Introduction to Information Retrieval http://informationretrieval.org

IIR 3: Dictionaries and tolerant retrieval

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Overview

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

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

Problems in tokenization

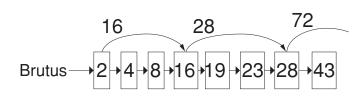
- What are the delimiters? Space? Apostrophe? Hyphen?
- For each of these: sometimes they delimit, sometimes they don't.
- No whitespace in many languages! (e.g., Chinese)
- No whitespace in Dutch, German, Swedish compounds (Lebensversicherungsgesellschaftsangestellter)

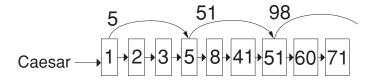
Problems with equivalence classing

- 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

Skip pointers





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

```
TO, 993427:

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

BE, \text{178239:} \langle \text{1:} \langle 17, \text{25} \rangle; \text{4:} \langle 17, \text{191, 291, 430, 434} \rangle; \text{5:} \langle 14, \text{19, 101} \rangle; \text{...} \rangle
```

Document 4 is a match!

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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Recap

 Tolerant retrieval: What to do if there is no exact match between query term and document term

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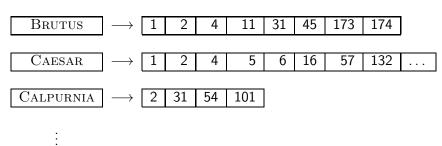
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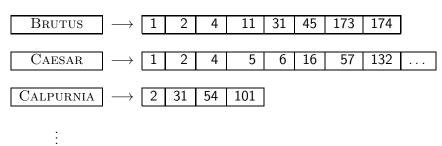
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dictionary postings

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Dictionaries

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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
00 1 .	41.	4 1 .

space needed:

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?

Data structures for looking up term

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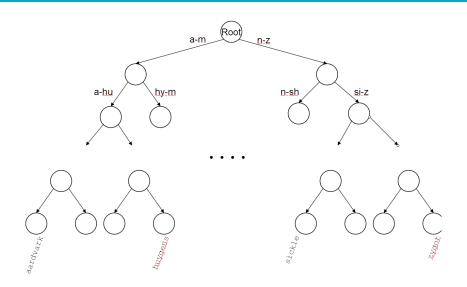
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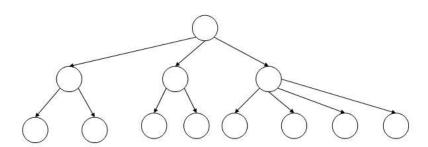
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- B-tree definition: every internal node has a number of children in the interval [a, b] where a, b are appropriate positive integers, e.g., [2, 4].

Dictionaries

Binary tree



B-tree



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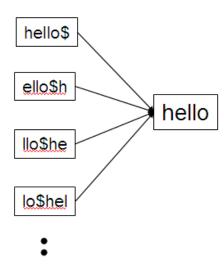
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- Basic idea: Rotate every wildcard query, so that the * occurs at the end.
- Store each of these rotations in the dictionary, say, in a B-tree

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 \rightarrow term mapping



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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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k-gram (bigram, trigram, . . .) indexes

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 - Permuterm index doesn't require postfiltering.

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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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- 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

Spelling correction

```
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, j] = j
  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\}
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Operations: insert (cost 1), delete (cost 1), replace (cost 1), copy
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```

(cost 0)

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
		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
		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

 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

Using edit distance for spelling correction

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- Then suggest terms in the intersection to the user.
- ullet \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?

Di	ctionaries	Wildcard queries	Edit distanc	e Spelling c	orrection Sou
		S	n	0	W
	0	1 1	2 2	3 3	4 4
0	1 1				
S	2 2				
I	3 3				
0	4 4				

Di	ctionaries	Wildcard queries	Edit distanc	e Spelling c	orrection Sou
		S	n	0	W
	0	1 1	2 2	3 3	4 4
0	$\frac{1}{1}$	1 2 ?			
S	2 2				
I	3 3				
0	4 4				

Di	ctionaries	V	Vildcard	queries	Edit distance		e S	pelling c	orrection	Soı
			S		r	n		0		V
	0	-	1 1		2	2	3	3 3		4
0	1 1	-	2	2 1						
S	2 2	-								
I	3 3	-								
0	4	-								

Di	ctionaries	,	Wildcard	l queries	Edi	t distanc	e S	pelling c	orrection	Sou
			S		r	n		0		V
	0	_	1	1		2	3	3	4	4
0	$\frac{1}{1}$	_	1 2	2 1	2 2	3 ?				
S	2 2	_								
I	3 3	_								
0	4	_								

Di	ctionaries	Wildcard queries	Edit distanc	e Spelling c	orrection Sou
		S	n	0	W
	0	1 1	2 2	3 3	4 4
0	1 1	1 2 2 1	2 3 2 2		
s	2 2				
I	3 3				
0	4 4				

Di	ctionaries	Wildcard queries	Edit distand	e Spelling co	orrection Sou
		S	n	0	W
	0	1 1	2 2	3 3	4 4
0	1 1	1 2 2 1	2 3 2 2	2 4 3 ?	
S	2 2				
I	3 3				
0	4 4				

Di	ctionarie	es	Wildcard	l queries	Edit distance		e S	pelling c	orrection S	
			S		r	n		0		٧
	_	0	1	1		2	3	3	4	4
0		1 1	<u>1</u> 2	2 1	2 2	3 2	3	2		
S		2								
I		3								
0		4								

Di	ctionari	es	Wildcard	I queries	Edi	t distanc	e S	Spelling correction		
			S		r	n		0		V
		0	1	1	2	2	3	3	4	4
0		1	<u>1</u> 2	2 1	2 2	3 2	3	2	<u>4</u> 3	<u>5</u>
S		2								
I		3								
0		4								

Di	ictionar	ies	Wildcard	l queries	Edi	t distanc	e S	Spelling correction		
			S		r	n		0		V
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S		2								
I	_	3								
o		4								

Di	ictionaries	Wildcard queries	Edit distand	e Spelling c	orrection Sou
		S	n	0	W
	0	1 1	2 2	3 3	4 4
0	1 1	1 2 2 1	2 3 2 2	2 4 3 2	4 5 3 3
S	2 2	1 2 3 ?			
I	3 3				
o	4 4				

Di	ctionaries	,	Wildcard queries		Edit distance		e S	pelling c	orrection Sc	
			S		r	n		0		٧
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I		3								
0		1								

Di	ctionar	ries	Wildcard	l queries	Edit distance		e S	pelling c	orrection	Sou
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Di	ctionari	es	Wildcard	l queries	Edi	t distanc	e S	pelling c	orrection	Sou
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Di	ctionar	ies	Wildcard	l queries	Edi	t distanc	e S	pelling c	orrection	Sou
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Di	ctionar	ies	Wildcard	l queries	Edi	t distanc	e S	pelling c	orrection	Sou
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		3								
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Di	ctiona	ries	Wildcard	l queries	Edi	t distanc	e S	pelling c	orrection	Soı
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Di	ctionar	ies	Wildcard	l queries	Edi	t distanc	e S	pelling c	orrection	Sou
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Di	ctionarie	s	Wildcard	l queries	Edi	t distanc	e S	pelling c	orrection	Sou
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		3	3 4	?						
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Di	ctionar	ies	Wildcard	l queries	Edi	t distanc	e S	pelling c	orrection	Soı
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Di	ctionar	ies	Wildcard	l queries	Edi	t distanc	e S	pelling c	orrection	Soı
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D	ictiona	ries	Wildcard	l queries	Edi	t distanc	e S	pelling c	orrection	Soı
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Die	ctionar	ries	Wildcard	l queries	Edi	t distanc	e S	pelling c	orrection	Sou
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Di	ctionari	es	Wildcard	l queries	Edi	t distanc	e S	pelling c	orrection	Soı
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D	ictiona	ries	Wildcard	l queries	Edi	t distanc	e S	2 4 4 5 3 2 3 3 3 3 4 3 3 4 3		
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I		3	3 4	2	3	3 2	3	3	4	4
o		4								

Di	ctionarie	es	Wildcard	l queries	Edi	t distanc	e S	2 4 5 3 2 3 3 3 4 4 3 3 4 4 4 4		
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S		2	3	2 1	2 2	3 2	3			
I		3	3 4	2	3	3 2	3	3	4 4	4
0		4	4 5	3						

Di	ctionari	es	Wildcard	l queries	Edi	t distanc	e S	2 4 5 3 2 3 3 3 3 3 4 3 3 3 4 3			
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S		2	<u>1</u> 3	2 1	2 2	3 2	3				
I		3	3 4	2	3	3 2	3	3	4	4	
0		4	4 5	3							

Di	ctionar	ies	Wildcard	l queries	Edi	t distanc	e S	pelling c	orrection	Sou
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S		2	<u>1</u> 3	2 1	2 2	3 2	3	3	3 4	3
I		3	3 4	2	3	3 2	3	3	4	4
0		4	4 5	3	3 4	3				

Di	ictiona	ries	Wildcard	l queries	Edi	t distanc	e S	2 4 5 3 2 3 3 3 4 3 3 4 4 3 3 4 4		
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∥ ,		3	3	2	2	3	3	4	4	4
'		3	4	2	3	2	3	3	4	4
		4	4	3	3	3				
0		4	5	3	4	3				

	Die	ctionar	ries	Wildcard	l queries	Edi	t distanc	e S	pelling c	orrection	Soı		
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			3	3 4	2	3	3 2	3 3	3	4	4		
c)		4	4 5	3	$\frac{3}{4}$	3	2	7				

Di	ctionaries	s '	Wildcard	l queries	Edi	t distanc	e S	pelling c	orrection S	
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s	II ——	2 2	3	2 1	2 2	3 2	3 3	3	3 4	3
I	II ——	3	3 4	2	3	3 2	3 3	3	4 4	4
0	II ———	4	4	3	3	3	2	4		

Die	ctionar	ries	Wildcard	l queries	Edi	t distanc	c e S	pelling c	orrection	Sou
			9	5	r	1	()	V	V
		0	1	1		2	3	3	4	4
0		1	<u>1</u> 2	2 1	2 2	3 2	3	2	⁴ / ₃	5 3
S	_	2	<u>1</u> 3	2 1	2 2	3 2	3	3	3 4	3
I	_	3	3 4	2	3	3 2	3 3	3	4	4
0		4	4 5	3	3 4	3	4	2	4 3	5 ?

Di	ctionar	ies	Wildcard	l queries	Edi	t distand	e S	pelling c	orrection	Sou
			9	S	r	1	()	V	V
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0		1	<u>1</u> 2	2 1	2 2	3 2	3	2	⁴ / ₃	5 3
s		2	<u>1</u> 3	2 1	2 2	3 2	3	3	<u>3</u> 4	3
I		3	3 4	2	3	3 2	3	3	4	4
0		4	4 5	3	3 4	3	4	<u>4</u> <u>2</u>	4 3	5 3

	Dio	ctionar	ies	Wildcard	l queries	Edi	t distanc	e S	pelling co	orrection	Soun
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	0		1	2	1	2	2	3	2	3	3
I			2	1	2	2	3	3	3	3	4
	S		2	3	1	2	2	3	3	4	3
	ı		3	3	2	2	3	3	4	4	4
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Die	ctionar	ries	Wildcard	l queries	Edi	t distanc	e S	pelling co	orrection	Soı
			:	5	r	ı	()	٧	٧
		0	1	1	2	2	3	3	4	4
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		2	1	2	2	3	3	3	3	4
S		2	3	1	2	2	3	3	4	3
ı		3	3	2	2	3	3	4	4	4
1		3	4	2	3	2	3	3	4	4
		4	4	3	3	3	2	4	4	5
0		4	5	3	4	3	4	2	3	3

How do I read out the editing operations that transform OSLO into SNOW ?

Di	ctionar	ies	Wildcard	d queries	Edi	t distanc	e S	pelling co	orrection	Soun
			9	S	r	า	()	١	٧
		0	1	1	2	2	3	3	4	4
0		1	1	2	2	3	2	4	4	5
		1	2	1	2	2	3	2	3	3
S		2	$\frac{1}{2}$	2	2	3	3	3	3	4
		2	3	1	2	2	3	3	4	3
lı		3	_3	2	_2	3	3	4	4	4
		3	4	2	3	2	3	3	4	4
0		4	4	3	3	3	2	4	4	5
		4	5	3	4	3	4	2	3	3

W

operation | input | output

*

insert

cost

Di	ctionar	ies	Wildcard	l queries	Edi	t distand	e Sp	pelling co	rrection	Sound
			:	5	r	1	(0	V	V
		0	1	1	2	2	3	3	4	4
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S		2	3	2 1	2 2	3 2	3	3	3 4	3
ı		3	3 4	2	3	3 2	3 3	3	4	4
0	_	4	<u>4</u> 5	3	3 4	3	4	2	4 3	5 3

cost	operation	input	output
0	(copy)	0	0
1	insert	*	W

Dio	ctionar	ies	Wildcard	l queries	Edit	distance	: Spe	elling corr	ection	Sounde
			:	S	ı	n	(0	٧	٧
		0	1	1	2	2	3	3	4	4
		1	1	2	2	3	2	4	4	5
0		1	2	1	2	2	3	2	3	3
		2	1	2	2	3	3	3	3	4
S		2	3	1	2	2	3	3	4	3
		3	3	2	2	3	3	4	4	4
1		3	4	2	3	2	3	3	4	4
		4	4	3	3	3	2	4	4	5
0		4	5	3	4	3	4	2	3	3

	cost	operation	input	output
_	1	replace	I	n
	0	(copy)	0	0
	1	insert	*	W

Di	ctionar	ries	Wildcard	queries	Edit	distance	Spel	ling corre	ction	Soundex
			:	S	r	ı	()	١	٧
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		0	1	_				_		
0		1	_1	2	2	3	2	4	4	5
O		1	2	1	2	2	3	2	3	3
S		2	1	2	2	3	3	3	3	4
5		2	3	1	2	2	3	3	4	3
		3	3	2	2	3	3	4	4	4
		3	4	2	3	2	3	3	4	4
0		4	4	3	3	3	2	4	4	5
U		4	5	3	4	3	4	2	3	3

cost	operation	input	output
0	(copy)	S	S
1	replace	1	n
0	(copy)	0	0
1	insert	*	W

Di	ctionaries V	Vildcard queries	Edit distance	Spelling correct	ion Soundex
		S	n	0	W
	0	1 1	2 2	3 3	4 4
0	1 1	1 2 2 1	2 3 2 2	2 4 3 2	4 5 3 3
S	2 2	1 2 3 1	2 3 2 2	3 3 3 3	3 4 4 3
ı	3 3	3 2 4 2	2 3 3 2	3 4 3 3	4 4 4
0	4 4	4 3 5 3	3 3 4 3	2 4 4 2	4 5 3 3

cost	operation	input	output
1	delete	0	*
0	(copy)	S	S
1	replace	I	n
0	(copy)	0	0
1	insert	*	W

		(2	ā	a	i	t	(;	ā	a	i	į
	 0	1	1	2	2	3	3	4	4	5	5	6	6
С	1	0 2	2 0	2 1	3 1	3 2	4 2	3 3	5 3	5 4	6 4	6 5	7 5
а	2	3	1	0 2	2 0	2 1	3 1	3 2	2	3	5 3	5 4	6 4
t	3	3 4	2	3	1	2	0	2 1	3 1	3 2	2	3	5 3

			(C		a	•	t	(á	a	1	t
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а	_	2 2	3	1	2	0	2 1	3 1	3 2	2	3	5 3	5 4	6 4
t		3	3 4	2	3	1	2	2 0	2 1	3 1	3 2	2	3	5 3

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

			(C	á	a	į	ţ	(á	a	1	t
		0	1	1	2	2	3	3	4	4	5	5	6	6
С		1 1	2	0	2 1	3 1	3 2	2	3	5 3	5 4	6 4	6 5	5
а	_	2 2	3	1	<u>0</u> 2	2 0	2 1	3 1	3 2	2	3	5 3	5 4	6 4
t		3	3 4	2	3	1 1	0 2	2 0	2 1	3 1	3 2	2	3	5 3

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

			(C	ā	a	į	ţ	(á	a	1	t
	_	0	1	1	2	2	3	3	4	4	5	5	6	6
С	-	1 1	0 2	0	2 1	3 1	3 2	2	3	5 3	5 4	6 4	6 5	5
а	_	2	3	1	0 2	0	2 1	3 1	3 2	2	3	5 3	5 4	6 4
t	_	3	3 4	2	3	1 1	2	2 0	2 1	3 1	3 2	2	3	5 3

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

			(C	ā	Э	i	ţ	(á	a	1	t
	_	0	1	1	2	2	3	3	4	4	5	5	6	6
С	_	1 1	0 2	0	2 1	3 1	3 2	2	3	5 3	5 4	6 4	6 5	7 5
а	_	2 2	3	1	0 2	0	2 1	3 1	3 2	2	3	5 3	5 4	6 4
t	_	3	3 4	2	3	1 1	0 2	0	2 1	3 1	3 2	2	3 3	5 3

cost	operation	input	output
0	(copy)	С	С
0	(copy)	а	а
0	(copy)	t	t
1	insert	*	С
1	insert	*	а
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- Recap
- 2 Dictionaries
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- 4 Edit distance
- Spelling correction
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 - Can correct form/from error above

Correcting documents

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- In IR, we use document correction primarily for OCR'ed documents. (OCR = optical character recognition)
- The general philosophy in IR is: don't change the documents.

Correcting queries

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- Why is this problematic?

Alternatives to using the term vocabulary

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Distance between misspelled word and "correct" word

Several alternatives

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- Edit distance and Levenshtein distance

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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.

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k-gram indexes for spelling correction

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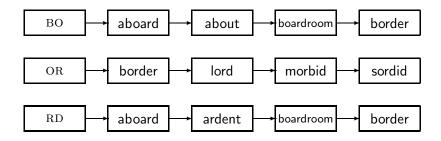
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- E.g., only vocabulary terms that differ by at most 3 k-grams

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

• 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

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 - automatic vs. suggested correction

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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.

```
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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Soundex

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- Soundex is the basis for finding phonetic (as opposed to orthographic) alternatives.
- 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

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

- Retain H
- ERMAN → ORMON
- ORMON → 06505
- \bullet 06505 \to 06505

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

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

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

Soundex

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How useful is Soundex?

- Not very for information retrieval
- Ok for "high recall" tasks in other applications (e.g., Interpol)
- 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://cislmu.org
 - 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