Lecture 2: Data structures and Algorithms for Indexing

Information Retrieval
Computer Science Tripos Part II

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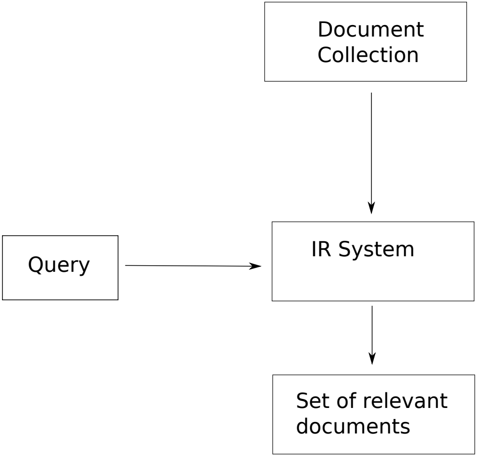
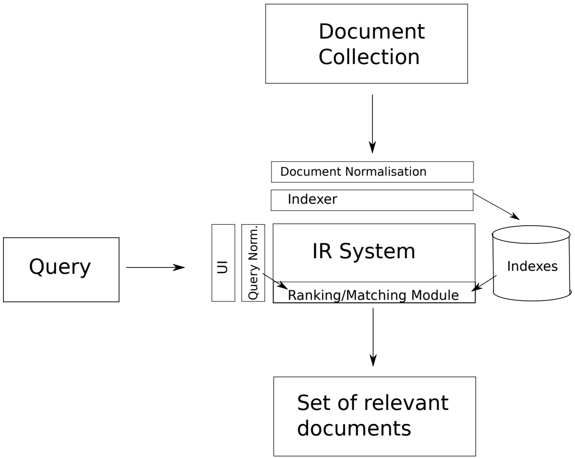
[1]Adapted from Simone Teufel's original slides

IR System Components



IR System Components



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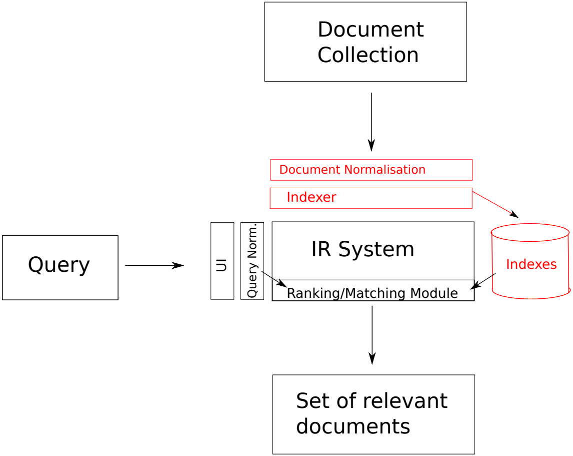


Today: The indexer

Overview

1. Index construction
   - Postings list and Skip lists
   - Single-pass Indexing
2. Document and Term Normalisation
   - Documents
   - Terms
   - Reuter RCV1 and Heap's Law

Index construction

The major steps in inverted index construction:

- Collect the documents to be indexed.
- Tokenize the text.
- Perform linguistic preprocessing of tokens.
- Index the documents that each term occurs in.

Example: index creation by sorting

Doc 1:
I did enact Julius Caesar: I was killed i' the Capitol;Brutus killed me.

⟹ Tokenisation

Doc 2:
So let it be with Caesar. The noble Brutus hath told you Caesar was ambitious.

⟹ Tokenisation

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

⟹ Sorting

Term (sorted)	docID
ambitious	2
be	2
brutus	1
brutus	2
capitol	2
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	2
let	2
me	1
noble	2
so	2
the	1
the	2
told	2
you	2
was	1
was	1
with	2

Index creation; grouping step ("uniq")

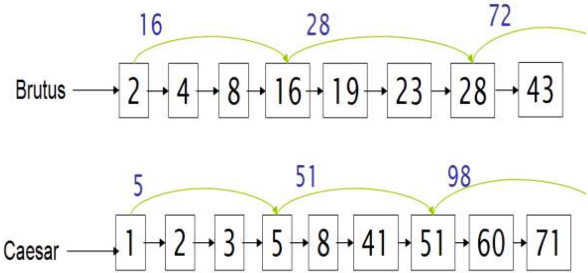
Term & doc. freq.			Postings list
ambitious	1	→	2
be	1	→	2
brutus	2	→	1 → 2
capitol	1	→	1
caesar	2	→	1 → 2
did	1	→	1
enact	1	→	1
hath	1	→	2
I	1	→	1
i'	1	→	1
it	1	→	2
julius	1	→	1
killed	1	→	1
let	1	→	2
me	1	→	1
noble	1	→	2
so	1	→	2
the	2	→	1 → 2
told	1	→	2
you	1	→	2
was	2	→	1 → 2
with	1	→	2

- Primary sort by term (dictionary)
- Secondary sort (within postings list) by document ID
- Document frequency (= length of postings list):
  - for more efficient Boolean searching (later today)
  - for term weighting (lecture 4)
- keep Dictionary in memory
- keep Postings List (much larger) on disk

Data structures for Postings Lists

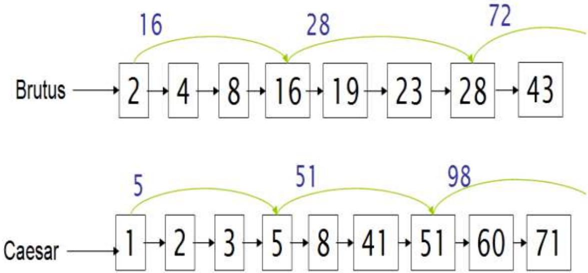
- Singly linked list
  - Allow cheap insertion of documents into postings lists (e.g., when recrawling)
  - Naturally extend to skip lists for faster access
- Variable length array
  - Better in terms of space requirements
  - Also better in terms of time requirements if memory caches are used, as they use contiguous memory
- Hybrid scheme: linked list of variable length array for each term.
  - write posting lists on disk as contiguous block without explicit pointers
  - minimises the size of postings lists and number of disk seeks

Optimisation: Skip Lists



- Some postings lists can contain several million entries
- Check skip list if present to skip multiple entries
- $sqrt(L)$ Skips can be placed evenly for a list of length L.

Tradeoff Skip Lists



- Number of items skipped vs. frequency that skip can be taken
- More skips: each pointer skips only a few items, but we can frequently use it.
- Fewer skips: each skip pointer skips many items, but we can not use it very often.
- Skip pointers used to help a lot, but with today's fast CPUs, they don't help that much anymore.

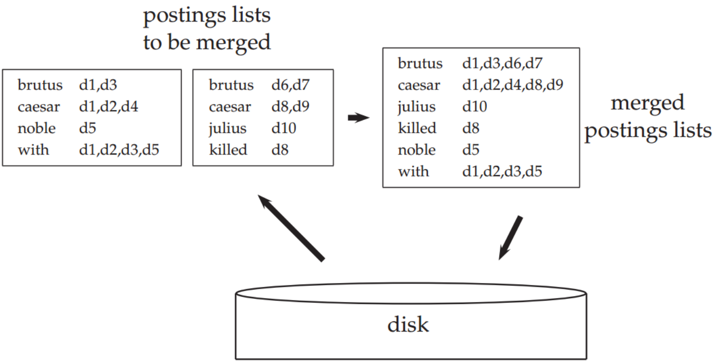
Algorithm: single-pass in-memory indexing or SPIMI

- As we build index, we parse docs one at a time.
- The final postings for any term are incomplete until the end.
- But for large collections, we cannot keep all postings in memory and then sort in-memory at the end
- We cannot sort very large sets of records on disk either (too many disk seeks, expensive)
- Thus: We need to store intermediate results on disk.
- We need a scalable Block-Based sorting algorithm.

Single-pass in-memory indexing (1)

- Abbreviation: SPIMI
- Key idea 1: Generate separate dictionaries for each block.
- Key idea 2: 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.
- Worked example!

Single-pass in-memory indexing (2)



Single-pass in-memory indexing (3)

- We could save space in memory by assigning term-ids to terms for each block-based dictionary
- However, we then need to have an in-memory term-term-id mapping which often does not fit in memory (on a single machine at least)
- This approach is called *blocked sort-based indexing* BSBI and you can read about it in the book (Chapter 4.2)

Overview

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- To build an inverted index, we need to get from
  - Input: $\boxed{\text{Friends, Romans, countrymen. So let it be with Caesar...}}$
  - Output: $\boxed{\text{friend}}$ $\boxed{\text{roman}}$ $\boxed{\text{countryman}}$ $\boxed{\text{so}}$
  - Each token is a candidate for a postings entry.
  - What are valid tokens to emit?

Documents

- Up to now, we assumed that
  - We know what a document is.
  - We can “machine-read” each document
- More complex in reality

Parsing a document

- We need do deal with format and language of each document
- Format could be excel, pdf, latex, word...
- What language is it in?
- What character set is it in?
- Each of these is a statistical classification problem
- Alternatively we can use heuristics

Character decoding

Text is not just a linear stream of logical "characters"...

- Determine correct character encoding (Unicode UTF-8) – by ML or by metadata or heuristics.
- Compressions, binary representation (DOC)
- Treat XML characters separately (`&amp`)

Format/Language: Complications

- A single index usually contains terms of several languages.
- Documents or their components can contain multiple languages/format, for instance a French email with a Spanish pdf attachment
- What is the document unit for indexing?
  - a file?
  - an email?
  - an email with 5 attachments?
  - an email thread?
- Answering the question “What is a document?” is not trivial.
- Smaller units raise precision, drop recall
- Also might have to deal with XML/hierarchies of HTML documents etc.

Normalisation

- Need to normalise words in the indexed text as well as query terms to the same form
- Example: We want to match U.S.A. to USA
- We most commonly implicitly define equivalence classes of terms.
- Alternatively, we could do asymmetric expansion:

> window → window, windows
> windows → Windows, windows, window
> Windows → Windows

- Either at query time, or at index time
- More powerful, but less efficient

Tokenisation

Mr. O’Neill thinks that the boys’ stories about Chile’s capital aren’t amusing.

neill	aren’t
oneill	arent
o’neill	are n’t
o’ neill	aren t
o neill	
?	?

Tokenisation problems: One word or two? (or several)

- Hewlett-Packard
- State-of-the-art
- co-education
- the hold-him-back-and-drag-him-away maneuver
- data base
- San Francisco
- Los Angeles-based company
- cheap San Francisco-Los Angeles fares
- York University vs. New York University

Numbers

20/3/91
3/20/91
Mar 20, 1991
B-52
100.2.86.144
(800) 234-2333
800.234.2333

- Older IR systems may not index numbers...
- ... but generally it's a useful feature.

Chinese: No Whitespace

莎拉波娃现在居住在美国东南部的佛罗里达。今年４月９日，莎拉波娃在美国第一大城市纽约度过了１８岁生日。生日派对上，莎拉波娃露出了甜美的微笑。

- Need to perform word segmentation
- Use a lexicon or supervised machine-learning

Chinese: Ambiguous segmentation

和尚

- As one word, means “monk”
- As two words, means “and” and “still”

Other cases of “no whitespace”: Compounding

Compounding in Dutch, German, Swedish

German

Lebensversicherungsgesellschaftsangestellter
leben+s+versicherung+s+gesellschaft+s+angestellter

Other cases of “no whitespace”: Agglutination

“Agglutinative” languages do this not just for compounds:

Inuit

tusaatsiarunnangittualuujunga
(= “I can’t hear very well”)

Finnish

epäjärjestelmällistyttämättömyydellänsäkäänköhän
(= “I wonder if – even with his/her quality of not having been made unsystematized”)

Turkish

Çekoslovakyalılaştıramadıklarımızdanmşçasına
(= “as if you were one of those whom we could not make resemble the Czechoslovacian people”)

Japanese

ノーベル平和賞を受賞したワンガリ・マータイさんが名誉会長を務めるＭＯＴＴＡＩＮＡＩキャンペーンの一環として、毎日新聞社とマガジンハウスは「私 の、もったいない」を募集します。皆様が日ごろ「もったいない」と感じて実践していることや、それにまつわるエピソードを８００字以内の文章にまとめ、簡 単な写真、イラスト、図などを添えて１０月２０日までにお送りください。大賞受賞者には、５０万円相当の旅行券とエコ製品２点の副賞が贈られます。

- Different scripts (alphabets) might be mixed in one language.
- Japanese has 4 scripts: kanja, katakana, hiragana, Romanji
- no spaces

- Direction of writing changes in some scripts (writing systems); e.g., Arabic.

استقلت الجزائر في سنة 1962 بعد 132 عاما من الاحتلال الفرنسي.

← → ← → ← START

'Algeria achieved its independence in 1962 after 132 years of French occupation.'

- Rendering vs. conceptual order
- Bidirectionality is not a problem if Unicode encoding is chosen

Accents and diacritics

- résumé vs. resume
- Universität
- Meaning-changing in some languages:

  peña = cliff, pena = sorrow
  (Spanish)

- Main questions: will users apply it when querying?

Case Folding

- Reduce all letters to lower case
- Even though case can be semantically distinguishing

Fed vs. fed
March vs. march
Turkey vs. turkey
US vs. us

- Best to reduce to lowercase because users will use lowercase regardness of correct capitalisation.

Stop words

- Extremely common words which are of little value in helping select documents matching a user need

a, an, and, are, as, at, be, by, for, from, has, he, in, is, it, its, of, on, that, the, to, was, were, will, with

- Used to be standard in older IR systems.
- Need them to search for

to be or not to be
prince of Denmark
bamboo in water

- Length of practically used stoplists has shrunk over the years.
- Most web search engines do index stop words.

More equivalence classing

- Thesauri: semantic equivalence, car = automobile
- Soundex: phonetic equivalence, Muller = Mueller; lecture 3

Lemmatisation

- Reduce inflectional/variant forms to base form

am, are, is → be
car, car's, cars', cars → car
the boy's cars are different colours → the boy car be different color

- Lemmatisation implies doing "proper" reduction to dictionary headword form (the lemma)
- Inflectional morphology (cutting → cut)
- Derivational morphology (destruction → destroy)

Stemming

- Stemming is a crude heuristic process that chops off the ends of words in the hope of achieving what "principled" lemmatisation attempts to do with a lot of linguistic knowledge.
- language dependent, but fast and space-efficient
- does not require a stem dictionary, only a suffix dictionary
- Often both inflectional and derivational

> automate, automation, automatic → automat

- Root changes (deceive/deception, resume/resumption) aren't dealt with, but these are rare

- M. Porter, “An algorithm for suffix stripping”, Program 14(3):130-137, 1980
- Most common algorithm for stemming English
- Results suggest it is at least as good as other stemmers
- Syllable-like shapes + 5 phases of reductions
- Of the rules in a compound command, select the top one and exit that compound (this rule will have affecte the longest suffix possible, due to the ordering of the rules).

Stemming: Representation of a word

[C] (VC){m}[V]

C : one or more adjacent consonants
V : one or more adjacent vowels

[ ] : optionality
( ) : group operator
{**x**} : repetition x times
m : the "measure" of a word

shoe	$[sh]_C[oe]_V$	m=0
Mississippi	$[M]_C([i]_V[ss]_C)([i]_V[ss]_C)([i]_V[pp]_C)[i]_V$	m=3
ears	$([ea]_V[rs]_C)$	m=1

Notation: measure *m* is calculated on the word **excluding** the suffix of the rule under consideration

Porter stemmer: selected rules

SSES $\rightarrow$ SS
IES $\rightarrow$ I
SS $\rightarrow$ SS
S $\rightarrow$

caresses $\rightarrow$ caress
cares $\rightarrow$ care

(m>0) EED $\rightarrow$ EE

feed $\rightarrow$ feed
agreed $\rightarrow$ agree
BUT: freed, succeed

(*v*) ED $\rightarrow$

plastered $\rightarrow$ plaster
bled $\rightarrow$ bled

Three stemmers: a comparison

Such an analysis can reveal features that are not easily visible from the variations in the individual genes and can lead to a picture of expression that is more biologically transparent and accessible to interpretation.

Porter Stemmer

such an analysi can reveal featur that ar not easili visibl from the variat in the individu gene and can lead to a pictur of express that is more biolog transpar and access to interpret

Lovins Stemmer

such an analys can reve featur that ar not eas vis from th vari in th individu gen and can lead to a pictur of expres that is mor biolog transpar and acces to interpres

Paice Stemmer

such an analys can rev feat that are not easy vis from the vary in the individ gen and can lead to a pict of express that is mor biolog transp and access to interpret

Does stemming improve effectiveness?

- In general, stemming increases effectiveness for some queries and decreases it for others.

Example queries where stemming helps

tartan sweaters → sweater, sweaters
sightseeing tour san francisco → tour, tours

Example queries where stemming hurts

operational research → "oper" = operates, operatives, operate, operation, operational, operative

operating system → operates, operatives, operate, operation, operational, operative

operative dentistry → operates, operatives, operate, operation, operational, operative

Phrase Queries

- We want to answer a query such as [cambridge university] – as a phrase.
- The Duke of Cambridge recently went for a term-long course to a famous university should not be a match
- About 10% of web queries are phrase queries.
- Consequence for inverted indexes: no longer sufficient to store docIDs in postings lists.
- Two ways of extending the inverted index:
  - biword index
  - positional index

Biword indexes

- Index every consecutive pair of terms in the text as a phrase.

Friends, Romans, Countrymen

Generates two biwords:

- friends romans
- romans countrymen

- Each of these biwords is now a vocabulary term.
- Two-word phrases can now easily be answered.

Longer phrase queries

- A long phrase like cambridge university west campus can be represented as the Boolean query

cambridge university AND university west AND west campus

- We need to do post-filtering of hits to identify subset that actually contains the 4-word phrase.

Issues with biword indexes

- Why are biword indexes rarely used?

Issues with biword indexes

- Why are biword indexes rarely used?
- False positives, as noted above
- Index blowup due to very large term vocabulary

Positional indexes

- Positional indexes are a more efficient alternative to biword indexes.
- Postings lists in a nonpositional index: each posting is just a docID
- Postings lists in a positional index: each posting is a docID and a list of positions (offsets)

Positional indexes: Example

Query: "to_1 be_2 or_3 not_4 to_5 be_6"

to,	993427:
$<$ 1:	$<$ 7, 18, 33, 72, 86, 231$>$;
2:	$<$1, 17, 74, 222, 255$>$;
4:	$<$8, 16, 190, 429, 433$>$;
5:	$<$363, 367$>$;
7:	$<$13, 23, 191$>$;
...	...$>$

be,	178239:
$<$ 1:	$<$ 17, 25$>$;
4:	$<$ 17, 191, 291, 430, 434$>$;
5:	$<$14, 19, 101$>$;
...	...$>$

Document 4 is a match.
(As always: docid, term, doc freq; new: offsets)

Proximity search

- We just saw how to use a positional index for phrase searches.
- We can also use it for proximity search.

employment /4 place

- Find all documents that contain employment and place within 4 words of each other.
- HIT: Employment agencies that place healthcare workers are seeing growth.
- NO HIT: Employment agencies that have learned to adapt now place healthcare workers.

Proximity search

- Use the positional index
- Simplest algorithm: look at cross-product of positions of (i) "employment" in document and (ii) "place" in document
- Very inefficient for frequent words, especially stop words
- Note that we want to return the actual matching positions, not just a list of documents.
- This is important for dynamic summaries etc.

Proximity intersection

```
PositionalIntersect(p1, p2, k)
answer ←<>
while p1 6= nil and p2 6= nil
do if docID(p1) = docID(p2)
     then l ← <>
        pp1 ← positions(p1)
        pp2 ← positions(p2)
        while pp1 6= nil
        do while pp2 6= nil
            do if |pos(pp1)  pos(pp2)| ≤ k
                 then Add(l , pos(pp2))
                 else if pos(pp2) > pos(pp1)
                     then break
                 pp2 ← next(pp2)
             while l ≠<> and |l [0]  pos(pp1)| > k
             do Delete(l [0])
             for each ps  l
             do Add(answer , hdocID(p1), pos(pp1), psi)
             pp1 ← next(pp1)
         p1 ← next(p1)
          p2 ← next(p2)
      else if docID(p1) < docID(p2)
         then p1 ← next(p1)
         else p2 ← next(p2)
return answer
```

Combination scheme

- Biword indexes and positional indexes can be profitably combined.
- Many biwords are extremely frequent: Michael Jackson, Britney Spears etc
- For these biwords, increased speed compared to positional postings intersection is substantial.
- Combination scheme: Include frequent biwords as vocabulary terms in the index. Do all other phrases by positional intersection.
- Williams et al. (2004) evaluate a more sophisticated mixed indexing scheme. Faster than a positional index, at a cost of 26% more space for index.
- For web search engines, positional queries are much more expensive than regular Boolean queries.

RCV1 collection

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- Shakespeare's collected works are not large enough to demonstrate scalable index construction algorithms.

N	documents	800,000
M	terms (= word types)	400,000
T	non-positional postings	100,000,000

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- English newswire articles published in a 12 month period (1995/6)

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Effect of preprocessing for Reuters

size of	word types (terms)			non-positional postings			positional postings (word tokens)		
	dictionary			non-positional index			positional index		
	size	Δ	cml	size	Δ	cml	size	Δ	cml
unfiltered	484,494			109,971,179			197,879,290		
no numbers	473,723	-2	-2	100,680,242	-8	-8	179,158,204	-9	-9
case folding	391,523	-17	-19	96,969,056	-3	-12	179,158,204	-0	-9
30 stopw's	391,493	-0	-19	83,390,443	-14	-24	121,857,825	-31	-38
150 stopw's	391,373	-0	-19	67,001,847	-30	-39	94,516,599	-47	-52
stemming	322,383	-17	-33	63,812,300	-4	-42	94,516,599	-0	-52

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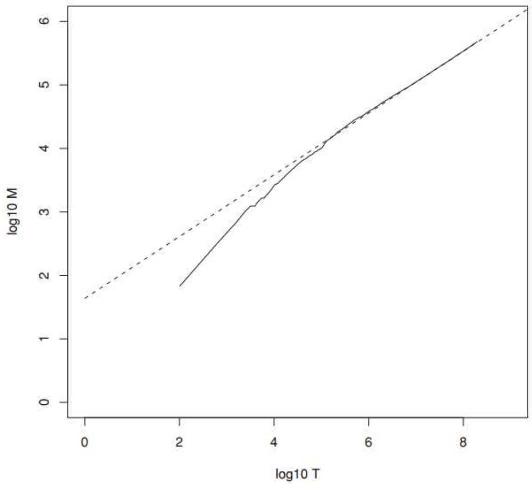
- Heaps' law is linear in log-log space.
  - It is the simplest possible relationship between collection size and vocabulary size in log-log space.
  - Empirical law



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.

Take-away

- Understanding of the basic unit of classical information retrieval systems: words and documents: What is a document, what is a term?
- Tokenization: how to get from raw text to terms (or tokens)
- More complex indexes for phrases

Reading

- MRS Chapter 2.2
- MRS Chapter 2.4
- MRS Chapter 4.3