
IBM Model 1 and the EM Algorithm

Philipp Koehn

14 September 2017



Lexical Translation



- How to translate a word → look up in dictionary

Haus — house, building, home, household, shell.

- Multiple translations
 - some more frequent than others
 - for instance: **house**, and **building** most common
 - special cases: **Haus** of a **snail** is its **shell**
- Note: In all lectures, we translate from a foreign language into English

Collect Statistics



2

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

Translation of <i>Haus</i>	Count
house	8,000
building	1,600
home	200
household	150
shell	50

Estimate Translation Probabilities



3

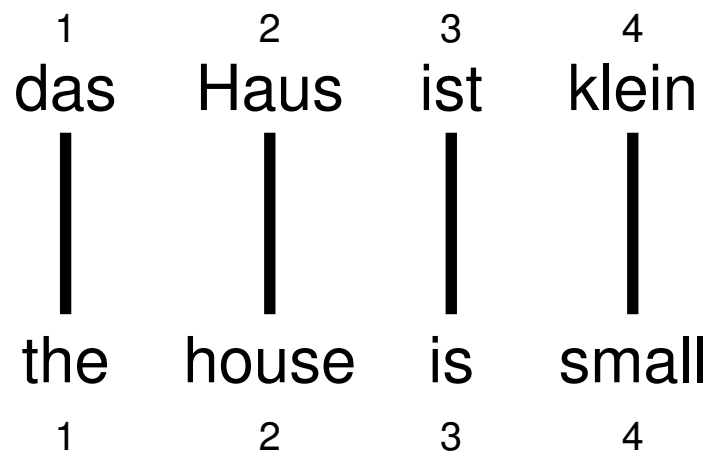
Maximum likelihood estimation

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

Alignment



- In a parallel text (or when we translate), we align words in one language with the words in the other



- Word positions are numbered 1–4

Alignment Function



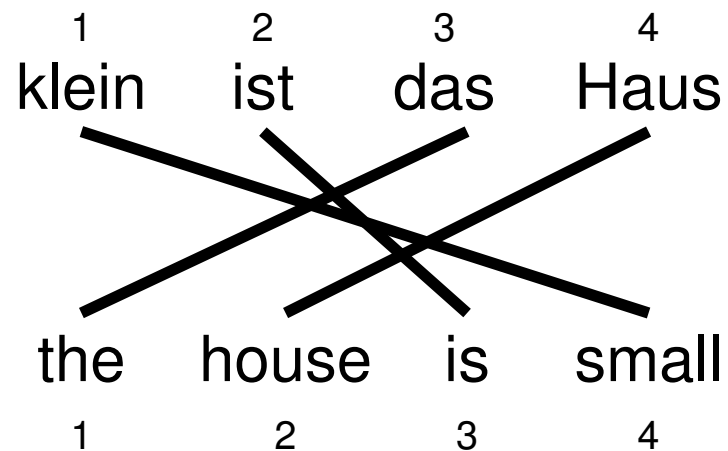
- Formalizing alignment with an alignment function
- Mapping an English target word at position i to a German source word at position j with a function $a : i \rightarrow j$
- Example

$$a : \{1 \rightarrow 1, 2 \rightarrow 2, 3 \rightarrow 3, 4 \rightarrow 4\}$$

Reordering



Words may be reordered during translation

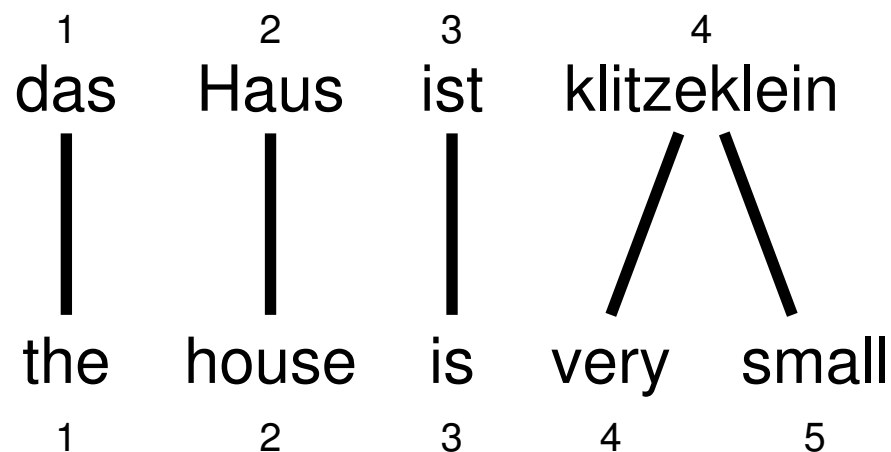


$$a : \{1 \rightarrow 3, 2 \rightarrow 4, 3 \rightarrow 2, 4 \rightarrow 1\}$$

One-to-Many Translation



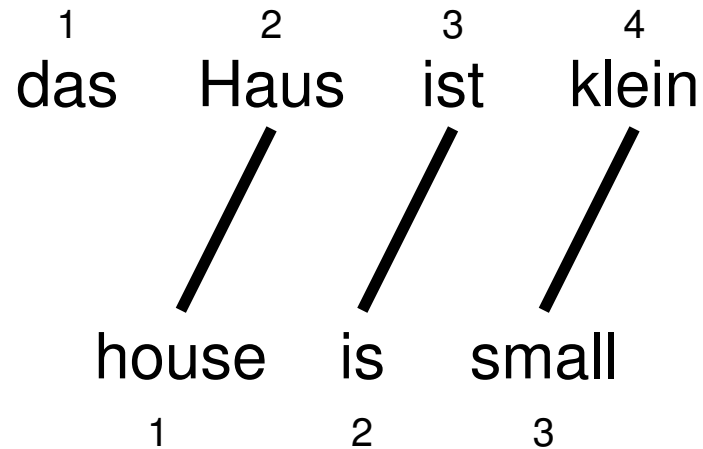
A source word may translate into multiple target words



$$a : \{1 \rightarrow 1, 2 \rightarrow 2, 3 \rightarrow 3, 4 \rightarrow 4, 5 \rightarrow 4\}$$

Dropping Words

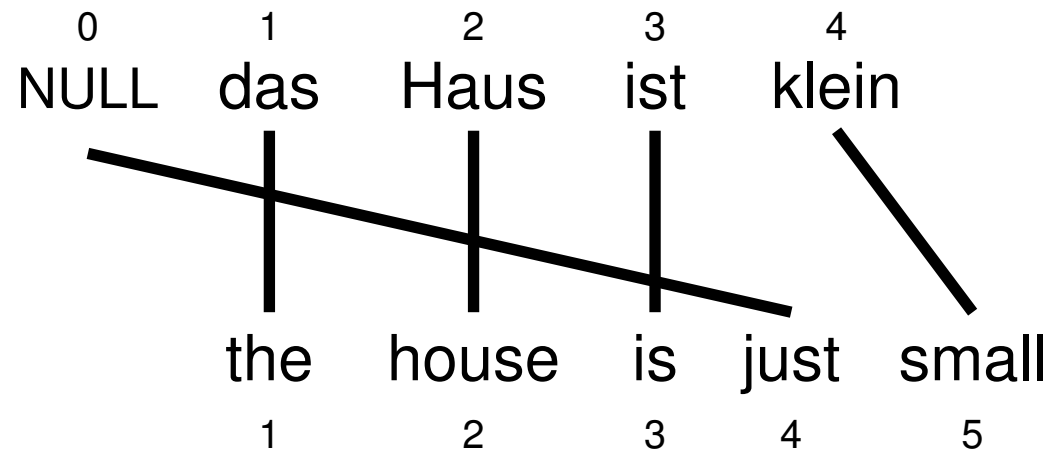
Words may be dropped when translated
(German article **das** is dropped)



$$a : \{1 \rightarrow 2, 2 \rightarrow 3, 3 \rightarrow 4\}$$

Inserting Words

- Words may be added during translation
 - The English **just** does not have an equivalent in German
 - We still need to map it to something: special NULL token



$$a : \{1 \rightarrow 1, 2 \rightarrow 2, 3 \rightarrow 3, 4 \rightarrow 0, 5 \rightarrow 4\}$$

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 $\mathbf{f} = (f_1, \dots, f_{l_f})$ of length l_f
 - to an English sentence $\mathbf{e} = (e_1, \dots, e_{l_e})$ 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

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
household	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

$$\begin{aligned} p(e, a|f) &= \frac{\epsilon}{4^3} \times t(\text{the}|\text{das}) \times t(\text{house}|\text{Haus}) \times t(\text{is}|\text{ist}) \times t(\text{small}|\text{klein}) \\ &= \frac{\epsilon}{4^3} \times 0.7 \times 0.8 \times 0.8 \times 0.4 \\ &= 0.0028\epsilon \end{aligned}$$

finding translations

Centauri-Arcturan Parallel Text

1a. ok-voon ororok sprok .

1b. at-voon bichat dat .

2a. ok-drubel ok-voon anak plok sprok .

2b. at-drubel at-voon pippat rrat dat .

3a. erok sprok izok hihok ghirok .

3b. totat dat arrat vat hilat .

4a. ok-voon anak drok brok jok .

4b. at-voon krat pippat sat lat .

5a. wiwok farok izok stok .

5b. totat jjat quat cat .

6a. lalok sprok izok jok stok .

6b. wat dat krat quat cat .

7a. lalok farok ororok lalok sprok izok enemok .

7b. wat jjat bichat wat dat vat eneat .

8a. lalok brok anak plok nok .

8b. iat lat pippat rrat nnat .

9a. wiwok nok izok kantok ok-yurp .

9b. totat nnat quat oloat at-yurp .

10a. lalok mok nok yorok ghirok klok .

10b. wat nnat gat mat bat hilat .

11a. lalok nok crrrok hihok yorok zanzanok .

11b. wat nnat arrat mat zanzanat .

12a. lalok rarok nok izok hihok mok .

12b. wat nnat forat arrat vat gat .

Translation challenge: **farok crrrok hihok yorok klok kantok ok-yurp**

(from Knight (1997): Automating Knowledge Acquisition for Machine Translation)



em algorithm

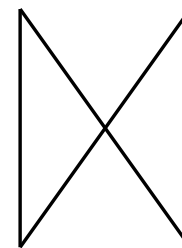
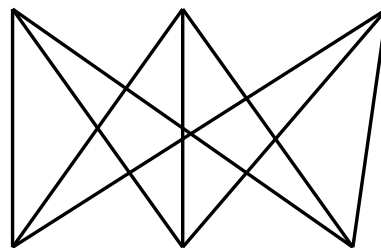
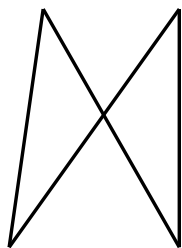
- We would like to estimate the lexical translation probabilities $t(e|f)$ from a parallel corpus
- ... but we do not have the alignments
- Chicken and egg problem
 - if we had the *alignments*,
→ we could estimate the *parameters* of our generative model
 - if we had the *parameters*,
→ we could estimate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

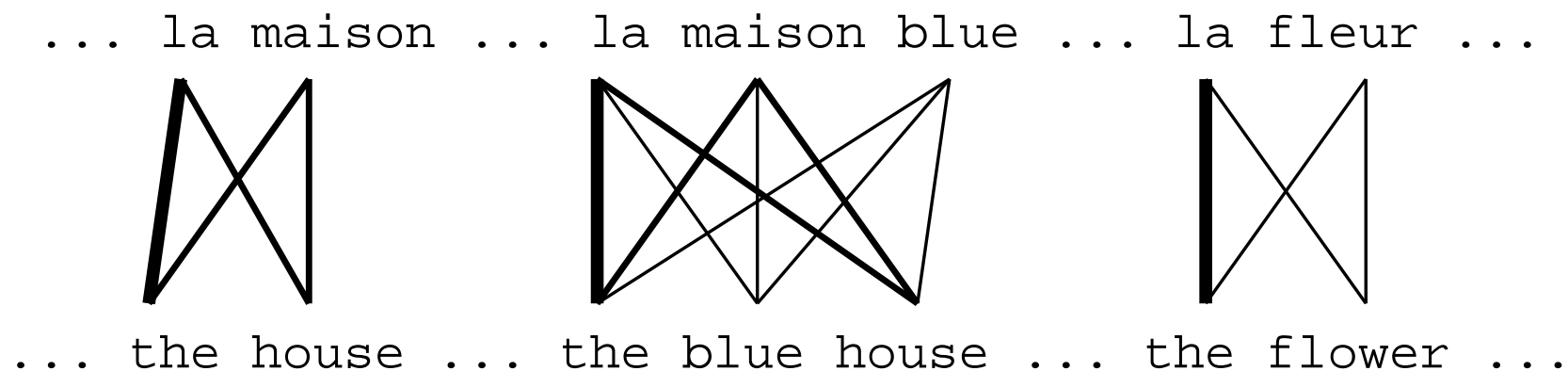
... la maison ... la maison blue ... la fleur ...



... the house ... the blue house ... the flower ...

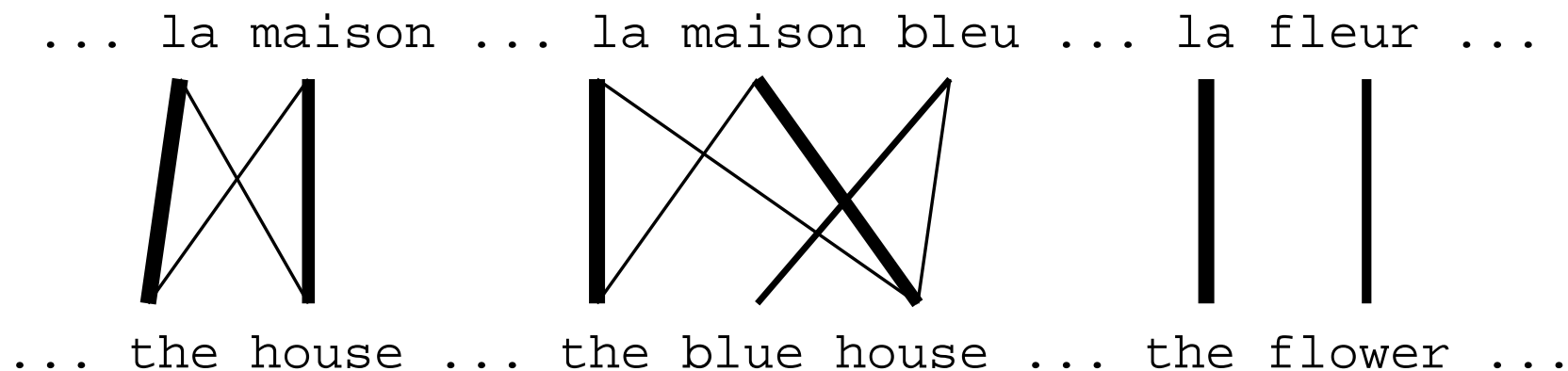
- Initial step: all alignments equally likely
- Model learns that, e.g., **la** is often aligned with **the**

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

... la maison ... la maison bleu ... la fleur ...
/ | | X | |
... the house ... the blue house ... the flower ...

- Convergence
- Inherent hidden structure revealed by EM

EM Algorithm

21



... la maison ... la maison bleu ... la fleur ...
/ | | X | |
... the house ... the blue house ... the flower ...



$p(\text{la}|\text{the}) = 0.453$
 $p(\text{le}|\text{the}) = 0.334$
 $p(\text{maison}|\text{house}) = 0.876$
 $p(\text{bleu}|\text{blue}) = 0.563$
...

- Parameter estimation from the aligned corpus

IBM Model 1 and EM

- EM Algorithm consists of two steps
- Expectation-Step: Apply model to the data
 - parts of the model are hidden (here: alignments)
 - using the model, assign probabilities to possible values
- Maximization-Step: Estimate model from data
 - take assign values as fact
 - collect counts (weighted by probabilities)
 - estimate model from counts
- Iterate these steps until convergence

IBM Model 1 and EM

- We need to be able to compute:
 - Expectation-Step: probability of alignments
 - Maximization-Step: count collection

IBM Model 1 and EM

- Probabilities

$$\begin{aligned} p(\text{the}|\text{la}) &= 0.7 & p(\text{house}|\text{la}) &= 0.05 \\ p(\text{the}|\text{maison}) &= 0.1 & p(\text{house}|\text{maison}) &= 0.8 \end{aligned}$$

- Alignments



$$p(\mathbf{e}, a|\mathbf{f}) = 0.56 \quad p(\mathbf{e}, a|\mathbf{f}) = 0.035 \quad p(\mathbf{e}, a|\mathbf{f}) = 0.08 \quad p(\mathbf{e}, a|\mathbf{f}) = 0.005$$

$$p(a|\mathbf{e}, \mathbf{f}) = 0.824 \quad p(a|\mathbf{e}, \mathbf{f}) = 0.052 \quad p(a|\mathbf{e}, \mathbf{f}) = 0.118 \quad p(a|\mathbf{e}, \mathbf{f}) = 0.007$$

- Counts

$$\begin{aligned} c(\text{the}|\text{la}) &= 0.824 + 0.052 & c(\text{house}|\text{la}) &= 0.052 + 0.007 \\ c(\text{the}|\text{maison}) &= 0.118 + 0.007 & c(\text{house}|\text{maison}) &= 0.824 + 0.118 \end{aligned}$$

IBM Model 1 and EM: Expectation Step

- We need to compute $p(a|\mathbf{e}, \mathbf{f})$
- Applying the chain rule:

$$p(a|\mathbf{e}, \mathbf{f}) = \frac{p(\mathbf{e}, a|\mathbf{f})}{p(\mathbf{e}|\mathbf{f})}$$

- We already have the formula for $p(\mathbf{e}, \mathbf{a}|\mathbf{f})$ (definition of Model 1)

IBM Model 1 and EM: Expectation Step

- We need to compute $p(\mathbf{e}|\mathbf{f})$

$$\begin{aligned} p(\mathbf{e}|\mathbf{f}) &= \sum_a p(\mathbf{e}, a|\mathbf{f}) \\ &= \sum_{a(1)=0}^{l_f} \dots \sum_{a(l_e)=0}^{l_f} p(\mathbf{e}, a|\mathbf{f}) \\ &= \sum_{a(1)=0}^{l_f} \dots \sum_{a(l_e)=0}^{l_f} \frac{\epsilon}{(l_f + 1)^{l_e}} \prod_{j=1}^{l_e} t(e_j | f_{a(j)}) \end{aligned}$$

IBM Model 1 and EM: Expectation Step

$$\begin{aligned} p(\mathbf{e}|\mathbf{f}) &= \sum_{a(1)=0}^{l_f} \dots \sum_{a(l_e)=0}^{l_f} \frac{\epsilon}{(l_f + 1)^{l_e}} \prod_{j=1}^{l_e} t(e_j | f_{a(j)}) \\ &= \frac{\epsilon}{(l_f + 1)^{l_e}} \sum_{a(1)=0}^{l_f} \dots \sum_{a(l_e)=0}^{l_f} \prod_{j=1}^{l_e} t(e_j | f_{a(j)}) \\ &= \frac{\epsilon}{(l_f + 1)^{l_e}} \prod_{j=1}^{l_e} \sum_{i=0}^{l_f} t(e_j | f_i) \end{aligned}$$

- Note the trick in the last line
 - removes the need for an exponential number of products
 - this makes IBM Model 1 estimation tractable

The Trick

(case $l_e = l_f = 2$)

$$\begin{aligned} \sum_{a(1)=0}^2 \sum_{a(2)=0}^2 &= \frac{\epsilon}{3^2} \prod_{j=1}^2 t(e_j | f_{a(j)}) = \\ &= t(e_1 | f_0) t(e_2 | f_0) + t(e_1 | f_0) t(e_2 | f_1) + t(e_1 | f_0) t(e_2 | f_2) + \\ &\quad + t(e_1 | f_1) t(e_2 | f_0) + t(e_1 | f_1) t(e_2 | f_1) + t(e_1 | f_1) t(e_2 | f_2) + \\ &\quad + t(e_1 | f_2) t(e_2 | f_0) + t(e_1 | f_2) t(e_2 | f_1) + t(e_1 | f_2) t(e_2 | f_2) = \\ &= t(e_1 | f_0) (t(e_2 | f_0) + t(e_2 | f_1) + t(e_2 | f_2)) + \\ &\quad + t(e_1 | f_1) (t(e_2 | f_1) + t(e_2 | f_1) + t(e_2 | f_2)) + \\ &\quad + t(e_1 | f_2) (t(e_2 | f_2) + t(e_2 | f_1) + t(e_2 | f_2)) = \\ &= (t(e_1 | f_0) + t(e_1 | f_1) + t(e_1 | f_2)) (t(e_2 | f_2) + t(e_2 | f_1) + t(e_2 | f_2)) \end{aligned}$$

- Combine what we have:

$$\begin{aligned} p(\mathbf{a}|\mathbf{e}, \mathbf{f}) &= p(\mathbf{e}, \mathbf{a}|\mathbf{f})/p(\mathbf{e}|\mathbf{f}) \\ &= \frac{\frac{\epsilon}{(l_f+1)^{l_e}} \prod_{j=1}^{l_e} t(e_j|f_{a(j)})}{\frac{\epsilon}{(l_f+1)^{l_e}} \prod_{j=1}^{l_e} \sum_{i=0}^{l_f} t(e_j|f_i)} \\ &= \prod_{j=1}^{l_e} \frac{t(e_j|f_{a(j)})}{\sum_{i=0}^{l_f} t(e_j|f_i)} \end{aligned}$$

IBM Model 1 and EM: Maximization Step

30



- Now we have to collect counts
- Evidence from a sentence pair \mathbf{e}, \mathbf{f} that word e is a translation of word f :

$$c(e|f; \mathbf{e}, \mathbf{f}) = \sum_a p(a|\mathbf{e}, \mathbf{f}) \sum_{j=1}^{l_e} \delta(e, e_j) \delta(f, f_{a(j)})$$

- With the same simplification as before:

$$c(e|f; \mathbf{e}, \mathbf{f}) = \frac{t(e|f)}{\sum_{i=0}^{l_f} t(e|f_i)} \sum_{j=1}^{l_e} \delta(e, e_j) \sum_{i=0}^{l_f} \delta(f, f_i)$$

IBM Model 1 and EM: Maximization Step

31



After collecting these counts over a corpus, we can estimate the model:

$$t(e|f; \mathbf{e}, \mathbf{f}) = \frac{\sum_{(\mathbf{e}, \mathbf{f})} c(e|f; \mathbf{e}, \mathbf{f})}{\sum_e \sum_{(\mathbf{e}, \mathbf{f})} c(e|f; \mathbf{e}, \mathbf{f})}$$

IBM Model 1 and EM: Pseudocode

Input: set of sentence pairs (**e**, **f**)

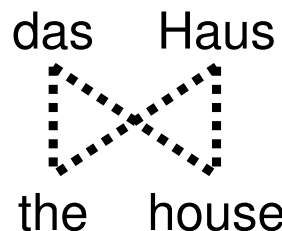
Output: translation prob. $t(e|f)$

```
1: initialize  $t(e|f)$  uniformly
2: while not converged do
3:   // initialize
4:    $\text{count}(e|f) = 0$  for all  $e, f$ 
5:    $\text{total}(f) = 0$  for all  $f$ 
6:   for all sentence pairs (e, f) do
7:     // compute normalization
8:     for all words  $e$  in e do
9:        $\text{s-total}(e) = 0$ 
10:      for all words  $f$  in f do
11:         $\text{s-total}(e) += t(e|f)$ 
12:      end for
13:    end for
```

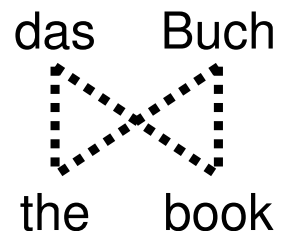
```
14:   // collect counts
15:   for all words  $e$  in e do
16:     for all words  $f$  in f do
17:        $\text{count}(e|f) += \frac{t(e|f)}{\text{s-total}(e)}$ 
18:        $\text{total}(f) += \frac{t(e|f)}{\text{s-total}(e)}$ 
19:     end for
20:   end for
21: end for
22: // estimate probabilities
23: for all foreign words  $f$  do
24:   for all English words  $e$  do
25:      $t(e|f) = \frac{\text{count}(e|f)}{\text{total}(f)}$ 
26:   end for
27: end for
28: end while
```

Convergence

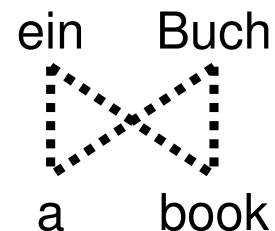
das Haus
the house



das Buch
the book



ein Buch
a book



e	f	initial	1st it.	2nd it.	3rd it.	...	final
the	das	0.25	0.5	0.6364	0.7479	...	1
book	das	0.25	0.25	0.1818	0.1208	...	0
house	das	0.25	0.25	0.1818	0.1313	...	0
the	buch	0.25	0.25	0.1818	0.1208	...	0
book	buch	0.25	0.5	0.6364	0.7479	...	1
a	buch	0.25	0.25	0.1818	0.1313	...	0
book	ein	0.25	0.5	0.4286	0.3466	...	0
a	ein	0.25	0.5	0.5714	0.6534	...	1
the	haus	0.25	0.5	0.4286	0.3466	...	0
house	haus	0.25	0.5	0.5714	0.6534	...	1

Perplexity

- How well does the model fit the data?
- Perplexity: derived from probability of the training data according to the model

$$\log_2 PP = - \sum_s \log_2 p(\mathbf{e}_s | \mathbf{f}_s)$$

- Example ($\epsilon=1$)

	initial	1st it.	2nd it.	3rd it.	...	final
$p(\text{the haus} \text{das haus})$	0.0625	0.1875	0.1905	0.1913	...	0.1875
$p(\text{the book} \text{das buch})$	0.0625	0.1406	0.1790	0.2075	...	0.25
$p(\text{a book} \text{ein buch})$	0.0625	0.1875	0.1907	0.1913	...	0.1875
perplexity	4095	202.3	153.6	131.6	...	113.8

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
- Computationally biggest change in Model 3
 - trick to simplify estimation does not work anymore
 - exhaustive count collection becomes computationally too expensive
 - sampling over high probability alignments is used instead

word alignment

Word Alignment

Given a sentence pair, which words correspond to each other?











	michael	geht	davon	aus	,	dass	er	im	haus	bleibt
michael										
assumes										
that										
he										
will										
stay										
in										
the										
house										

Word Alignment?

	john	wohnt	hier	nicht
john				
does		?		?
not				
live				
here				

Is the English word **does** aligned to the German **wohnt** (verb) or **nicht** (negation) or neither?

Word Alignment?

	john	biss	ins	grass
john				
kicked				
the				
bucket				

How do the idioms **kicked the bucket** and **biss ins grass** match up?
Outside this exceptional context, **bucket** is never a good translation for **grass**

Measuring Word Alignment Quality

- Manually align corpus with *sure* (S) and *possible* (P) alignment points ($S \subseteq P$)
- Common metric for evaluation word alignments: Alignment Error Rate (AER)

$$\text{AER}(S, P; A) = \frac{|A \cap S| + |A \cap P|}{|A| + |S|}$$

- $\text{AER} = 0$: alignment A matches all sure, any possible alignment points
- However: different applications require different precision/recall trade-offs

symmetrization

Word Alignment with IBM Models

- IBM Models create a **many-to-one** mapping
 - words are aligned using an alignment function
 - a function may return the same value for different input (one-to-many mapping)
 - a function can not return multiple values for one input (no many-to-one mapping)
- Real word alignments have **many-to-many** mappings

- Run IBM Model training in both directions

→ two sets of word alignment points

- Intersection: high precision alignment points
- Union: high recall alignment points
- Refinement methods explore the sets between intersection and union

Example

english to spanish

	Maria no daba una				bofetada a		la bruja		verde
Mary	■								
did						■			
not		■							
slap			■	■	■				
the							■		
green									■
witch								■	

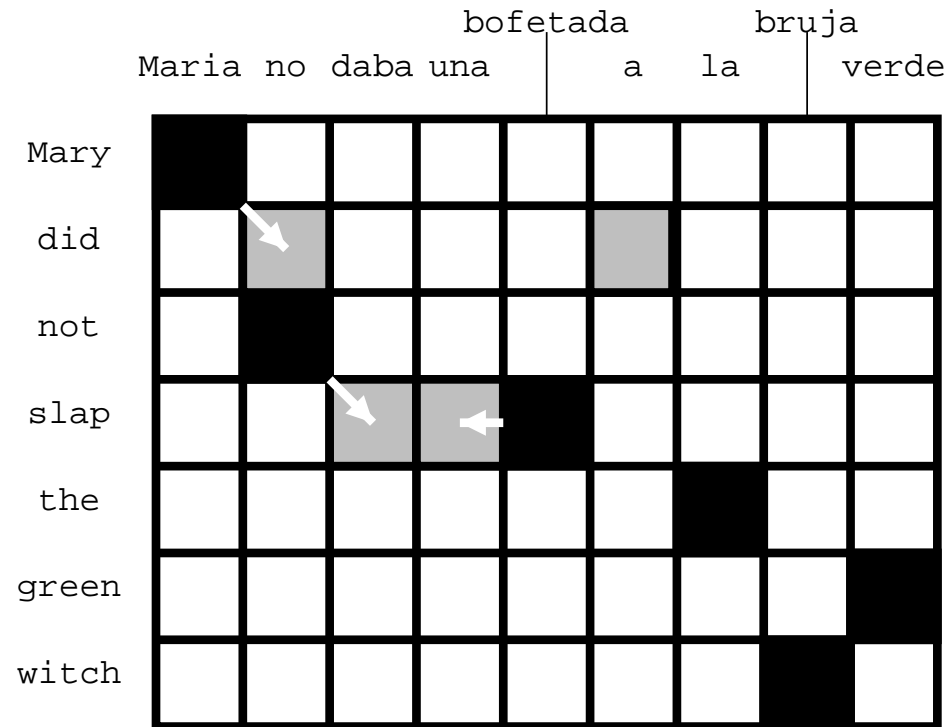
spanish to english

	Maria no daba una				bofetada a		la bruja		verde
Mary	■								
did		■	■						
not		■							
slap						■			
the							■		
green									■
witch								■	

intersection

	Maria no daba una				bofetada a		la bruja		verde
Mary	■								
did									
not		■							
slap						■			
the							■		
green									■
witch								■	

Growing Heuristics



black: intersection

grey: additional points in union

- Add alignment points from union based on heuristics:
 - directly/diagonally neighboring points
 - finally, add alignments that connect unaligned words in source and/or target
- Popular method: grow-diag-final-and