



# Lecture 4.3: Learning lexical translations

IBM model 1

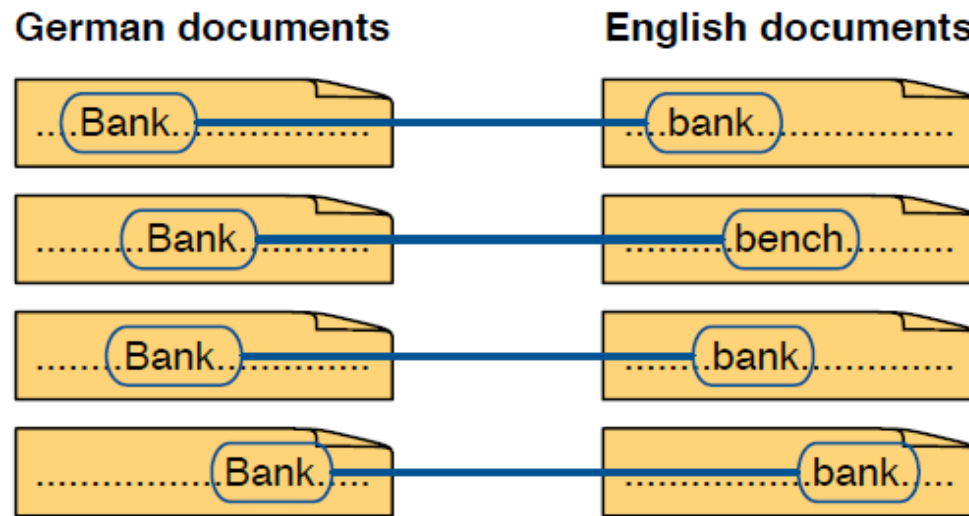
*Preparation for the lab*  
*slides borrowed from Philipp Koehn*

# Guessing game:

Indonesian	English	
Ayam bakar	Grilled chicken	
Ayam goreng	Fried chicken	
Bebek goreng	Fried duck	
Ikan bakar	Grilled fish	
Ikan goreng	? ?	

Goreng=?  
 Ayam=?  
 Bakar=?  
 Ikan=?  
 Bebek=?

- Collect counts, infer probabilities



$$\Rightarrow p(\text{bank}|\text{Bank}) = 0.75, p(\text{bench}|\text{Bank}) = 0.25$$

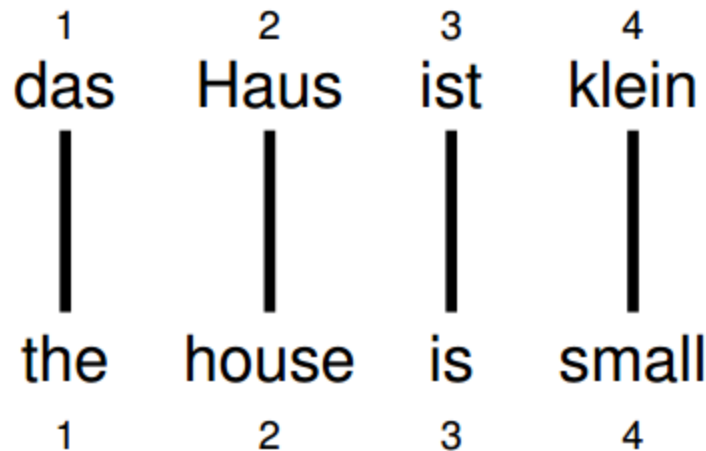


Courtesy of Philipp Koehn, Professor  
at The Johns Hopkins University



# Alignments

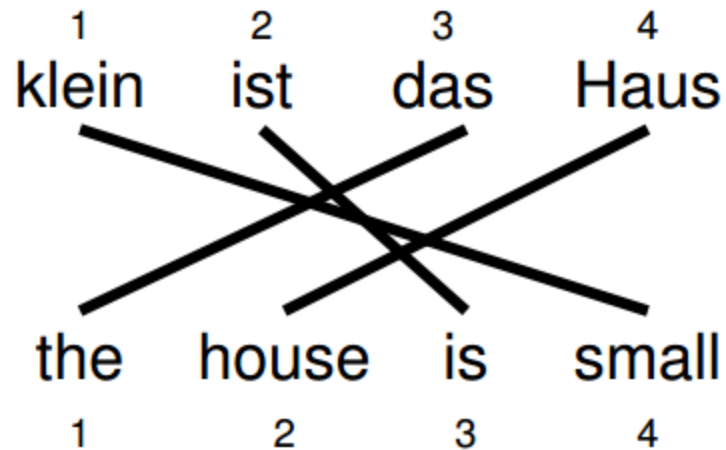
- Alignments are the “links” between words in parallel sentences
- Word positions numbered 1-4



English target word at position  $i$  to a German source word at position  $j$  with a function  $a : i \rightarrow j$

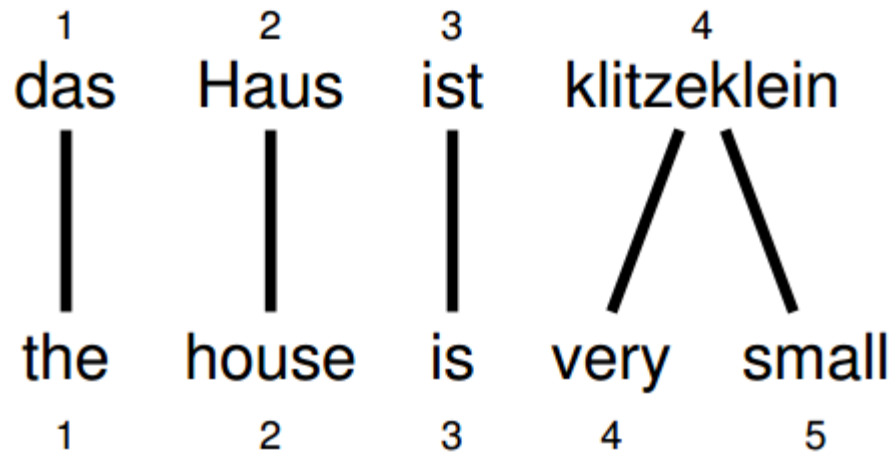
$$a : \{1 \rightarrow 1, 2 \rightarrow 2, 3 \rightarrow 3, 4 \rightarrow 4\}$$

# Alignment reordering



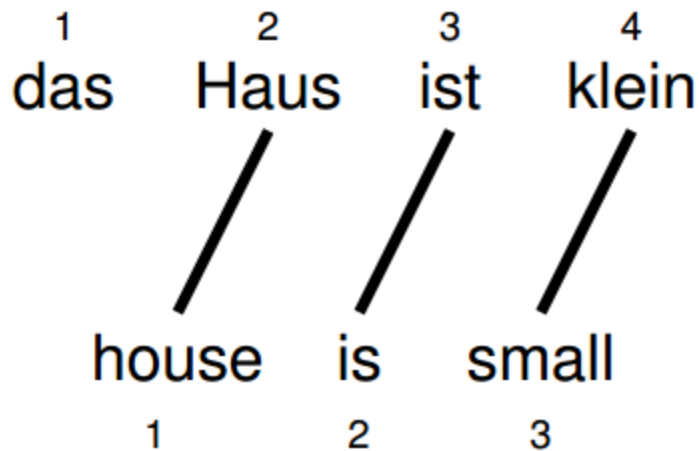
$$a : \{1 \rightarrow 3, 2 \rightarrow 4, 3 \rightarrow 2, 4 \rightarrow 1\}$$

# Alignment: one to many

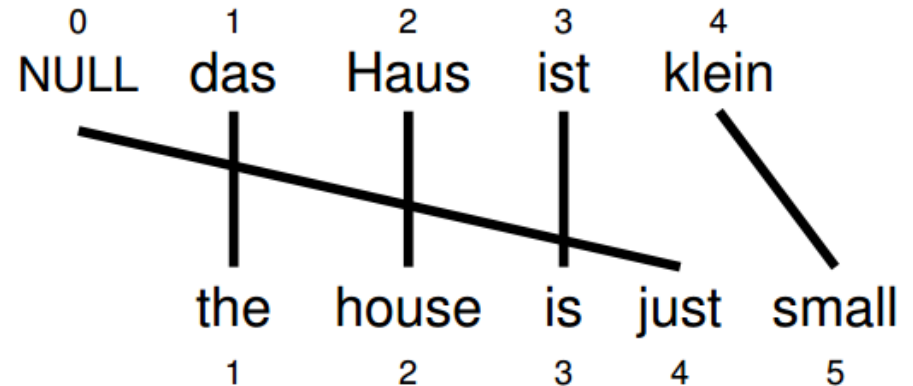


$$a : \{1 \rightarrow 1, 2 \rightarrow 2, 3 \rightarrow 3, 4 \rightarrow 4, 5 \rightarrow 4\}$$

# Dropping/insert words



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



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

# 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  $f = (f_1, \dots, f_{l_f})$  of length  $l_f$
  - to an English sentence  $e = (e_1, \dots, e_{l_e})$  of length  $l_e$
  - with an alignment of each English word  $e_j$  to a foreign word  $f_i$  according to the alignment function  $a : j \rightarrow i$

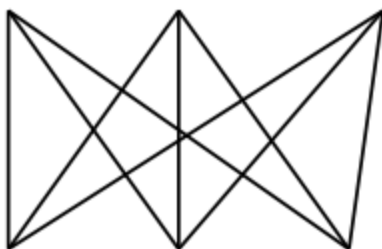
$$p(\mathbf{e}, a | \mathbf{f}) = \frac{\epsilon}{(l_f + 1)^{l_e}} \prod_{j=1}^{l_e} t(e_j | f_{a(j)})$$

- parameter  $\epsilon$  is a normalization constant



- Incomplete data
  - if we had complete data, we 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

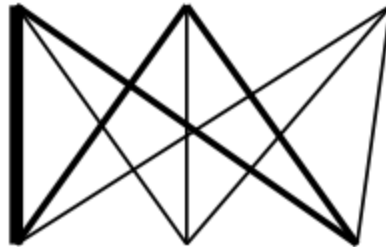
... la maison ... la maison blue ... la fleur ...



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

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

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



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

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

... la maison ... la maison bleu ... la fleur ...



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



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

... la maison ... la maison bleu ... la fleur ...



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

- Convergence
- Inherent hidden structure revealed by EM

... la maison ... la maison bleu ... la fleur ...

... 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

- **Probabilities**

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

- **Alignments**

			
$p(\mathbf{e}, a \mathbf{f}) = 0.56$	$p(\mathbf{e}, a \mathbf{f}) = 0.035$	$p(\mathbf{e}, a \mathbf{f}) = 0.08$	$p(\mathbf{e}, a \mathbf{f}) = 0.005$
$p(a \mathbf{e}, \mathbf{f}) = 0.824$	$p(a \mathbf{e}, \mathbf{f}) = 0.052$	$p(a \mathbf{e}, \mathbf{f}) = 0.118$	$p(a \mathbf{e}, \mathbf{f}) = 0.007$

- **Counts**

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

# IBM model 1 pseudo code

**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



<i>e</i>	<i>f</i>	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