Einführung in die Computerlinguistik
Machine Translation

Alexander Fraser and Robert Zangenfeind

Center for Information and Language Processing

2020-01-20

Dieses Foliensatz wurde von Prof. Dr. Hinrich Schütze erstellt.

Fehler und Mängel sind ausschließlich meine Verantwortung.

Outline

Outline

Fred Jelinek

Fred Jelinek

IBM Watson approach to NLP

IBM Watson approach to NLP

- sequence model

IBM Watson approach to NLP

- sequence model
- in most cases: given an observation or evidence,
  select the most likely sequence that caused the observation

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.

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.

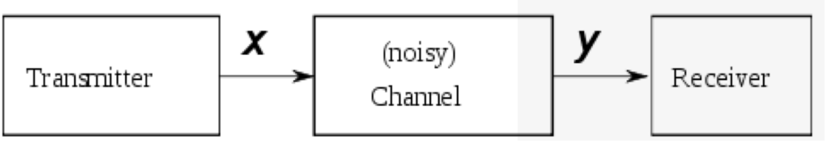
IBM Watson approach to NLP

- 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.

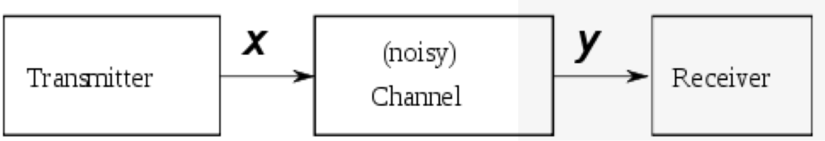
$$
\begin{aligned}
& \operatorname{argmax}_{\text{word-sequence}} P(\text{word-sequence}|\text{evidence}) \\
= \; & \operatorname{argmax}_{\text{word-sequence}} \frac{P(\text{evidence}|\text{word-sequence})P(\text{word-sequence})}{P(\text{evidence})} \\
= \; & \operatorname{argmax}_{\text{word-sequence}} \; P(\text{evidence}|\text{word-sequence}) \quad P(\text{word-sequence})
\end{aligned}
$$

Noisy channel

Noisy channel



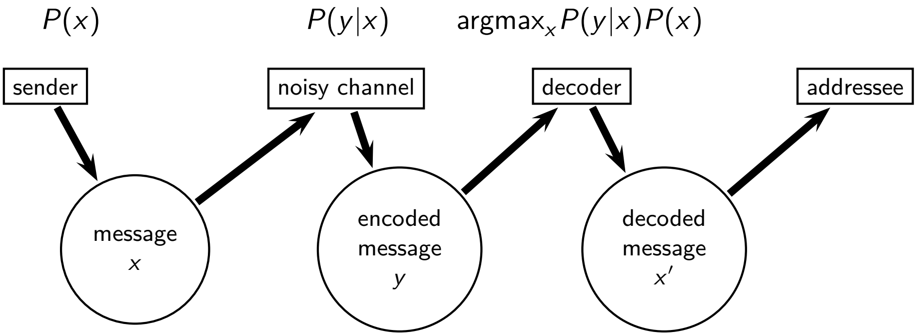
Noisy channel



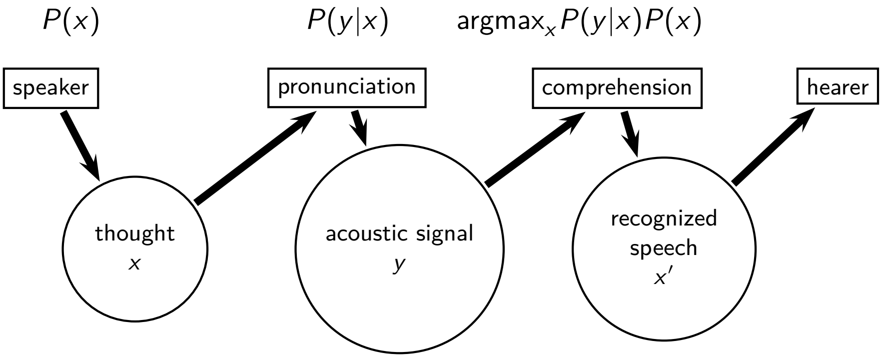
Well-known examples of applications of noisy channel model?

Decode 788884278

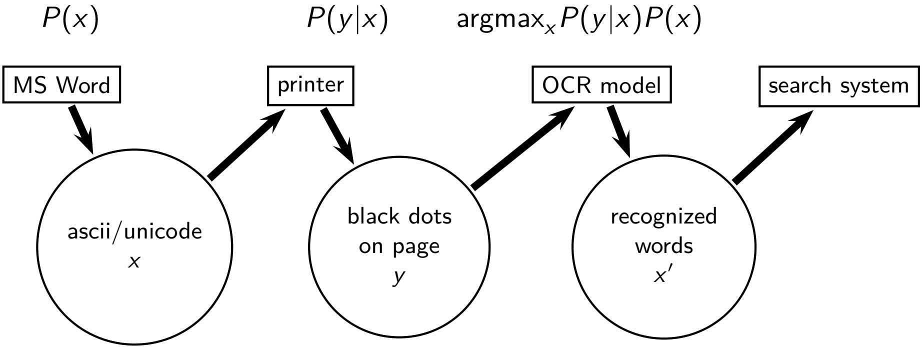
Noisy channel: Information theory / telecommunications



Noisy channel: Speech recognition



Noisy channel: Optical character recognition



Part-of-speech tagging

Part-of-speech tagging

- Given a sequence of words (a sentence), how do we compute the corresponding (disambiguated) part-of-speech sequence?

Part-of-speech tagging

- Given a sequence of words (a sentence), how do we compute the corresponding (disambiguated) part-of-speech sequence?
- Example:

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"

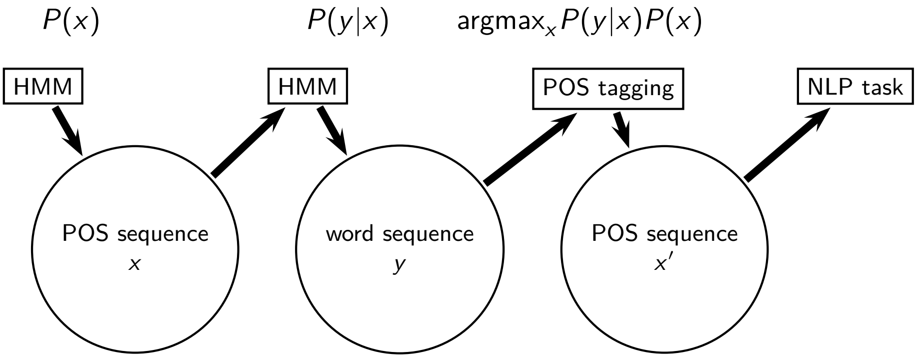
Part-of-speech tagging

- 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"

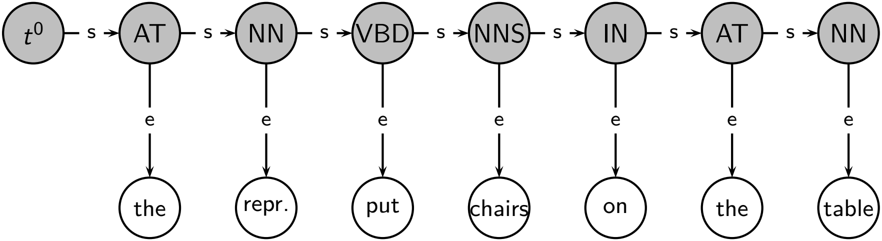
Part-of-speech tagging

- 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"
- $t_{1,n} = \text{argmax}_{t_{1,n}} P(t_{1,n}|w_{1,n}) = \text{argmax}_{t_{1,n}} P(w_{1,n}|t_{1,n})P(t_{1,n})$

Noisy channel: Part-of-speech tagging



Noisy channel: Part-of-speech tagging



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.

$$
\begin{aligned}
& \operatorname{argmax}_{\text{word-sequence}} P(\text{word-sequence}|\text{evidence}) \\
= \quad & \operatorname{argmax}_{\text{word-sequence}} \frac{P(\text{evidence}|\text{word-sequence})P(\text{word-sequence})}{P(\text{evidence})} \\
= \quad & \operatorname{argmax}_{\text{word-sequence}} \quad P(\text{evidence}|\text{word-sequence}) \quad P(\text{word-sequence})
\end{aligned}
$$

Classical approach to speech recognition

$$
\begin{aligned}
& \text{argmax}_{\text{word-sequence}} P(\text{word-sequence}|\text{evidence}) \\
= \quad & \text{argmax}_{\text{word-sequence}} \frac{P(\text{evidence}|\text{word-sequence}) P(\text{word-sequence})}{P(\text{evidence})} \\
= \quad & \text{argmax}_{\text{word-sequence}} \quad P(\text{evidence}|\text{word-sequence}) \quad P(\text{word-sequence})
\end{aligned}
$$

Classical approach to speech recognition

$$
\begin{aligned}
& \operatorname{argmax}_{\text{word-sequence}} P(\text{word-sequence}|\text{evidence}) \\
= \quad & \operatorname{argmax}_{\text{word-sequence}} \frac{P(\text{evidence}|\text{word-sequence})P(\text{word-sequence})}{P(\text{evidence})} \\
= \quad & \operatorname{argmax}_{\text{word-sequence}} \quad P(\text{evidence}|\text{word-sequence}) \quad P(\text{word-sequence})
\end{aligned}
$$

- word sequence: sequence of words

Classical approach to speech recognition

$$
\begin{aligned}
& \text{argmax}_{\text{word-sequence}} P(\text{word-sequence}|\text{evidence}) \\
= \quad & \text{argmax}_{\text{word-sequence}} \frac{P(\text{evidence}|\text{word-sequence}) P(\text{word-sequence})}{P(\text{evidence})} \\
= \quad & \text{argmax}_{\text{word-sequence}} \quad P(\text{evidence}|\text{word-sequence}) \quad P(\text{word-sequence})
\end{aligned}
$$

- word sequence: sequence of words
- evidence: acoustic signal

Classical approach to speech recognition

$$
\begin{aligned}
& \mathrm{argmax}_{\text{word-sequence}} P(\text{word-sequence}|\text{evidence}) \\
= \quad & \mathrm{argmax}_{\text{word-sequence}} \frac{P(\text{evidence}|\text{word-sequence}) P(\text{word-sequence})}{P(\text{evidence})} \\
= \quad & \mathrm{argmax}_{\text{word-sequence}} \quad P(\text{evidence}|\text{word-sequence}) \quad P(\text{word-sequence})
\end{aligned}
$$

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

Classical approach to optical character recognition

$$
\begin{aligned}
& \text{argmax}_{\text{word-sequence}} P(\text{word-sequence}|\text{evidence}) \\
= \quad & \text{argmax}_{\text{word-sequence}} \frac{P(\text{evidence}|\text{word-sequence}) P(\text{word-sequence})}{P(\text{evidence})} \\
= \quad & \text{argmax}_{\text{word-sequence}} \quad P(\text{evidence}|\text{word-sequence}) \quad P(\text{word-sequence})
\end{aligned}
$$

Classical approach to optical character recognition

$$
\begin{aligned}
& \text{argmax}_{\text{word-sequence}} P(\text{word-sequence}|\text{evidence}) \\
= \quad & \text{argmax}_{\text{word-sequence}} \frac{P(\text{evidence}|\text{word-sequence})P(\text{word-sequence})}{P(\text{evidence})} \\
= \quad & \text{argmax}_{\text{word-sequence}} \quad P(\text{evidence}|\text{word-sequence}) \quad P(\text{word-sequence})
\end{aligned}
$$

- word sequence: sequence of words

Classical approach to optical character recognition

$$
\begin{aligned}
& \text{argmax}_{\text{word-sequence}} P(\text{word-sequence}|\text{evidence}) \\
= \quad & \text{argmax}_{\text{word-sequence}} \frac{P(\text{evidence}|\text{word-sequence}) P(\text{word-sequence})}{P(\text{evidence})} \\
= \quad & \text{argmax}_{\text{word-sequence}} \quad P(\text{evidence}|\text{word-sequence}) \quad P(\text{word-sequence})
\end{aligned}
$$

- word sequence: sequence of words
- evidence: image

Classical approach to optical character recognition

$$
\begin{aligned}
& \text{argmax}_{\text{word-sequence}} P(\text{word-sequence}|\text{evidence}) \\
= \quad & \text{argmax}_{\text{word-sequence}} \frac{P(\text{evidence}|\text{word-sequence}) P(\text{word-sequence})}{P(\text{evidence})} \\
= \quad & \text{argmax}_{\text{word-sequence}} \quad P(\text{evidence}|\text{word-sequence}) \quad P(\text{word-sequence})
\end{aligned}
$$

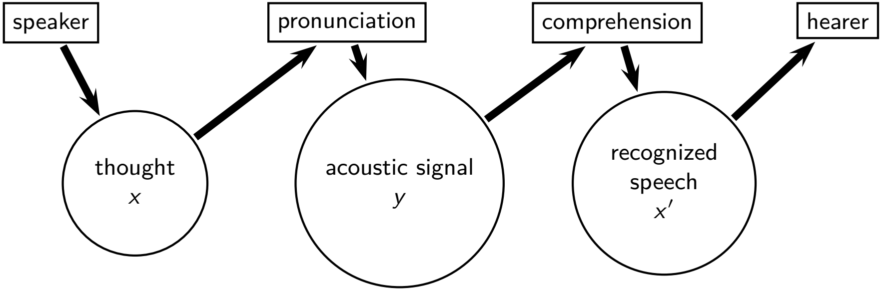
- word sequence: sequence of words
- evidence: image
- P(evidence|word-sequence): a model of how a machine (e.g., a desktop printer) translates a sequence of words into printed letters/symbols

Exercise: Noisy channel model for machine translation?

speech

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

$P(x)$ $P(y|x)$ $\text{argmax}_x P(y|x)P(x)$



Classical approach to machine translation (French→English)

$$\begin{aligned} & \mathrm{argmax}_{\text{word-sequence}} P(\text{word-sequence}|\text{evidence}) \\ = \quad & \mathrm{argmax}_{\text{word-sequence}} \frac{P(\text{evidence}|\text{word-sequence}) P(\text{word-sequence})}{P(\text{evidence})} \\ = \quad & \mathrm{argmax}_{\text{word-sequence}} \quad P(\text{evidence}|\text{word-sequence}) \quad P(\text{word-sequence}) \end{aligned}$$

Classical approach to machine translation (French→English)

$$
\begin{aligned}
& \operatorname{argmax}_{\text{word-sequence}} P(\text{word-sequence}|\text{evidence}) \\
= \quad & \operatorname{argmax}_{\text{word-sequence}} \frac{P(\text{evidence}|\text{word-sequence}) P(\text{word-sequence})}{P(\text{evidence})} \\
= \quad & \operatorname{argmax}_{\text{word-sequence}} \quad P(\text{evidence}|\text{word-sequence}) \quad P(\text{word-sequence})
\end{aligned}
$$

- word sequence: sequence of English words

Classical approach to machine translation (French→English)

$$
\begin{aligned}
& \mathrm{argmax}_{\text{word-sequence}} P(\text{word-sequence}|\text{evidence}) \\
= \quad & \mathrm{argmax}_{\text{word-sequence}} \frac{P(\text{evidence}|\text{word-sequence})P(\text{word-sequence})}{P(\text{evidence})} \\
= \quad & \mathrm{argmax}_{\text{word-sequence}} \quad P(\text{evidence}|\text{word-sequence}) \quad P(\text{word-sequence})
\end{aligned}
$$

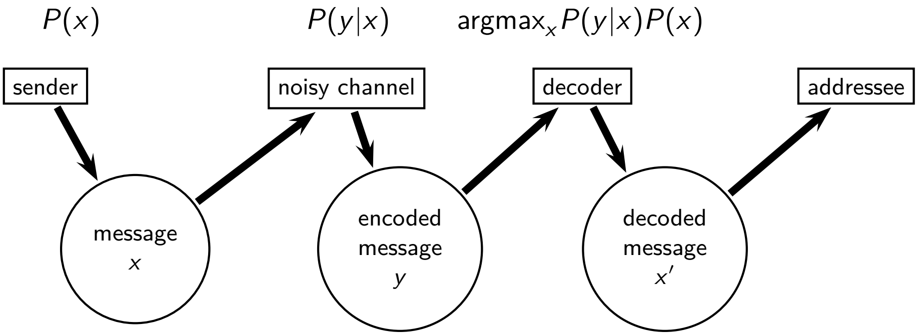
- word sequence: sequence of English words
- evidence: sequence of French words

Classical approach to machine translation (French→English)

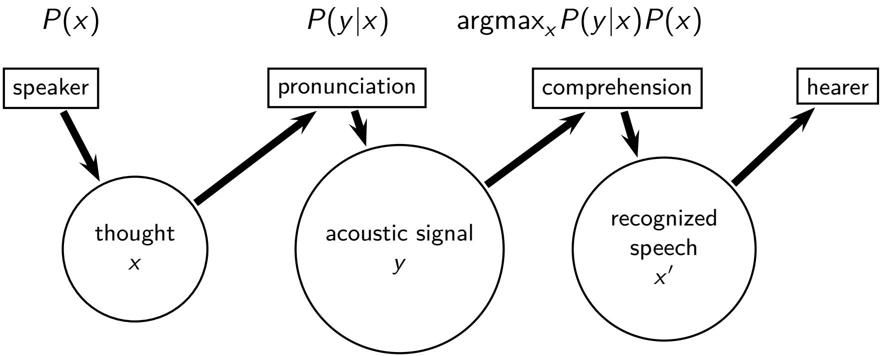
$$
\begin{aligned}
& \operatorname{argmax}_{\text{word-sequence}} P(\text{word-sequence}|\text{evidence}) \\
= \quad & \operatorname{argmax}_{\text{word-sequence}} \frac{P(\text{evidence}|\text{word-sequence})P(\text{word-sequence})}{P(\text{evidence})} \\
= \quad & \operatorname{argmax}_{\text{word-sequence}} \quad P(\text{evidence}|\text{word-sequence}) \quad P(\text{word-sequence})
\end{aligned}
$$

- word sequence: sequence of English words
- evidence: sequence of French words
- P(evidence|word-sequence): a model of how humans translate a sequence of English words into a sequence of French words

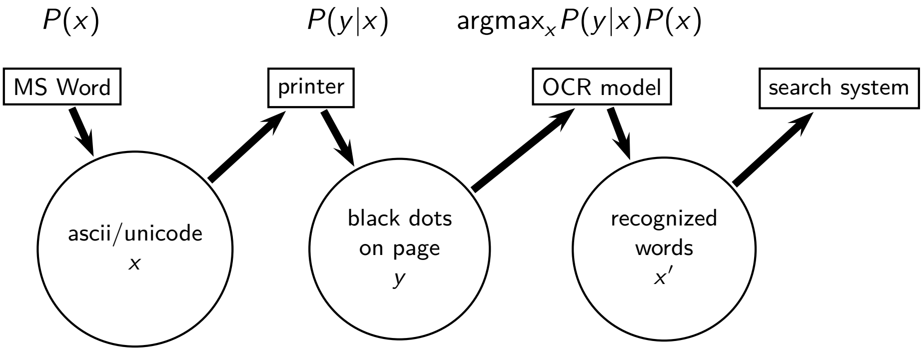
Noisy channel: Information theory / telecommunications



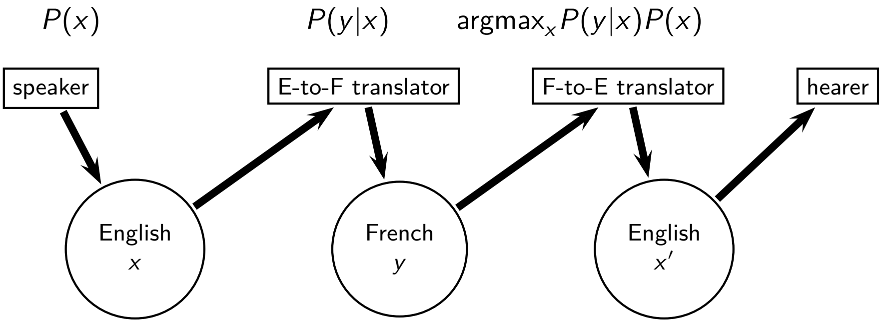
Noisy channel: Speech recognition



Noisy channel: Optical character recognition



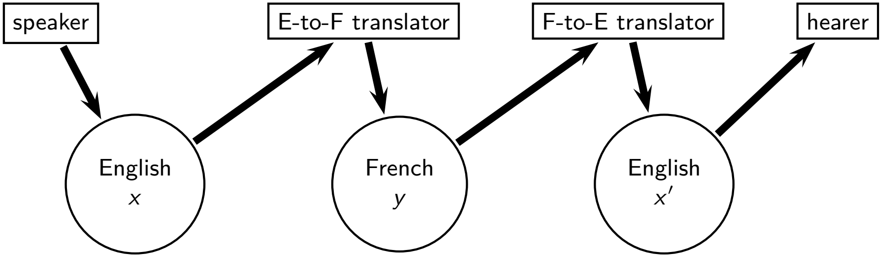
Noisy channel: French-to-English machine translation



Outline

Noisy channel: French-to-English machine translation

$P(x)$ $\quad$ $P(y|x)$ $\quad$ $\text{argmax}_x P(y|x)P(x)$



The two key components of the model

$$
\begin{aligned}
& \operatorname{argmax}_{\text{word-sequence}} P(\text{word-sequence}|\text{evidence}) \\
= \quad & \operatorname{argmax}_{\text{word-sequence}} \frac{P(\text{evidence}|\text{word-sequence}) P(\text{word-sequence})}{P(\text{evidence})} \\
= \quad & \operatorname{argmax}_{\text{word-sequence}} \quad P(\text{evidence}|\text{word-sequence}) \quad P(\text{word-sequence})
\end{aligned}
$$

The two key components of the model

$$
\begin{aligned}
& \operatorname{argmax}_{\text{word-sequence}} P(\text{word-sequence}|\text{evidence}) \\
= \; & \operatorname{argmax}_{\text{word-sequence}} \frac{P(\text{evidence}|\text{word-sequence})P(\text{word-sequence})}{P(\text{evidence})} \\
= \; & \operatorname{argmax}_{\text{word-sequence}} P(\text{evidence}|\text{word-sequence}) \; P(\text{word-sequence})
\end{aligned}
$$

translation model

The two key components of the model

$$
\begin{aligned}
& \operatorname{argmax}_{\text{word-sequence}} P(\text{word-sequence}|\text{evidence}) \\
= \; & \operatorname{argmax}_{\text{word-sequence}} \frac{P(\text{evidence}|\text{word-sequence}) P(\text{word-sequence})}{P(\text{evidence})} \\
= \; & \operatorname{argmax}_{\text{word-sequence}} \; P(\text{evidence}|\text{word-sequence}) \; P(\text{word-sequence})
\end{aligned}
$$

language model

The two key components of the model

$$
\begin{aligned}
& \text{argmax}_{\text{word-sequence}} P(\text{word-sequence}|\text{evidence}) \\
= \quad & \text{argmax}_{\text{word-sequence}} \frac{P(\text{evidence}|\text{word-sequence}) P(\text{word-sequence})}{P(\text{evidence})} \\
= \quad & \text{argmax}_{\text{word-sequence}} \; P(\text{evidence}|\text{word-sequence}) \; P(\text{word-sequence})
\end{aligned}
$$

translation model

How to build a 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

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.

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)

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)

Empty cept

- Our model is a generative model: The French sentence is generated based on the English sentence.

Empty cept

- 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.

Empty cept

- 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

Empty cept

- 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.

Empty cept

- 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.

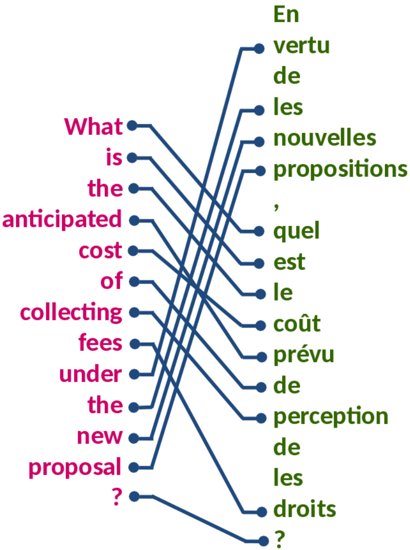
Empty cept

- 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.

Empty cept

- 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:

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

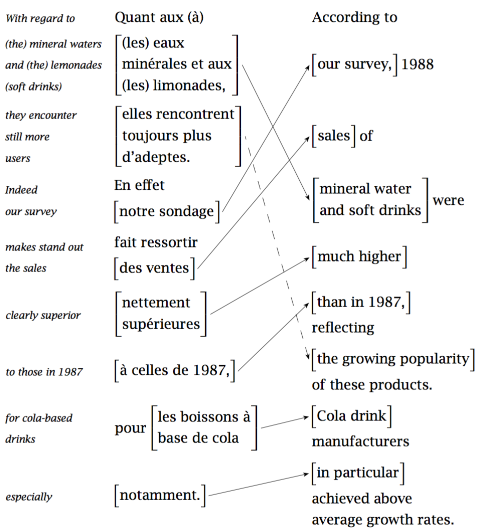
$P(f_j|\text{fees})$

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

$P(f_j|e_0)$

"Linguistic" word/phrase alignment of a parallel corpus

“Linguistic” word/phrase alignment of a parallel corpus



Basic translation model

Basic translation model

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

Basic translation model

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

- e: English sentence, e_i: i^{th} word in e

Basic translation model

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

- e: English sentence, e_i: i^{th} word in e
- l: length of English sentence

Basic translation model

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

- 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

Basic translation model

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

- 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
- m: length of French sentence

Basic translation model

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

- 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
- m: length of French sentence
- e_{a_j} is the English word that f_j is aligned with – this assumes that the alignment is a (total) function: $a : \{1, 2, \ldots, m\} \mapsto \{0, 1, \ldots, l\}$

Basic translation model

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

- 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
- m: length of French sentence
- e_{a_j} is the English word that f_j is aligned with – this assumes that the alignment is a (total) function: $a : \{1, 2, \ldots, m\} \mapsto \{0, 1, \ldots, l\}$
- There is a special word e_0, the empty cept, that all unaligned French words are aligned to.

Basic translation model

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

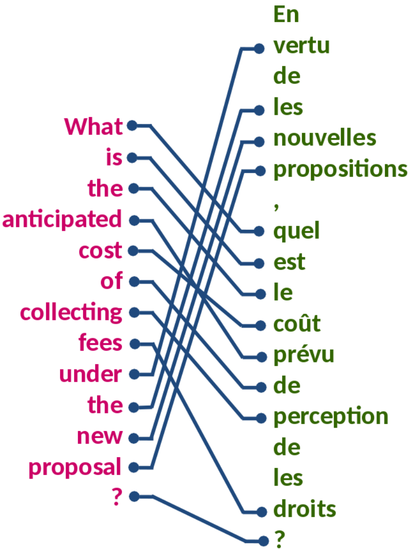
- e: English sentence, e_i: i^{th} word in e
- l: length of English sentence
- f: French sentence, f_j: j^{th} word in f
- m: length of French sentence
- e_{a_j} is the English word that f_j is aligned with – this assumes that the alignment is a (total) function: $a : \{1, 2, \ldots, m\} \mapsto \{0, 1, \ldots, l\}$
- There is a special word e_0, the empty cept, that all unaligned French words are aligned to.
- $P(f_j|e_{a_j})$ is the probability of e_{a_j} being translated as f_j.

Basic translation model

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

- 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
- m: length of French sentence
- e_{a_j} is the English word that f_j is aligned with – this assumes that the alignment is a (total) function: $a : \{1, 2, \ldots, m\} \mapsto \{0, 1, \ldots, l\}$
- There is a special word e_0, the empty cept, that all unaligned French words are aligned to.
- $P(f_j|e_{a_j})$ is the probability of e_{a_j} being translated as f_j.
- $P(< a_1, \ldots, a_m >)$ is the probability of alignment $< a_1, \ldots, a_m >$.

Exercise: Estimating word translation probabilities



Estimate:

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

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

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

$P(f_j|e_0)$

Basic translation model

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

- 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
- m: length of French sentence
- e_{a_j} is the English word that f_j is aligned with – this assumes that the alignment is a (total) function: $a : \{1, 2, \ldots, m\} \mapsto \{0, 1, \ldots, l\}$
- There is a special word e_0, the empty cept, that all unaligned French words are aligned to.
- $P(f_j|e_{a_j})$ is the probability of e_{a_j} being translated as f_j.
- $P(< a_1, \ldots, a_m >)$ is the probability of alignment $< a_1, \ldots, a_m >$.

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

Basic translation model

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

- 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
- m: length of French sentence
- e_{a_j} is the English word that f_j is aligned with – this assumes that the alignment is a (total) function: $a : \{1, 2, \ldots, m\} \mapsto \{0, 1, \ldots, l\}$
- There is a special word e_0, the empty cept, that all unaligned French words are aligned to.
- $P(f_j|e_{a_j})$ is the probability of e_{a_j} being translated as f_j.
- $P(< a_1, \ldots, a_m >)$ is the probability of alignment $< a_1, \ldots, a_m >$.

Exercise

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

What's bad about this model

What's bad about this model

- Collocations, noncompositional combinations: “piece of cake”

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.

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"

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.

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"

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)

What's bad about this model (2)

- Morphology: "Kind" – "Kindes"

What's bad about this model (2)

- Morphology: "Kind" – "Kindes"
- Gender and case

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

Outline

The two key components of the model

$$
\begin{aligned}
& \operatorname{argmax}_{\text{word-sequence}} P(\text{word-sequence}|\text{evidence}) \\
= \quad & \operatorname{argmax}_{\text{word-sequence}} \frac{P(\text{evidence}|\text{word-sequence})P(\text{word-sequence})}{P(\text{evidence})} \\
= \quad & \operatorname{argmax}_{\text{word-sequence}} \; P(\text{evidence}|\text{word-sequence}) \; P(\text{word-sequence})
\end{aligned}
$$

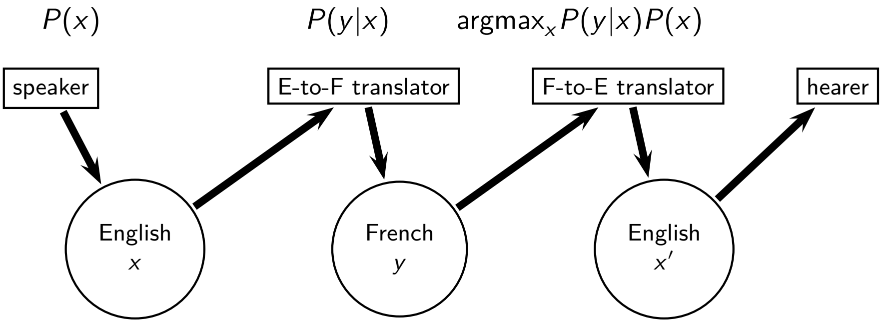
translation model

The two key components of the model

$$\begin{aligned}
& \operatorname{argmax}_{\text{word-sequence}} P(\text{word-sequence}|\text{evidence}) \\
= \quad & \operatorname{argmax}_{\text{word-sequence}} \frac{P(\text{evidence}|\text{word-sequence})P(\text{word-sequence})}{P(\text{evidence})} \\
= \quad & \operatorname{argmax}_{\text{word-sequence}} \quad P(\text{evidence}|\text{word-sequence}) \quad P(\text{word-sequence})
\end{aligned}$$

language model

Noisy channel: French-to-English machine translation



Why the language model is important

Why the language model is important

- Classical example from speech recognition

Why the language model is important

- Classical example from speech recognition
- The following two are almost indistinguishable acoustically.

Why the language model is important

- Classical example from speech recognition
- The following two are almost indistinguishable acoustically.
- “wreck a nice beach”

Why the language model is important

- Classical example from speech recognition
- The following two are almost indistinguishable acoustically.
- “wreck a nice beach”
- “recognize speech”

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.

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.

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.
- $P(\text{"wreck a nice beach"}) \ll P(\text{"recognize speech"})$

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

Bigram language model

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

Bigram language model

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

- Key problem: How do we estimate the parameters?

Bigram language model

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

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

Maximum likelihood = Relative frequency

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.

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:

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

Why maximum likelihood does not work

Why maximum likelihood does not work

- Suppose that "Dr." and "Cooper" are frequent in our corpus. Frequency of "Dr." $= 10000$

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.

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 $P(\text{Cooper}|\text{Dr.})$?

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

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 $P(\text{Cooper}|\text{Dr.})$?
- $$P_{ML}(\text{Cooper}|\text{Dr.}) = \frac{C(\text{Dr. Cooper})}{C(\text{Dr.})} = \frac{0}{10000} = 0$$
- This means that in machine translation, any English sentence containing "Dr. Cooper" would be deemed impossible and could not be output by the translator.

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

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 $P(\text{Cooper}|\text{Dr.})$?
- $$P_{ML}(\text{Cooper}|\text{Dr.}) = \frac{C(\text{Dr. Cooper})}{C(\text{Dr.})} = \frac{0}{10000} = 0$$
- 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 $w_i, w_{i+1}, \ldots, w_{j-1}, w_j$.

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 $w_i, w_{i+1}, \ldots, w_{j-1}, w_j$.

Better estimator:

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

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 $w_i, w_{i+1}, \ldots, w_{j-1}, w_j$.

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".

Exercise

the three women saw the small mountain behind the large mountain

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

Besonders klausurrelevant

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

Besonders klausurrelevant

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