Text Retrieval and Web Search
IIR 2: The term vocabulary and postings lists

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(Based on slides by Hinrich Schütze at `informationretrieval.org`)

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Overview

Motivation

"In 2000, the Institute of Medicine reported that an estimated 98,000 preventable patient deaths occur annually in US hospitals due to . . . "

Take-away

- Understanding of the basic unit of classical information retrieval systems: what is a token?
- Tokenization: how to get from raw text to words (or tokens)
- More complex indexes: skip pointers and phrases

Outline

1. Tokenization
2. Normalization
3. Skip pointers
4. Phrase queries

Definitions

- Document – File, email, newspaper article, tweet, Facebook post, etc. A column in the term-document incidence matrix.
- Token == Word – A delimited string of characters as it appears in a document.
- Term – A "**normalized**" (case, morphology, spelling etc) and **unique** word. It is included in the index.
- Type – An equivalence class of tokens (e.g., "USA" and "U.S.A"). Not necessarily in the index.

Normalization

- Need to “normalize” words in indexed text as well as query terms into the same form.
- Example: We want to match *U.S.A.* and *USA*
- We most commonly implicitly define equivalence classes of terms, which are created during normalization.
- There are also explicit equivalence classes:
  - Soundex: IIR 3 (phonetic equivalence, Muller = Mueller)
  - Thesauri: IIR 9 (semantic equivalence, car = automobile)
- What’s the best way to handle (explicit) equivalence classes?

Normalization: Other languages

- Normalization and language detection interact.
- *PETER WILL NICHT MIT.* $\rightarrow$ MIT $=$ mit
- *He got his PhD from MIT.* $\rightarrow$ MIT $\neq$ mit

Recall: Inverted index construction

- Input:

Friends, Romans, countrymen.	So let it be with Caesar	...

- Output:

friend	roman	countryman	so	...

- Each token is a candidate for a postings entry.
- 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 terms?

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

Tokenization 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
- What is a simple heuristic?

Numbers

- 3/20/91
- 20/3/91
- Mar 20, 1991
- 100.2.86.144
- (800) 234-2333
- 800.234.2333
- Older IR systems may not index numbers . . .
- . . . but generally it's a useful feature.
- 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’.

Other cases of "no whitespace"

- Compounds in Dutch, German, Swedish
- Computerlinguistik → Computer + Linguistik
- Lebensversicherungsgesellschaftsangestellter (life insurance company employee)
- → leben + versicherung + gesellschaft + angestellter
- Inuit: tusaatsiarunnanngittualuujunga (I can't hear very well.)
- Many other languages with segmentation difficulties: Finnish, Urdu, ...

- Have you read "The Awful German Language" by Mark Twain?

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。

Japanese

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4 different “alphabets”: Chinese characters, hiragana syllabary for inflectional endings and function words, katakana syllabary for transcription of foreign words and other uses, and latin. No spaces (as in Chinese).

Arabic script: Bidirectionality

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

$\leftarrow \rightarrow \quad \leftarrow \rightarrow \qquad\qquad \leftarrow$ START

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

It's hard and boring!

- This is a big pain for any IR/NLP software. Let's look at Stanford's CoreNLP.
- It's best if you don't do this at home but instead use existing software:
  - NLTK in Python: `http://www.nltk.org/book/ch03.html`
  - CoreNLP in Java: `http://stanfordnlp.github.io/CoreNLP/simple.html`

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Accents and diacritics

- Accents: résumé vs. resume (simple omission of accent)
- 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, Romanian)

Case folding

- Reduce all letters to lower case
- Even though case can be semantically meaningful
  - capitalized words in mid-sentence
  - MIT vs. mit
  - Fed vs. fed
  - ...
- It's often best to lowercase everything. Why?

Stop words

- stop words = extremely common words which would appear to be of little value in helping select documents matching a user need
- Examples: *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*
- Stop word elimination used to be standard in older IR systems.
- But you need stop words for phrase queries, e.g. "King of Denmark"
- Most web search engines index stop words.

Lemmatization

- Reduce inflectional/variant forms to base form
- Example: *am, are, is* $\rightarrow$ *be*
- Example: *car, cars, car's, cars'* $\rightarrow$ *car*
- Example: *the boy's cars are different colors* $\rightarrow$ *the boy car be different color*
- Lemmatization implies doing "proper" reduction to dictionary headword form (the lemma).
- Inflectional morphology (*cutting* $\rightarrow$ *cut*) vs. derivational morphology (*destruction* $\rightarrow$ *destroy*)
- Use WordNet for proper lemmatization. For a quick hack...

Stemming

- Definition of stemming: Crude heuristic process that chops off the ends of words in the hope of achieving what "principled" lemmatization attempts to do with a lot of linguistic knowledge.
- Language dependent
- Often inflectional and derivational
  - Example for derivational: *automate, automatic, automation* all reduce to *automat*
  - Example for inflectional: *am, are, is* reduce to *be*

Porter algorithm

- Most common algorithm for stemming English
- Results suggest that it is at least as good as other stemming options
- Conventions + 5 phases of reductions
- Phases are applied sequentially
- Each phase consists of a set of commands.
  - Sample command: Delete final *ement* if what remains is longer than 1 character
  - replacement $\rightarrow$ replac
  - cement $\rightarrow$ cement
- 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

WordNet Lemmatization

- Based on morphological analysis + dictionary lookup rather than "chopping" suffixes
- What are the advantages/disadvantages?
- Demo: `http://textanalysisonline.com/nltk-wordnet-lemmatizer`
- Code:
  - Python: `http://www.nltk.org/_modules/nltk/stem/wordnet.html`
  - Java: `http://stanfordnlp.github.io/CoreNLP/simple.html`

Does stemming improve effectiveness?

- In general, stemming increases effectiveness for some queries, and decreases effectiveness for others.
- Queries where stemming is likely to help: [tartan sweaters], [sightseeing tour san francisco]
- (equivalence classes: {sweater,sweaters}, {tour,tours})
- 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 Do they use WordNet?
- Non-latin alphabets
- Umlauts
- Compounds
- Numbers

Outline

Recall basic intersection algorithm

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

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

Intersection $\Longrightarrow$

Recall basic intersection algorithm

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Intersection	$\Longrightarrow$	$\boxed{2} \to \boxed{31}$

Recall basic intersection algorithm

BRUTUS	$\longrightarrow$	1 → 2 → 4 → 11 → 31 → 45 → 173 → 174
CALPURNIA	$\longrightarrow$	2 → 31 → 54 → 101
Intersection	$\Longrightarrow$	2 → 31

Recall basic intersection algorithm

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- Linear in the length of the postings lists.

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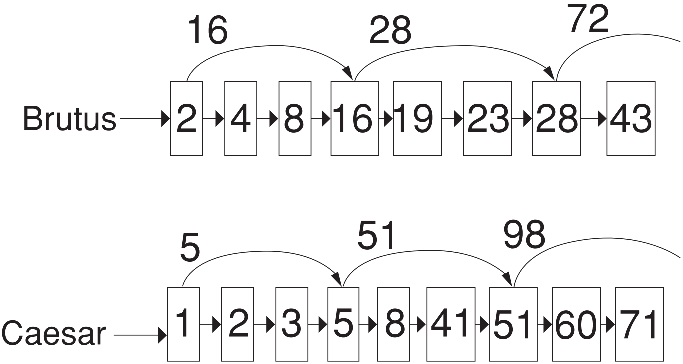
- Linear in the length of the postings lists.
- Can we do better?

Skip pointers

- Skip pointers allow us to skip postings that will not figure in the search results.
- This makes intersecting postings lists more efficient.
- Some postings lists contain several million entries – so efficiency can be an issue even if basic intersection is linear.
- Where do we put skip pointers?
- How do we make sure intersection results are correct?

Skip lists: 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)
              else if hasSkip(p2) and (docID(skip(p2)) ≤ docID(p1))
                      then while hasSkip(p2) and (docID(skip(p2)) ≤ docID(p1))
                           do p2 ← skip(p2)
                      else p2 ← next(p2)
return answer
```

Exercise

Where do we place skips?

- Tradeoff: number of items skipped vs. frequency skip can be taken
- 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)

- Simple heuristic: for postings list of length P, use $\sqrt{P}$ evenly-spaced skip pointers.
- This ignores the distribution of query terms.
- Easy if the index is static; harder in a dynamic environment because of updates.
- How much do skip pointers help?
- They used to help a lot.
- With today's fast CPUs and in-memory indices, they don't help that much anymore.

Outline

Phrase queries

- We want to answer a query such as [stanford university] – as a phrase.
- Thus *The inventor Stanford Ovshinsky never went to university* should not be a match.
- The concept of phrase query has proven easily understood by users.
- About 10% of web queries are phrase queries.
- Consequence for inverted index: it no longer suffices 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.
- For example, *Friends, Romans, Countrymen* would generate two biwords: *"friends romans"* and *"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 *"stanford university palo alto"* can be represented as the Boolean query "STANFORD UNIVERSITY" AND "UNIVERSITY PALO" AND "PALO ALTO"
- 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

Positional indexes: Example

Query: *"to_1 be_2 or_3 not_4 to_5 be_6"*

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⟩;
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5: ⟨14, 19, 101⟩; . . . ⟩

Positional indexes: Example

Query: *"to_1 be_2 or_3 not_4 to_5 be_6"*

TO, 993427:

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

BE, 178239:

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Document 4 is a match!

Proximity search

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

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 ≠ 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
```

This is a tricky algorithm! A few notes:

- $pp2$ is not reset between iterations over $pp1$!
- l stores likely solutions (for values of $pp2$). It is not reset either between iterations over $pp1$!
- But l is filtered in each iteration (lines 14 – 15), to purge solutions from the previous value of $pp1$. This is a constant time operation of $O(k)$. Why?
- What is the overall complexity of this algorithm then?

Exercise!

$\textsc{to}$, 993427:

$\langle \ldots;$

4: $\langle$ 8, 16, 190, 429, 433 $\rangle$;

$\ldots \rangle$

$\textsc{be}$, 178239:

$\langle \ldots;$

4: $\langle$ 17, 180, 191, 291, 430 $\rangle$;

$\ldots \rangle$

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.

Take-away

- Understanding of the basic unit of classical information retrieval systems: what is a token?
- Tokenization: how to get from raw text to words (or tokens)
- More complex indexes: skip pointers and phrases