



Spelling Correction

Independent Word Spelling Correction

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> Topics to be covered

- Recap:
 - Phrase Queries
 - Proximity Search
 - Permuterm Index
 - Bi-gram Indexes
- Spelling Correction
 - Independent Word Spelling Correction
 - Spelling Detection
 - Specific tasks in Spelling Correction
 - ➤ More topics to come up ... Stay tuned ...!!



Recap: Information Retrieval

- Information Retrieval (IR) is finding material (usually documents) of an unstructured nature (usually text) that satisfies an information need from within large collections (usually stored on computers).
- These days we frequently think first of web search, but there are many other cases:
 - E-mail search
 - Searching your laptop
 - Corporate knowledge bases
 - Legal information retrieval
 - and so on . . .



Recap: Phrase queries

- We want to be able to answer queries such as <u>"stanford university"</u> – as a phrase
- Thus the sentence "I went to university at Stanford" is not a match.
 - The concept of phrase queries has proven easily understood by users; one of the few "advanced search" ideas that works
 - Many more queries are implicit phrase queries
- For this, it no longer suffices to store only
 - <term : docs> entries



Recap: Wild-card queries: *

- mon*: find all docs containing any word beginning with "mon".
- Easy with binary tree (or B-tree) dictionary: retrieve all words in range: mon ≤ w < moo
- *mon: find words ending in "mon": harder
 - Maintain an additional B-tree for terms backwards.

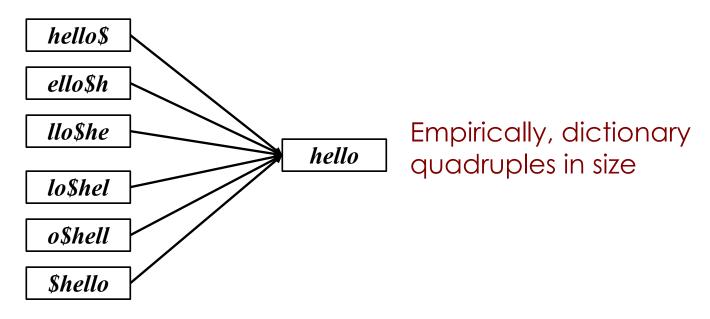
Can retrieve all words in range: **nom ≤ w < non**.

From this, how can we enumerate all terms meeting the wild-card query **pro*cent**?



Recap: Permuterm index

- Add a \$ to the end of each term
- Rotate the resulting term and index them in a B-tree
- For term hello, index under:
 - hello\$, ello\$h, llo\$he, lo\$hel, o\$hell, \$hello
 where \$ is a special symbol

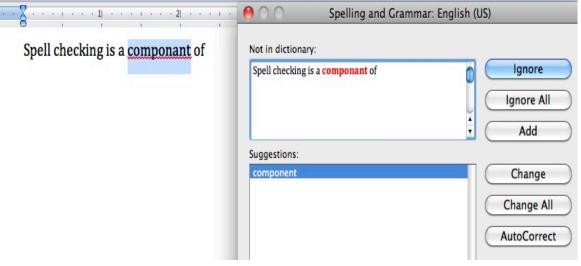




Spelling Correction

Apps For Spelling Correction

Word processing



Web search



natural langage processing

Showing results for <u>natural language</u> processing Search instead for natural language processing

Phones



Spelling Tasks

- Spelling Error Detection
- Spelling Error Correction:
 - Autocorrect
 - hte→the
 - Suggest a correction
 - Suggestion lists

Types of spelling errors

- Non-word Errors
 - graffe → giraffe
- Real-word Errors
 - Typographical errors
 - three →there
 - Cognitive Errors (homophones)
 - piece > peace,
 - too → two
 - your →you're
- Non-word correction was mainly context insensitive
- Real-word correction almost needs to be context sensitive

Non-word spelling errors

- Non-word spelling error detection:
 - Any word not in a dictionary is an error
 - The larger the dictionary the better ... up to a point
 - (The Web is full of mis-spellings, so the Web isn't necessarily a great dictionary ...)
- Non-word spelling error correction:
 - Generate candidates: real words that are similar to error
 - Choose the one which is best:
 - Shortest weighted edit distance
 - Highest noisy channel probability

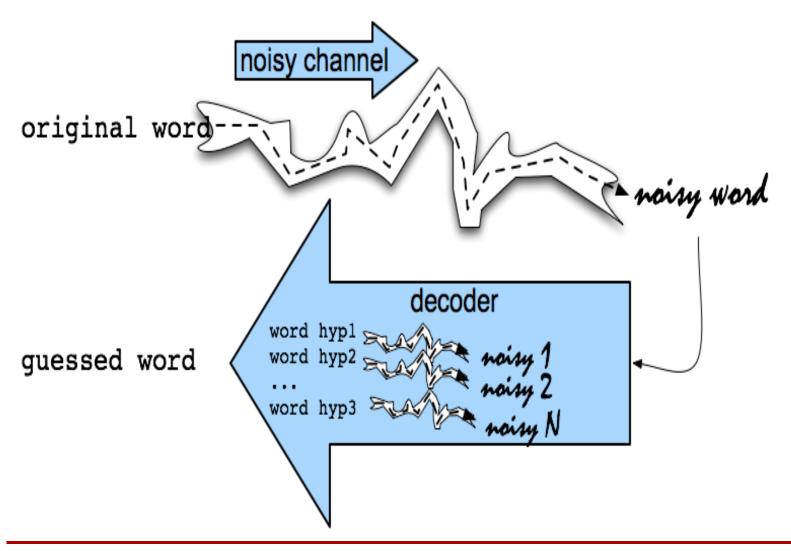


INDEPENDENT WORD SPELLING CORRECTION

The Noisy Channel Model of Spelling



Noisy Channel Intuition





Noisy Channel - Bayes' Rule

- We see an observation x of a misspelled word
- Find the correct word ŵ

$$\hat{w} = \underset{w \in V}{\operatorname{argmax}} P(w \mid x)$$

$$= \underset{w \in V}{\operatorname{argmax}} \frac{P(x \mid w)P(w)}{P(x)}$$

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Noisy channel model

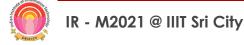
History: Noisy channel for spelling proposed around 1990

IBM

 Mays, Eric, Fred J. Damerau and Robert L. Mercer. 1991. Context based spelling correction. Information Processing and Management, 23(5), 517–522

AT&T Bell Labs

 Kernighan, Mark D., Kenneth W. Church, and William A. Gale. 1990. <u>A spelling correction</u> <u>program based on a noisy channel model</u>. Proceedings of COLING 1990, 205-210



Non-word spelling error - example

acress

Candidate Generation

- Words with similar spelling
 - Small edit distance to error
- Words with similar pronunciation
 - Small distance of pronunciation to error

Candidate Testing: Damerau-Levenshtein edit distance

- Minimal edit distance between two strings, where edits are:
 - Insertion
 - Deletion
 - Substitution
 - Transposition of two adjacent letters

Words within 1 of acress

Error	Candidate Correction	Correct Letter	Error Letter	Type
acress	actress	t	_	deletion
acress	cress	_	a	insertion
acress	caress	ca	ac	transposition
acress	access	C	r	substitution
acress	across	0	е	substitution
acress	acres	_	S	Insertion / deletion



Candidate Generation

- 80% of errors are within edit distance 1
- Almost all errors within edit distance 2
- Also allow insertion of space or hyphen
 - thisidea → this idea
 - inlaw → in-law
- Can also allow merging words
 - data base → database
 - For short texts like a query, can just regard whole string as one item from which to produce edits

How do you generate the candidates?

- Run through dictionary, check edit distance with each word
- Generate all words within edit distance ≤ k (e.g., k = 1 or 2)
 and then intersect them with dictionary
- Use a character k-gram index and find dictionary words that share "most" k-grams with word (e.g., by Jaccard coefficient)
 - see IIR sec 3.3.4
- Compute them fast with a Levenshtein finite state transducer
- Have a precomputed map of words to possible corrections



A Paradigm ...

- We want the best spell corrections
- Instead of finding the very best, we
 - Find a subset of pretty good corrections
 - (say, edit distance at most 2)
 - Find the best amongst them
- These may not be the actual best
- This is a recurring paradigm in IR including finding the best docs for a query, best answers, best ads ...
 - Find a good candidate set
 - Find the top K amongst them and return them as the best

With candidates Generated: Now back to Bayes' Rule

- We see an observation x of a misspelled word
- Find the correct word \hat{w}

$$\hat{w} = \underset{w \in V}{\operatorname{argmax}} P(w \mid x)$$

$$= \underset{w \in V}{\operatorname{argmax}} \frac{P(x \mid w)P(w)}{P(x)}$$

$$= \underset{w \in V}{\operatorname{argmax}} P(x \mid w) P(w)$$

What's P(w)?

Language Model

 Take a big supply of words (your document collection with T tokens); let C(w) = # occurrences of w

$$P(w) = \frac{C(w)}{T}$$

 In other applications – you can take the supply to be typed queries (suitably filtered) – when a static dictionary is inadequate

Unigram Prior probability

Counts from 404,253,213 words in Corpus of Contemporary English (COCA)

word	Frequency of word	P(w)							
actress	9,321	.0000230573							
cress	220	.0000005442							
caress	686	.0000016969							
access	37,038	.0000916207							
across	120,844	.0002989314							
acres	12,874	.0000318463							



Channel model probability

- Error model probability, Edit probability
- Kernighan, Church, Gale 1990

- Misspelled word x = x1, x2, x3... xm
- Correct word w = w1, w2, w3,..., wn

- P(x|w) = probability of the edit
 - (deletion/insertion/substitution/transposition)

Computing error probability: confusion "matrix"

```
del[x,y] : count(xy typed as x)
ins[x,y] : count(x typed as xy)
sub[x,y] : count(y typed as x)
trans[x,y] : count(xy typed as yx)
```

Insertion and deletion conditioned on previous character

Confusion matrix for substitution

sub[X, Y] = Substitution of X (incorrect) for Y (cor
--

X	Y (correct)																									
	a	b	С	d	e	f	g	h	i	j	k	1	m	n	0	p	q	r	S	t	u	v	w	Х	У	Z
a	0	0	7	1	342	0	0	2	118	0	1	0	0	3	76	0	0	1	35	9	9	0	1	0	5	0
ь	0	0	9	9	2	2	3	1	0	0	0	5	11	5	0	10	0	0	2	I	0	0	8	0	0	0
c	6	5	0	16	0	9	5	0	0	0	1	0	7	9	1	10	2	5	39	40	1	3	7	1	1	0
d	1	10	13	0	12	0	5	5	0	0	2	3	7	3	0	1	0	43	30	22	0	0	4	0	2	0
c	388	0	3	11	0	2	2	0	89	0	0	3	0	5	93	0	0	14	12	6	15	0	1	0	18	0
f	0	15	0	3	1	0	5	2	0	0	0	3	4	1	0	0	0	6	4	12	0	0	2	0	0	0
g	4	1	11	11	9	2	0	0	0	1	1	3	0	0	2	1	3	5	13	21	0	0	1	0	3	0
h	1	8	0	3	0	0	0	0	0	0	2	0	12	14	2	3	0	3	1	11	0	0	2	0	0	0
i	103	0	0	0	146	0	1	0	0	0	0	6	0	0	49	0	0	0	2	1	47	0	2	1	15	0
j	0	1	1	9	0	0	1	0	0	0	0	2	1	0	0	0	0	0	5	0	0	0	0	0	0	0
k	1	2	8	4	1	1	2	5	0	0	0	0	5	0	2	0	0	0	6	0	0	0	. 4	0	0	3
1	2	10	1	4	0	4	5	6	13	0	1	0	0	14	2	5	0	11	10	2	0	0	0	0	0	0
m	1	3	7	8	0	2	0	6	0	0	4	4	0	180	0	6	0	0	9	15	13	3	2	2	3	0
n	2	7	6	5	3	0	1	19	1	0	4	35	78	0	0	7	0	28	5	7	0	0	1	2	0	2
0	91	1	1	3	116	0	0	0	25	0	2	0	0	0	0	14	0	2	4	14	39	0	0	0	18	0
p	0	11	1	2	0	6	5	0	2	9	0	2	7	6	15	0	0	1	3	6	0	4	1	0	0	0
q	0	0	1	0	0	0	27	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
r	0	14	0	30	12	2	2	8	2	0	5	8	4	20	1	14	0	0	12	22	4	0	0	1	0	0
s	11	8	27	33	35	4	0	1	0	1	0	27	0	6	1	7	0	14	0	15	0	0	5	3	20	1
t	3	4	9	42	7	5	19	5	0	1	0	14	9	5	5	6	0	11	37	0	0	2	19	0	7	6
u	20	0	0	0	44	0	0	0	64	0	0	0	0	2	43	0	0	4	0	0	0	0	2	0	8	0
v	0	0	7	0	0	3	0	0	0	0	0	1	0	0	1	0	0	0	8	3	0	0	0	0	0	0
w	2	2	1	0	1	0	0	2	0	0	1	0	0	0	0	7	0	6	3	3	1	0	0	0	0	0
х	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	9	0	0	0	0	0	0	0
у	0	0	2	0	15	0	1	7	15	0	0	0	2	0	6	1	0	7	36	8	5	0	0	1	0	0
z	0	0	0	7	0	0	0	0	0	0	0	7	5	0	0	0	0	2	21	3	0	0	0	0	3	0



Nearby keys



Generating the confusion matrix

- Peter Norvig's list of errors
- Peter Norvig's list of counts of single-edit errors
 - All Peter Norvig's ngrams data links: http://norvig.com/ngrams/

Summary

In this class, we focused on:

- (a) Recap: Positional Indexes
 - i. Positional Index Size
 - ii. Wild card Queries
 - iii. Permuterm index
- (b) Spelling Correction
 - Types of Spelling Correction
 - ii. Noisy Channel modelling for Spell Correction
 - iii. Spelling Suggestions



Acknowledgements

Thanks to ALL RESEARCHERS:

- 1. Introduction to Information Retrieval Manning, Raghavan and Schutze, Cambridge University Press, 2008.
- 2. Search Engines Information Retrieval in Practice W. Bruce Croft, D. Metzler, T. Strohman, Pearson, 2009.
- Information Retrieval Implementing and Evaluating Search Engines Stefan Büttcher, Charles L. A. Clarke and Gordon V. Cormack, MIT Press, 2010.
- 4. Modern Information Retrieval Baeza-Yates and Ribeiro-Neto, Addison Wesley, 1999.
- Many Authors who contributed to SIGIR / WWW / KDD / ECIR
 / CIKM / WSDM and other top tier conferences
- Prof. Mandar Mitra, Indian Statistical Institute, Kolkatata (https://www.isical.ac.in/~mandar/)





Questions It's Your Time





