Introduction to Information Retrieval

http://informationretrieval.org

IIR 2: The term vocabulary and postings lists

Hinrich Schütze

Center for Information and Language Processing, University of Munich

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Overview

Outline

1. Recap
2. Documents
3. Terms
   - General + Non-English
   - English
4. Skip pointers
5. Phrase queries

Inverted index

For each term t, we store a list of all documents that contain t.

dictionary		postings								
BRUTUS	$\longrightarrow$	1	2	4	11	31	45	173	174	
CAESAR	$\longrightarrow$	1	2	4	5	6	16	57	132	...
CALPURNIA	$\longrightarrow$	2	31	54	101					
⋮										

Intersecting two postings lists

$$\textsc{Brutus} \longrightarrow \boxed{1} \to \boxed{2} \to \boxed{4} \to \boxed{11} \to \boxed{31} \to \boxed{45} \to \boxed{173} \to \boxed{174}$$

$$\textsc{Calpurnia} \longrightarrow \boxed{2} \to \boxed{31} \to \boxed{54} \to \boxed{101}$$

Intersection $\Longrightarrow$

Intersecting two postings lists

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Constructing the inverted index: Sort postings

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
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Westlaw: Example queries

Information need: Information on the legal theories involved in preventing the disclosure of trade secrets by employees formerly employed by a competing company

Query: "trade secret" /s disclos! /s prevent /s employe!

Information need: Requirements for disabled people to be able to access a workplace

Query: disab! /p access! /s work-site work-place (employment /3 place)

Information need: Cases about a host's responsibility for drunk guests

Query: host! /p (responsib! liab!) /p (intoxicat! drunk!) /p guest

Does Google use the Boolean model?

- On Google, the default interpretation of a query [w_1 w_2 $\ldots w_n$] is w_1 AND w_2 AND $\ldots$ AND w_n
- Cases where you get hits that do not contain one of the w_i:
  - anchor text
  - page contains variant of w_i (morphology, spelling correction, synonym)
  - long queries (n large)
  - boolean expression generates very few hits
- Simple Boolean vs. Ranking of result set
  - Simple Boolean retrieval returns matching documents in no particular order.
  - Google (and most well designed Boolean engines) rank the result set – they rank good hits (according to some estimator of relevance) higher than bad hits.

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- Tokenization: how to get from raw text to words (or tokens)
- More complex indexes: skip pointers and phrases

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Documents

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  - We know what a document is.
  - We can "machine-read" each document.
- This can be complex in reality.

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- Alternative: use heuristics

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- Also: XML

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- Type – The same as a term in most cases: an equivalence class of tokens.

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- Why don't you want to put *window*, *Window*, *windows*, and *Windows* in the same equivalence class?

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- *He got his PhD from MIT.* $\rightarrow$ MIT $\neq$ mit

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- What are valid tokens to emit?

Exercises

In June, the dog likes to chase the cat in the barn. – How many word tokens? How many word types?

Why tokenization is difficult – even in English. Tokenize: *Mr. O'Neill thinks that the boys' stories about Chile's capital aren't amusing.*

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- York University vs. New York University

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- Google example

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。

Ambiguous segmentation in Chinese

和尚

The two characters can be treated as one word meaning 'monk' or as a sequence of two words meaning 'and' and 'still'.

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- Many other languages with segmentation difficulties: Finnish, Urdu, ...

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。

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End user can express query entirely in hiragana!

Arabic script

ك ِ ت ا ب ٌ ⇐ كِتَابٌ

un b ā t i k

/kitābun/ *‘a book’*

Arabic script: Bidirectionality

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

← → ← → ← START

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

Arabic script: Bidirectionality

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

Bidirectionality is not a problem if text is coded in Unicode.

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- Most important criterion: How are users likely to write their queries for these words?

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- Umlauts: Universität vs. Universitaet (substitution with special letter sequence "ae")
- Most important criterion: How are users likely to write their queries for these words?
- Even in languages that standardly have accents, users often do not type them. (Polish?)

Outline

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- Reduce all letters to lower case

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- It's often best to lowercase everything since users will use lowercase regardless of correct capitalization.

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- Thesauri: IIR 9 (semantic equivalence, car = automobile)

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- Inflectional morphology (*cutting* $\rightarrow$ *cut*) vs. derivational morphology (*destruction* $\rightarrow$ *destroy*)

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- Example for derivational: *automate, automatic, automation* all reduce to *automat*

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  - Sample command: Delete final *ement* if what remains is longer than 1 character
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- Sample convention: Of the rules in a compound command, select the one that applies to the longest suffix.

Porter stemmer: A few rules

Rule			**Example**		
SSES	$\rightarrow$	SS	caresses	$\rightarrow$	caress
IES	$\rightarrow$	I	ponies	$\rightarrow$	poni
SS	$\rightarrow$	SS	caress	$\rightarrow$	caress
S	$\rightarrow$		cats	$\rightarrow$	cat

Three stemmers: A comparison

Sample text: 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

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- Porter Stemmer equivalence class *oper* contains all of *operate operating operates operation operative operatives operational*.
- Queries where stemming hurts: [operational AND research], [operating AND system], [operative AND dentistry]

Exercise: What does Google do?

- Stop words
- Normalization
- Tokenization
- Lowercasing
- Stemming
- Non-latin alphabets
- Umlauts
- Compounds
- Numbers

Outline

Recall basic intersection algorithm

BRUTUS $\longrightarrow$ $\boxed{1} \rightarrow \boxed{2} \rightarrow \boxed{4} \rightarrow \boxed{11} \rightarrow \boxed{31} \rightarrow \boxed{45} \rightarrow \boxed{173} \rightarrow \boxed{174}$

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- Linear in the length of the postings lists.
- Can we do better?

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- Where do we put skip pointers?
- How do we make sure insection results are correct?

Basic idea

34 128

BRUTUS 2 4 8 34 35 64 128

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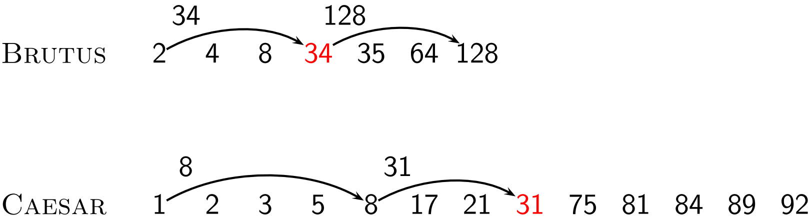
34
128
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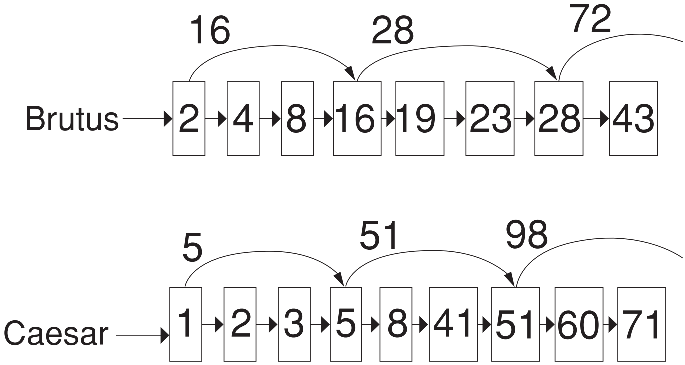
Skip lists: Larger example



Intersecting with skip pointers

```
IntersectWithSkips(p1, p2)
answer ← ⟨ ⟩
while p1 ≠ NIL and p2 ≠ NIL
do if docID(p1) = docID(p2)
      then Add(answer, docID(p1))
           p1 ← next(p1)
           p2 ← next(p2)
      else if docID(p1) < docID(p2)
              then if hasSkip(p1) and (docID(skip(p1)) ≤ docID(p2))
                      then while hasSkip(p1) and (docID(skip(p1)) ≤ docID(p2))
                              do p1 ← skip(p1)
                      else p1 ← next(p1)
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                      then while hasSkip(p2) and (docID(skip(p2)) ≤ docID(p1))
                              do p2 ← skip(p2)
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return answer
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- More skips: Each skip 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.

Where do we place skips? (cont)

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- With today's fast CPUs, they don't help that much anymore.

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- Two-word phrases can now easily be answered.

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

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TO, 993427:

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Document 4 is a match!

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- For example: employment /4 place
- Find all documents that contain EMPLOYMENT and PLACE within 4 words of each other.
- *Employment agencies that place healthcare workers are seeing growth* is a hit.
- *Employment agencies that have learned to adapt now place healthcare workers* is not a hit.

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- This is important for dynamic summaries etc.

"Proximity" intersection

```
PositionalIntersect(p1, p2, k)
answer ← ⟨ ⟩
while p1 ≠ NIL and p2 ≠ NIL
do if docID(p1) = docID(p2)
      then l ← ⟨ ⟩
           pp1 ← positions(p1)
           pp2 ← positions(p2)
           while pp1 ≠ NIL
           do while pp2 ≠ 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, ⟨docID(p1), pos(pp1), ps⟩)
              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
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- 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.

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- Let's look at the example of phrase queries.
- Why are they more expensive than regular Boolean queries?
- Can you demonstrate on Google that phrase queries are more expensive than Boolean queries?

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 words (or tokens)
- More complex indexes: skip pointers and phrases

Resources

- Chapter 2 of IIR
- Resources at `http://cislmu.org`
  - Porter stemmer
  - A fun number search on Google