Einführung in die Computerlinguistik
Statistical Natural Language Processing

Hinrich Schütze & Robert Zangenfeind

Centrum für Informations- und Sprachverarbeitung, LMU München

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Take-away

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- Noisy channel model: early work was based on understanding StatNLP as “decoding messages”
- Language models: probability models that distinguish more vs less likely word sequences

Outline

Unser Plan

- Teilgebiete der Linguistik
  - Phonetik und Phonologie
  - Morphologie
  - Syntax
  - Semantik
  - Pragmatik
- Statistische Sprachverarbeitung

Outline

Statistical Natural Language Processing

Statistical Natural Language Processing

Definition

Statistical Natural Language Processing (StatNLP) uses methods of supervised, semisupervised and unsupervised learning to address tasks that involve written or spoken (human) language.

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an important / the most important subfield of machine learning
also a subject of statistics, but the emphasis is different

Typical StatNLP applications

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Applications that use some StatNLP

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speech recognition
optical character recognition

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information retrieval

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  - traditional computational linguistics
  - a large group of researchers that use simple statistical methods
  - a small group of researchers that do active research on machine learning methods

Recent big success story 1

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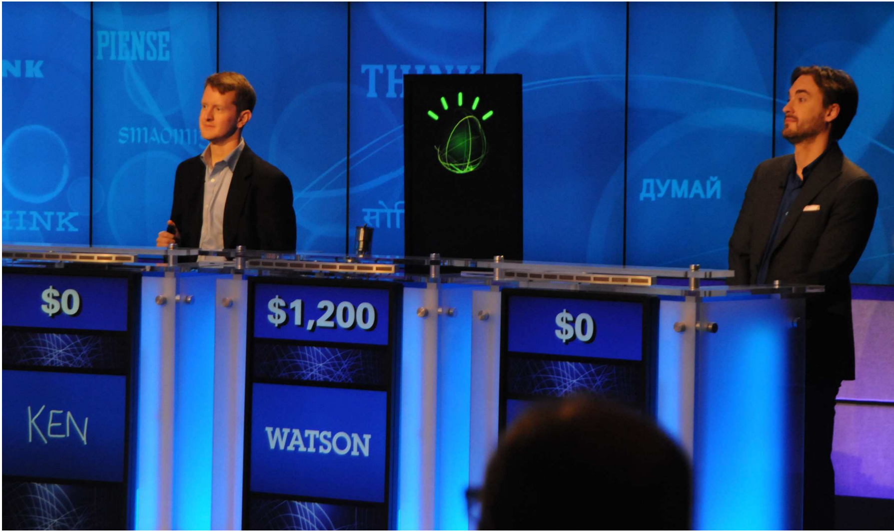

Recent big success story 2

Recent big success story 2

Recent big success story 3

Google Translate – more on this later

Outline

1. What is StatNLP?
2. Noisy channel model
3. Language models

Fred Jelinek

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IBM Watson approach to NLP

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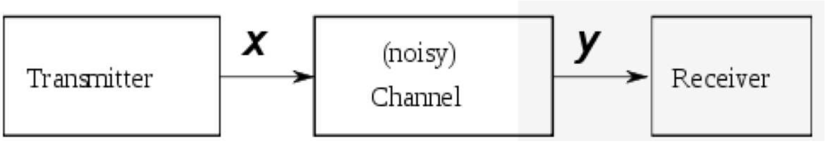

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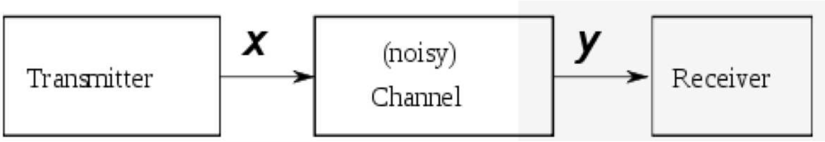

Well-known examples of applications of noisy channel model?

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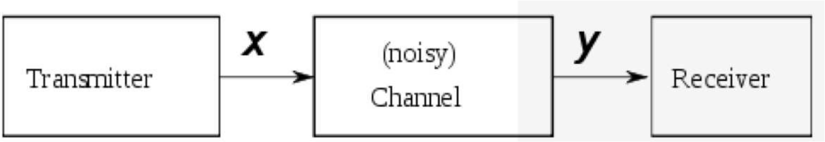

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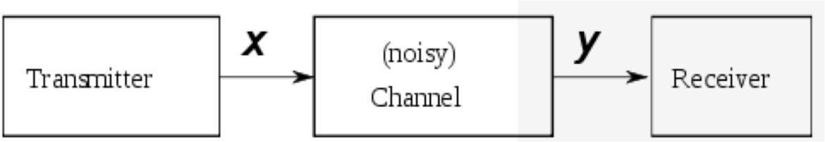

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Noisy (actually, non-noisy) channel example: T9

Decode 788884278

Conditional probability

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- Definition: $P(A|B) = \frac{P(A \cap B)}{P(B)}$ $(P(B) > 0)$

Venn diagram

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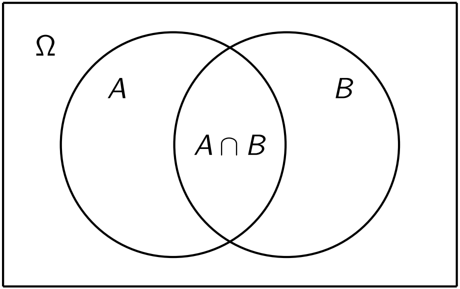

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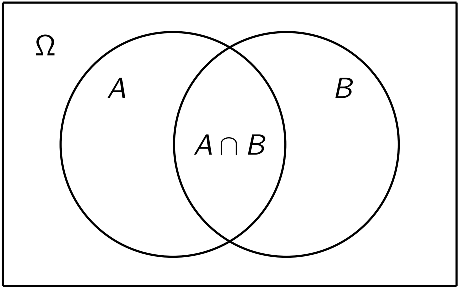

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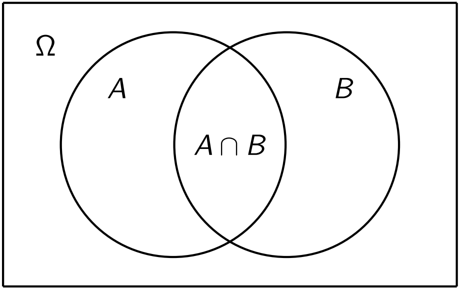

To compute $P(A|B)$: Divide the area of $A \cap B$ by the area of B.
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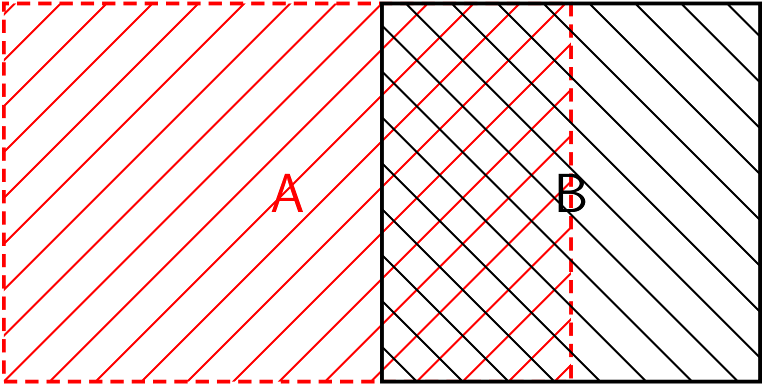
Exercise



Compute $P(A|B) = P(AB)/P(B)$ and $P(B|A) = P(AB)/P(A)$

Bayes' theorem

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- Follows from
  $P(A) = P(A \cap B) + P(A \cap \overline{B}) = P(A|B)P(B) + P(A|\overline{B})P(\overline{B})$

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- $P(A) = P(A|B)$, $P(B) = P(B|A)$

Testing for independence

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- Why $\approx$?

Testing for independence: Example

A = champagne, B = sparkling

Testing for independence: Exercise

(a) compute numbers for a pair of words of your choice; (b) find two independent words

Cooccurrence counts of the words tree and missile. E.g., there are 10 documents that contain both tree and missile; there are 100 documents that contain missile and do not contain tree.

	tree	not tree
missile	10	100
not missile	1000	?

Replace the question mark in the table by a number that makes the two words independent of each other.

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

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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

Build a noisy channel machine translation model for translating French into English.

Classical approach to machine translation (French→English)

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- evidence: sequence of French words

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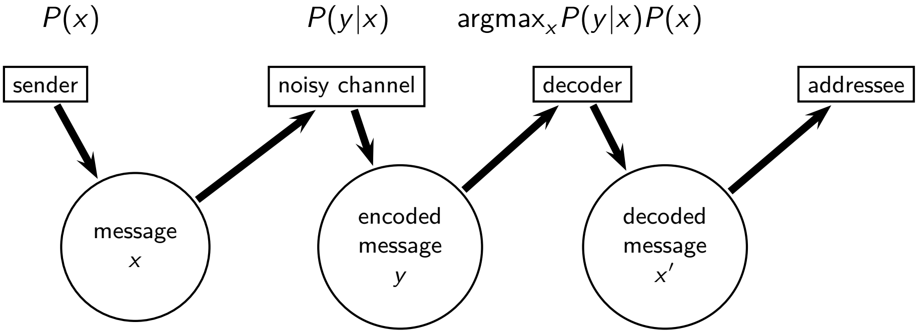
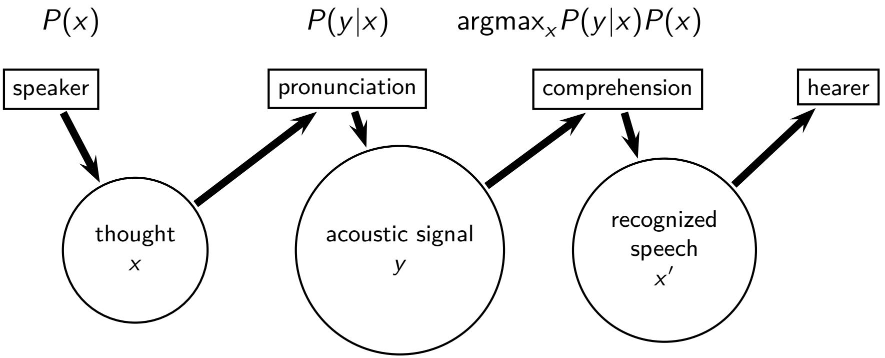
\end{aligned}$$

- 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

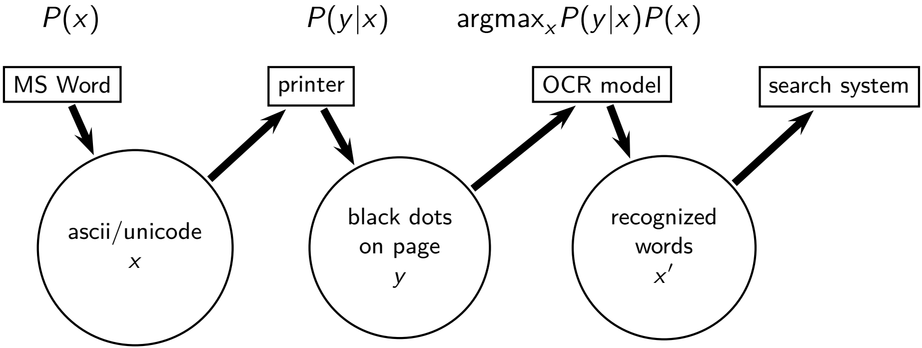
Noisy channel: Information theory / telecommunications



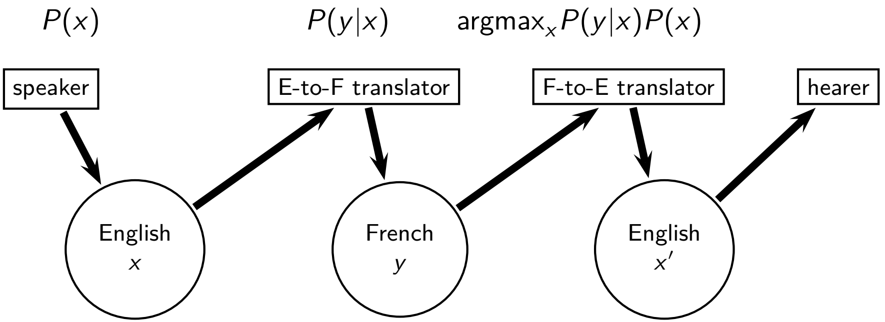
Noisy channel: Speech recognition



Noisy channel: Optical character recognition



Noisy channel: French-to-English machine translation



The two key components of the model

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translation model

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language model

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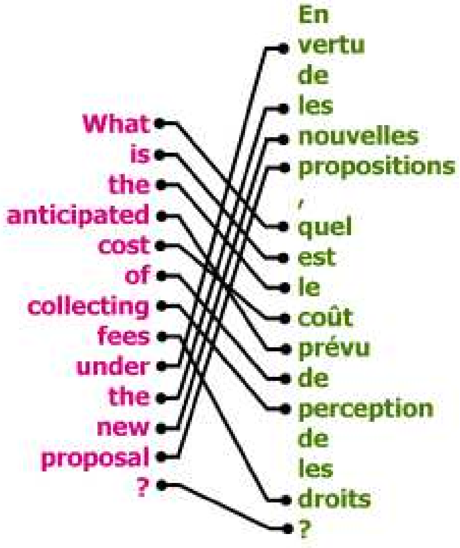
- Also: need a decoding/search algorithm because the search space is huge

Estimating word translation probabilities



Estimate:

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

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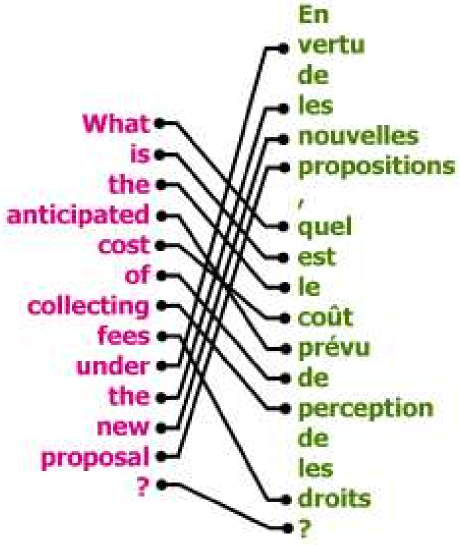

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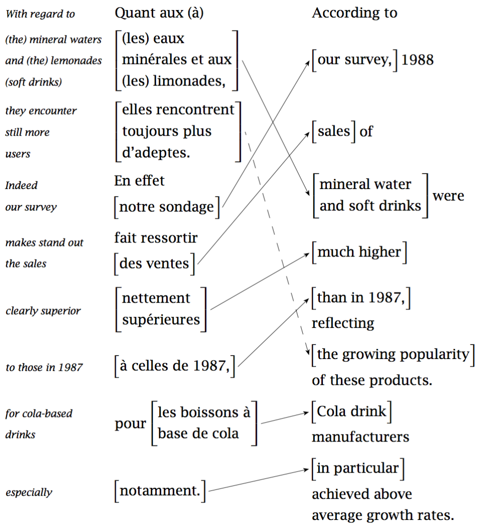

Basic translation model

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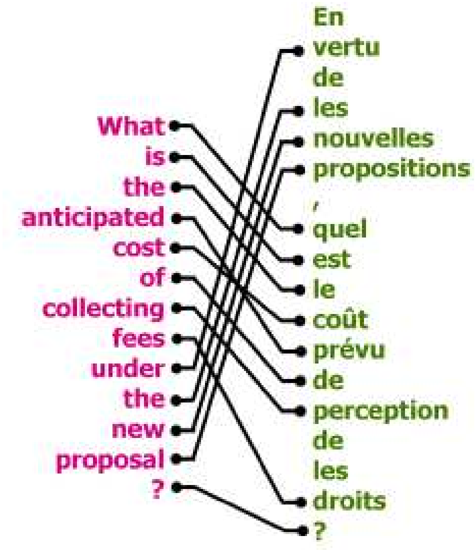

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Formalization of alignment

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
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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

Exercise

Devise a set of rules that will translate words like *flanierst*, *garniert*, and *Kiefer* correctly.
Devise a set of rules that will handle case correctly.
Devise a set of rules that will handle long-distance dependencies correctly.

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Outline

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translation model

language model

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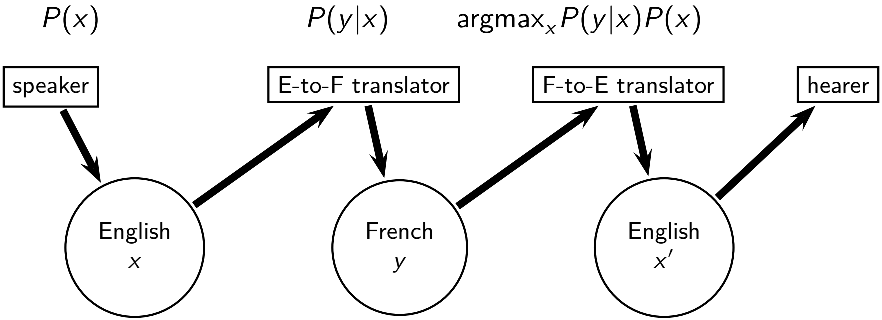

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- We'll choose "recognize speech" based on this.

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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

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

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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Better estimator:

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

Laplace

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

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Better estimator:

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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”.

Laplace: Better, but not great

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

$$p_L(\text{be}|\text{would}) = \frac{18454 + 1}{83735 + 256873} \approx 0.05$$

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 $p(\text{saw}|\text{the})$

Order of language models

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- We have looked at a bigram model, order $= 2$.

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- We have looked at a bigram model, order $= 2$.
- In many applications, notably in machine translation, language models of higher order are used: 7-gram, 8-gram, 9-gram models.

Take-away

- Statistical Natural Language Processing (StatNLP): Introduction
- Noisy channel model: early work was based on understanding StatNLP as "decoding messages"
- Language models: probability models that distinguish more vs less likely word sequences