(Bonus) Spell Correction

LING83800: METHODS IN COMPUTATIONAL LINGUISTICS II

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Judging similarity

- The spelling of “psuedo” and “pseudo” are pretty similar
- More similar than the spelling of “Stanford” and “Sanrio”?
- Presumably we all share the same basic intuitions, but actually formalizing and implementing that mental knowledge is proto-typical of the challenges common in NLP

How similar are two strings?

- Spell correction
  - The user typed "graffe"

  Which is closest?
    - graf
    - graft
    - grail
    - giraffe

- Computational Biology
  - Align two sequences of nucleotides

  AGGCTATCACCTGACCTCCAGGCCGATGCCC
  TAGCTATCACGACCGCGGTCGATTTGCCCGAC

  - Resulting alignment:

  -AGGCTATCACCTGACCTCCAGGCCGA--TGCCC---
  TAG-CTATCAC--GACCGC--GGTCGATTTGCCCGAC

- Also for Machine Translation, Information Extraction, Speech Recognition

Distance Measures

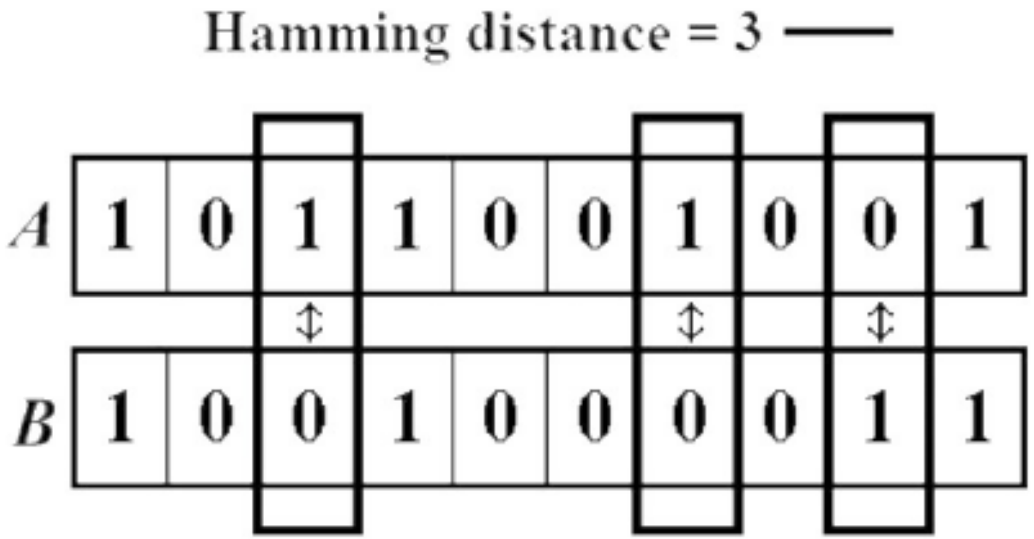
- Hamming distance: “How many substitutions do I need to perform to change one string into another”

```python
def hamming_distance(string1, string2):
    dist_counter = 0
    for n in range(len(string1)):
        if string1[n] != string2[n]:
            dist_counter += 1
    return dist_counter
```

Distance Measures

- Simple mapping like Hamming Distance is insufficient

- We don't want to assume strings of equal length – we'd like a general solution



Edit Distance

- The minimum edit distance between two strings…

…is the minimum number of editing operations

  - Insertion
  - Deletion
  - Substitution

…needed to transform one into the other

Edit Distance

- Two strings and their **alignment**:

```
I N T E * N T I O N
| | | | | | | | | |
* E X E C U T I O N
```

Edit Distance

```
I N T E * N T I O N
| | | | | | | | | |
* E X E C U T I O N
```

- If each operation has cost of 1
  - Distance between these is 5
- If substitutions cost 2 (Levenshtein)
  - Distance between them is 8

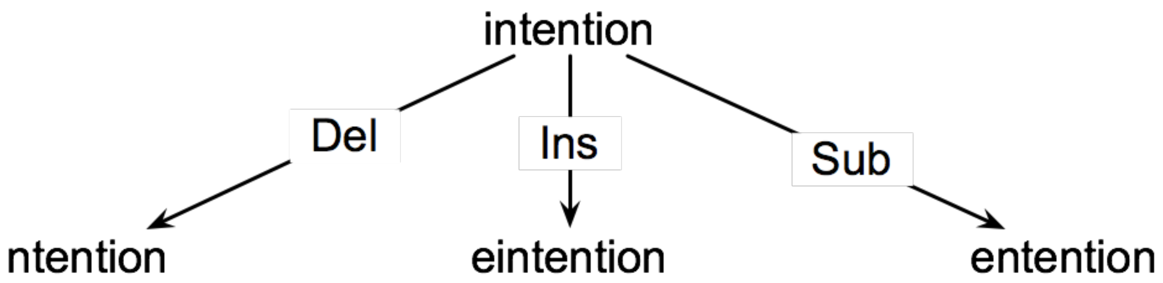
Other NLP applications of Edit Distance

- Evaluating Machine Translation and speech recognition

```
R Spokesman confirms    senior government adviser was shot
H Spokesman said    the senior            adviser was shot dead
                 S    I             D                       I
```

How to find Min Edit Distance?

- Searching for a path (sequence of edits) from the start string to the final string:
  - **Initial state**: the word we're transforming
  - **Operators**: insert, delete, substitute
  - **Goal state**: the word we're trying to get to
  - **Path cost**: what we want to minimize: the number of edits

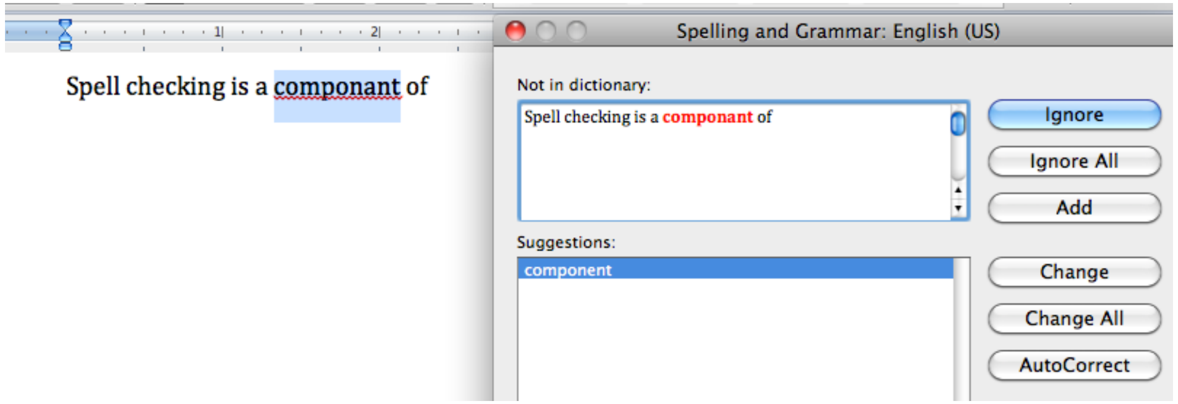


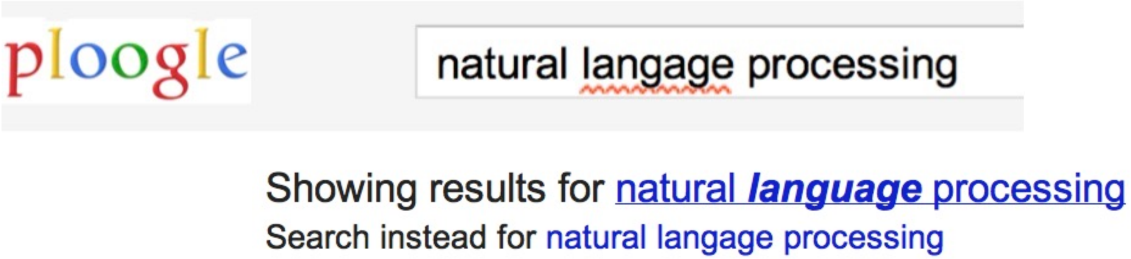
Minimum Edit as a Search

- But the space of all edit sequences is huge!
  - We can’t afford to navigate naïvely
  - Lots of distinct paths wind up at the same state.
    - We don’t have to keep track of all of them
    - Just the shortest path to each of those revisited states.

Spelling Correction

Lots of applications





Spelling Tasks

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

Types of Errors

- Non-word Errors
  - *graffe →giraffe*
- Real-word Errors
  - Typographical errors
    - *three →there*
  - Cognitive Errors (homophones)
    - *piece→peace,*
    - *too → two*

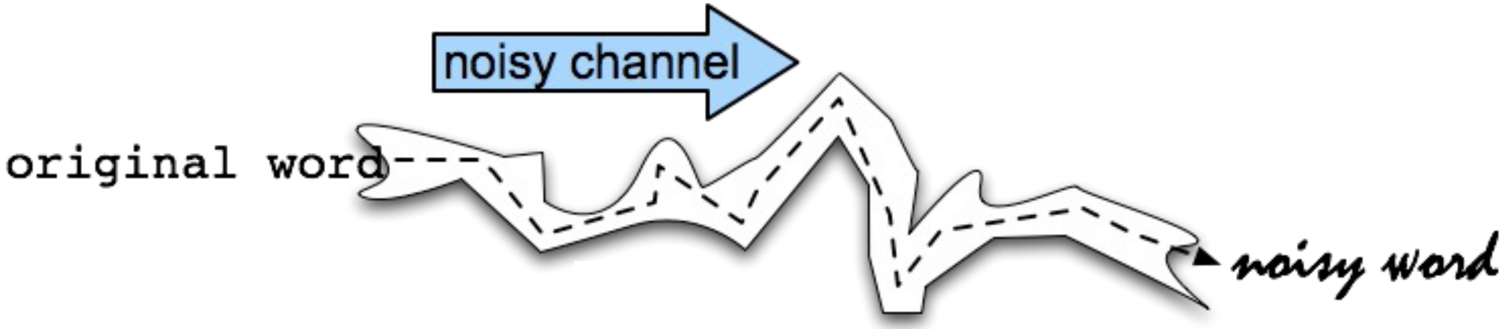
Non-word spelling errors

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

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
  - Classifier

Noisy Channel Model



Noisy Channel Model

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

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

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Language model

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

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

spelling

Noisy Channel Model

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

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

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

$$= \underset{w \in V}{\operatorname{argmax}} \underbrace{P(x \mid w)}_{\text{Channel probability}} \underbrace{P(w)}_{\text{Prior probability}}$$

Noisy Channel Model for Spelling

function NOISY CHANNEL SPELLING(*word x*, *dict D*, lm, *editprob*) **returns** *correction*

if $x \notin D$
  candidates, edits $\leftarrow$ All strings at edit distance 1 from x that are $\in D$, and their edit
  for each c, e in candidates, edits
    channel $\leftarrow$ editprob(e)
    prior $\leftarrow$ lm(x)
    $score[c]$ = log *channel* + log *prior*
  return $\text{argmax}_c \ score[c]$

Figure B.2 Noisy channel model for spelling correction for unknown words.

Non-word spelling error example

acress

What are some possible replacement candidates?

- 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

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`

Language models

- Use any of the language modeling algorithms we’ve learned
- Unigram, bigram, trigram
  - With various possible smoothing schemes

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

But how do we estimate the channel model?

$$P(x|w)$$

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)
```

Confusion Matrix

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

Deriving a confusion matrix from a corpus

- For now let's assume we have access to this data to derive a confusion matrix

Estimating the channel model

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

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

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 x10^{-10}
- P("versatile across whose") = .000021*.000006 = 1 x10^{-10}

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Real-word spelling errors

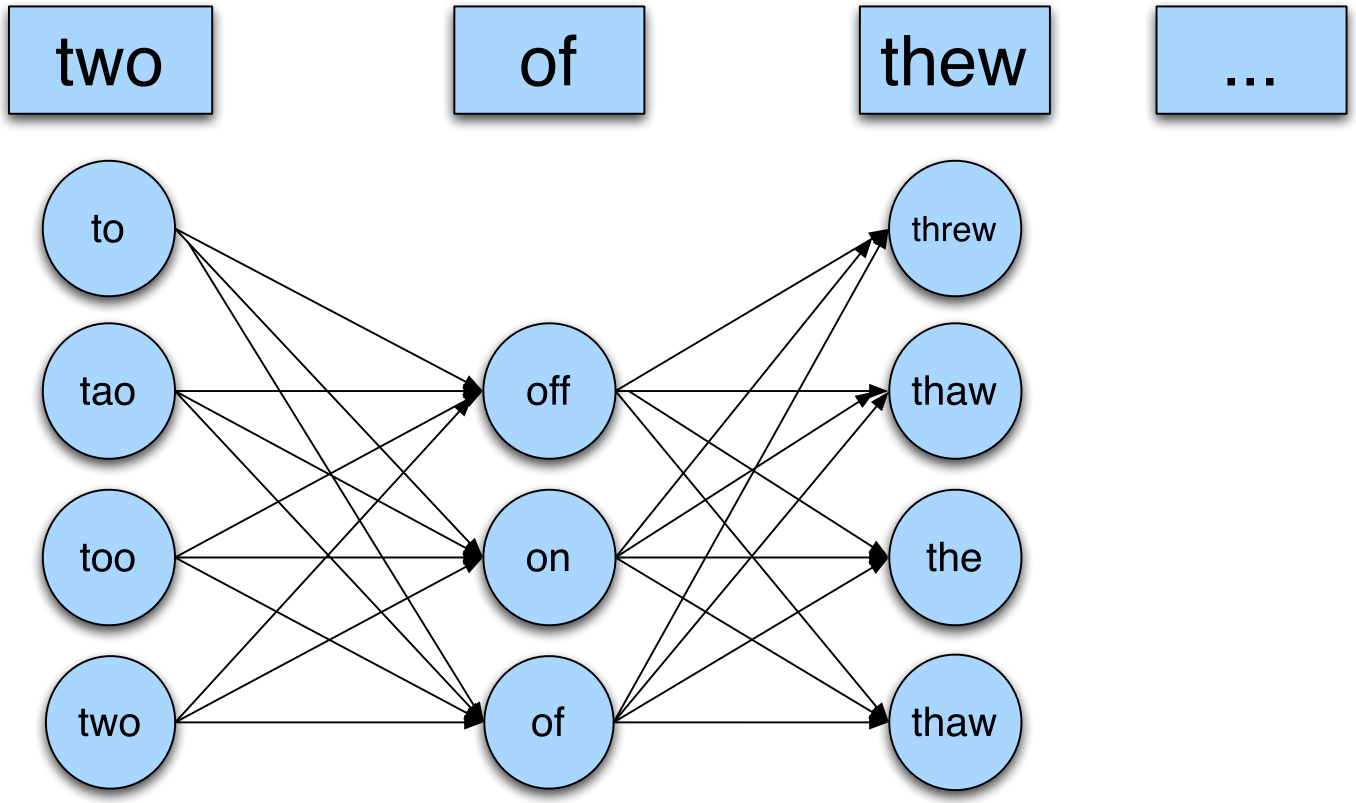
- …leaving in about fifteen ***minuets*** to go to her house.
- The design ***an*** construction of the system…
- Can they ***lave*** him my messages?
- The study was conducted mainly ***be*** Caplan and Kodner.

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

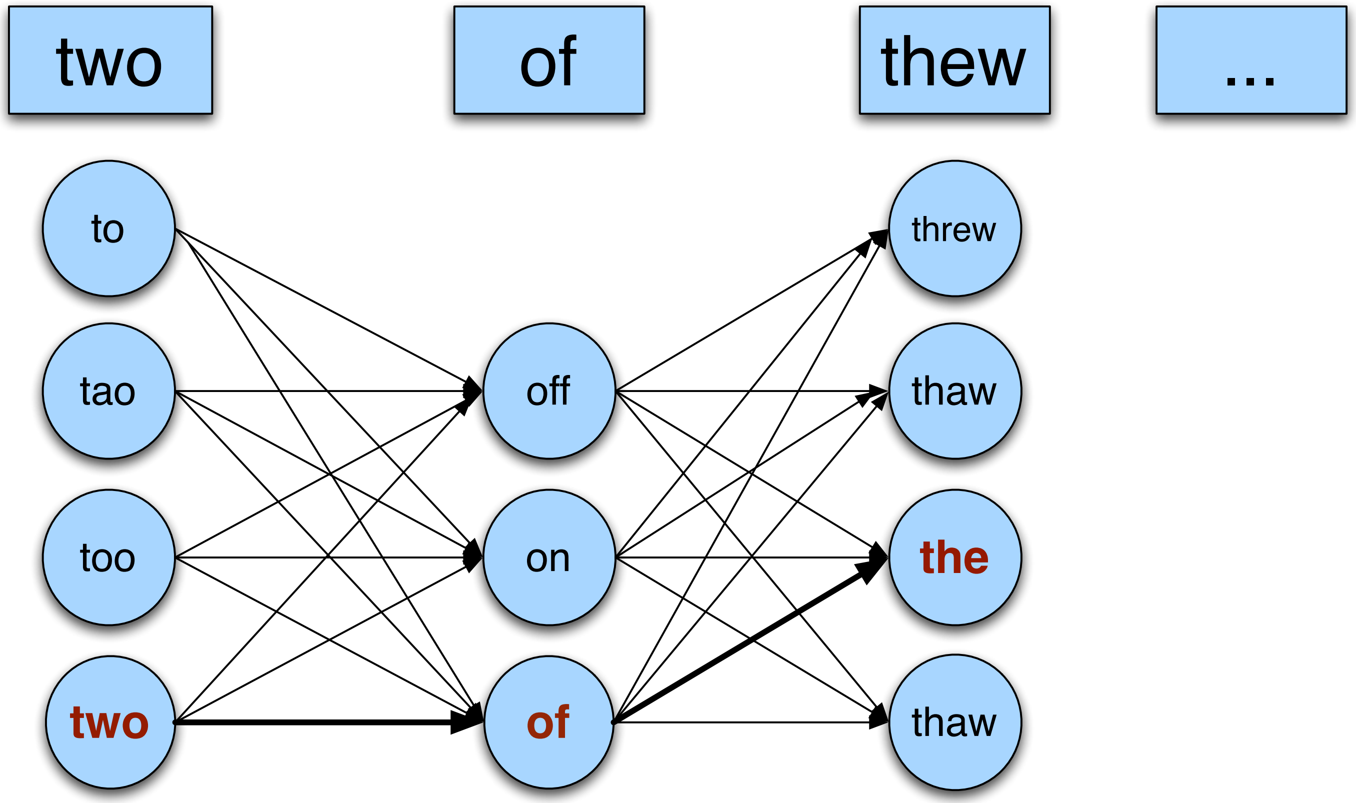
Noisy channel for real-word spell correction

- 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



Noisy channel for real-word spell correction

- 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")

- Obviously this depends on the application
  - .90 (1 error in 10 words)
  - .95 (1 error in 20 words)
  - .99 (1 error in 100 words)
  - .995 (1 error in 200 words)

Probability of no error

- What is the channel probability for a correctly typed word?
- P("the" | "the")

- Obviously this depends on the application
  - .90 (1 error in 10 words)
  - .95 (1 error in 20 words)
  - .99 (1 error in 100 words)
  - .995 (1 error in 200 words)

$$p(x|w) = \begin{cases} \alpha & \text{if } x = w \\ \dfrac{1-\alpha}{|C(x)|} & \text{if } x \in C(x) \\ 0 & \text{otherwise} \end{cases}$$

- Pick a value alpha which approximates this

"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