

Einführung in die Computerlinguistik

Machine Translation

Hinrich Schütze

Center for Information and Language Processing

2019-01-14

Outline

- 1 Noisy channel model
- 2 Machine translation
- 3 Language models

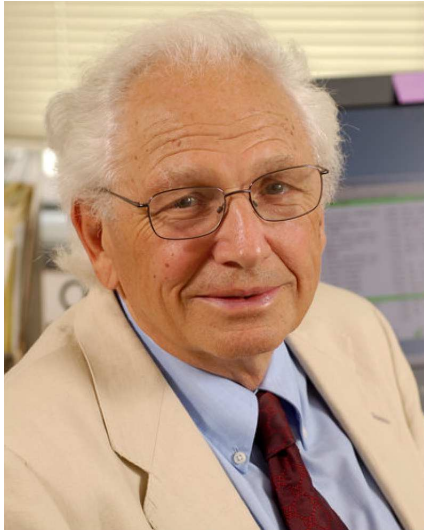
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Fred Jelinek

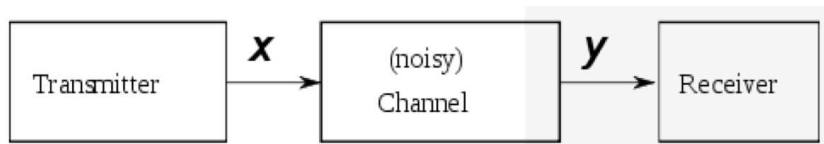


IBM Watson approach to NLP

- sequence model
- in most cases: given an observation or **evidence**, select the most likely sequence that caused the observation
- We will only consider **word** sequences for now.

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Noisy channel

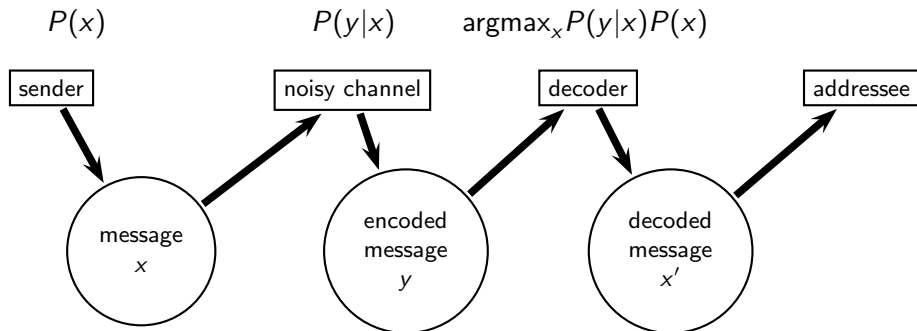


Well-known examples of applications of noisy channel model?

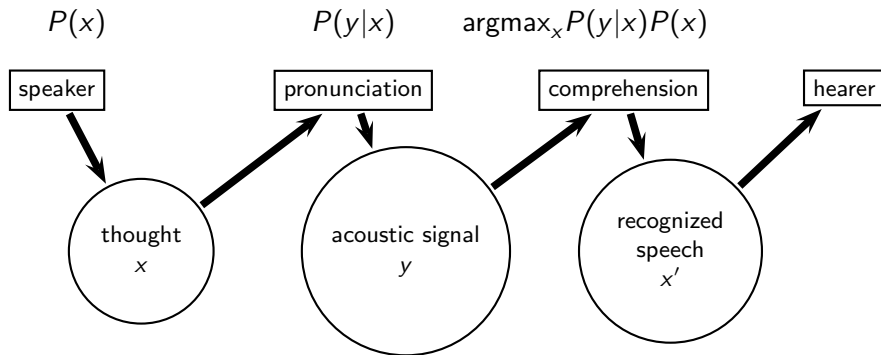
Decode 788884278



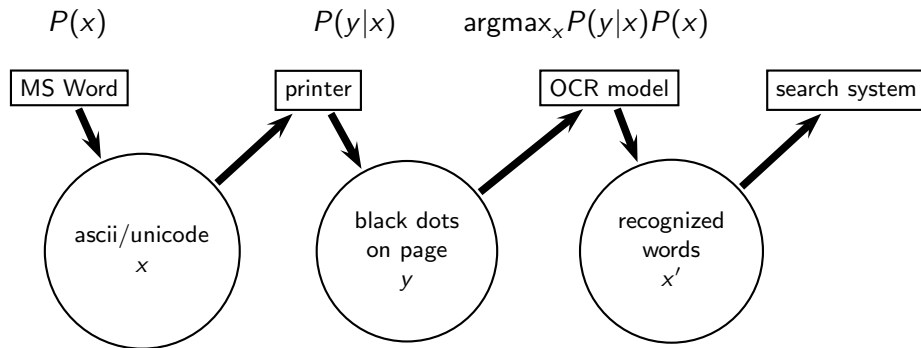
Noisy channel: Information theory / telecommunications



Noisy channel: Speech recognition



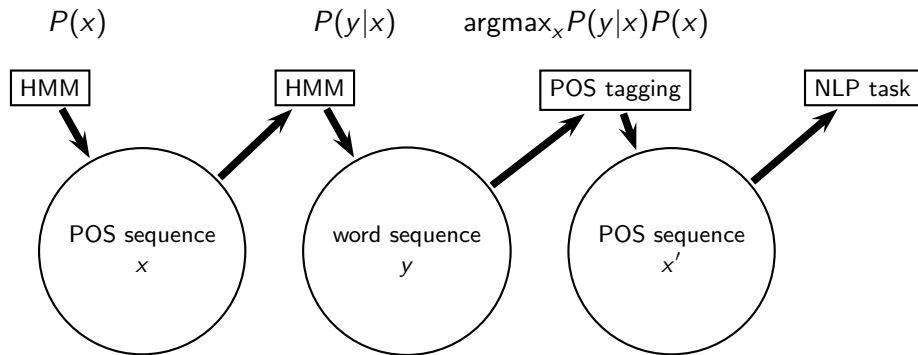
Noisy channel: Optical character recognition



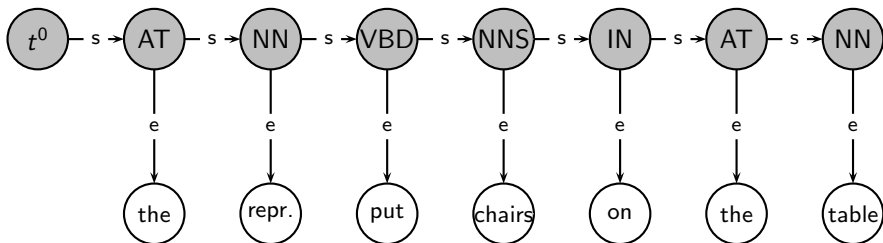
Part-of-speech tagging

- Given a sequence of words (a sentence), how do we compute the corresponding (disambiguated) part-of-speech sequence?
- Example:
 - Input: “the representative put chairs on the table”
 - Output: “AT NN VBD NNS IN AT NN”
- $t_{1,n} = \operatorname{argmax}_{t_{1,n}} P(t_{1,n} | w_{1,n}) = \operatorname{argmax}_{t_{1,n}} P(w_{1,n} | t_{1,n}) t_{1,n}$

Noisy channel: Part-of-speech tagging



Noisy channel: Part-of-speech tagging



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Classical approach to speech recognition

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- word sequence: sequence of words
- evidence: acoustic signal
- $P(\text{evidence}|\text{word-sequence})$: a model of how humans translate a sequence of (written) words into acoustics

Classical approach to optical character recognition

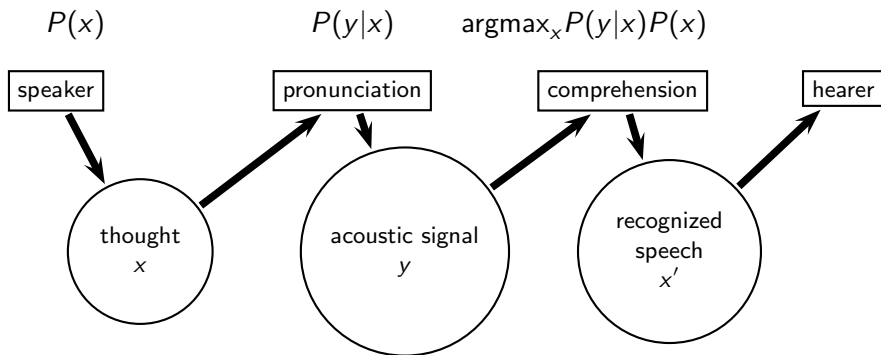
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- word sequence: sequence of words
- evidence: image
- $P(\text{evidence}|\text{word-sequence})$: a model of how a machine (e.g., a desktop printer) translates a sequence of words into printed letters/symbols

Exercise: Noisy channel model for machine translation?

speech

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- evidence: acoustic signal
- $P(\text{evidence}|\text{word-sequence})$: a model of how humans translate a sequence of (written) words into acoustics

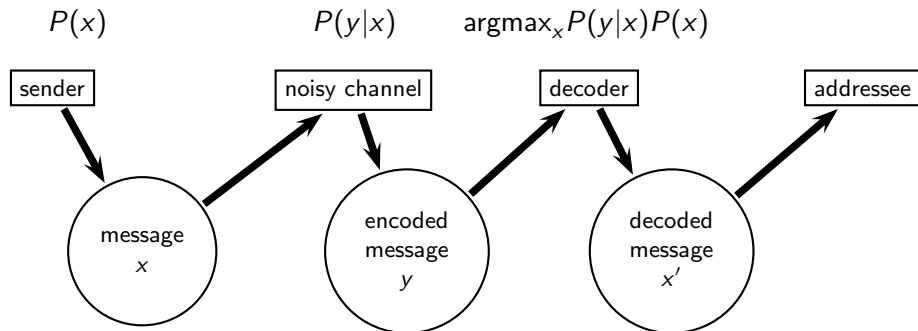


Classical approach to machine translation (French→English)

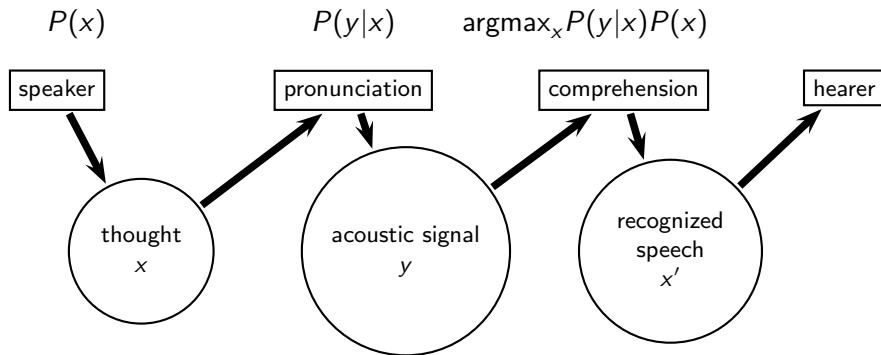
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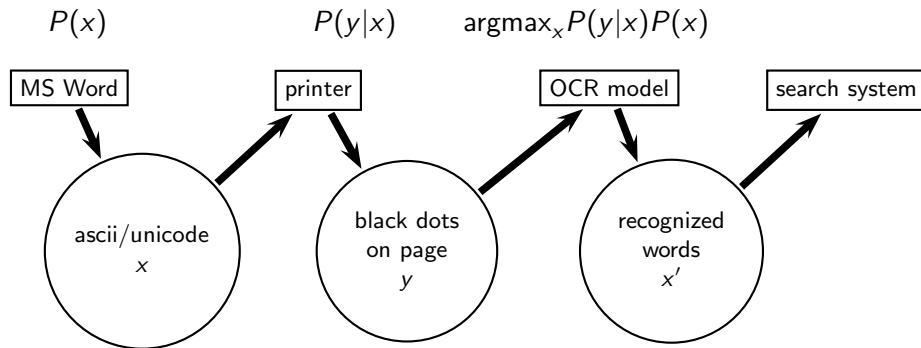
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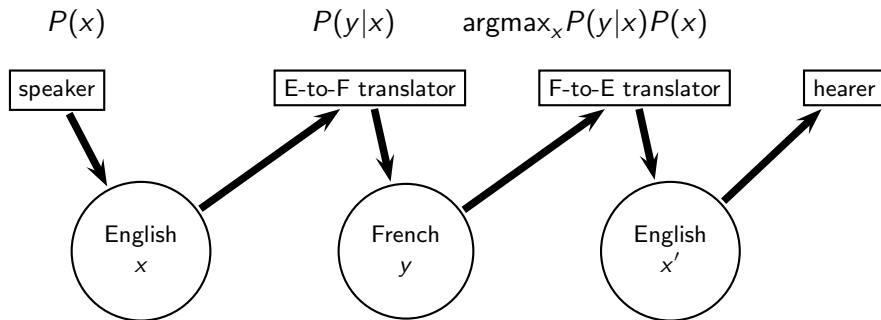
Noisy channel: Speech recognition



Noisy channel: Optical character recognition



Noisy channel: French-to-English machine translation



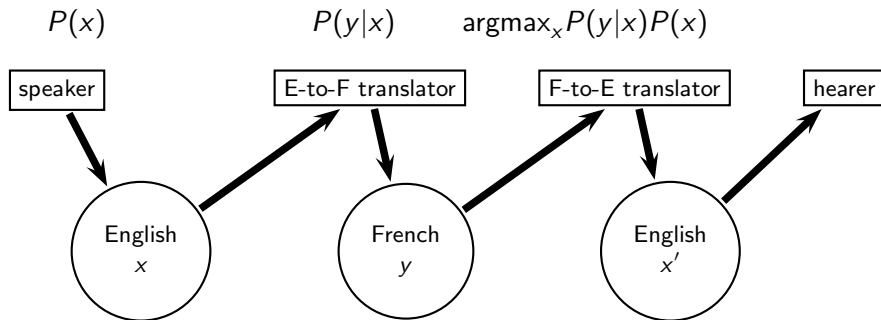
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Noisy channel: French-to-English machine translation




The two key components of the model

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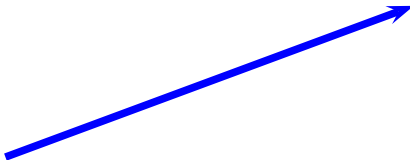
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translation model 

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translation model 

How to build a translation model

- Find a **parallel corpus** – a body of text where each sentence is available in two or more languages
- IBM Watson used the Canadian Hansards, the proceedings of the Canadian Parliament.
- Compute a word alignment for the parallel corpus (next slide)
- Estimate a translation model from the word alignment (that is, the model that models how humans generate French sentences from English sentences)

- Our model is a generative model: The French sentence is generated based on the English sentence.
- Every French word is “caused” by an English word.
- causation = alignment
- But many French words are not aligned, i.e., they have no plausible English word they correspond to.
- To cover these unaligned French words, we introduce the “empty cept” e_0 .
- The empty cept e_0 is an artificial English word that all unaligned French words are aligned with.
- Now every French word is “caused” by an English word.

Exercise: Estimating word translation probabilities



Estimate:

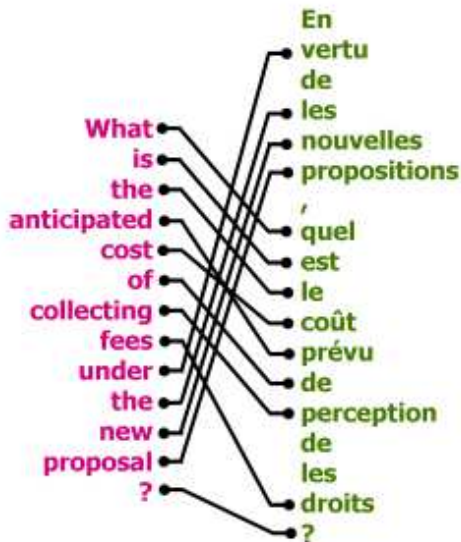
$$P(e_i | \text{nouvelles})$$

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$$P(f_j | \text{the})$$

$$P(f_j | e_0)$$

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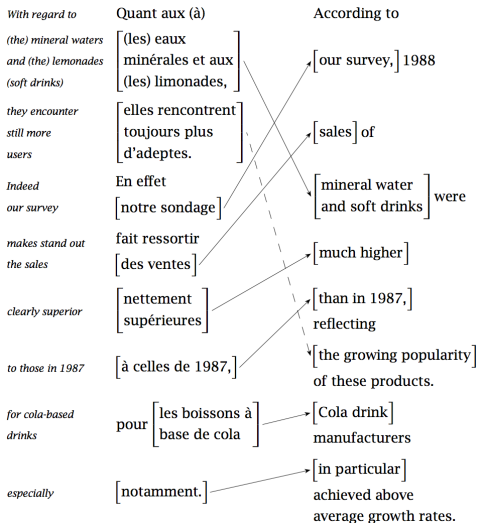
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“Linguistic” word/phrase alignment of a parallel corpus



Basic translation model

$$P(f|e) \propto \sum_{a_1=0}^l \cdots \sum_{a_m=0}^l P(< a_1, \dots, a_m >) \prod_{j=1}^m P(f_j | e_{a_j})$$

- e : English sentence, e_i : i^{th} word in e
- l : length of English sentence
- f : French sentence, f_j : j^{th} word in f
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- e_{a_j} is the English word that f_j is aligned with – this assumes that the alignment is a (total) function:
 $a : \{1, 2, \dots, m\} \mapsto \{0, 1, \dots, l\}$
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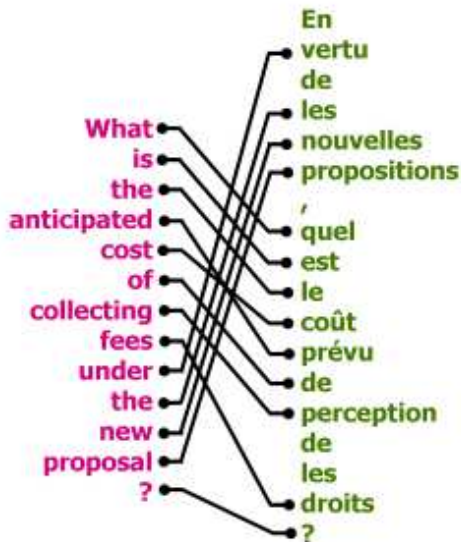
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Formalization of alignment

e_0	e_1	e_2
empty cept	they	descended

f_1	f_2	f_3
runter	gingen	sie

a_1	a_2	a_3	a_1	a_2	a_3	a_1	a_2	a_3
0	0	0	1	0	0	2	0	0
0	0	1	1	0	1	2	0	1
0	0	2	1	0	2	2	0	2
0	1	0	1	1	0	2	1	0
0	1	1	1	1	1	2	1	1
0	1	2	1	1	2	2	1	2
0	2	0	1	2	0	2	2	0
0	2	1	1	2	1	2	2	1
0	2	2	1	2	2	2	2	2

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What's bad about this model? What type of linguistic phenomenon will not be translated correctly?

What's bad about this model

- Collocations, noncompositional combinations: “piece of cake”
 - Assumption violated: Each English word generates German translations **independent** of the other words.
- Compounds: “Kirschkuchen” vs. “cherry pie”
 - Assumption violated: For each German/French word there is a **single** English word responsible for it.
- Unlikely alignments: “siehst Du” vs. “(do) you see”
 - Assumption violated: The probability of a particular **alignment is independent of the words**.

What's bad about this model (2)

- Morphology: “Kind” – “Kindes”
- Gender and case
- Syntax: which types of differences between German syntax and English syntax could be a problem?


Google Translate

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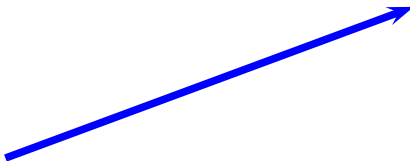
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translation model 

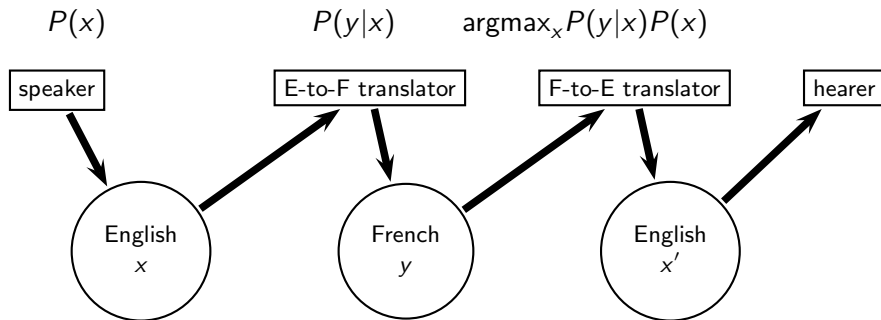
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language model



Noisy channel: French-to-English machine translation



Why the language model is important

- Classical example from speech recognition
- The following two are almost indistinguishable acoustically.
- “wreck a nice beach”
- “recognize speech”
- If we had only the translation model $P(y|x)$, then we would not be able to make a good decision.
- We need the language model for this decision.
- $P(\text{“wreck a nice beach”}) \ll P(\text{“recognize speech”})$
- We’ll choose “recognize speech” based on this.

Bigram language model

$$P(w_{1,2,\dots,n}) = \prod_{i=1}^n P(w_i|w_{i-1})$$

- Key problem: How do we estimate the parameters?
- $P(w_i|w_{i-1})$?

Maximum likelihood = Relative frequency

$$P_{ML}(w_2|w_1) = \frac{C(w_1 w_2)}{C(w_1)}$$

where $C(e)$ is the number of times the event e occurred in the training set.

Example:

$$p_{ML}(\text{be}|\text{would}) = \frac{C(\text{would be})}{C(\text{would})} = \frac{18454}{83735} \approx 0.22$$

Why maximum likelihood does not work

- Suppose that “Dr.” and “Cooper” are frequent in our corpus. Frequency of “Dr.” = 10000
- But suppose that the sequence “Dr. Cooper” does not occur in the corpus.
- What is the maximum likelihood estimate of $P(\text{Cooper}|\text{Dr.})$?

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$$P_{ML}(\text{Cooper}|\text{Dr.}) = \frac{C(\text{Dr. Cooper})}{C(\text{Dr.})} = \frac{0}{10000} = 0$$

- This means that in machine translation, any English sentence containing “Dr. Cooper” would be deemed impossible and could not be output by the translator.
- This problem is called sparseness.
- Ideally, we would need knowledge about events and their probability that never occurred in our training corpus.

Laplace = Add-one smoothing

$$P_L(w_2|w_1) = \frac{C(w_1 w_2) + 1}{C(w_1) + |V|}$$

where $C(e)$ is the number of times the event e occurred in the training set, V is the vocabulary of the training set and $w_{i:j}$ is the sequence of words $w_i, w_{i+1}, \dots, w_{j-1}, w_j$.

Better estimator:

$$P_L(\text{Cooper}|\text{Dr.}) = \frac{0 + 1}{10000 + 256873} \approx 0.0000037 > 0$$

So now our machine translation system has a chance of finding a good English translation that contains the phrase “Dr. Cooper”.

the three women saw the small mountain behind the large mountain

Compute maximum likelihood and laplace estimates for:
 $P(\text{three}|\text{the})$ and $P(\text{saw}|\text{the})$

- Noisy channel model
- Translation models
- Estimation of translation models
- Language models
- Estimation of language models

- $P(e)$
- $P(f|e)$
- empty cept
- $\operatorname{argmax} P(f|e)P(e)$