Introduction to

# Information Retrieval

CS276: Information Retrieval and Web Search

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Wildcard queries and Spelling Correction

# WILD-CARD QUERIES

# 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*** ?

# Query processing

- At this point, we have an enumeration of all terms in the dictionary that match the wild-card query.
- We still have to look up the postings for each enumerated term.
- E.g., consider the query:

  ***se*ate*** *AND* ***fil*er***

  This may result in the execution of many Boolean *AND* queries.

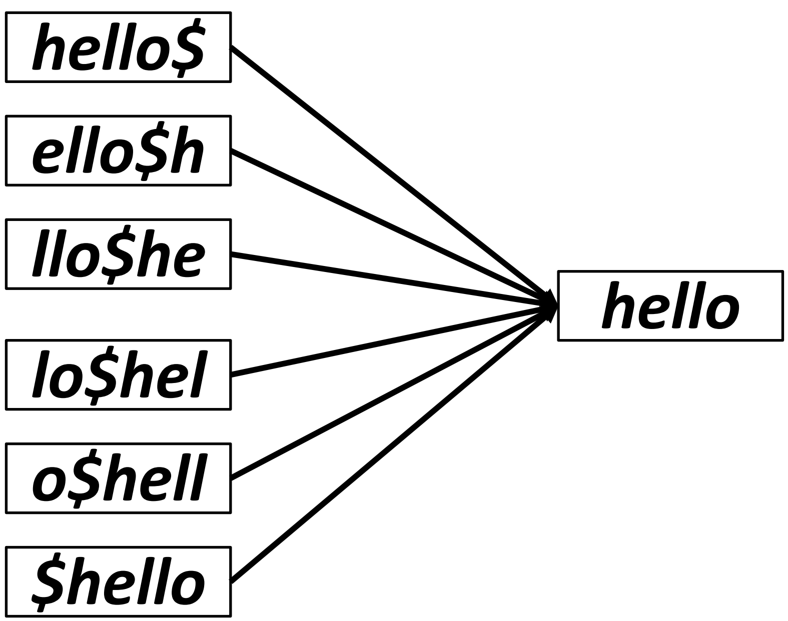
# B-trees handle *'s at the end of a query term

- How can we handle *'s in the middle of query term?
  - ***co*tion***
- We could look up ***co**** AND ****tion*** in a B-tree and intersect the two term sets
  - Expensive
- The solution: transform wild-card queries so that the *'s occur at the end
- This gives rise to the **Permuterm** Index.

# 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.




Empirically, dictionary quadruples in size

# Permuterm query processing

- (Add ***$***), rotate * to end, lookup in permuterm index
- Queries:
  - **X** lookup on **X$** ***hello$*** for ***hello***
  - **X*** lookup on $**X*** ***$hel**** for ***hel****
  - ***X** lookup on **X$*** ***llo$**** for ****llo***
  - ***X*** lookup on **X*** ***ell**** for ****ell****
  - **X*Y** lookup on **Y$X*** ***lo$h*** for ***h*lo***
  - **X*Y*Z** treat as a search for **X*Z** and post-filter

    For ***h*a*o***, search for ***h*o*** by looking up ***o$h**** and post-filter ***hello*** and retain ***halo***

# Bigram (*k*-gram) indexes

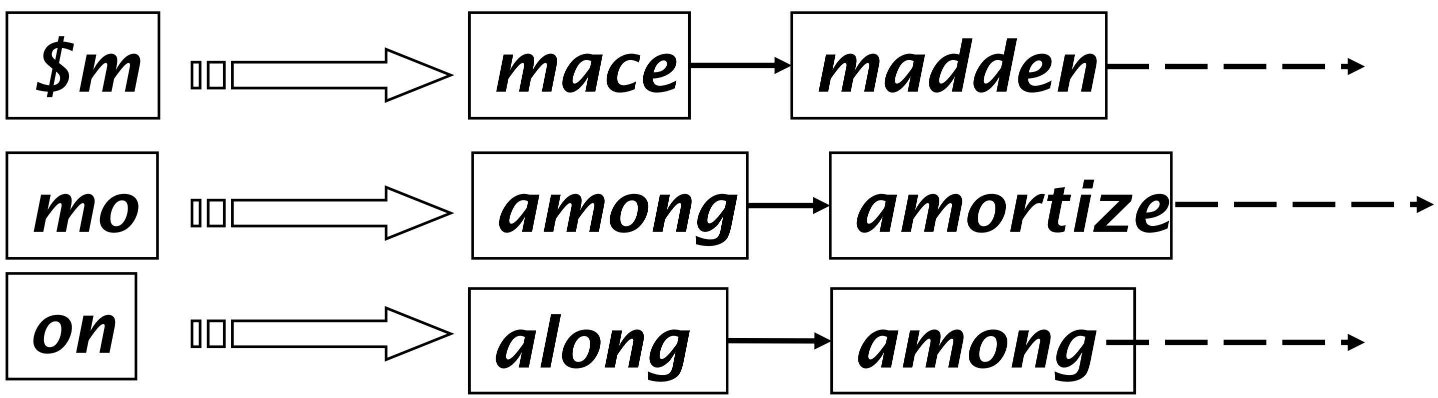
- Enumerate all *k*-grams (sequence of *k* chars) occurring in any term
- *e.g.,* from text "***April is the cruelest month***" we get the 2-grams (*bigrams*)

  $a,ap,pr,ri,il,l$,$i,is,s$,$t,th,he,e$,$c,cr,ru,
  ue,el,le,es,st,t$, $m,mo,on,nt,h$

  - $ is a special word boundary symbol
- Maintain a *second* inverted index *from bigrams to dictionary terms* that match each bigram.

# Bigram index example

- The *k*-gram index finds *terms* based on a query consisting of *k*-grams (here *k*=2).

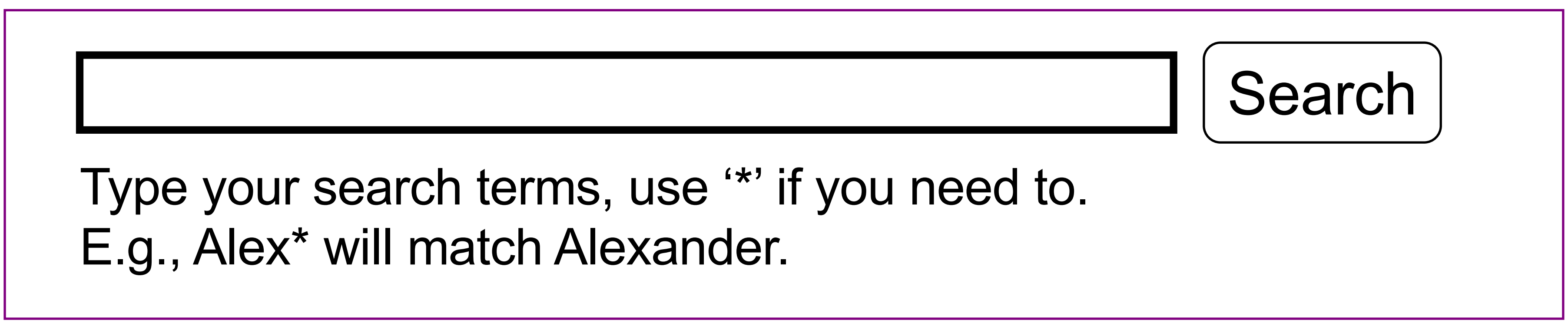


# Processing wild-cards

- Query ***mon**** can now be run as
  - ***$m** AND **mo** AND **on***
- Gets terms that match AND version of our wildcard query.
- But we'd enumerate ***moon***.
- Must post-filter these terms against query.
- Surviving enumerated terms are then looked up in the term-document inverted index.
- Fast, space efficient (compared to permuterm).

# Processing wild-card queries

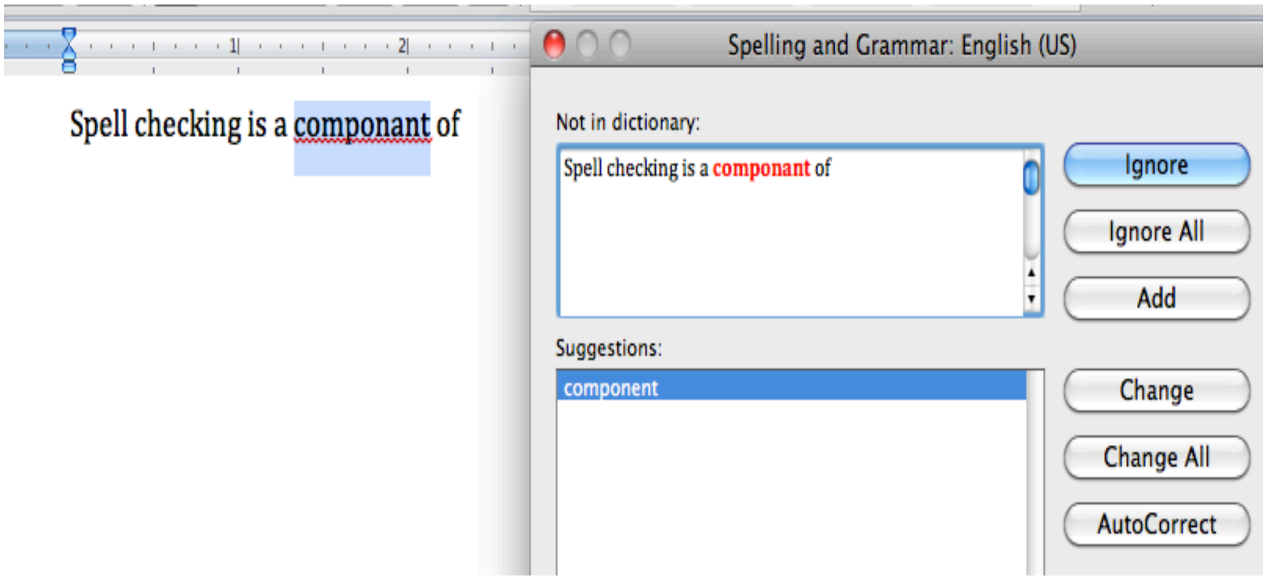
- As before, we must execute a Boolean query for each enumerated, filtered term.
- Wild-cards can result in expensive query execution (very large disjunctions…)
  - pyth* AND prog*
- If you encourage “laziness” people will respond!



# SPELLING CORRECTION

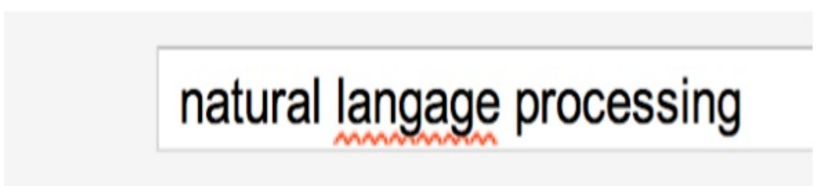
# Applications for spelling correction

Word processing




Phones


Web search




Showing results for natural ***language*** processing

Search instead for natural langage processing

# Rates of spelling errors

Depending on the application, ~1–20% error rates

**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

# 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*

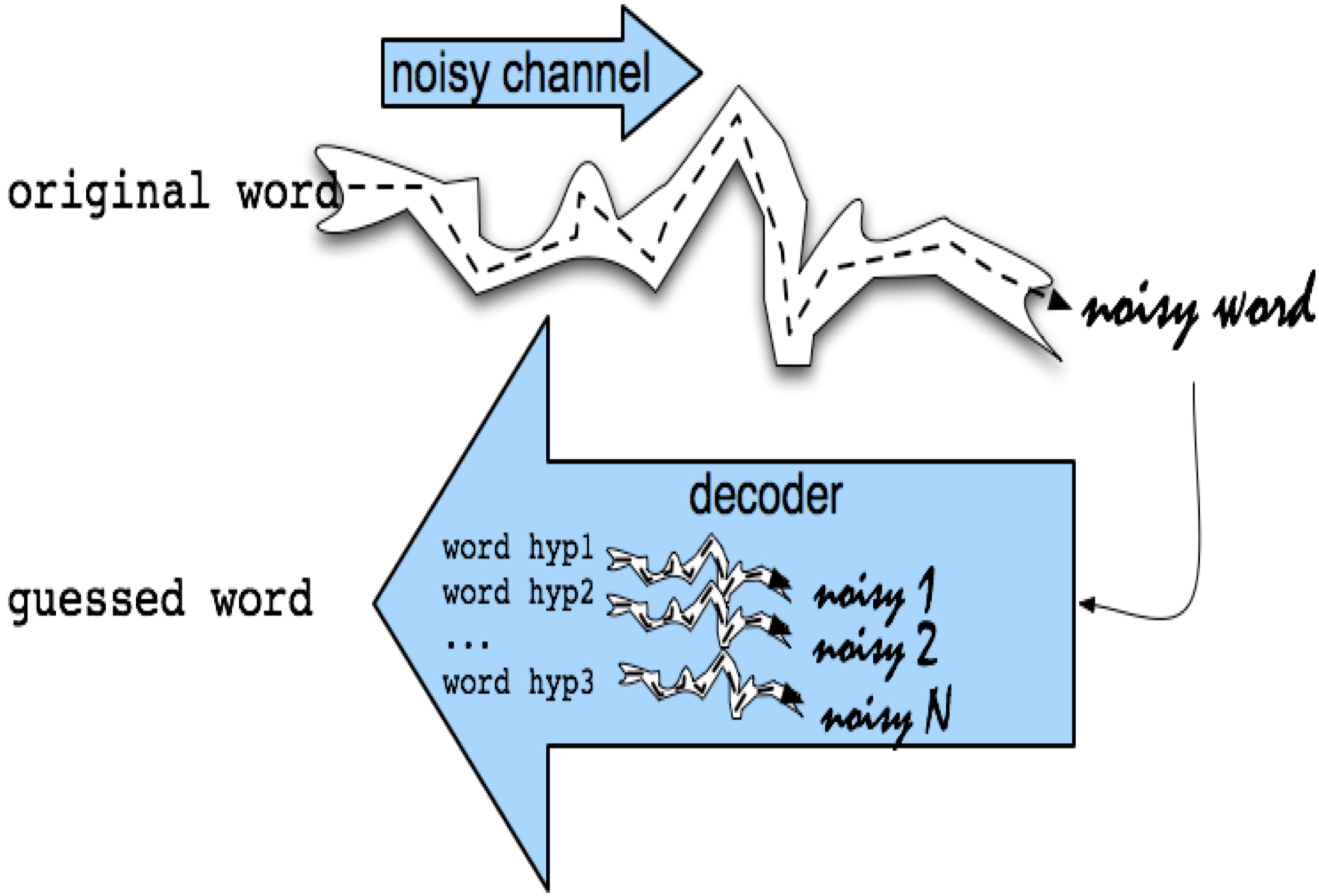
# Terminology

- We just discussed *character bigrams and k-grams*:
  - *st, pr, an …*
- We can also have *word bigrams and n-grams*:
  - *palo alto, flying from, road repairs*

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 $\hat{w}$

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

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

Bayes

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

Prior

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. 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

- 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 |

# 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)
   - see *IIR* sec 3.3.4
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 *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 $x = x_1, x_2, x_3 \ldots x_m$
- 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(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

# 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

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

# Smoothing probabilities: Add-1 smoothing

- But if we use the 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:

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

# Channel model for acress

| Candidate Correction | Correct Letter | Error Letter | x/w | P(x/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 |

# 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)

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 $x_1, x_2, x_3, \ldots, x_n$
- Generate a set of candidates for each word $x_i$
  - Candidate($x_1$) = {$x_1$, $w_1$, $w'_1$, $w''_1$, …}
  - Candidate($x_2$) = {$x_2$, $w_2$, $w'_2$, $w''_2$, …}
  - Candidate($x_n$) = {$x_n$, $w_n$, $w'_n$, $w''_n$, …}
- Choose the sequence W that maximizes $P(W|x_1, \ldots, x_n)$

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

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

# 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**
  - 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:

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

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

# All the important fine points

- Note that we have several probability distributions for words
  - 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 x$10^{-10}$
- P("versatile across whose") = .000021*.000006 = 1 x$10^{-10}$

# Using a bigram language model

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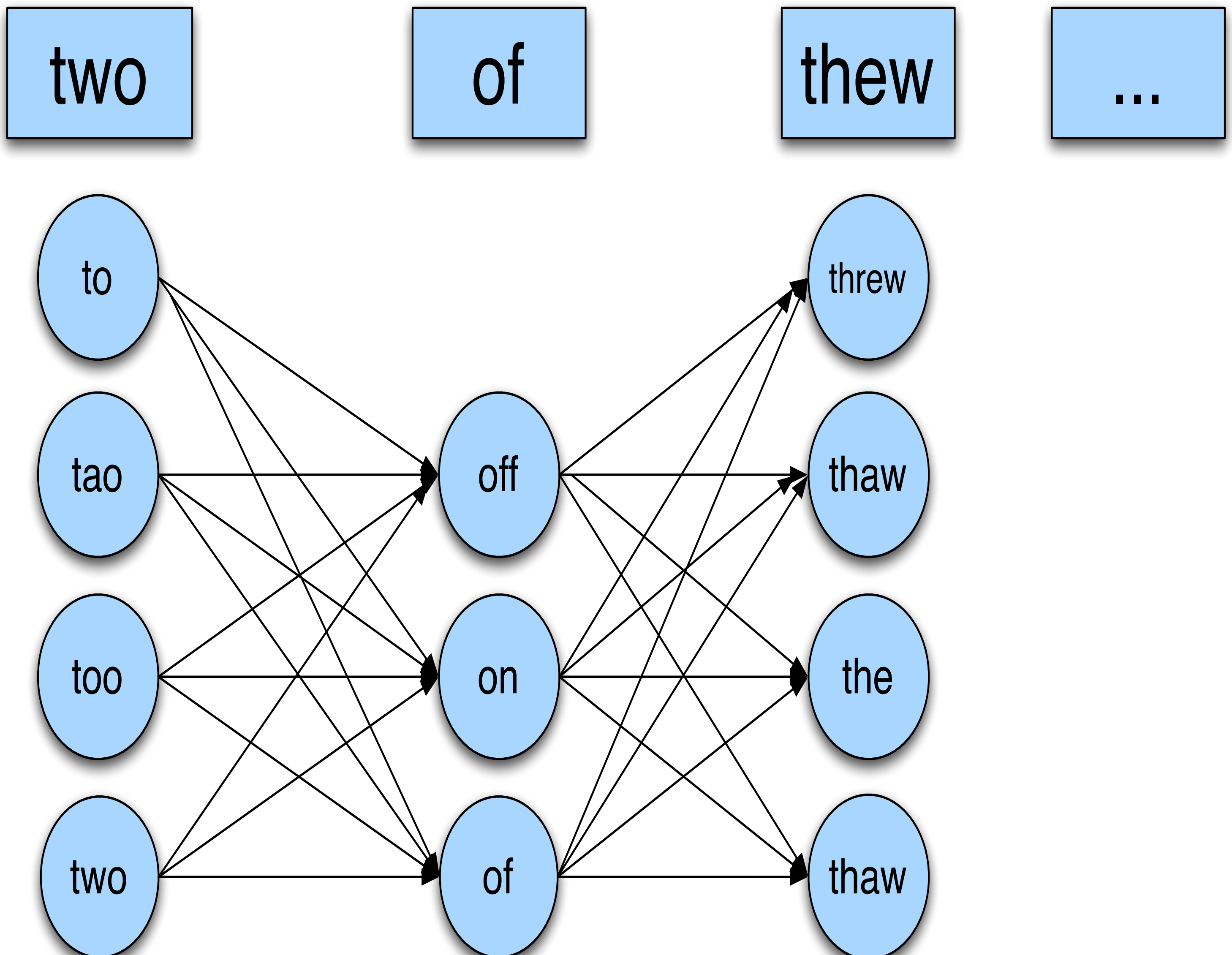
# Noisy channel for real-word spell correction



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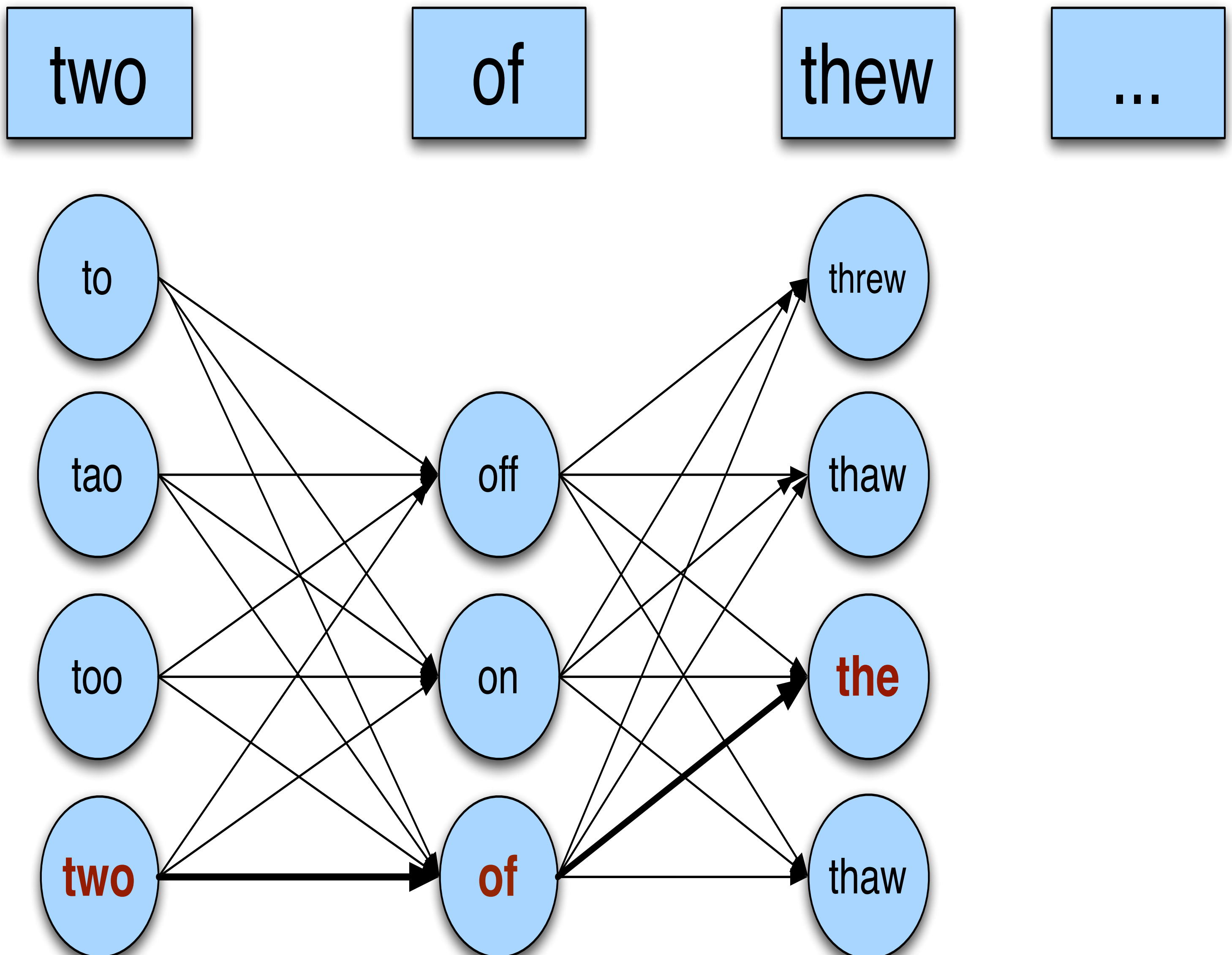

# Simplification: One error per sentence

- 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
  - Not all Android phones need have the same error model
  - But spell correction may be done at the system level