CS3245

Information Retrieval

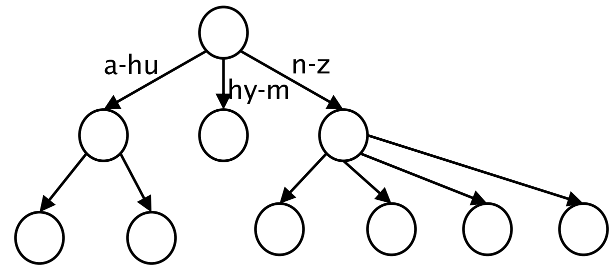
5

Lecture 5: Index Construction

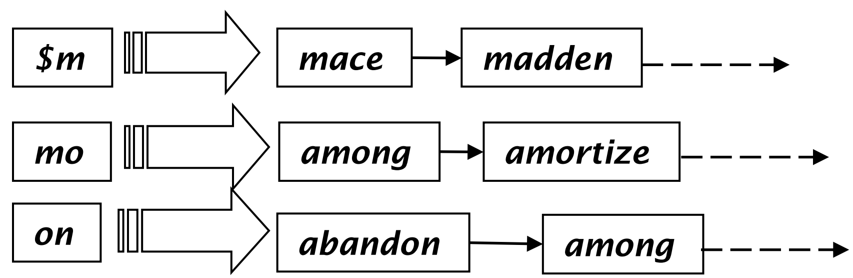
Live Q&A
https://pollev.com/jin

Last Time

- Dictionary data structures



- Tolerant retrieval
  - Wildcards
  - Spelling correction
  - Soundex



Today: Index construction

- How to make index construction scalable?
  1. BSBI (simple method)
  2. SPIMI (more realistic)
  3. Distributed Indexing

- How to handle changes to the index?
  1. Dynamic Indexing

Hardware basics

Many design decisions in information retrieval are based on the characteristics of hardware

Especially with respect to the bottleneck:

Hard Drive Storage

- Seek Time – time to access a random location
- Transfer Time – time to transfer a data block

Hardware basics

- Disk seeks: No data is transferred from disk during seeks
  - Better to transfer one large (sequential) chunk of data than many small (scattered) chunks.
  - Other factors: Caching, I/O controller

- Memory is ***much*** faster but **limited in quantity**.
  - Servers used in IR systems now typically have tens of GB of main memory.
  - Available space on disk is several (2–3) orders of magnitude larger.

Hardware assumptions

symbol	statistic	value
s	average seek time	8 ms = 8×10^{-3} s
b	transfer time per byte	0.006 μs = 6×10^{-9} s
	processor's clock rate	34^{9} s^{-1} (Intel i7 6th gen)
p	low-level operation (e.g., compare & swap a word)	0.01 μs = 10^{-8} s
	size of main memory	8 GB or more
	size of disk space	1 TB or more

Stats from a 2016 HP Z Z240 3.4GHz Black SFF i7-6700

Hardware assumptions (Flash SSDs)

symbol	statistic	value
s	average seek time	.1 ms = 1×10^{-4} s
b	transfer time per byte	0.002 μs = 2×10^{-9} s

100x faster seek,
3x faster transfer time.
(But price 8x more per GB of storage)

WD 4 TB Black
S$ 311 (circa Jan 2016)

Samsung 850 Evo (1 TB)
S$ 630 (circa Jan 2016)

Seek and transfer time combined in another industry metric: IOPS

RCV1: Our collection for this lecture

- The successor to the Reuters-21578, which you used for your homework assignment. Larger by 35 times.
  - Not really large enough either, but it is publicly available and is a more plausible example.

- One year of Reuters newswire (part of 1995 and 1996)

Reuters RCV1 statistics

symbol	statistic	value
N	documents	800,000
L	avg. # tokens per doc	200
M	terms (= vocabulary size)	400,000
	avg. # bytes per term	7.5
T	term-docID pairs (= tokens)	100,000,000

Recap: Index Construction (Week 2)

- Sequence of (Term, 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	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

Recap: Index Construction (Week 2)

- Sort by terms
  - And then docID

We focus on this sort step.
We have 100M pairs to sort.

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

→

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

Scaling index construction

- At **~11.5** bytes per pair: ~7.5 bytes for term + 4 bytes for docID

- T = 100,000,000 in the case of RCV1: ~1.1GB
  - So … we can do this easily in memory nowadays, but typical collections are much larger. E.g. the *New York Times* provides an index of >150 years of newswire

- Thus, we need to make use of the **harddisk**.

BSBI: Blocked sort-based Indexing

- 8-byte (4+4) records *(termID, docID).*
  - 400,000 terms
  - Create a **dictionary** to map **terms** to **termIDs** of 4 bytes

Term	TermID
noble	22
Caesar	1250
killed	952
Brutus	3391
…	…

- These are generated as we parse docs.
- Must now sort 100M 8-byte records by *termID*.

BSBI: Blocked sort-based Indexing

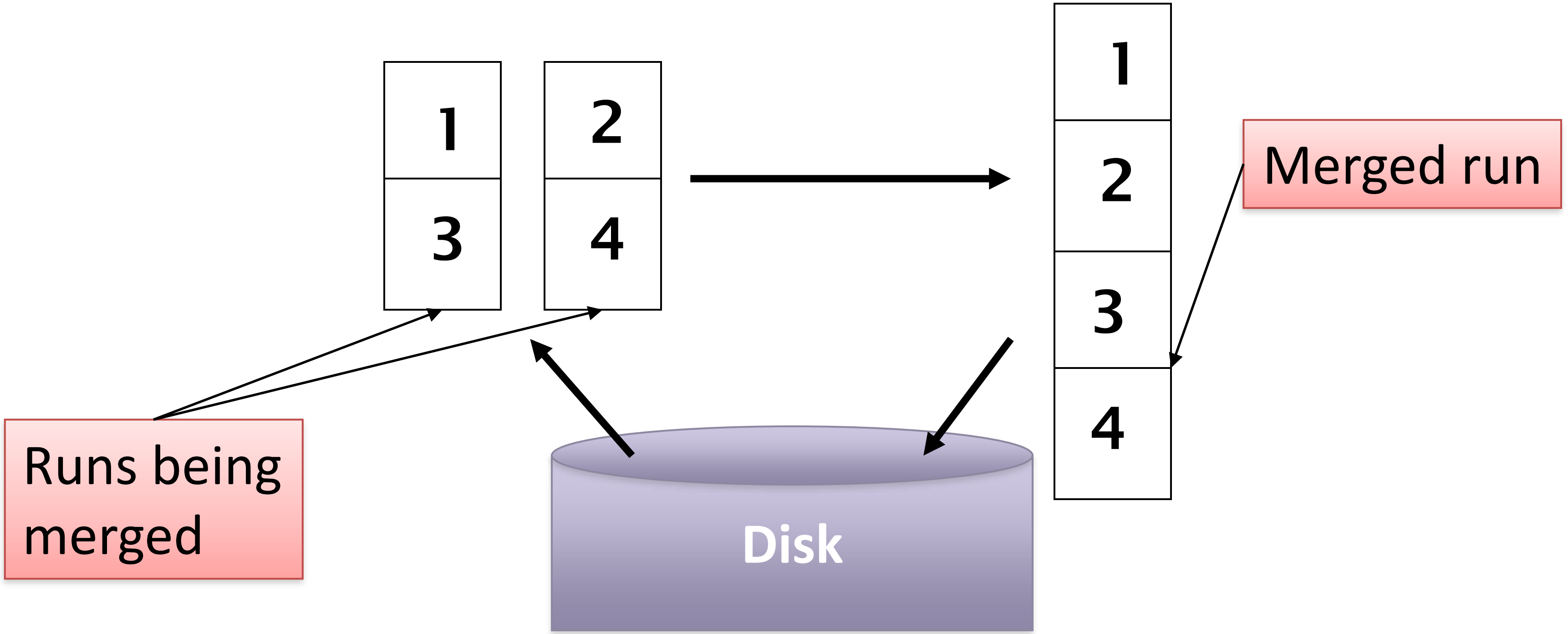
- Define a Block as ~ **10M** such records
  - Can easily fit a couple into memory.
  - Will have **10** such blocks for our collection.

- Basic idea of algorithm:
  - Map the terms to term ID during generation
  - Accumulate records for each block, **sort**, create the posting lists and write to disk.
  - **Merge** the blocks into bigger blocks recursively.
  - Reverse the mapping

```
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)
```

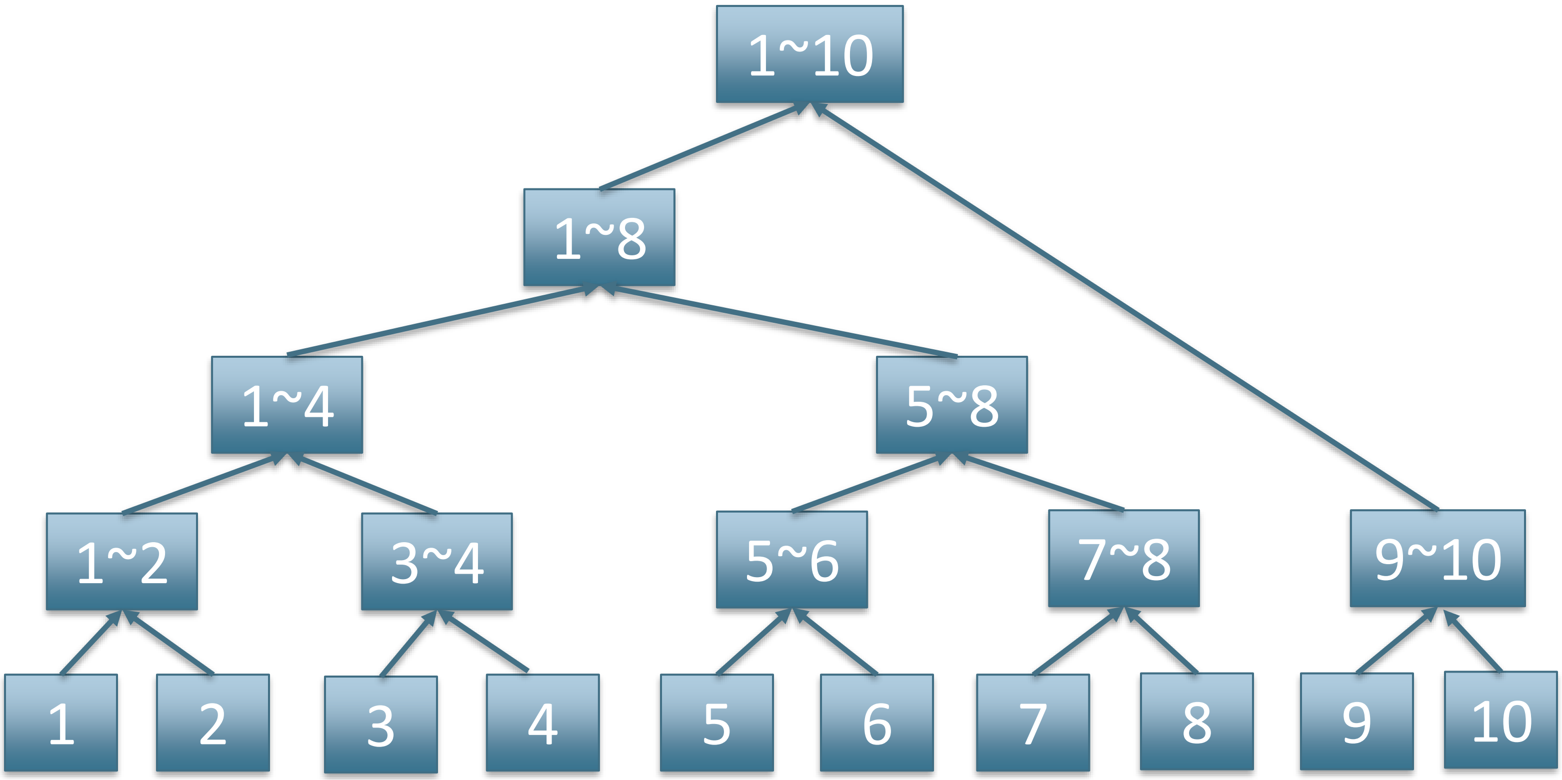
How to merge the sorted runs?

- Can do binary merges,
- Read into memory runs **in blocks of 10M**, merge, write back.



How to merge the sorted runs?

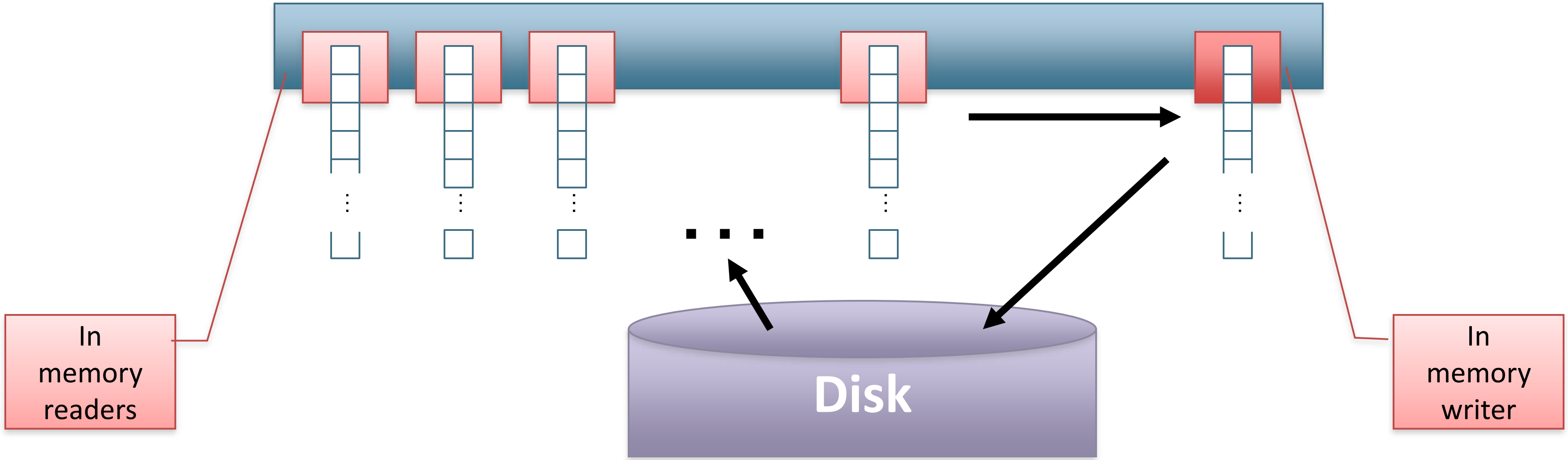
- 2-way Merge: Merge tree of $\log_2 10$ ~= 4 layers.



How to merge the sorted runs?

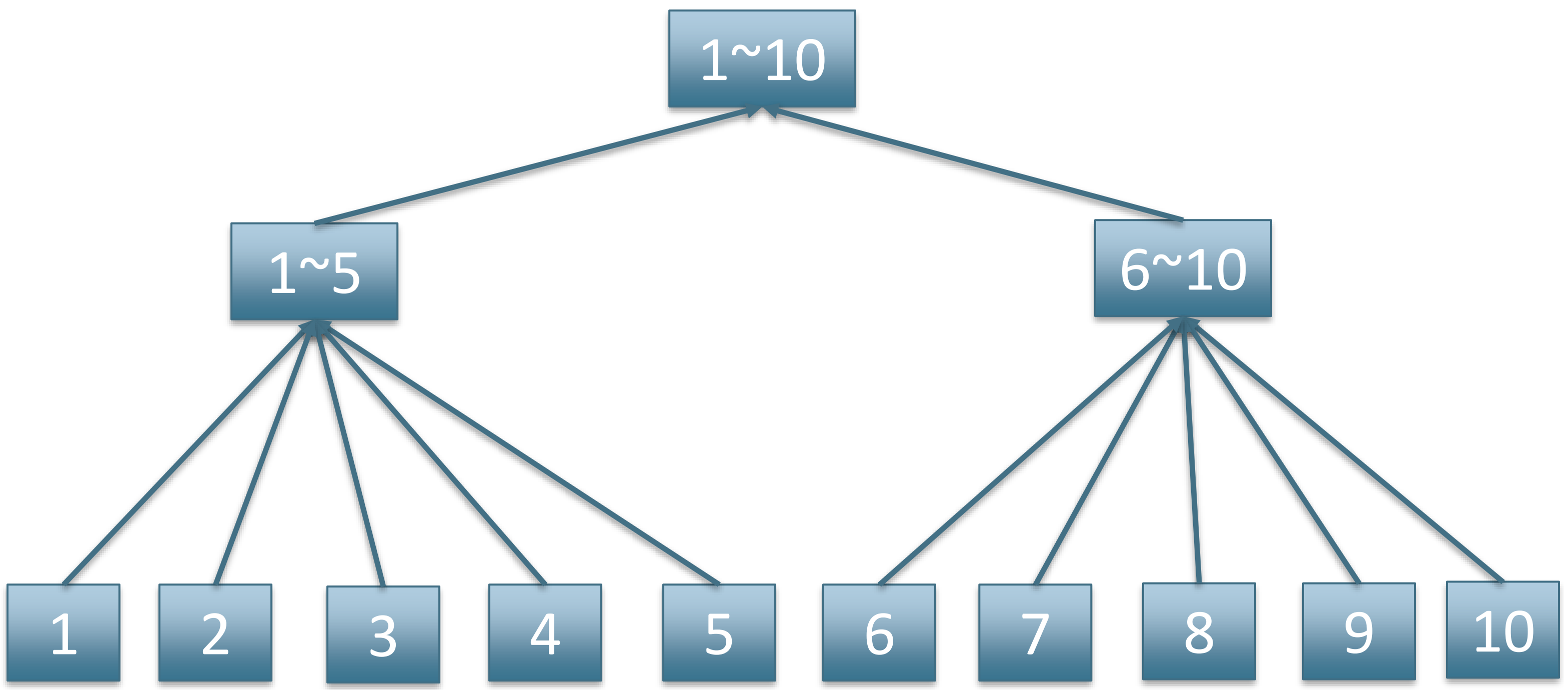
Second method (better):

- It is more efficient to do a *n*-way merge, where you are reading from all blocks simultaneously
- Providing you read **decent-sized chunks** of each block into memory and then write out **a decent-sized output chunk**, then your efficiency isn't lost by disk seeks



How to merge the sorted runs?

- 5-way Merge: Merge tree of $\log_5 10 = 2$ layers.



Remaining problems with BSBI

- The dictionary must fit into memory
  - Hard to guarantee since it grows dynamically
  - May end up crashing if the dictionary is too big

- A fixed block size must be decided in advance
  - Too small: could be slow since more blocks need to be processed.
  - Too big: may end up crashing if too much memory is used by other applications.

SPIMI: Single-pass in-memory indexing

- **Key idea 1**: Generate an index (i.e., a **real** dictionary + postings lists) as the pairs are processed
- **Key idea 2**: Go as far as memory allows, write out the index and then merge later
- Advantages:
  - No need to keep a single dictionary in memory
  - No need to wait for a fixed-size block to be filled up
  - Able to adapt to the availability of memory

SPIMI: Single-pass in-memory indexing

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
…	…

Hash the pairs into the index

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

Inverted Index (Hash Table in memory)

Sort terms and write out

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

Inverted Index (Files on disk)

Merge with other blocks later

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: Efficiency

- Faster than BSBI
  - No sorting of pairs
  - Only sorting of dictionary terms
- Even faster with compression
  - Compression of terms
  - Compression of postings

More about this in W6.

DISTRIBUTED INDEXING

Distributed indexing

- For web-scale indexing (don’t try this at home!):
  - must use a distributed computing cluster
- Individual machines are fault-prone
  - Can unpredictably slow down or fail

How do we exploit such a pool of machines?

Google Data Centers

- Google data centers mainly contain commodity machines, and are distributed worldwide.
- One here in Jurong West (~200K servers back in 2011)
- Must be fault tolerant. Even with 99.9+% uptime, there often will be one or more machines down in a data center.
- As of 2001, they have fit their entire web index in-memory (RAM; of course, spread over many machines)

https://youtu.be/XZmGGAbHqa0

http://www.gizmodo.com.au/2010/04/googles-insane-number-of-servers-visualised/

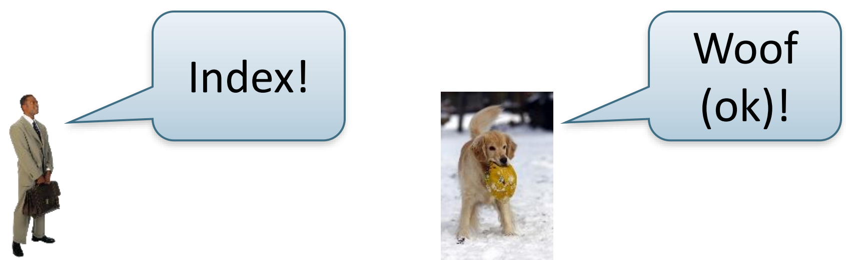
http://www.google.com/about/datacenters/inside/streetview/

http://www.straitstimes.com/business/10-things-you-should-know-about-google-data-centre-in-jurong

Architecture of distributed indexing

- Maintain a *master* machine directing the indexing job – considered "safe".
  - Master nodes can fail too!

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



Parallel tasks

- We will use two sets of parallel tasks
  - Parsers 
  - Inverters 
- Break the input document collection into *splits*
- Each split is a subset of documents (corresponding to blocks in BSBI/SPIMI)

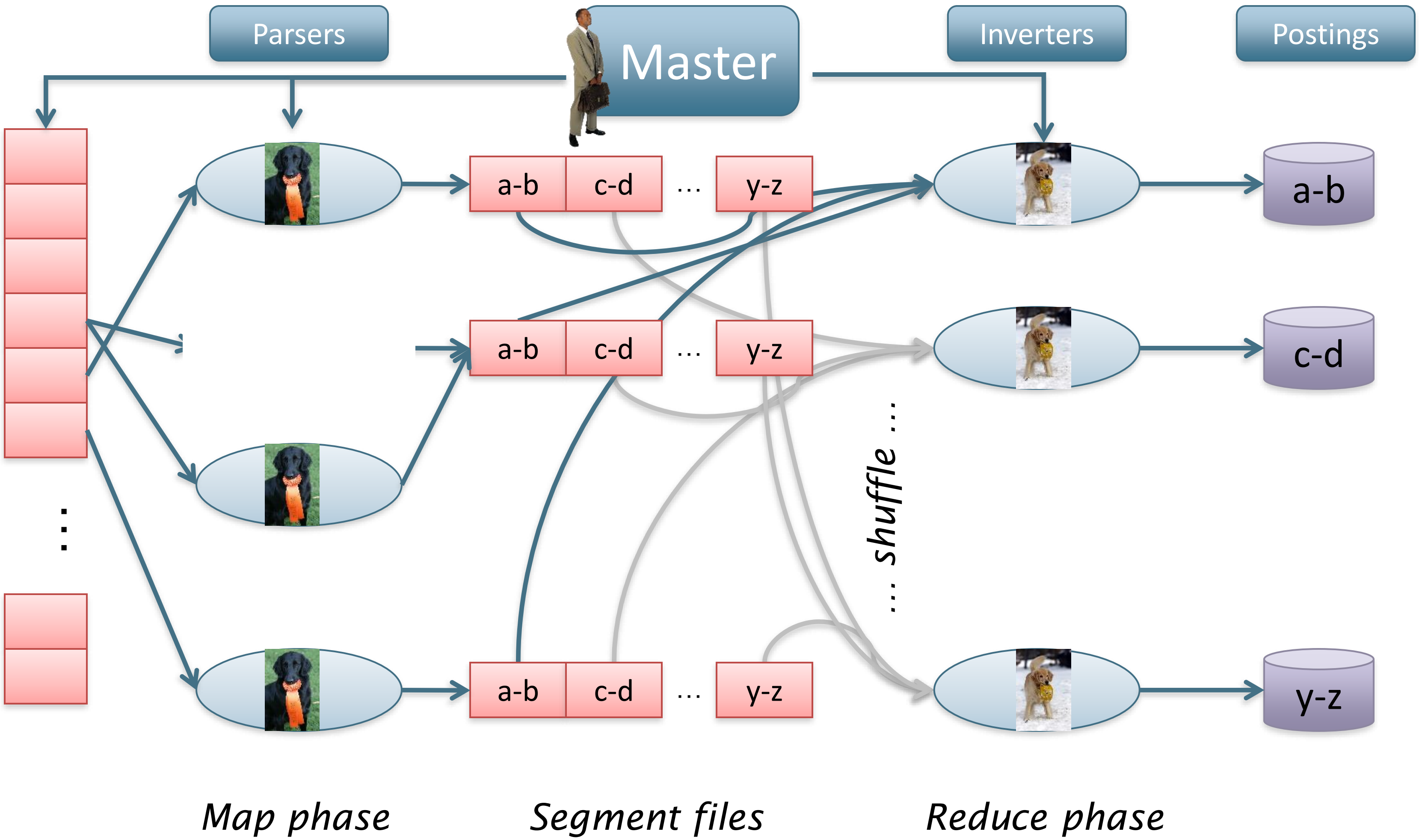
Parsers

- Master assigns a split to an idle parser machine
- Parser reads a document at a time and emits (term, doc) 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.
  - (e.g., ***a-b, c-d, …, y-z***) – here *j* = 13.
- Now to complete the index inversion

Inverters 

- An inverter collects all (term,doc) pairs (= postings) for one term-partition.
- Sorts and writes to postings lists

Data flow


Parsers
Master
Inverters
Postings
a-b
c-d
…
y-z
… shuffle …
Map phase
Segment files
Reduce phase

MapReduce

- The index construction algorithm we just described is an instance of MapReduce.
- MapReduce (Dean and Ghemawat 2004) is a robust and conceptually simple framework for distributed computing
  … without having to write code for the distribution part.
- They describe the Google indexing system (ca. 2002) as consisting of a number of phases, each implemented in MapReduce.

MapReduce for indexing

Schema of map and reduce functions

- **map**: input → list(k, v) **reduce**: (k, list(v)) → output

Instantiation of the schema for index construction

- **map**: **blocks of** web collection → list(term, docID) **in segment files**

- **reduce**: (<term1, list(docID)>, <term2, list(docID)>, …) **from segment files for the same partition** → **consolidated blocks of** (term1: postings list1, term 2: postings list2, …)

MapReduce

- **map**
  - d1 : Caesar came, Caesar conquered. d2 : Caesar died →
  - (caesar, d2), (died,d2), (caesar, d1), (came, d1), (caesar, d1), (conquered, d1)
- **Reduce**
  - <caesar, (d2, d1, d1)>, <died, (d2)>, <came, (d1)>, <conquered, (d1)> →
  - <caesar, (d1, d2)>, <came, (d1)>, <conquered, (d1)>, <died, (d2)>

DYNAMIC INDEXING

Dynamic indexing

- Up to now, we have assumed that collections are static.
- In practice, they rarely are!
  - 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 (yet impractical) approach: re-index every time

2^{nd} simplest approach

- Two indexes
  - One "big" main index (let say **I**)
  - One "small" (in memory) auxiliary index (let say **Z**)
- Mechanism
  - Add: new docs goes to the auxiliary index
  - Delete: maintain a list of deleted docs
  - Update: delete + add
  - Search: search both, merge results and omit deleted docs
- Need to perform **linear merge** when auxiliary index is too large.

Linear Merge

- Let say…
  - The capacity of the auxiliary index **Z** is **n** pairs of (term, docID)
  - The main index **I** can be arbitrarily large
  - Initially both are empty
- The algorithm
  - Once Z is full, write out **Z** and merge with **I**

Linear Merge

- Example:
  - The 1st set of **n** pairs, write out **Z** (**n** items) and merge with **I** (**0** items) → merge **n + 0 = n** items into **I**
  - The 2nd set of **n** pairs, write out **Z** (**n** items) and merge with **I** (**n** items) → merge **n + n** = **2*n** items into **I**
  - The 3rd set of **n** pairs, write out **Z** (**n** items) and merge with **I** (**2*n** items) → merge **n + 2*n = 3*n** items into **I**
  - The 4th set of **n** pairs, write out **Z** (**n** items) and merge with **I** (**3*n** items) → merge **n + 3*n = 4*n** items into **I**
  - …

Linear Merge

- Let say there are a total **T** pairs for which require **k** merges (i.e., k = T / n)

- Cost of merging
  - n + 2 * n + 3 * n + 4 * n … + k * n
    = (k * (k+1) / 2) * n
    ~= nk^2
    ~= **$O(T^2)$**

Logarithmic merge

- Idea: maintain a series of indexes
  - Z: In memory, with the same capacity as I_0 (= n)
  - I_0, I_1, …: on disk, each twice as large as the previous one.

Loop for log levels

- If Z gets too big (= n), write to disk as I_0,
  or merge with I_0 (if I_0 already exists) as I_1
- Either write I_1 to disk as I_1,
  or merge with I_1 (if I_1 already exists) to form I_2

  … etc.

Logarithmic merge

- Example:
  - The 1st set of **n** pairs, write out **Z** (**n** items) as $\mathbf{I_0}$
  - The 2nd set of **n** pairs, write out **Z** (**n** items) but $\mathbf{I_0}$ already exists → merge **n + n** = **2*n** items into $\mathbf{I_1}$ (and $\mathbf{I_0}$ is gone)
  - The 3rd set of **n** pairs, write out **Z** (**n** items) as $\mathbf{I_0}$
  - …

	I_0	I_1	I_2
0	0	0	0
n	1	0	0
2*n	0	1	0
3*n	1	1	0
4*n	0	0	1

The presence (1) or absence (0) of the indexes on disk

Logarithmic merge

- Example:
  - …
  - The 4th set of **n** pairs, write out **Z** (**n** items) but $\mathbf{I_0}$ already exists → merge **n + n** = **2*n** items into a new index $\mathbf{I_1}$ but $\mathbf{I_1}$ already exists → merge **2*n + 2*n = 4*n** items into a new index $\mathbf{I_2}$ (and $\mathbf{I_0}$ and $\mathbf{I_1}$ are gone).

	I_0	I_1	I_2
0	0	0	0
n	1	0	0
2*n	0	1	0
3*n	1	1	0
4*n	0	0	1

The presence (1) or absence (0) of the indexes on disk

```
LMergeAddToken(indexes, Z_0, token)
Z_0 ← Merge(Z_0, {token})
if |Z_0| = n
  then for i ← 0 to ∞
         do if I_i ∈ indexes
              then Z_{i+1} ← Merge(I_i, Z_i)
                     (Z_{i+1} is a temporary index on disk.)
                   indexes ← indexes − {I_i}
              else I_i ← Z_i      (Z_i becomes the permanent index I_i.)
                   indexes ← indexes ∪ {I_i}
                   Break
       Z_0 ← ∅
```

```
LogarithmicMerge()
Z_0 ← ∅      (Z_0 is the in-memory index.)
indexes ← ∅
while true
do LMergeAddToken(indexes, Z_0, getNextToken())
```

Logarithmic merge

- Cost of merging
  - Each posting is touched *O(log* T) times, so complexity is *O(T log T)*
  - E.g., let n = 4, T = 32, the first pair is touched 4 times (as compared to 8 times in linear merge)
- So logarithmic merge is much more efficient for indexing
- But query processing now is slower
  - Merging results from *O(log T)* indexes (as compared to 2)

Summary

- Indexing
  - Both basic as well as important variants
    - BSBI – sort key values to merge, needs dictionary
    - SPIMI – build mini indexes and merge them, no dictionary
  - Distributed
    - Described MapReduce architecture – a good illustration of distributed computing
  - Dynamic
    - Tradeoff between querying and indexing complexity

Resources for today's lecture

- Chapter 4 of IIR
- MG Chapter 5
- Original publication on MapReduce: Dean and Ghemawat (2004)
- Original publication on SPIMI: Heinz and Zobel (2003)