

SIT330-770: Natural Language Processing

Week 4 - N-gram Language Models

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SIT330-770: Natural Language Processing

Week 4.1 - Introduction to N-grams

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Language Models in **NLP**

What is a Language Model?



- A model to assign a probability to a sentence
 - Machine Translation:
 - $P(\text{high winds tonight}) > P(\text{large winds tonight})$
 - Spell Correction
 - The office is about fifteen **minuets** from my house!
 - $P(\text{about fifteen minutes from}) > P(\text{about fifteen minuets from})$
 - Speech Recognition
 - $P(\text{I saw a van}) \gg P(\text{eyes awe of an})$
 - + Summarization, question, answering, etc., etc.!!

Why?

- Goal: compute the probability of a sentence or sequence of words:

$$P(W) = P(w_1, w_2, w_3, w_4, w_5 \dots w_n)$$

- Related task: probability of an upcoming word:

$$P(w_5 | w_1, w_2, w_3, w_4)$$

- A model that computes either of these:

$P(W)$ or $P(w_n | w_1, w_2 \dots w_{n-1})$ is called a **language model**.

- Better: **the grammar** But **language model** or **LM** is standard

How to compute $P(W)$



- How to compute this joint probability:
 - $P(\text{its, water, is, so, transparent, that})$
- Intuition: let's rely on the Chain Rule of Probability

- Recall the definition of conditional probabilities

$$p(B|A) = P(A,B)/P(A) \quad \text{Rewriting: } P(A,B) = P(A)P(B|A)$$

- More variables:

$$P(A,B,C,D) = P(A)P(B|A)P(C|A,B)P(D|A,B,C)$$

- The Chain Rule in General

$$P(x_1, x_2, x_3, \dots, x_n) = P(x_1)P(x_2|x_1)P(x_3|x_1, x_2)\dots P(x_n|x_1, \dots, x_{n-1})$$

The Chain Rule applied to compute joint probability of words in sentence



$$P(w_1 w_2 \dots w_n) = \prod_i P(w_i | w_1 w_2 \dots w_{i-1})$$

$P(\text{"its water is so transparent"}) =$

$$P(\text{its}) \times P(\text{water} | \text{its}) \times P(\text{is} | \text{its water})$$

$$\times P(\text{so} | \text{its water is}) \times P(\text{transparent} | \text{its water is so})$$

How to estimate these probabilities



- Could we just count and divide?

$$P(\text{the lits water is so transparent that}) = \frac{\text{Count}(\text{its water is so transparent that the})}{\text{Count}(\text{its water is so transparent that})}$$

- No! Too many possible sentences!
- We'll never see enough data for estimating these



Andrei Markov

- Simplifying assumption:

$$P(\text{the water is so transparent that}) \approx P(\text{that})$$

- Or maybe

$$P(\text{the water is so transparent that}) \approx P(\text{transparent that})$$

$$P(w_1 w_2 \dots w_n) \approx \prod_i P(w_i | w_{i-k} \dots w_{i-1})$$

- In other words, we approximate each component in the product

$$P(w_i | w_1 w_2 \dots w_{i-1}) \approx P(w_i | w_{i-k} \dots w_{i-1})$$

$$P(w_1 w_2 \dots w_n) \approx \prod_i P(w_i)$$

- Some automatically generated sentences from a unigram model

fifth, an, of, futures, the, an, incorporated, a, a, the,
inflation, most, dollars, quarter, in, is, mass

thrift, did, eighty, said, hard, 'm, july, bullish

that, or, limited, the

- Condition on the previous word:

$$P(w_i | w_1 w_2 \dots w_{i-1}) \approx P(w_i | w_{i-1})$$

texaco, rose, one, in, this, issue, is, pursuing, growth, in, a,
boiler, house, said, mr., gurria, mexico, 's, motion, control,
proposal, without, permission, from, five, hundred, fifty, five, yen
outside, new, car, parking, lot, of, the, agreement, reached
this, would, be, a, record, november

- We can extend to trigrams, 4-grams, 5-grams
- In general this is an insufficient model of language
 - because language has **long-distance dependencies**:

“The computer which I had just put into the machine room on the fifth floor crashed.”

- But we can often get away with N-gram models

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Week 4.2 - Estimating N-gram Probabilities

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Language Models in **NLP**

- The Maximum Likelihood Estimate

$$P(w_i | w_{i-1}) = \frac{\text{count}(w_{i-1}, w_i)}{\text{count}(w_{i-1})}$$

$$P(w_i | w_{i-1}) = \frac{c(w_{i-1}, w_i)}{c(w_{i-1})}$$

An example



$$P(w_i | w_{i-1}) = \frac{c(w_{i-1}, w_i)}{c(w_{i-1})}$$

< s > I am Sam < /s >

< s > Sam I am < /s >

< s > I do not like green eggs and ham < /s >

$$P(I | < s >) = \frac{2}{3} = .67$$

$$P(< /s > | Sam) = \frac{1}{2} = 0.5$$

$$P(Sam | < s >) = \frac{1}{3} = .33$$

$$P(Sam | am) = \frac{1}{2} = .5$$

$$P(am | I) = \frac{2}{3} = .67$$

$$P(do | I) = \frac{1}{3} = .33$$

More examples: Berkeley Restaurant Project sentences



- can you tell me about any good cantonese restaurants close by
- mid priced thai food is what i'm looking for
- tell me about chez panisse
- can you give me a listing of the kinds of food that are available
- i'm looking for a good place to eat breakfast
- when is caffe venezia open during the day

- Out of 9,222 sentences

	i	want	to	eat	chinese	food	lunch	spend
i	5	827	0	9	0	0	0	2
want	2	0	608	1	6	6	5	1
to	2	0	4	686	2	0	6	211
eat	0	0	2	0	16	2	42	0
chinese	1	0	0	0	0	82	1	0
food	15	0	15	0	1	4	0	0
lunch	2	0	0	0	0	1	0	0
spend	1	0	1	0	0	0	0	0

Raw bigram probabilities



- Normalize by unigrams:

i	want	to	eat	chinese	food	lunch	spend
2533	927	2417	746	158	1093	341	278

- Result:

	i	want	to	eat	chinese	food	lunch	spend
i	0.002	0.33	0	0.0036	0	0	0	0.00079
want	0.0022	0	0.66	0.0011	0.0065	0.0065	0.0054	0.0011
to	0.00083	0	0.0017	0.28	0.00083	0	0.0025	0.087
eat	0	0	0.0027	0	0.021	0.0027	0.056	0
chinese	0.0063	0	0	0	0	0.52	0.0063	0
food	0.014	0	0.014	0	0.00092	0.0037	0	0
lunch	0.0059	0	0	0	0	0.0029	0	0
spend	0.0036	0	0.0036	0	0	0	0	0

Bigram estimates of sentence probabilities



$P(< s > | \text{I want english food } < /s >) =$

$$P(\text{I} | < s >)$$

$$\times P(\text{want} | \text{I})$$

$$\times P(\text{english} | \text{want})$$

$$\times P(\text{food} | \text{english})$$

$$\times P(< /s > | \text{food})$$

$$= .000031$$

What kinds of knowledge?



- $P(\text{english} | \text{want}) = .0011$
- $P(\text{chinese} | \text{want}) = .0065$
- $P(\text{to} | \text{want}) = .66$
- $P(\text{eat} | \text{to}) = .28$
- $P(\text{food} | \text{to}) = 0$
- $P(\text{want} | \text{spend}) = 0$
- $P(\text{i} | <\text{s}>) = .25$

- We do everything in log space
 - Avoid underflow
 - (also adding is faster than multiplying)

$$\log(p_1 \times p_2 \times p_3 \times p_4) = \log p_1 + \log p_2 + \log p_3 + \log p_4$$

- SRILM
 - <http://www.speech.sri.com/projects/srilm/>
- KenLM
 - <https://kheafield.com/code/kenlm/>

AUG

3

All Our N-gram are Belong to You

Posted by Alex Franz and Thorsten Brants, Google Machine Translation Team

Here at Google Research we have been using word [n-gram models](#) for a variety of R&D projects,

...

That's why we decided to share this enormous dataset with everyone. We processed 1,024,908,267,229 words of running text and are publishing the counts for all 1,176,470,663 five-word sequences that appear at least 40 times. There are 13,588,391 unique words, after discarding words that appear less than 200 times.

- serve as the incoming 92
- serve as the incubator 99
- serve as the independent 794
- serve as the index 223
- serve as the indication 72
- serve as the indicator 120
- serve as the indicators 45
- serve as the indispensable 111
- serve as the indispensable 40
- serve as the individual 234

<http://googleresearch.blogspot.com/2006/08/all-our-n-gram-are-belong-to-you.html>

Google Book N-grams



- <https://books.google.com/ngrams/>

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Week 4.3 - Evaluation and Perplexity

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Language Models in **NLP**

- "Extrinsic (in-vivo) Evaluation"

To compare models A and B

1. Put each model in a real task
 - Machine Translation, speech recognition, etc.
2. Run the task, get a score for A and for B
 - How many words translated correctly
 - How many words transcribed correctly
3. Compare accuracy for A and B

- Extrinsic evaluation not always possible
 - Expensive, time-consuming
 - Doesn't always generalize to other applications
- Intrinsic evaluation: **perplexity**
 - Directly measures language model performance at predicting words.
 - Doesn't necessarily correspond with real application performance
 - But gives us a single general metric for language models
 - Useful for large language models (LLMs) as well as n-grams

- We train parameters of our model on a **training set**.
- We test the model's performance on data we haven't seen.
 - A **test set** is an unseen dataset; different from training set.
 - Intuition: we want to measure generalization to unseen data
 - An **evaluation metric** (like **perplexity**) tells us how well our model does on the test set.

- If we're building an LM for a specific task
 - The test set should reflect the task language we want to use the model for
- If we're building a general-purpose model
 - We'll need lots of different kinds of training data
 - We don't want the training set or the test set to be just from one domain or author or language.

We can't allow test sentences into the training set

- Or else the LM will assign that sentence an artificially high probability when we see it in the test set
- And hence assign the whole test set a falsely high probability.
- Making the LM look better than it really is

This is called “Training on the test set”

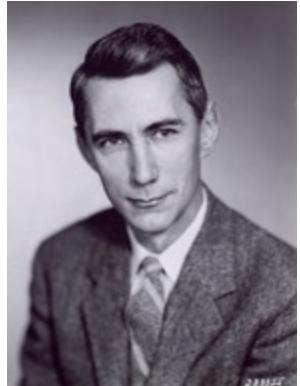
Bad science!

- If we test on the test set many times we might implicitly tune to its characteristics
 - Noticing which changes make the model better.
- So we run on the test set only once, or a few times
- That means we need a third dataset:
 - A **development test set** or, **devset**.
 - We test our LM on the devset until the very end
 - And then test our LM on the **test set** once

Intuition of perplexity as evaluation metric: How good is our language model?



- Intuition: A good LM prefers "real" sentences
 - Assign higher probability to "real" or "frequently observed" sentences
 - Assigns lower probability to "word salad" or "rarely observed" sentences?



Claude Shannon

The Shannon Game: How well can we predict the next word?

- Once upon a _____
- That is a picture of a _____
- For breakfast I ate my usual _____

time	0.9
dream	0.03
midnight	0.02
...	
and	1e-100

Unigrams are terrible at this game (Why?)

A good LM is one that assigns a higher probability to the next word that actually occurs

Intuition of perplexity 3: The best language model is one that best predicts the entire unseen test set



- We said: a good LM is one that assigns a higher probability to the next word that actually occurs.
- Let's generalize to all the words!
 - The best LM assigns high probability to the entire test set.
- When comparing two LMs, A and B
 - We compute $P_A(\text{test set})$ and $P_B(\text{test set})$
 - The better LM will give a higher probability to (=be less surprised by) the test set than the other LM.

Intuition of perplexity 4: Use perplexity instead of raw probability



- Probability depends on size of test set
 - Probability gets smaller the longer the text
 - Better: a metric that is **per-word**, normalized by length
- **Perplexity** is the inverse probability of the test set, normalized by the number of words

$$\begin{aligned} PP(W) &= P(w_1 w_2 \dots w_N)^{-\frac{1}{N}} \\ &= \sqrt[N]{\frac{1}{P(w_1 w_2 \dots w_N)}} \end{aligned}$$

Perplexity is the **inverse** probability of the test set, normalized by the number of words

$$\begin{aligned} PP(W) &= P(w_1 w_2 \dots w_N)^{-\frac{1}{N}} \\ &= \sqrt[N]{\frac{1}{P(w_1 w_2 \dots w_N)}} \end{aligned}$$

(The inverse comes from the original definition of perplexity from cross-entropy rate in information theory)

Probability range is $[0,1]$, perplexity range is $[1, \infty]$

Minimizing perplexity is the same as maximizing probability

Intuition of perplexity 6: N-grams



$$PP(W) = P(w_1 w_2 \dots w_N)^{-\frac{1}{N}}$$

$$= \sqrt[N]{\frac{1}{P(w_1 w_2 \dots w_N)}}$$

Chain rule:

$$PP(W) = \sqrt[N]{\prod_{i=1}^N \frac{1}{P(w_i | w_1 \dots w_{i-1})}}$$

Bigrams:

$$PP(W) = \sqrt[N]{\prod_{i=1}^N \frac{1}{P(w_i | w_{i-1})}}$$

Intuition of perplexity 7: Weighted average branching factor



- Perplexity is also the **weighted average branching factor** of a language.
- **Branching factor:** number of possible next words that can follow any word
- Example: Deterministic language $L = \{\text{red, blue, green}\}$
 - Branching factor = 3 (any word can be followed by red, blue, green)
- Now assume LM A where each word follows any other word with equal probability $\frac{1}{3}$
- Given a test set $T = \text{"red red red red blue"}$
 - $\text{Perplexity}_A(T) = P_A(\text{red red red red blue})^{-1/5} = ((\frac{1}{3})^5)^{-1/5} = (\frac{1}{3})^{-1} = 3$
- But now suppose red was very likely in training set, such that for LM B:
 - $P(\text{red}) = .8 \quad p(\text{green}) = .1 \quad p(\text{blue}) = .1$
- We would expect the probability to be higher, and hence the perplexity to be smaller:
 - $\text{Perplexity}_B(T) = P_B(\text{red red red red blue})^{-1/5}$

Holding test set constant:
Lower perplexity = better language model



- Training 38 million words, test 1.5 million words, WSJ

N-gram Order	Unigram	Bigram	Trigram
Perplexity	962	170	109

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Week 4.4 - Sampling and Generalization

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Language Models in **NLP**

The Shannon (1948) Visualization Method

Sample words from an LM



Claude Shannon



- **Unigram:**

REPRESENTING AND SPEEDILY IS AN GOOD APT OR COME CAN DIFFERENT
NATURAL HERE HE THE A IN CAME THE TO OF TO EXPERT GRAY COME TO
FURNISHES THE LINE MESSAGE HAD BE THESE.

- **Bigram:**

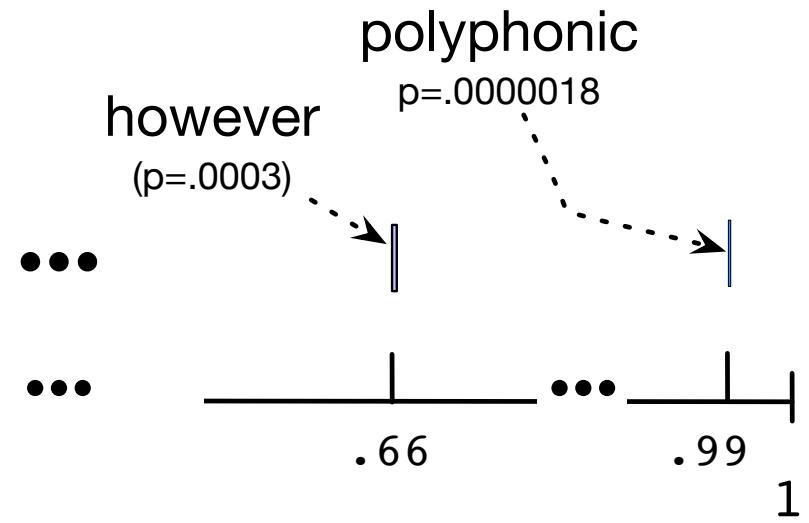
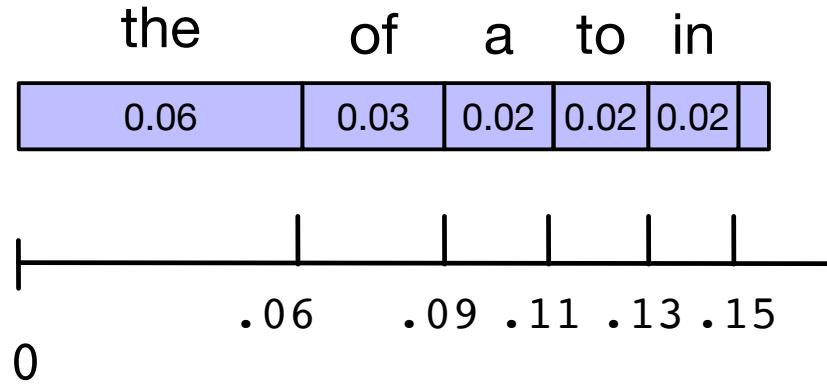
THE HEAD AND IN FRONTAL ATTACK ON AN ENGLISH WRITER THAT THE
CHARACTER OF THIS POINT IS THEREFORE ANOTHER METHOD FOR THE LETTERS
THAT THE TIME OF WHO EVER TOLD THE PROBLEM FOR AN UNEXPECTED.

How Shannon sampled those words in 1948



"Open a book at random and select a letter at random on the page. This letter is recorded. The book is then opened to another page and one reads until this letter is encountered. The succeeding letter is then recorded. Turning to another page this second letter is searched for and the succeeding letter recorded, etc."

Sampling a word from a distribution



Visualizing Bigrams the Shannon Way



Choose a random bigram (s , w)

s I

according to its probability $p(w|s)$

I want

Now choose a random bigram (w , x)
according to its probability $p(x|w)$

want to

to eat

eat Chinese

Chinese food

food $/s$

And so on until we choose $/s$

I want to eat Chinese food

Then string the words together

Note: there are other sampling methods



- Used for neural language models
- Many of them avoid generating words from the very unlikely tail of the distribution
- We'll discuss when we get to neural LM decoding:
 - Temperature sampling
 - Top-k sampling
 - Top-p sampling

1
gram

–To him swallowed confess hear both. Which. Of save on trail for are ay device and
rote life have
–Hill he late speaks; or! a more to leg less first you enter

2
gram

–Why dost stand forth thy canopy, forsooth; he is this palpable hit the King Henry. Live
king. Follow.
–What means, sir. I confess she? then all sorts, he is trim, captain.

3
gram

–Fly, and will rid me these news of price. Therefore the sadness of parting, as they say,
'tis done.
–This shall forbid it should be branded, if renown made it empty.

4
gram

–King Henry. What! I will go seek the traitor Gloucester. Exeunt some of the watch. A
great banquet serv'd in;
–It cannot be but so.

N=884,647 tokens, V=29,066

Shakespeare produced 300,000 bigram types out of $V^2 = 844$ million possible bigrams.

- So 99.96% of the possible bigrams were never seen (have zero entries in the table)
- That sparsity is even worse for 4-grams, explaining why our sampling generated actual Shakespeare.

1
gram

Months the my and issue of year foreign new exchange's september were recession exchange new endorsed a acquire to six executives

2
gram

Last December through the way to preserve the Hudson corporation N. B. E. C. Taylor would seem to complete the major central planners one point five percent of U. S. E. has already old M. X. corporation of living on information such as more frequently fishing to keep her

3
gram

They also point to ninety nine point six billion dollars from two hundred four oh six three percent of the rates of interest stores as Mexico and Brazil on market conditions

Can you guess the author? These 3-gram sentences are sampled from an LM trained on who?



- 1) They also point to ninety nine point six billion dollars from two hundred four oh six three percent of the rates of interest stores as Mexico and gram Brazil on market conditions
- 2) This shall forbid it should be branded, if renown made it empty.
- 3) "You are uniformly charming!" cried he, with a smile of associating and now and then I bowed and they perceived a chaise and four to wish for.

- If task-specific, use a training corpus that has a similar genre to your task.
 - If legal or medical, need lots of special-purpose documents
- Make sure to cover different kinds of dialects and speaker/authors.
 - Example: *African-American Vernacular English (AAVE)*
 - One of many varieties that can be used by African Americans and others
 - Can include the auxiliary verb **finna** that marks immediate future tense:
 - "My phone finna die"

- N-grams only work well for word prediction if the test corpus looks like the training corpus
 - But even when we try to pick a good training corpus, the test set will surprise us!
 - We need to train robust models that generalize!
- One kind of generalization: **Zeros**
 - Things that don't ever occur in the training set
 - But occur in the test set

- Training set:
 - ... ate lunch
 - ... ate dinner
 - ... ate a
 - ... ate the
- Test set
 - ... ate lunch
 - ... ate breakfast

$$P(\text{"breakfast"} \mid \text{ate}) = 0$$

- Bigrams with zero probability
 - Will hurt our performance for texts where those words appear!
 - And mean that we will assign 0 probability to the test set!
- And hence we cannot compute perplexity (can't divide by 0)!

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Week 4.5 - Smoothing: Add-one
(Laplace) smoothing

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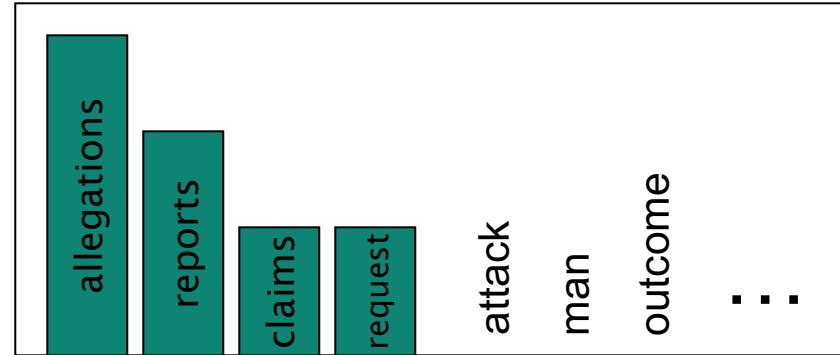
Language Models in **NLP**

The intuition of smoothing (from Dan Klein)



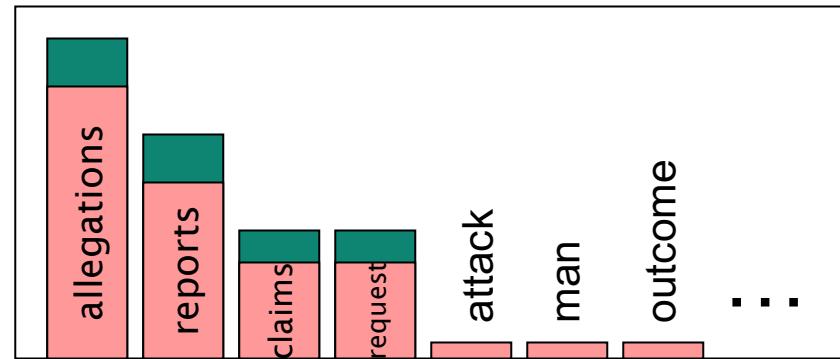
- When we have sparse statistics:

$P(w | \text{denied the})$
3 allegations
2 reports
1 claims
1 request
7 total



- Steal probability mass to generalize better

$P(w | \text{denied the})$
2.5 allegations
1.5 reports
0.5 claims
0.5 request
2 other
7 total



- Also called Laplace smoothing
- Pretend we saw each word one more time than we did
- Just add one to all the counts!

- MLE estimate:
$$P_{MLE}(w_i | w_{i-1}) = \frac{c(w_{i-1}, w_i)}{c(w_{i-1})}$$

- Add-1 estimate:
$$P_{Add-1}(w_i | w_{i-1}) = \frac{c(w_{i-1}, w_i) + 1}{c(w_{i-1}) + V}$$

- The maximum likelihood estimate
 - of some parameter of a model M from a training set T
 - maximizes the likelihood of the training set T given the model M
- Suppose the word “bagel” occurs 400 times in a corpus of a million words
- What is the probability that a random word from some other text will be “bagel”?
- MLE estimate is $400/1,000,000 = .0004$
- This may be a bad estimate for some other corpus
 - But it is the **estimate** that makes it **most likely** that “bagel” will occur 400 times in a million word corpus.

Berkeley Restaurant Corpus: Laplace smoothed bigram counts



	i	want	to	eat	chinese	food	lunch	spend
i	6	828	1	10	1	1	1	3
want	3	1	609	2	7	7	6	2
to	3	1	5	687	3	1	7	212
eat	1	1	3	1	17	3	43	1
chinese	2	1	1	1	1	83	2	1
food	16	1	16	1	2	5	1	1
lunch	3	1	1	1	1	2	1	1
spend	2	1	2	1	1	1	1	1

Laplace-smoothed bigrams



$$P^*(w_n|w_{n-1}) = \frac{C(w_{n-1}w_n) + 1}{C(w_{n-1}) + V}$$

	i	want	to	eat	chinese	food	lunch	spend
i	0.0015	0.21	0.00025	0.0025	0.00025	0.00025	0.00025	0.00075
want	0.0013	0.00042	0.26	0.00084	0.0029	0.0029	0.0025	0.00084
to	0.00078	0.00026	0.0013	0.18	0.00078	0.00026	0.0018	0.055
eat	0.00046	0.00046	0.0014	0.00046	0.0078	0.0014	0.02	0.00046
chinese	0.0012	0.00062	0.00062	0.00062	0.00062	0.052	0.0012	0.00062
food	0.0063	0.00039	0.0063	0.00039	0.00079	0.002	0.00039	0.00039
lunch	0.0017	0.00056	0.00056	0.00056	0.00056	0.0011	0.00056	0.00056
spend	0.0012	0.00058	0.0012	0.00058	0.00058	0.00058	0.00058	0.00058

Reconstituted counts



$$c^*(w_{n-1}w_n) = \frac{[C(w_{n-1}w_n) + 1] \times C(w_{n-1})}{C(w_{n-1}) + V}$$

	i	want	to	eat	chinese	food	lunch	spend
i	3.8	527	0.64	6.4	0.64	0.64	0.64	1.9
want	1.2	0.39	238	0.78	2.7	2.7	2.3	0.78
to	1.9	0.63	3.1	430	1.9	0.63	4.4	133
eat	0.34	0.34	1	0.34	5.8	1	15	0.34
chinese	0.2	0.098	0.098	0.098	0.098	8.2	0.2	0.098
food	6.9	0.43	6.9	0.43	0.86	2.2	0.43	0.43
lunch	0.57	0.19	0.19	0.19	0.19	0.38	0.19	0.19
spend	0.32	0.16	0.32	0.16	0.16	0.16	0.16	0.16

Compare with raw bigram counts



	i	want	to	eat	chinese	food	lunch	spend
i	5	827	0	9	0	0	0	2
want	2	0	608	1	6	6	5	1
to	2	0	4	686	2	0	6	211
eat	0	0	2	0	16	2	42	0
chinese	1	0	0	0	0	82	1	0
food	15	0	15	0	1	4	0	0
lunch	2	0	0	0	0	1	0	0
spend	1	0	1	0	0	0	0	0

	i	want	to	eat	chinese	food	lunch	spend
i	3.8	527	0.64	6.4	0.64	0.64	0.64	1.9
want	1.2	0.39	238	0.78	2.7	2.7	2.3	0.78
to	1.9	0.63	3.1	430	1.9	0.63	4.4	133
eat	0.34	0.34	1	0.34	5.8	1	15	0.34
chinese	0.2	0.098	0.098	0.098	0.098	8.2	0.2	0.098
food	6.9	0.43	6.9	0.43	0.86	2.2	0.43	0.43
lunch	0.57	0.19	0.19	0.19	0.19	0.38	0.19	0.19
spend	0.32	0.16	0.32	0.16	0.16	0.16	0.16	0.16

Add-1 estimation is a blunt instrument



- So add-1 isn't used for N-grams:
 - We'll see better methods
- But add-1 is used to smooth other NLP models
 - For text classification
 - In domains where the number of zeros isn't so huge.

SIT330-770: Natural Language Processing

Week 4.6 - Interpolation, Backoff, and Web-Scale LMs

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Language Models in **NLP**

- Sometimes it helps to use **less** context
 - Condition on less context for contexts you haven't learned much about
- **Backoff:**
 - use trigram if you have good evidence,
 - otherwise bigram, otherwise unigram
- **Interpolation:**
 - mix unigram, bigram, trigram
- Interpolation works better

- Simple interpolation

$$\begin{aligned}\hat{P}(w_n | w_{n-2} w_{n-1}) &= \lambda_1 P(w_n | w_{n-2} w_{n-1}) \\ &\quad + \lambda_2 P(w_n | w_{n-1}) \\ &\quad + \lambda_3 P(w_n)\end{aligned}\qquad \sum_i \lambda_i = 1$$

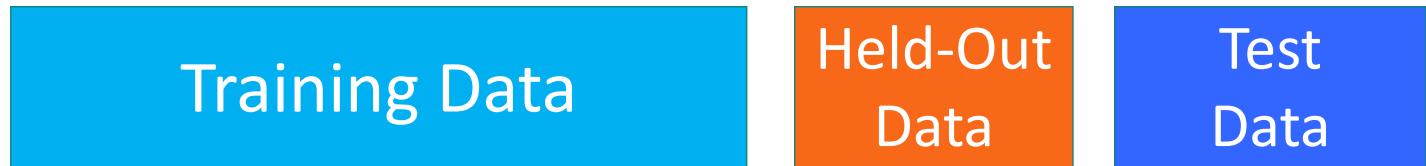
- Lambdas conditional on context:

$$\begin{aligned}\hat{P}(w_n | w_{n-2} w_{n-1}) &= \lambda_1(w_{n-2}^{n-1}) P(w_n | w_{n-2} w_{n-1}) \\ &\quad + \lambda_2(w_{n-2}^{n-1}) P(w_n | w_{n-1}) \\ &\quad + \lambda_3(w_{n-2}^{n-1}) P(w_n)\end{aligned}$$

How to set the lambdas?



- Use a **held-out** corpus



- Choose λ s to maximize the probability of held-out data:
 - Fix the N-gram probabilities (on the training data)
 - Then search for λ s that give largest probability to held-out set:

$$\log P(w_1 \dots w_n \mid M(\lambda_1 \dots \lambda_k)) = \sum_i \log P_{M(\lambda_1 \dots \lambda_k)}(w_i \mid w_{i-1})$$

Unknown words: Open versus closed vocabulary tasks



- If we know all the words in advanced
 - Vocabulary V is fixed
 - Closed vocabulary task
- Often we don't know this
 - **Out Of Vocabulary** = OOV words
 - Open vocabulary task
- Instead: create an unknown word token <UNK>
 - Training of <UNK> probabilities
 - Create a fixed lexicon L of size V
 - At text normalization phase, any training word not in L changed to <UNK>
 - Now we train its probabilities like a normal word
 - At decoding time
 - If text input: Use UNK probabilities for any word not in training

- How to deal with, e.g., Google N-gram corpus
- Pruning
 - Only store N-grams with count > threshold.
 - Remove singletons of higher-order n-grams
 - Entropy-based pruning
- Efficiency
 - Efficient data structures like tries
 - Bloom filters: approximate language models
 - Store words as indexes, not strings
 - Use Huffman coding to fit large numbers of words into two bytes
 - Quantize probabilities (4-8 bits instead of 8-byte float)

- “Stupid backoff” (Brants *et al.* 2007)
- No discounting, just use relative frequencies

$$S(w_i | w_{i-k+1}^{i-1}) = \begin{cases} \frac{\text{count}(w_{i-k+1}^i)}{\text{count}(w_{i-k+1}^{i-1})} & \text{if } \text{count}(w_{i-k+1}^i) > 0 \\ 0.4S(w_i | w_{i-k+2}^{i-1}) & \text{otherwise} \end{cases}$$

$$S(w_i) = \frac{\text{count}(w_i)}{N}$$

- Add-1 smoothing:
 - OK for text categorization, not for language modeling
- The most commonly used method:
 - Extended Interpolated Kneser-Ney
- For very large N-grams like the Web:
 - Stupid backoff

- Discriminative models:
 - choose n-gram weights to improve a task, not to fit the training set
- Parsing-based models
- Caching Models
 - Recently used words are more likely to appear

$$P_{CACHE}(w | history) = \lambda P(w_i | w_{i-2}w_{i-1}) + (1 - \lambda) \frac{c(w \in history)}{|history|}$$

- These perform very poorly for speech recognition (why?)

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Week 4.7 - Kneser-Ney Smoothing

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Language Models in **NLP**

Absolute discounting: just subtract a little from each count



- Suppose we wanted to subtract a little from a count of 4 to save probability mass for the zeros
- How much to subtract ?
- Church and Gale (1991)'s clever idea
- Divide up 22 million words of AP Newswire
 - Training and held-out set
 - for each bigram in the training set
 - see the actual count in the held-out set!
- It sure looks like $c^* = (c - .75)$

Bigram count in training	Bigram count in heldout set
0	.0000270
1	0.448
2	1.25
3	2.24
4	3.23
5	4.21
6	5.23
7	6.21
8	7.21
9	8.26

- Save ourselves some time and just subtract 0.75 (or some d)!

$$P_{\text{AbsoluteDiscounting}}(w_i \mid w_{i-1}) = \frac{c(w_{i-1}, w_i) - d}{c(w_{i-1})} + \lambda(w_{i-1}) P(w)$$

discounted bigram Interpolation weight

unigram

- (Maybe keeping a couple extra values of d for counts 1 and 2)
- But should we really just use the regular unigram $P(w)$?

- Better estimate for probabilities of lower-order unigrams!
 - Shannon game: *I can't see without my reading _____ Kongses* ?
 - “Kong” turns out to be more common than “glasses”
 - ... but “Kong” always follows “Hong”
- The unigram is useful exactly when we haven’t seen this bigram!
- Instead of $P(w)$: “How likely is w ”
- $P_{\text{continuation}}(w)$: “How likely is w to appear as a novel continuation?
 - For each word, count the number of bigram types it completes
 - Every bigram type was a novel continuation the first time it was seen

$$P_{\text{CONTINUATION}}(w) \propto |\{w_{i-1} : c(w_{i-1}, w) > 0\}|$$

- How many times does w appear as a novel continuation:

$$P_{CONTINUATION}(w) \propto |\{w_{i-1} : c(w_{i-1}, w) > 0\}|$$

- Normalized by the total number of word bigram types

$$|\{(w_{j-1}, w_j) : c(w_{j-1}, w_j) > 0\}|$$

$$P_{CONTINUATION}(w) = \frac{|\{w_{i-1} : c(w_{i-1}, w) > 0\}|}{|\{(w_{j-1}, w_j) : c(w_{j-1}, w_j) > 0\}|}$$

- Alternative metaphor: The number of # of word types seen to precede w

$$|\{w_{i-1} : c(w_{i-1}, w) > 0\}|$$

- Normalized by the # of words preceding all words:

$$P_{CONTINUATION}(w) = \frac{|\{w_{i-1} : c(w_{i-1}, w) > 0\}|}{\sum_{w'} |\{w'_{i-1} : c(w'_{i-1}, w') > 0\}|}$$

- A frequent word (Kong) occurring in only one context (Hong) will have a low continuation probability

$$P_{KN}(w_i \mid w_{i-1}) = \frac{\max(c(w_{i-1}, w_i) - d, 0)}{c(w_{i-1})} + \lambda(w_{i-1}) P_{CONTINUATION}(w_i)$$

λ is a normalizing constant; the probability mass we've discounted

$$\lambda(w_{i-1}) = \frac{d}{c(w_{i-1})} \left| \{w : c(w_{i-1}, w) > 0\} \right|$$

the normalized discount

The number of word types that can follow w_{i-1}
= # of word types we discounted
= # of times we applied normalized discount

Kneser-Ney Smoothing: Recursive formulation



$$P_{KN}(w_i | w_{i-n+1}^{i-1}) = \frac{\max(c_{KN}(w_{i-n+1}^i) - d, 0)}{c_{KN}(w_{i-n+1}^{i-1})} + \lambda(w_{i-n+1}^{i-1}) P_{KN}(w_i | w_{i-n+2}^{i-1})$$

$$c_{KN}(\bullet) = \begin{cases} \text{count}(\bullet) & \text{for the highest order} \\ \text{continuation count}(\bullet) & \text{for lower order} \end{cases}$$

Continuation count = Number of unique single word contexts for \bullet

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Week 4.8 – The Spelling Correction Task

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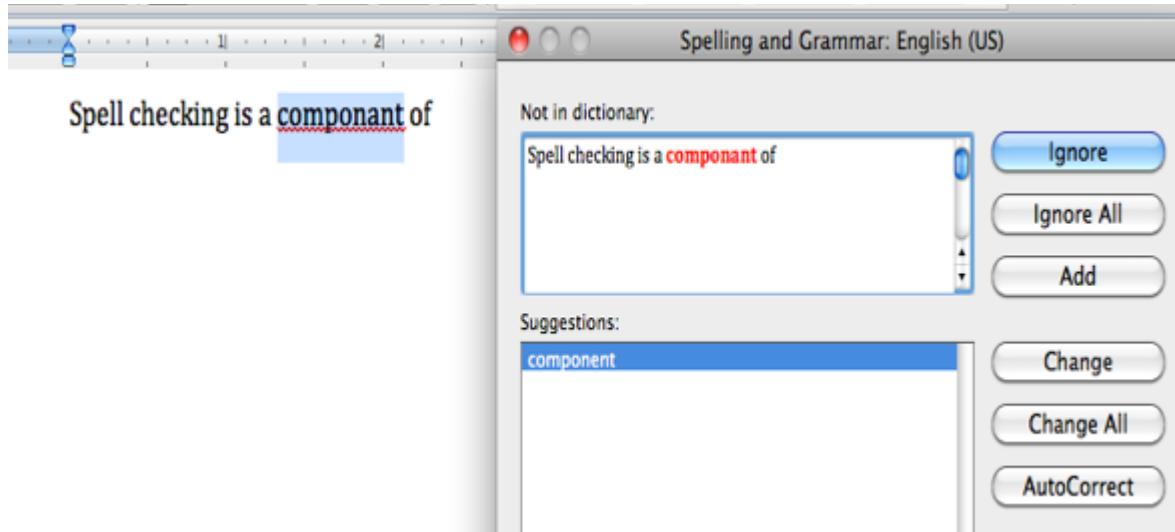


Language Models in NLP

Applications for spelling correction



Word processing



Phones



Showing results for [natural language processing](#)
Search instead for [natural langage processing](#)

- 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

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](#)

- 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

- 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 from Heathrow to LAX* → *Flying from Heathrow to LAX*

- “**a stellar and versatile across whose combination of sass and glamour...**”
- Counts from the Corpus of Contemporary American English with
- addC₁ smoothing
- $P(\text{actress} \mid \text{versatile}) = .000021$ $P(\text{whose} \mid \text{actress}) = .0010$
- $P(\text{across} \mid \text{versatile}) = .000021$ $P(\text{whose} \mid \text{across}) = .000006$
- $P(\text{"versatile actress whose"}) = .000021 * .0010 = 210 \times 10^{-10}$
- $P(\text{"versatile across whose"}) = .000021 * .000006 = 1 \times 10^{-10}$

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Week 4.9 – The Noisy Channel Model of Spelling

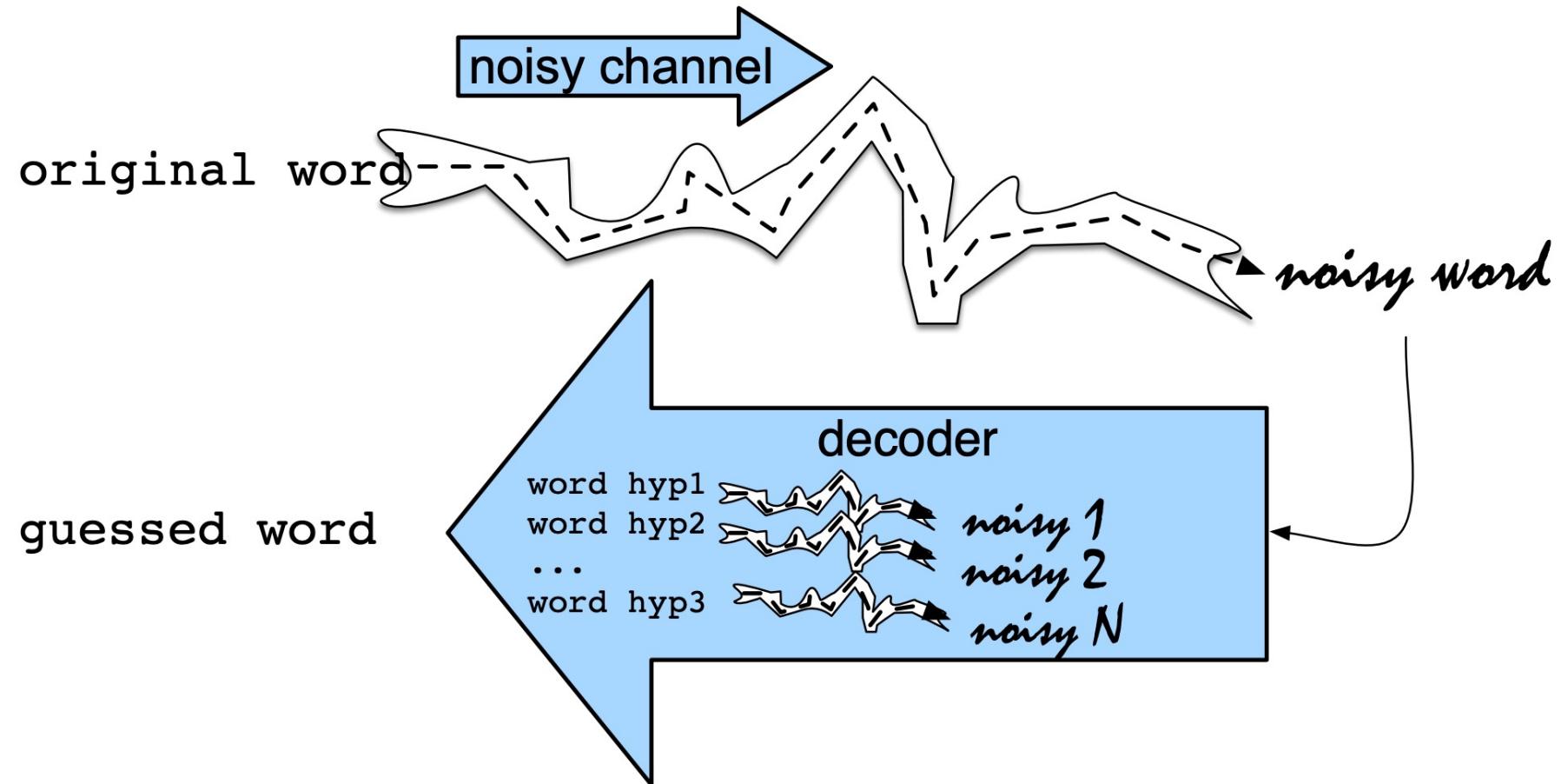
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Language Models in **NLP**

Noisy Channel Intuition



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

$$\begin{aligned}\hat{w} &= \operatorname{argmax}_{w \in V} P(w | x) \\ &= \operatorname{argmax}_{w \in V} \frac{P(x | w)P(w)}{P(x)} \\ &= \operatorname{argmax}_{w \in V} P(x | w)P(w)\end{aligned}$$

The likelihood or
channel model

Prior probability or
Language Model

Non-word spelling error example



acress

- 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
acress	acres	-	s	insertion

- 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

- Use any of the language modeling algorithms we've learned
- Unigram, bigram, trigram
- Web-scale spelling correction
 - Stupid backoff

- 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

- **Error model probability, Edit probability**
- *Kernighan, Church, Gale 1990*
- *Misspelled word* $x = x_1, x_2, x_3 \dots x_m$
- *Correct word* $w = w_1, w_2, w_3, \dots, w_n$
- $P(x|w)$ = 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



$\text{sub}[X, Y] = \text{Substitution of } X \text{ (incorrect) for } Y \text{ (correct)}$

X	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	
	Y (correct)																										
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	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	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	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	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	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	0
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	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	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
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	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	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	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	0
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	0
u	20	0	0	0	44	0	0	0	64	0	0	0	2	43	0	0	4	0	0	0	0	0	2	0	8	0	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	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	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	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	0
z	0	0	0	7	0	0	0	0	0	0	0	7	5	0	0	0	0	2	21	3	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/>

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

Noisy channel probability 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

Noisy channel probability for *acress*



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

Noisy channel probability for **acress**



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

- “**a stellar and** versatile **acress** whose **combination of sass and glamour...**”
- Counts from the Corpus of Contemporary American English with add-1 smoothing
- $P(\text{actress} \mid \text{versatile}) = .000021$ $P(\text{whose} \mid \text{actress}) = .0010$
- $P(\text{across} \mid \text{versatile}) = .000021$ $P(\text{whose} \mid \text{across}) = .000006$
- $P(\text{"versatile actress whose"}) = .000021 * .0010 = 210 \times 10^{-10}$
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- “**a stellar and** versatile **acress** whose combination of sass and glamour...”
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- 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)

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Week 4.10 – Real-word spelling errors

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Language Models in **NLP**

- ...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](#)

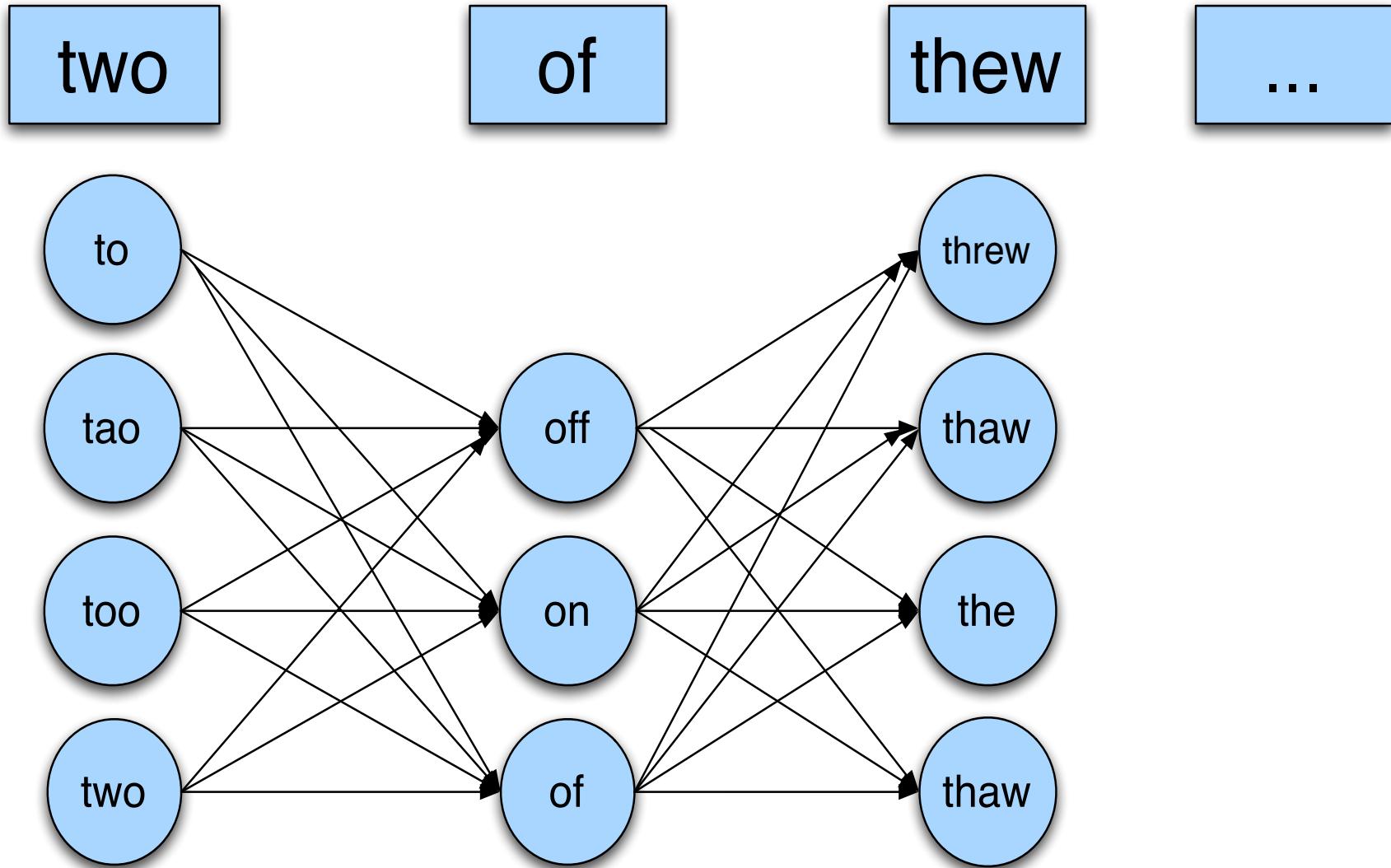
- For each word in sentence (phrase, query ...)
 - Generate *candidate set*
 - the word itself
 - all single-letter edits that are English words
 - words that are homophones
 - (all of this can be pre-computed!)
- Choose best candidates
 - Noisy channel model

Noisy channel for real-word spell correction

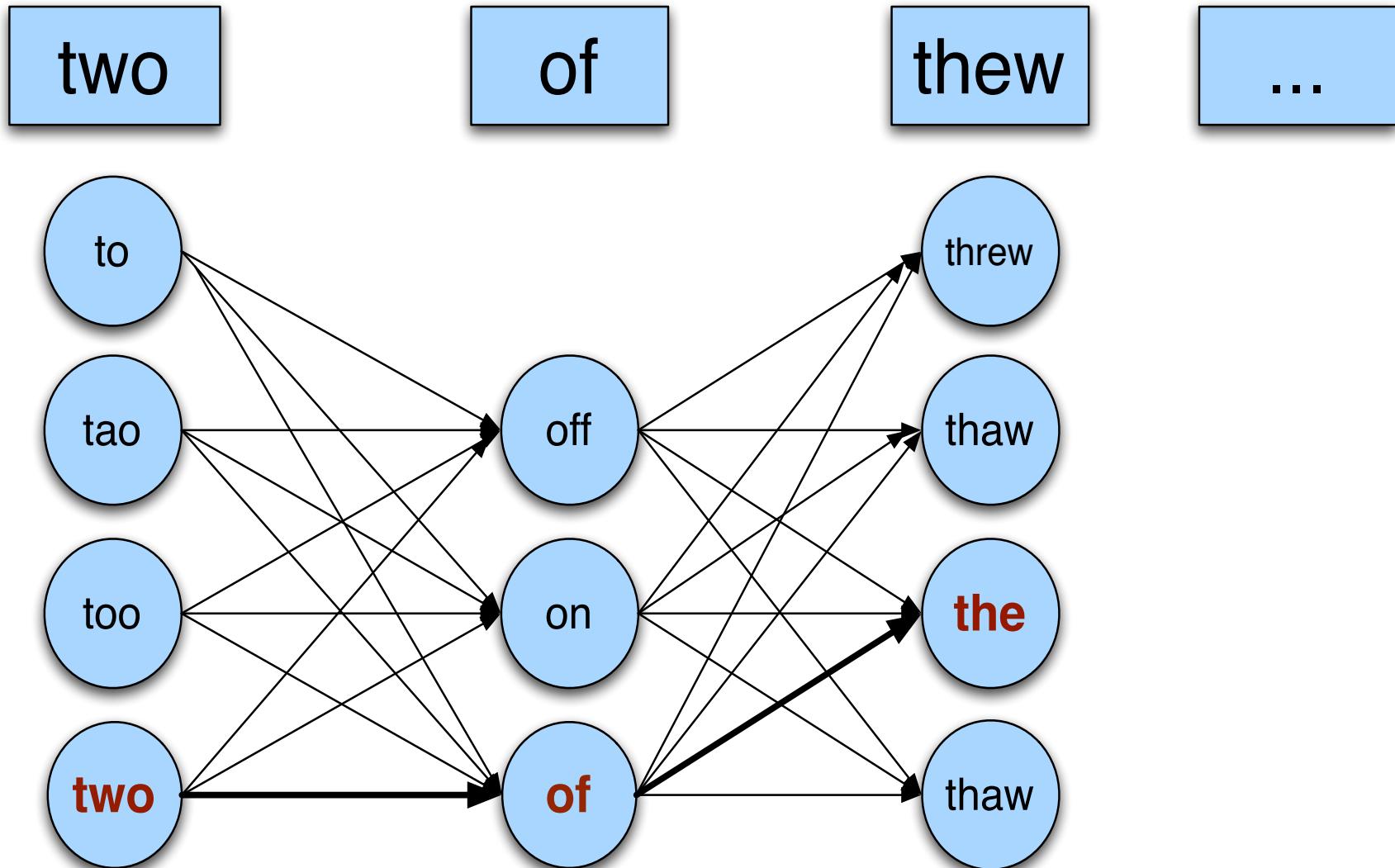


- Given a sentence $w_1, w_2, w_3, \dots, w_n$
- Generate a set of candidates for each word w_i
 - Candidate(w_1) = $\{w_1, w'_1, w''_1, w'''_1, \dots\}$
 - Candidate(w_2) = $\{w_2, w'_2, w''_2, w'''_2, \dots\}$
 - Candidate(w_n) = $\{w_n, w'_n, w''_n, w'''_n, \dots\}$
- Choose the sequence W that maximizes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

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, w''_2, w_3, w_4 two **off** thew
 - w_1, w_2, w'_3, w_4 two of **the**
 - 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, $P(w|w)$

- What is the channel probability for a correctly typed word?
- $P(\text{"the"}|\text{"the"})$
 - 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

SIT330-770: Natural Language Processing

Week 4.11 – State of the art noisy systems

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Language Models in **NLP**

- If very confident in correction
 - Autocorrect
- Less confident
 - Give the best correction
- Less confident
 - Give a correction list
- Unconfident
 - Just flag as an error

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

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

- Learn λ from a development test set

- Metaphone, used in GNU aspell
 - Convert misspelling to metaphone pronunciation
 - “Drop duplicate adjacent letters, except for C.”
 - “If the word begins with 'KN', 'GN', 'PN', 'AE', 'WR', drop the first letter.”
 - “Drop 'B' if aver 'M' and if it is at the end of the word”
 - ...
- Find words whose pronunciation is 1-2 edit distance from misspelling's
- Score result list
 - Weighted edit distance of candidate to misspelling
 - Edit distance of candidate pronunciation to misspelling pronunciation

- 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

- Factors that could influence $p(\text{misspelling}|\text{word})$
 - The source letter
 - The target letter
 - Surrounding letters
 - The position in the word
 - Nearby keys on the keyboard
 - Homology on the keyboard
 - Pronunciations
 - Likely morpheme transformations

Nearby keys



- Instead of just channel model and language model
- Use many features in a classifier (next lecture).
- Build a classifier for a specific pair like:

whether/weather

- “cloudy” within +- 10 words
- ___ to VERB
- ___ or not