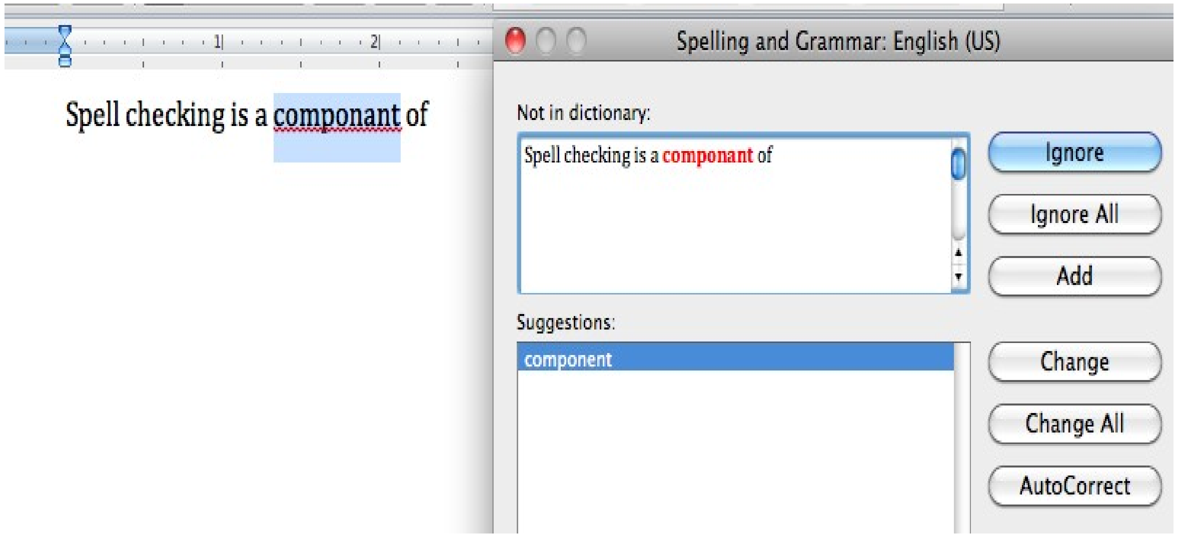
Probabilistic Models of Spelling

Disclaimer : These slides are taken from the lecture of “CS276: Information Retrieval and Web Search” by Christopher Manning and Pandu Nayak.

Applications for spelling correction

Word processing


Spell checking is a componant of

Spelling and Grammar: English (US)

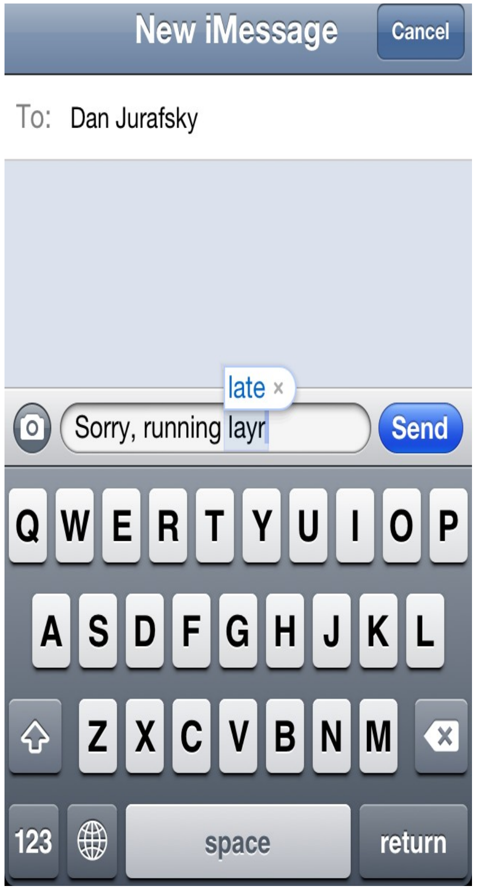
Not in dictionary:

Spell checking is a componant of

Suggestions:

component

Phones

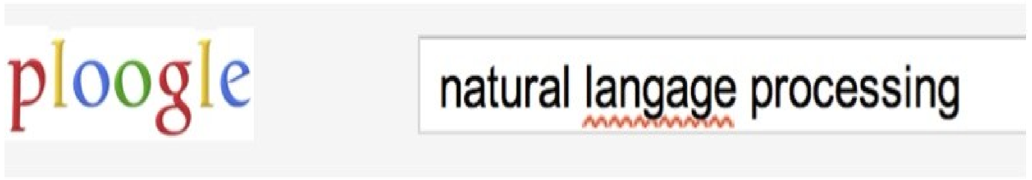


To: Dan Jurafsky

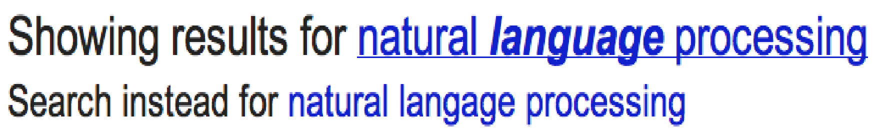
Sorry, running layr

late

Web search



natural langage processing


Showing results for natural *language* processing

Search instead for natural langage processing

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 historically 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

Real word & non-word spelling errors

- For each word *w*, generate candidate set:
  - Find candidate words with similar ***pronunciations***
  - Find candidate words with similar ***spellings***
  - Include *w* in candidate set
- Choose best candidate
  - Noisy Channel view of spell errors
  - Context-sensitive – so have to consider whether the surrounding words "make sense"
  - *Flying form Heathrow to LAX* → *Flying from Heathrow to LAX*

Terminology

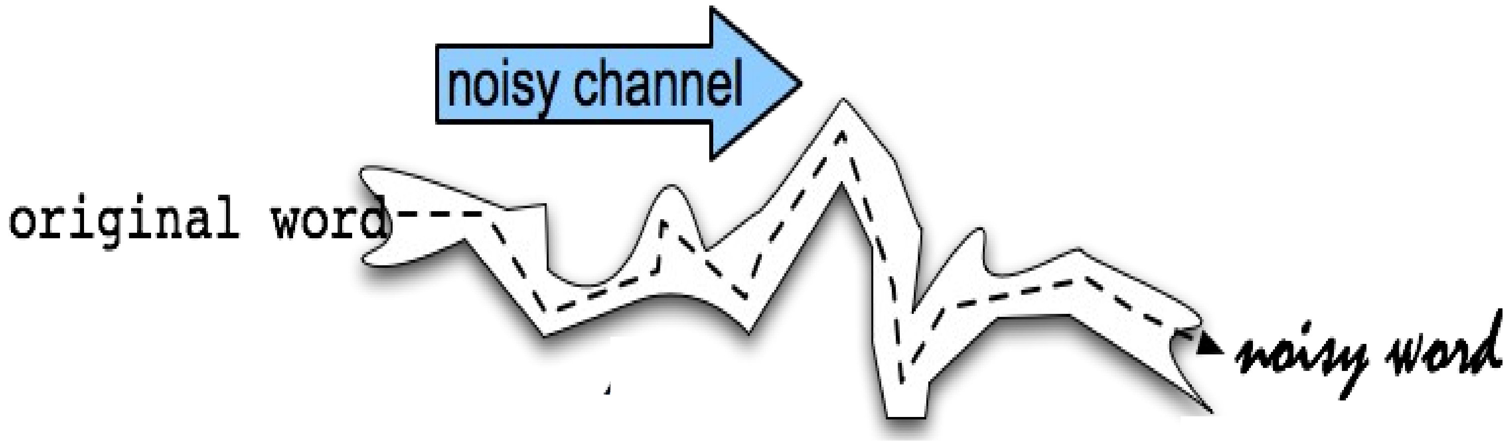
- These are *character bigrams*:
  - *st, pr, an …*
- These are *word bigrams*:
  - *palo alto, flying from, road repairs*
- In today's class, we will generally deal with *word* bigrams

Similarly trigrams, *k*-grams etc

The Noisy Channel Model of Spelling

independent word Spelling Correction

Noisy Channel Intuition



Noisy Channel = Bayes' Rule

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

$$P(w|x) ¿$$

$$\frac{P(x|w)P(w)}{P(x)} ¿$$

Bayes

$$P(x|w)P(w) ¿$$

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. A spelling correction program based on a noisy channel model. 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	o	e	substitution
acress	acres	-	s	insertion

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?

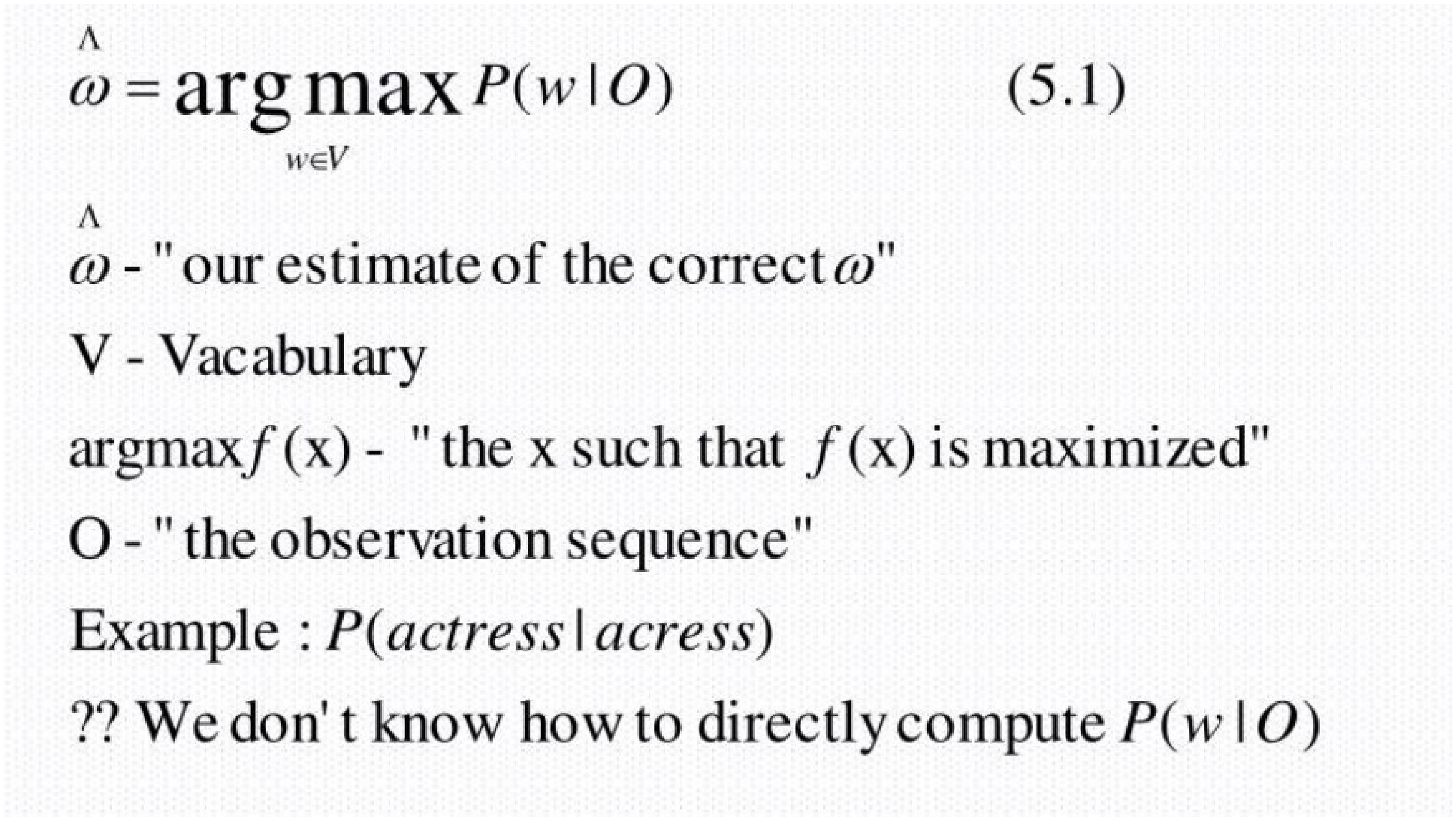
1. Run through dictionary, check edit distance with each word
2. Generate all words within edit distance ≤ *k* (e.g., *k* = 1 or 2) and then intersect them with dictionary
3. Use a character *k*-gram index and find dictionary words that share “most” *k*-grams with word (e.g., by Jaccard coefficient)
4. Compute them fast with a Levenshtein finite state transducer
5. 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

Let’s say we’ve generated candidates: Now back to Bayes’ Rule

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



$$\hat{\omega} = \underset{w \in V}{\arg\max} P(w \mid O) \qquad (5.1)$$

$\hat{\omega}$ - "our estimate of the correct ω"

V - Vacabulary

argmax f (x) - "the x such that f (x) is maximized"

O - "the observation sequence"

Example : $P(actress \mid acress)$

?? We don't know how to directly compute $P(w \mid O)$

Bayes' rule

$$p(x \mid y) = \frac{p(y \mid x)\, p(x)}{p(y)} \qquad (5.2)$$

Substituting (5.2) into (5.1) to get (5.3)

$$\hat{\omega} = \underset{\omega \in V}{\arg\max} \frac{p(O \mid w)\, p(w)}{p(O)} \qquad (5.3)$$

$p(w)$, the probability of the word itself.

$p(O \mid w)$, explain in next session.

$p(O)$, can be ignored, since it is a constant to each word.

$$\hat{\omega} = \underset{\omega \in V}{\arg\max} \overbrace{p(O \mid w)}^{likelihood} \overbrace{p(w)}^{prior} \qquad (5.5)$$

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* $x = x_1, x_2, x_3 \ldots x_m$
- *Correct word* $w = w_1, w_2, w_3, \ldots, w_n$

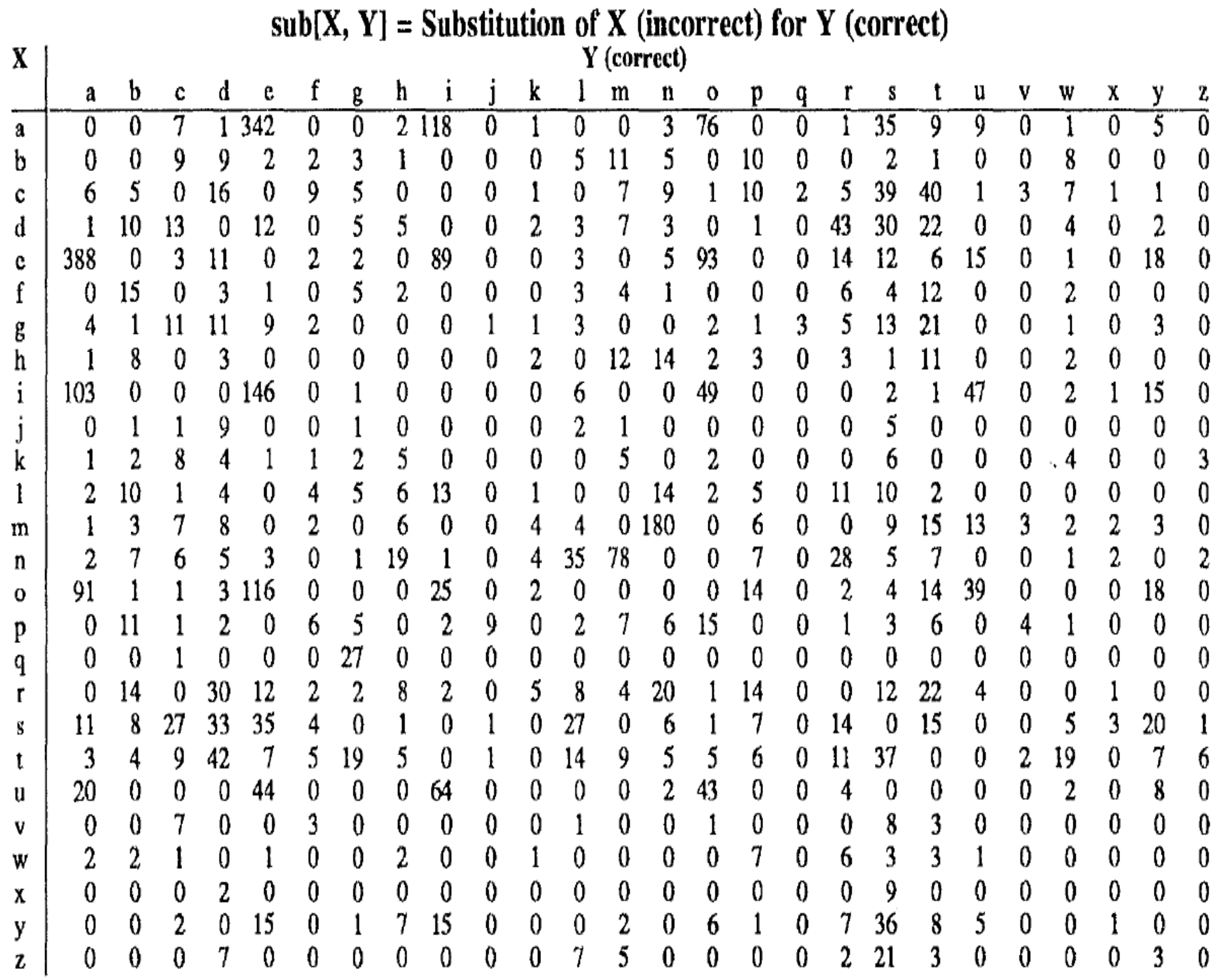
- $P(O|w)$ = probability of the edit
  - (deletion/insertion/substitution/transposition)

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

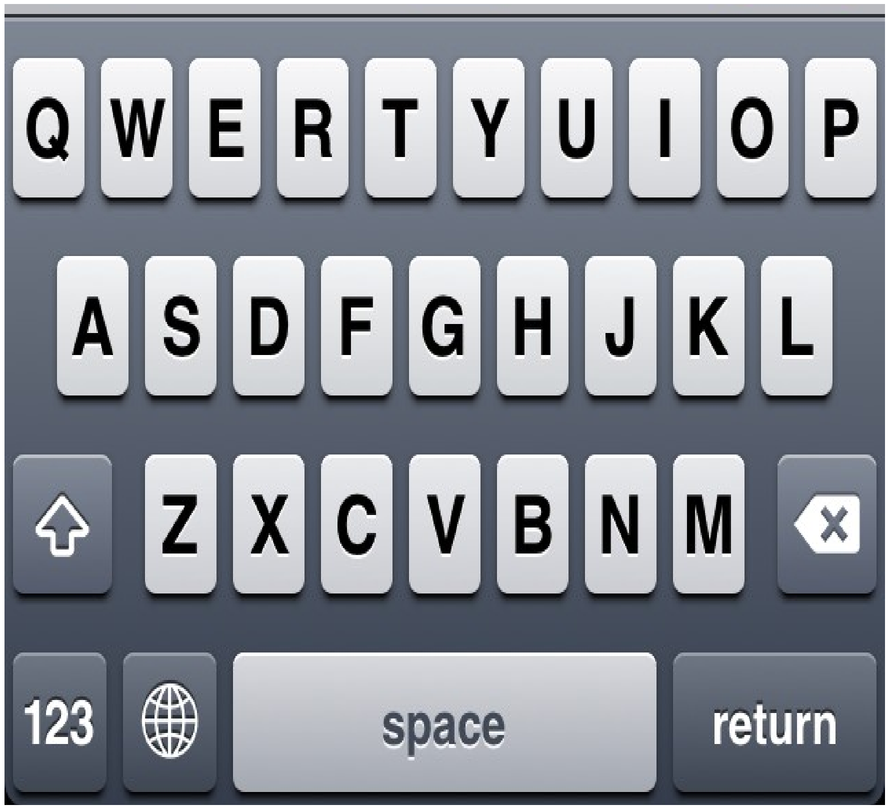
Confusion matrix for substitution



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

X	Y (correct)																									
	a	b	c	d	e	f	g	h	i	j	k	l	m	n	o	p	q	r	s	t	u	v	w	x	y	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
b	0	0	9	9	2	2	3	1	0	0	0	5	11	5	0	10	0	0	2	1	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
e	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
l	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
o	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
x	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
y	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



Channel model

Kernighan, Church, Gale 1990

$$P(x|w) = \begin{cases} \frac{\mathrm{del}[w_{i-1}, w_i]}{\mathrm{count}[w_{i-1} w_i]}, & \text{if deletion} \\ \frac{\mathrm{ins}[w_{i-1}, x_i]}{\mathrm{count}[w_{i-1}]}, & \text{if insertion} \\ \frac{\mathrm{sub}[x_i, w_i]}{\mathrm{count}[w_i]}, & \text{if substitution} \\ \frac{\mathrm{trans}[w_i, w_{i+1}]}{\mathrm{count}[w_i w_{i+1}]}, & \text{if transposition} \end{cases}$$

Smoothing probabilities: Add-1 smoothing

- But if we use the confusion matrix example, unseen errors are impossible!
- They'll make the overall probability 0. That seems too harsh
  - e.g., in Kernighan's chart q➔a and a➔q are both 0, even though they're adjacent on the keyboard!
- A simple solution is to add 1 to all counts and then if there is a |A| character alphabet, to normalize appropriately:

$$\text{If substitution, } P(x|w) = \frac{\text{sub}[x,w]+1}{\text{count}[w]+A}$$

Channel model for `acress`

Candidate Correction	Correct Letter	Error Letter	*x|w*	*P(x|w)*
actress	t	-	c|ct	.000117
cress	-	a	a|#	.00000144
caress	ca	ac	ac|ca	.00000164
access	c	r	r|c	.000000209
across	o	e	e|o	.0000093
acres	-	s	es|e	.0000321
acres	-	s	ss|s	.0000342

Candidate Correction	Correct Letter	Error Letter	x|w	P(x|w)	P(w)	10^9 * P(x|w) * P(w)
actress	t	-	c|ct	.000117	.0000231	2.7
cress	-	a	a|#	.00000144	.000000544	.00078
caress	ca	ac	ac|ca	.00000164	.00000170	.0028
access	c	r	r|c	.000000209	.0000916	.019
across	o	e	e|o	.0000093	.000299	2.8
acres	-	s	es|e	.0000321	.0000318	1.0
acres	-	s	ss|s	.0000342	.0000318	1.0

Candidate Correction	Correct Letter	Error Letter	*x*|*w*	*P*(*x*|*w*)	*P*(*w*)	10^9 * *P*(*x*|*w*)*P*(*w*)
actress	t	-	c|ct	.000117	.0000231	2.7
cress	-	a	a|#	.00000144	.000000544	.00078
caress	ca	ac	ac|ca	.00000164	.00000170	.0028
access	c	r	r|c	.000000209	.0000916	.019
across	**o**	**e**	**e|o**	**.0000093**	**.000299**	**2.8**
acres	-	s	es|e	.0000321	.0000318	1.0
acres	-	s	ss|	.0000342	.0000318	1.0

Context-Sensitive Spelling Correction

Spelling Correction with the Noisy Channel

Real-word spelling errors

- `…leaving in about fifteen` ***`minuets`*** `to go to her house.`
- `The design` ***`an`*** `construction of the system…`
- `Can they` ***`lave`*** `him my messages?`
- `The study was conducted mainly` ***`be`*** `John Black.`

- 25-40% of spelling errors are real words Kukich 1992

Context-sensitive spelling error fixing

- For each word in sentence (phrase, query …)
  - Generate *candidate set*
    - the word itself
    - all single-letter edits that are English words
    - words that are homophones
    - (all of this can be pre-computed!)
- Choose best candidates
    - Noisy channel model

Noisy channel for real-word spell correction

- Given a sentence $w_1, w_2, w_3, \ldots, w_n$
- Generate a set of candidates for each word w_i
  - Candidate(w_1) = $\{w_1, w'_1, w''_1, w'''_1, \ldots\}$
  - Candidate(w_2) = $\{w_2, w'_2, w''_2, w'''_2, \ldots\}$
  - Candidate(w_n) = $\{w_n, w'_n, w''_n, w'''_n, \ldots\}$
- Choose the sequence W that maximizes P(W)

Incorporating context words: Context-sensitive spelling correction

- Determining whether **actress** or **across** is appropriate will require looking at the context of use
- We can do this with a better **language model** (may be another day)

- A **bigram language model** conditions the probability of a word on (just) the previous word

$$P(w_1 \ldots w_n) = P(w_1)P(w_2|w_1)\ldots P(w_n|w_{n-1})$$

Incorporating context words

- For unigram counts, P(w) is always non-zero
  - if our dictionary is derived from the document collection
- This won't be true of $P(w_k | w_{k-1})$. We need to **smooth**
- We could use add-1 smoothing on this conditional distribution
- But here's a better way – interpolate a unigram and a bigram:

$$P_{li}(w_k | w_{k-1}) = \lambda P_{uni}(w_k) + (1-\lambda) P_{bi}(w_k | w_{k-1})$$

- $P_{bi}(w_k | w_{k-1}) = C(w_{k-1}, w_k) / C(w_{k-1})$

All the important fine points

- Note that we have several probability distributions for words
- You might want/need to work with log probabilities:
  - $\log P(w_1 \ldots w_n) = \log P(w_1) + \log P(w_2 | w_1) + \ldots + \log P(w_n | w_{n-1})$
  - Otherwise, be very careful about floating point underflow

Using a bigram language model

- "a stellar and versatile **acress** whose combination of sass and glamour…"
- Counts from the Corpus of Contemporary American English with add-1 smoothing
  - P(actress|versatile)=.000021 P(whose|actress) = .0010
  - P(across|versatile) =.000021 P(whose|across) = .000006

  - P("versatile actress whose") = .000021*.0010 = 210 $\times 10^{-10}$
  - P("versatile across whose") = .000021*.000006 = 1 $\times 10^{-10}$

Using a bigram language model

- “a stellar and versatile **acress** whose combination of sass and glamour…”
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- **P(“versatile actress whose”) = .000021*.0010 = 210 x10^{-10}**
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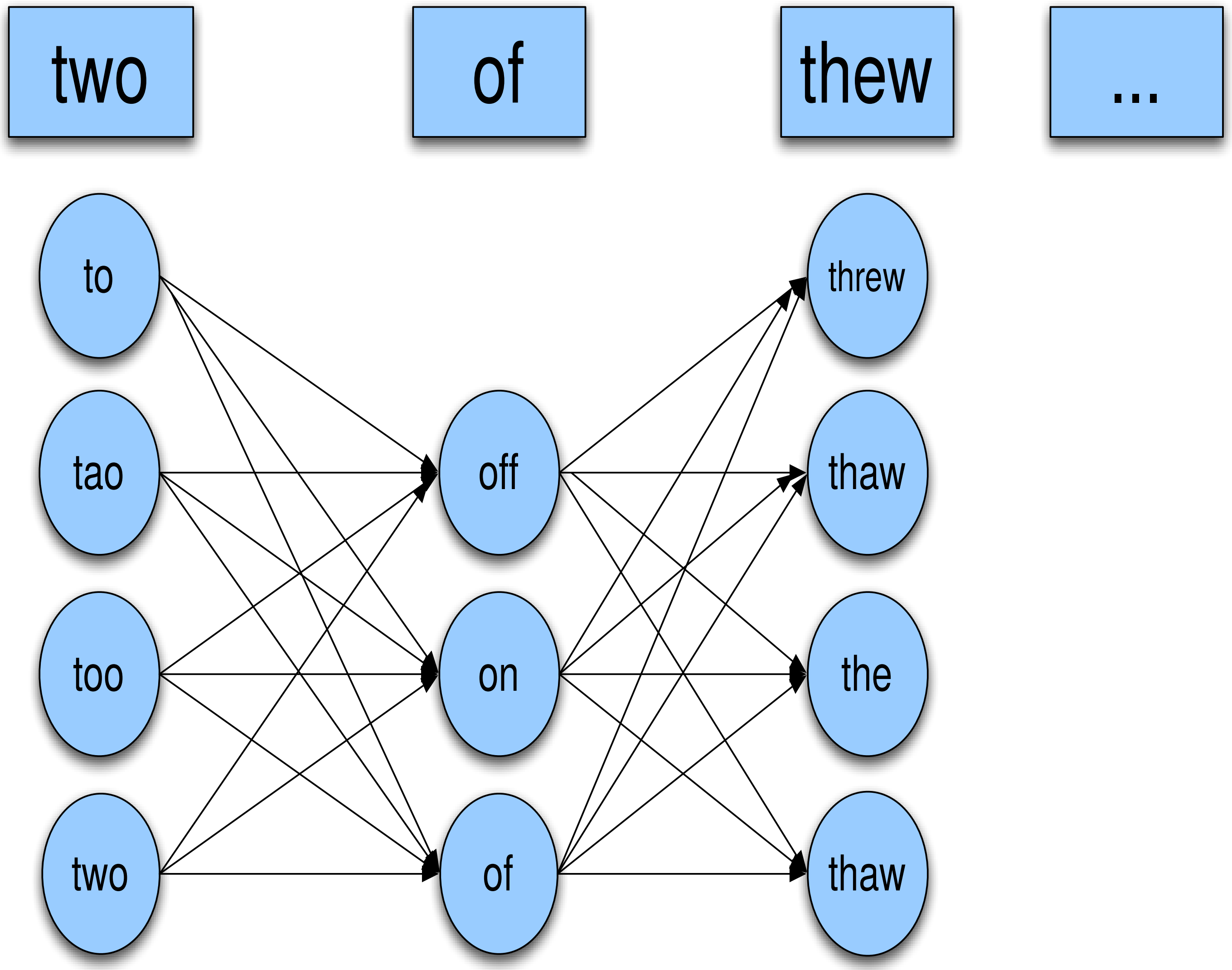
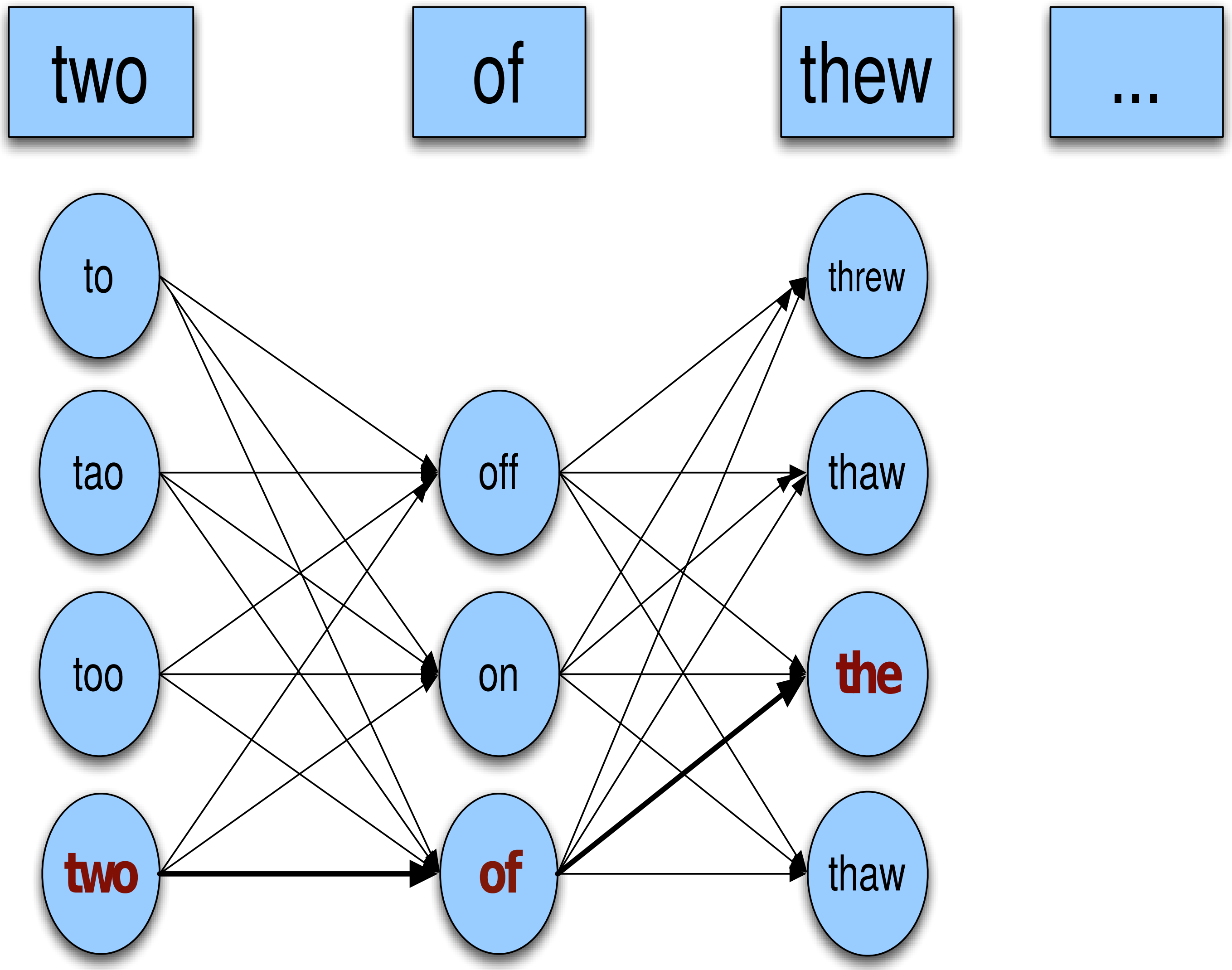
Noisy channel for real-word spell correction



Noisy channel for real-word spell correction



Simplification: One error per sentence

- Out of all possible sentences with one word replaced
  - w_1, $\mathbf{w''_2}$,w_3,w_4 two **off** thew
  - w_1,w_2,$\mathbf{w'_3}$,w_4 two of **the**
  - $\mathbf{w'''_1}$,w_2,w_3,w_4 **too** of thew
  - …
- Choose the sequence W that maximizes P(W)

Where to get the probabilities

- Language model
  - Unigram
  - Bigram
  - etc.
- Channel model
  - Same as for non-word spelling correction
  - <u>Plus need probability for no error, *P(w|w)*</u>

Probability of no error

- What is the channel probability for a correctly typed word?
- P("the" | "the")
  - If you have a big corpus, you can estimate this percent correct
- But this value depends strongly on the application
  - .90 (1 error in 10 words)
  - .95 (1 error in 20 words)
  - .99 (1 error in 100 words)