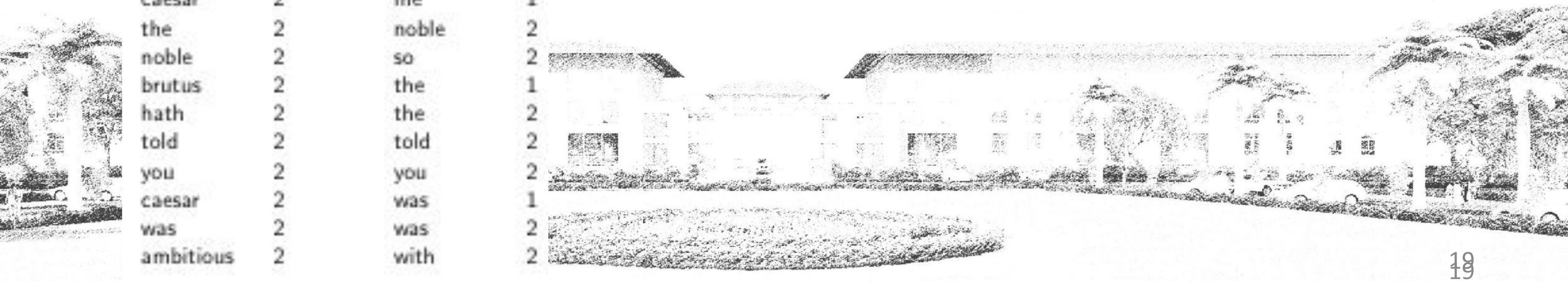
Index construction in IIR 1: Sort postings in memory



term	docID
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

$\Longrightarrow$

term	docID
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



Sort-Based Index Construction

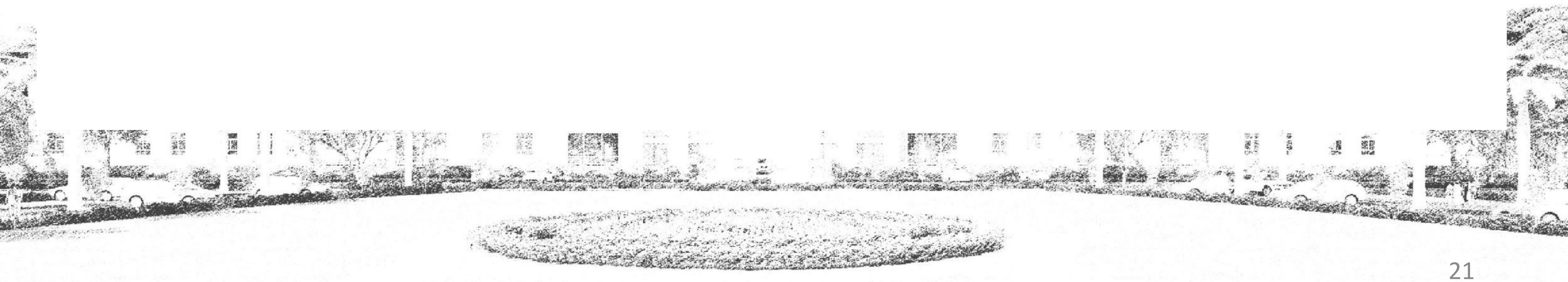
- As we build index, we parse docs one at a time
- Final postings (any term) are incomplete until the end
- Can we keep all postings in memory and then do the sort in-memory at the end?
- No, not for large collections
- At 10–12 bytes per postings entry, we need a lot of space for large collections.
- T = 100,000,000 in the case of RCV1: we can do this in memory on a typical machine
- But in-memory index construction does not scale for large collections.
- Thus: We need to store intermediate results on disk

Same algorithm for disk?

- Can we use the same index construction algorithm for larger collections, but by using disk instead of memory?

- No: Sorting T = 100,000,000 records on disk is too slow – too many disk seeks

- We need an external sorting algorithm.



"External" sorting algorithm

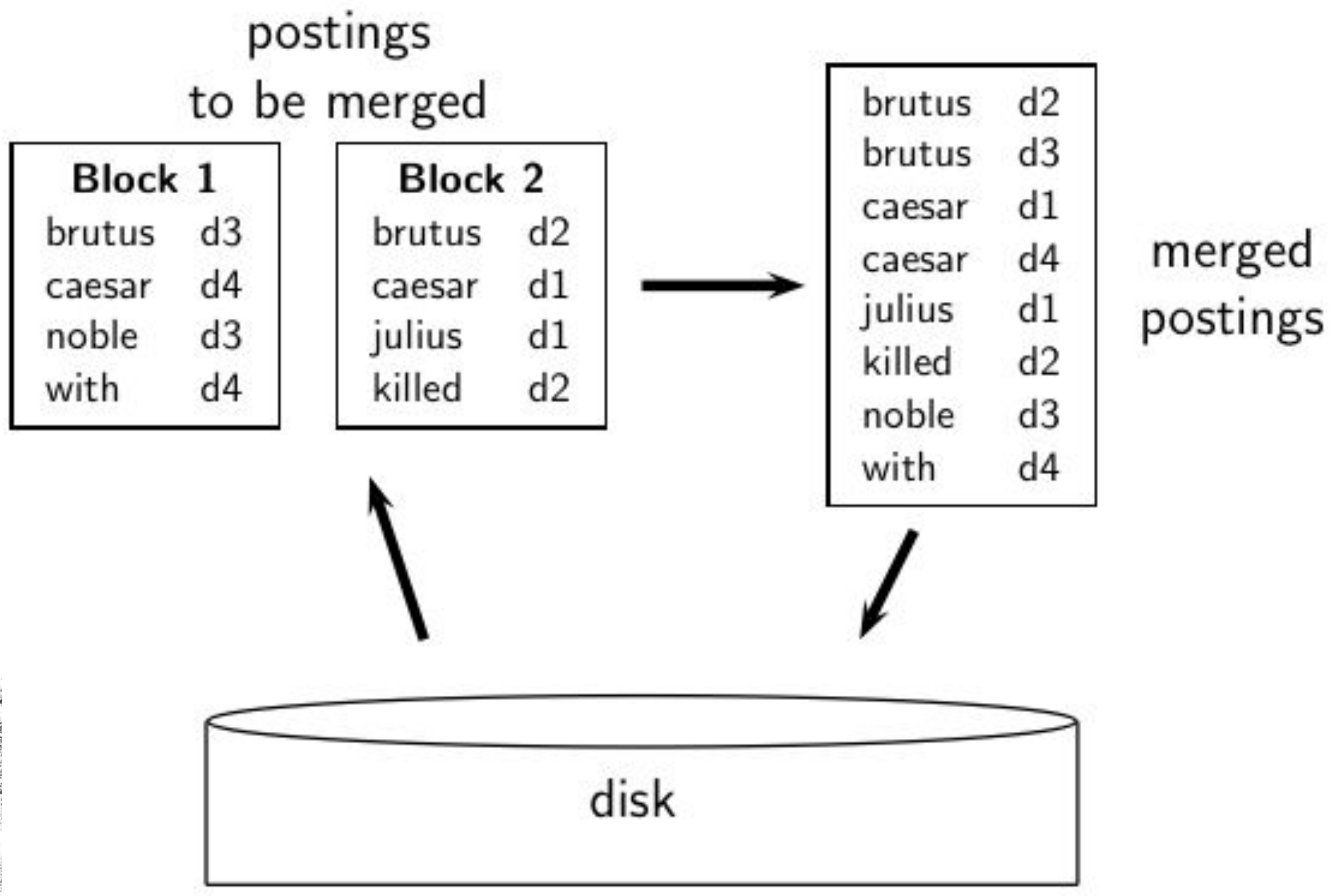
- We must sort T = 100,000,000 non-positional postings.
  - Each posting has size 12 bytes (4+4+4: termID, docID, document frequency).
- Define a block to consist of 10,000,000 such postings
  - We can easily fit that many postings into memory.
  - We will have 10 such blocks for RCV1.
- Basic idea of algorithm:
  - For each block:

    (i) accumulate postings

    (ii) sort in memory

    (iii) write to disk
- Then merge the blocks into one long sorted order.

Merging two blocks



Blocked Sort-Based Indexing

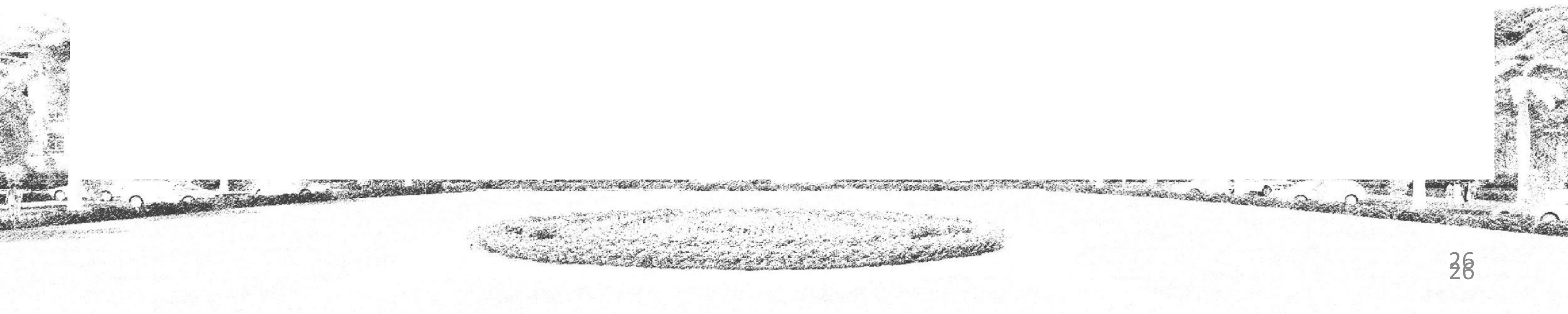
```
BSBIndexConstruction()
n ← 0
while (all documents have not been processed)
do $n \leftarrow n + 1$
    block ← ParseNextBlock()
    BSBI-Invert(block)
    WriteBlockToDisk(block, $f_n$)
MergeBlocks($f_1, \ldots, f_n; f_{\text{merged}}$)
```

- Key decision: What is the size of one block?

Single Pass In Memory Indexing (SPIMI) Algorithm

Problem with sort-based algorithm

- ✧ Our assumption was: we can keep the dictionary in memory.
- ✧ We need the dictionary (which grows dynamically) in order to implement a term to termID mapping.
- ✧ Actually, we could work with term,docID postings instead of termID,docID postings . . .
- ✧ . . . but then intermediate files become very large. (We would end up with a scalable, but very slow index construction method.)



26

Single-pass in-memory indexing

- Key idea 1: Generate separate dictionaries for each block – no need to maintain term-termID mapping across blocks.
- Key idea 2: Don’t sort. 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.

SPIMI-Invert

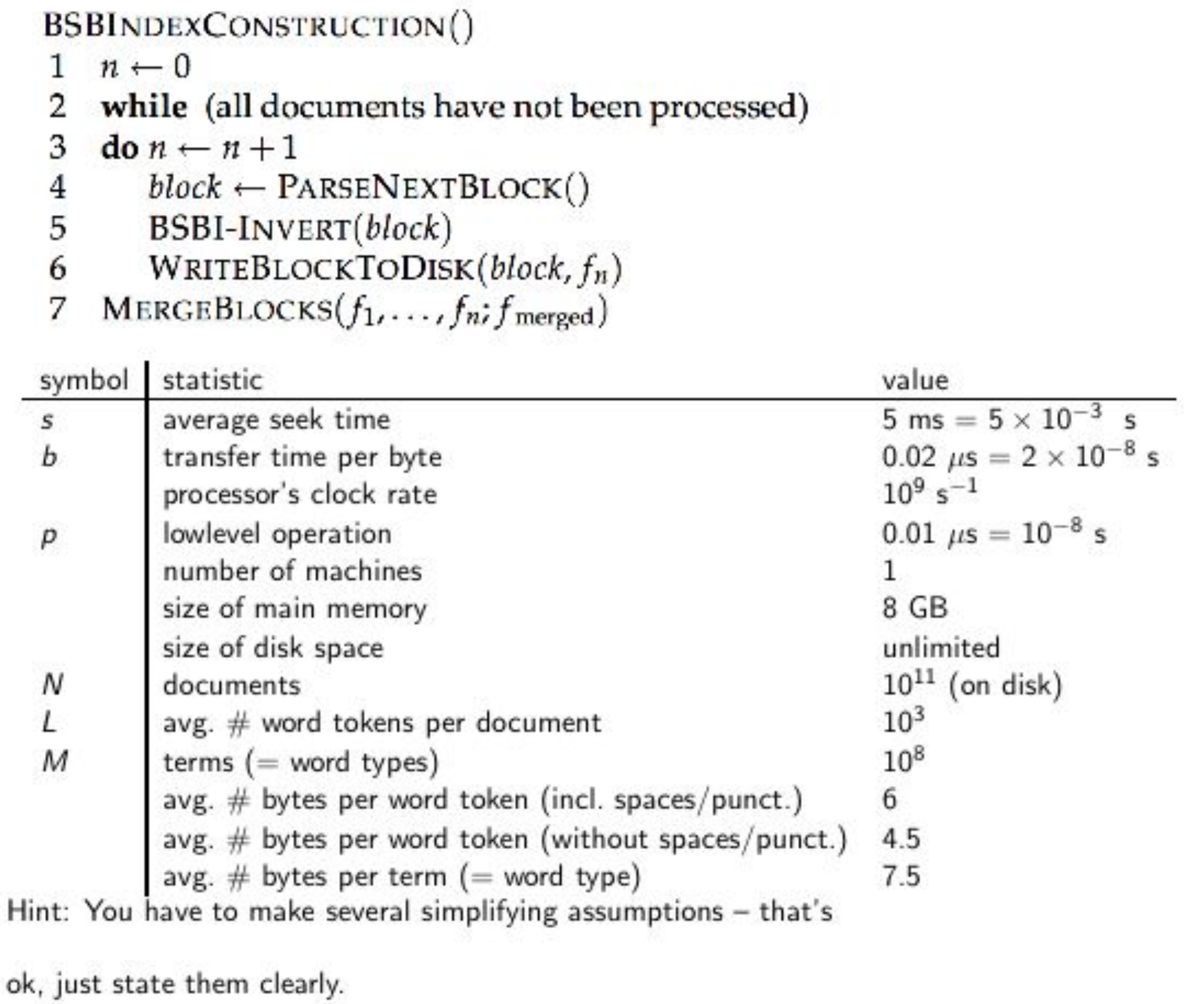
```
SPIMI-INVERT(token_stream)
output_file ← NEWFILE()
dictionary ← NEWHASH()
while (free memory available)
do token ← next(token_stream)
    if term(token) ∉ dictionary
      then postings_list ← ADDTODICTIONARY(dictionary, term(token))
      else postings_list ← GETPOSTINGSLIST(dictionary, term(token))
    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
```

Merging of blocks is analogous to BSBI.

SPIMI: Compression

- Compression makes SPIMI even more efficient.
  - Compression of terms
  - Compression of postings

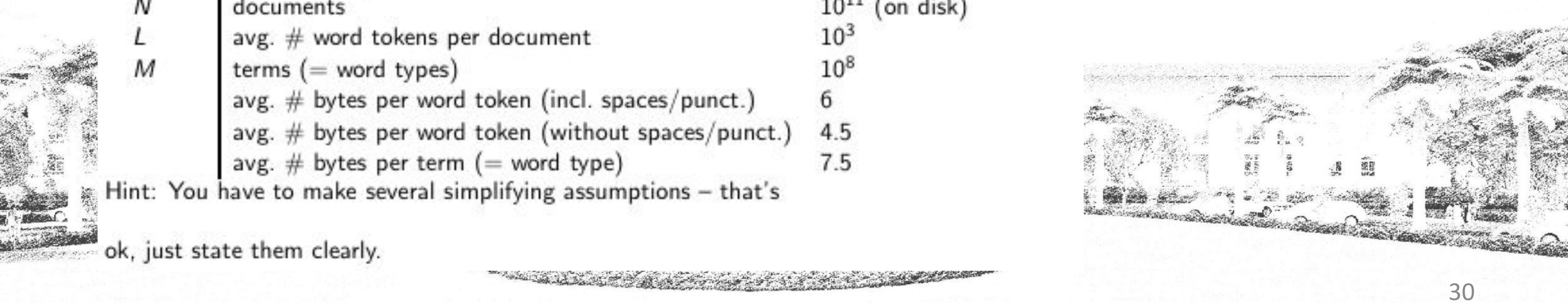
Exercise: Time 1 machine needs for Google size collection



```
BSBINDEXCONSTRUCTION()
1  $n \leftarrow 0$
2  while (all documents have not been processed)
3  do $n \leftarrow n + 1$
4      $block \leftarrow$ PARSENEXTBLOCK()
5      BSBI-INVERT($block$)
6      WRITEBLOCKTODISK($block, f_n$)
7  MERGEBLOCKS($f_1, \ldots, f_n; f_{\text{merged}}$)
```

symbol	statistic	value
s	average seek time	5 ms $= 5 \times 10^{-3}$ s
b	transfer time per byte	0.02 μs $= 2 \times 10^{-8}$ s
	processor's clock rate	10^9 s^{-1}
p	lowlevel operation	0.01 μs $= 10^{-8}$ s
	number of machines	1
	size of main memory	8 GB
	size of disk space	unlimited
N	documents	10^{11} (on disk)
L	avg. # word tokens per document	10^3
M	terms (= word types)	10^8
	avg. # bytes per word token (incl. spaces/punct.)	6
	avg. # bytes per word token (without spaces/punct.)	4.5
	avg. # bytes per term (= word type)	7.5

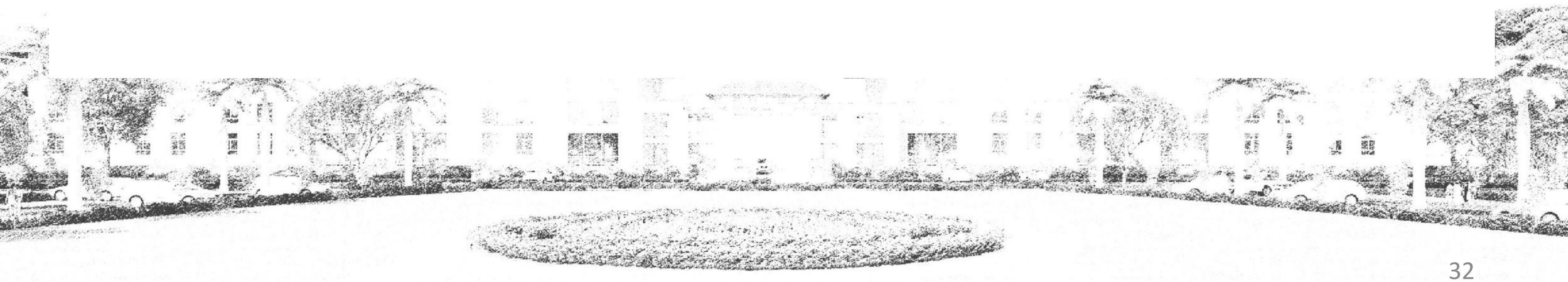
Hint: You have to make several simplifying assumptions – that's ok, just state them clearly.



Distributed Indexing

Distributed indexing

- For web-scale indexing (don't try this at home!): must use a distributed computer cluster
- Individual machines are fault-prone.
- Can unpredictably slow down or fail.
- How do we exploit such a pool of machines?



Google data centers (2007, Gartner)

- Google data centers contain commodity machines.
- Data centers are distributed all over the world.
- 1 million servers, 3 million processors/cores
- Google installs 100,000 servers each quarter.
- Based on expenditures of 200–250m dollars/year
  - 10% of the computing capacity of the world!
- If in a non-fault-tolerant system with 1000 nodes, each node has 99.9% uptime, what is the uptime of the system (assuming it does not tolerate failures)?
  - Answer: 63%
- Suppose a server will fail after 3 years. For an installation of 1m servers, what is the interval between machine failures?
  - Answer: less than two minutes

Distributed indexing

- Maintain a master machine directing the indexing job – considered “safe”
- Break up indexing into sets of parallel tasks
- Master machine assigns each task to an idle machine from a pool.

Parallel tasks

- We will define two sets of parallel tasks and deploy two types of machines to solve them:

- Parsers
- Inverters

- Break the input document collection into splits (corresponding to blocks in BSBI/SPIMI)
- Each split is a subset of documents.

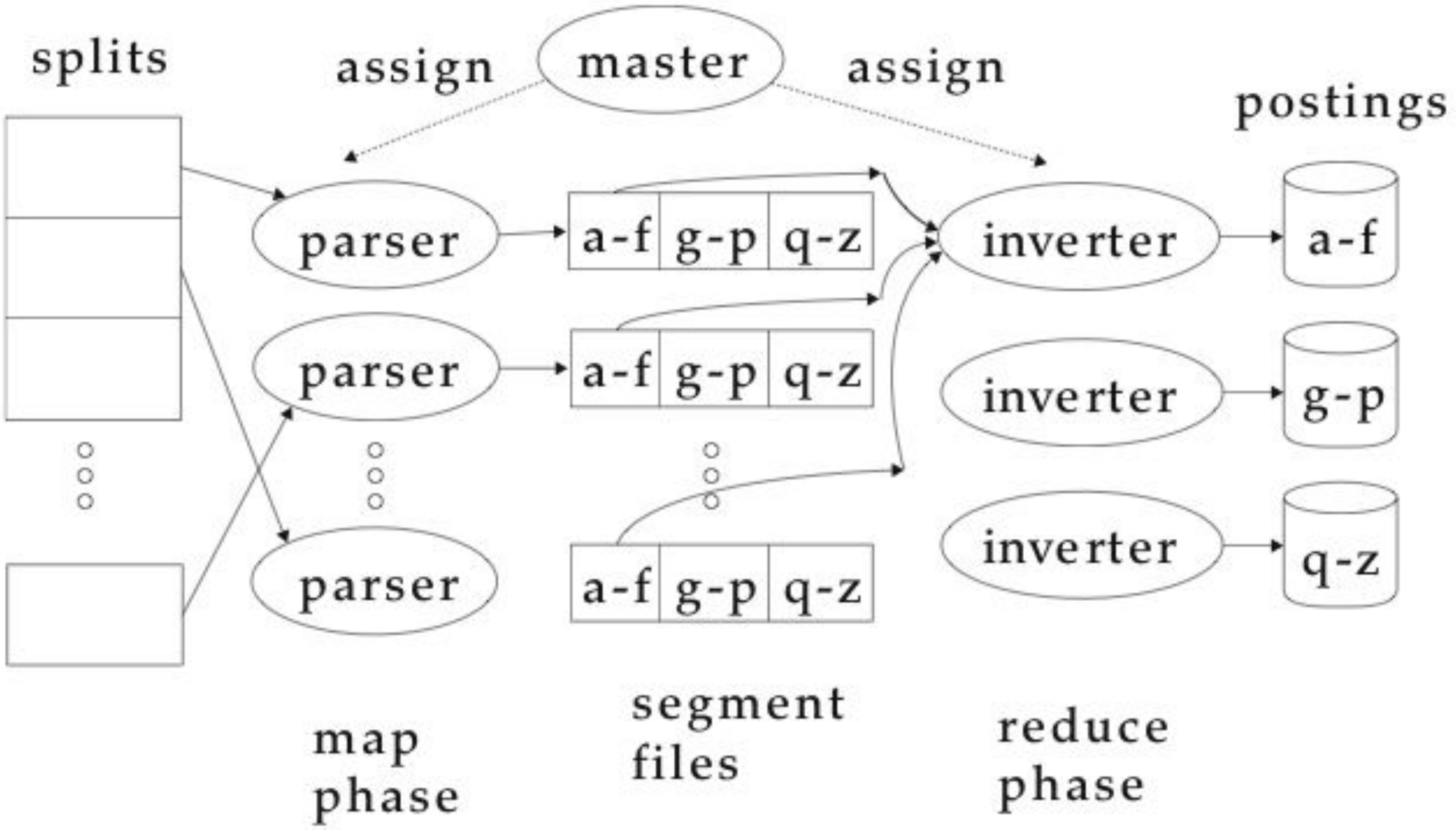
Parsers

- Master assigns a split to an idle parser machine.
- Parser reads a document at a time and emits (term,docID)-pairs.
- Parser writes pairs into j term-partitions.
- Each for a range of terms' first letters
- E.g., a-f, g-p, q-z (here: j = 3)

Inverters

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

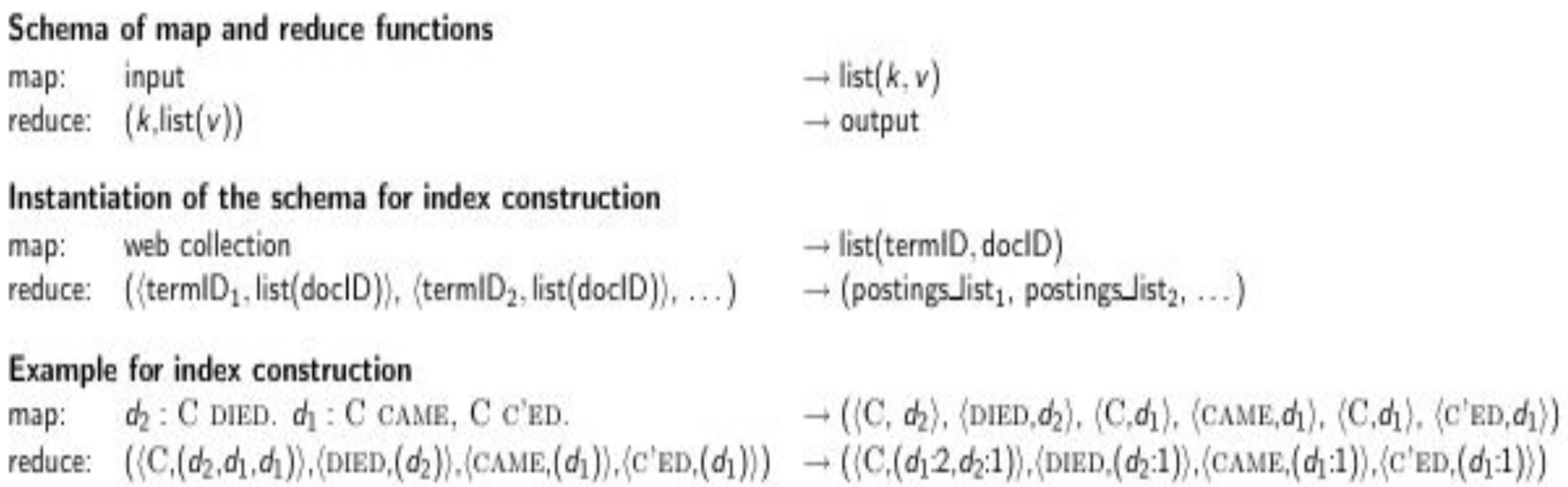
Data flow


splits
assign
master
assign
postings
parser
a-f
g-p
q-z
inverter
a-f
parser
a-f
g-p
q-z
inverter
g-p
parser
a-f
g-p
q-z
inverter
q-z
map phase
segment files
reduce phase

MapReduce

- The index construction algorithm we just described is an instance of MapReduce.
- MapReduce is a robust and conceptually simple framework for distributed computing . . .
- . . .without having to write code for the distribution part.
- The Google indexing system (ca. 2002) consisted of a number of phases, each implemented in MapReduce.
- Index construction was just one phase.
- Another phase: transform term-partitioned into document-partitioned index.

Index construction in MapReduce



Schema of map and reduce functions

map:	input	$\rightarrow$ list(k, v)
reduce:	(k,list(v))	$\rightarrow$ output

Instantiation of the schema for index construction

map:	web collection	$\rightarrow$ list(termID, docID)
reduce:	($\langle$termID$_1$, list(docID)$\rangle$, $\langle$termID$_2$, list(docID)$\rangle$, ...)	$\rightarrow$ (postings_list$_1$, postings_list$_2$, ...)

Example for index construction

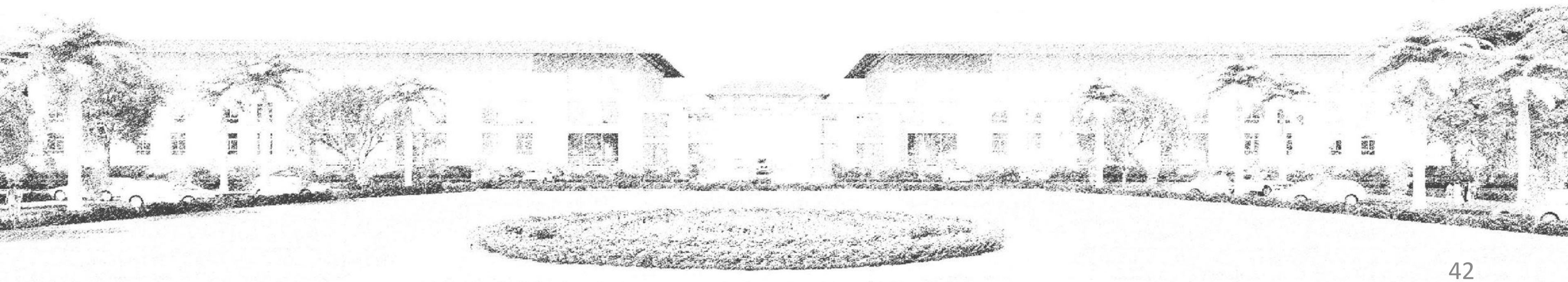
map:	d_2 : C DIED. d_1 : C CAME, C C'ED.	$\rightarrow$ ($\langle$C, $d_2\rangle$, $\langle$DIED,$d_2\rangle$, $\langle$C,$d_1\rangle$, $\langle$CAME,$d_1\rangle$, $\langle$C,$d_1\rangle$, $\langle$C'ED,$d_1\rangle$)
reduce:	($\langle$C,(d_2,d_1,d_1)$\rangle$,$\langle$DIED,(d_2)$\rangle$,$\langle$CAME,(d_1)$\rangle$,$\langle$C'ED,(d_1)$\rangle$)	$\rightarrow$ ($\langle$C,(d_1:2,d_2:1)$\rangle$,$\langle$DIED,(d_2:1)$\rangle$,$\langle$CAME,(d_1:1)$\rangle$,$\langle$C'ED,(d_1:1)$\rangle$)

Exercise

- ✧ What information does the task description contain that the master gives to a parser?
- ✧ What information does the parser report back to the master upon completion of the task?
- ✧ What information does the task description contain that the master gives to an inverter?
- ✧ What information does the inverter report back to the master upon completion of the task?

Dynamic indexing

- Up to now, we have assumed that collections are static.
- They rarely are: Documents are inserted, deleted and modified.
- This means that the dictionary and postings lists have to be dynamically modified.



Dynamic indexing: Simplest approach

- Maintain big main index on disk
- New docs go into small auxiliary index in memory.
- Search across both, merge results
- Periodically, merge auxiliary index into big index
- Deletions:
    - Invalidation bit-vector for deleted docs
    - Filter docs returned by index using this bit-vector

Issue with auxiliary and main index

- Frequent merges
- Poor search performance during index merge
  - Merging of the auxiliary index into the main index is not that costly if we keep a separate file for each postings list.
- Merge is the same as a simple append.
- But then we would need a lot of files – inefficient.
- Assumption: The index is one big file.
  - In reality: Use a scheme somewhere in between (e.g., split very large postings lists into several files, collect small postings lists in one file etc)

Logarithmic Merge

- ✧ Logarithmic merging amortizes the cost of merging indexes over time.
  - → Users see smaller effect on response times.
- ✧ Maintain a series of indexes, each twice as large as the previous one.
- ✧ Keep smallest (Z0) in memory
- ✧ Larger ones (I0, I1, . . .) on disk
- ✧ If Z0 gets too big (> n), write to disk as I0
  - ■ . . . or merge with I0 (if I0 already exists) and write merger to I1 etc.

```
LMergeAddToken($indexes, Z_0, token$)
  $Z_0 \leftarrow$ Merge($Z_0, \{token\}$)
  if $|Z_0| = n$
    then for $i \leftarrow 0$ to $\infty$
           do if $I_i \in indexes$
                then $Z_{i+1} \leftarrow$ Merge($I_i, Z_i$)
                     ($Z_{i+1}$ is a temporary index on disk.)
                     $indexes \leftarrow indexes - \{I_i\}$
                else $I_i \leftarrow Z_i$     ($Z_i$ becomes the permanent index $I_i$.)
                     $indexes \leftarrow indexes \cup \{I_i\}$
                     Break
         $Z_0 \leftarrow \emptyset$

LogarithmicMerge()
  $Z_0 \leftarrow \emptyset$     ($Z_0$ is the in-memory index.)
  $indexes \leftarrow \emptyset$
  while true
  do LMergeAddToken($indexes, Z_0$, getNextToken())
```

Binary numbers: $I_3 I_2 I_1 I_0 = 2^3 2^2 2^1 2^0$

- 0001
- 0010
- 0011
- 0100
- 0101
- 0110
- 0111
- 1000
- 1001
- 1010
- 1011
- 1100

Logarithmic Merge

- Number of indexes bounded by O(log T) (T is total number of postings read so far)
- So query processing requires the merging of O(log T) indexes
- Time complexity of index construction is O(T log T)
- because each of T postings is merged O(log T) times.
    - Auxiliary index: index construction time is O(T^2) as each posting is touched in each merge
- Suppose auxiliary index has size a

$$a + 2a + 3a + 4a + \ldots + na = a\frac{n(n+1)}{2} = O(n^2)$$

- So logarithmic merging is an order of magnitude more efficient

Dynamic indexing at large search engines

✧ Often a combination
- Frequent incremental changes
- Rotation of large parts of the index that can then be swapped in
- Occasional complete rebuild (becomes harder with increasing size – not clear if Google can do a complete rebuild)

Acknowledgements

Thanks to ALL RESEARCHERS:

1. Introduction to Information Retrieval Manning, Raghavan and Schutze, Cambridge University Press, 2008.
2. Search Engines Information Retrieval in Practice W. Bruce Croft, D. Metzler, T. Strohman, Pearson, 2009.
3. Information Retrieval Implementing and Evaluating Search Engines Stefan Büttcher, Charles L. A. Clarke and Gordon V. Cormack, MIT Press, 2010.
4. Modern Information Retrieval Baeza-Yates and Ribeiro-Neto, Addison Wesley, 1999.
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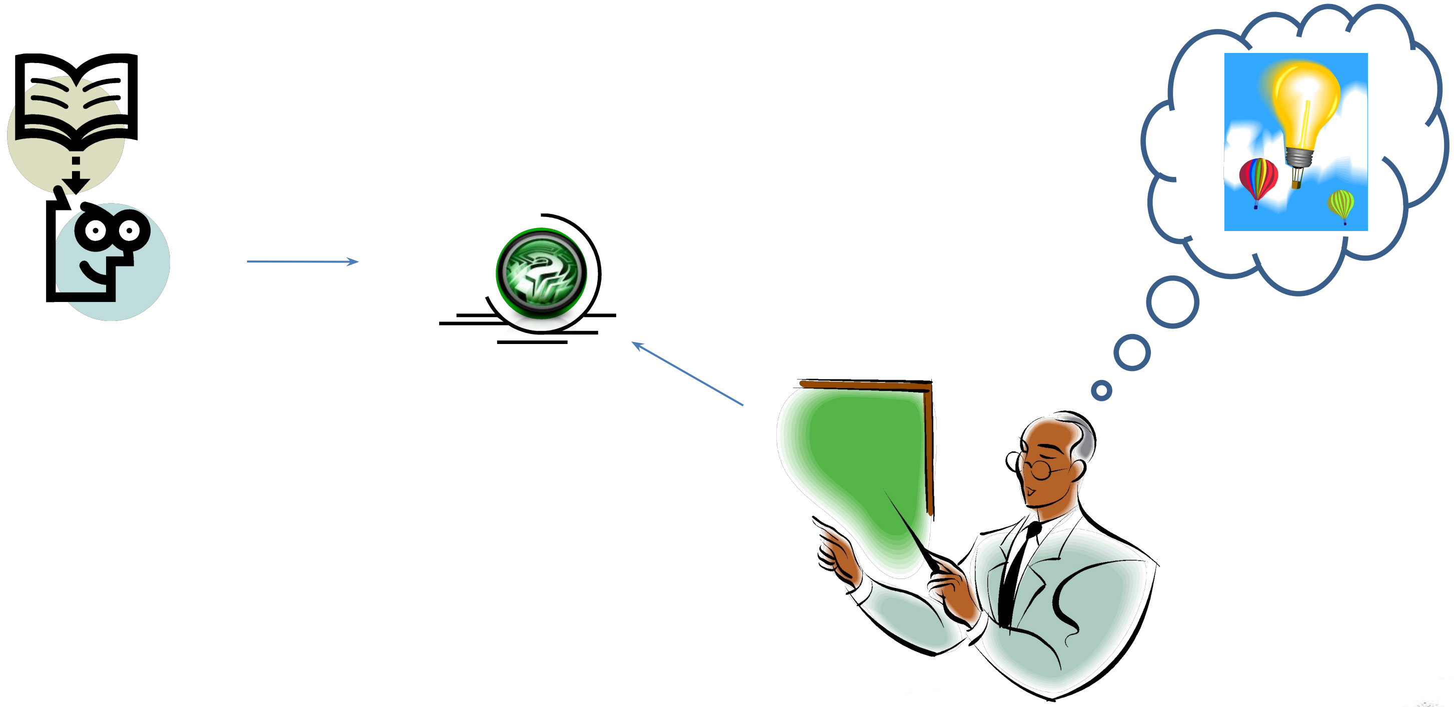

… Questions ???