Introduction to Information Retrieval

http://informationretrieval.org

IIR 3: Dictionaries and tolerant retrieval

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2008.04.29

Overview

Outline

Type/token distinction

- Token – An instance of a word or term occurring in a document.

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- 12 tokens, 9 types

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- No whitespace in English: *database*, *whitespace*

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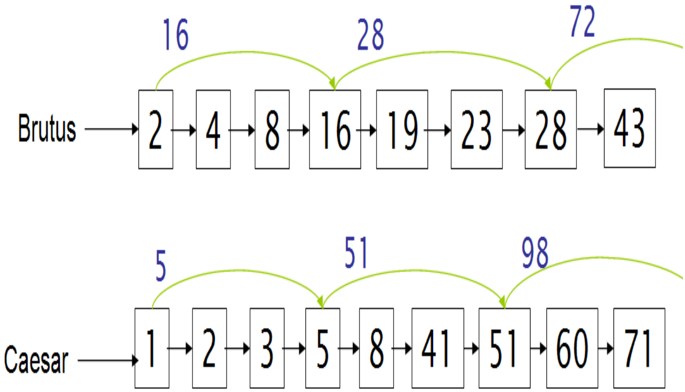
  - Accents, umlauts

Skip pointers



Positional indexes

- Postings lists in a positional index: each posting is a docID and a list of positions
- Example: to_1 be_2 or_3 not_4 to_5 be_6

TO, 993427:
$\langle$ 1, 6: $\langle$7, 18, 33, 72, 86, 231$\rangle$;
2, 5: $\langle$1, 17, 74, 222, 255$\rangle$;
4, 5: $\langle$8, 16, 190, 429, 433$\rangle$;
5, 2: $\langle$363, 367$\rangle$;
7, 3: $\langle$13, 23, 191$\rangle$; ... $\rangle$

BE, 178239:
$\langle$ 1, 2: $\langle$17, 25$\rangle$;
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Document 4 is a match.

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

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Inverted index

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

BRUTUS	⟶	1	2	4	11	31	45	173	174	
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- Assume that we store these entries in an array.

Dictionary as array of fixed-width entries

	term	document frequency	pointer to postings list
	a	656,265	$\longrightarrow$
	aachen	65	$\longrightarrow$
	...	...	...
	zulu	221	$\longrightarrow$
space needed:	20 bytes	4 bytes	4 bytes

How do we look up an element in this array at query time?

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  - How many terms are we likely to have?

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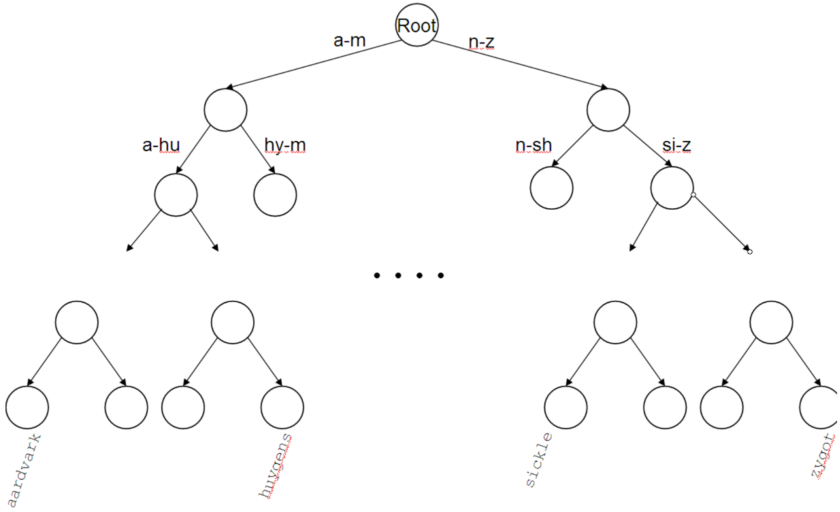
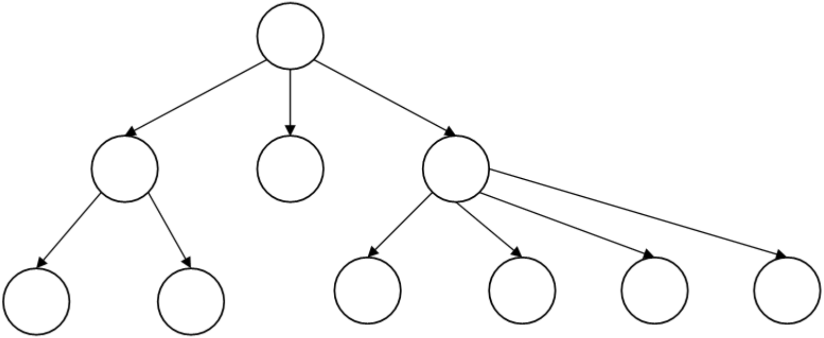
- Note that we need a standard ordering for characters in order to be able to use trees.

Binary tree



B-tree



Outline

1. Recap
2. Dictionaries
3. Wildcard queries
4. Spelling correction
5. Soundex

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- This may result in the execution of many Boolean AND queries.

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- Basic idea: Rotate every wildcard query, so that the * occurs at the end.

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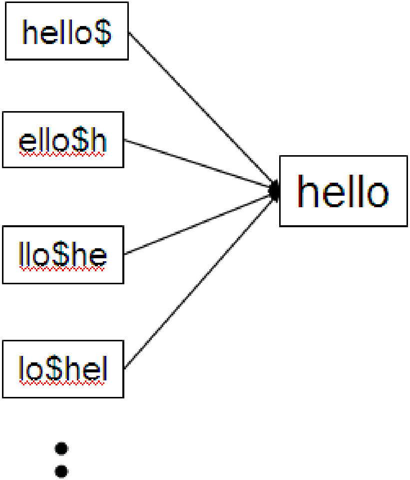
Permuterm → term mapping



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- But permuterm index is more common name.

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

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

Postings list in a 3-gram index

etr → BEETROOT → METRIC → PETRIFY → RETRIEVAL

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- *k*-gram indexes are fast and space efficient (compared to permuterm indexes).

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- Most straightforward semantics: Conjunction of disjunctions

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Outline

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- Damerau-Levenshtein includes transposition as a fourth possible operation.

Levenshtein distance: Computation

		f	a	s	t
	0	1	2	3	4
c	1	1	2	3	4
a	2	2	1	2	3
t	3	3	2	2	2
s	4	4	3	2	3

Levenshtein distance: algorithm

$\textsc{LevenshteinDistance}(s_1, s_2)$

for $i \leftarrow 0$ **to** $|s_1|$
do $m[i, 0] = i$
for $j \leftarrow 0$ **to** $|s_2|$
do $m[0, j] = j$
for $i \leftarrow 1$ **to** $|s_1|$
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    then $m[i, j] = \min\{m[i-1, j] + 1, m[i, j-1] + 1, m[i-1, j-1]\}$
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			f		a		s		t	
		0	**1**	**1**	**2**	**2**	**3**	**3**	**4**	**4**
c		**1**	*1*	*2*	**2**	3	**3**	4	**4**	5
		1	*2*	*1*	**2**	**2**	**3**	**3**	**4**	**4**
a		**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*
		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 my upper left neighbor (copy or replace)	cost of getting here from my upper neighbor (delete)
cost of getting here from my left neighbor (insert)	the minimum of the three possible "movements"; the cheapest way of getting here

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- Overlapping subproblems: Need most distances of substrings 3 times (moving right, diagonally, down)

`http://ifnlp.org/lehre/teaching/2008-SS/ir/editdist2.pdf`

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- Modify dynamic programming to handle weights.

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- Or do automatic correction – but this is potentially expensive and disempowers the user.

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- Bigrams: *bo, or, rd, dr, ro, oo, om*

k-gram indexes for spelling correction: *bordroom*

BO → aboard → about → boardroom → border

OR → border → lord → morbid → sordid

RD → aboard → ardent → boardroom → border

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- How can we turn this into a normalized measure of overlap?

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- Suppose we have 7 alternatives for *flew*, 19 for *form* and 3 for *munich*, how many "corrected" phrases will we enumerate?

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- More efficient alternative: look at "collection" of queries, not documents

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  - Guess: Spelling correction of major search engines is efficient enough to be run on every query.

Peter Norvig's complete spelling corrector in only 21 lines of code!

Outline

1. Recap
2. Dictionaries
3. Wildcard queries
4. Spelling correction
5. Soundex

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  - Build and search an index on the reduced forms

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4. Repeatedly remove one out of each pair of consecutive identical digits
5. 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

Example: Soundex of *HERMAN*

- Retain H

Example: Soundex of *HERMAN*

- Retain H
- *ERMAN* $\rightarrow$ *0RM0N*

Example: Soundex of *HERMAN*

- Retain H
- *ERMAN* $\rightarrow$ *0RM0N*
- *0RM0N* $\rightarrow$ *06505*

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Example: Soundex of *HERMAN*

- Retain H
- *ERMAN* → *0RM0N*
- *0RM0N* → *06505*
- *06505* → *06505*
- *06505* → *655*

Example: Soundex of *HERMAN*

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

Example: Soundex of *HERMAN*

- Retain H
- *ERMAN* → *0RM0N*
- *0RM0N* → *06505*
- *06505* → *06505*
- *06505* → *655*
- Return *H655*
- Will *HERMANN* generate the same code?

Compute soundex code of your last name.

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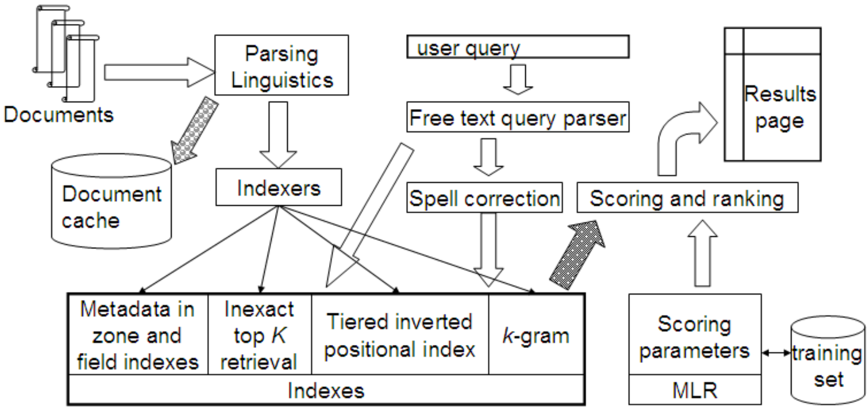
- Zobel and Dart (1996) suggest better alternatives for phonetic matching in IR.

The complete search system



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