Introduction to Information Retrieval http://informationretrieval.org

IIR 3: Dictionaries and tolerant retrieval

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Dictionaries Wildcard queries Edit distance Spelling correction Sounder

Overview

- Recap
- 2 Dictionaries
- Wildcard queries
- 4 Edit distance
- Spelling correction
- Soundex

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Outline

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Type/token distinction

- Token an instance of a word or term occurring in a document
- Type an equivalence class of tokens
- In June, the dog likes to chase the cat in the barn.
- 12 word tokens, 9 word types

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Problems in tokenization

- What are the delimiters? Space? Apostrophe? Hyphen?
- For each of these: sometimes they delimit, sometimes they don't.
- No whitespace in many languages! (e.g., Chinese)
- No whitespace in Dutch, German, Swedish compounds (Lebensversicherungsgesellschaftsangestellter)

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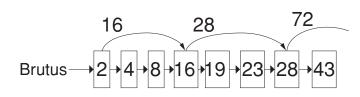
Problems with equivalence classing

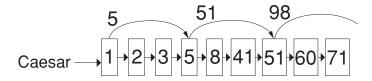
- A term is an equivalence class of tokens.
- How do we define equivalence classes?
- Numbers (3/20/91 vs. 20/3/91)
- Case folding

- Stemming, Porter stemmer
- Morphological analysis: inflectional vs. derivational
- Equivalence classing problems in other languages
 - More complex morphology than in English
 - Finnish: a single verb may have 12,000 different forms
 - Accents, umlauts

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Skip pointers





Positional indexes

Recap

- 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
- Example query: "to1 be2 or3 not4 to5 be6"

```
TO, 993427:

$\left( 1: \left\langle 7, 18, 33, 72, 86, 231 \right\rangle; \left\langle 1, 17, 74, 222, 255 \right\rangle; \left\langle 8, 16, 190, 429, 433 \right\rangle; \left\langle 363, 367 \right\rangle; \left\langle 13, 23, 191 \right\rangle; \ldots \right\rangle$

BE, 178239:

$\left\langle 1: \left\langle 17, 25 \right\rangle; \left\langle 17, 191, 291, 430, 434 \right\rangle; \left\langle 14, 19, 101 \right\rangle; \ldots \right\rangle$;
```

Document 4 is a match!

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Positional indexes

- With a positional index, we can answer phrase queries.
- With a positional index, we can answer proximity queries.

Take-away

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Inverted index

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

dictionary

postings

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- Assume for the time being that we can store this information in a fixed-length entry.
- Assume that we store these entries in an array.

term	document	pointer to
	frequency	postings list
а	656,265	\longrightarrow
aachen	65	\longrightarrow
zulu	221	\longrightarrow
20	4	4 1

space needed: 20 by

20 bytes 4 bytes

4 bytes

How do we look up a query term q_i in this array at query time? That is: which data structure do we use to locate the entry (row) in the array where q_i is stored?

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 - How many terms are we likely to have?

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 - need to rehash everything periodically if vocabulary keeps growing

Trees

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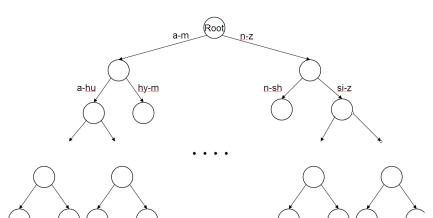
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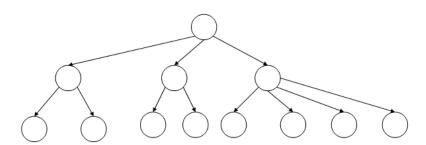
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- B-tree definition: every internal node has a number of children in the interval [a, b] where a, b are appropriate positive integers, e.g., [2, 4].



B-tree



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- Then retrieve documents that contain any of these terms

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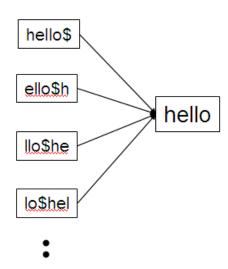
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- Store each of these rotations in the dictionary, say, in a B-tree

Permuterm index

• For term HELLO: add hello\$, ello\$h, llo\$he, lo\$hel, o\$hell, and \$hello to the B-tree where \$ is a special symbol

Permuterm → term mapping



Permuterm index

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- But permuterm index is the more common name.

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- Problem: Permuterm more than quadruples the size of the dictionary compared to a regular B-tree. (empirical number)

k-gram indexes

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- Maintain an inverted index from bigrams to the terms that contain the bigram

Postings list in a 3-gram inverted index



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<u>k-gram (bigram, trigram, ...)</u> indexes

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Exercise

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- Exercise: Why doesn't Google fully support wildcard queries?

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- Somewhat alleviated by Google Suggest

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- The general philosophy in IR is: don't change the documents.

Correcting queries

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- Why is this problematic?

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- The term vocabulary of the collection, appropriately weighted

Distance between misspelled word and "correct" word

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- k-gram overlap

Edit distance

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- Levenshtein distance cat-act: 2
- Damerau-Levenshtein distance cat-act: 1
- Damerau-Levenshtein includes transposition as a fourth possible operation.

Levenshtein distance: Computation

		f	а	S	t
	0	1	2	3	4
С	1	1	2	3	4
а	2	2	1	2	3
t	3	3	2	2	2
S	4	4	3	2	3

```
LEVENSHTEINDISTANCE(s_1, s_2)
     for i \leftarrow 0 to |s_1|
  2 do m[i, 0] = i
  3 for j \leftarrow 0 to |s_2|
  4 do m[0, i] = i
  5 for i \leftarrow 1 to |s_1|
     do for j \leftarrow 1 to |s_2|
          do if s_1[i] = s_2[i]
  8
                then m[i,j] = \min\{m[i-1,j]+1, m[i,j-1]+1, m[i-1,j-1]\}
  9
                else m[i,j] = \min\{m[i-1,j]+1, m[i,j-1]+1, m[i-1,j-1]+1\}
 10
      return m[|s_1|, |s_2|]
Operations: insert (cost 1), delete (cost 1), replace (cost 1), copy
(cost 0)
```

Spelling correction

```
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Levenshtein distance: Example

			f	á	a	9	5		t
	 0	1	1		2	3	3	4	4
С	1	1	2	2	3	3	4	4	5
	1	2	1	2	2	3	3	4	4
	2	2	2	1	3	3	4	4	5
a	2	3	2	3	1	2	2	3	3
	3	3	3	3	2	2	3	2	4
t	3	4	3	4	2	3	2	3	2
S	4	4	4	4	3	2	3	3	3
	4	5	4	5	3	4	2	3	3

Each cell of Levenshtein matrix

cost of getting here from	cost of getting here		
my upper left neighbor	from my upper neighbor		
(copy or replace)	(delete)		
	the minimum of the		
cost of getting here from	three possible "move-		
my left neighbor (insert)	ments"; the cheapest		
	way of getting here		

Levenshtein distance: Example

		f	а	S	t
	0	1 1	2 2	3 3	4 4
С	1	1 2	2 3	3 4	4 5
	1	2 1	2 2	3 3	4 4
а	2	2 2	1 3	3 4	4 5
	2	3 2	3 1	2 2	3 3
t	3	3 3	3 2	2 3	2 4
ı	3	4 3	4 2	3 2	3 2
S	4	4 4	4 3	2 3	3 3
3	4	5 4	5 3	4 2	3 3

 Optimal substructure: The optimal solution to the problem contains within it subsolutions, i.e., optimal solutions to subproblems.

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- Subproblem in the case of edit distance: what is the edit distance of two prefixes
- Overlapping subsolutions: We need most distances of prefixes
 3 times this corresponds to moving right, diagonally, down.

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- We now require a weight matrix as input.
- Modify dynamic programming to handle weights

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- $\bullet \rightarrow$ exercise in a few slides

Exercise

- Compute Levenshtein distance matrix for OSLO SNOW
- What are the Levenshtein editing operations that transform cat into catcat?

Dictionaries	Wildcard queries	Edit distance	Spelling co	orrection Sour
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How do I read out the editing operations that transform OSLO into SNOW?

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cost	operation	input	output
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cost	operation	input	output
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cost	operation	input	output
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cost	operation	input	output
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0	(copy)	t	t
1	insert	*	С
1	insert	*	а
1	insert	*	t

Outline

- Recap
- 2 Dictionaries
- Wildcard queries
- 4 Edit distance
- Spelling correction
- 6 Soundex

Spelling correction

 Now that we can compute edit distance: how to use it for isolated word spelling correction – this is the last slide in this section.

Spelling correction

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- Context-sensitive spelling correction
- General issues

k-gram indexes for spelling correction

• Enumerate all k-grams in the query term

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- Example: bigram index, misspelled word bordroom

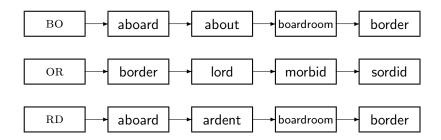
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- Threshold by number of matching k-grams
- E.g., only vocabulary terms that differ by at most 3 k-grams

k-gram indexes for spelling correction: *bordroom*



Context-sensitive spelling correction

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- Suppose we have 7 alternatives for *flew*, 20 for *form* and 3 for *munich*, how many "corrected" phrases will we enumerate?

Context-sensitive spelling correction

Context-sensitive spelling correction

• The "hit-based" algorithm we just outlined is not very efficient.

Context-sensitive spelling correction

- The "hit-based" algorithm we just outlined is not very efficient.
- More efficient alternative: look at "collection" of queries, not documents

General issues in spelling correction

User interface

User interface

• automatic vs. suggested correction

- User interface
 - automatic vs. suggested correction
 - Did you mean only works for one suggestion.

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 - Maybe just on queries that match few documents.

General issues in spelling correction

User interface

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Cost

- Spelling correction is potentially expensive.
- Avoid running on every query?
- Maybe just on queries that match few documents.
- Guess: Spelling correction of major search engines is efficient enough to be run on every query.

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)
```

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- Example: chebyshev / tchebyscheff
- Algorithm:
 - Turn every token to be indexed into a 4-character reduced form
 - Do the same with query terms
 - Build and search an index on the reduced forms

Soundex algorithm

- Retain the first letter of the term.
- Change all occurrences of the following letters to '0' (zero): A, E, I, O, U, H, W, Y
- Ohange letters to digits as follows:
 - B, F, P, V to 1
 - C, G, J, K, Q, S, X, Z to 2
 - D,T to 3
 - L to 4
 - M, N to 5
 - R to 6
- Repeatedly remove one out of each pair of consecutive identical digits
- Remove all zeros from the resulting string; pad the resulting string with trailing zeros and return the first four positions, which will consist of a letter followed by three digits

Retain H

- Retain H
- ERMAN → ORMON

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- $0RM0N \rightarrow 06505$

- Retain H
- ERMAN → ORMON
- 0RM0N → 06505
- $06505 \rightarrow 06505$

- Retain H
- ERMAN → ORMON
- 0RM0N → 06505
- 06505 → 06505
- $06505 \rightarrow 655$

- Retain H
- ERMAN → ORMON
- 0RM0N → 06505
- $06505 \rightarrow 06505$
- $06505 \rightarrow 655$
- Return *H655*

- Retain H
- ERMAN → ORMON
- 0RM0N → 06505
- 06505 → 06505
- 06505 → 655
- Return *H655*
- Note: HERMANN will generate the same code

Soundex

How useful is Soundex?

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- Zobel and Dart (1996) suggest better alternatives for phonetic matching in IR.

Exercise

• Compute Soundex code of your last name

Take-away

- Tolerant retrieval: What to do if there is no exact match between query term and document term
- Wildcard queries
- Spelling correction

Resources

- Chapter 3 of IIR
- Resources at http://ifnlp.org/ir
 - trie vs hash vs ternary tree
 - Soundex demo
 - Edit distance demo
 - Peter Norvig's spelling corrector
 - Google: wild card search, spelling correction gone wrong, a misspelling that is more frequent that the correct spelling