Machine Translation

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Word-Based Models

Adapted from material by Philipp Koehn

Fred Jelinek showing off his ASR work at IBM (he later worked on MT)

Roadmap

- Introduction to MT
- Components of MT system
- Word-based models
- Beyond word-based models

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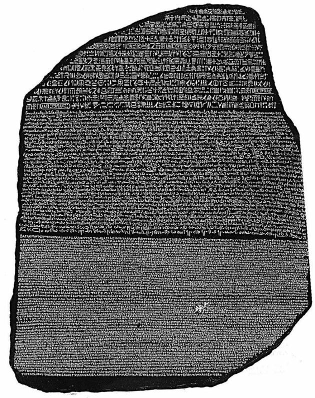
- Introduction to MT
- Components of MT system
- Word-based models
- Beyond word-based models: phrase-based and neural

Books by Philip Koehn

What unlocks translations?



- Parallel data: Two languages, same meaning
- Rosetta stone: allowed us understand to Egyptian

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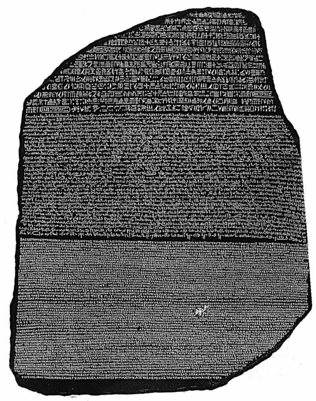
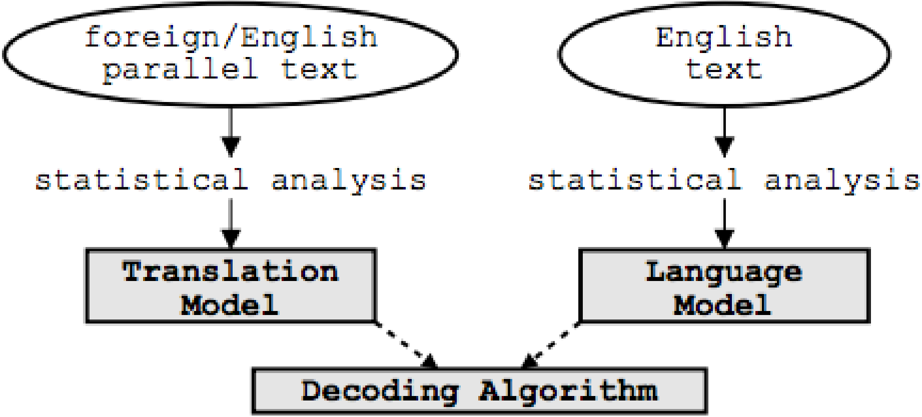


- Parallel data: Two languages, same meaning
- Rosetta stone: allowed us understand to Egyptian
- Where do we get them?
  - Some governments require translations (Canada, EU, Hong Kong)
  - Newspapers
  - Internet



Pieces of Machine Translation System

Terminology

- Source language: **f** (foreign)
- Target language: **e** (english)

Collect Statistics

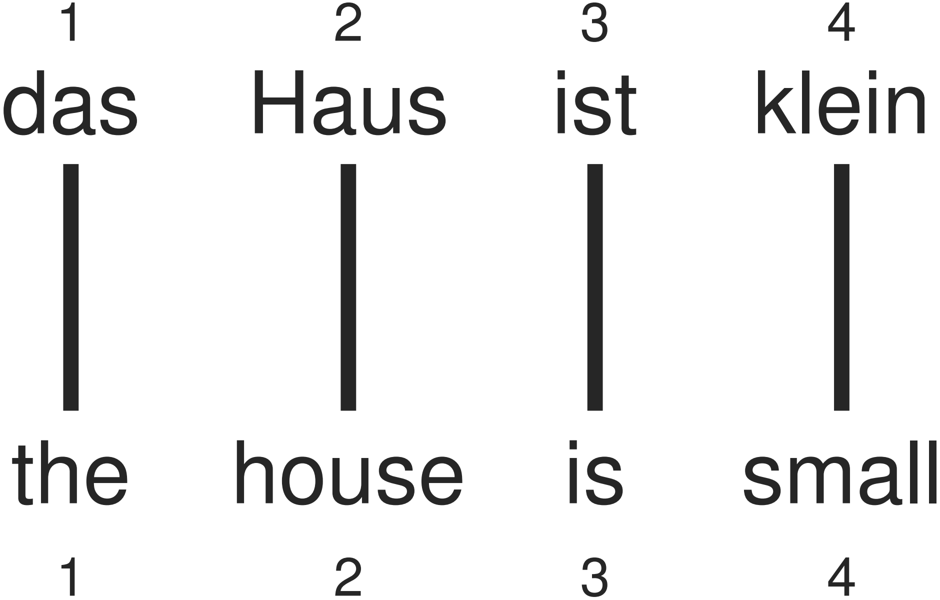
Look at a parallel corpus (German text along with English translation)

Translation of Haus	**Count**
house	8,000
building	1,600
home	200
household	150
shell	50

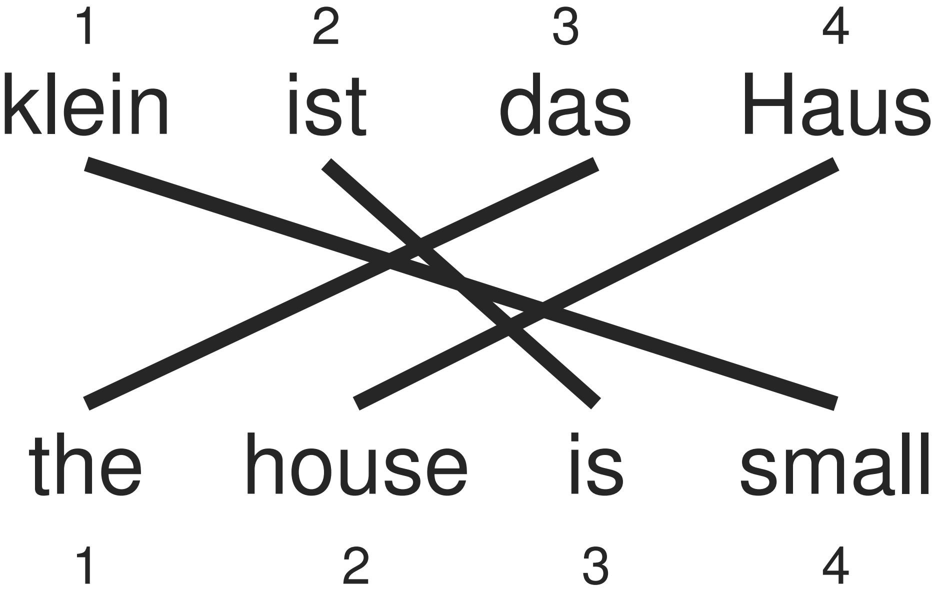
Estimate Translation Probabilities

Maximum likelihood estimation

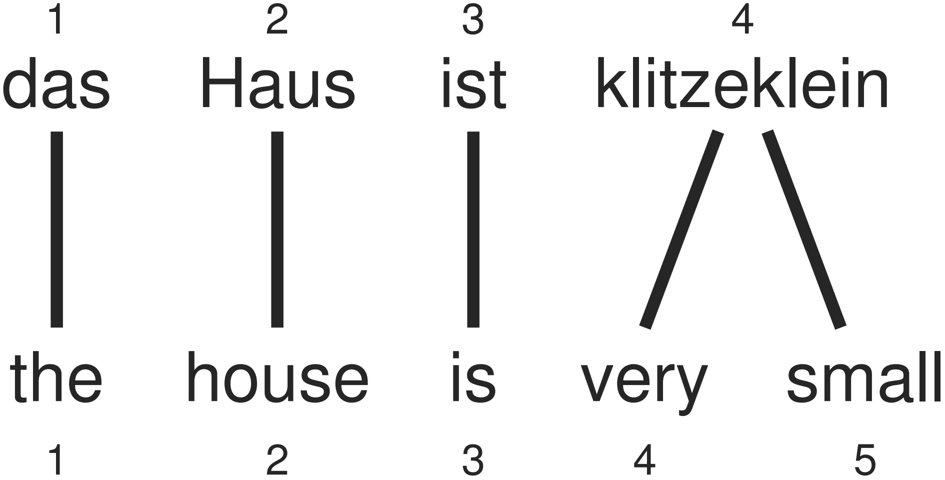
$$p_f(e) = \begin{cases} 0.8 & \text{if } e = \text{house}, \\ 0.16 & \text{if } e = \text{building}, \\ 0.02 & \text{if } e = \text{home}, \\ 0.015 & \text{if } e = \text{household}, \\ 0.005 & \text{if } e = \text{shell}. \end{cases}$$



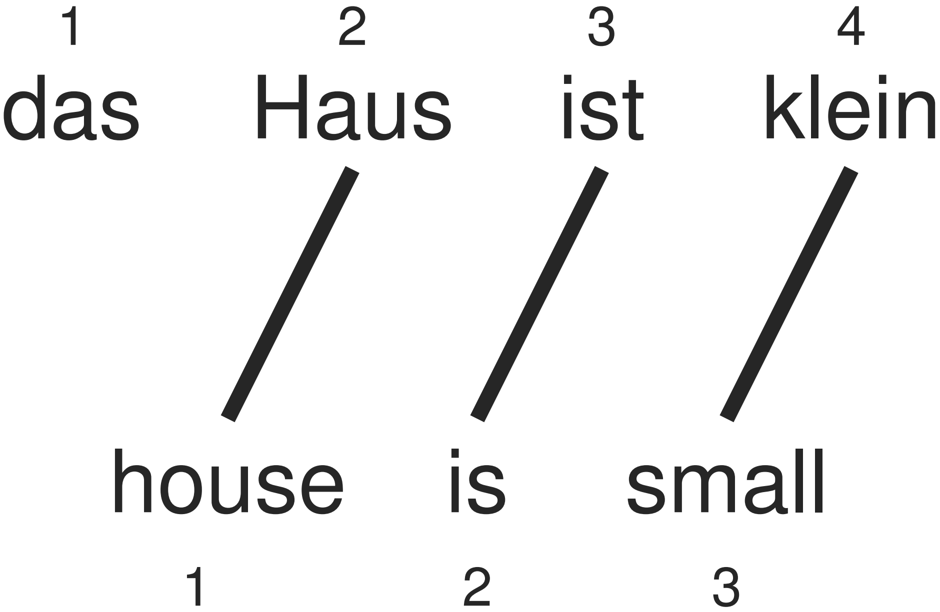
Best case



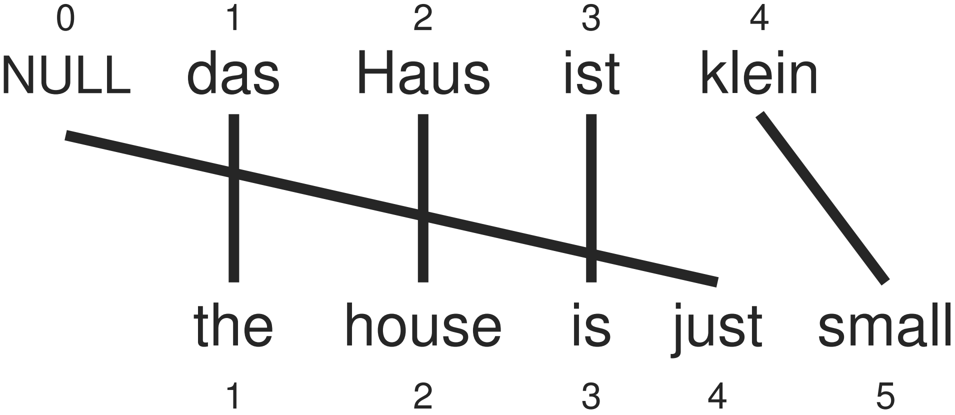
Words may be reordered during translation



A source word may translate into multiple target words



Words may be dropped when translated (das)



Words may be added during translation (just)

A family of lexical translation models

- A family translation models
- Uncreatively named: Model 1, Model 2, ...
- Foundation of all modern translation algorithms
- First up: Model 1

IBM Model 1

- Generative model: break up translation process into smaller steps
  - IBM Model 1 only uses lexical translation
- Translation probability
  - for a foreign sentence $\mathbf{f} = (f_1, ..., f_{l_f})$ of length l_f
  - to an English sentence $\mathbf{e} = (e_1, ..., e_{l_e})$ of length l_e
  - with an alignment of each English word e_j to a foreign word f_i according to the alignment function $a : j \rightarrow i$

$$p(\mathbf{e}, a|\mathbf{f}) = \frac{\epsilon}{(l_f + 1)^{l_e}} \prod_{j=1}^{l_e} t(e_j|f_{a(j)})$$

  - parameter ϵ is a normalization constant

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Example

das

e	$t(e\|f)$
the	0.7
that	0.15
which	0.075
who	0.05
this	0.025

Haus

e	$t(e\|f)$
house	0.8
building	0.16
home	0.02
family	0.015
shell	0.005

ist

e	$t(e\|f)$
is	0.8
's	0.16
exists	0.02
has	0.015
are	0.005

klein

e	$t(e\|f)$
small	0.4
little	0.4
short	0.1
minor	0.06
petty	0.04

$$\begin{aligned} p(e,a|f) &= \frac{\epsilon}{5^4} \times t(\text{the}|\text{das}) \times t(\text{house}|\text{Haus}) \times t(\text{is}|\text{ist}) \times t(\text{small}|\text{klein}) \\ &= \frac{\epsilon}{5^4} \times 0.7 \times 0.8 \times 0.8 \times 0.4 \\ &= 0.00029\epsilon \end{aligned}$$

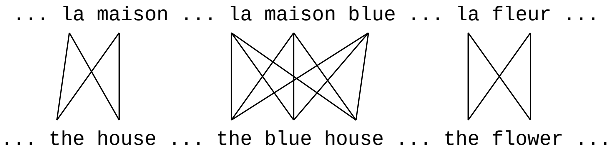
Learning Lexical Translation Models

- We would like to estimate the lexical translation probabilities $t(e|f)$ from a parallel corpus
- ... but we do not have the alignments
- Chicken and egg problem
  - if we had the alignments,
    $\longrightarrow$ we could estimate the parameters of our generative model
  - if we had the parameters,
    $\longrightarrow$ we could estimate the alignments

EM Algorithm

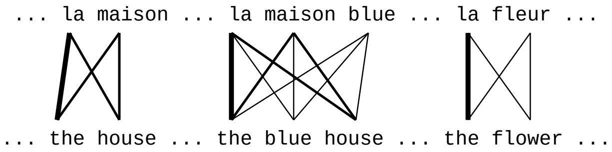
- Incomplete data
  - if we had complete data, would could estimate model
  - if we had model, we could fill in the gaps in the data
- Expectation Maximization (EM) in a nutshell
  1. initialize model parameters (e.g. uniform)
  2. assign probabilities to the missing data
  3. estimate model parameters from completed data
  4. iterate steps 2–3 until convergence

EM Algorithm



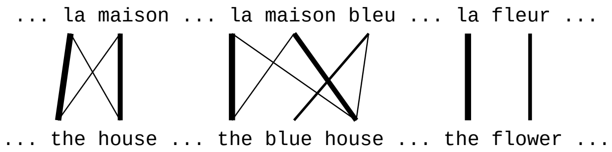
- Initial step: all alignments equally likely
- Model learns that, e.g., la is often aligned with the

EM Algorithm



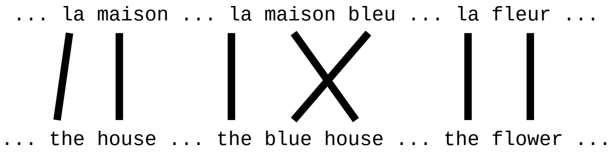
- After one iteration
- Alignments, e.g., between la and the are more likely

EM Algorithm



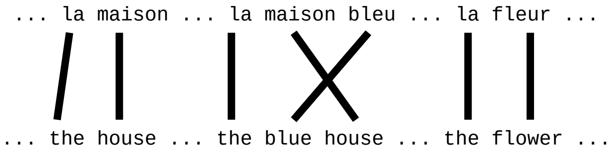
- After another iteration
- It becomes apparent that alignments, e.g., between fleur and flower are more likely (pigeon hole principle)

EM Algorithm



- Convergence
- Inherent hidden structure revealed by EM

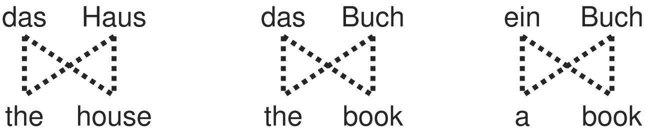
EM Algorithm



p(la|the) = 0.453
p(le|the) = 0.334
p(maison|house) = 0.876
p(bleu|blue) = 0.563
...

- Parameter estimation from the aligned corpus

Convergence



e	*f*	initial	1st it.	2nd it.	...	final
the	das	0.25	0.5	0.6364	...	1
book	das	0.25	0.25	0.1818	...	0
house	das	0.25	0.25	0.1818	...	0
the	buch	0.25	0.25	0.1818	...	0
book	buch	0.25	0.5	0.6364	...	1
a	buch	0.25	0.25	0.1818	...	0
book	ein	0.25	0.5	0.4286	...	0
a	ein	0.25	0.5	0.5714	...	1
the	haus	0.25	0.5	0.4286	...	0
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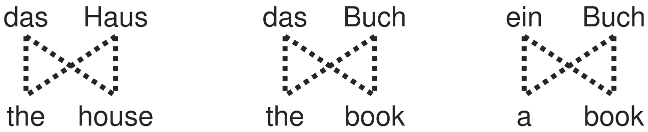

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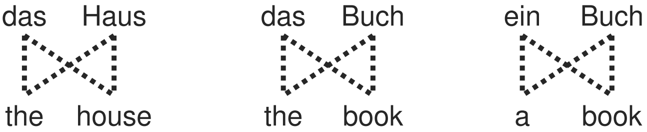

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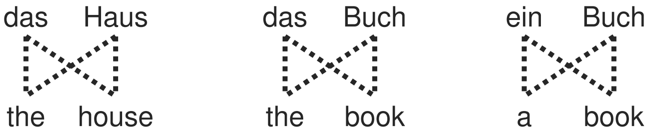

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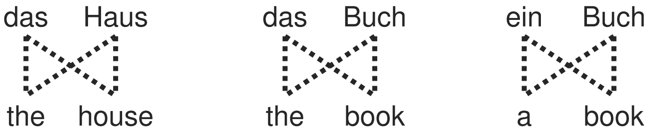

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Ensuring Fluent Output

- Our translation model cannot decide between small and little
- Sometime one is preferred over the other:
  - small step: 2,070,000 occurrences in the Google index
  - little step: 257,000 occurrences in the Google index
- Language model
  - estimate how likely a string is English
  - based on n-gram statistics

$$\begin{aligned} p(\mathbf{e}) &= p(e_1, e_2, \ldots, e_n) \\ &= p(e_1)p(e_2|e_1)\ldots p(e_n|e_1, e_2, \ldots, e_{n-1}) \\ &\simeq p(e_1)p(e_2|e_1)\ldots p(e_n|e_{n-2}, e_{n-1}) \end{aligned}$$

Noisy Channel Model

- Bayes rule

$$p(a|b) = \frac{p(b|a)p(a)}{p(b)} \tag{1}$$

(2)

Noisy Channel Model

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- Turning English into Foreign

$$= \arg\max_{\mathbf{e}} p(\mathbf{e}) \tag{2}$$

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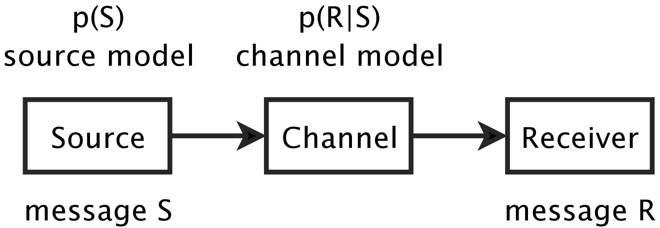

- Applying Bayes rule also called noisy channel model
  - we observe a distorted message R (here: a foreign string **f**)
  - we have a model on how the message is distorted (here: translation model)
  - we have a model on what messages are probably (here: language model)
  - we want to recover the original message S (here: an English string **e**)

Higher IBM Models

IBM Model 1	lexical translation
IBM Model 2	adds absolute reordering model
IBM Model 3	adds fertility model
IBM Model 4	relative reordering model
IBM Model 5	fixes deficiency

- Only IBM Model 1 has global maximum
  - ▶ training of a higher IBM model builds on previous model
- Compuationally biggest change in Model 3
  - ▶ trick to simplify estimation does not work anymore
  - $\longrightarrow$ exhaustive count collection becomes computationally too expensive
  - ▶ sampling over high probability alignments is used instead

Legacy

- IBM Models were the pioneering models in statistical machine translation
- Introduced important concepts
  - generative model
  - EM training
  - reordering models

Attention vs. Alignment

What does Attention in Neural Machine Translation Pay Attention to?

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