CS276 – Information Retrieval and Web Search

Checking in. By the end of this week you need to have:

- Watched the online videos corresponding to the first 6 chapters of *IIR* **or/and** read chapters 1–6 of the book
- Done programming assignment 1 (due Thursday)
- Submitted 5 search queries for the Stanford domain (for PA3)
- Oh, and problem set 1 was due last Thursday ☺

Today: Probabilistic models of spelling correction for PA2

- You should also look at chapter 3 video/book for other material

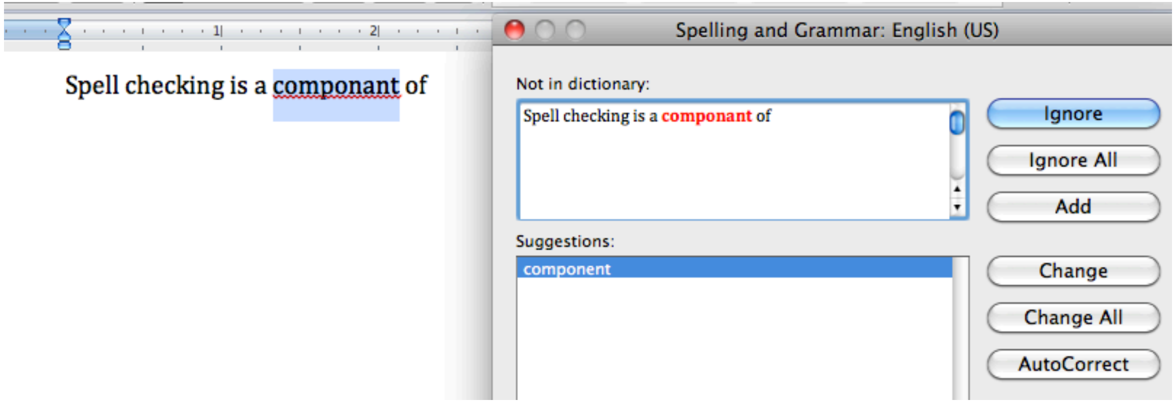
Thursday: Class lab on map-reduce

Spelling Correction and the Noisy Channel

The Spelling Correction Task

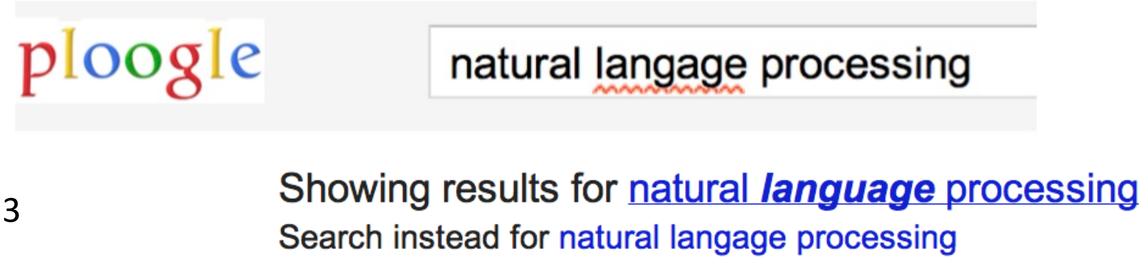
Applications for spelling correction

Word processing



Phones

Web search



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*

Rates of spelling errors

26%: Web queries Wang *et al.* 2003

13%: Retyping, no backspace: Whitelaw *et al.* English&German

7%: Words corrected retyping on phone-sized organizer

2%: Words uncorrected on organizer Soukoreff &MacKenzie 2003

1-2%: Retyping: Kane and Wobbrock 2007, Gruden et al. 1983

Non-word spelling errors

- Non-word spelling error detection:
  - Any word not in a ***dictionary*** is an error
  - The larger the dictionary the better
- 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

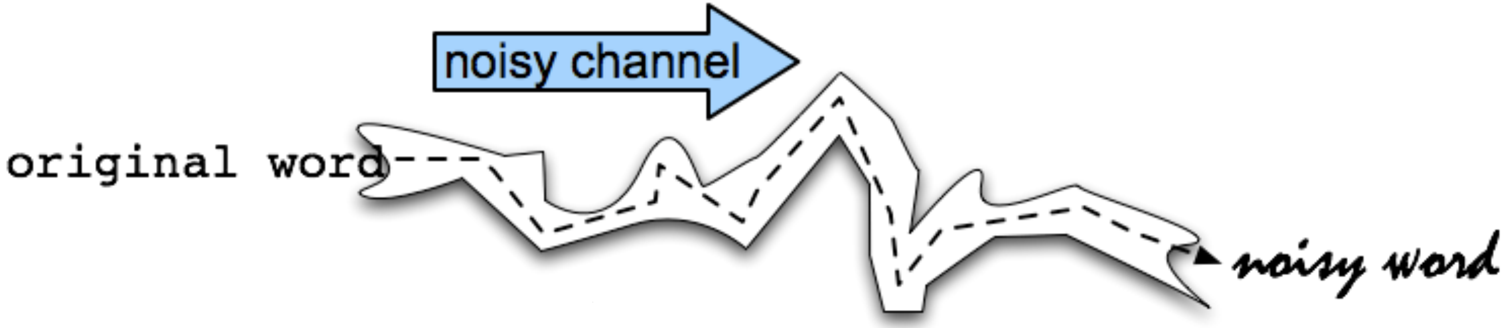
Real word spelling errors

- For each word *w*, generate candidate set:
  - Find candidate words with similar ***pronunciations***
  - Find candidate words with similar ***spelling***
  - Include *w* in candidate set
- Choose best candidate
  - Noisy Channel

Spelling Correction and the Noisy Channel

The Noisy Channel Model of Spelling

Noisy Channel Intuition



Noisy Channel aka Bayes' Rule

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

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

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

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

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 edit distance of pronunciation to error

Damerau-Levenshtein edit distance

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

- See *IIR* sec 3.3.3 for edit distance

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
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`

Wait, 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)
   - see *IIR* sec 3.3.4
4. Compute them fast with a Levenshtein finite state transducer
5. Have a precomputed hash of words to possible corrections

Language Model

- Just use the unigram probability of words
  - Take big supply of words (your document collection with *T* tokens)

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

Unigram Prior probability

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

word	Frequency of word	P(word)
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* $w = w_1, w_2, w_3, \ldots, w_n$

- $P(x|w)$ = 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(x typed as y)
trans[x,y]:  count(xy typed as yx)
```

Insertion and deletion conditioned on previous character

Confusion matrix for spelling errors

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

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/

Channel model

Kernighan, Church, Gale 1990

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

Smoothing probabilities: Add-1 smoothing

- But if we use the last slide, 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 one to all counts and then if there is a |A| character alphabet, to normalize appropriately:

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

Channel model for acress

Candidate Correction	Correct Letter	Error Letter	x|w	P(x|word)
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

Noisy channel probability for acress

Candidate Correction	Correct Letter	Error Letter	x|w	P(x|word)	P(word)	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

Noisy channel probability for acress

Candidate Correction	Correct Letter	Error Letter	x|w	P(x|word)	P(word)	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

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**
  - You learned/can learn a lot about language models in CS124 or CS224N
  - Here we present just enough to be dangerous/do the assignment

- 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:

$$P_{li}(w_k|w_{k-1}) = \lambda P_{uni}(w_1) + (1-\lambda)P_{mle}(w_k|w_{k-1})$$

  - $P_{mle}(w_k|w_{k-1}) = C(w_k|w_{k-1}) / C(w_{k-1})$
  - This is called a "maximum likelihood estimate" (mle)
  - For categorical variables you get an mle by just counting and dividing

All the important fine points

- Our unigram probability $P_{uni}(w_k) = C(w_k) / T$ is also an mle
  - This is okay if our dictionary is only words in the document collection – will be non-zero
  - Otherwise we'd need to smooth it to avoid zeroes (e.g., add-1 smoothing)
- Note that we have several probability distributions for words
  - Keep them straight!
- 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
- Our query may be words anywhere in a document
  - We'll start the bigram estimate of a sequence with a unigram estimate
  - Often, people instead condition on a start-of-sequence symbol, but not good here
  - Because of this, the unigram and bigram counts have different totals. Not a problem

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 $\times 10^{-10}$

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Evaluation

- Some spelling error test sets
  - Wikipedia's list of common English misspelling
  - Aspell filtered version of that list
  - Birkbeck spelling error corpus
  - Peter Norvig's list of errors (includes Wikipedia and Birkbeck, for training or testing)

Spelling Correction and the Noisy Channel

Real-Word Spelling Correction

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

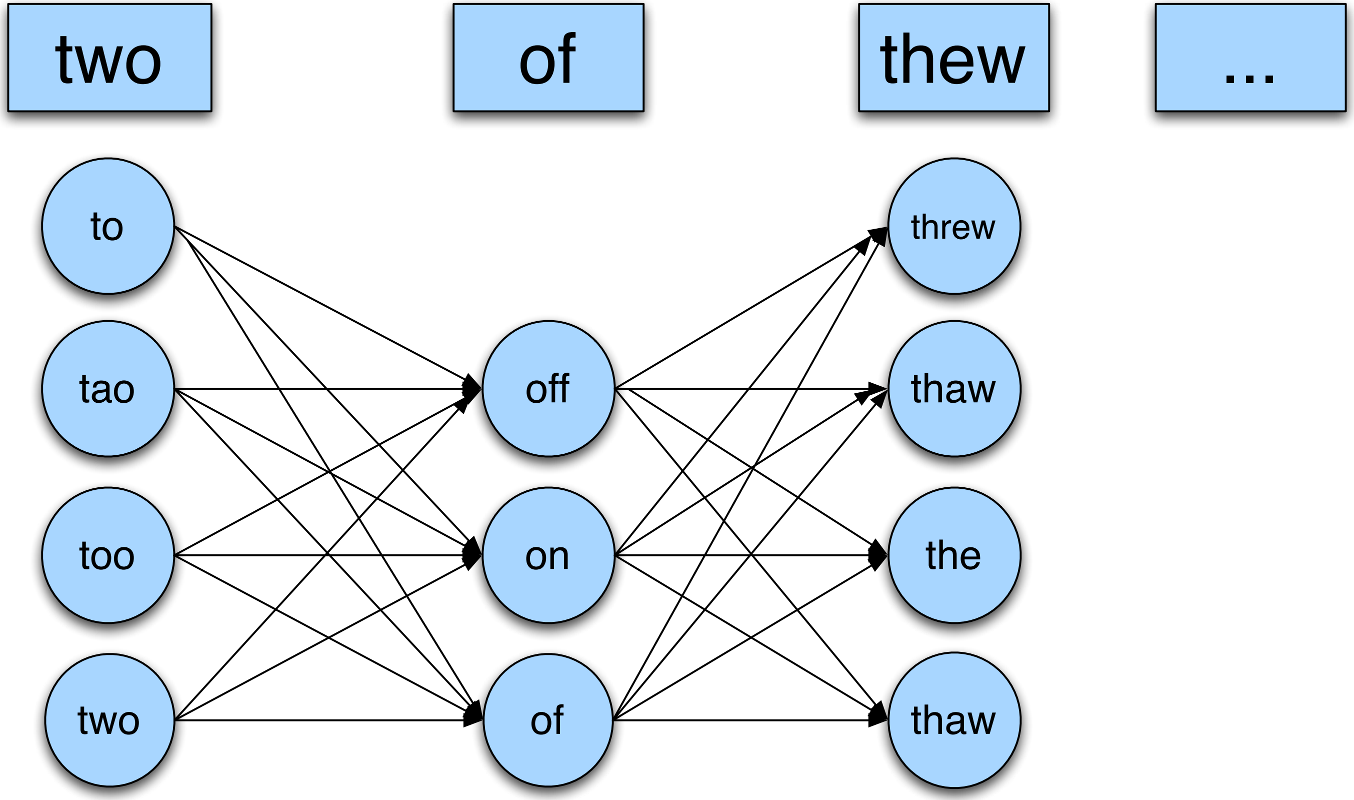
Solving real-word spelling errors

- For each word in sentence
  - Generate *candidate set*
    - the word itself
    - all single-letter edits that are English words
    - words that are homophones
- Choose best candidates
    - Noisy channel model

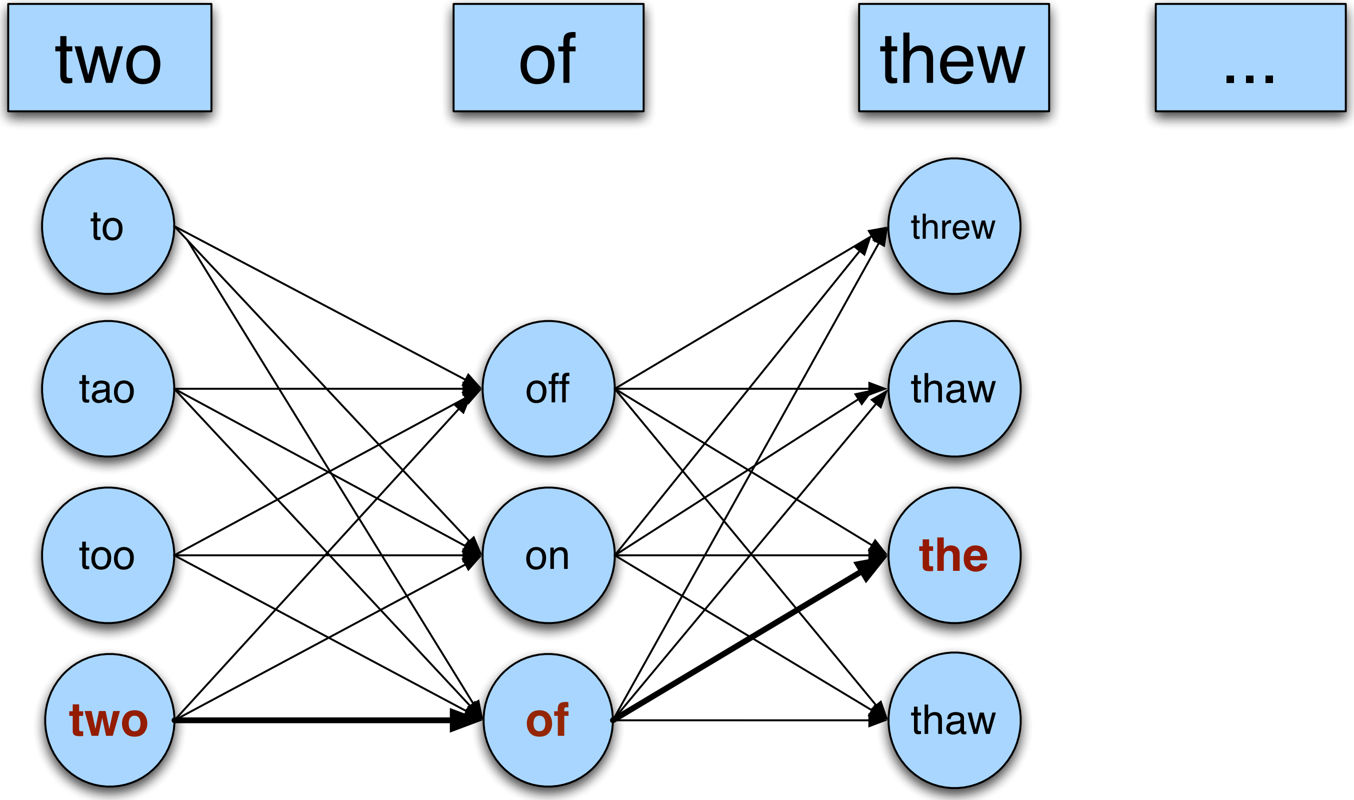
Noisy channel for real-word spell correction

- 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 ,…}
  - Candidate(w_2) = {w_2, w'_2 , w''_2 , w'''_2 ,…}
  - Candidate(w_n) = {w_n, w'_n , w''_n , w'''_n ,…}
- Choose the sequence W that maximizes P(W)

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
  - Plus need probability for no error, $P(w|w)$

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)

Peter Norvig's "thew" example

x	w	x|w	P(x|w)	P(w)	10^9 P(x|w)P(w)
thew	the	ew|e	0.000007	0.02	144
thew	thew		0.95	0.00000009	90
thew	thaw	e|a	0.001	0.0000007	0.7
thew	threw	h|hr	0.000008	0.000004	0.03
thew	thwe	ew|we	0.000003	0.00000004	0.0001

State of the art noisy channel

- We never just multiply the prior and the error model
- Independence assumptions → probabilities not commensurate
- Instead: Weight them

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

- Learn λ from a development test set

Improvements to channel model

- Allow richer edits (Brill and Moore 2000)
  - ent→ant
  - ph→f
  - le→al
- Incorporate pronunciation into channel (Toutanova and Moore 2002)
- Incorporate device into channel

Nearby keys