Einführung in die Computerlinguistik
Machine Translation

Hinrich Schütze

Center for Information and Language Processing

2019-01-14

Outline

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Fred Jelinek

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IBM Watson approach to NLP

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- sequence model

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Noisy channel

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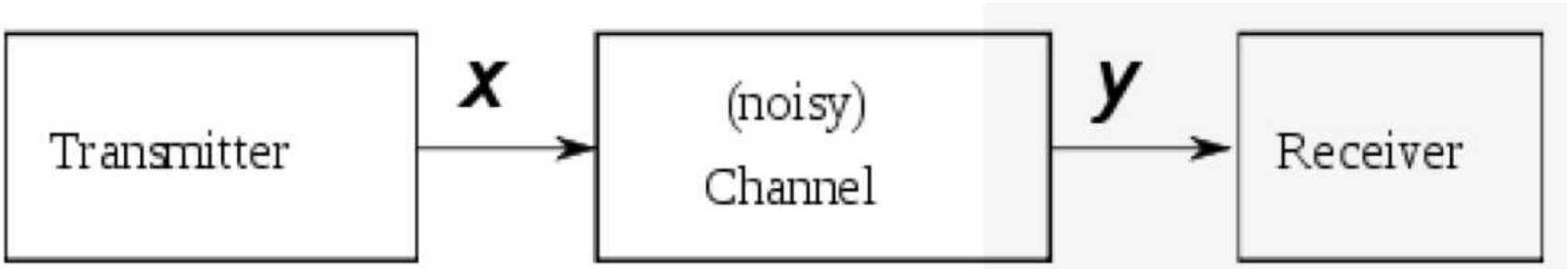

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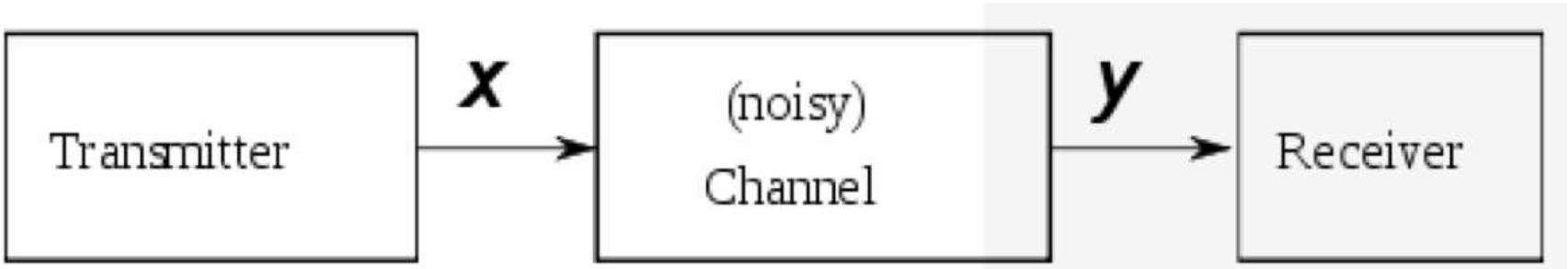

Well-known examples of applications of noisy channel model?

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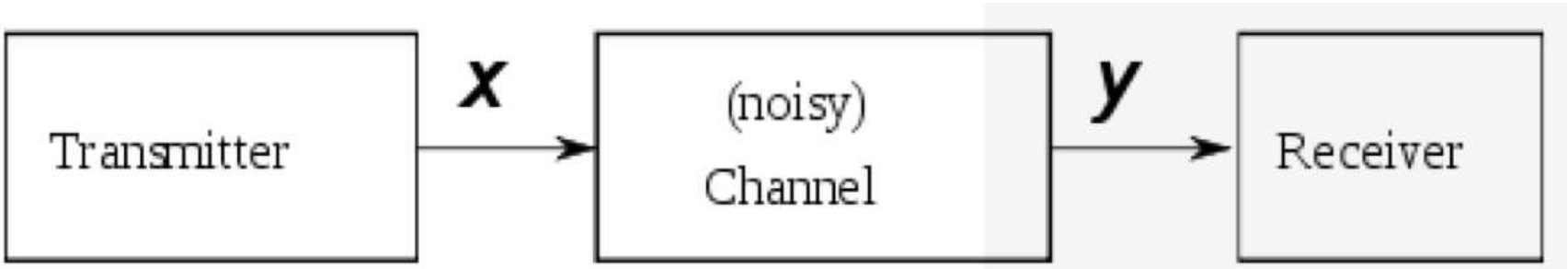

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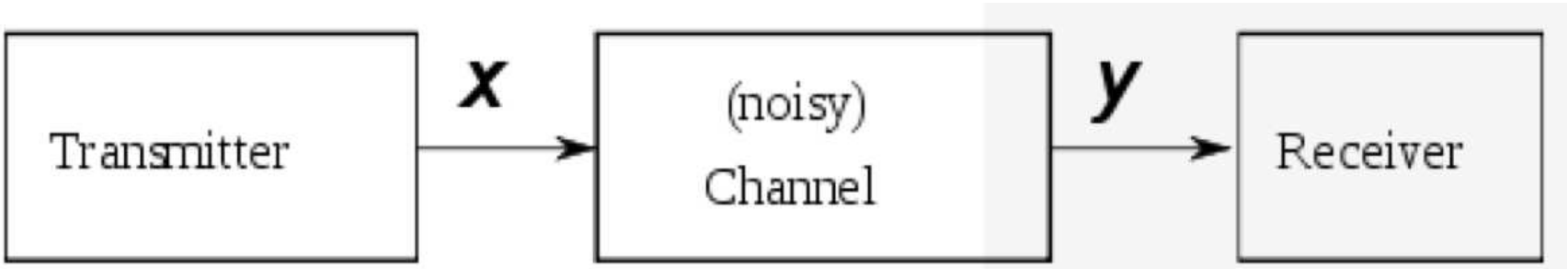

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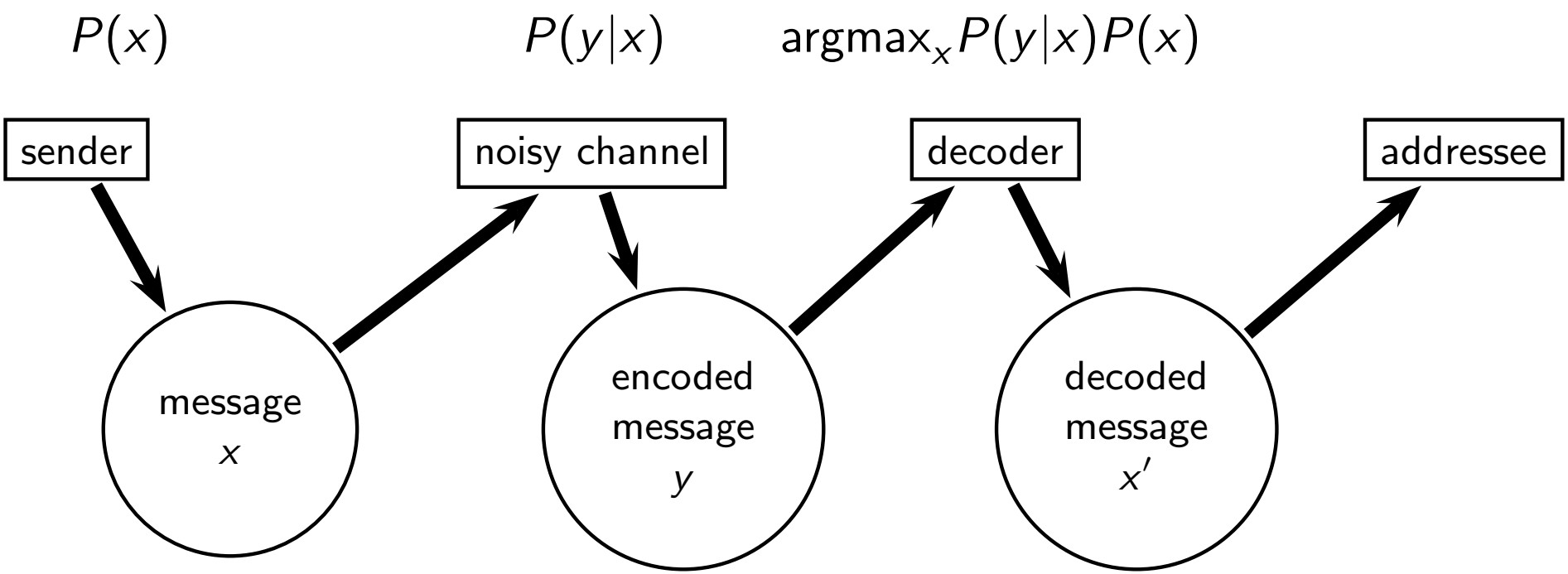
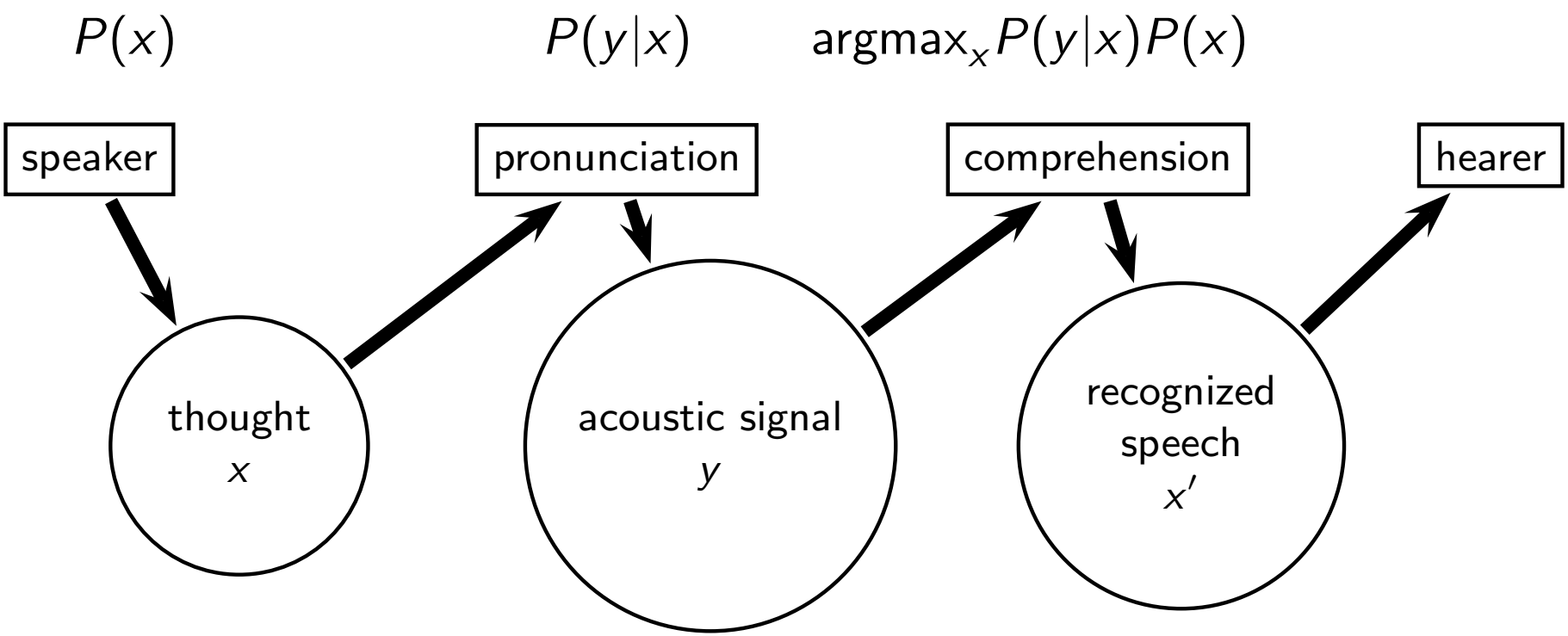
Decode 788884278

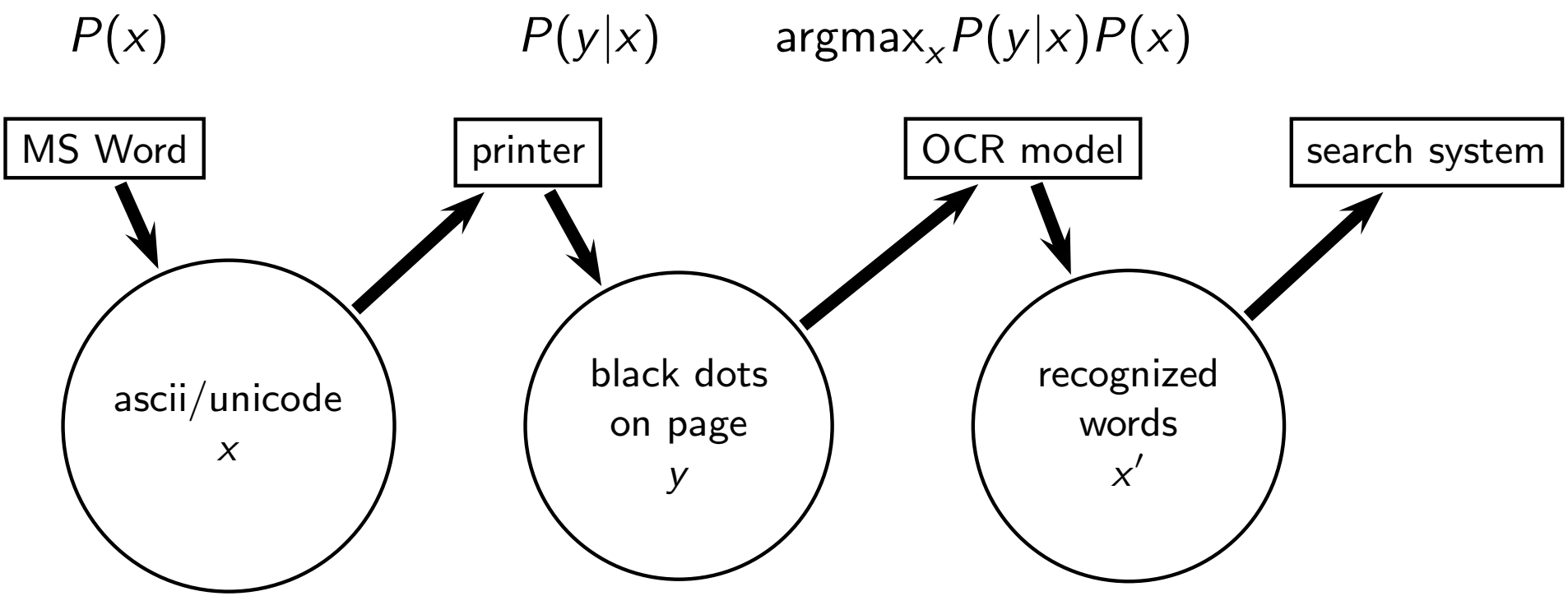
Noisy channel: Information theory / telecommunications



Noisy channel: Speech recognition



Noisy channel: Optical character recognition



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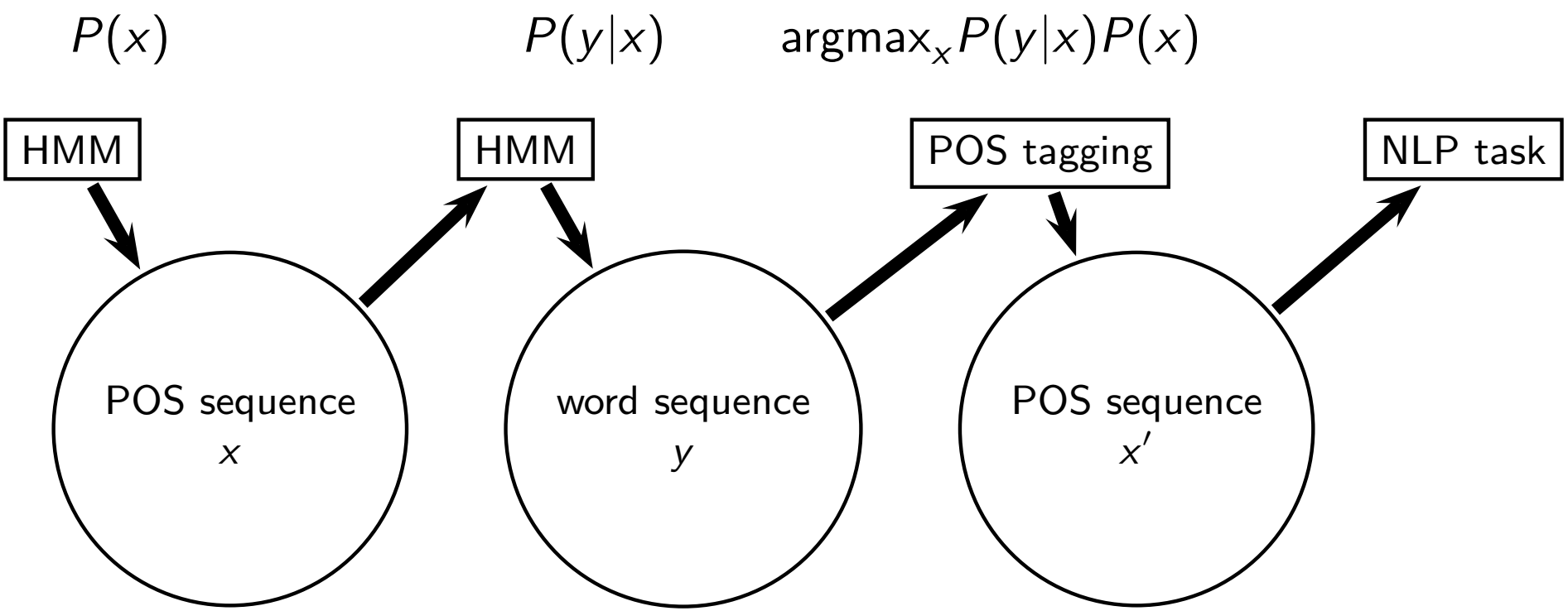

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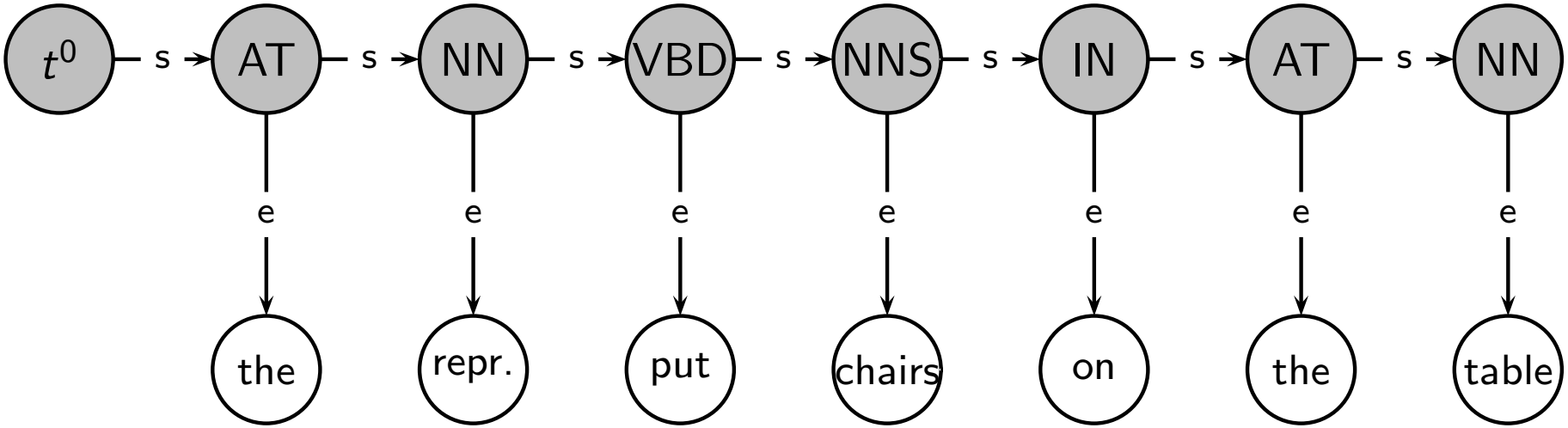

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- evidence: image
- P(evidence|word-sequence): a model of how a machine (e.g., a desktop printer) translates a sequence of words into printed letters/symbols

Exercise: Noisy channel model for machine translation?

speech

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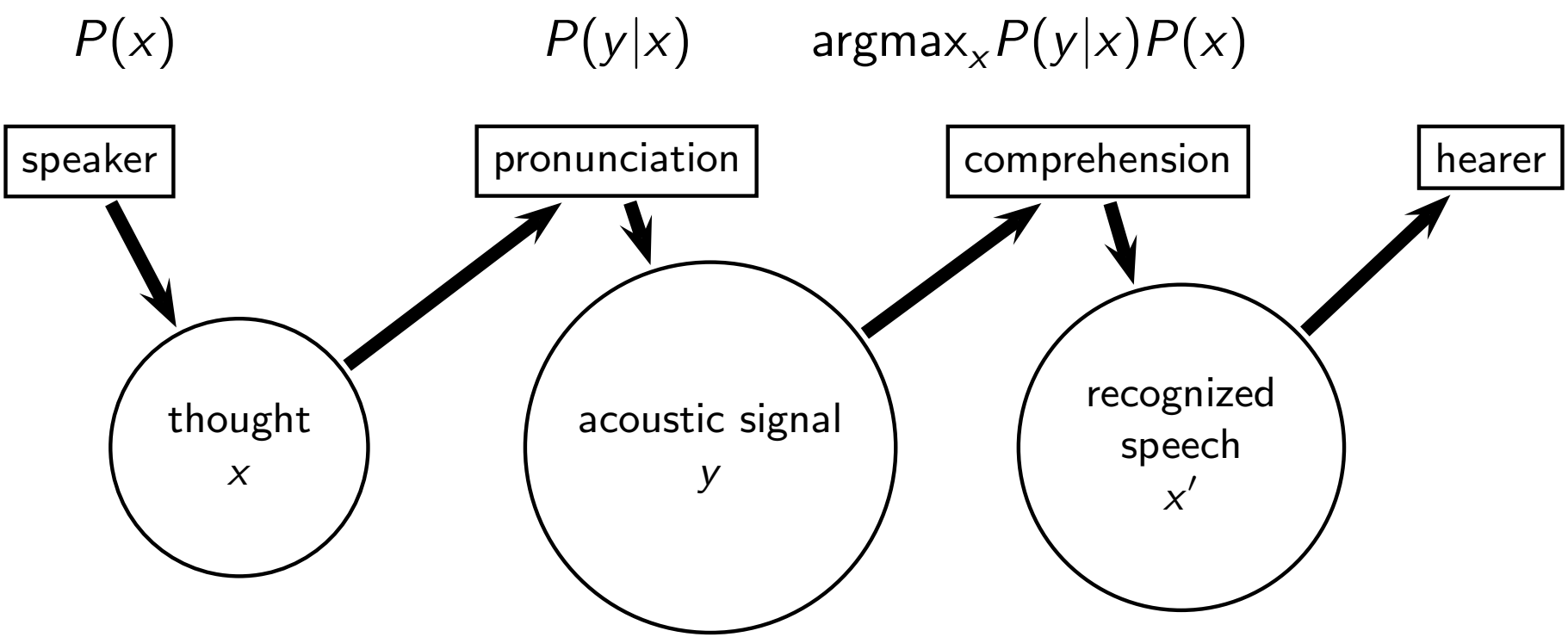

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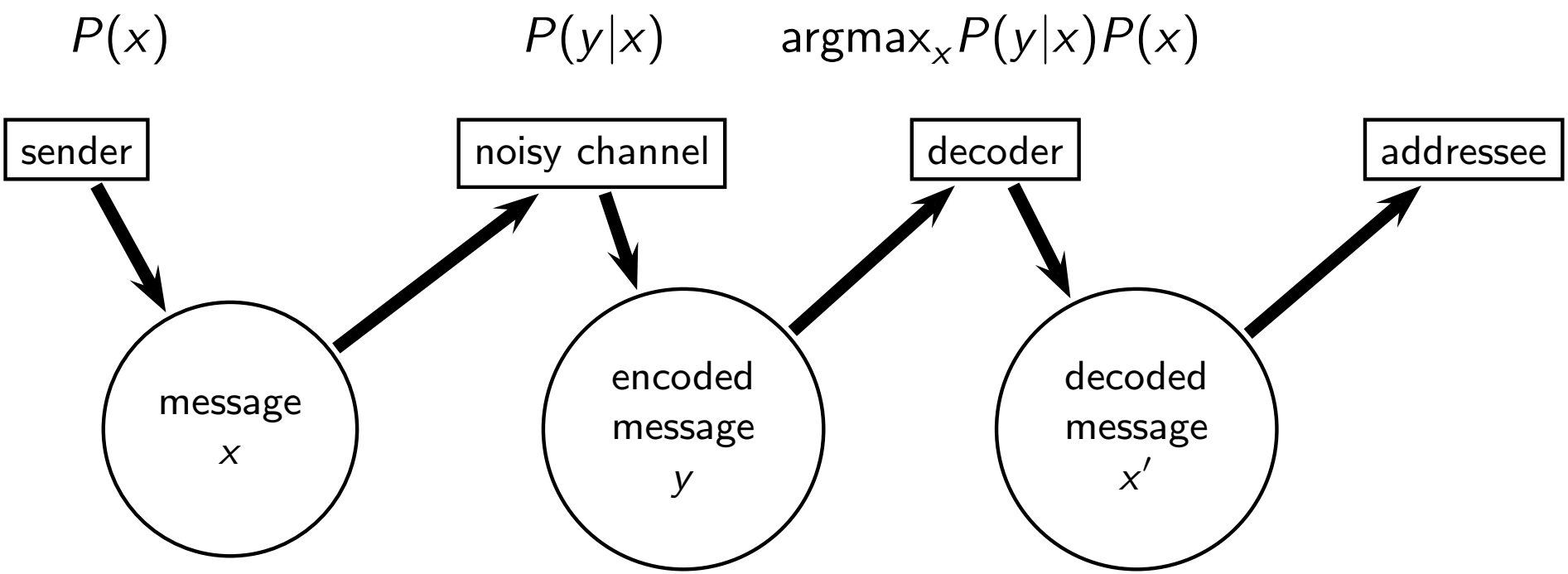
Noisy channel: Information theory / telecommunications



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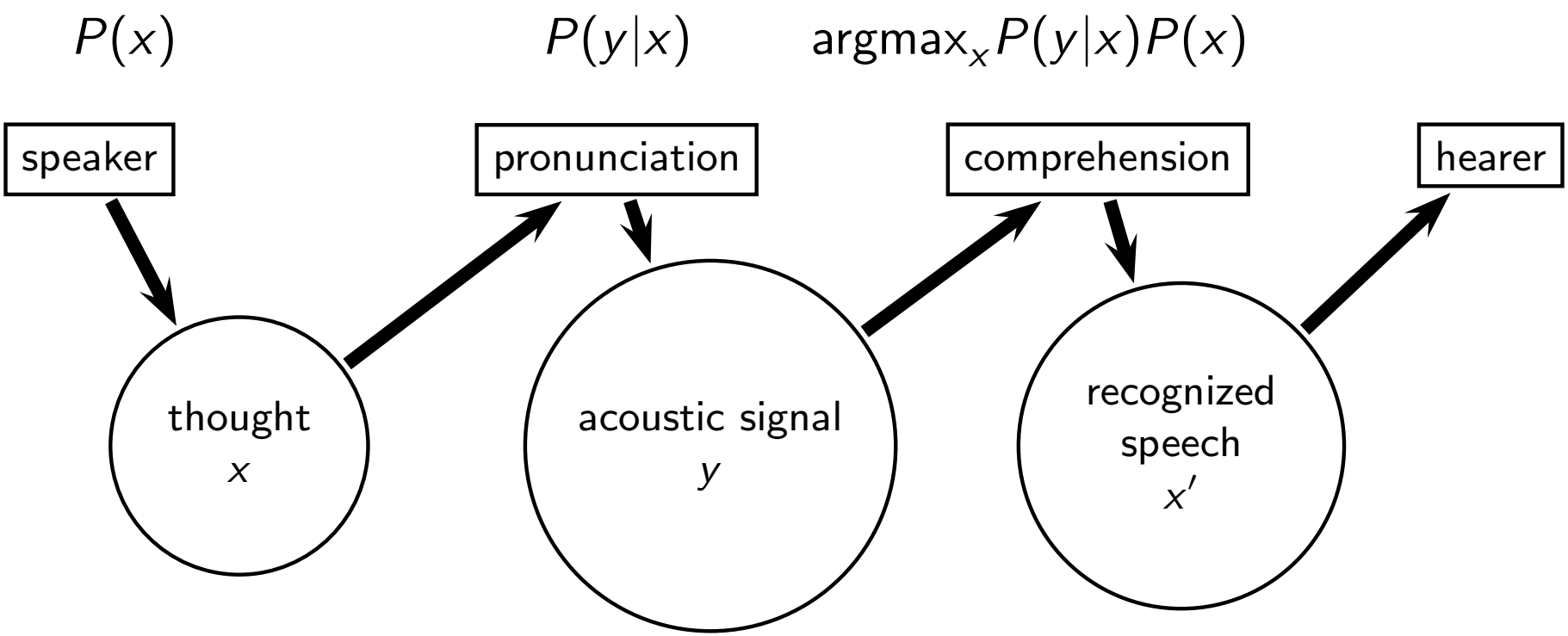

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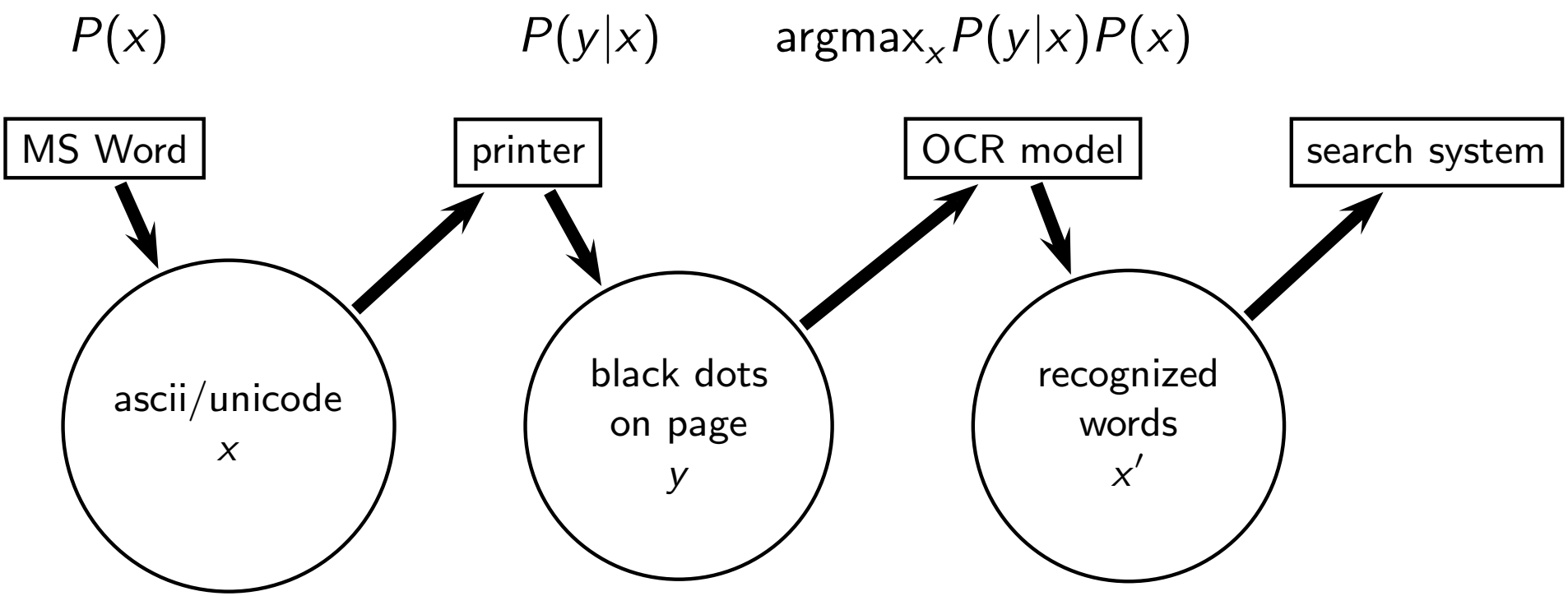

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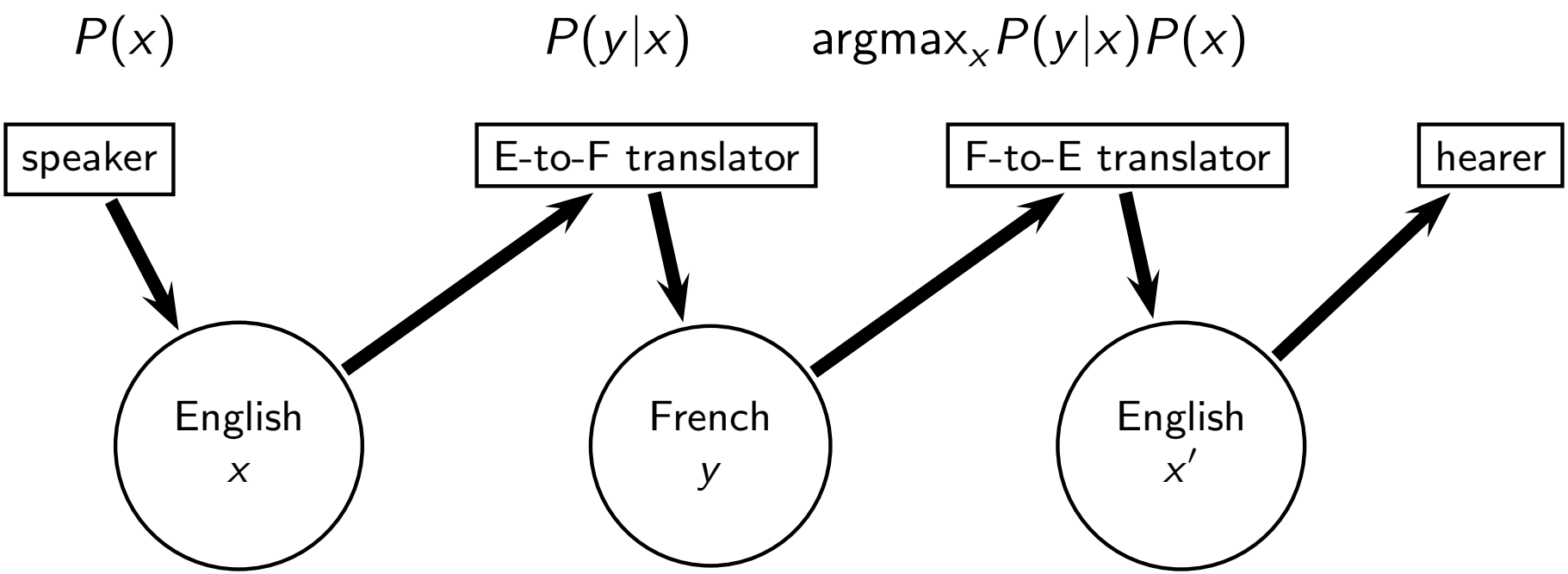

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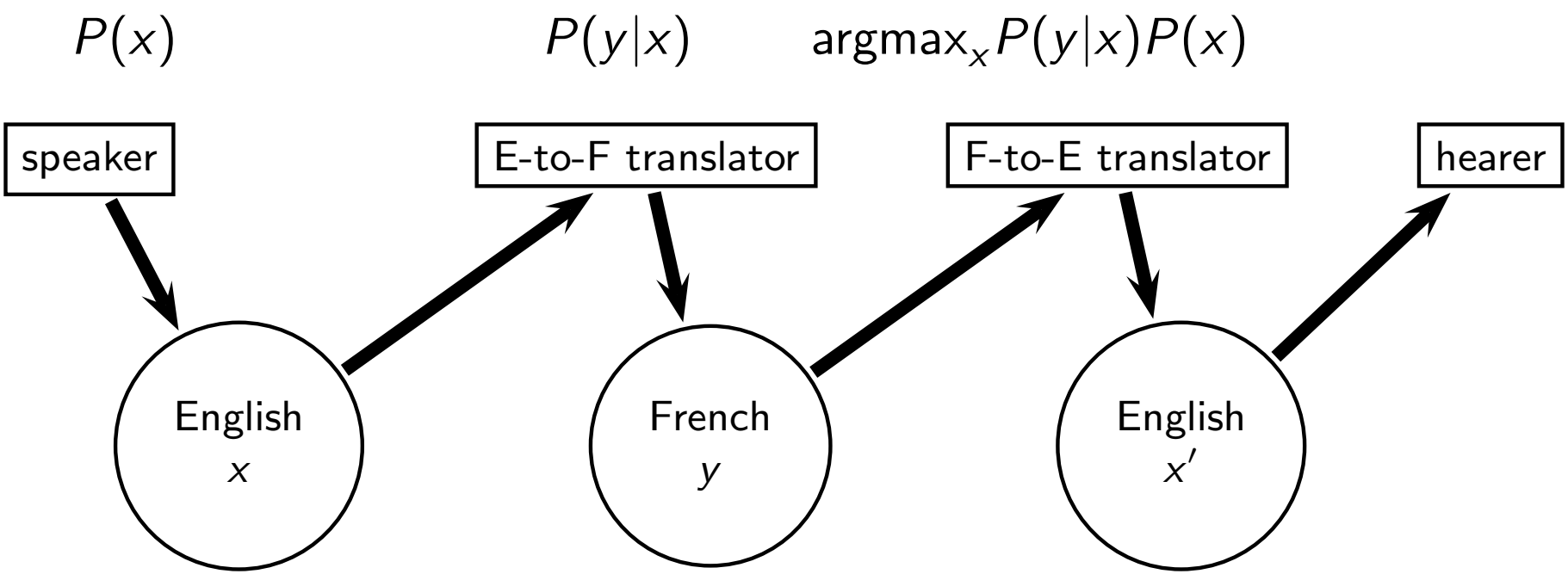

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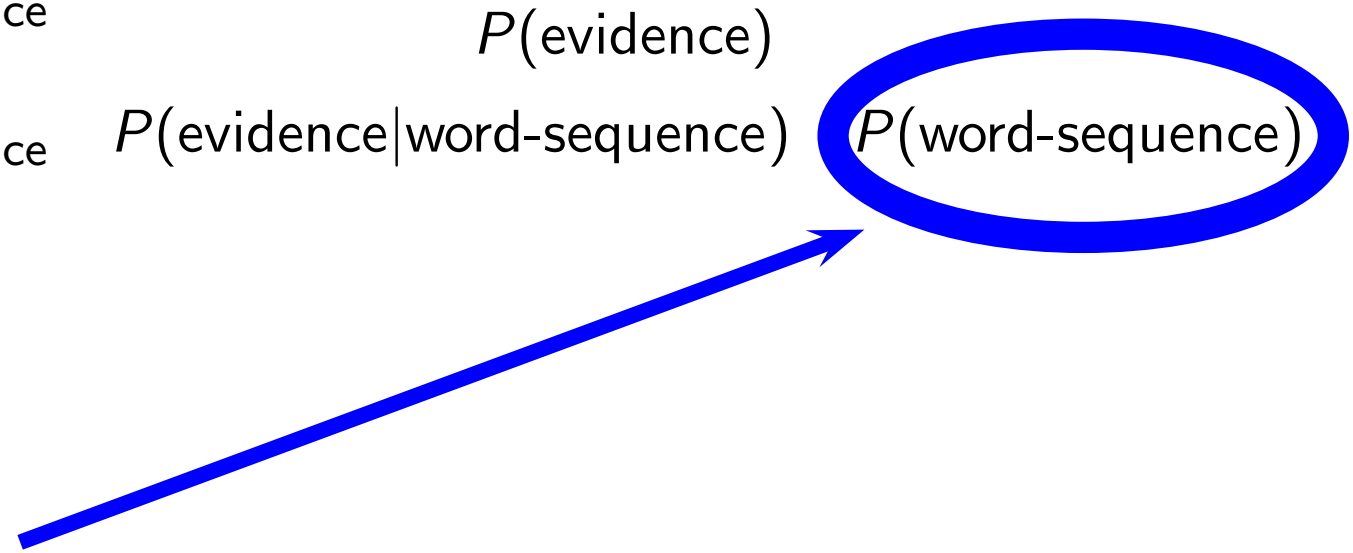

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- Find a parallel corpus – a body of text where each sentence is available in two or more languages
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- Compute a word alignment for the parallel corpus (next slide)
- Estimate a translation model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

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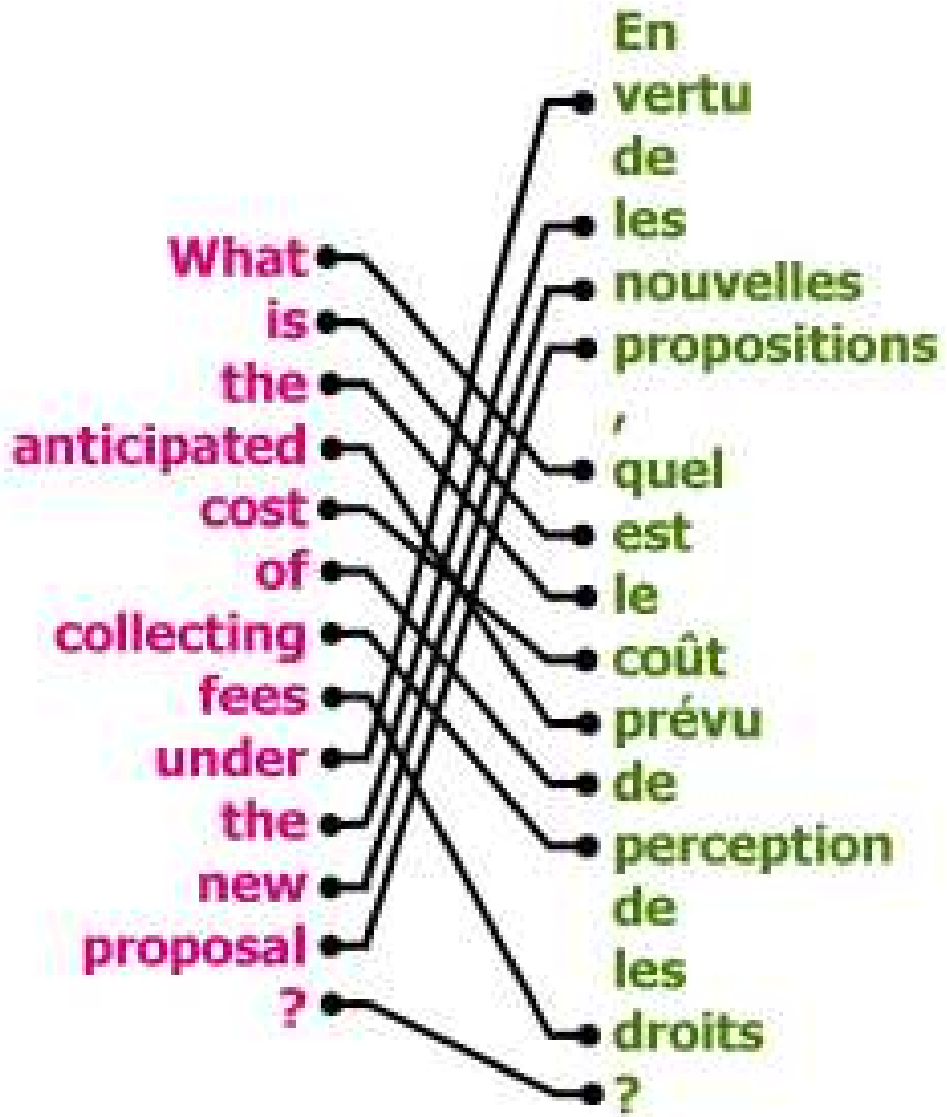
Exercise: Estimating word translation probabilities



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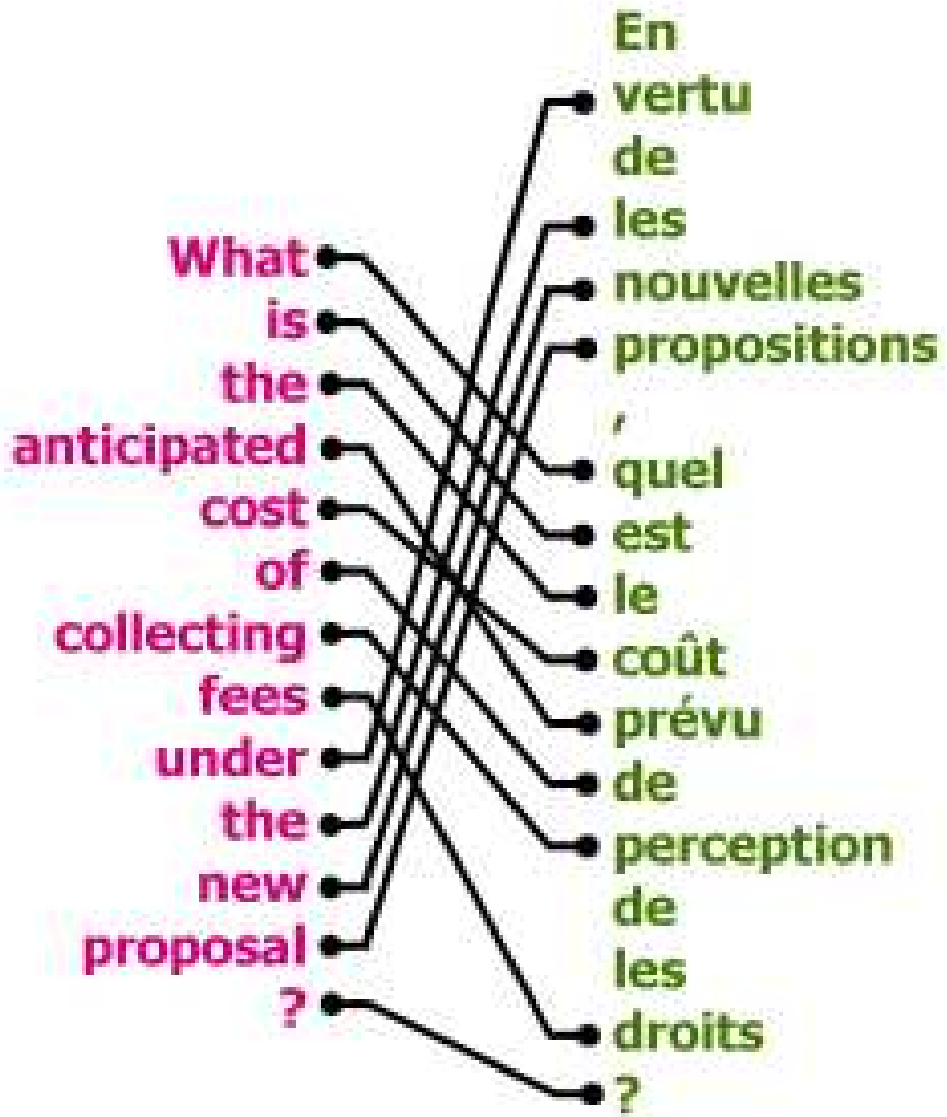

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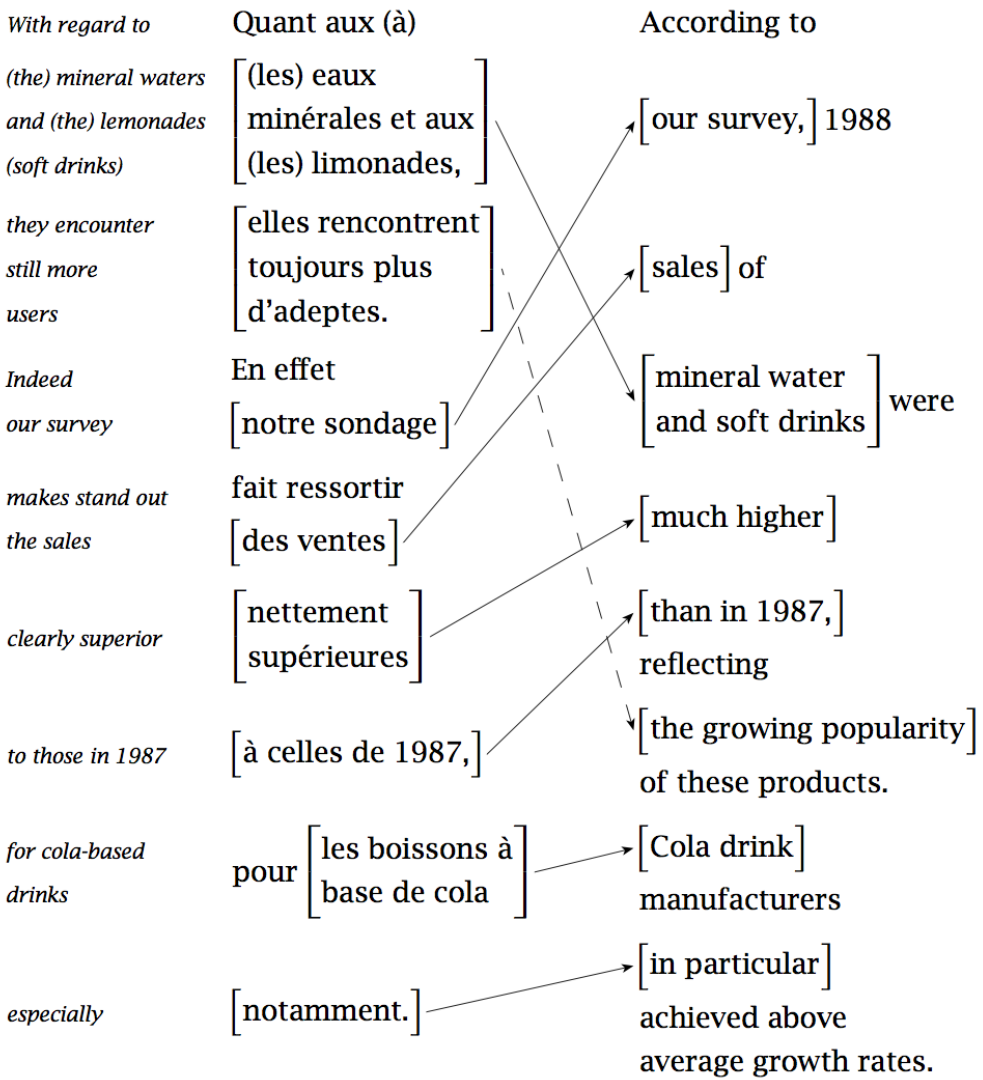

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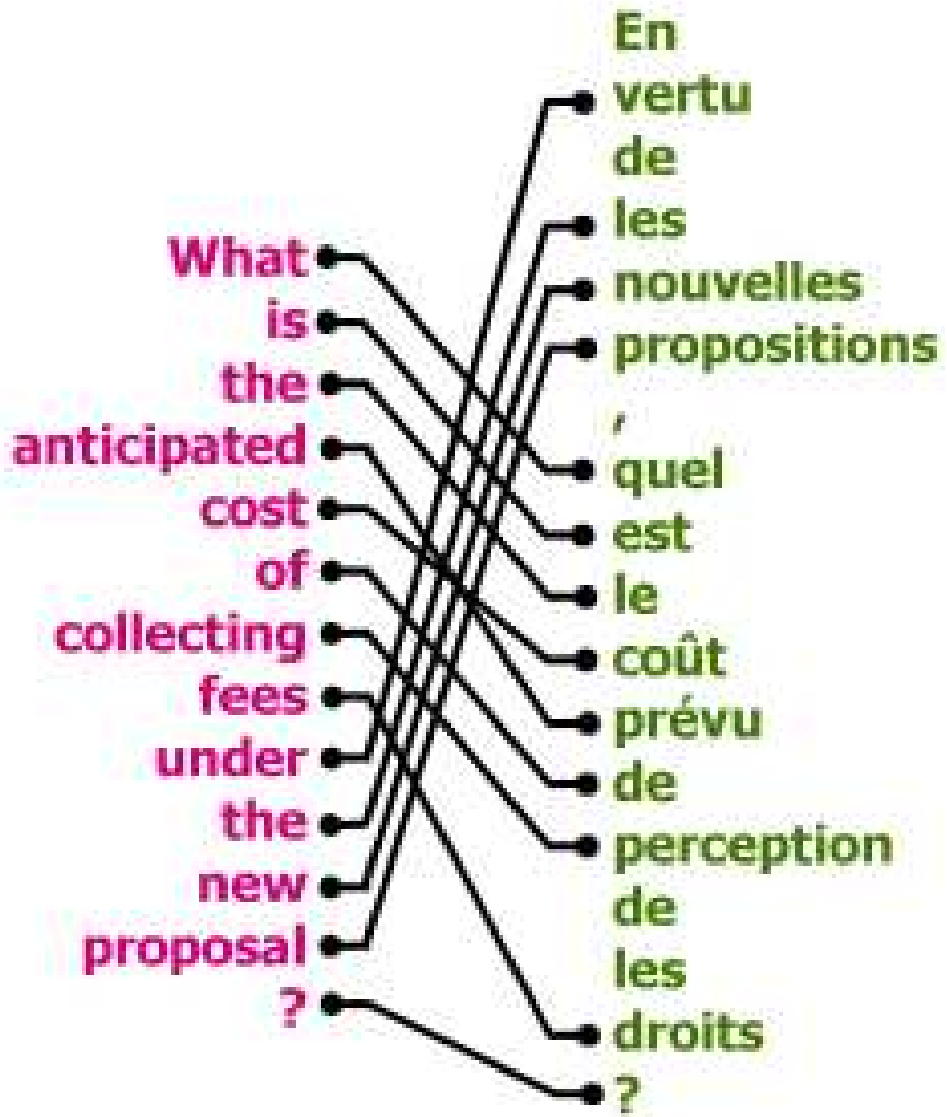
Exercise: Estimating word translation probabilities



Estimate:

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

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

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

$P(f_j|e_0)$

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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
0	0	0
0	0	1
0	0	2
0	1	0
0	1	1
0	1	2
0	2	0
0	2	1
0	2	2

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

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

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

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- 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

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

translation model

The two key components of the model

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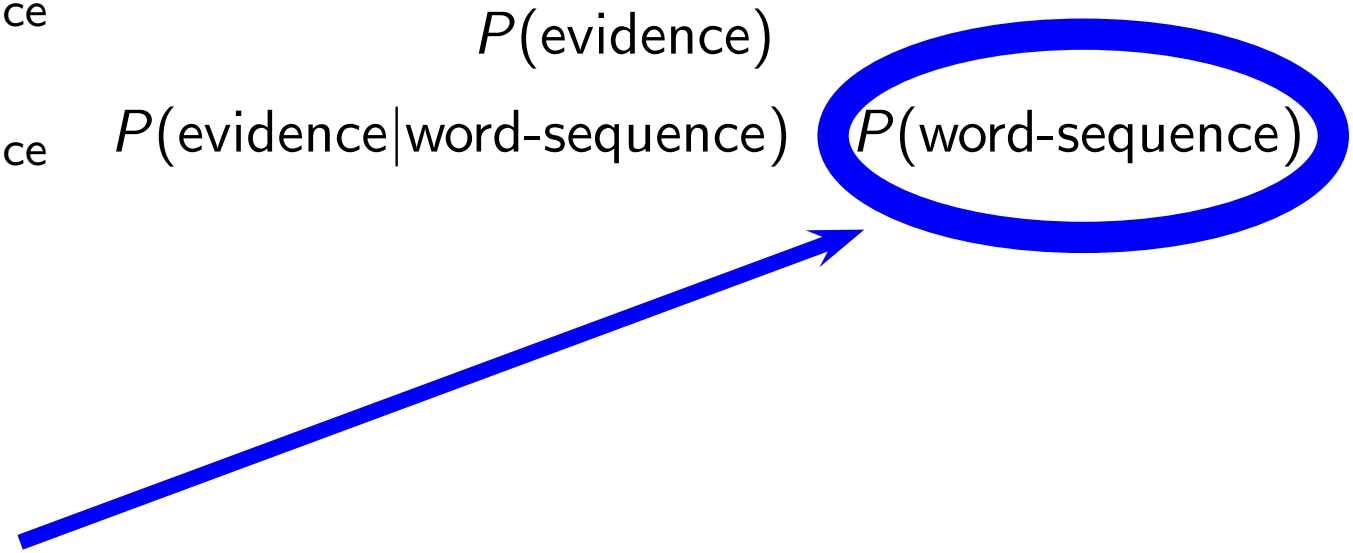
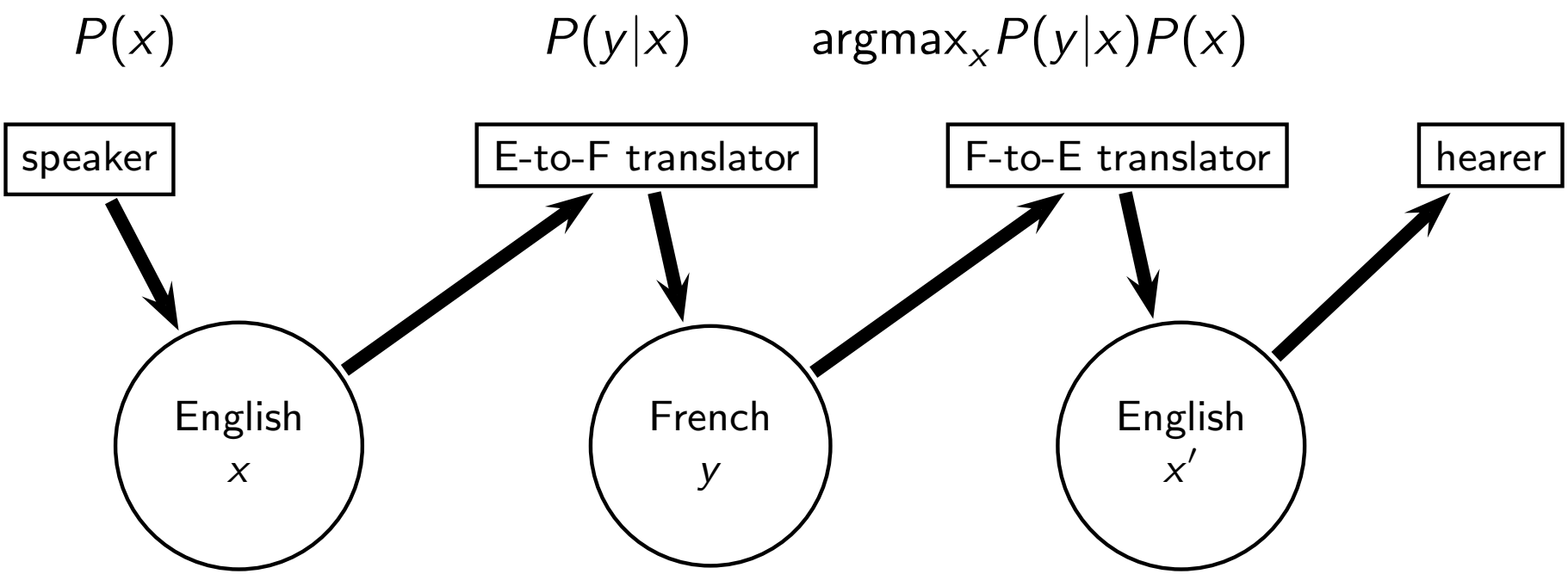


Noisy channel: French-to-English machine translation



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- We'll choose "recognize speech" based on this.

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Example:

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

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

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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
- argmax$P(f|e)P(e)$